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UNIVERSITY OF PIRAEUS
SCHOOL OF MARITIME AND INDUSTRIAL STUDIES

DEPARTMENT OF INDUSTRIAL MANAGEMENT AND TECHNOLOGY

“Exploring regulatory designs and product-service offerings to empower end-users and incentivise demand flexibility: A modelling framework in support to low-carbon energy systems”

Doctoral dissertation thesis

By

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Athens, January 2022

Vassilis Stavrakas

"Από το σκοτάδι στο φως απολαμβάνω τη μετάβαση
τόσο μοναδικός που με χάνουνε στη μετάφραση"

Abstract (in Greek)

Η Ευρωπαϊκή Ένωση έχει αναλάβει σταθερά έναν ηγετικό ρόλο στο διεθνές τοπίο χάραξης πολιτικών για το κλίμα και την ενέργεια υιοθετώντας σχετικές στρατηγικές και προωθώντας μια φιλόδοξη «Πράσινη Συμφωνία» για την επίτευξη κλιματικής ουδετερότητας έως το 2050. Αν και ο δρόμος προς την κλιματική ουδετερότητα είναι μακρινός και γεμάτος αβεβαιότητες, οι αποφάσεις είναι επείγουσες: οι υπεύθυνοι χάραξης πολιτικής πρέπει από τώρα να πάρουν τις σωστές αποφάσεις που θα δημιουργήσουν τις κατάλληλες συνθήκες για ενεργειακά συστήματα τα οποία θα βασίζονται σε μεγάλα μερίδια ανανεώσιμων πηγών ενέργειας μέχρι τα μέσα του αιώνα. Οι αποφάσεις αυτές έχουν συνέπειες πολλαπλών διαστάσεων, η αξιολόγηση των οποίων, τόσο σε εθνικό όσο και σε Ευρωπαϊκό επίπεδο, δεν μπορεί να πραγματοποιηθεί βάσει εμπειρικών/ πειραματικών μεθόδων. Κατά συνέπεια, οι φορείς χάραξης πολιτικών βασίζουν τη διαδικασία λήψης αποφάσεων σε αποτελέσματα και προβλέψεις υπολογιστικών εργαλείων μοντελοποίησης/ προσομοίωσης. Τα υπολογιστικά εργαλεία αυτά μπορούν να υποστηρίξουν το σχεδιασμό πολιτικών προς ένα αβέβαιο μέλλον, ενώ μπορούν, επίσης, να αξιολογήσουν ήδη υπάρχουσες πολιτικές παρέχοντας εμπεριστατωμένη επιχειρηματολογία σχετικά με την αποτελεσματικότητα τους.

Οι εξελίξεις στο πεδίο της μοντελοποίησης/ προσομοίωσης ενεργειακών συστημάτων έχουν αδιαμφισβήτητα προχωρήσει πολύ γρήγορα τις τελευταίες δύο δεκαετίες με την αύξηση της λεπτομέρειας απεικόνισης των διάφορων τομέων τελικής κατανάλωσης και του αντίστοιχου χαρτοφυλακίου τεχνολογιών. Παρόλα αυτά, οι συγκεκριμένες εξελίξεις έχουν επιφέρει, παράλληλα, και μία αύξηση της υπολογιστικής πολυπλοκότητας των υπολογιστικών εργαλείων αυτών, τα οποία γίνονται ολοένα και μεγαλύτερα και πιο σύνθετα, παραμένοντας συνεχώς στα όρια αυτού που είναι υπολογιστικά εφικτό. Ωστόσο, δεν είναι ακόμα σαφές εάν τα υφιστάμενα υπολογιστικά εργαλεία μοντελοποίησης/ προσομοίωσης ενεργειακών συστημάτων γίνονται καλύτερα, με την έννοια του αν είναι ικανά να δώσουν απαντήσεις σε όλα τα κρίσιμα θέματα του ενεργειακού σχεδιασμού στο δρόμο προς την κλιματική ουδετερότητα του 2050, με τρόπο ο οποίος θα είναι χρήσιμος για τους τελικούς χρήστες των αποτελεσμάτων τους.

Ένα από τα μεγαλύτερα μειονεκτήματα των υφιστάμενων εργαλείων είναι ότι εστιάζουν περισσότερο στο κομμάτι της προσφοράς ενέργειας, ενώ η πλευρά της ζήτησης παραμένει ελλιπώς εκπροσωπούμενη, εστιάζοντας κυρίως σε σενάρια βελτίωσης της ενεργειακής εξοικονόμησης. Επιπρόσθετα, η ανάγκη για διεπιστημονικότητα επιτάσσει όχι μόνο τη διερεύνηση του “*τι*”, αλλά και την αξιολόγηση της σκοπιμότητας και της επιθυμητότητας, από την άποψη του “*πότε*”, του “*πού*”, και, ιδιαίτερα, του για “ποιον.” Χωρίς τους απαραίτητους μετασχηματισμούς συμπεριφοράς των κοινωνικών υποδομών, ο κόσμος αντιμετωπίζει μια ανεπαρκή απάντηση στην πρόκληση της κλιματικής αλλαγής. Λαμβάνοντας υπόψιν ότι οι συμπεριφορικοί μετασχηματισμοί θα ξεκινήσουν από τον τομέα της ζήτησης, μιας και εκεί οι τελικοί χρήστες/ καταναλωτές έχουν πιο άμεσο ρόλο, χρειαζόμαστε ένα ολιστικό πλαίσιο διεπιστημονικότητας για την επαρκή μοντελοποίηση/ προσομοίωση του ρόλου και της επίδρασης των ανθρώπινων επιλογών στη μετάβαση προς οικονομίες/ κοινωνίες χαμηλών εκπομπών διοξειδίου του άνθρακα, ξεκινώντας από τις επιθυμίες των ατόμων και αναλύοντας επαρκώς το “*πώς*” αυτά αλληλοεπιδρούν με το ενεργειακό και οικονομικό τοπίο, οδηγώντας σε συστημική αλλαγή σε μάκρο-επίπεδο.

Σε αυτό το πλαίσιο, προκύπτει η ανάγκη βελτίωσης των υφιστάμενων υπολογιστικών εργαλείων μοντελοποίησης/ προσομοίωσης ενεργειακών συστημάτων, καθώς επίσης η ανάπτυξη νέων που θα αποσκοπούν στην περαιτέρω διερεύνηση ακραίων σεναρίων ενεργειακής μετάβασης και καινοτόμων ερευνητικών ερωτήσεων που αφορούν όλο το φάσμα της ενεργειακής βιωσιμότητας. Τα υπολογιστικά εργαλεία νέας γενιάς θα πρέπει να στοχεύουν στην απλή και κατανοητή αναπαράσταση των υπό μελέτη συστημάτων, καθώς επίσης και στον αρθρωτό τρόπο περαιτέρω ανάπτυξης/ εφαρμογής τους, ώστε να επιτρέπεται η εύκολη διασύνδεσή τους με άλλα πιο εξειδικευμένα εργαλεία. Με αυτό τον τρόπο θα

είναι εφικτή η διερεύνηση πρόσθετων ερευνητικών ερωτημάτων της ενεργειακής μετάβασης, προσφέροντας πιο εύρωστη και απτή υποστήριξη στους διάφορους τελικούς χρήστες και ενδιαφερόμενα μέρη. Επίσης, η επίλυση θεμάτων διαφάνειας και ανοιχτής πρόσβασης είναι ζωτικής σημασίας, επίσης, ιδιαίτερα στα πλαίσια προώθησης ενός εποικοδομητικού διαλόγου κατά τη διαδικασία χάραξης πολιτικών και λήψης αποφάσεων.

Λαμβάνοντας υπόψιν τα άνωθεν, είναι απαραίτητο να διευρύνουμε το πεδίο εφαρμογής των υπολογιστικών εργαλείων μοντελοποίησης/ προσομοίωσης ενεργειακών συστημάτων σε ζητήματα διαχείρισης της ενεργειακής ζήτησης και επίτευξης ευελιξίας, ενσωματώνοντας παράλληλα πτυχές που αφορούν τη (επενδυτική) συμπεριφορά των τελικών χρηστών/ καταναλωτών, ώστε να επιτευχθεί ο σχεδιασμός των κατάλληλων πολιτικών που θα επιτρέψουν στους τελικούς χρήστες/ καταναλωτές να συμμετέχουν πιο ενεργά στην επικείμενη ενεργειακή μετάβαση, καθώς, επίσης, και να αξιολογηθεί επαρκώς το απαραίτητο χαρτοφυλάκιο τεχνολογιών ενεργειακής μετάβασης.

Σε αυτό το πλαίσιο, αντικείμενο της παρούσας Διδακτορικής Διατριβής αποτελεί η ανάπτυξη υπολογιστικών εργαλείων μοντελοποίησης/ προσομοίωσης ενεργειακών συστημάτων που εστιάζουν στο ρεαλιστικό σχεδιασμό, και στην ανάπτυξη και εφαρμογή καινοτόμων ρυθμιστικών πλαισίων και προϊόντων/ υπηρεσιών για την ενδυνάμωση του ρόλου των τελικών χρηστών/ καταναλωτών στην ενεργειακή μετάβαση και στην παροχή κινήτρων με σκοπό την αύξηση της ευελιξίας της ζήτησης. Οι δομές μοντελοποίησης που αναπτύχθηκαν βελτιώνουν τα υφιστάμενα υπολογιστικά εργαλεία προσομοίωσης μοντελοποιώντας επαρκώς τα χαρακτηριστικά του προβλήματος, και υποστηρίζοντας τη διαδικασία λήψης αποφάσεων των εθνικών φορέων χάραξης πολιτικής για το σχεδιασμό αποτελεσματικότερων εργαλείων πολιτικής στα πλαίσια επίτευξης των κλιματικών και ενεργειακών στόχων.

Μέσω μιας εμπεριστατωμένης ανάλυσης όλων των παραμέτρων του προβλήματος και της ανάπτυξης μίας βάσης τεκμηρίωσης, αναπτύχθηκαν πιο ρεαλιστικά και διαφανή υπολογιστικά εργαλεία μοντελοποίησης, εστιάζοντας στην αρθρωτή δομή ανάπτυξης και εφαρμογής, τα οποία μπορούν να χρησιμοποιηθούν για να προσομοιώσουν διάφορες πτυχές του ενεργειακού συστήματος και να εξερευνήσουν/ αξιολογήσουν τη σχέση κόστους-οφέλους υπαρχόντων αλλά και καινοτόμων ρυθμιστικών πλαισίων, προϊόντων και υπηρεσιών για όλους τους εμπλεκόμενους φορείς. Η διαθεσιμότητα πραγματικών και εθνικά αντιπροσωπευτικών δεδομένων τα οποία συλλέχθηκαν στο πλαίσιο έργων χρηματοδοτούμενων από την Ευρωπαϊκή Επιτροπή, διαμόρφωσαν το σχεδιασμό του μεθοδολογικού πλαισίου μοντελοποίησης και αποτέλεσαν σημαντικό στοιχείο της προτεινόμενης προσέγγισης καθώς και των αποτελεσμάτων της.

Τέλος, η εφαρμογή του προτεινόμενου πλαισίου μοντελοποίησης και προσομοίωσης στην πραγματική μελέτη περίπτωσης του μίγματος των εργαλείων εθνικής πολιτικής, καθώς και των τεχνολογιών ανανεώσιμων πηγών ενέργειας και εξοικονόμησης, στον Ελληνικό οικιακό τομέα, επέτρεψε την αξιολόγηση της πληρότητας και της αξιοπιστίας των αποτελεσμάτων που παρέχει η προτεινόμενη Διδακτορική Διατριβή. Αυτό επιτεύχθηκε μέσω της ανάπτυξης των πλαισίων μοντελοποίησης/ προσομοίωσης σε στενή συνεργασία με τους εθνικούς φορείς χάραξης πολιτικής και τα ενδιαφερόμενα μέρη του Ελληνικού ενεργειακού συστήματος.

Λέξεις-Κλειδιά: Ανανεώσιμες πηγές ενέργειας; Αξιολόγηση πολιτικών; Απόκριση της ζήτησης; Ελλάδα; Ενεργειακή και κλιματική πολιτική; Ενεργειακός συμψηφισμός; Ιδιοκατανάλωση; Μοντελοποίηση και προσομοίωση ενεργειακών συστημάτων; Μοντελοποίηση με συστήματα πρακτόρων; Πολιτική σταθερής ταρίφας; Ποσοτικοποίηση αβεβαιότητας; Συστήματα αποθήκευσης ενέργειας; Συστήματα διαχείρισης της ζήτησης; Τεχνολογική διάχυση; Φωτοβολταϊκά συστήματα.

Abstract

The actions proposed by the European Green Deal aim at increasing the European Union's climate ambition and are expected to lead to the complete transformation of the current energy system, by investing in feasible and innovative technological options, and by empowering end-users (i.e., citizens and consumers) and including them in the energy transition. In this context, energy system models have been used for policy advice and in policymaking processes in Europe, such as to explore potential energy futures or alternative socio-technical pathways and scenarios.

While existing models have provided valuable information about how to make marginal modifications to the current energy system in ways that will reduce costs, and, thereby, enhance economic growth, they were not designed to support the transition to energy systems dominated by intermittent renewable energy sources. Accelerating the energy transition towards climate neutrality by 2050 in Europe requires us to develop a new set of modelling tools, able to represent and analyse the drivers and barriers to complete decarbonisation, including decentralisation, a large-scale expansion of fluctuating renewables-based power leading to a vastly increased need for system-side flexibility, sector coupling, including the electrification of mobility and heating, and the impacts of different market designs on the behaviour of energy sector actors. In addition, without the necessary behavioural and societal transformations, the world faces an inadequate response to the climate crisis challenge. This could result from poor uptake of low-carbon technologies, continued high-carbon intensive lifestyles, or economy-wide rebound effects.

In this context, it is important to acknowledge that the shift to a more decentralised vision of a low carbon energy system in Europe, where end-users take ownership of the energy transition, benefit from new technologies to reduce their bills, and actively participate in the market, implies that part of the necessary infrastructure will be only developed if they are willing to invest in the technological capabilities required. However, while technological infrastructure is already available, business models and regulatory innovations are needed in order to find ways to maximise the value of the technological capabilities, as well as to monetise them, to compensate end-users.

This doctoral dissertation thesis builds on these insights, and, by developing two new energy system models, contributes to the analysis of innovative regulatory designs and product-service offerings that could incentivise end-users to actively participate in the energy transition and invest in demand flexibility. In particular, the thesis acknowledges the need to improve understanding on how the interactions between the key characteristics of end-users' behaviour affect investment decisions, and on the specific benefits of different technological capacities for engaging end-users and incentivising household-level changes towards energy autonomy. In this context, the dissertation thesis is structured around three main pillars:

- In the first pillar, the thesis asks questions of "*what*," "*how*," and "*why*," considering the problem of policy instrument design as a multifaceted problem with different objectives to satisfy instead of just a fixed target. It focuses on the policy landscape of the past ("*what*") and "*how*" this has incentivised end-users so far to participate to the energy transition. This allows to learn from past failures ("*why*") by identifying evaluation objectives and criteria that could be used to make better-informed judgments on policy instrument (re)design and selection to, eventually, (re)adjust future planning and decision-making. To this end, an analytical framework that facilitates the systematic exploration of the impact that policy measures have on the electricity system and its components was developed, building on the premise that understanding and quantifying the major monetary flows in the electricity market can contribute to the efficiency assessment of policy interventions, and that assessing how a policy measure affects the performance of the energy market requires the quantification of both the benefits and the costs attributed to it.

- In the second pillar, the dissertation thesis focuses on the interaction between the policy landscape and end-users, i.e., the technological infrastructure required and its role in empowering end-users to participate more actively to the energy transition. Alternative regulatory designs, which are currently showcased in different geographical and socioeconomic contexts in the EU were considered, to evaluate their potential effectiveness in driving investments in the necessary technological infrastructure. Considering that people and their social interactions greatly influence the diffusion and use of technology and further shape overall technological transition dynamics, investment criteria, and different decision-making behaviours were also explored, since many technical innovations and public policies often fail because they do not sufficiently consider what matters to people (i.e., the motivating factors shaping their adoption preferences). To do so, a new energy system model, the Agent-based Technology adOption Model (ATOM), was developed, which, apart from exploring the expected effectiveness of technology adoption under regulatory designs of interest, allows to consider and explicitly quantify the uncertainties that are related to agents' preferences and decision-making criteria (i.e., behavioural uncertainty).
- In the third pillar, the approach of the two previous pillars is expanded by focusing on the end-users' perspective. The main premise is that, in order for end-users to have a more active participation to the energy transition, they first need to become more aware of the benefits from investing in new technological capabilities. While technological infrastructure is often available, business models and regulatory innovations are needed to find ways to maximise the value of these technological capabilities, as well as to monetise them, to compensate end-users. To this end, "*game changer*" business models in terms of different configurations of innovative product-service offerings, which could incentivise end-users to invest in demand flexibility, were evaluated. In addition, market-oriented regulatory designs, which eliminate aspects of subsidisation and implement more advanced market rules that could affect the behaviour and consumption patterns of end-users were explored. To do so, a fully integrated dynamic high-resolution model embodying key features that are not found together in existing demand-side management models was developed. In particular, the hybrid bottom-up Dynamic high-Resolution dEmand-sidE Management (DREEM) model combines key features of both statistical and engineering models and serves as an entry point in demand-side management modelling in the building sector, by expanding the computational capabilities of existing building energy simulation models, to assess the benefits and limitations of demand flexibility for residential end-users.

Finally, to test the analytical framework developed under the first pillar, and to demonstrate the usefulness and the applicability of the two new energy system models, this dissertation thesis used as a testing ground the case of Greece. In this context, feasible and robust decarbonisation pathways were developed and agreed with a variety of stakeholders under the European Commission-funded Horizon 2020 projects "CARISMA," "TRANSrisk," and "SENTINEL," which were, then, modelled via the developed agent-based and demand-side management modelling architectures. This enabled to identify not just least-cost pathways, which have traditionally dominated modelling exercises, but rather institutionally and socially preferred, and politically realistic transition pathways, in line with current and increased decarbonisation ambitions.

Keywords: Agent-based modelling; Battery storage; Demand-Response; Demand-side management Energy policy; Energy system modelling; Feed-in-tariff; Greece; Net-metering; Policy assessment; RES generation; RES support mechanisms; Self-consumption; Smart home; Solar PV; Technology adoption; Uncertainty quantification.

Table of Contents

List of Tables

List of Figures

Chapter 1 - Introduction to the PhD thesis

Nomenclature

Acronyms & abbreviations			
ABM	Agent-based model	H2020	Horizon 2020 Research Programme
ATOM	Agent-based Technology adOption Model	LTS50	Long-Term Strategy for 2050
BSAM	Business Strategy Assessment Model	MS	Member state
CHP	Combined heat and power	NECP	National Energy and Climate Plan
CO_2	Carbon dioxide	NEEAP	National Energy Efficiency Action Plan
DR	Demand-Response	NEM	Net-metering
DREEM	Dynamic high-Resolution dEmand-sidE Management	NREAP	National Renewable Energy Action Plan
DSM	Demand-side management	PV	Photovoltaic
EC	European Commission	RED	Renewable Energy Directive
ECCP	European Climate Change Programme	RES	Renewable energy sources
EED	Energy Efficiency Directive	RES-E	Electricity generation from RES
ETS	Emission Trading System	SC	Self-consumption
EU	European Union	SC-ST	Self-consumption with storage
FiP	Feed-in-premium	TEEM	TEESlab Modelling
FiT	Feed-in-tariff	TEESlab	Technoeconomics of Energy Systems laboratory
GHG	Greenhouse gas	TOU	Time-of-Use
HELAPCO	Hellenic Association of Photovoltaic Companies	UNFCCC	United Nations Framework Convention on Climate Change

1. Introduction

This Chapter introduces the background and motivation of this dissertation thesis as well as the main pillars that this thesis contributes to. It also summarises the main challenges and formulate our research questions addressing key issues in the frame of energy system modelling.

1.1. Background and problem formulation

During the last two decades, the European Union (EU) has been a global leader in fighting climate change through its ambitious policies [1,2], since 1991 and the launch of the first Community strategy, aiming to limit carbon dioxide (CO_2) emissions and improving energy efficiency. Climate change mitigation efforts have thus been underway for many years now, driven not only by the EU's own priorities, but, also, by the need to fulfil its international commitment under the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol and more recently, the Paris Agreement [3]. As a direct strategic action, the European Climate Change Programme (ECCP) was introduced leading to a mix of different climate change mitigation measures. This led to the introduction of the EU legislation to be transposed and implemented at a Member State (MS) level. The 2020 climate and energy package, adopted in 2009, was a turning point, with climate and energy policies integrated in a single package of targets for reducing greenhouse gas (GHG) emissions, and measures for the further deployment of renewable energy sources (RES) and energy efficiency improvements. This structure is largely maintained in the EU's package towards 2030. It has also been widely acknowledged that the energy sector is responsible for a major proportion of the total GHG emissions, and that the EU is focusing on actions to decarbonise it, including the promotion of RES and energy efficiency upgrades. Towards this direction, the "Winter Package," published in November 2016 by the European Commission (EC), addressed all areas of the energy system, shaping the policy framework for the post-2020 period [4,5].

EU's progressive climate efforts have been accelerated over the past few years. and at the end of 2019 the EC announced the European "Green Deal," which is a comprehensive strategy navigating the EU to become the world's first climate-neutral continent by 2050 [6]. In particular, the European "Green Deal" includes the 2030 Climate Target Plan, which aims at reducing net GHG emissions by at least 55% by 2030 (compared to the 1990 levels). This is a significant increase relative to the previous target of at least 40%, set in the EU's "2030 Climate and Energy framework[1]." According to the EU's 2030 climate and energy framework, besides the outdated target of at least 40% GHG emission reduction compared to 1990 levels, the other two key targets for 2030 are: **(i)** at least 32% share of renewable energy (Renewable Energy Directive- RED II [7]), and **(ii)** at least 32.5% improvement in energy efficiency (Energy Efficiency Directive- EED [8]). These two targets are still in effect.

The Green Deal presented an initial roadmap of the key policies and measures needed to transform the EU's economy for a sustainable future. The key elements/ policy areas of the Green Deal are:

- Increasing the EU's Climate ambition for 2030 and 2050.
- Supplying clean, affordable, and secure energy.
- Mobilising industry for a clean and circular economy.
- Building and renovating in an energy and resource efficient way.
- Accelerating the shift to sustainable and smart mobility.
- Zero pollution ambition for a toxic-free environment.
- Preserving and restoring ecosystems and biodiversity.
- Fair, healthy, and environmentally friendly food system.
- Financing the transition.

[1] https://ec.europa.eu/clima/policies/strategies/2030_en

- “Leave no one behind” (just transition).

For achieving climate neutrality, key legislation and policies have been outlined in the EU climate action and the Green Deal[2]:

- Reducing GHG emissions of electricity generation, industry, and aviation sectors via the EU Emissions Trading System (EU ETS); Contribution of forestry and land use to GHG emission reduction; GHG emission reduction from transport using, for instance, CO_2 emission standards for vehicles.
- Setting national GHG emission targets for non-EU-ETS sectors, such as transport, buildings, and agriculture.
- Boosting energy efficiency, RES, and governance of the EU MS energy and climate policies as well as promoting innovative low-carbon technologies.
- Phasing down climate-warming fluorinated GHGs, protecting the ozone layer, and adapting to the impacts of climate change.
- Funding climate action.

Finally, in 2020, a Recovery plan was also set by the EC, the European Parliament, and EU leaders, to enable EU countries to repair the economic and social damage caused by the COVID-19 crisis [9]. For this task, a total of €1.8 trillion, which is the largest stimulus package ever financed through the EU budget, have been reserved. Furthermore, financial support and technical assistance will be offered to help those that are most affected by the energy transition, the so-called “Just Transition Mechanism.” At least €100 billion, over the period 2021-2027, will be mobilised for the most affected regions[3]. As a result, mobilising additional public and private funding, and pushing investments in research and innovation, combined with multiple instruments foreseen in the recovery plan for Europe, will give an additional push to the expected transformation of the EU’s energy system.
At the same time, though, the way leading to such deep transformation comprises numerous challenges and uncertainties. For more than twenty years, energy system modelling has been at the heart of the EU’s future climate and energy scenarios, assisting policymakers to unpack and face those challenges [10]. However, models applied in the EU policymaking have been criticised for lack of transparency and conservative assumptions [11]. Thus, new ambitions, as set in the European “Green Deal,” require better-adapted modelling tools for addressing challenges and uncertainties of energy transition. One of their main desired features is to reflect, as precisely as possible, on the concerns, needs, and demands of stakeholders interested in, and affected by, European climate and energy policies [12].

1.1.1. Energy system models and their role in the European policy landscape

In view of the recent EU climate commitments, policymakers face the challenge of making decisions about new renewables-dominated energy systems, like for example, designing policies supporting the decarbonisation of the energy system. or dealing with sector coupling, while balancing the interests of the involved actors at the same time. Because real world experimentation is in large scale not possible, energy system models can serve as “*laboratories*” to allow policymakers to explore different decarbonisation options in a virtual world and generate an understanding of the policy domain [13].

Energy system models are purposeful mathematical simplifications of reality- “*smaller, less detailed, less complex, or all together*,” but they are also shaped by, and potentially shaping, the social world, in which they are embedded [14]. The same holds true for the modellers themselves, who define the model’s nature-based theories, empirics, and also their ideas and mental models, respectively [15]. Thus, computer models and mental models are mutually dependent. In this regard, models can function

[2] https://ec.europa.eu/clima/policies/eu-climate-action_en
[3] https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

as "*discursive*," or "*negotiation*" spaces, bringing together different social worlds- such as represented by scientists and policymakers- and enabling these worlds to create a shared understanding, work together, and negotiate knowledge and policy [16,17]. Hence, energy system models can support governmental decision-making processes [18]; however, they cannot be a "*final decision for the policy process to [be] simply implement[ed]*" [13].

Pfenninger *et al.* (2014) distinguish between four key groups of energy system models relevant for national and international climate policies: **(i).** energy system optimisation models, **(ii).** energy system simulation models, **(iii).** power system and electricity market models, and **(iv).** qualitative and mixed-methods scenarios [19]. Optimisation and simulation are common underlying methodologies of energy system models (cf. [18]), which provide solutions of lowest economic costs of the energy transition, and represent developments of energy systems based on potentials, costs, policies, and constraints, respectively. Those energy system models are often combined, or completed, with macroeconomic models. Different approaches to modelling are represented by agent-based models, or models based on network and fuzzy theory (e.g., [20,21]). Depending on the problem formulation and input data, diverse model types are suitable to be deployed in policymaking in different ways: while some models help to understand long-term developments and answer a wide range of energy policy questions, others answer precise policy questions, relevant to specific sectors or localities [22].

Energy system models have been used for policy advice and in policymaking processes in Europe, such as to explore potential energy futures, or alternative socio-technical pathways and scenarios [23]. They are contributing to energy policymaking processes indirectly by referring either to model-based studies or to scenarios published in other contexts. Dedicated model runs are conducted for particular policy processes and directly used by official government institutions for policy guidance. In this context, governments seem to have different approaches and practices to modelling [24].

While some of them do model runs internally, other governments commission modelling-based studies. For example, in the UK, the MARKAL model, and subsequently TIMES-UK, have been helping to underpin energy and climate policies for over 35 years [25]. Currently, modelling has been embedded and institutionalised in the energy policy community and contributes to target-oriented climate policy in the UK. Another example provides Switzerland, where after the Fukushima nuclear disaster, the government commissioned the consulting company "Prognos" to carry out a modelling-based study, determining how the Swiss energy system should develop until 2050 [26]. Although the feasibility of future energy scenarios drawn in the Swiss Energy Strategy 2050 have been questioned [27] and evaluated with other models [28], the policies resulting from the modelling were largely adopted the way "Prognos" suggested it. For more relevant European cases see [29].

Finally, a recent survey found that among 48 investigated energy system modelling tools, almost two-third had a direct or indirect policy impact. Over a third of the modelling tools did not have any identifiable policy contribution, because they are rather new in-house developments, mainly used within academic research, or because their application had a limited scope [30]. Thus, many energy system models fall short of their potential in policymaking [31], as their existing structures have been monolithic and unable to address the multifaced problems related to the ongoing energy transition. There are certain main challenges and limitations with existing energy system models, along the policy process, that cause the gap between the design of models in research and their use in policy [32].

1.1.2. Inefficiencies of existing energy system models

Decarbonising the European energy system depends on continuing the shift from fossil to RES-based power generation, combined with a shift of both mobility and heating from being fuel-based to being primarily electrified in conjunction with an increase in energy efficiency [33]. This has important ramifications for energy system planning. Solar and wind power are both intermittent, while offering

the possibility of greater decentralisation. Indicators such as levelized or marginal costs matter a great deal for planning a cost-effective energy system, and yet unlike with thermal power generation, differences in the needs for reserve capacity, storage, and transmission and distribution grid capacity can affect average costs even more [34,35]. Given these facts, the potential synergies (or conflicts) from electrifying transport and heating become of crucial importance.
At the same time, factors other than cost take on additional meaning. The land footprint of RES-based energy supply, together with potential additional need for power transmission, have raised crucial issues of public acceptance [36,37]. Public acceptance, in turn, is closely associated with issues of participation, infrastructure ownership, and the match between local supply and local demand [38,39]. The reality is that there is not one possible RES-based system of the future, but rather many possible systems. They differ in critical ways, average and marginal costs being only one among many, with diverse impacts on different stakeholder groups [40].
In 2011, the EC analysed and published its long-term energy strategy options in the Roadmap 2050 [41]. The kinds of models on which the Roadmap relied, and on which national and European energy planners continue to primarily rely, were originally developed in response to the energy supply and price shocks of the 1970s and 1980s, the same shocks that led to the creation of institutions such as the International Energy Agency (IEA). Examples of these types of models include TIMES/ MARKAL and PRIMES. The goal of these models was to assist national-level energy planners in reducing overall energy system costs, while staying within fossil-fuel supply constraints, to optimise an already well-oiled machinery in order to enhance security and cost-effectiveness [42].
The models have evolved over time and are now very detailed in their representation of current technologies, capacities, and constraints, including the expansion and limited resource potential of renewables. Now the EC and national energy planners will need to move forward from the European Energy Roadmap 2050. The Roadmap envisioned a RES-based energy system, and, yet did not specify any details with regards to the choices between different possible system designs, choices that need to be made now. The modelling framework that was sufficient in 2011, for the level of detail that the Roadmap offered, is not sufficient today.
As Europe now starts to truly implement the energy transition as envisioned in the energy union strategy (COM/2015/080) [43], many specific decisions have been and still need to be made– and all need specific policy advice, including with models. The recent decisions on the Buildings, Energy Efficiency and Renewables Directives, and the upcoming decisions on an integrated electricity market design are examples of such issues. They are also examples of policy issues that cannot be meaningfully analysed with the existing models because they are too coarse and are unable to represent the mechanisms that are at play. In particular:

- The RED II holds several innovations with great impact on Europe's energy strategy and for the feasibility of modelling the future with existing models [44]. In this context, it foresees a 32% share of renewable energy by 2030, almost a doubling from 2015 [45]. Given the technological maturity of renewable power source, this will likely mean a renewable power share of at least 40% and more likely 50%, or higher. This means that RES, and especially fluctuating RES, will no longer be an addition to the system; they will be the dominant part. This will vastly increase the need for power system changes, including improved flexibility on all timescales from seconds to seasons.

Existing models were not built to handle the temporal fluctuations of RES, and thus, they cannot advise policy decisions that foresees RES-dominant systems.

- In addition, the RED II also requires MS to open their national support schemes to investors in other countries, which will change the geography of the power supply, as RES expansion will no longer necessarily be strongest in countries with the most advantageous support schemes but may expand in places where, either generation costs are lowest (enabling the lowest auction bids), or where additional generation has especially high value (enabling lower auction bids as the cost recovery from spot sales can be higher).

Models with low geographic and/ or temporal resolution cannot represent any of these factors.

- On the other hand, the Directives on the Energy Performance of Buildings require all new buildings to be near-zero energy buildings from 2020, and very high energy standards for the existing building stock upon renovation [46,47]. This means that **(a).** they must use very little heat and that they must- on-site, or nearby- produce the energy they still need from RES, and that **(b).** buildings must have, or be prepared to include later, charging stations for electric cars. These Directives, and especially combined with the self-generation and self-consumption rules of the RED II, imply that the energy of the future will be much more decentral, with a marked increase of RES-based power feed-in at low voltage levels and high additional loads resulting from home-charging of electric cars. It is still not clear, and existing models cannot assist with learning this as they lack the necessary temporal and spatial resolution, what the effect on local grids will be, or how this will affect the overall energy trajectory of Europe. Further, it has great ramifications for sector coupling by essentially removing most of the heat demand, with questions arising about the impact and necessity of electrification of heat, or about the consistency in simultaneous decisions for district heating systems and combined heat and power (CHP).

Existing models are not well-suited to analyse such cross-sectoral impacts.

- Finally, the EEDs, including the recently adopted Directive of 2018, foresee both the continuation of the energy intensity improvements in energy-consuming products, and importantly also on smart technologies and smart meters, while it also seeks to improve and adapt consumers' energy consumption patterns by enhancing the visibility of energy costs and prices for the end consumer [48]. Thus, current EU policy seeks to improve the flexibility of demand and cost responsiveness of consumers. Both these issues will be particularly important on short time-scales, hours, or less [49], but such impacts cannot be identified by current models, especially as their time-resolution is much too low. Upcoming decisions of importance in particular includes harmonised rules for the electricity market design, including a decision on the role of capacity markets, pricing in supply-side flexibility and priority dispatch of RES [50]. These market design decisions will greatly influence how investors behave, both in the short and the long terms, and they will therefore, to a large extent, determine what type of power system Europe will have in the future. We do not yet know what these decisions will be, but:

The existing framework of energy system models cannot adequately analyse any of these issues, both because they are too coarse in temporal and spatial resolution, and because they generally have no sufficiently explicit representation of investor behaviour.

Table 1.1 synthesises a set of key issues that energy system planners now need to grapple with, and what modern energy system models need to accomplish for the transition to climate neutrality in Europe by 2050.

The existing framework of energy system models used for policy advice in the EU and elsewhere do an inadequate job at these, because they are too coarse and do not acknowledge that a decarbonised energy system will function very different than the current system, leading to entirely different modelling requirements.

Table 1.1. Key energy planning issues and modelling requirements for the transition to climate neutrality by 2050 in Europe as synthesised from [19,51].

a/a	Energy planning issue	What energy system models need to be able to do
1	**Decentralisation and variability in electricity supply**	Representing a future infrastructure that includes large shares of decentralised RES and operate under a variety of objectives (e.g., self-consumption, cost minimisation, revenue maximisation through aggregation, etc.).
2	**Need for flexibility**	Accurately representing the flexibility potential of RES and consumers/ prosumers (both capabilities and limitations) and simulating different strategies for the utilisation of this flexibility.
3	**Integration of energy sectors (electricity, heating/ cooling, and gas)**	Putting demand at the centre of the system to model different energy carriers in a unified way (demand service).
4	**Short- and long-term market dynamics**	Capturing the effect of short- to mid-term market effects on longer-term investment decisions and consumer behaviour.
5	**Social drivers/ constraints and societal reactions to energy trajectories**	Capturing how societal actors interact and shape the energy future, including in far-from-cost-optimal ways, especially the way their strategies may co-evolve, and how they react to energy system developments and create pressure to redirect policies and the overall energy trajectory.
6	**Non-economic determinants and barriers (including financing-related issues) for the necessary investments**	Accurately and explicitly representing the factors often dismissed as "non-economic factors."
7	**Uncertainty quantification**	Explicitly and transparently handle uncertainty in key parameters (e.g., learning rates, technology costs and availability, etc.) in systematic manner (i.e., not ex-post in a sensitivity analysis based on arbitrary parameter variations).

1.1.3. Energy system modelling for the transition to climate neutrality by 2050 in Europe

The existing models have provided valuable information about how to make marginal modifications to the current system in ways that will reduce costs, and, thereby, enhance economic growth. In this context, nearly all of their details have been oriented towards the existing energy system. As a result, they were not designed to support transitions to energy systems dominated by intermittent RES [52]. One easy criticism, repeatedly raised, is that their temporal and spatial resolution is too coarse to model the behaviour of intermittent RES, although one has to acknowledge that more recent versions of these models have made a great deal of progress in this area.

In addition, a fundamental challenge is that most of these models are very complex and, therefore, difficult to understand, raising issues of transparency [53] and lack of trust [54]. To use them properly, one has to comprehend all of their components as well as the interactions between these components. Given the additional level of detail that has come with designing an energy system based on intermittent RES, their complexity has expanded to the point where it is extremely difficult to understand why they give the results that they do. This problem could be exacerbated even more, if one were to further develop and expand such models in order to consider other issues relevant to energy system planning. For example, synergies and conflicts associated with sector coupling, factors limiting or enhancing public acceptance and diffusion of new technologies, etc. Third, most models are "one-size fits-all" tools. However, having complex structures does not automatically mean that they are better-suited to user needs. As shown by Gaschnig *et al*., (2020), users of models and modelling results have specific needs for energy system models, which cannot be covered by "*all-rounders*," but by specific targeted and tailored tools [12].

Accelerating the energy transition towards climate neutrality by 2050 in Europe requires us to develop a new set of modelling suites, able to represent and analyse the drivers and barriers to complete decarbonisation, including decentralisation, a large-scale expansion of fluctuating RES-based power leading to a vastly increased need for system-side flexibility, sector coupling, including the electrification of mobility and heating, and the impacts of different market designs on the behaviour of energy sector actors. This often goes beyond improving the models' resolution, as it fundamentally requires the development of a new modelling framework for the transition to climate neutrality (**Table 1.1**).

Large, difficult to maintain monolithic models can no longer deal with the more decentralised and dynamic European energy landscape. By instead creating a system where smaller, more specialised models can be combined in a modular fashion to answer pressing questions, offers a more resilient and robust approach to providing complex energy system information to stakeholders that require it. It is unworkable to provide the level of detail that the energy transition requires, and the level of transparency that stakeholders demand, in a single model that is "*one-size-fits-all*."

That is why we need modelling structures that are *modular*, made up of *independent*, but *interlinked* components. These can be applied as required and stakeholders can ignore the components that are not relevant to their needs. Making it possible to link several of these models together, on a mix-and-match basis, solves the conundrum of how to get enough detail while maintaining transparency and usability. At the same time such an approach leads to a more comprehensible, transparent, and workable system, useful to a broad range of users. Moreover, there are almost certain to be unknown unknowns, factors for one country that prove to be important, but which nobody has yet thought of. So, we need to be able to add new models that go into detail on these new factors, or add these factors into existing models, when and if such issues raise their ugly heads. Thus, modellers must also develop tools that will address specific transition challenges in specific geographical contexts, also considering diverse spatial focus [55].

<u>Modular models are nothing new</u>: Many current models, in particular IAMs, such as the IMAGE model [56], incorporate different modules that can be separately run. In all of these cases, however, the modules were designed to be combined together: the structure and function of a core module defined the structure and function of the other. What we need, by contrast, is to develop a platform where model users can link together models that were never designed to be run together. New models can be brought in and added, to provide detail about aspects of the system, or problems in need of being addressed, which prior modellers may never have thought of. Such a modelling framework could become a truly open platform for the entire stakeholder community to be able to use, and could be adaptable, both to their individual needs, and to dealing with the kind of unforeseen issues that any complex system throws up [57].

In addition, for linking energy system models together and allowing them to be run on a mix-and-match basis, model interface protocols are required. These are the algorithms that translate the output from one model into a form that can be used as input for another, forming robust soft linkages. Such interface protocols need to be open source and transparent, so that anybody is able to make use of them to link additional models to other models, so that specialised modelling suites to provide answers to specific research questions of interest are created.

They also need to be oriented towards uncertainty, creating a set of algorithms that will enable the tracing of cascading uncertainties through multiple models. For example, one model (X) might drill down energy demand to the level of individual heating and cooling technologies mandated by specific building codes. The resulting time patterns of aggregate building energy demand could then be used by an energy supply system model (Y) to identify the optimum mix of energy supply, considering other energy demand sectors such as mobility and industry. The suggested platform could also enable model X to be used to test the sensitivity of model Y's results to factors that the developers of model Y had never even thought about. For example, an energy system model (Y) may produce an optimal supply scenario for a given year in the future such as 2030. Such a scenario may include the construction of new power lines, and there may be some embedded or implicit assumptions concerning how fast such power lines can be constructed. But that speed of planning and construction depends on a number of factors, including unpredictable (ex-ante) aspects of participatory processes for stakeholder engagement [58]. A different model (X) would capture these elements. So how sensitive is the optimal scenario to a change in the participation rules in a given jurisdiction?

→ *Current models simply do not allow one to answer this question quantitatively. New modelling suites must be able to allow for such configurations.*

Finally, by actively engaging policymakers and other stakeholders in the modelling process, the gap between modelling and policymaking can be counteracted, and the chance of energy system models being of tangible value to different end-users increases [59]. As a result, various forms of stakeholder-informed modelling, such as participatory modelling, mediated modelling, companion modelling, group model building, or participatory simulation (for a review see: Voinov and Bousquet, 2010 [60]), must be incorporated into next-generation modelling suites. In this context, policymakers can be engaged at different stages of the model development: from data collection, through model development and validation, to interpretation of model results and model use [61].

1.2. Scope and objective

At the core of this PhD thesis is the recognition that the actions proposed in the "Green Deal" document, aiming at increasing the EU's climate ambition, are expected to lead to the complete transformation of the current energy system, by investing in feasible and innovative technological options, and by empowering end-users/ citizens and including them in the energy transition. In addition, the EU energy union strategy especially stresses out the importance of putting "*citizens at the core*" of the energy transition and envisions a Union where "*citizens take ownership of the energy transition, benefit from new technologies to reduce their bills, participate actively in the market, and where vulnerable consumers are protected*" [62].

Furthermore, common across all energy system models is the need to balance energy supply and demand. However, recent scientific literature acknowledges that energy demand is rarely a modelling outcome, but rather an exogenous input assumption, either as a static demand, or with some elasticity. This requires that modellers represent energy demand for the variety of the different sectors at the relevant temporal and spatial resolution of their modelling tools [51]. Especially in the case of thermal demand, several projects have endeavoured to simulate it using both bottom-up and top-down approaches [63], but their incorporation by energy modelling tools is currently limited.

Reliance on demand-side modelling tools that also consider behavioural aspects of end-users is key to understanding future profile shapes of the upcoming transition, but so far has been underutilised. However, scientific support to climate action is not only about exploring capacity of "*what*," in terms of policy and outcome, but also about assessing feasibility and desirability, in terms of "*when*," "*where*," and especially for "*whom*." Without the necessary behavioural and societal transformations, the world faces an inadequate response to the climate crisis challenge. This could result from poor uptake of low-carbon technologies, continued high-carbon intensive lifestyles, or economy-wide rebound effects [64].

In this context, it is important to acknowledge that the shift to a more decentralised vision of a low carbon energy system in Europe, where end-users (consumers/ citizens) take ownership of the energy transition, benefit from new technologies to reduce their bills, and actively participate in the market, implies, that part of the necessary infrastructure will be only developed if they are willing to invest in/ pursue the technological capabilities required. However, considering that it is unlikely for them to invest in new technological capabilities having the support (e.g., flexibility, etc.) of the energy system as their primary goal, it is reasonable to assume that they may only invest according to a value stemming from increased proportion of the self-produced energy that they consume.

While technological infrastructure is already available, business models and regulatory innovation are needed in order to find ways to maximise the value of the technological capabilities, as well as to monetise them, to compensate end-users [65]. The current European regulatory framework, though, leads to conditions where business models do not bring the full value of demand-side capabilities, even when the latter are already there, due to conflicts between the interests of end-users and market actors [66]. Given that in modern energy systems technological innovation will continuously pose new challenges to existing regulatory frameworks, innovation in regulation should be as important as regulating innovation [67]. As a result, efficient policymaking around Europe should explore "*game changer*" business models that incentivise all involved actors to incorporate demand flexibility into the markets that can valorise it.

The PhD thesis builds on this realisation and, by developing two new energy system models, contributes to the analysis of innovative regulatory designs and product-service offerings that could incentivise end-users to actively participate in the energy transition and invest in demand flexibility. In particular, the thesis acknowledges the need to improve understanding on how the interactions between the key characteristics of consumers'/ citizens' behaviour affect investment decisions, and on the specific benefits of different technological capacities for engaging consumers/ citizens and incentivising household-level changes towards energy autonomy. To do so, feasible and robust decarbonisation pathways were developed and agreed with a variety of stakeholders under the EC-funded Horizon 2020 projects "CARISMA[4]," "TRANSrisk[5]," and "SENTINEL[6]," which were, then, modelled via the developed agent-based and demand-side management modelling architectures. This enabled to identify not just least-cost pathways, which have traditionally dominated modelling exercises, but rather institutionally and socially preferred, and politically realistic transition pathways, in line with current and increased decarbonisation ambitions.

1.3. Research questions (RQs)

This thesis has as a starting point the above-mentioned requirements and needs for improving energy system modelling towards more efficient and better-informed decision-making. However, considering that the identified requirements and needs cover a wide spectrum of the energy system, and thus, of the field of energy system modelling, in this thesis, we mainly focus on the two following user needs:

- We need a new modelling framework, which will be demand-side oriented, adequately and in detail representing all different aspects of end-use, and which will also allow for a more transdisciplinary perspective on the role of human choices and behaviours in influencing the neutral-carbon transition. The starting point for such a framework needs to be considering the desires of individuals and analysing how these interact with the energy and economic landscape, leading to a systemic change at the macro-level.
- We need to expand our scope, from analysing policy effects, to understanding the adoption of the necessary technological infrastructure, to, finally, empowering end-users to actively participate to the energy transition.

In this context, the overarching research question of this dissertation thesis is shaped as follows:

How could energy system models be used to evaluate the adoption of regulatory designs and product-service offerings that empower end-users and incentivise demand flexibility in support of low-carbon energy systems?

[4] http://carisma-project.eu/
[5] http://transrisk-project.eu/
[6] https://sentinel.energy/

To answer this overarching research question, the dissertation thesis comprises of three stand-alone research chapters, i.e., "*Chapter 2 - Analysing policy effects*," "*Chapter 3 - Understanding technology adoption*," and "*Chapter 4 - Empowering end-users*," each one of which contributes to one of the three pillars on which this thesis builds, namely: **(i). Policy**, **(ii). Technology**, and **(iii). End-users** (Figure 1.1).

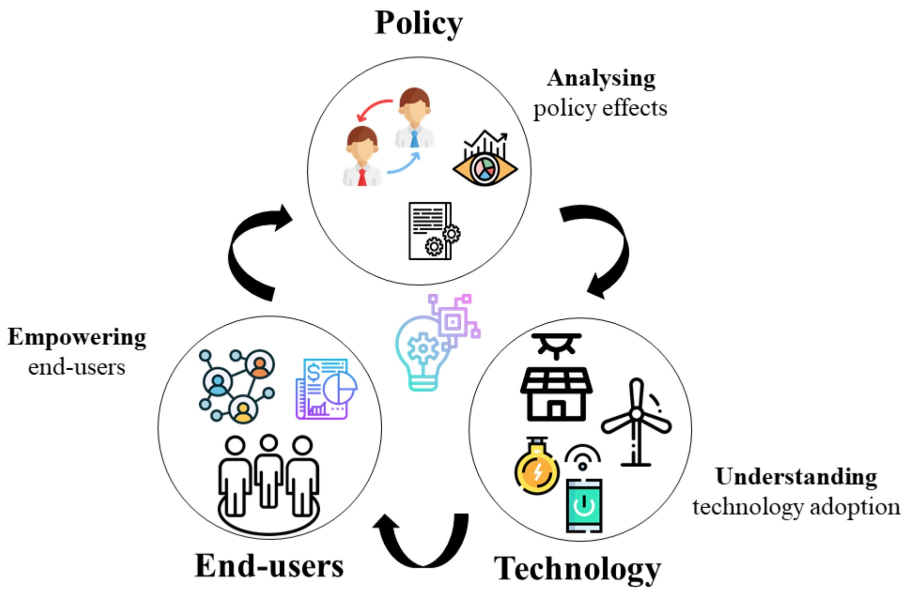


Figure 1.1. The interaction cycle between the three main pillars on which this dissertation thesis builds.

In the first pillar of the thesis, we ask questions of "*what*," "*how*," and "*why*," considering the problem of policy instrument design as a multifaceted problem with different objectives to satisfy instead of just a fixed target. We focus on the policy landscape of the past ("*what*") and "*how*" this has served the ultimate goal of this thesis, which is to identify regulatory designs that could empower end-users to participate more actively to the energy transition by investing in technological infrastructure that increase demand flexibility. Analysing and evaluating policy effects of the past, thus, is an essential first step to understand "*how*" regulatory designs have performed so far in terms of impacting the energy system and the individual components/ elements that comprise it. This allows to learn from past failures ("*why*") by identifying evaluation objectives and criteria that could be used to make better-informed judgments on policy instrument (re)design and selection in order to, eventually, (re)adjust future planning and decision-making.

In the second pillar of the thesis, we focus on the interaction between the policy landscape and end-users, i.e., the technological infrastructure required and its role in empowering end-users to participate more actively to the energy transition. We consider alternative regulatory designs, which are currently showcased in different geographical and socioeconomic contexts in the EU, to evaluate their potential effectiveness in driving investments in the necessary technological infrastructure. Considering that people and their social interactions greatly influence the diffusion and use of technology and further shape overall technological transition dynamics, we also explore investment criteria and different decision-making behaviours, since many technical innovations and public policies often fail because they do not sufficiently consider what matters to people (i.e., the motivating factors shaping their adoption preferences).

In the third pillar of the thesis, we expand the approach of the two previous pillars by focusing more on the end-users' perspective. Our main premise is that, in order for end-users to have a more active participation to the energy transition, they need first to become more aware of the benefits from investing in new technological capabilities. While technological infrastructure is often available,

business models and regulatory innovation are needed in order to find ways to maximise the value of these technological capabilities as well as to monetise them to compensate end-users. To this end, we evaluate "*game changer*" business models in terms of different configurations of innovative product-service offerings, which could incentivise end-users to invest in demand flexibility. We also explore market-oriented regulatory designs, which eliminate aspects of subsidisation and implement more advanced market rules that could affect the behaviour and consumption patterns of end-users.
These three pillars shape the overall flowchart of the dissertation thesis (Figure 1.2) and allow us to answer to the overarching research question by further decomposing it into the three following thematic research questions (**RQ$_{1\text{-}3}$**), which are dealt with in one or more of the research chapters (**Sections 2-4**):

RQ$_1$ *How did the regulatory design of the past affect the transition to a low-carbon energy system?*

RQ$_2$ *How could alternative regulatory designs incentivise consumers to invest in technological infrastructure for the transition to a low-carbon energy system?*

RQ$_3$ *How could new regulatory designs and novel product-service offerings incentivise consumers to invest in the necessary technological infrastructure for the transition to a low-carbon energy system?*

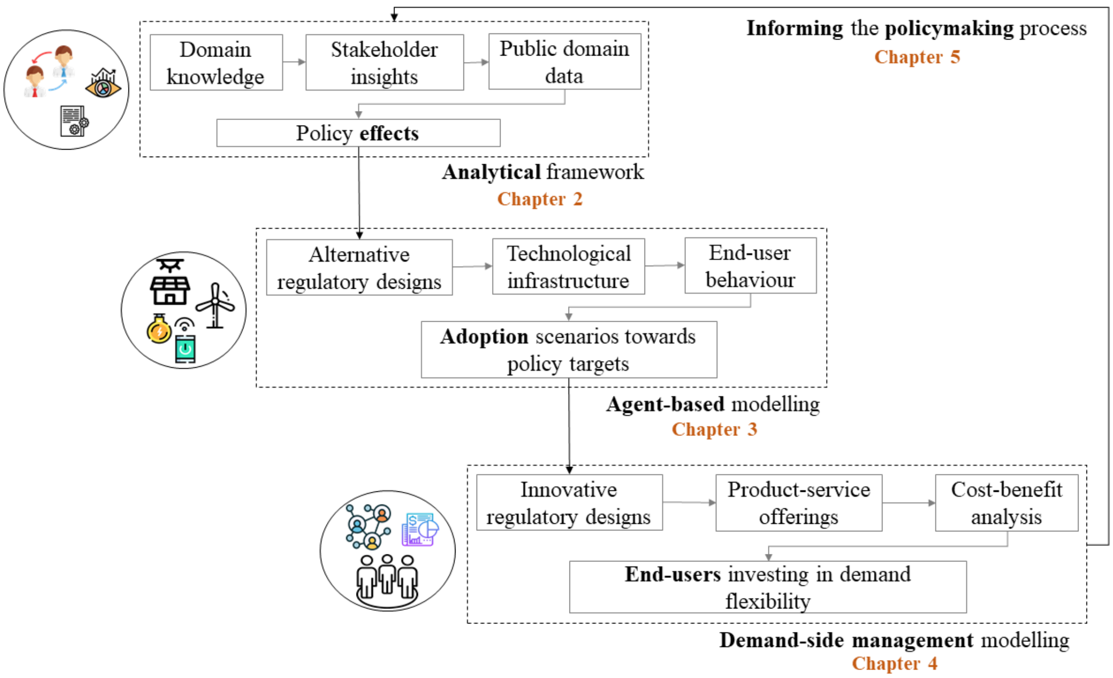


Figure 1.2. Flowchart: Implementation steps to provide answers to the three thematic research questions that comprise the overarching research question of the dissertation thesis, in accordance with the three pillars and the interaction cycle between them.

1.3.1. RQ$_1$. How did the regulatory design of the past affect the transition to a low-carbon energy system?

One of the most utilised policy mechanism to support electricity generation from RES (RES-E) has been the feed-in-tariff (FiT) scheme, providing security and high profits to investors [68]. Many EU MS have adopted the FiT scheme [69–71], which proved to be the main driver for the drastically increased RES-installed capacity over the period 2008 to 2015. However, despite the large growth, in many cases, policymakers failed to respond to the negative implications of the scheme in a decisive manner [72]. Although the FiT scheme was mostly designed as a generous subsidy to help initiate RES investments, it has been gradually decreasing or even ceased; thus, sustaining the growth of new RES installations has been challenging ever since. Increased RES deployment due to generous schemes as FiT, has sparked a debate across Europe regarding the effects of the enhanced RES integration on the performance of the energy market [73]. This debate challenges the premise that higher volumes of RES can enter every year the EU internal market and be absorbed progressively by the existing mechanisms. However, while most studies so far have focused on a technoeconomic analysis of the regulatory design and efficiency of the different RES-E support mechanisms [74–77], there is a knowledge gap on the impact of such mechanisms on the performance of the energy market and its interaction with the RES-E sector. Despite the learning progress of the past years, important regulatory questions remain still unanswered, while policymakers face the challenge of making decisions about technologies, spatial requirements, democratisation, and others aspects of unfamiliar RES-dominated energy systems, like for example, balancing interests of end-users in designing policies to support the decarbonisation of the energy system [78,79], etc. In view of a high-RES market design in line with the EU Target Electricity Model, regulatory efforts need to expand their approach to carefully review how the energy market performance has been affected by the different support mechanisms both in the short- and the long-term, as well as assess past mechanisms to optimise market performance in both time horizons. Thus, a structured approach, aiming at filling knowledge gaps on the effect that the regulatory design of the past has had on the electricity system and its components is of paramount importance.

Chapter 2 addresses this gap by presenting an analytical framework that facilitates the systematic exploration of the impact that policy measures have on the electricity system and its components. To do so, we built on the premise that understanding and quantifying the major monetary flows in the electricity market can contribute to the efficiency assessment of policy interventions, and that assessing how a policy measure affects the performance of the energy market requires the quantification of both the benefits and the costs attributed to it. By exploring the monetary flows in the energy market, one adopts a holistic view, which can provide insights on the interactions between different components of the benefits and costs, as well as on the possible conflicts or alliances between the involved actors of the system. Consequently, government officials and consultants in the policy community can gain a clearer perspective on how to devise a roadmap of least resistance for a policy measure to attain its goals, given that, while European RES targets have already been set, governance of RES-E support beyond 2020 at the EU level remains still undefined.

Overall, **Chapter 2** contributes to the first thematic research question of the thesis (**RQ$_1$**) by paving the way for a more comprehensive, detailed, and better-structured evaluation of RES-E regulatory designs than what currently prevails.

1.3.2. RQ$_2$. How could alternative regulatory designs incentivise consumers to invest in technological infrastructure for the transition to a low-carbon energy system?

Solar photovoltaic (PV) systems have been proven to be one of the key technologies for the transition to a low-carbon energy system. In this context, PV self-consumption (SC) is becoming extremely important, especially in the case of residential buildings, with consumers taking the role of “prosumers.” Typically, SC encompasses the adoption and further diffusion of a wide range of technologies and systems such as small-scale PV, battery storage, and smart-grid devices, which bring demand flexibility into the market. A growing number of recent studies in the literature have been assessing PV SC and its economics [80,81]. The findings show that if PV SC at the residential level becomes economically competitive soon, end-users will be willing to self-consume electricity instead of buying it from the grid [82,83]. Such a massive and radical change could impact national power systems around the world, especially if the necessary regulatory framework is not in place, and influence the interests of the electricity market stakeholders [84].

Aiming at overcoming the difficulties encountered in the post-FiT era, policymakers seek new legal mechanisms based on a combination of tax benefits and other incentives; Net-metering (NEM), feed-in-premium (FiP), and tenders are considered such mechanisms that could raise, once again, end-users' willingness to invest [85]. However, regulatory and financial challenges related to the need for novel market business models and supporting mechanisms remain the main obstacles to the sustained exponential growth of PV technology. Therefore, policymakers should focus on an optimal mix of PV power and other RES technologies; they should also anticipate the risks and uncertainties related to further PV adoption [84].

Scientific literature highlights the importance of understanding consumer behavioural patterns with respect to PV adoption to guarantee the effectiveness of future policies [86]. Because of the multitude of factors influencing the decision to invest in an innovative energy technology such as PV, agent-based models (ABMs) provide a suitable framework to simulate the adoption decision-making process of the members of a heterogeneous social system; the framework is based on members' individual preferences, behavioural rules, and communication within a social network [87,88]. ABMs perceive a system as a collection of autonomous decision-making entities called "agents" and provide an intuitive framework to consider the explicit characteristics of both technology and human behaviour [89]. Instead of using regression to extrapolate growth based on past trends- the typical approach used by policymakers so far- modelling agents' decisions and interactions represents a more "*real-world*" process [90].

Optimisation models, so far, implicitly assume that there is some centralised control over the energy system; this is often not the case, especially for small-scale, privately-owned technologies, such as PV. ABMs address this limitation by introducing a layer of control and decision-making, thereby allowing greater understanding of macro-phenomena [91]. Many technical innovations and public policies often fail because they do not sufficiently consider what matters to people (i.e., the motivating factors shaping their adoption preferences). People and their social interactions greatly influence the diffusion and use of technology, and shape further technological transition dynamics. However, transitions are difficult to scientifically understand because of the influence of a broad range of contextual factors that affect policy processes, society, and agency. Thus, considering the diversity of interests, motivations, and other factors that inform people's choices helps to reduce the uncertainty that may lead to policy failure [92].

While recent studies in the scientific literature have already addressed the issue of PV adoption by using an ABM, one limitation of existing models is that they often fail to capture uncertainties related to agency (i.e., individuals or households that make decisions independently) [21]. **Chapter 3** addresses this gap by presenting the Agent-based Technology adOption Model (ATOM), which, apart from exploring the expected effectiveness of technology adoption under regulatory designs of interest, allows to consider and explicitly quantify the uncertainties that are related to agents' preferences and decision-making criteria (i.e., behavioural uncertainty). To develop ATOM, the initial framework of the Business Strategy Assessment Model (BSAM) [93,94] has been expanded and further developed, focusing on consumers/ citizens, rather than on power generators, as the unit of analysis. ATOM is part of the Technoeconomics of Energy Systems laboratory-TEESlab[7] Modeling (TEEM) suite and serves as an entry point in technology adoption modelling by including a strong component of decision-making behaviour- and policy-contingent scenario elements that correlate technology adoption with its value to end-users.

Overall, **Chapter 3** contributes to the second thematic research question of the thesis (**RQ$_2$**) by:

- Presenting a new ABM that explores the expected effectiveness of PV adoption under alternative regulatory designs of interest and specifies the values of the agent-related

[7] https://teeslab.unipi.gr/

parameters under consideration, according to the plausibility of the model's results compared to historical data/ observations.

- Bridging the disciplines of uncertainty analysis and ABM policy assessment by showing how uncertainty in energy system modelling can influence effective policy design.

1.3.3. RQ$_3$. How could new regulatory designs and novel product-service offerings incentivise consumers to invest in technological infrastructure for the transition to a low-carbon energy system?

For the energy transition to happen in a manner that end-users are empowered to actively participate, transforming from passive consumers to prosumers [95], end-use products and service offerings need to be properly assessed [96]. To foster their role and evaluate their impact into the future energy regime, the modelling of user interaction and resource management needs to be considered first through demand-side management (DSM) modelling exercises. DSM typically encompasses the entire range of management functions associated with directing demand-side activities, including programme planning, evaluation, implementation, and monitoring. Its main objective is to improve the energy system at the side of the end-user in terms of consumption and cost effectiveness [97]. Different aspects of DSM range from improving energy efficiency up to sophisticated real-time control of distributed energy resources through smart devices with incentives for promoting certain consumption/ production patterns [98]. By doing so, DSM adds significant economic value to all actors involved and interacting with each other in the modern energy network [99].

For the time being, policy mechanisms like, e.g., NEM, FiP, tenders, SC with storage subsidisation, etc., are mainly considered as transition policies from the FiT scheme towards market-oriented schemes that eliminate aspects of subsidisation and implement more advanced market rules (e.g., dynamic cost-reflective pricing, etc.) [100,101]. Innovative DSM aspects, like Time-of-Use (TOU) and Demand-Response (DR) practices, which aim at shifting the demand from peak to off-peak times, could be such innovative market-oriented regulatory designs. TOU tariffs are usually sent beforehand to allow end-user to adapt to new market prices, while DR signals have a more direct impact on the behaviour and consumption patterns of end-users [102].

On the other hand, DSM modelling can support different types of end-users as, e.g., electricity distribution network operators, demand aggregators, government agencies, electricity retailers, etc. Accurate DSM modelling could be also beneficial for testing DR schemes that are primarily offered to residential end-users and could provide directions for the development of innovative regulatory designs and product-service offerings related to the smart-grid paradigm. However, most models in the scientific literature address DSM partially, or in a simplified manner, used most of the times for forecasting purposes. The main challenge of DSM models is being flexible enough, while at the same time including all important aspects of end-use [100].

Chapter 4 addresses this gap by presenting a fully integrated dynamic high-resolution model embodying key features that are not found together in existing DSM models. In particular, the hybrid bottom-up Dynamic high-Resolution dEmand-sidE Management (DREEM) model combines key features of both statistical and engineering models and serves as an entry point in DSM modelling in the building sector, by expanding the computational capabilities of existing Building Energy Simulation models to assess the benefits and limitations of demand flexibility for residential end-users. The novelty of the DREEM model lies mainly in its modularity, as its structure is decomposed into individual modules characterised by the main principles of component- and modular-based system modelling approach, namely "*the interdependence of decisions within modules*; *the independence of decisions between modules*; *and the hierarchical dependence of modules on components embodying standards and design rules*" [103].

This modular approach allows for more flexibility in terms of possible system configurations and computational efficiency towards a wide range of scenarios studying different aspects of end-use. It also provides the ability to incorporate future technological breakthroughs in a detailed manner, such as the inclusion of heat pumps, or electric vehicles, in view of energy transitions envisioning the full electrification of the heating and transport sectors. The latter makes the DREEM model competitive compared to other models in the field, since scientific literature acknowledges that there are limitations to how much technological detail can be incorporated without running into computational and other difficulties [104]. DREEM is also part of the TEEM suite.

Overall, **Chapter 4** contributes to the third thematic research question of the thesis (**RQ$_3$**) by:

- Developing a DSM model that, based on the strengths of object-oriented programming and equation-based system modelling approaches [105], is: **(i.)** input–output free, **(ii.)** modular, **(iii.)** hierarchical with control capabilities, which helps in managing the complexity of large systems, **(iv.)** universal, **(v.)** able to provide more realistic representations of the dynamic systems, **(vi.)** able to integrate end-users' behaviour along with determination of end-use qualities, and policies supporting RES, and **(vii.)** able to allow faster development and simulation.
- Developing and testing via simulation control strategies the coordination of technologies as electricity storage and smart thermostats toward increasing demand flexibility by increasing the consumption of electricity generated from RES.
- Suggesting implications for policy and practice, which could enable the design of novel regulatory designs that ensure clear incentives for end-users to invest in technological infrastructure that increase demand flexibility.

1.4. Case specification: Energy transition in Greece

To test the analytical framework that we developed to answer the first thematic research question (**RQ$_1$**), and to demonstrate the usefulness and the applicability of the two new energy system models that we developed to answer the second and the third thematic research questions (**RQ$_{2\text{-}3}$**), this thesis used as a testing ground the case of Greece. In this sub-section, thus, we provide the geographic and socioeconomic context of the dissertation thesis by presenting the main specifications of the energy transition in Greece, and by describing how each thematic research question has been adapted and answered for this case study.

1.4.1. Climate and energy targets by 2030 and by 2050

Greece is a transcontinental country with a diverse geographical landscape and a large potential in RES [100]. It presents a very recent case of a radical change in the planning of the energy system development. Although the introduction of renewable energy was actively promoted in the energy policy agenda over the past ten years [106], indigenous lignite continued to play a major role in the electricity generation in all scenario analysis and policies formulated until 2019. However, in the second half of 2019, Greece took the political decision of phasing-out lignite-fired power plants in a short time horizon (initially by 2028), which called for extensive energy system modelling to analyse its effect on the further development of the national energy system.
Modelling work resulted in the development of the revised National Energy and Climate Plan (NECP) that outlines the energy and climate objectives, policy priorities, and targets of the country until 2030 [107] and the development of the Long-Term Strategy for 2050 (LTS50), which presents the different viable options and energy transition scenarios in accordance with the long-term European vision for climate neutrality [108]. Recently, it has been announced that the lignite phase-out will be completed by 2025 [109], while a revision of the NECP and LTS50 documents is currently work in progress to account for the effects of the COVID-19 outbreak [110]. For the transition to the post-lignite era, special

focus is also given on the regions where the power plants exist to alleviate effects from the loss of employment and analyse overall consequences in the whole supply chain of the lignite-fired plants [111].

Energy system modelling in Greece was introduced over the past decade on a wider scale to support policy decisions in the energy sector. This development was considerably driven by the implementation of the EU law, as the EED, resulting in the development of the 1st National Energy Efficiency Action Plan (NEEAP) [112], and the RED [113], resulting in the development of the 1st National Renewable Energy Action Plan (NREAP) [114] (**Figure 1.3**). One of the reasons why energy system models have not been broadly used in policymaking before is that open-access to the models, as well as to their databases and their high-resolution results have not been often available to policy/ decision-makers in Greece. This has caused policymakers to become less familiar with the processes and requirements for using such models. However, the implementation of the EU's Governance Regulation and, in consequence, the compilation of the recent NECP and LTS50 documents, induced a very broad application of energy system modelling with meaningful to significant impact at all stages of the documents' preparation. This trend is expected to be additionally strengthened with the introduction of a set of monitoring and verification procedures, aiming at directing and supporting data collection, continuous monitoring of modelling activities, and periodic verification of modelling outcomes [10].

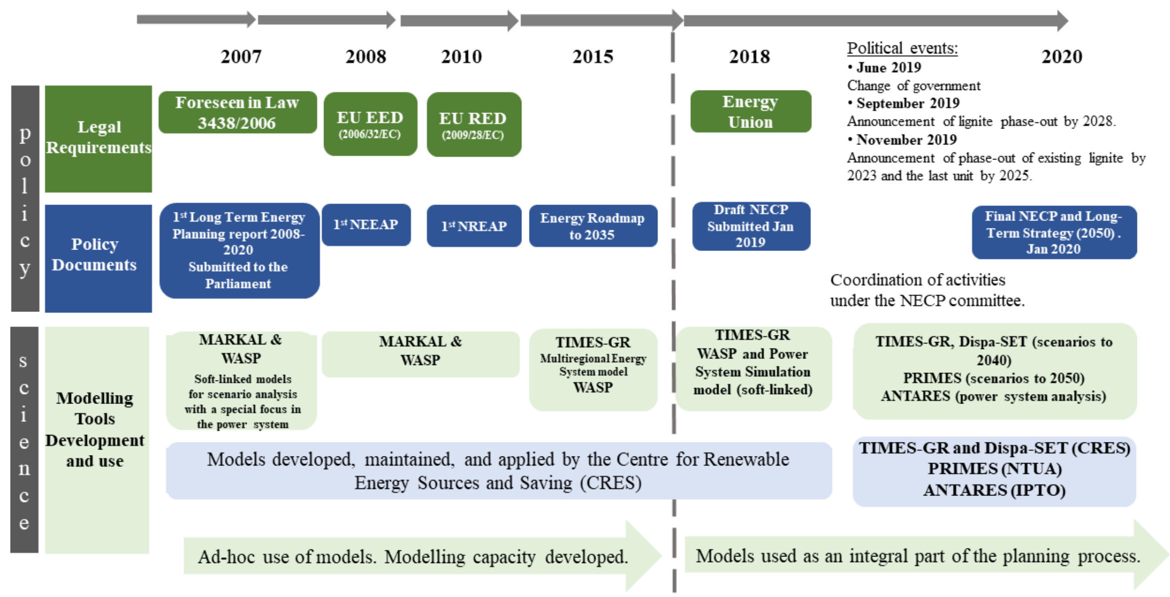


Figure 1.3. Timeline of energy system models' development to support policy documents and decision-making in Greece over the past decade. Source: [10].

According to the recently published version of the NECP, Greece has committed to the redesign of the energy sector from production to end-use, along the axes of sustainability, environmental protection, and climate change mitigation. Special focus has been also given to energy security and affordability for all. Towards this direction, the diversification of energy supply and the energy independence of the country are of primary importance, enhancing the role of Greece as energy hub, promoting financial stability, and facilitating resource management. Furthermore, the design of competitive energy markets is crucial to promoting sustainability and transparency in product and service provision as well as their price. Finally, as new competitive technologies enter the market, innovation in terms of investments and activities is promoted. The national targets for 2030, as dictated by the latest NECP, are presented in Figure 1.4. For the achievement of these targets the NECP lays down policy priorities, which are defined along the dimensions of the Energy Union, which aim at: **(i.)** decarbonisation in terms of both GHG emissions and removals and renewable energy, improving **(ii.)** energy efficiency and **(iii.)** energy security, and enhancing **(iv.)** the internal energy market and **(v.)** research, innovation, and competitiveness. Particular areas of interest for additional sectors as agriculture, shipping, and tourism are also included.

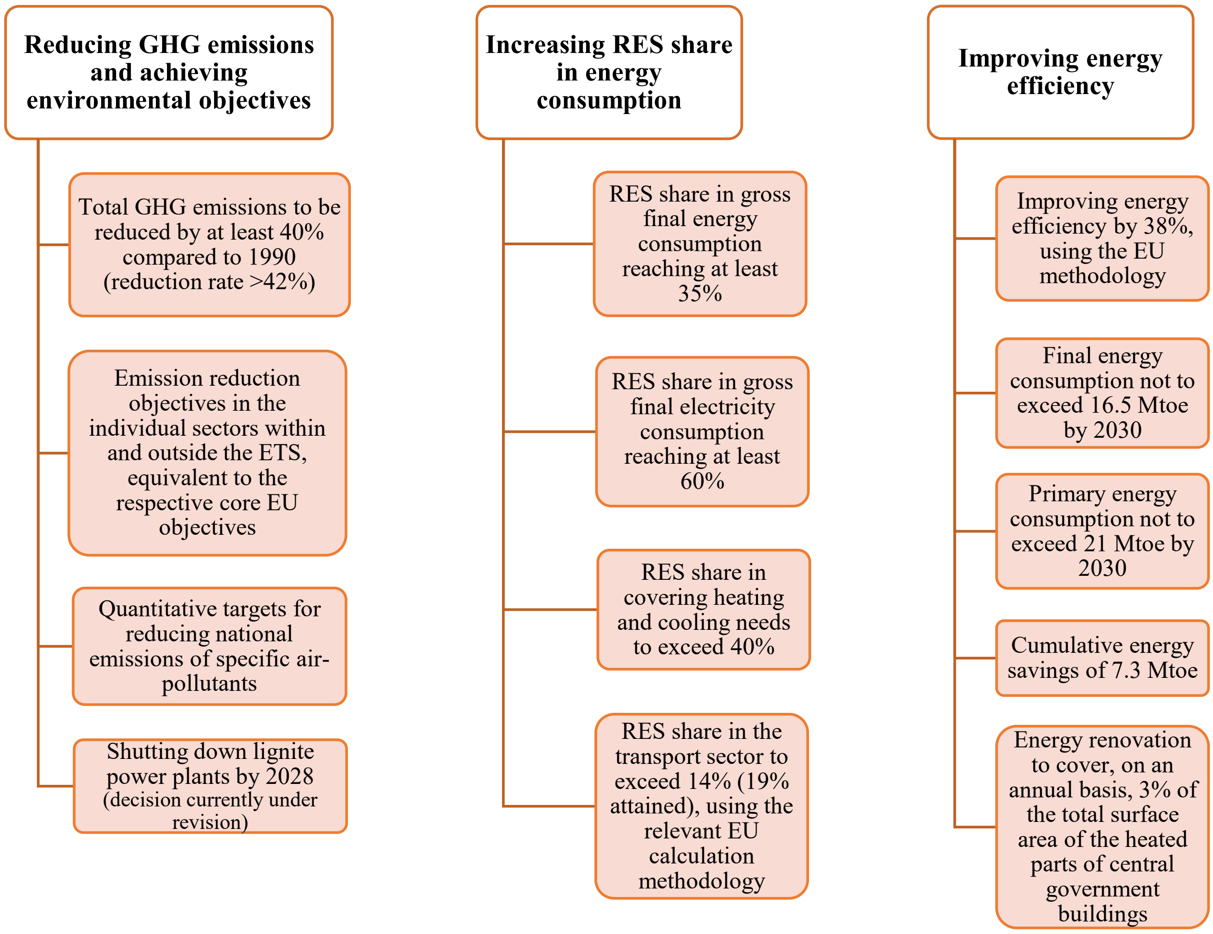


Figure 1.4. National targets of the energy transition by 2030 in Greece for the three main priorities outlined in the Greek Energy and National Plan. Source: [107].

Regarding long-term strategy, all scenarios analysed in the LTS50 document assume the achievement of the NECP targets by 2030, as the NECP document does not incorporate further goals, priorities, and policy measures for the post-2030 period. In particular, the "NECP-2030" scenario foresees the continuation of the current NECP policies post 2030, while it lacks specific targets and further policy measures post 2030. On the other hand, the "NECP-2050" scenario, which aims at significant GHG emission reduction by 2050, foresees the reinforcement of NECP policies with larger intensity after 2030 compared to the 2020-2030 period. It includes the following policy priorities, which are also included in the alternative, more ambitious LTS50 scenarios: **1.** cross-sectoral energy efficiency improvements, emphasising in large-scale energy renovation of households and buildings, **2.** cross-sectoral RES development, especially in the power sector, and elimination of CO_2 emissions from fossil fuels in electricity generation, **3.** electrification of transport and heating, **4.** development of domestic fuels and biogas with advanced methods, and **5.** electricity and expansion of gas interconnections and sector coupling. The alternative LTS50 scenarios are the following:

- The "Energy efficiency and electrification for 2°C (EE2)" scenario.
- The "New energy carriers for 2°C (NC2)" scenario.
- The "Energy efficiency and electrification for 1.5°C (EE1.5)" scenario.
- The "New energy carriers for 1.5°C (NC1.5)" scenario.

The “EE2/1.5” scenarios consider that it is economically and technologically uncertain to develop new climate-neutral energy carriers that will replace fossil fuels, promoting to a very high degree, thus, the electrification of energy uses in all sectors and the improvement of energy efficiency, including transformations in the direction of circular economy in industry and green technologies in transport. They also include large-scale development of biofuels and biogas to replace fossil fuels in areas where full electrification is not possible. For climate neutrality, electricity generation must have zero carbon footprint and will therefore be based on large-scale RES development.

On the other hand, the “NC2/1.5” scenarios assume that appropriate policies at the EU level ensure the gradual maturation of technologies and means to produce hydrogen, biogas, and synthetic methane with climate-neutral standards. Nevertheless, ambitious policies are being pursued to improve energy efficiency and electrification of transport and heating because otherwise the volume of electricity generation, and, consequently, RES capacities, would increase to unattainable levels, since green hydrogen and synthetic methane can only be produced via electricity. The targets for improving energy efficiency and electrification in the “NC2/1.5” scenarios are slightly lower than those in the “EE2/1.5” scenarios, while emissions from fuel use in the “NC2/1.5” scenarios are reduced using zero or low-carbon footprint gases and hydrocarbons. In the “EE2/1.5” scenarios emissions are avoided due to the very ambitious improvement of energy efficiency, electrification, and the increased use of biomass.

Figure 1.5 presents the main targets regarding GHG emissions, final energy consumption, and RES share in electricity generation towards 2030 and 2050, as specified in the different scenarios of the NECP and LTS50 policy documents.

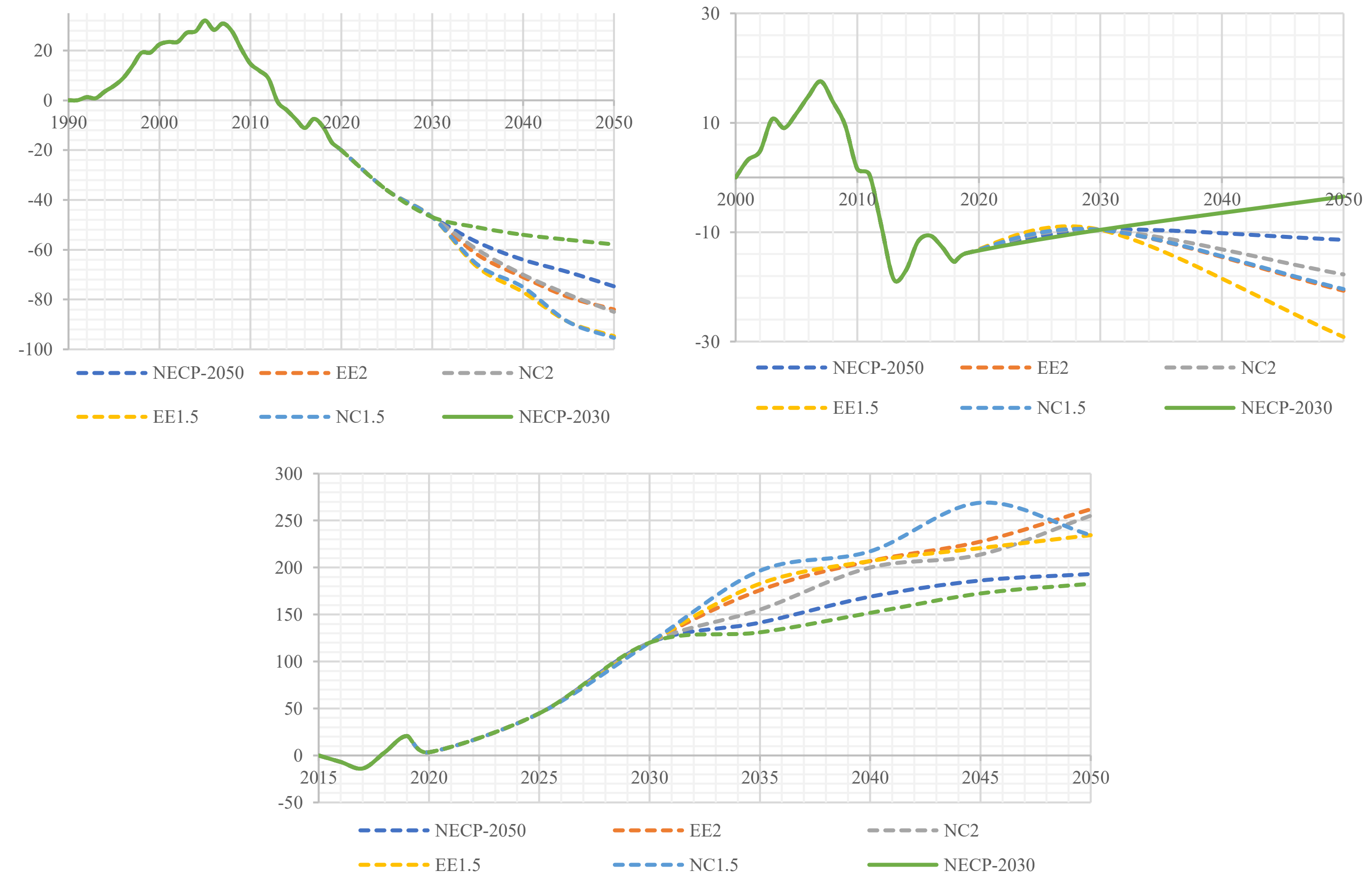


Figure 1.5. Main targets of the energy transition towards 2030 and 2050 in Greece according to the different scenario specifications: **(a).** Percentage change of GHG emissions ([107,108,115]), **(b).** Percentage change of final energy consumption ([107,108,116]), **(c).** Percentage change of RES share in electricity generation ([107,108,117]).

1.4.2. Regulatory designs and product-service offerings to empower end-users and incentivise demand flexibility in the residential sector in Greece

During the past decade, small residential PV systems in Greece have gained investors' attention, mainly owing to the profitable FiT scheme and simplified installation procedures that have been introduced by the special programme for the deployment of PV on buildings and roofs [118]. However, despite the RES boom over the period 2009 to 2013 owing to the FiT scheme, high investment costs led to a significant deficit to the special account for RES, which was responsible for funding the agreed contracts [119]. To counterbalance negative economic implications, the Greek government imposed an extra tax on the consumers' income from RES-E generation, which came simultaneously with a reduction of the tariffs [72]. These retroactive cuts to the tariffs shook the confidence of investors in the stability of the expected revenues [120,121] and led to a complete shutdown of the RES market, with the domestic PV market, indicatively, shrinking during 2014-2017 to approximately 1% of its 2013 size [106], as also visualised in Figure 1.6.

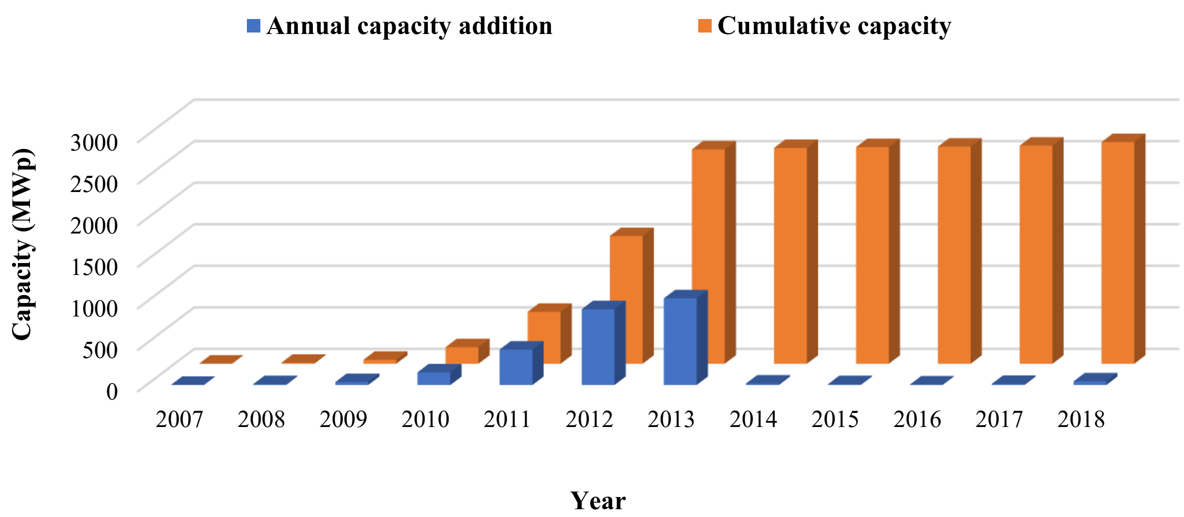


Figure 1.6. PV adoption in Greece during the period 2007-2018 based on historical data published by the Hellenic Association of Photovoltaic Companies (HELAPCO) [122].

RQ$_1$. How did the regulatory design of the past affect the transition to a low-carbon energy system in Greece?

Literature studies have already assessed the effects of the FiT legislation in Greece upon the resulting RES penetration and investments [120], also addressing the impact of the imposed retroactive reduction upon the profitability of specific RES systems to their owners [118], and the resulting surcharge on the electricity prices owing to the massive PV penetration achieved [122]. However, while a literature consensus providing an account of the scheme's profitability, mainly through a technoeconomic spectrum, has already been established, there is still a knowledge gap on how the scheme affected the structure and the performance of the Greek energy market [119].

To address this gap, in **Chapter 2**, we applied an analytical framework based on domain knowledge, stakeholder insights, and public domain data, to analyse the main drivers and interactions that governed the major monetary flows and causal relationships within the Greek wholesale electricity market over the period 2009-2013. In view of a market design that foresees sector coupling and the development of a single European electricity market, the focal point of the national energy transition is the formulation of a new electricity mix that will be based on the integration of high shares of RES. Thus, it is important to ensure that the regulatory environment adapts to the new situation to avoid legislative failures of the past. Consequently, given the importance of increasing reliance on RES-E, our work can trigger wave of research and denote structural and regulatory adaptations and adjustments needed towards the achievement of the national decarbonisation targets.

Regulatory efforts to reach the standards of other European markets that experienced a transition from a high FiT status to a market-based environment have been put in place, with a NEM scheme taking the place of the effective, but very generous FiT scheme. This new scheme was legislated in 2014 by the Government Gazette Issue B'3583/31.12.2014 and came into effect during the second half of 2015 [123].

RQ_2. How could alternative regulatory designs incentivise consumers to invest in technological infrastructure for the transition to a low-carbon energy system in Greece?

Recent scientific literature has already highlighted the importance of studying the profitability and the effects of NEM or SC schemes related to PV systems [124]. Scientific studies have also acknowledged that a NEM regulatory design must be considered in combination with flexibility measures to maximise SC in residential buildings. Declining PV costs, along with rising retail prices and the phasing out of the FiT scheme, have made PV SC a more financially attractive choice for end-users than exporting to the grid. Such flexibility measures mainly refer to the further deployment of automated control technologies and electricity storage; further, they facilitate the large-scale integration of electricity from variable RES with the existing power system [125]. A particular focus is placed on the joint operation of SC with battery storage because it is the latest trend in small-scale PV systems [124].

To address these gaps, in **Chapter 3**, we use ATOM to explore the evolution of the market share of small-scale PV systems (i.e., installed capacity of up to 10 kWpeak) in Greece, under two different policy support schemes of interest. In particular, the applicability of the model is demonstrated by exploring the expected effectiveness of the NEM scheme, which has been operational since mid-2015, and of a proposed SC support scheme that subsidises residential storage (SC-ST) with a share of 25%, during the period 2018-2025.

In addition, scientific studies have acknowledged that the return of investment in such support schemes is highly related to the unpredictability of electricity prices, thereby increasing the uncertainty experienced by consumers [75]. To address this gap, we use ATOM to explore scenarios of small-scale PV adoption, under the two policy schemes under study, by assuming an annual increase in the Greek electricity retail price based on historical data/ observations.

Finally, the main challenge of decentralised generation and prosuming is that the initial cost of RES technologies may be prohibitive for investments, despite the benefits over the investment's lifetime [126]. While PV SC already seems attractive, electricity storage is still not a profitable solution owing to high costs and short lifetime. Only a sustained decrease in investment costs would lead to economically viable storage projects [124]. To address this gap, we use ATOM to explore the effectiveness of the SC-ST scheme under study in driving investments in small-scale PV systems in Greece by assuming different feasible scenarios of decreasing investment costs.

RQ_3. How could novel product-service offerings along with new regulatory designs incentivise consumers to invest in technological infrastructure for the transition to a low-carbon energy system in Greece?

Digitalisation is expected to enable better DSM and create more opportunities for active participation of end-users in Greece, through the provision of novel product-service offerings (e.g., smart appliances, Internet-of-Things, smart meters, prosuming, DR, etc.) [55]. However, the vision of a more decentralised and digitalised Greek energy system has an important implication; part of the necessary infrastructure will be only developed if end-users are willing to invest in it. Considering that it is unlikely for end-users to invest in new technological capabilities having the support (e.g., flexibility, etc.) of the energy system as their primary goal, it is reasonable to assume that they may only invest

according to a value stemming from increased proportion of the self-produced energy that they consume and/ or the energy savings that they achieve, as, in both cases, they benefit from lower energy bills.
While technological infrastructure is already available, business models and regulatory innovation are needed in order to find ways to maximise the value of the technological capabilities as well as to monetise them, to compensate end-users. However, the current regulatory framework in Greece, leads to conditions where business models do not bring the full value of demand-side capabilities, even when the latter are already there, due to conflicts between the interests of end-users and market actors. Given that in modern energy systems technological innovation will continuously pose new challenges to existing regulatory frameworks, innovation in regulation should be as important as regulating innovation. As a result, national policymaking should explore innovative business models that incentivise all involved actors to incorporate demand flexibility into the markets that can valorise it.
To address this need, in **Chapter 4**, we use DREEM to develop such a preliminary business model and to explore benefits of investing in technological infrastructure, as solar PV and electricity storage installations, a smart thermostat and an advanced control device that regulates their dwelling's energy performance, for residential end-users, while they also comply, when possible, to market dynamic price-based DR signals. The potential for additional revenue sources for other power actors involved and benefits through the provision of services to the grid is also evaluated.

1.5. Structure

The current dissertation thesis is structured in five chapters as depicted in Figure 1.7, namely:
Chapter 1 - Introduction to the PhD thesis: In this first chapter, we have provided a background on the field of energy system modelling, and we have presented the formulation of the main problem, by which this dissertation thesis was mainly inspired. Based on the identified gaps and needs, we then have justified the main scope and objectives of the thesis, which have been further translated into the overarching research question that the thesis intends to answer, along with the individual thematic research questions that are addressed in each one of the following research chapters. The chapter has concluded with presenting the main specifications of the energy transition in Greece, which has been used as a case study to demonstrate the applicability and the usefulness of the analytical framework and of the two energy system models that have been developed in this thesis.
Chapter 2 - Analysing policy effects: In the second chapter, we present the analytical framework that was developed to facilitate the systematic exploration of the impact that policy measures have on the energy system and its components. The applicability of the framework is demonstrated for the case of the FiT policy scheme in Greece during the period 2009-2013 and specific policy-relevant implications are discussed.
Chapter 3 - Understanding technology adoption: In the third chapter, we present a new agent-based technology adoption model, ATOM, which serves as an entry point in technology adoption modelling by including a strong component of behaviour- and policy-contingent scenario elements that correlate technology adoption with its value to end-users. We also demonstrate the applicability and usefulness of the model by exploring adoption scenarios of small-scale PV systems in the residential sector in Greece toward the national targets of 2025 under different (alternative to the FiT scheme) regulatory designs of interest. Results are then discussed and insightful implications for policy and practice are derived.
Chapter 4 - Empowering end-users: In the fourth chapter, we present a new dynamic high-resolution DSM model, DREEM, which combines key features of both statistical and engineering models, and serves as an entry point in DSM modelling in the building sector, by expanding the computational capabilities of existing BES models, to assess the benefits and limitations of demand flexibility for residential end-users. The applicability and usefulness of the model are demonstrated for the residential sector in Greece, while interesting results and policy implications are derived and discussed.

Chapter 5 - Discussion and conclusions: Finally, in the last chapter of this dissertation thesis, we discuss overall results, while we reflect on the implications of the thesis for end-users from the fields of policy and practice, and of energy system modelling. We also summarise the advances and the contribution of the thesis to the scientific literature considering methodological novelties and insightful results for the case of Greece, along with the contribution of the thesis to the fields of research and academia by presenting the overall metrics that have been achieved. The chapter concludes with a series of considerations on limitations of the thesis and, most importantly, on concrete suggestions for further research in the field of energy system modelling outlining areas for further application of both ATOM and DREEM.

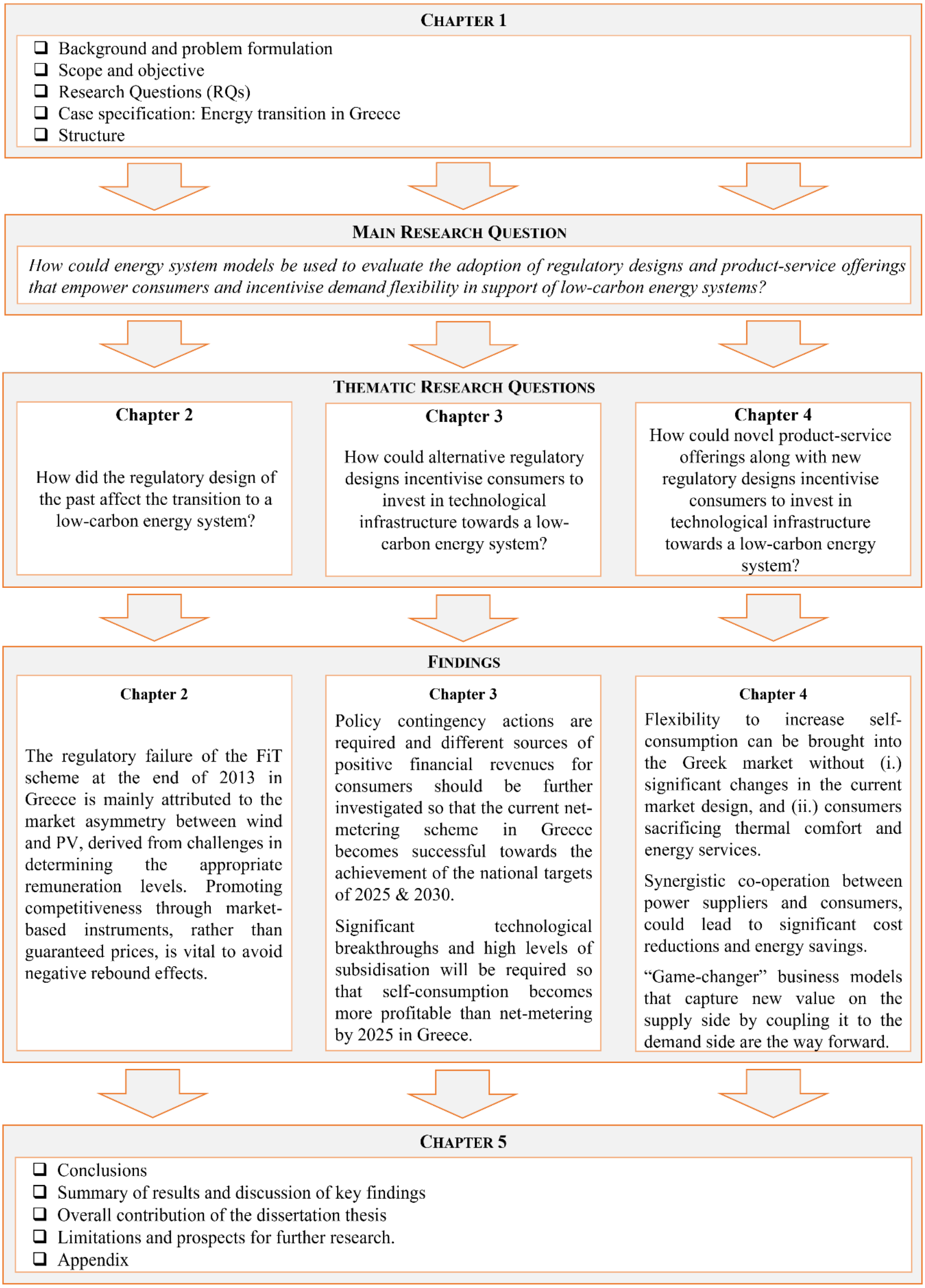


Figure 1.7. Graphical overview and structure of the dissertation thesis.

References

[1] Wurzel RKW, Connelly J, Liefferink D. The European Union in International Climate Change Politics. Still Taking a Lead? London and New York: Routledge; 2016.

[2] Oberthür S. The European Union's Performance in the International Climate Change Regime. J Eur Integr 2011;33:667–82. doi:10.1080/07036337.2011.606690.

[3] Stavrakas V, Spyridaki N-A, Flamos A. Striving towards the deployment of bio-energy with carbon capture and storage (BECCS): A review of research priorities and assessment needs. Sustain 2018;10. doi:10.3390/su10072206.

[4] Rosenow J, Cowart R, Bayer E, Fabbri M. Assessing the European Union's energy efficiency policy: Will the winter package deliver on 'Efficiency First'? Energy Res Soc Sci 2017;26:72–9. doi:10.1016/J.ERSS.2017.01.022.

[5] Michas S, Stavrakas V, Spyridaki N, Flamos A. Identifying Research Priorities for the further development and deployment of Solar Photovoltaics. Int J Sustain Energy 2019:276–96. doi:10.1080/14786451.2018.1495207.

[6] European Commission. The European Green Deal. 2019. doi:10.1128/AAC.03728-14.

[7] European Commission. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources (recast). Off J Eur Union 2018.

[8] European Commission. Directive 2006/32/EC of the European Parliament and of the Council of 5 April 2006 on energy end-use efficiency and energy services and repealing Council Directive 93/76/EEC 2006.

[9] European Commission. Recovery plan for Europe 2020.

[10] Süsser D, Ceglarz A, Gaschnig H, Stavrakas V, Giannakidis G, Flamos A, et al. The use of energy modelling results for policymaking in the EU, Deliverable 1.1, SENTINEL. 2020.

[11] Graf A, Buck M. The cost of renewable energy: A critical assessment of the Impact Assessments underlying the Clean Energy for all Europeans-Package. Berlin: Agora Energiewende; 2017.

[12] Gaschnig H, Süsser D, Ceglarz A, Stavrakas, V., Giannakidis G, Flamos A, Sander, et al. User needs for an energy system modeling platform for the European energy transition. Deliverable 1.2. Sustainable Energy Transitions Laboratory (SENTINEL) project. Eur Comm Inst Adv Sustain Stud (IASS), Potsdam 2020.

[13] Gilbert N, Ahrweiler P, Barbrook-Johnson P, Narasimhan KP, Wilkinson H. Computational modelling of public policy: Reflections on practice. Jasss 2018;21. doi:10.18564/jasss.3669.

[14] Van Egmond S, Zeiss R. Modeling for Policy. Science-based models as performative boundary objects for Dutch policy making. Sci Stud (St Bonaventure) 2010;23:58–78. doi:10.1093/oxfordhb/9780199548453.003.0038.

[15] Ellenbeck S, Lilliestam J. How modelers construct energy costs: Discursive elements in Energy System and Integrated Assessment Models. Energy Res Soc Sci 2019;47:69–77. doi:10.1016/j.erss.2018.08.021.

[16] Evans R. Economic Models and Economic Policy: What Economic Forecasters Can Do for Government. In: Den Butter FAG, Morgan MS, editors. Empir. Model. Policy-Making, (London, New York, Routledge: 2000, p. 206–80.

[17] Star SL, Griesemer JR. Amateurs and Professionals in Berkeley ' s Museum of Vertebrate Zoology , 1907-39. Soc Stud Sci 1989;19:387–420.

[18] Lopion P, Markewitz P, Robinius M, Stolten D. A review of current challenges and trends in energy systems modeling. Renew Sustain Energy Rev 2018;96:156–66. doi:10.1016/j.rser.2018.07.045.

[19] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. Renew Sustain Energy Rev 2014;33:74–86. doi:10.1016/j.rser.2014.02.003.

[20] Süsser D. People-powered local energy transition: Mitigating climate change with community-based renewable energy in North Frisia. Universität Hamburg, 2016.

[21] Stavrakas V, Papadelis S, Flamos A. An agent-based model to simulate technology adoption quantifying

behavioural uncertainty of consumers. Appl Energy 2019;255:113795. doi:10.1016/j.apenergy.2019.113795.

[22] Savvidis G, Siala K, Weissbart C, Schmidt L, Borggrefe F, Kumar S, et al. The gap between energy policy challenges and model capabilities. Energy Policy 2019;125:503–20. doi:10.1016/j.enpol.2018.10.033.

[23] Geels FW, McMeekin A, Pfluger B. Socio-technical scenarios as a methodological tool to explore social and political feasibility in low-carbon transitions: Bridging computer models and the multi-level perspective in UK electricity generation (2010–2050). Technol Forecast Soc Change 2018. doi:10.1016/j.techfore.2018.04.001.

[24] Süsser D, Ceglarz A, Gaschnig H, Stavrakas V, Flamos, Alexandros, Giannakidis G, Lilliestam J. Model-based policymaking or policy-based modelling? How energy models and energy policy interact. Energy Res Soc Sci 2021;75:101984.

[25] Taylor PG, Upham P, McDowall W, Christopherson D. Energy model, boundary object and societal lens: 35 years of the MARKAL model in the UK. Energy Res Soc Sci 2014;4:32–41. doi:10.1016/j.erss.2014.08.007.

[26] Prognos AG. Die Energieperspektiven für die Schweiz bis 2050 - Energienachfrage und Elektrizitätsangebot in der Schweiz 2000 - 2050 - Ergebnisse der modellrechningen für das Energiesystem. Swiss Fed Off Energy 2012:1–842.

[27] Piot M. Energiestrategie 2050 der Schweiz. 13 Symp Energieinnovation 2014:21–3.

[28] Redondo PD, Van Vliet O. Modelling the Energy Future of Switzerland after the Phase out of Nuclear Power Plants. Energy Procedia 2015;76:49–58. doi:10.1016/j.egypro.2015.07.843.

[29] Süsser D, Ceglarz A, Gaschnig H, Stavrakas V, Flamos A, Giannakidis G, et al. Model-based policymaking or policy-based modelling? How energy models and energy policy interact. Energy Res Soc Sci 2021;75:101984. doi:10.1016/j.erss.2021.101984.

[30] Chang M, Zinck Thellufsen J, Zakeri B, Pickering B, Pfenninger S, Lund H. Observed trends and modelling paradigms. Deliverable 4.1. Sustainable Energy Transitions Laboratory (SENTINEL) project. European Commission. 2020.

[31] McIntosh BS, Giupponi C, Voinov AA, Smith C, Matthews KB, Monticino M, et al. Bridging the Gaps Between Design and Use: Developing Tools to Support Environmental Management and Policy. In: A.J. Jakeman, A.A. Voinov, A.E. Rizzoli SHC, editor. Dev. Integr. Environ. Assess., Elsevier; 2008, p. 33–48. doi:10.1016/S1574-101X(08)00603-0.

[32] Capros P, De Vita A, Tasios N, Siskos P, Kannavou M, Petropoulos A, et al. EU Reference Scenario 2016. 2016. doi:10.2833/9127.

[33] European Commission. The Energy Union gets simplified , robust and transparent governance : Commission welcomes ambitious agreement 2018.

[34] Grams CM, Beerli R, Pfenninger S, Staffell I, Wernli H. Balancing Europe's wind-power output through spatial deployment informed by weather regimes. Nat Clim Chang 2017;7:557–62. doi:10.1038/NCLIMATE3338.

[35] Staffell I, Pfenninger S. The increasing impact of weather on electricity supply and demand. Energy 2018;145:65–78. doi:10.1016/j.energy.2017.12.051.

[36] Martin N, Madrid López C, Talens Peiró L, Süsser D, Gaschnig H, Lilliestam J. Observed trends and modelling paradigms on the social and environmental aspects of the energy transition. Deliverable 2.1. Sustainable Energy Transitions Laboratory (SENTINEL) project. European Commission. 2020.

[37] Madrid-Lopez C, Süsser D, Stavrakas V, Lilliestam J, Flamos A, Talens-Peiro L, et al. Model development to match ENVIRO, QTDIAN and ATOM to user needs. Deliverable 2.4. Sustainable Energy Transitions Laboratory (SENTINEL) project. 2021. doi:https://doi.org/10.5281/zenodo.4912686.

[38] Lilliestam J, Blumer Y, Geddes A, Labordena M, Späth L, Van Vliet O. More than costs: On the fit between solar and renewable electricity policy motivations and energy system models. Sol Power Technol Environ Impacts Futur Prospect 2014:24–55.

[39] Blumer YB, Moser C, Patt A, Seidl R. The precarious consensus on the importance of energy security: Contrasting views between Swiss energy users and experts. Renew Sustain Energy Rev 2015;52:927–36. doi:10.1016/j.rser.2015.07.081.

[40] Lilliestam J, Hanger S. Shades of green: Centralisation, decentralisation and controversy among European renewable electricity visions. Energy Res Soc Sci 2016;17:20–9. doi:10.1016/j.erss.2016.03.011.

[41] European Commission. Energy Roadmap 2050. Policy 2012:1–9. doi:10.2833/10759.

[42] Jebaraj S, Iniyan S. A review of energy models. Renew Sustain Energy Rev 2006;10:281–311. doi:10.1016/j.rser.2004.09.004.

[43] European Commission. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank, A Framework Strategy for a Resilient Energy Union with a Forward-Looking 2015.

[44] European Commission. Europe leads the global clean energy transition : Commission welcomes 2018.

[45] European Commission. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank, Third Report on the State of the Energy Union 2017.

[46] European Commission. Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings 2010.

[47] European Commission. Directive (EU) 2018/844 of the European Parliament and of the Council of 30 May 2018 amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency 2018.

[48] European Commision. Energy efficiency first : Commission welcomes agreement on energy efficiency 2018.

[49] Aryandoust A, Lilliestam J. The potential and usefulness of demand response to provide electricity system services. Appl Energy 2017;204:749–66. doi:10.1016/j.apenergy.2017.07.034.

[50] European Commission. The Clean Energy Package Online capacity-building material 2016.

[51] Chang M, Thellufsen JZ, Zakeri B, Pickering B, Pfenninger S, Lund H, et al. Trends in tools and approaches for modelling the energy transition. Appl Energy 2021;290. doi:10.1016/j.apenergy.2021.116731.

[52] Welsch M, Howells M, Hesamzadeh MR, Ó Gallachóir B, Deane P, Strachan N, et al. Supporting security and adequacy in future energy systems: The need to enhance long-term energy system models to better treat issues related to variability. Intern J Energy Res 2014;39:377–96. doi:10.1002/er.3250.

[53] Pfenninger S, DeCarolis J, Hirth L, Quoilin S, Staffell I. The importance of open data and software: Is energy research lagging behind? Energy Policy 2017;101:211–5. doi:10.1016/j.enpol.2016.11.046.

[54] Pfenninger S. Energy scientists must show their workings. Nature 2017;542:393. doi:10.1038/542393a.

[55] Stavrakas V, Ceglarz A, Kleanthis N, Giannakidis G, Schibline A, Süsser D, et al. Case specification and scheduling. Deliverable 7.1. Sustainable Energy Transitions Laboratory (SENTINEL) project 2021. doi:10.5281/ZENODO.4699518.

[56] van Vuuren DP, Kok M, Lucas PL, Prins AG, Alkemade R, van den Berg M, et al. Pathways to achieve a set of ambitious global sustainability objectives by 2050: Explorations using the IMAGE integrated assessment model. Technol Forecast Soc Change 2015;98:303–23. doi:10.1016/j.techfore.2015.03.005.

[57] Süsser D, Gaschnig H, Ceglarz A, Stavrakas V, Flamos A, Lilliestam J. Better suited or just more complex? On the fit between user needs and modeller-driven improvements of energy system models. Energy 2022;239:121909. doi:10.1016/j.energy.2021.121909.

[58] Matthew C, Devine-Wright P. Dis[1] Matthew C, Devine-Wright P. Discourses of Energy Infrastructure Development: A Q-Method Study of Electricity Transmission Line Siting in the UK. Environ Plan A Econ Sp 2011;43:942–60.courses of Energy Infrastructure Development: A Q-Method Study of. Environ Plan A Econ Sp 2011;43:942–60.

[59] McDowall W, Geels FW. Ten challenges for computer models in transitions research: Commentary on

Holtz et al. Environ Innov Soc Transitions 2017;22:41–9. doi:10.1016/j.eist.2016.07.001.

[60] Voinov A, Bousquet F. Modelling with stakeholders. Environ Model Softw 2010;25:1268–81. doi:10.1016/j.envsoft.2010.03.007.

[61] Krumm A, Süsser D, Blechinger P. Modelling social aspects of the energy transition: What is the current representation of social factors in energy models? Energy 2022;239:121706. doi:10.1016/j.energy.2021.121706.

[62] European Commission. Energy union 2021.

[63] Oconnell N, Pinson P, Madsen H, Omalley M. Benefits and challenges of electrical demand response: A critical review. Renew Sustain Energy Rev 2014;39:686–99. doi:10.1016/j.rser.2014.07.098.

[64] Nikas A, Lieu J, Sorman A, Gambhir A, Turhan E, Baptista BV, et al. The desirability of transitions in demand: Incorporating behavioural and societal transformations into energy modelling. Energy Res Soc Sci 2020;70:101780. doi:10.1016/j.erss.2020.101780.

[65] Li K, Liu L, Wang F, Wang T, Duić N, Shafie-khah M, et al. Impact factors analysis on the probability characterized effects of time of use demand response tariffs using association rule mining method. Energy Convers Manag 2019;197. doi:10.1016/j.enconman.2019.111891.

[66] Wolisz H, Punkenburg C, Streblow R, Müller D. Feasibility and potential of thermal demand side management in residential buildings considering different developments in the German energy market. Energy Convers Manag 2016;107:86–95. doi:10.1016/j.enconman.2015.06.059.

[67] Rubino A. Network charges in a low CO2 world. Nat Energy 2018;3:255–6. doi:10.1038/s41560-018-0115-2.

[68] Butler L, Neuhoff K. Comparison of feed-in tariff, quota and auction mechanisms to support wind power development. Renew Energy 2008;33:1854–67. doi:10.1016/j.renene.2007.10.008.

[69] Campoccia A, Dusonchet L, Telaretti E, Zizzo G. An analysis of feed'in tariffs for solar PV in six representative countries of the European Union. Sol Energy 2014;107:530–42. doi:10.1016/j.solener.2014.05.047.

[70] Li SJ, Chang TH, Chang SL. The policy effectiveness of economic instruments for the photovoltaic and wind power development in the European Union. Renew Energy 2017;101:660–6. doi:10.1016/j.renene.2016.09.005.

[71] Fuchs C, Kasten J, Vent M. Current State and Future Prospective of Repowering Wind Turbines: An Economic Analysis. Energies 2020;13:3048. doi:10.3390/en13123048.

[72] Koumparou I, Christoforidis GC, Efthymiou V, Papagiannis GK, Georghiou GE. Configuring residential PV net-metering policies – A focus on the Mediterranean region. Renew Energy 2017;113:795–812. doi:10.1016/j.renene.2017.06.051.

[73] Batlle C, Pérez-Arriaga IJ, Zambrano-Barragán P. Regulatory design for RES-E support mechanisms: Learning curves, market structure, and burden-sharing. Energy Policy 2012;41:212–20. doi:10.1016/j.enpol.2011.10.039.

[74] Eid C, Reneses Guillén J, Frías Marín P, Hakvoort R. The economic effect of electricity net-metering with solar PV: Consequences for network cost recovery, cross subsidies and policy objectives. Energy Policy 2014;75:244–54. doi:10.1016/j.enpol.2014.09.011.

[75] Nikolaidis AI, Milidonis A, Charalambous CA. Impact of fuel-dependent electricity retail charges on the value of net-metered PV applications in vertically integrated systems. Energy Policy 2015;79:150–60. doi:10.1016/j.enpol.2015.01.010.

[76] Ramïrez FJ, Honrubia-Escribano A, Gï¿½mez-Lï¿½zaro E, Pham DT. Combining feed-in tariffs and net-metering schemes to balance development in adoption of photovoltaic energy: Comparative economic assessment and policy implications for European countries. Energy Policy 2017;102:440–52. doi:10.1016/j.enpol.2016.12.040.

[77] Danchev S, Maniatis G, Tsakanikas A. Returns on investment in electricity producing photovoltaic systems under de-escalating feed-in tariffs: The case of Greece. Renew Sustain Energy Rev 2010;14:500–

5. doi:10.1016/j.rser.2009.08.008.

[78] Michas S, Stavrakas V, Papadelis S, Flamos A. A transdisciplinary modeling framework for the participatory design of dynamic adaptive policy pathways. Energy Policy 2020;139. doi:10.1016/j.enpol.2020.111350.

[79] Sotiriou C, Michopoulos A, Zachariadis T. On the cost-effectiveness of national economy-wide greenhouse gas emissions abatement measures. Energy Policy 2019;128:519–29. doi:10.1016/j.enpol.2019.01.028.

[80] Lang T, Ammann D, Girod B. Profitability in absence of subsidies: A techno-economic analysis of rooftop photovoltaic self-consumption in residential and commercial buildings. Renew Energy 2016;87:77–87. doi:10.1016/j.renene.2015.09.059.

[81] Bertsch V, Geldermann J, Lühn T. What drives the profitability of household PV investments, self-consumption and self-sufficiency? Appl Energy 2017;204:1–15. doi:10.1016/j.apenergy.2017.06.055.

[82] De Boeck L, Van Asch S, De Bruecker P, Audenaert A. Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability. Renew Energy 2016;87:42–53. doi:10.1016/j.renene.2015.09.063.

[83] Beck T, Kondziella H, Huard G, Bruckner T. Assessing the influence of the temporal resolution of electrical load and PV generation profiles on self-consumption and sizing of PV-battery systems. Appl Energy 2016;173:331–42. doi:10.1016/j.apenergy.2016.04.050.

[84] Yu HJJ. A prospective economic assessment of residential PV self-consumption with batteries and its systemic effects: The French case in 2030. Energy Policy 2018;113:673–87. doi:10.1016/j.enpol.2017.11.005.

[85] Kyritsis A, Voglitsis D, Papanikolaou N, Tselepis S, Christodoulou C, Gonos I, et al. Evolution of PV systems in Greece and review of applicable solutions for higher penetration levels. Renew Energy 2017;109:487–99. doi:10.1016/j.renene.2017.03.066.

[86] Sommerfeld J, Buys L, Vine D. Residential consumers' experiences in the adoption and use of solar PV. Energy Policy 2017;105:10–6. doi:10.1016/j.enpol.2017.02.021.

[87] MacAl CM, North MJ. Tutorial on agent-based modelling and simulation. J Simul 2010;4:151–62. doi:10.1057/jos.2010.3.

[88] Ringler P, Keles D, Fichtner W. Agent-based modelling and simulation of smart electricity grids and markets - A literature review. Renew Sustain Energy Rev 2016;57:205–15. doi:10.1016/j.rser.2015.12.169.

[89] Taylor R, Besa MC, Forrester J. Agent-Based Modelling: A Tool for Addressing the Complexity of Environment and Development Policy Issues. 2016.

[90] Nikolic I, Ghorbani A. A Method for Developing Agent-based Models of Socio-technical Systems. IEEE Int. Conf. Networking, Sens. Control (ICNSC), 2011, IEEE; 2011, p. 44–9.

[91] Zhang T, Nuttall W-J. Evaluating Government's Policies on Promoting Smart Metering Diffusion in Retail Electricity Markets via Agent-Based Simulation. J Prod Innov Manag 2011;28:169–86.

[92] Edmonds, B., Lucas P, Rouchier J, Taylor R. Human Societies: Understanding Observed Social Phenomena. In Simulating Social Complexity. In: Edmonds B, Meyer R, editors. Underst. Complex Syst., Berlin, Heidelberg: Springer; 2013, p. 709–748.

[93] Papadelis S, Flamos A, Androulaki S. Setting the framework for a Business Strategy Assessment Model. Int J Energy Sect Manag 2012;6:488–517. doi:10.1108/17506221211281993.

[94] Kontochristopoulos Y, Michas S, Kleanthis N, Flamos A. Investigating the market effects of increased RES penetration with BSAM: A wholesale electricity market simulator. Energy Reports 2021;7:4905–29. doi:10.1016/j.egyr.2021.07.052.

[95] Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy 2016;1:16032. doi:10.1038/nenergy.2016.32.

[96] Geelen D, Reinders A, Keyson D. Empowering the end-user in smart grids: Recommendations for the

design of products and services. Energy Policy 2013;61:151–61. doi:10.1016/j.enpol.2013.05.107.

[97] Lampropoulos I, Kling WL, Ribeiro PF, Van Den Berg J. History of demand side management and classification of demand response control schemes. IEEE Power Energy Soc Gen Meet 2013:1–5. doi:10.1109/PESMG.2013.6672715.

[98] Palensky P, Dietrich D. Demand side management: Demand response, intelligent energy systems, and smart loads. IEEE Trans Ind Informatics 2011;7:381–8. doi:10.1109/TII.2011.2158841.

[99] Albadi MH, El-Saadany EF. Demand Response in Electricity Markets: An Overview. 2007 IEEE Power Eng Soc Gen Meet 2007:1–5. doi:10.1109/PES.2007.385728.

[100] Stavrakas V, Flamos A. A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector. Energy Convers Manag 2020;205. doi:10.1016/j.enconman.2019.112339.

[101] Mart H, Coronas S, Alonso À, Hoz J De, Matas J. Renewable Energy Auction Prices : Near Subsidy-Free ? Energies 2020;13.

[102] Su H, Zio E, Zhang J, Chi L, Li X, Zhang Z. A systematic data-driven Demand Side Management method for smart natural gas supply systems. Energy Convers Manag 2019;185:368–83. doi:10.1016/j.enconman.2019.01.114.

[103] Pereverza K, Pasichnyi O, Kordas O. Modular participatory backcasting: A unifying framework for strategic planning in the heating sector. Energy Policy 2019;124:123–34. doi:10.1016/j.enpol.2018.09.027.

[104] Nikas A, Doukas H, Papandreou A. A Detailed Overview and Consistent Classification of Climate-Economy Models. In: Doukas H, Flamos A, Lieu J, editors. Underst. Risks Uncertainties Energy Clim. Policy Multidiscip. Methods Tools a Low Carbon Soc., Springer, Cham; 2018, p. 1–54. doi:10.1007/978-3-030-03152-7.

[105] Wetter M, Haugstetter C. Modelica versus TRNSYS–A comparison between an equation-based and a procedural modeling language for building energy simulation. Second Natl. IBPSA-USA Conf. Cambridge, MA August 2-4, 2006 Model., vol. 11, 2006, p. 262–9.

[106] Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-Baltvilks J, et al. Barriers to and consequences of a solar-based energy transition in Greece. Environ Innov Soc Transitions 2019. doi:10.1016/j.eist.2018.12.004.

[107] Ministry of Environment and Energy. National Energy and Climate Plan: Greece. 2019.

[108] Ministry of Environment and Energy. Long Term Strategy for 2050 (In Greek). 2019.

[109] Στάσσης: Τέλος ο λιγνίτης στη ΔΕΗ το 2025 (in Greek) n.d.

[110] Fintikakis G. The revision of the CO2 targets launches in more than ... 10 GW the required new RES by 2030 - The ESEK is rewritten from the beginning. 2021.

[111] Ministry of Environment and Energy. Just Transition Development Plan of lignite areas. 2020.

[112] Ministry of Environment and Energy. 1st National Energy Efficiency Action Plan (NEEAP) 2008.

[113] European Commission. Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC 2009:16–62.

[114] Ministry of Environment and Energy. 1st National Renewable Energy Action Plan (NREAP) 2010.

[115] UNFCCC. GHG data from UNFCCC 2021.

[116] Eurostat. Database 2021.

[117] IEA. Data and statistics 2021.

[118] Anagnostopoulos P, Spyridaki NA, Flamos A. A “new-deal” for the development of photovoltaic investments in Greece? A parametric techno-economic assessment. Energies 2017;10:1173. doi:10.3390/en10081173.

[119] Karteris M, Papadopoulos AM. Legislative framework for photovoltaics in Greece: A review of the

sector's development. Energy Policy 2013;55:296–304. doi:10.1016/j.enpol.2012.12.001.

[120] Papadelis S, Stavrakas V, Flamos A. What do capacity deployment rates tell us about the efficiency of electricity generation from renewable energy sources support measures in Greece? Energies 2016;9. doi:10.3390/en9010038.

[121] Flamos A. A sectoral micro-economic approach to scenario selection and development: The case of the greek power sector. Energies 2016;9:1–12. doi:10.3390/en9020077.

[122] HELAPCO. Greek PV Market statistics - 2017. Hell Assoc Photovolt Co 2018:1–5.

[123] Giannini E, Moropoulou A, Maroulis Z, Siouti G. Penetration of photovoltaics in Greece. Energies 2015;8:6497–508. doi:10.3390/en8076497.

[124] Tselepis S. The PV market developments in Greece, net-metering study cases. Conf. 31st EUPVSEC, Hamburg: 2015.

[125] Camilo FM, Castro R, Almeida ME, Pires VF. Economic assessment of residential PV systems with self-consumption and storage in Portugal. Sol Energy 2017;150:353–62. doi:10.1016/j.solener.2017.04.062.

[126] Kyritsis A, Roman E, Kalogirou SA, Nikoletatos J, Agathokleous R, Mathas E, et al. Households with Fibre Reinforced Composite BIPV modules in Southern Europe under Net Metering Scheme. Renew Energy 2017:1–10. doi:10.1016/j.renene.2017.09.068.

[127] Nanaki EA, Xydis GA. Deployment of Renewable Energy Systems: Barriers, Challenges, and Opportunities. Adv Renew Energies Power Technol 2018;2:207–29. doi:10.1016/B978-0-12-813185-5.00005-X.

Chapter 2 - Analysing policy effects

Nomenclature

Acronyms & abbreviations			
ARDL	Autoregressive distributed lag	LAGIE	Hellenic Operator of Electricity Market
CA	Cointegration analysis	LOLE	Loss of load expectation
CEMS	Continuous emission monitoring system	LOLP	Loss of load probability
CO_2	Carbon dioxide	MEE	Ministry of Environment and Energy
COPT	Capacity outage probability table	MWV	Marginal water value
CRES	Centre of Renewable Energy Sources and Savings	NEM	Net-metering
DAS	Day-ahead scheduling	NO_X	Nitrogen oxide
ECM	Error-correction model	PM	Particulate matter
ELCC	Effective load carrying capability	PV	Photovoltaic
EC	European Commission	RES	Renewable energy sources
EU	European Union	RES-E	Electricity generation from RES
FiP	Feed-in-premium	SIMP	System imbalances marginal price
FiT	Feed-in-tariff	SMP	System marginal price
GHG	Greenhouse gas	SO_2	Sulfur dioxide
H2020	Horizon 2020 Research Programme	USA	United States of America
HEDNO	Hellenic Electricity Distribution Network Operator	VAR	Vector autoregressive
IPTO	Independent Power Transmission Operator	VCRM	Variable cost recovery mechanism
KPI	Key performance indicator	VECM	Vector error-correction modelling
List of symbols & parameters			
C_A	Additional generation capacity of a new generator	m	Index
C_E	Capacity of the existing system's configuration	$p_j(X)$	Probability of outage capacity when adding the j^{th} unit
CF_t	Capacity factor at time t	p^{NCP}	Non-compliance penalty
C_j	Equivalent perfectly reliable capacity of the j^{th} unit	Pr_t	Probability at a given time t
d	index	t	Index
$EFORd_j$	Demand equivalent forced outage rate of the j^{th} unit	W_t	Feature of an input dataset at time t
ε_t^p	CO_2 emission coefficient	X	Outage capacity
G_t^{RES}	RES-E generation during year t	x_j	j^{th} feature of an input dataset
h	Index	Y_t	Feature of an input dataset at time t
i	Index	Z_t	Feature of an input dataset at time t
j	Index	ΔE_t^p	Annual CO_2 emissions avoided
L_t	System's total load at time t	ΔL	Additional load that can be integrated into the new system's configuration

2. An ex-post assessment of RES-E support in Greece by investigating the monetary flows and the causal relationships in the electricity market

Abstract

One way to perceive the electricity market is as a network of actors connected through transactions and monetary flows. By exploring the monetary flows in the electricity market, one adopts a holistic view which can provide insights on the interactions between different components of the benefits and costs, as well as on the possible conflicts, or alliances between the involved actors of the system. The importance of such an analysis becomes even more evident when considering if the system's state would change due to either the effectuation of a policy measure or a shift in the external drivers of the system. Additionally, by identifying conditions of conflicting interests between the involved actors, one can devise a roadmap of least resistance for a policy measure to attain its goals. Our work is based on the premise that understanding and quantifying the monetary flows in the electricity market can contribute to the efficiency assessment of policy interventions in the market. We present a structured analytical framework and the results of a quantitative analysis based on available public domain data, for the identification of the main drivers and interactions that governed the major monetary flows in the Greek wholesale electricity market, from 2009 to 2013 and the ex-post assessment of the market impact of the feed-in-tariff scheme that was in place during this period.

Keywords: Greece; Feed-in-tariff; Market design; Climate policy; Policy assessment; Energy regulation; RES support mechanisms; Security of energy supply.

2.1. Introduction

To achieve climate goals implied by the Paris Agreement, the energy sector in the European Union (EU) should maintain its momentum towards a transition to a zero-carbon, sustainable electricity system by 2050 [1,2]. Renewable energy sources (RES) are significant contributors to this goal [3,4]. Although RES were not market competitive at first [5], electricity generation from RES (RES-E) has been growing rapidly over the last years, owing to economies of scale, technological progress, and financial support mechanisms [6]. One of the most utilized RES-E support mechanism has been the Feed-in-Tariff (FiT) scheme, providing security and high profits to investors [7,8]. Many EU Member States have adopted FiT [9–11], which proved to be the main driver for the drastically increased RES installed capacity over the period 2008 to 2015. However, despite the large growth, in many cases, policymakers failed to respond in a decisive manner to the negative implications of the scheme [12], as indicated by several examples across Europe [13–16].

Although FiTs were mostly designed as a generous subsidy to help initiate RES investments, the scheme has been gradually decreasing, or even ceased, and, thus, sustaining the growth of new RES installations has been challenging ever since. Although financial support is of substantial importance to incentivise new RES investments, it has to be designed in a way that does not result in public deficits or burdening costs for consumers. Introduction of closer-to-market oriented policies that compensate consumers with real-time electricity prices may be the way forward [12]. Aiming at overcoming the difficulties encountered in the post-FiT era, policymakers seek new legal mechanisms based on a combination of tax benefits and other incentives; Net-Metering (NEM), Feed-in-Premium (FiP), and tenders are considered such mechanisms, that could raise, once again, consumers' willingness to invest [17]. For the time being, though, these mechanisms should be mainly considered as transition policies from FiT towards self-consumption schemes closer to the market, that eliminate aspects of subsidisation and implement more advanced market rules (i.e., dynamic cost-reflective pricing) [18,19].

Increased RES deployment due to generous schemes as FiT, has sparked a debate across Europe regarding the effects of the enhanced RES integration on the performance of the energy market [20]. This debate challenges the premise that higher volumes of RES can enter every year the EU internal market and be absorbed progressively by the existing mechanisms. However, while most studies so far have focused on a technoeconomic analysis of the regulatory design and efficiency of the different RES-E support mechanisms [21–24], there is a knowledge gap on the impact of such mechanisms on the performance of the energy market and its interaction with the RES-E sector. Despite the learning progress of the past years, important regulatory questions still remain unanswered, with the long-term relationship between RES-E and conventional markets remaining ambiguous, mainly owing to two structural changes (**Figure 2.1**) [25]:

- The intermittency in the RES-E generation requires now more challenging conventional generation capacity services to the market, while these services need to be reduced in order to achieve decarbonisation targets.
- The day-ahead electricity price declines reaching a zero value to become equal to the marginal and opportunity costs of large RES-E integration, while there is going to be a higher variation of daily average prices.

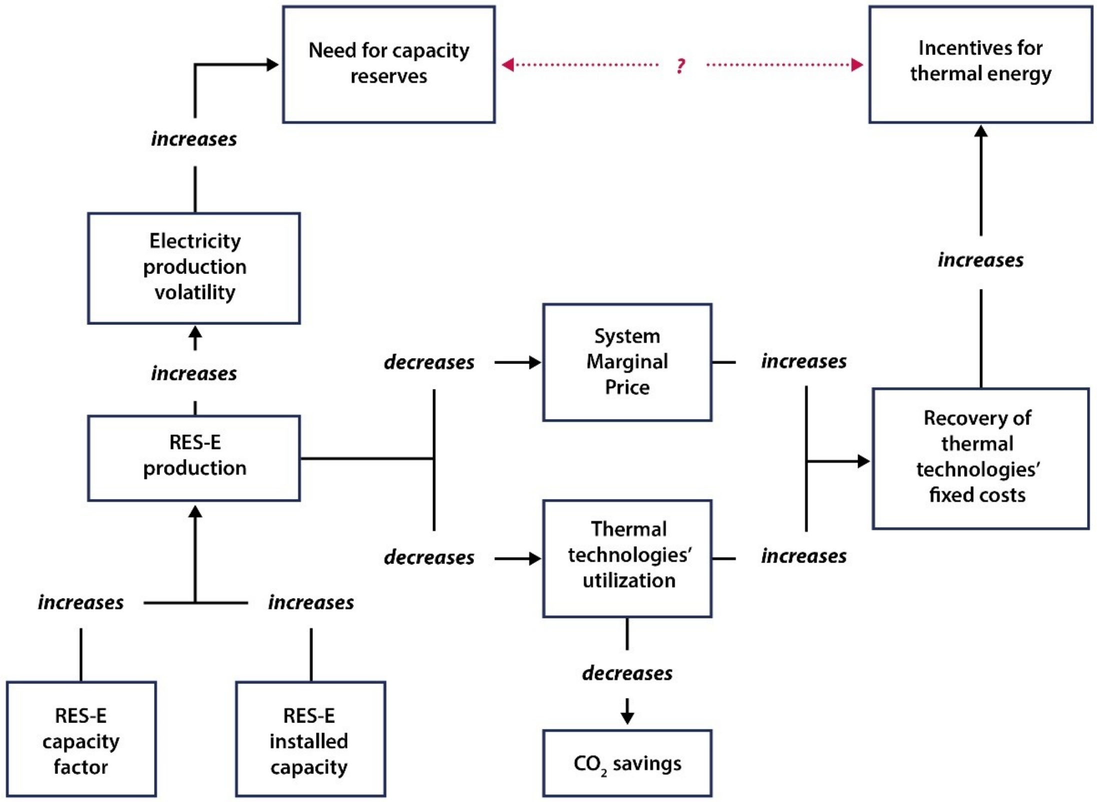


Figure 2.1. The impact of the RES-E growth on different aspects of the EU electricity market over the past few years.

Increasing RES shares brings new dynamics to the current fossil-based energy systems, which makes the decision-making process about the energy future more complex. Policymakers face the challenge of making decisions about technologies, spatial requirements, democratisation, and other aspects of unfamiliar RES-dominated energy systems, like for example, balancing interests of involved actors in designing policies to support the decarbonisation of the energy system [26,27]. So far, studies suggest that RES and conventional generators, operate within the same market but with very different business models; a market operating only with RES would be a market with zero marginal and opportunity costs that compensates agents through subsidies [28], while the thermal market is based on bidding competition as well as fuel and electricity spread risk. As a result, existing market mechanisms may not be the ones that can effectively support the evolution of these two "worlds." In view of a high-RES market design in line with the EU Target Electricity Model, thus, regulatory efforts need to expand their approach to carefully: **a.** review how the energy market's performance is affected by the different support mechanisms both in the short- and the long-term as well as **b.** assess past and/ or modern mechanisms to optimise market performance in both time horizons. However, the outcomes of policy mechanisms depend on more than variables such as price and quantity; they depend on institutions that may be part of the environment surrounding a policy [29]. As a result, a structured approach aiming at facilitating the systematic exploration of the effect that policy measures have on the electricity system and its components, and filling knowledge gaps, either at a national or at an EU level, is of paramount importance.

This chapter sheds light on the debate regarding the competition between conventional and RES-E generation, as well as on the role that RES-E remuneration played in this debate, by perceiving the electricity market as a network of actors connected through transactions and monetary flows. In particular, our work builds on the premise that understanding and quantifying the major monetary flows in the electricity market can contribute to the efficiency assessment of policy interventions, and that assessing how a policy measure affects the performance of the energy market requires the quantification of both the benefits and the costs attributed to it. By exploring the monetary flows in the energy market, on the one hand, one adopts a holistic view, which can provide insights on the interactions between different components of the benefits and costs, as well as on the possible conflicts or alliances between the involved actors of the system. By identifying conditions of conflicting interests between the involved actors, on the other hand, one can devise a roadmap of least resistance for a policy measure to attain its goals. The novelty of this approach becomes more evident when considering if the system's state would change due to either the effectuation of a policy measure or a shift in the external drivers of the system.

To this end, in this chapter, we developed and applied an analytical framework based on public domain data to identify and present the main drivers and interactions that governed the major monetary flows and causal relationships within the Greek wholesale electricity market over the period 2009-2013. This was the period that the FiT scheme contributed to a remarkable RES boom in the country, which was then suspended by institutional and legislative failures, combined with an adverse fiscal environment. The latter resulted to a stagnation of the RES market to this day and a gradual phase out of the FiT scheme [30].

Literature studies have already assessed the effects of the FiT legislation in Greece upon the resulting RES penetration and investments (see [24,31]), also addressing the impact of the imposed retroactive reduction upon the profitability of specific RES systems to their owners [32], and the resulting surcharge on the electricity prices owing to the massive solar photovoltaic (PV) penetration achieved [33]. However, while a literature consensus providing an account of the scheme's profitability, mainly through a technoeconomic spectrum, has already been established, there is still a knowledge gap on how the scheme affected the structure and the performance of the energy market, also highlighted in recent scientific literature [34].

Furthermore, one of the main priorities of the recently revised National Energy and Climate Plan (NECP) is the goal for phasing out all lignite-fired power plants by 2028 [35], an objective which is at the heart of the European Green Deal [36], and in line with the EU's commitment to global climate action under the Paris Agreement and climate neutrality by 2050 [37,38]. In view of a market design that foresees sector coupling and the development of a single electricity market in Europe, the focal point of the national energy transition is the formulation of a new electricity mix that will be based on the integration of high shares of RES. In order for this transition to happen in a fair and socially just manner, with "no one being left behind," it is important to ensure that the regulatory environment adapts to the new situation, also to avoid legislative failures of the past. Thus, given the importance of increasing reliance on RES-E, our work can trigger wave of research and denote structural and regulatory adaptations and adjustments needed towards the achievement of the national decarbonisation targets.

The remainder of this chapter is organised as follows: **Section 2.2** presents the analytical framework of our work. **Section 2.3** presents the application of our framework using as an illustrative case study the electricity market in Greece to quantify the main benefits and costs attributed to the RES-E generation achieved from the FiT scheme over the period 2009 to 2013. **Section 2.4** presents and discusses the results of our work, while **Section 2.5** provides conclusions and reports key implications for market and industry professionals, consultants in the policy community, and government officials.

2.2. Materials and Methods

Our analytical framework comprises of the following main methodological steps:

2.2.1. Step 1: Identifying the relevant monetary flows

As a first step, we map the relevant monetary flows and the respective causal relationships in the electricity market under study, based on domain knowledge, literature review, and tacit knowledge embedded in stakeholders.

2.2.2. Step 2: Quantifying costs and benefits from RES-E generation

As a next step, we consider the main costs and benefits of RES-E generation. In our framework costs and benefits are modeled as:

- <u>Costs</u>: Fiscal support of RES-E generation. Taxes are not considered. The levy often paid by RES-E producers to the local municipalities has only a distributional effect, thus, it is omitted.
- <u>Benefits</u>: Substitution of fossil-fueled generation by RES-E could be measured by the induced reduction in the wholesale day-ahead electricity price, or in the fossil fuel usage. In order to omit transfer payments, we check if there is any energy consumption or savings, e.g., regarding fossil fuel use, or the net impact on public expenditures, etc.

To quantify the benefits attributed to the RES-E generation the following sub-steps are implemented:

I. Estimating the mix of the conventional-powered generation that is substituted by the RES-E generation, and

II. Estimating the capacity value of the RES-E generation, while keeping the electricity system's reliability at a designated level.

Note that balancing costs that derive from uncertainties of the short-term forecasting of the RES-E generation are not taken into consideration, while the reduction in capacity payments due to the capacity value of RES-E generators is considered as benefit.

Sub-step 2.1: Estimating the mix of the conventional-powered generation that is substituted by the RES-E generation

An econometric approach often used to model the relations of the different variables that rule the electricity market is Cointegration Analysis (CA) and Vector Error-Correction Modelling (VECM) [39]. The rationale behind CA is that if a steady relationship between a set of variables, for a sufficiently long-time period, can be proven, then causal interactions between these variables can be inferred. Usually in literature, CA is applied to model the wholesale spot electricity price as a function of its fundamental underlying drivers, like **a.** demand for electricity consumption; **b.** RES-E generation; **c.** fuel prices; and **d.** capacity availability. In this work, we apply an econometric approach that considers the randomness and exogeneity of RES-E generation patterns and identifies the average capacity reduction for conventional generators substituted by the RES-E generation. In doing so, the following two points are considered:

- Regarding the system's load, increasing the RES-E generation must result in equally decreasing of the conventional generation, so that the electricity generated is always equal to demand plus total losses, and
- Avoiding results of the conventional generation in increasing the RES-E generation, which varies with marginal costs of the dispatchable generator. As a result, the impact of the RES-E generation differentiates according to demand levels (i.e., high or low).

Our premise is that in a market where average load is constant, an equilibrium between electricity and fuel prices can be identified. For example, Jong and Schneider (2009) developed a multi-market modelling framework that showed that natural gas and electricity prices are cointegrated at long-term forward price levels, since both markets are highly linked when considering physical transportation [40]. Bosco et al., (2010) examined the causal relationships affecting the wholesale electricity prices in six major European countries, revealing four highly integrated central European markets, which shared a common trend in natural gas prices [41]. Ferkingstad et al., (2011) also acknowledged that natural gas prices highly influence electricity prices, while coal and oil prices play a lesser role [42]. Finally, Furió and Chuliá (2012) used a VECM to reveal that the forward prices of crude oil and natural gas are important components in the formation process of the electricity price. They also showed that causation, both in price and volatility, is transferred from oil and natural gas to the electricity forward market [43].

Sub-step 2.2: Estimating the capacity value of the RES-E generation, while keeping the electricity system's reliability at a designated level

Capacity values determine the contribution of generators to designated levels of adequacy and reliability. Capacity values can be quantified via installed capacity, capacity factors, and effective load carrying capability (ELCC). Evaluating ELCC is imperative to optimise RES integration for the planning of the long-term reliability of the power system, while different kinds of uncertainty are introduced [44]. Loss of load probability (LOLP) and loss of load expectation (LOLE) are the main metrics that evaluate the generation adequacy of the power system. LOLP is defined as the probability that total load is higher than the available generation capacity at a given time, while LOLE is the cumulative time during which load is higher than the available generation capacity [45,46]. LOLP can be expressed as:

$$\mathrm{LOLP(t)} = \mathrm{Pr_t}(\mathrm{C_E} < \mathrm{L_t}) \tag{1}$$

where:

- $\mathrm{C_E}$: the total available (in service) capacity of the existing system's configuration, and
- $\mathrm{L_t}$: the system's total load at time t.

The annual system's LOLE is respectively calculated as:

$$\mathrm{LOLE_{year}} = \sum_{t=1}^{8760} \mathrm{Pr_t}\{\, \mathrm{C_E} < \mathrm{L_t}\} \tag{2}$$

ELCC of a new generator about to be added to an existing electricity system is equivalent to the amount of additional load that can be integrated into the system, without jeopardising the designated reliability level defined by the LOLE of the system, before adding the new generator. More specifically, assuming a LOLE index of acceptable ranges for the existing system, the concept of ELCC is represented as:

$$\sum_{t=1}^{n} \mathrm{Pr_t}\{\, \mathrm{C_E} < \mathrm{L_t}\} = \sum_{t=1}^{n} \mathrm{Pr_t}\{(\mathrm{C_E} + \mathrm{C_A}) < (\mathrm{L_t} + \Delta\mathrm{L})\} \tag{3}$$

where:

- $\mathrm{C_A}$: the additional generation capacity of the new generator (i.e., capacity value), and
- $\Delta\mathrm{L}$: the additional load that can be integrated into the new system's configuration.

Finally, we calculate the Capacity Outage Probability Table (COPT) of the electricity system. The COPT is built using an iterative algorithm, in which generating units are sequentially added to produce a table that consists of all the possible capacity outage states of the system, along with their respective cumulative probability [45]. Each unit is incorporated in the COPT, both at an operating (on) state and a non-operating (off) state. Long-term unavailability statistics are used in order to find the probability that a unit is on forced outage (i.e., off state). The COPT is calculated by a chained convolution of the binomial distributions for the on/ off states of each unit:

$$\mathrm{p_j(X)} = \mathrm{p_{j-1}(X)} \cdot \left(1 - \mathrm{EFORd_j}\right) + \mathrm{p_{j-1}}\left(\mathrm{X} - \mathrm{C_j}\right) \cdot \mathrm{EFORd_j} \tag{4}$$

where:

- X: the outage capacity in MW,

- $p_j(X)$: the probability of outage capacity when adding the j^{th} unit.
- $p_{j-1}(X)$: the probability of outage capacity before adding the j^{th} unit.
- C_j : the equivalent perfectly reliable capacity of the j^{th} unit.
- $EFORd_j$: the demand equivalent forced outage rate of the j^{th} unit.

2.3. Application to the electricity market in Greece

Despite the RES boom over the period 2009 to 2013 owing to the FiT scheme [34], high investment costs led to a significant deficit of the Greek RES Special Account, which was responsible for funding the agreed contracts. To counterbalance negative economic implications, the Greek government imposed an extra tax on the consumers' income from the RES-E generation, which came simultaneously with a reduction on the tariffs [12]. This led to a complete shutdown of the RES market, with the domestic PV market indicatively shrinking during 2014-2017 to approximately 1% of its 2013 size [30]. Over the past three years, regulatory efforts to reach the standards of other European markets that experienced a transition from a high FiT status to a market-based environment have been put in place, with a NEM scheme having been legislated [12].

Literature studies have already assessed the effects of the FiT legislation in Greece upon the resulting RES penetration and investments, also addressing the impact of the imposed retroactive reduction upon the profitability of specific RES systems to their owners and the resulting surcharge on electricity prices owing to the massive PV penetration achieved. While a literature consensus providing an account of the scheme's profitability, mainly through a technoeconomic spectrum, has been already established, there is still a knowledge gap on how the scheme affected the structure and the performance of the energy market. In the following sections, we demonstrate the applicability of our analytical framework, as presented in **Section 2.2**, using as an illustrative case study the electricity market in Greece over the period 2009 to 2013.

2.3.1. Identifying the relevant monetary flows

In the context of the European Commission (EC) Horizon 2020 (H2020) "TRANSrisk[8]" project, a workshop to engage with stakeholders from different groups and institutions, including the Centre of Renewable Energy Sources and Savings (CRES), the Independent Power Transmission Operator (IPTO), the Hellenic Electricity Distribution Network Operator (HEDNO), and the Greek Ministry of Environment and Energy (MEE), along with researchers and experts from private sector industries that are involved in the provision of greenhouse gas (GHG) emissions, was carried out. Building on their feedback and domain knowledge, the major monetary flows within the wholesale electricity market in Greece over the period 2009 to 2013, are visualised in **Figure 2.2**, if the equipment manufacturers and distributers, and the aspects of job creation and energy security, are excluded.

[8] http://transrisk-project.eu/

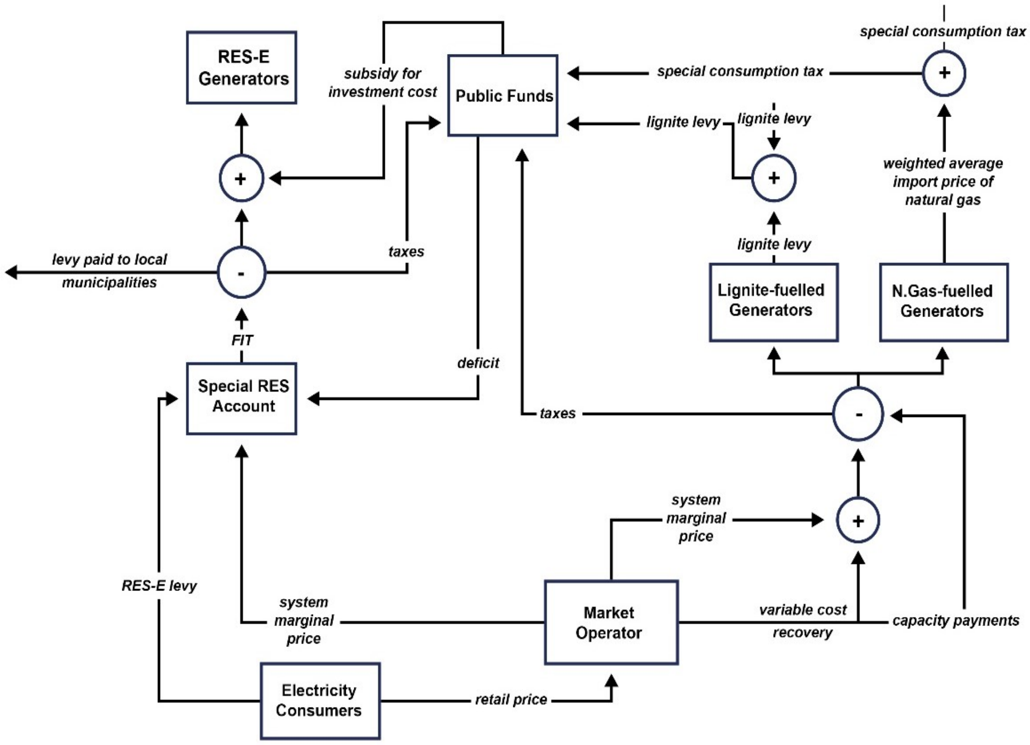


Figure 2.2. Major monetary flows within the wholesale electricity market over the period 2009 to 2013 in Greece.

Over the period under study, compensation for the electricity produced from conventional generators was taking place at the System Marginal Price (SMP) as derived from the Day-Ahead Scheduling (DAS) market. During DAS, offers made were firm, exposing generators to a penalty payment if they did not comply with a delivery equal to the ex-post imbalance price. IPTO was responsible for determining an ex-post System Imbalance Marginal Price (SIMP) in an hourly basis by executing the ex-post imbalance pricing procedure after the DAS process. This procedure was comparable to the DAS process, but used the actual demand, the actual availability of generators, and the actual RES-E generation. Deviations of generators could be either instructed (i.e., deviations of the actual generation from the scheduled one), or uninstructed. Generators with positive instructed deviations were paid the equivalent SIMP, while negative deviations were charged as bid. On the other hand, positive uninstructed deviations were not paid, whereas negative and load deviations were settled at the relevant SIMP. The Variable Cost Recovery Mechanism (VCRM) provided extra payments so that generators ended up profitable if this was not succeeded through market revenues.

The Greek capacity adequacy mechanism supplied conventional generators with capacity payments through which they were able to accumulate a portion of their fixed costs. In particular, each generator had issued a number of Capacity Availability Tickets for the next five reliability years, the total number of which was equal to the generator unit's net capacity. Each ticket was valid for one reliability year and each year IPTO, by estimating the available capacity of each generator based on its EFORd, was allocating to every ticket an available capacity value of 1-EFORd. Each generator could reach an agreement with IPTO to acquire a fund equal to the available capacity of the ticket multiplied by a non-compliance penalty value $\mathrm{P^{NCP}}$ when the generator was unavailable in the DAS market. As a result, the payment that was received by a generator j was [47,48]:

$$\mathrm{payment} = \mathrm{P^{NCP}} \cdot \left(1 - \mathrm{EFORd_j}\right)^2 \tag{5}$$

where $\mathrm{P^{NCP}}$ was equal to 35,000 €/MW·year until 31/10/2010, and to 45,000 €/MW·year from 1/11/2010 until the end of 2013.

On the other hand, remuneration of RES-E generators was paid through the Special RES Account, with its outflows being the FiT payments and its main inflows being:

- The payments to RES-E generators for each MWh generated at SMP, and
- The RES-E levy directly paid by final consumers. This levy was basically the monetary difference between the tariff and SMPs, or between the tariff and the average variable costs for non-interconnected regions such as islands.

However, as FiTs were higher than SMPs, the Hellenic Operator of Electricity Market (LAGIE) was facing a deficit that should be covered by the RES-E levy, whose level was decided by the administration of the Greek Ministry of Development. This annual deficit was equal to [49]:

$$\sum_{t=1}^{n}\sum_{h=1}^{8760}\left[(\mathrm{SMP_h}-\mathrm{FiT_t})\cdot \mathrm{RES_h^t}\right] \tag{6}$$

where:

- $\mathrm{SMP_h}$ was the System Marginal Price during hour h,
- $\mathrm{FiT_t}$ was the Feed-in-Tariff reimbursement for technology t,
- $\mathrm{RES_h^t}$ was the RES-E generation (MW) during hour h, from technology t.

Typically, the RES-E generation reduces the SMP due to the merit order effect [28] and thus, lower SMPs led to an increase of the required levy, and as a result to the total deficit. This led to questions about the design of the RES-E levy mechanism. Considering the latter, the deficit of the RES Account was excluded from our analysis, since: **a)** it only answered the question of who is in charge of paying for the FiT reimbursements, and **b)** it did not reflect the actual costs of the RES-E generation, as SMPs may typically vary regardless of the RES-E generation.

2.3.2. Quantifying costs and benefits from the RES-E generation

The major costs and benefits attributed to the RES-E generation from FiTs are:

- Costs: Paying for the FiT reimbursements.
- Benefits: Under the assumption that the SMP reduction due to the substitution of the conventional generation by the RES-E generation is balanced by VCRM, a better way to approximate economic benefits owing to the offset of fossil-fuelled generators, is the reduction in fuel use. Given that lignite is an indigenous energy source in Greece [50], monetising the lignite consumption avoided due to the RES-E generation can be calculated by considering the lignite export price. However, there are no trends for the price of the lignite-fuelled generation in liberalised markets as its transport over longer distances is considered an uneconomic choice due to its low calorific value. As an alternative, the pre-tax avoided cost of natural gas imports and lignite use, as well as the avoided CO_2 emissions owing to offsets from the RES-E generation, will be regarded as benefits.

Kaldellis and Kapsalis (2014) combined historical data for Carbon Dioxide (CO_2), Sulfur Dioxide (SO_2), Nitrogen Oxide (NO_x), and Particulate Matter (PM) emissions from the main Greek lignite-fuelled generators with electricity generation data, to estimate each generator's emission contribution (i.e., emission factors) [51]. Emission factors (kg/MWh) for each major lignite-fuelled generator in Greece are presented in **Table A1** in **Appendix A**. Additionally, Gouw et al., (2014) used data from continuous emission monitoring systems (CEMS) to investigate the CO_2, NO_X, and SO_2 emission factors of natural gas-fuelled power generation units in the United States of America (USA) [52]. Their analysis showed that generation from combined cycle technology that is fired by natural gas contributes to average emissions at 44% of the CO_2 of the coal-fuelled generator. The latter was also assumed valid for the case of Greece.

Annual CO_2 emissions avoided due to RES-E generation were estimated as:

$$\Delta E_t^p = G_t^{RES} \cdot \varepsilon_t^{CO_2} \tag{7}$$

where:

- G_t^{RES}: the RES-E generation during year t (kWh).
- ε_t^p: CO_2 emission coefficient of the displaced fossil-fuelled generator during year t $\left(\frac{\text{kg of } CO_2}{\text{kWh avoided}}\right)$.

Estimating the mix of the conventional powered generation that is substituted by the RES-E generation

In this section, CO_2 emissions avoided during the period under study are quantified to estimate the fossil-fuelled generation that was substituted by the RES-E generation and measure the avoided cost of natural gas imports.

Based on domain knowledge and stakeholder insights, the causal relationships within the electricity market in Greece are visualised in **Figure 2.3**. The solid line arrows show causal relationships that are viewed as certain, whereas the dashed ones represent relationships that are plausible to exist and should be verified. Note that the term "causal relationship" is used as a way to indicate that "if Z_t includes a set of properly selected explanatory variables, we can predict Y_{t+1} based on lagged values of Y_t and Z_t, and we can add the lagged values of W_t (i.e., W_t contains unique information for predicting Y_{t+1}) to achieve a better prediction. Therefore, it could be implied that there is a (Granger) "causal relationship from W_t to Y_t ($W_t \rightarrow Y_t$) " [53].

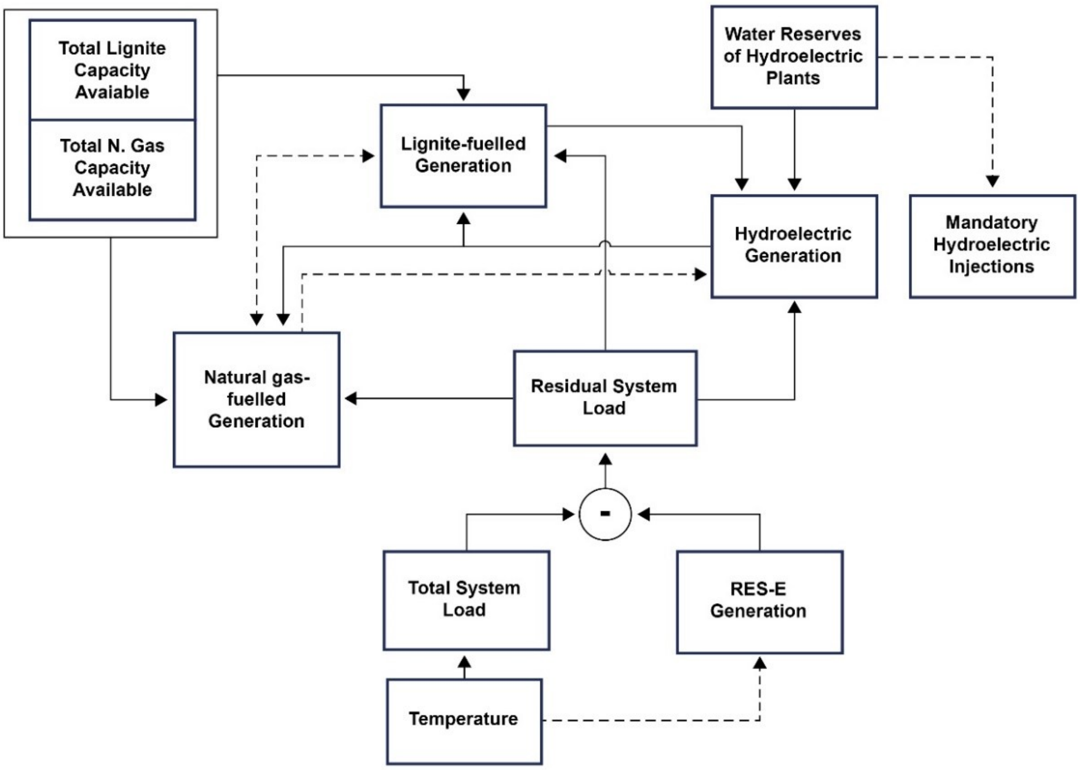


Figure 2.3. Causal relationships within the wholesale electricity market in Greece over the period 2009 to 2013.

According to the Granger causal relationships between the fossil-fuelled and the RES-E generation, the total electricity load and the system's available capacities, the latter three variables are considered exogenous. Regarding electricity load, residential and commercial consumers are late to realise the variation of the wholesale price, since they are charged with the most common tariff in Greece (i.e., "G1" tariff) [54]. Consequently, since consumers purchase electricity at a constant price, demand volatility is caused by exogenous factors, which do not relate to the wholesale price. Moreover, causal relationships between the natural gas-fuelled generation, the lignite-fuelled generation, and the hydroelectric generation should be further investigated. One should expect to identify a causal relationship between the residual load and the lignite-fuelled, the natural gas-fuelled, and the hydroelectric generation.

CA is applied to estimate the displacement of lignite- and natural gas-fuelled generation by the RES-E generation owing to FiTs in the Greek wholesale market over the period 2009 to 2013. To model the long-run equilibrium relationships, a set of explanatory variables must be selected, such that: **(a)** variables are exogenous, thus the dependent variable has no reverse causations with any of the explanatory variables, **(b)** no relevant variables are excluded from the analysis as this would lead to false results, because the regressors and the error term are correlated, **(c)** unnecessary explanatory variables are excluded as they would add noise to the estimations, and **(d)** multiple, significantly correlated variables must be avoided. Their inclusion would make individual coefficients to drastically change regarding variations in the model or the data, hence, be falsely and unstably estimated.

Due to the fact that high-frequency data for the PV RES-E generation over the period under study are not available, our work focused on wind RES-E generation data. This was possible since available load data was adjusted by the ex-post PV RES-E output. **Figure 2.4** and **Figure 2.5** depict the daily electricity demand and the actual wind RES-E generation during the period under study. Since calculating the correlation between two non-stationary variables is not useful, either due to a deterministic or a stochastic trend, we detrended the load time series and used the wind capacity factor instead of the actual wind RES-E generation.

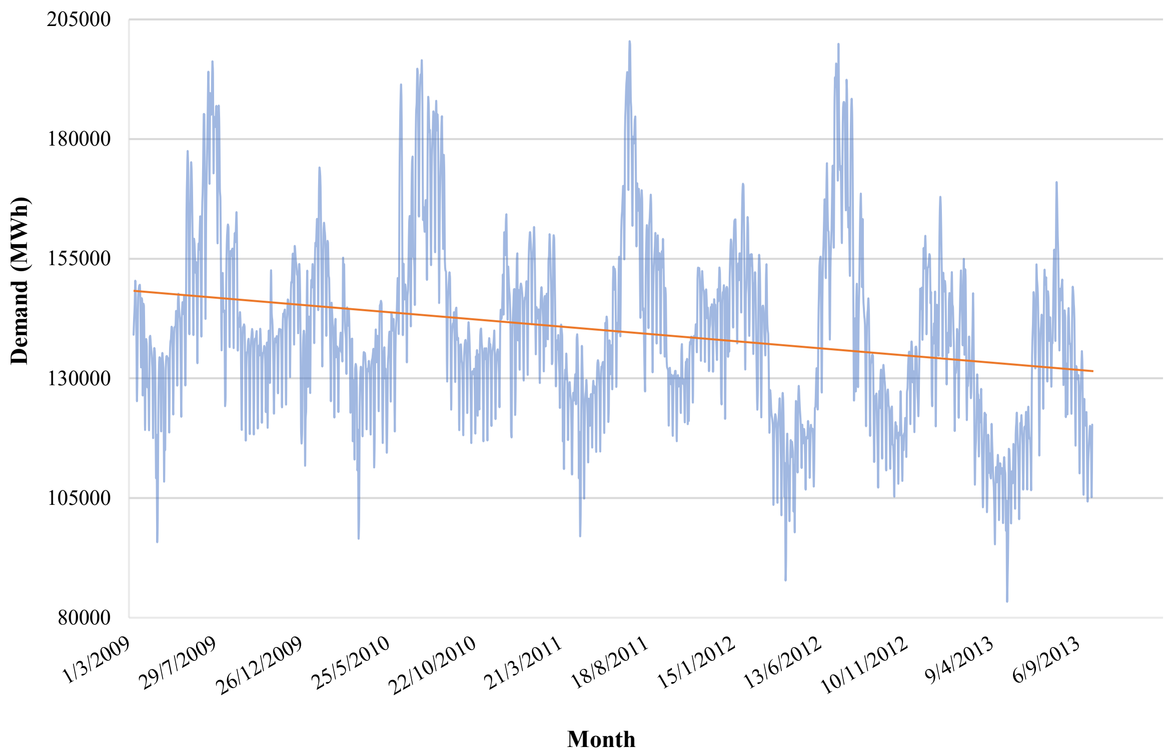


Figure 2.4. Data of daily electricity demand in Greece over the period March 2009 to November 2013.

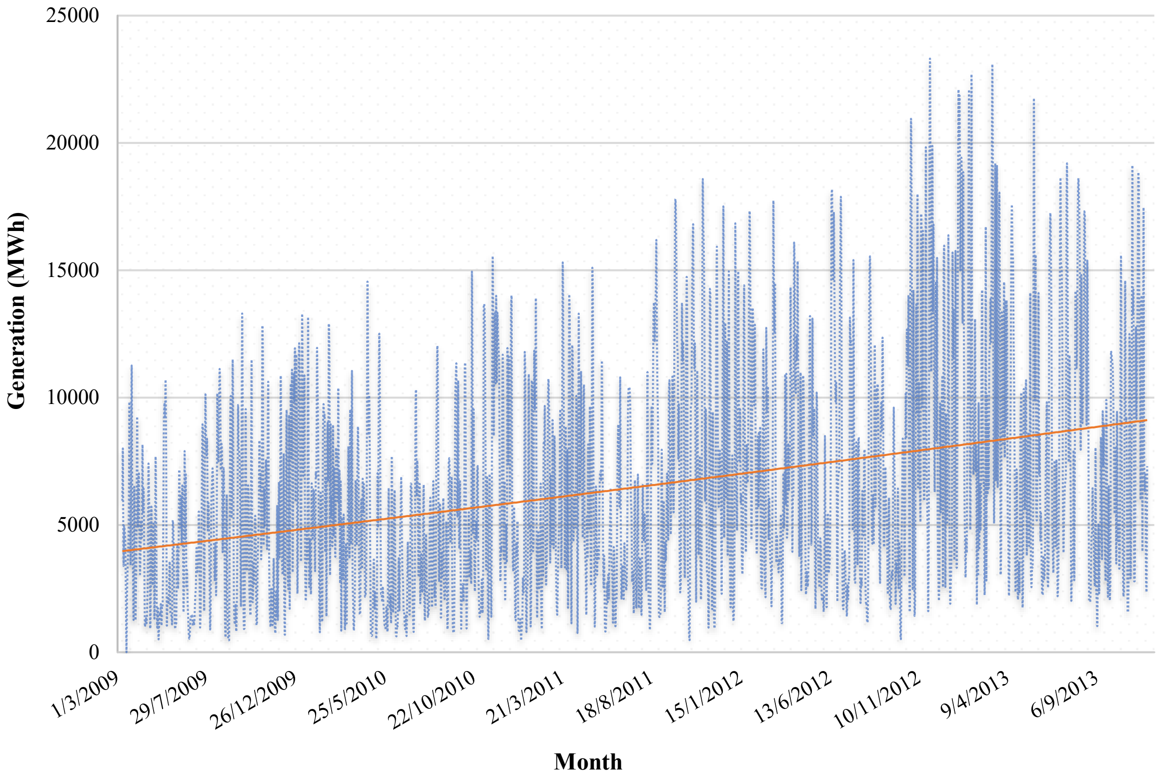


Figure 2.5. Daily wind power generation in Greece over the period March 2009 to November 2013.

The capacity factor is bounded and, hence, stationary: $\mathrm{CF}_t \in [0,1]$. **Figure 2.6** depicts the daily wind capacity factor for the period under study in Greece. As visualised in **Figure A1** in **Appendix A**, the mean value of the correlation between the detrended load and the wind capacity factor is -0.05. This implies that no clear pattern throughout time could be identified and that the assumption that the load and the wind RES-E generation are uncorrelated is considered pertinent.

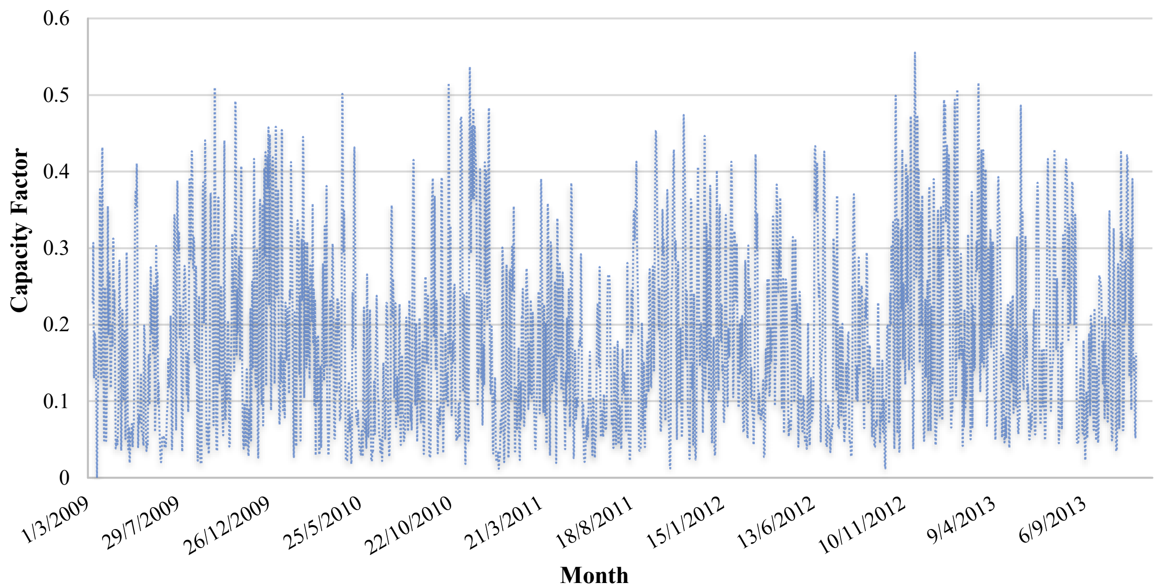


Figure 2.6. Daily wind capacity factor in Greece over the period March 2009 to November 2013.

Figure 2.7 and **Figure 2.8** present the actual daily lignite- and natural gas-fuelled generation during the period 2009-2013. The fact that the daily natural gas-fuelled generation is ascending during this period, rather than descending due to the merit order effect, is because of the combined impact of the important capacity additions and the effect of VCRM. The total available capacity for lignite-fuelled generators determines the final lignite-fuelled output, so if residual load levels remain the same, a reduction in the available capacity should cause an equivalent reduction in the output. The same applies to the relationship between the total available capacity and the final output of the natural gas-fuelled generators. Furthermore, for the constant residual load, a reduction in the available lignite (natural gas) capacity should cause an increase in the natural gas-fuelled (lignite-fuelled) generation.

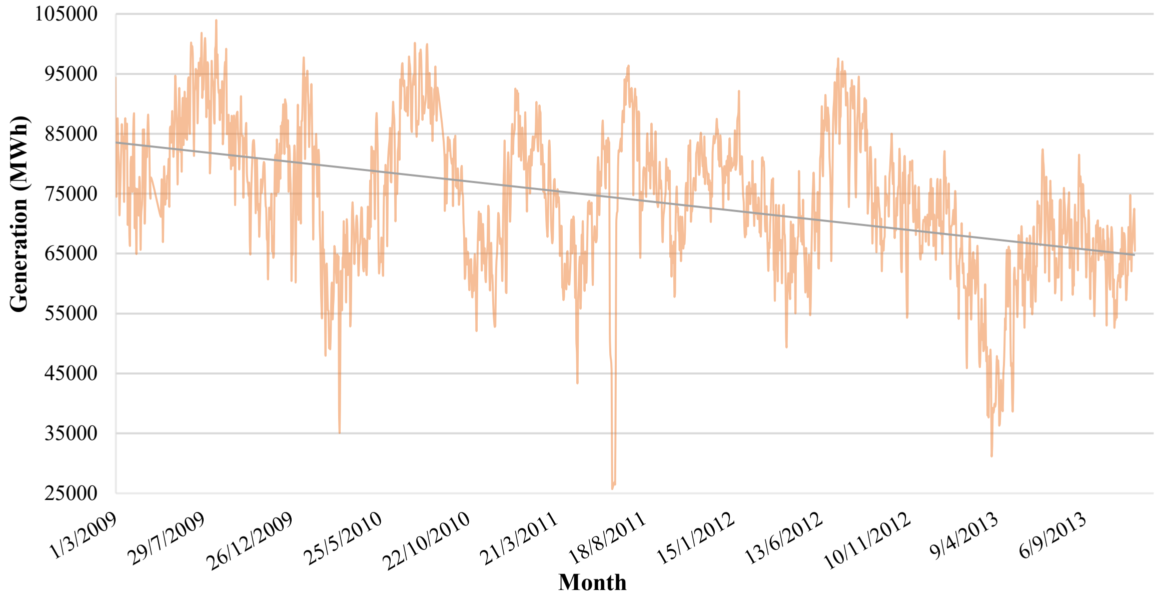


Figure 2.7. Daily generation from lignite-fuelled plants in Greece over the period March 2009 to November 2013.

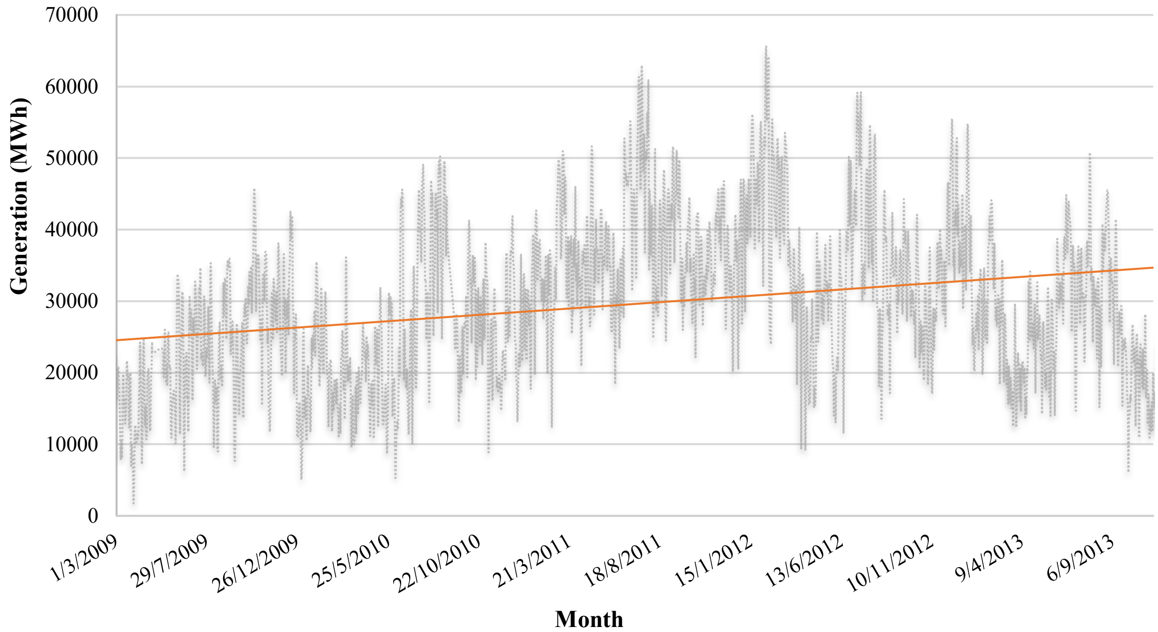


Figure 2.8. Daily generation from natural gas-fuelled plants in Greece over the period March 2009 to November 2013.

On the other hand, **Figure 2.9** presents the evolution of the natural gas-fuelled and the hydroelectric generation over the period 2009 to 2013. Note that when hydro generation is high, natural gas-fuelled generation is low. For each time period, the hydroelectric generation depends on the comparison between the marginal water value (MWV) and the expected SMP. The value of water is linked with its opportunity cost, and thus, expected income relies on the future values of stochastic hydro inflow and electricity prices as well as on the current reservoir levels. The substantial change of the MWV curve does not alter its general shape over the years [55]. MWV and storage have a converse trend, with the curve being almost flat for most of the storage levels, reaching zero at the upper bound, but ascending abruptly as storage descends towards the other end. The latter highlights the system's ability to cope with different inflows and storage levels at average costs. However, in case that storage values become immoderate, water turns out to be very valuable in order to avert a probable shortage.

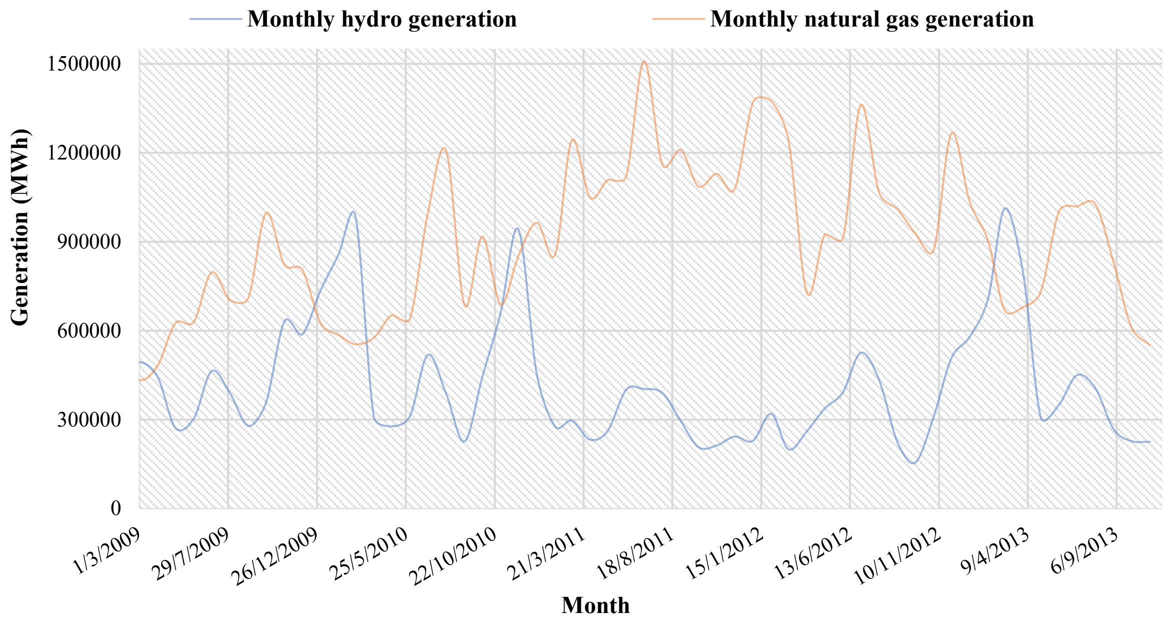


Figure 2.9. Monthly hydro and natural gas-fuelled generation in Greece over the period March 2009 to September 2013.

The MWV value could be described by two components (**Figure 2.10**) based on the way that the marginal cost of the hydroelectric generation is calculated, namely: **(a)** the $C_{1,d,m}$ component, reflecting the substitute value of thermal generation in the case of hydroelectric generation (i.e., impact on SMP), and **(b)** the $C_{2,d,m}$ component, where d is a day and m is a month index, reflecting current reservoir levels.

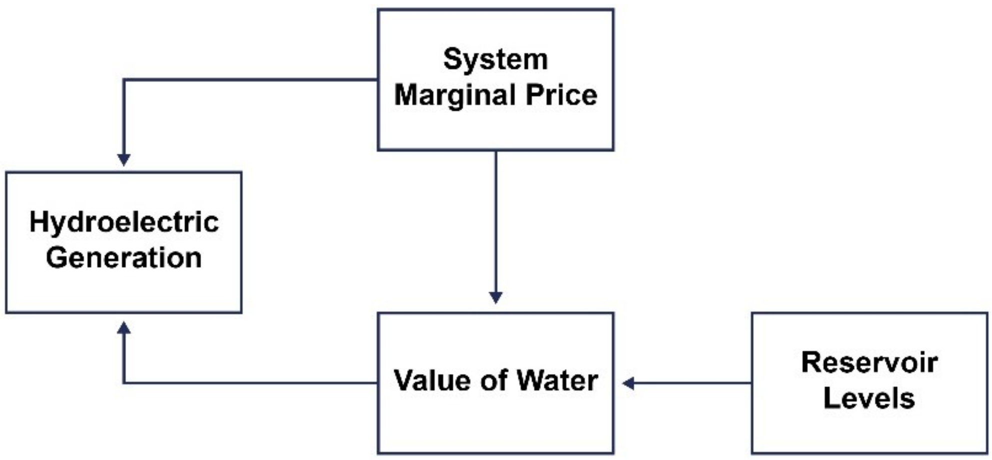


Figure 2.10. Components of the hydroelectric generation in Greece over the period March 2009 to September 2013.

The daily $C_{1,d,m}$ component derived from the following formula:

$$C_{1,d,m} = (1 + \sigma_{d,m}) \cdot C_{TH,m} \tag{8}$$

where:

- $\sigma_{d,m}$ is a factor capable of adjusting to the volatility of fuel prices. It was calculated on a daily basis as the total price change of the different fuels $\left(\Delta P_{fuel,m,d-1}\right)$ according to their contribution in the generation output $\left(a_{fuel,m}\right)$:

$$\sigma_{d,m} = \sum_{fuel} \left(a_{fuel,m} \cdot \Delta P_{fuel,m,d-1}\right) \tag{9}$$

The price variation of each fuel was calculated as the difference between the previous day and the average price of the same month for the last three years:

$$\Delta P_{fuel,m,d-1} = \frac{P_{fuel,d-1}}{\frac{1}{3} \cdot \sum_{y-3}^{y-1} P_{fuel,m(y)}} - 1 \tag{10}$$

Finally, $a_{fuel,m}$ was calculated as the average contribution in the total fossil-fuelled generation for the last three years:

$$a_{fuel,m} = \frac{1}{3} \sum_{y-3}^{y-1} \frac{G_{fuel,m(y)}}{G_{fossil,m(y)}} \tag{11}$$

- $C_{TH,m}$ is the reference displacement value of the thermal generation due to the hydroelectric generation. The reference value $C_{TH,m}$ was calculated as the rolling average of SMP during month m over the last three years, considering the respective hydroelectric generation variable $G_{m(y),h}^{hydro}$ over the same period:

$$C_{TH,m} = \frac{1}{3} \sum_{y-3}^{y-1} \left(\frac{\sum_h \left(SMP_{m(y),h} \cdot G_{m(y),h}^{hydro}\right)}{\sum_h G_{m(y),h}^{hydro}} \right) \tag{12}$$

The scheduling of the hydroelectric generation takes place according to the peak shaving method that is based on the heuristic idea that the generation should be allocated to the higher part of the system's load curve, which concerns the system's peak load [56]. Thus, the total available capacity of the hydroelectric generation, while being limited for a specific time period due to resource constraints, can be dispatched resulting to a significant decrease in the operating costs in the rest of the units. Hydroelectric generation is considered as an exogenous variable to both the conventional generation and SMP. As far as the relationship between lignite- and natural gas-fuelled generators is concerned, we consider that the continuous bidding 'game' between market agents has reached to an equilibrium, and, thus, a generator holds the same market share (i.e., constant generation), while the system's total load remains stable, unless a change in the available thermal capacity happens. Additionally, the RES-E and the hydroelectric generation affect both the lignite- and the natural gas-fuelled generation; thus, having RES-E and hydroelectric generation data in a model for the lignite-fuelled (natural gas-fuelled) generation, can provide natural gas-fuelled (lignite-fuelled) generation data without any other source of data being required.

A vector autoregressive (VAR) model between the lignite- and the natural gas-fuelled generation (i.e., dependent variables) and the total electricity load (shorthand: "**Load**"), the RES-E generation (shorthand: "**RES**"), the hydroelectric generation (shorthand: "**Hydro**"), and available fossil-fuelled capacities (shorthand: "**Lignite**" and "**NGas**") (i.e., explanatory variables), was modelled. Choosing the lags to be equal to 7, the partial autocorrelation diagram suggests that the natural gas-fuelled generation during hour t is correlated with the generation during the same hour of the previous days, as presented in **Figure A2** in **Appendix A**. This led us to model each hour of the day separately through an autoregressive distributed lag (ARDL)/ Bounds Testing methodology [57,58]. The ARDL modelling process implies that the lignite- and/ or the natural gas-fuelled generation during time t was based on past generation, modified by the new state of the electricity market incorporated into past values of the total load, the RES-E and the hydroelectric generation, and available fossil-fuelled capacities. For the lignite-fuelled (natural gas-fuelled) generation variable, the corresponding ARDL model had the following form:

$$q_{t,d}^{ng} = \sum_{i=1}^{p} a_i q_{t,d-i}^{ng} + \sum_{j=1}^{n} \beta_j X_{t,d-j} + \varepsilon_{t,d} \tag{13}$$

where:

- $q_{t,d}^{ng}$ is the actual generation by lignite-(natural gas-)fuelled generators during hour t and day d, and
- $X_{t,d} = \left[L_{t,d}, res_{t,d}, hydro_{t,d}, cap_{t,d}^{ng}, cap_{t,d}^{lig}\right]'$, where:
  - $L_{t,d}$ is the system load during hour t and day d,
  - $res_{t,d}$ is the actual RES-E generation during hour t and day d,
  - $hydro_{t,d}$ is the hydroelectric generation during hour t and day d, and
  - $cap_{t,d}^{ng}, cap_{t,d}^{lig}$ are the total available capacities during hour t and day d for natural gas-fueled and lignite-fueled generators, respectively.

Next, we formulated an unrestricted Error-Correction Model (ECM) between dependent variables and explanatory ones, chose the lag structure, and assured that the model was well-defined (i.e., model errors were serially independent). Additionally, we performed an F-test under the assumption that: "*If the coefficients of the lagged values of the explanatory variables are jointly equal to zero, then a long-run equilibrium relationship between dependent and explanatory variables cannot be concluded*." A typical difficulty with an F-test is that its distribution is not standard and that the exact critical values for the test are unknown. However, based on the range of the critical values for the asymptotic distribution of the F-statistic [58], we concluded that the coefficients are not nullified, thus, our assumption must be rejected (i.e., the F-statistic exceeded by far the upper bound). Since the test concluded in cointegration, the long-run equilibrium relationship of the variables under study is meaningful and can be estimated.

Estimating the capacity value of the RES-E generation, while keeping the electricity system's reliability at a designated level

Derived from an autocorrelated process, the density plot of the wind capacity factor is presented in **Figure A3** in **Appendix A**. However, the mean value of the plot provides very limited information on the generation adequacy risk, as the length of the investigation period required with wind generators is typically an open question. Wind's ELCC is usually calculated using one or more years of hourly generation data. However, this approach is effective enough when applied to long-term generation data of conventional generation and is not able to effectively represent the long-term performance characteristics of wind generators. Especially, when available data for wind generation is only for a single year, then the calculated LOLE will be a historical assessment rather than a predictive one, and as a result, an increase in the available years of time series data could result in an important wind generation volatility [45]. A way to overcome this difficulty is by finding in a yearly basis from 2009 to 2013, the month with the most volatile wind generation (i.e., difference between higher and lower daily wind generation). The corresponding days are shown in **Table A2** in **Appendix A**.

Hydroelectric generation is excluded from the COPT calculation due to its dependency on water reserves and the estimation of the wind's ELCC by comparing the system's LOLE before and after its configuration. **Table A3** in **Appendix A** presents the available fossil-fuelled power plants for the investigation period in Greece, alongside their net maximum capacity and EFORd. Then, for the same period, and using the hourly system load series data (i.e., without considering the wind RES-E generation), we calculated the LOLP in an hourly basis (i.e., for each hour of the year) as well as the yearly LOLE. In the case of low demand, in comparison to the installed generation capacity, LOLP is insignificant (**Figure A4** in **Appendix A**). If we add the total hours that the demand is lower than the load where the LOLP starts to become high enough (a threshold L_{TH}), we can calculate the LOLE using the residual load L_t^{net}. If the LOLE is assumed to be the same as adding a perfectly reliable resource of capacity CV_{wind}, the annual LOLE can be approximated as:

$$LOLE_{year,wind} \cong \sum_{t:\, L_t > L_{TH}} Pr_t\{\, C_E < L_t - CV_{wind}\} \tag{13}$$

2.4. Results and discussion

This section presents and discusses findings regarding the economic and environmental impact of the FiT scheme over the period 2009 to 2013 in Greece, along with its contribution to the reliability of the electricity system.

2.4.1. The long-run equilibrium relationship between conventional and wind RES-E generation

Although a VECM can be specified, our work was based on the premise that the long-run equilibrium relationship is the important aspect of the effect of the RES-E generation on the conventional generation. The coefficients of the long-run equilibrium relationship for the natural gas- and the lignite-fuelled generation, for four representative hours of the day, are presented in **Table 2.1**.

Table 2.1. The coefficients of the long-run equilibrium relationship for the natural gas- and the lignite-fuelled generation.

	Natural gas				Lignite			
	Hour of the Day							
	0	**10**	**16**	**20**	**0**	**10**	**16**	**20**
Load	0.32	0.41	0.38	0.46	0.41	0.35	0.37	0.34
RES	-0.37	-0.42	-0.40	-0.43	-0.31	-0.27	-0.33	-0.25
Hydro	-0.44	-0.37	-0.35	-0.28	-0.53	-0.46	-0.49	-0.40
NGas	0.36	0.30	0.28	0.30	-0.12	-0.10	-0.11	-0.08
Lignite	-0.22	-0.25	-0.24	-0.24	0.31	0.37	0.37	0.38

Although a distinct pattern is not visible, our outcomes imply that, over the period 2009 to 2013, 1 MWh of wind RES-E generation displaced on average 0.41 MWh of natural gas-fuelled generation and 0.29 MWh of lignite-fuelled generation.

2.4.2. Economic benefits due to wind RES-E generation

Excluding the consumption tax and the tariffs of the transmission system, the fuel cost of natural gas-fuelled generators is calculated as the natural gas price divided by their efficiency. If efficiency of natural gas-fuelled generators is assumed to be equal to their capacity-weighted average, which is 0.51, the evolution of the monthly weighted average import price of natural gas is depicted in **Figure 2.11**.

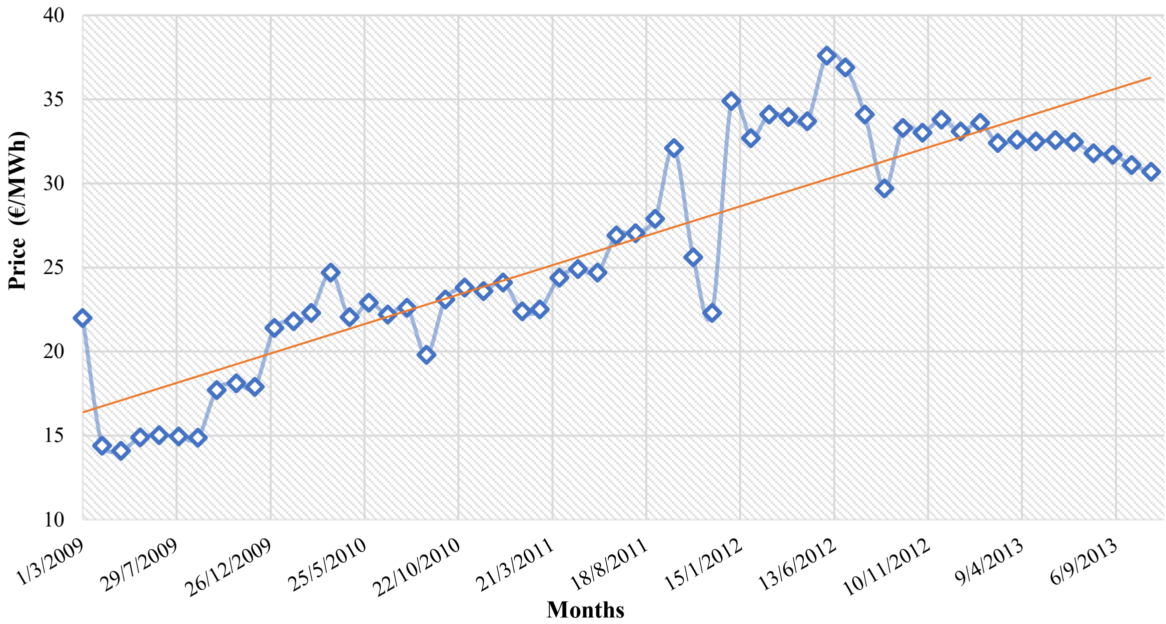


Figure 2.11. Evolution of the monthly weighted average import price of natural gas over the period 2009 to 2013 in Greece.

Considering the monthly weighted average import price of natural gas, economic benefits of natural gas imports avoided due to the substitute of the natural gas-fuelled generation from the wind RES-E generation over the period 2009 to 2013 are presented in **Figure 2.12**. Our results suggest that impact of the FiTs scheme on the public finances during this period was positive. In particular, from March of 2009 until the end of 2011, the economic benefits reached the €98.32 million in total, while from early 2012 to end of 2013, the respective benefits were one and a half times over (i.e., €147.2 million).

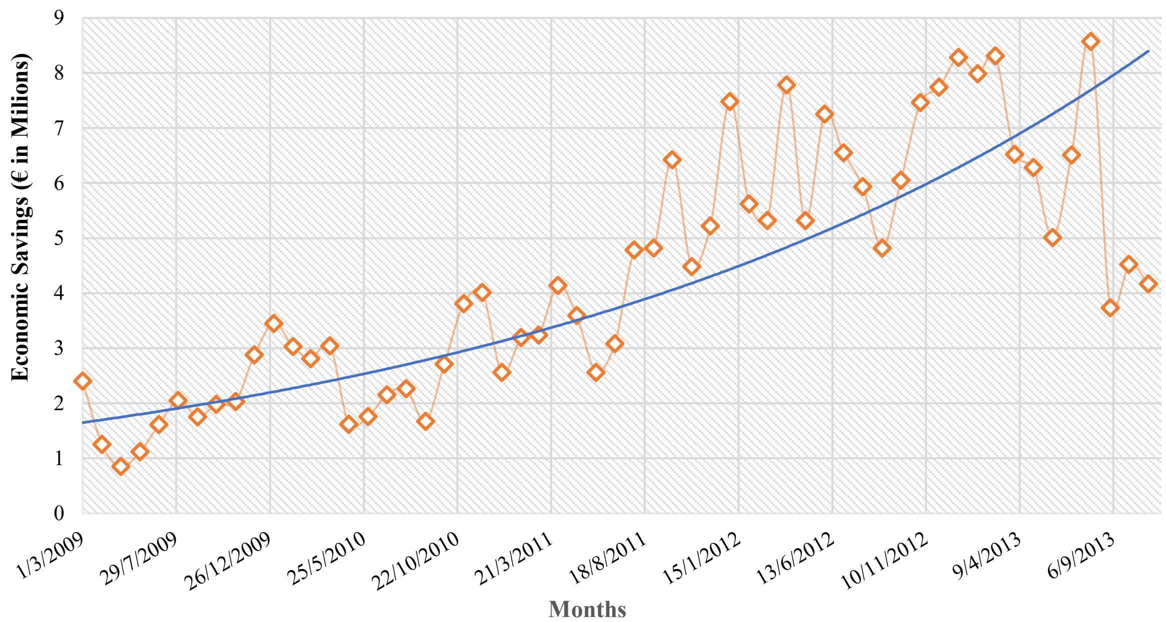


Figure 2.12. Economic benefits of natural gas imports avoided owing to the substitute of the natural gas-fuelled generation by the wind RES-E generation achieved with the FiT scheme over the period 2009 to 2013 in Greece.

2.4.3. Environmental benefits: CO_2 emissions savings due to wind RES-E generation

Figure 2.13 and **Figure 2.14** present the CO_2 emissions avoided owing to lignite- and natural gas-fueled generation offset by wind RES-E generation from FiTs, over the period 2009 to 2013. Considering that the electricity system in Greece relies heavily on a high share of lignite- and imported natural gas-fueled power plants, our results suggest that the high share of RES-E achieved by FiTs during the period 2009-2013 had also a significant environmental impact. In particular, from March 2009 to end of 2011, the cumulative emission savings owing to the wind RES-E generation from FiTs reached almost the 4 Mt of $CO_{2\text{-eq}}$, accounting for more than the 6% of the total GHG emissions reduction in Greece during the same period. Especially for the year 2011 it should be noted that almost all the major Lignite Thermal Power Stations (LTPSs) in Greece were not in a compliance status with the national obligations, with the largest one presenting the greatest emission excess (i.e., about 3.2 Mt/year more than permitted) [51]. Similar results, over the period 2009 to 2011, are also presented for the case of FiTs in Portugal, the electricity market of which has a very similar structure to the electricity market of Greece [59]. Additionally, the respective savings from early 2012 until the end of 2013 exceeded the ones of the previous period.

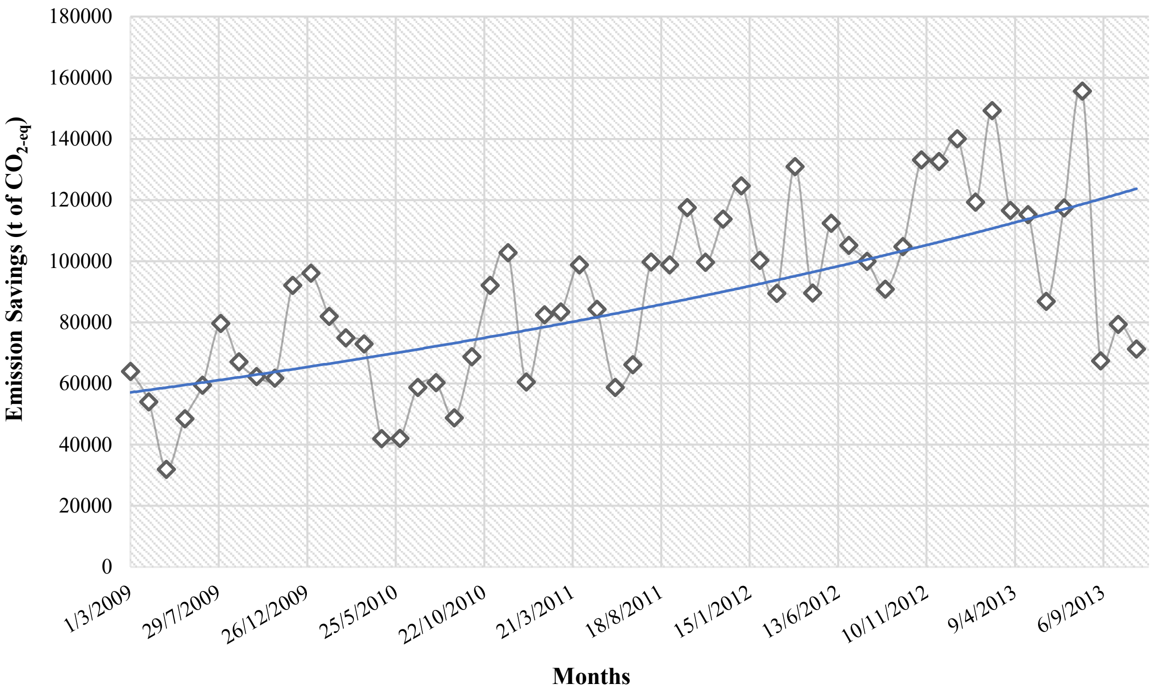


Figure 2.13. CO_2 emissions avoided owing to the lignite-fuelled generation offset by the wind RES-E generation from the FiT scheme over the period 2009 to 2013 in Greece.

The CO_2 emissions' reduction trend over the period under study in Greece has also been acknowledged by the scientific literature [60,61]. However, such a decrease can typically be attributed to the economic austerity of this period, as previous studies have already highlighted that positive economic activity is strongly coupled with, and mainly responsible for, CO_2 emissions increase [62,63]. Our results differentiate, as they explicitly estimate the emission savings owing to the lignite- and the natural gas-fuelled generation offset by the increased wind RES-E generation from the FiT scheme, providing, thus, a clearer perspective on the environmental performance of the FiT policy in Greece.

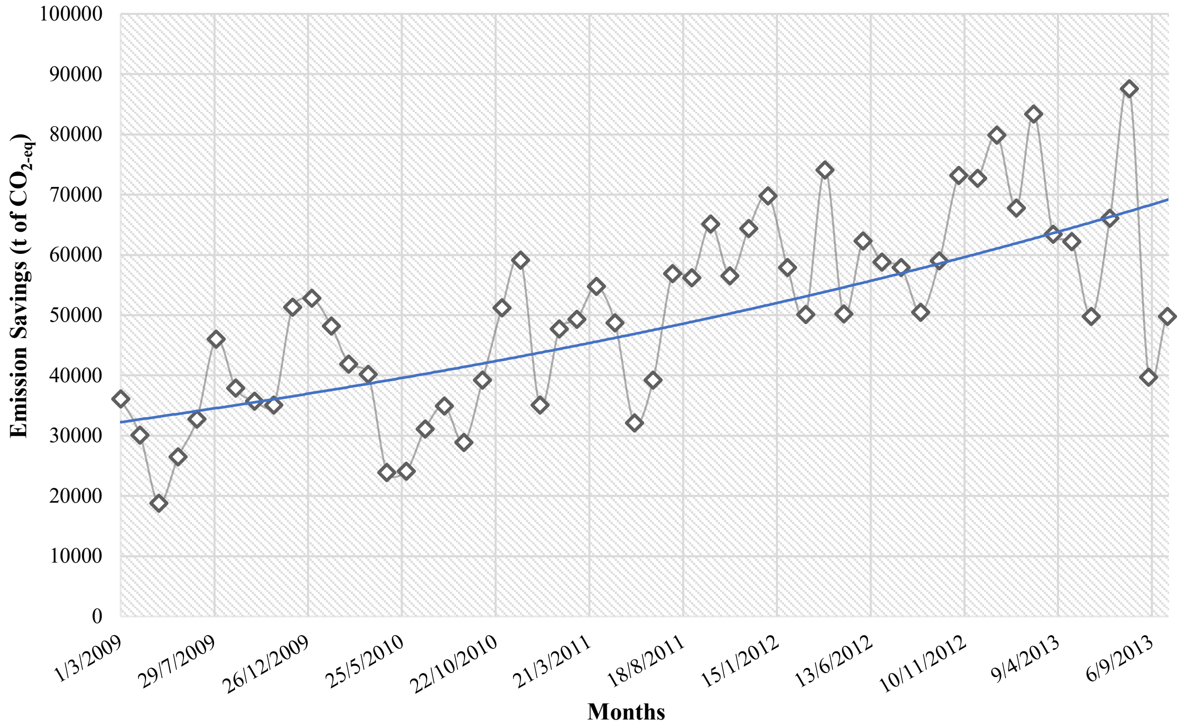


Figure 2.14. CO_2 emissions avoided owing to the natural gas-fuelled generation offset by the wind RES-E generation from the FiT scheme over the period 2009 to 2013 in Greece.

Note that including CO_2 emissions contributed by RES, owing to material processing, component and facility construction, and electricity intense utilisation of metals, during the initial fabrication stages, was out of the scope of our work. From this aspect, a tailor-made life-cycle environmental performance assessment, to address this issue in a more detailed manner, is needed, focusing on the development of an emission inventory of the electricity sector in Greece. The latter should include emissions, not only of conventional, but also of RES-E generation.

2.4.4. Capacity adequacy of the wind RES-E generation

The COPT for the electricity system in Greece over the period 2009 to 2013 is presented in **Figure 2.15**. Note that the x-axis corresponds to different capacity levels (MW) and the y-axis to the cumulative probability that the available capacity at any given time period t is equal to these capacity levels.

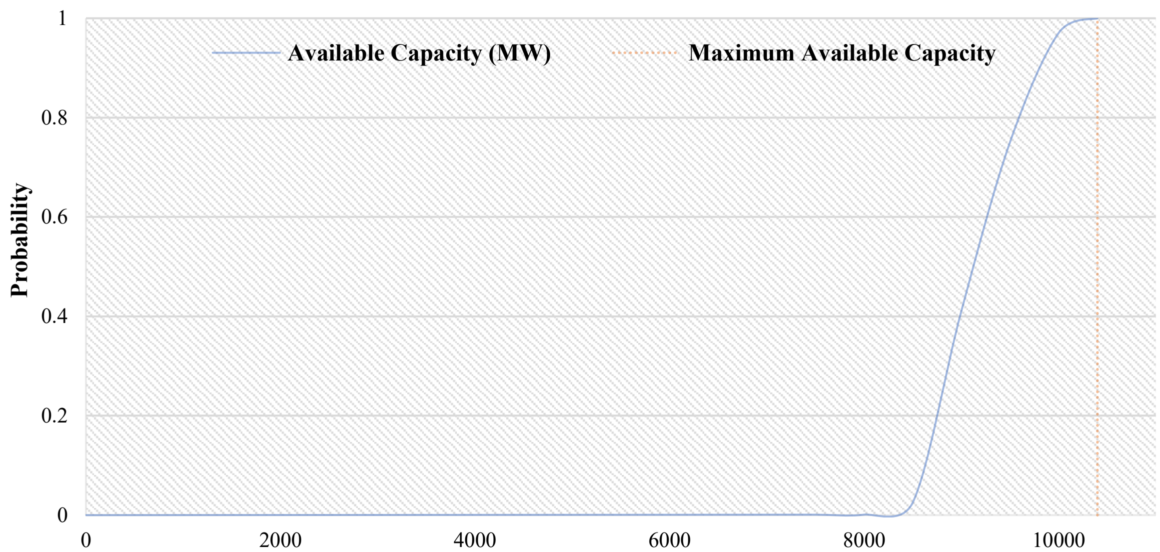


Figure 2.15. The COPT curve as a function of the system's available capacity for the electricity market in Greece.

If one chooses a threshold L_{TH} equal to 7,500MW, which corresponds to all hours in the 1% peak load period, then the annual LOLE, from October 2012 to September 2013, was found approximately 1.34 hours. Assuming that the LOLP function is linear between the threshold L_{TH} and the maximum observed load, which is approximately true at the upper end of the LOLP curve (**Figure A5** in **Appendix A**), leads to the following condition [64]:

$$\mathrm{CV_{wind}} = \mathrm{mean}(\mathrm{Wind}'_t) \tag{14}$$

where Wind'_t is the wind RES-E generation when residual load is greater than the threshold value of 7,500 MW. The LOLP curve as a function of the system' residual load is depicted in **Figure 2.16**.

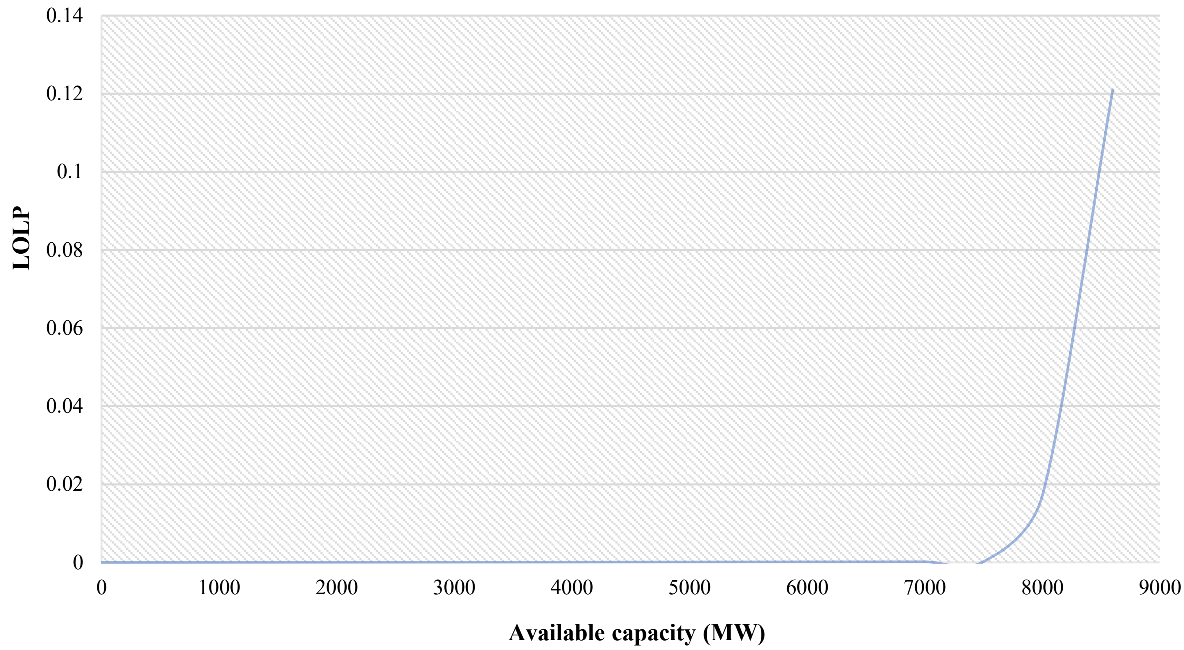


Figure 2.16. The LOLP curve as a function of the Greek residual load from October 2012 to September 2013.

The capacity adequacy value of wind RES-E generation was found equal to 239 MW, or, equivalently, 16% of the average wind RES-E capacity (i.e., 1,485 MW) during the same period, while the total wind RES-E generation was 3,416,125 MWh. As the capacity-weighted average EFORd of natural gas-fuelled generators was equal to 8.58%, the capacity displaced by the wind RES-E generation was 426.57 MW of a nominal fossil-fuelled generator with an EFORd of 8.58%. At the same time, given the capacity contributed by the wind RES-E generation (i.e., 239 MW), an annual capacity payment equal to €7,055 million, or, equivalently €4,750/MW is attributed as a cost to the wind RES-E generation from the FiT scheme.

Although a static analysis like ours can provide useful insights, a dynamic one is also imperative, due to the fact that, as the RES-E penetration increases, the peak period of the residual load shifts toward hours that the RES-E generation has lower capacity factors. This results to a condition where, mainly owing to increased reserve requirements, increasing RES-E capacity has diminishing returns in terms of its value. The relationship between wind and peak loads, for example, remains ambiguous over the years, as dictated by the respective patterns. It would be useful to have an estimation of the possible deviations of the capacity values during different time periods, in order to quantify the impact that limited data can have on the calculation results. Our analytical framework provides a good starting point for that; future studies can build on our work to assess the impact of newly introduced support mechanisms, as NEM or FiP, in different contexts across Europe.

2.5. Conclusions and implications for policy and practice

Over the period 2009 to 2013, RES in Greece have been treated as a special type of market participant, mainly owing to their non-dispatchable nature. During this period, RES-E has been compensated based on a FiT support mechanism, which was necessary for the investment initiation, not only in the country, but also in many national electricity systems across Europe. Despite the remarkable boom, as RES penetration progressively reached large-scale, and given the economic recession in Greece, market prices were distorted, and market efficiency was downgraded. Since then, although regulatory efforts to reach the standards of other European markets that experienced a transition from a high FiT status to a market-based environment have been put in place, progress remains slow. On the other hand, in spite of the learning progress of the past years, governments and regulatory agencies still remain uncertain about the necessary regulatory framework to incorporate larger shares of RES into the generation mix of a country or region.

While most studies on the regulatory design of RES-E support mechanisms focus on assessing the efficiency of the different alternatives, there is a knowledge gap on how these mechanisms affect the performance of the energy market. In view of a high-RES market design compatible with the EU Target Electricity Model, regulatory efforts need to include in their scope the interaction between the market and the RES-E sector. To this end, quantitative assessment studies filling knowledge gaps on the market effect of RES-E support mechanisms, either at a national or at an EU level, are of paramount importance. Although the FiT scheme is almost in the past in Greece, our work focused on its ex-post assessment to identify the main drivers and interactions that governed the major monetary flows and causal relationships within the wholesale electricity market over the period 2009 to 2013.

To do so, we developed an analytical framework that facilitated the systematic exploration of the impact that policy measures have on the electricity system and its components. Our framework was built on the premise that assessing how a policy measure affects the performance of the energy market requires the quantification of both the benefits and the costs attributed to it. By exploring the monetary flows in the electricity market, one adopts a holistic view that can provide insights on the interactions between different components of the benefits and costs, as well as on the possible conflicts or alliances between the involved actors of the system. As a result, government officials and consultants in the policy community can gain a clearer perspective on how to devise a roadmap of least resistance for a policy measure to attain its goals. Given that, while European RES targets have been set, governance of RES-E support beyond 2020 at an EU level remains undefined, our work contributes to the scientific literature by paving the way for a more comprehensive, detailed, and better-structured analysis of RES-E policy designs than what currently prevails.

Our results indicated that the share of the wind RES-E generation achieved by the FiT scheme, owing to the displacement of conventional generators, had a positive environmental impact, highlighting a reduction trend of CO_2 emissions. Understanding and analysing emission trends can contribute to the effective design of policies and practices targeting the achievement of the existing climate goals. However, the large-scale penetration of RES-E alone, does not necessarily imply a more environmental-friendly energy generation approach. Increasing the shares of RES-E in Greece is a step to the right direction; an efficient low-carbon transition though, also requires the inclusion of an appropriate regulatory framework designed to consider factors associated with the adverse impacts of the early stages in the life cycle of RES. Additionally, our work explicitly quantified the emission savings attributed to the FiT scheme, decoupled from issues of economic growth. From this aspect, policy priority for breaking the connection between economic growth and GHG emissions is vital to establish a stable RES support framework and a safe environment for investors.

On the other hand, while our results indicated that the capacity of the wind RES-E generation achieved by the FiT scheme in Greece did not compromise the reliability of the electricity system, compared to historical data available, this was almost 70% less than the total PV capacity achieved over the period under study. The latter, derived mainly from the fact that FiTs in Greece made it extremely challenging to determine the appropriate RES-E remuneration levels, led to a regulatory failure and market asymmetry at the end of 2013. As a result, since then, the existing market structure and mechanisms are unable to incentivise long-term investments and support the long-term growth of the necessary infrastructure. Considering that the country is still in financial distress, special attention must be paid to policy measures that do not undermine market competitiveness. As a result, to avoid similar rebound effects in the long-term, decision-makers should envision a more adaptive policymaking process, which, based on the concept of Key Performance Indicators (KPIs), will allow for contingency planning by monitoring cost reductions owing to technological progress and learning effects, also controlling the profit margin of prosumers and limiting public expenses and burdensome charges for consumers.

Appendix A

Table A1. Lignite-based thermal power stations in Greece sorted by their emission factors [51].

CO_2		SO_2		NO_x		PM	
Plant	**Value**	**Plant**	**Value**	**Plant**	**Value**	**Plant**	**Value**
Megalopolis A	1652	Megalopolis A	8.70	Ag. Dimitrios	2.16	Ptolemaida	2.78
Ptolemaida	1577	Amyntaio	8.65	Kardia	2.08	Kardia	0.68
Kardia	1500	Ag. Dimitrios	3.11	Amyntaio	1.37	Megalopolis A	0.42
Ag. Dimitrios	1435	Ptolemaida	2.73	Ptolemaida	1.36	Amyntaio	0.18
Amyntaio	1349	Florina	2.29	Megalopolis B	1.15	Megalopolis B	0.12
Megalopolis B	1340	Kardia	1.73	Megalopolis A	1.09	Ag. Dimitrios	0.10
Florina	1210	Megalopolis B	0.69	Florina	0.82	Florina	0.02

Table A2. The volatility of the wind RES-E generation during the period 2009-2013 in Greece.

	2009	**2010**	**2011**	**2012**	**2013**
Most volatile month	December	November	September	November	March
Day of max wind	2009/12/25	2010/11/23	2011/09/27	2012/11/29	2013/3/14
Max wind (MWh)	11756	15464	17753	23328	23014
Day of min wind	2009/12/08	2010/11/16	2011/09/1	2012/11/26	2013/3/1
Min wind (MWh)	682	556	1395	1626	2476
Volatility	±89%	±93%	±85%	±87%	±81%

Table A3. The main fossil-fuelled power plants during the period 2009-2013 in Greece (as accessed at http://www.admie.gr/fileadmin/groups/EDRETH/CAM/UCAP_12_13.pdf).

Plant name	Plant fuel	EFORd (%)	Net capacity (MW)
AG_DIMITRIOS1	lignite	8.302	274.000
AG_DIMITRIOS2	lignite	7.534	274.000
AG_DIMITRIOS3	lignite	7.074	283.000
AG_DIMITRIOS4	lignite	10.174	283.000
AG_DIMITRIOS5	lignite	5.355	342.000
AG_GEORGIOS8	natural gas	14.231	151.000
AG_GEORGIOS9	natural gas	3.229	188.000
ALIVERI3	oil	0.749	144.000
ALIVERI4	oil	1.767	144.000
ALOUMINIO	natural gas	42.390	334.000
AMYNDEO1	lignite	11.284	273.000
AMYNDEO2	lignite	11.472	273.000
ELPEDISON_THESS	natural gas	6.290	389.380
ELPEDISON_THISVI	natural gas	5.670	410.000
HERON1	natural gas	6.670	49.254
HERON2	natural gas	7.790	49.254
HERON3	natural gas	7.380	49.254
HERON_CC	natural gas	5.670	422.142
KARDIA1	lignite	9.815	275.000
KARDIA2	lignite	7.607	275.000
KARDIA3	lignite	9.658	280.000
KARDIA4	lignite	17.760	280.000

Plant name	Plant fuel	EFORd (%)	Net capacity (MW)
KOMOTINI	natural gas	5.880	476.300
LAVRIO1	oil	3.020	123.000
LAVRIO2	oil	8.970	287.000
LAVRIO3	natural gas	11.550	173.400
LAVRIO4	natural gas	6.490	550.200
LAVRIO5	natural gas	3.110	377.660
LIPTOL1	lignite	6.420	30.000
LIPTOL2	lignite	6.420	8.000
MEGALOPOLI1	lignite	20.485	113.000
MEGALOPOLI2	lignite	20.485	113.000
MEGALOPOLI3	lignite	20.485	255.000
MEGALOPOLI4	lignite	7.265	256.000
MELITI	lignite	10.141	289.000
PROTERGIA_CC	natural gas	5.670	432.700
KORINTHOS_POWER	natural gas	5.670	433.460
PTOLEMAIDA1	lignite	27.070	64.000
PTOLEMAIDA2	lignite	27.070	116.000
PTOLEMAIDA3	lignite	28.400	116.000
TOLEMAIDA4	lignite	27.080	274.000

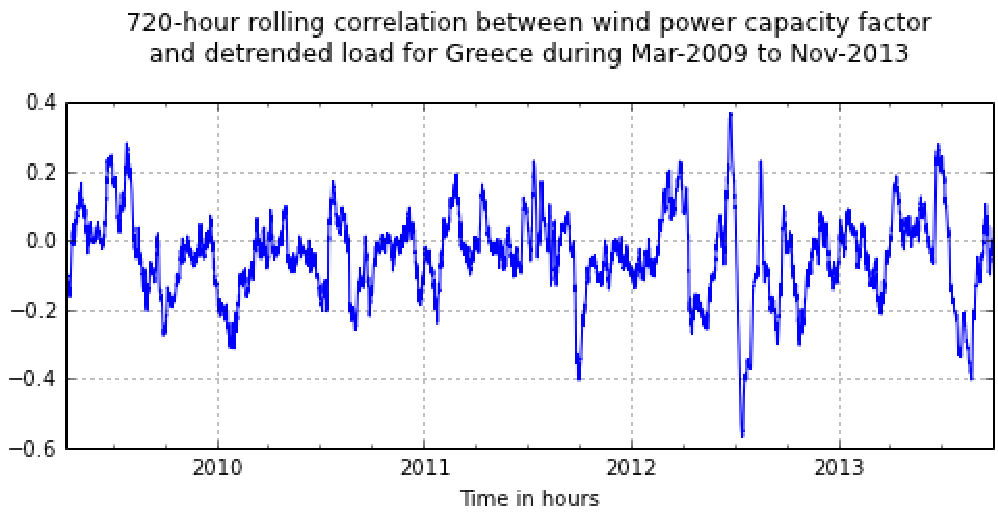


Figure A1. Rolling correlation between the wind power capacity factor and the detrended load.

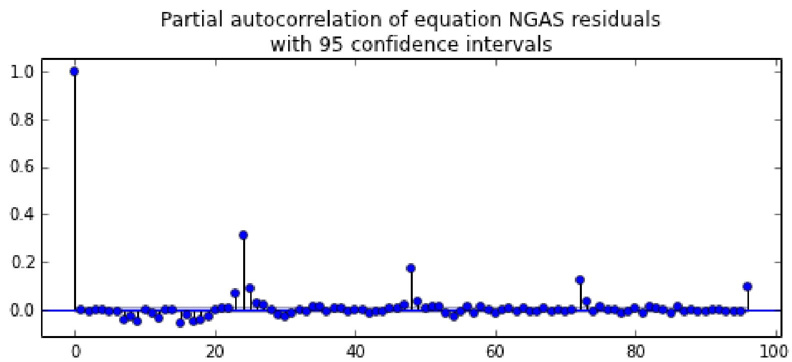


Figure A2. Autocorrelation plot for natural gas-fuelled generation.

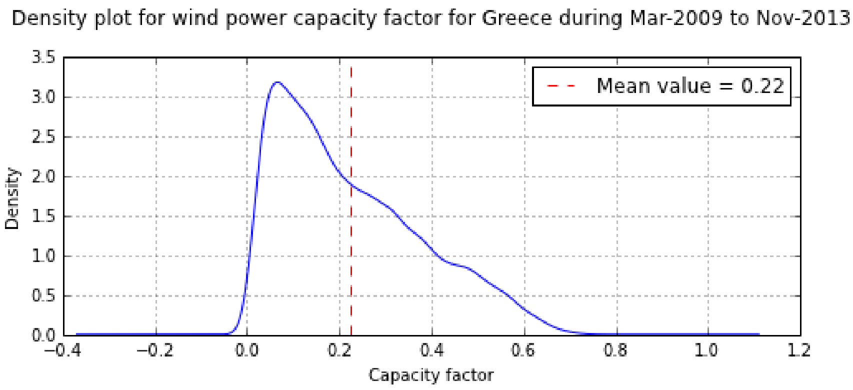


Figure A3. Density plot for the wind power capacity factor in Greece.

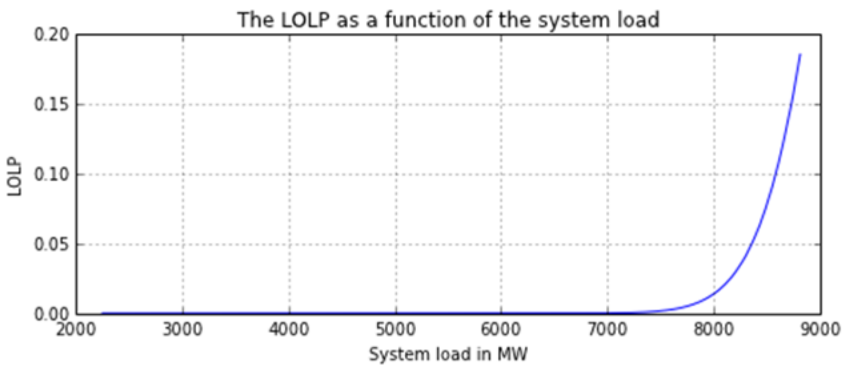


Figure A4. The LOLP as a function of the system load in Greece.

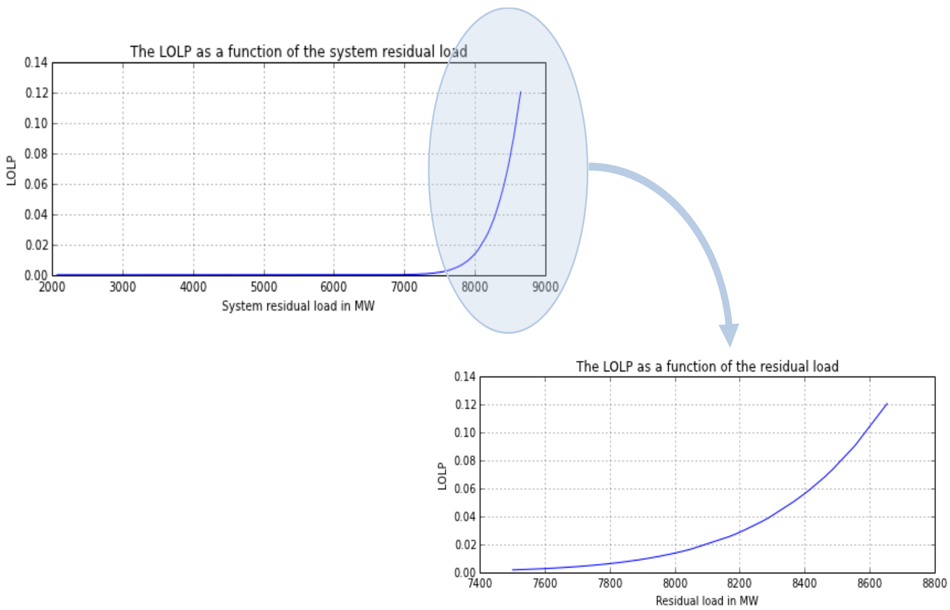


Figure A5. Assumed linearity of the LOLP function.

References

[1] Stavrakas V, Spyridaki N-A, Flamos A. Striving towards the deployment of bio-energy with carbon capture and storage (BECCS): A review of research priorities and assessment needs. Sustain 2018;10. doi:10.3390/su10072206.

[2] Michas S, Stavrakas V, Spyridaki N, Flamos A. Identifying Research Priorities for the further development and deployment of Solar Photovoltaics Identifying Research Priorities for the further development. Int J Sustain Energy 2018;0:1–21. doi:10.1080/14786451.2018.1495207.

[3] Cooper M. Renewable and distributed resources in a post-Paris low carbon future: The key role and political economy of sustainable electricity. Energy Res Soc Sci 2016;19:66–93. doi:10.1016/j.erss.2016.05.008.

[4] Vandyck T, Keramidas K, Saveyn B, Kitous A, Vrontisi Z. A global stocktake of the Paris pledges: Implications for energy systems and economy. Glob Environ Chang 2016;41:46–63. doi:10.1016/j.gloenvcha.2016.08.006.

[5] Ackermann T, Andersson G, Söder L. Overview of government and market driven programs for the promotion of renewable power generation. Renew Energy 2000;22:197–204. doi:10.1016/S0960-1481(00)00015-X.

[6] Hirth L. The market value of variable renewables: The effect of solar wind power variability on their relative price. Energy Econ 2013;38:218–36. doi:10.1016/j.eneco.2013.02.004.

[7] Butler L, Neuhoff K. Comparison of feed-in tariff, quota and auction mechanisms to support wind power development. Renew Energy 2008;33:1854–67. doi:10.1016/j.renene.2007.10.008.

[8] Ringel M. Fostering the use of renewable energies in the European Union: The race between feed-in tariffs and green certificates. Renew Energy 2006;31:1–17. doi:10.1016/j.renene.2005.03.015.

[9] Campoccia A, Dusonchet L, Telaretti E, Zizzo G. An analysis of feed'in tariffs for solar PV in six representative countries of the European Union. Sol Energy 2014;107:530–42. doi:10.1016/j.solener.2014.05.047.

[10] Li SJ, Chang TH, Chang SL. The policy effectiveness of economic instruments for the photovoltaic and wind power development in the European Union. Renew Energy 2017;101:660–6. doi:10.1016/j.renene.2016.09.005.

[11] Fuchs C, Kasten J, Vent M. Current State and Future Prospective of Repowering Wind Turbines: An Economic Analysis. Energies 2020;13:3048. doi:10.3390/en13123048.

[12] Koumparou I, Christoforidis GC, Efthymiou V, Papagiannis GK, Georghiou GE. Configuring residential PV net-metering policies – A focus on the Mediterranean region. Renew Energy 2017;113:795–812. doi:10.1016/j.renene.2017.06.051.

[13] De Boeck L, Van Asch S, De Bruecker P, Audenaert A. Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability. Renew Energy 2016;87:42–53. doi:10.1016/j.renene.2015.09.063.

[14] Antonelli M, Desideri U. The doping effect of Italian feed-in tariffs on the PV market. Energy Policy 2014;67:583–94. doi:10.1016/j.enpol.2013.12.025.

[15] Couture TD, Cory K, Kreycik C, Williams E. Policymaker's Guide to Feed-in Tariff Policy Design. 2010. doi:10.2172/984987.

[16] Frondel M, Schmidt CM, Vance C. Revisiting Germany's solar cell promotion: An unfolding disaster. Econ Anal Policy 2014;44:3–13. doi:10.1016/j.eap.2014.02.001.

[17] Kyritsis A, Voglitsis D, Papanikolaou N, Tselepis S, Christodoulou C, Gonos I, et al. Evolution of PV systems in Greece and review of applicable solutions for higher penetration levels. Renew Energy 2017;109:487–99. doi:10.1016/j.renene.2017.03.066.

[18] Stavrakas V, Flamos A. A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector. Energy Convers Manag 2020;205. doi:10.1016/j.enconman.2019.112339.

[19] Mart H, Coronas S, Alonso À, Hoz J De, Matas J. Renewable Energy Auction Prices : Near Subsidy-Free ? Energies 2020;13.

[20] Batlle C, Pérez-Arriaga IJ, Zambrano-Barragán P. Regulatory design for RES-E support mechanisms: Learning curves, market structure, and burden-sharing. Energy Policy 2012;41:212–20. doi:10.1016/j.enpol.2011.10.039.

[21] Eid C, Reneses Guillén J, Frías Marín P, Hakvoort R. The economic effect of electricity net-metering with solar PV: Consequences for network cost recovery, cross subsidies and policy objectives. Energy Policy 2014;75:244–54. doi:10.1016/j.enpol.2014.09.011.

[22] Nikolaidis AI, Milidonis A, Charalambous CA. Impact of fuel-dependent electricity retail charges on the value of net-metered PV applications in vertically integrated systems. Energy Policy 2015;79:150–60. doi:10.1016/j.enpol.2015.01.010.

[23] Ramïrez FJ, Honrubia-Escribano A, Gï¿½mez-Lï¿½zaro E, Pham DT. Combining feed-in tariffs and net-metering schemes to balance development in adoption of photovoltaic energy: Comparative economic assessment and policy implications for European countries. Energy Policy 2017;102:440–52. doi:10.1016/j.enpol.2016.12.040.

[24] Danchev S, Maniatis G, Tsakanikas A. Returns on investment in electricity producing photovoltaic systems under de-escalating feed-in tariffs: The case of Greece. Renew Sustain Energy Rev 2010;14:500–5. doi:10.1016/j.rser.2009.08.008.

[25] Papaioannou GP, Dikaiakos C, Dagoumas AS, Dramountanis A, Papaioannou PG. Detecting the impact of fundamentals and regulatory reforms on the Greek wholesale electricity market using a SARMAX/GARCH model. Energy 2017;142:1083–103. doi:10.1016/j.energy.2017.10.064.

[26] Michas S, Stavrakas V, Papadelis S, Flamos A. A transdisciplinary modeling framework for the participatory design of dynamic adaptive policy pathways. Energy Policy 2020;139. doi:10.1016/j.enpol.2020.111350.

[27] Sotiriou C, Michopoulos A, Zachariadis T. On the cost-effectiveness of national economy-wide greenhouse gas emissions abatement measures. Energy Policy 2019;128:519–29. doi:10.1016/j.enpol.2019.01.028.

[28] Newbery D, Pollitt, Michael G, Ritz RA, Strielkowski W. Market design for a high-renewables European electricity system. Renew Sustain Energy Rev 2018;91:697–707. doi:10.1016/j.rser.2018.04.025.

[29] Iychettira KK, Hakvoort RA, Linares P. Towards a comprehensive policy for electricity from renewable energy: An approach for policy design. Energy Policy 2017;106:169–82. doi:10.1016/j.enpol.2017.03.051.

[30] Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-Baltvilks J, et al. Barriers to and consequences of a solar-based energy transition in Greece. Environ Innov Soc Transitions 2019. doi:10.1016/j.eist.2018.12.004.

[31] Papadelis S, Stavrakas V, Flamos A. What do capacity deployment rates tell us about the efficiency of electricity generation from renewable energy sources support measures in Greece? Energies 2016;9. doi:10.3390/en9010038.

[32] Anagnostopoulos P, Spyridaki NA, Flamos A. A “new-deal” for the development of photovoltaic investments in Greece? A parametric techno-economic assessment. Energies 2017;10:1173. doi:10.3390/en10081173.

[33] Giannini E, Moropoulou A, Maroulis Z, Siouti G. Penetration of photovoltaics in Greece. Energies 2015;8:6497–508. doi:10.3390/en8076497.

[34] Karteris M, Papadopoulos AM. Legislative framework for photovoltaics in Greece: A review of the sector’s development. Energy Policy 2013;55:296–304. doi:10.1016/j.enpol.2012.12.001.

[35] Ministry of Environment and Energy. National Energy and Climate Plan of Greece. 2019.

[36] European Commission. Communication from the Commission: The European Green Deal. 2019. doi:10.1017/CBO9781107415324.004.

[37] Sotiriou C, Zachariadis T. Optimal timing of greenhouse gas emissions abatement in Europe. Energies 2019;12. doi:10.3390/en12101872.

[38] Taliotis C, Giannakis E, Karmellos M, Fylaktos N, Zachariadis T. Estimating the economy-wide impacts of energy policies in Cyprus. Energy Strateg Rev 2020;29:100495. doi:10.1016/j.esr.2020.100495.

[39] Engle RF, Granger CWJ. Co-Integration and Error Correction: Representation, Estimation, and Testing. Econometrica 1987;55:251. doi:10.2307/1913236.

[40] De Jong C, Schneider S. Cointegration between gas and power spot prices. J Energy Mark 2009;2:27–46. doi:10.21314/JEM.2009.023.

[41] Bosco B, Parisio L, Pelagatti, Matteo, Baldi F. Long-run relations in European electricity prices. J Appl Econom 2010;25:805–32. doi:10.1002/jae.1095.

[42] Ferkingstad E, Løland A, Wilhelmsen M. Causal modeling and inference for electricity markets. Energy Econ 2011;33:404–12. doi:10.1016/j.eneco.2010.10.006.

[43] Furió D, Chuliá H. Price and volatility dynamics between electricity and fuel costs: Some evidence for Spain. Energy Econ 2012;34:2058–65. doi:10.1016/j.eneco.2012.02.014.

[44] Chen Z, Wu L, Shahidehpour M. Effective load carrying capability evaluation of renewable energy via stochastic long-term hourly based SCUC. IEEE Trans Sustain Energy 2015;6:188–97. doi:10.1109/TSTE.2014.2362291.

[45] Keane A, Milligan M, Dent CJ, Hasche B, D'Annunzio C, Dragoon K, et al. Capacity value of wind power. vol. 26. 2011. doi:10.1109/TPWRS.2010.2062543.

[46] Kahn EP. Capability of Wind Generation : Initial Results with Public Data. Electr J 2004;17:85–95.

[47] Sakellaris K. The greek capacity adequacy mechanism: Design, incentives, strategic behavior and regulatory remedies. 6th Int. Conf. Eur. Energy Mark. EEM, IEEE; 2009, p. 1–6. doi:10.1109/EEM.2009.5207209.

[48] Biskas PN, Marneris IG, Chatzigiannis DI, Roumkos CG, Bakirtzis AG, Papalexopoulos A. High-level design for the compliance of the Greek wholesale electricity market with the Target Model provisions in Europe. Electr Power Syst Res 2017;152:323–41. doi:10.1016/j.epsr.2017.06.024.

[49] Flamos A. A sectoral micro-economic approach to scenario selection and development: The case of the greek power sector. Energies 2016;9:1–12. doi:10.3390/en9020077.

[50] Kaldellis JK, Zafirakis D, Kondili E. Contribution of lignite in the Greek electricity generation: Review and future prospects. Fuel 2009;88:475–89. doi:10.1016/j.fuel.2008.09.021.

[51] Kaldellis JK, Kapsali M. Evaluation of the long-term environmental performance of Greek lignite-fired power stations. Renew Sustain Energy Rev 2014;31:472–85. doi:10.1016/j.rser.2013.12.012.

[52] Gouw JA De, Parrish DD, Frost GJ, Trainer M. Reduced emissions of CO2, NOx, and SO2 from U.S. power plants owing to switch from coal to natural gas. Earth's Futur 2014;2:75–82. doi:10.1002/2013EF000196.Abstract.

[53] Granger CWJ. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica 1969;37:424–38.

[54] Stavrakas V, Papadelis S, Flamos A. An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers. Appl Energy 2019;255:113795. doi:10.1016/j.apenergy.2019.113795.

[55] Tipping JP, Read GE, Mcnickle D. The Incorporation of Hydro Storage into a Spot Price Model for the New Zealand Electricity Market. Sixth Eur. Energy Conf. Model. Energy Econ. Policy, Zurich: 2004, p. 1–25.

[56] Uddin M, Romlie MF, Abdullah MF, Abd Halim S, Abu Bakar AH, Chia Kwang T. A review on peak load shaving strategies. Renew Sustain Energy Rev 2018;82:3323–32. doi:10.1016/j.rser.2017.10.056.

[57] Pesaran MH, Shin Y. An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis in Econometrics and Economic Theory in the 20th Century: the Ragnar Frisch Centennial Symposium. Econom. Econ. Theory 20th Century Ragnar Frisch Centen. Symp., 1999, p. 1–31. doi:10.1017/CCOL521633230.

[58] Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. J Appl Econom 2001;16:289–326. doi:10.1002/jae.616.

[59] Behrens P, Rodrigues JFD, Brás T, Silva C. Environmental, economic, and social impacts of feed-in tariffs: A Portuguese perspective 2000-2010. Appl Energy 2016;173:309–19. doi:10.1016/j.apenergy.2016.04.044.

[60] Roinioti A, Koroneos C. The decomposition of CO2emissions from energy use in Greece before and during the economic crisis and their decoupling from economic growth. Renew Sustain Energy Rev 2017;76:448–59. doi:10.1016/j.rser.2017.03.026.

[61] Kim H, Kim M, Kim H, Park S. Decomposition Analysis of CO 2 Emission from Electricity Generation : Comparison of OECD Countries before and after the Financial Crisis. Energies 2020;13.

[62] Hatzigeorgiou E, Polatidis H, Haralambopoulos D. CO2 emissions in Greece for 1990-2002: A decomposition analysis and comparison of results using the Arithmetic Mean Divisia Index and Logarithmic Mean Divisia Index techniques. Energy 2008;33:492–9. doi:10.1016/j.energy.2007.09.014.

[63] Diakoulaki D, Mavrotas G, Orkopoulos D, Papayannakis L. A bottom-up decomposition analysis of energy-related CO2 emissions in Greece. Energy 2006;31:2638–51. doi:10.1016/j.energy.2005.11.024.

[64] Lu S, Diao R, Samaan N, Etingov P. Capacity Value of PV and Wind Generation in the NV Energy System. 2012.

Chapter 3 - Understanding technology adoption

Nomenclature

Acronyms & abbreviations			
ABM	Agent-based modelling/ agent-based model	MERRA-2	Modern-era retrospective analysis for research and applications, version 2
AC	Alternate current	MLE	Maximum likelihood estimation
ATOM	Agent-based Technology adOption Model	NEM	Net-metering
BSAM	Business Strategy Assessment Model	OPV	Organic photovoltaics
CAMS	Copernicus atmosphere monitoring service	PTC	Photovoltaic for utility system applications test condition
CHP	Micro-combined heat and power	PV	Photovoltaic
CO_2	Carbon dioxide emissions	RAE	Regulatory Authority for Energy
DC	Direct current	RECs	Renewable energy credits
EC	European Commission	RES	Renewable energy sources
ETMEAR	Special duty for reduction of gas emissions	SA	Sensitivity analysis
FiP	Feed-in-premium	SAPM	Sandia photovoltaic array performance model
FiT	Feed-in-tariff	SC	Self-consumption
GIS	Geographic information system	SC-ST	Self-consumption with storage
GP	Gaussian process	TEEM	TEESlab Modelling
GSA	Global sensitivity analysis	TEESlab	Technoeconomics of Energy Systems laboratory
IRR	Internal rate of return	UC	Uncertainty characterisation
LHD	Latin hypercube design	USA	United States of America
List of symbols & parameters			
A	Matrix	n	Number of features of an input dataset
B	Matrix	P(j)	Probability of investing in option j
capex	Capital expenditure	P_{resid}^{total}	Total benefits for consumers (€)
CAP_{PV}	Peak power capacity of the solar PV system (kW)	r_j	Resistance to invest in option j
C_{grid}	Charges for the total amount of electricity consumed (€/kWh)	s_B	Subsidy payment (€)
$C_{0,B}$	Initial battery investment cost $\left(\frac{€}{kWh}\right)$	S_j	First order effect sensitivity coefficient
C_{PV}	Charges for the total amount of electricity absorbed from the PV panel (€/kWh)	V	Variance
d	Discount rate	X	Input dataset
E	Expected value	x_j	j^{th} feature of an input dataset
E_{grid}	Total amount of electricity absorbed from the grid (kWh)	y	Output of interest

$E_{resid_{PV}}$	Total amount of electricity consumed from the PV panel (kWh)	z_i	Probability that the (discounted) payback period of the investment is equal to i
E_{resid}	Total residential demand for electricity (kWh)	μ^{CF}	Mean value of a Gaussian distribution
j	Index	ρ^{CF}	Precision of a Gaussian distribution
i	Index		
N	Number of input samples		

3. An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers

Abstract

A good estimation of consumers' expected response to specific policy measures is of paramount importance in the design of effective schemes for the adoption of new technologies. The decision-making process of consumers is influenced by a multitude of factors. In this context, agent-based modelling techniques provide an appropriate framework to model such private adoption decisions. However, the models currently in use often fail to capture uncertainties related to agency and their ability to replicate reality. In order to address this drawback, we developed an agent-based technology adoption model that is supported by a complete framework for parameter estimation and uncertainty quantification based on historical data and observations. The novelty of our model lies in obtaining realistic uncertainty bounds and splitting the total model output uncertainty in its major contributing uncertainty sources. In this chapter, we demonstrate the model's applicability by exploring the evolution of the market share of small-scale PV systems in Greece under two support schemes of interest. Our results indicated that, over 2018-2025, the net-metering scheme, currently operational, seems more effective than a proposed self-consumption scheme that subsidises residential storage by 25%; however, the former scheme's effectiveness is mainly related to the retail price of electricity. They also highlighted that storage investment costs need to follow a steep learning curve of at least a 10% annual reduction until 2025, for self-consumption to become attractive to consumers in Greece. Nevertheless, simulations showed that none of these two schemes can be as efficient as the previous feed-in-tariff scheme.

Keywords: Solar PV; Net-metering; Self-consumption; Technology adoption; Agent-based modelling; Uncertainty quantification.

3.1. Introduction

For a long time now, solar photovoltaic (PV) systems have been considered a viable substitute for conventional energy sources [1] and have proven to be one of the key technologies of electricity generation from renewable energy sources (RES); thus, they support the transition towards a low-carbon energy system [2]. In the context of this transition, PV self-consumption (SC) is becoming extremely important, especially in the case of residential buildings, with consumers taking the role of prosumers, that is, those who produce and consume energy locally. Typically, SC encompasses the adoption and further diffusion of a wide range of technologies and systems such as small-scale PV, battery storage, and smart-grid devices, which bring demand flexibility into the market. A growing number of recent studies in the literature has been assessing PV SC and its economics, focusing on systems that only use PV or on PV systems coupled with battery storage [3,4]. The findings show that if PV SC, at the residential level, becomes economically competitive soon, end-users will be willing to self-consume electricity instead of buying it from the grid [5,6]. Such a massive and radical change could impact national power systems around the world, especially if the necessary regulatory framework is not in place, and influence the interests of the electricity market stakeholders [7]. In addition, regulatory and financial challenges related to the need for novel market business models and supporting mechanisms are the main obstacles to the sustained exponential growth of PV technology [2]. Therefore, policymakers should focus on an optimal mix of PV power and other RES technologies; they should also anticipate the risks and uncertainties related to further PV adoption [7].

Sommerfeld et al., (2017) highlight the importance of understanding consumer behavioural patterns with respect to PV adoption to guarantee the effectiveness of future policies [8]. Because of the multitude of factors influencing a household’s decision to invest in an innovative energy technology such as PV, agent-based models (ABMs) provide a suitable framework to simulate the adoption decision process of the members of a heterogeneous social system; the framework is based on members’ individual preferences, behavioural rules, and communication within a social network [9,10]. ABM perceives a system as a collection of autonomous decision-making entities called “agents;” further, it is a very flexible modelling tool as it describes the micro-level behavior of agents and allows the inclusion of considerable detail about their decisions and (inter-)actions [11]. ABMs provide an intuitive framework to consider the explicit characteristics of both technology and human behavior, and are considered a part of the new generation of models that describe, in a richer and more nuanced way, sustainability problems and address policy issues [12].

Instead of using regression to extrapolate growth based on past trends- the typical approach used by policymakers so far- modelling agents’ decisions and interactions represents a more “real-world” process [13]. Optimisation models, so far, implicitly assume that there is some centralised control over the energy system; this is often not the case, especially for small-scale, privately-owned technologies, such as PV. ABMs address this limitation by introducing a layer of control and decision-making, thereby allowing greater understanding of macro-phenomena [14]. Many technical innovations and public policies often fail because they do not sufficiently consider what matters to people (i.e., the motivating factors shaping their adoption preferences). People and their social interactions greatly influence the diffusion and use of technology, and, further, shape overall technological transition dynamics. However, transitions are difficult to understand scientifically because of the influence of a broad range of contextual factors that affect policy processes, society, and agency. Considering the diversity of interests, motivations, and other factors that inform peoples’ choices helps to reduce the uncertainty that may lead to policy failure [15].

Recent studies in the literature have already addressed the issue of PV adoption by using ABMs. Haringa (2010) explored the potential for micro-generation by focusing on micro-combined heat and power (CHP), solar PV, and micro-wind turbines in the Netherlands’ domestic sector [16]. An ABM was implemented using households as the actors and monetary, social, and environmental factors in decision-making. Zhao et al., (2011) implemented a hybrid two-level (i.e., high and low) simulation modelling framework, using agent-based and system dynamics modelling techniques at both levels, to simulate the diffusion of PV systems [17]. Their framework was developed based on real data for residential areas in two different regions of the United States of America (USA); further, it illustrates, in a comprehensive and highly detailed way, the impact of various governmental policies that support the proper development of solar PV. This study investigates how the behaviour of residential customers on adopting grid-tied PV systems is influenced by factors such as “word-of-mouth” and advertisement effects, household income, and PV systems’ payback period.

Additionally, Robinson et al., (2013) used an ABM, along with geographic information system (GIS) data, to model solar PV diffusion on a real topology [18]. The model explored the impact of social, economic, demographic, and behavioural attributes of PV adopters; the structure and strength of information networks; and the role of agents holding extreme opinions about PV. Palmer et al., (2015) used an ABM to explore the expansion of the Italian PV market by considering the decision-making process of the agents; the process was based on their individual preferences, behavioural rules, and interactions/ communication within a social network [19]. Multiple criteria, such as the payback period of the investment, the environmental benefits in terms of reduction in carbon dioxide emissions (CO_2) emissions, the income of the household, and the influence of other agents who have already invested in the new technology, that affect the decision of the agents to invest, were incorporated into the model. Adepetu et al., (2016) designed and used an ABM to model PV-battery adoption in Ontario [20]. The decision-making process of the agents is described by the model using rational (i.e., economic and technical) and irrational (i.e., background, social, and environmental) factors. Finally, Pearce and Slade (2018) presented an ABM that simulates the adoption of small-scale PV systems under the feed-in-tariff (FiT) scheme in Great Britain [21]. According to the study, the agent-related parameters affecting the decision-making of each household are income, social network and contacts, total capital cost of the PV system, and payback period of the investment. The suggested model simulates the observed cumulative and average capacity installed over the period 2010-2016 by using historical data on FiT.

However, quantitative predictions derived from modelling outputs are not deterministic, and, thus, in each modelling application, several types of uncertainty, as input, parametric, and structural, are involved [22,23]. As per the definition used by Willems (2012), “[…]*model parameters are constant (time invariable), while model inputs are essentially time variable. Model-structural uncertainties have to do with the model’s limitations to describe the physical reality perfectly*.” [24]. One limitation of existing ABMs, though, is that they often fail to capture such uncertainties related to agency (i.e., individuals or households, who make decisions independently). Especially for the case of structural uncertainty scientific literature acknowledges that it has received substantially less attention from existing models [25].

Considering this gap, in this chapter, we present the Agent-based Technology adOption Model (ATOM). Apart from exploring the expected effectiveness of technology adoption under policy schemes of interest, the model allows us to consider and explicitly quantify the uncertainties that are related to agents’ preferences and decision-making criteria (i.e., behavioural uncertainty). More specifically, compared to existing models, the novelty of ATOM lies in obtaining realistic uncertainty bounds and splitting the total model output uncertainty in its major contributing sources, based on a variance decomposition framework [24] and an uncertainty characterisation (UC) method [26], while accounting for structural uncertainty. Thus, ATOM supports the definition of uncertainty ranges, considering the type (i.e., input, parametric, and structural) and the nature of uncertainty (i.e., epistemic, or aleatory), and how uncertainty propagates to the model outcomes over the planning time horizon.

Variance decomposition takes places for all the three main modules of ATOM (i.e., calibration, sensitivity analysis (SA), and scenario analysis). By allowing the user to select preliminary values for the agent-related parameters according to the plausibility of its results, based on historical data and observations (goodness-of-fit statistics), the model captures input uncertainty (i.e., calibration module). By deriving forward-looking simulations for different behavioural profiles (i.e., different set of agent-related parameters), from willing to invest to risk-averse consumers, ATOM captures parametric uncertainty (i.e., scenario analysis module). Both types of uncertainty are then propagated through the model and their contribution to the total model's output variance is quantified. The rest uncertainty is assumed to be explained by the model's structure. Note that the uncertainty propagation for the agent-related parameters is done for each one of them, allowing calculation of the sensitivity of each parameter to the model output, in the context of a variance-based sensitivity analysis (Sobol method) [26,27], and calculation of the relative contribution of the variance for each parameter to the total model output variance (i.e., SA module).

Furthermore, scenario analysis is a subsequent step in ABM to provide insights on more specific research questions, formulated and posed to the model to make comparisons among two or more situations and quantify the differences. In this work, we use ATOM to explore the evolution of the market share of small-scale PV systems (i.e., installed capacity of up to 10 kWpeak) in Greece, under two different policy support schemes of interest. Recent scientific literature has already highlighted the importance of studying different topics, such as the profitability and the effects of FiT, net-metering (NEM), or SC schemes related to PV systems [28]. To this end, the applicability of our model is demonstrated by exploring the expected effectiveness of the NEM scheme, which has been operational since mid-2015, in driving investments in small-scale PV and of a proposed SC support scheme that subsidises residential storage (hereafter, SC-ST) by 25%, during the period 2018-2025.

Scientific studies acknowledge that the return of investment in such support schemes is highly related to the unpredictability of electricity prices, thereby increasing the uncertainty experienced by consumers [29]. Thus, we use ATOM to explore scenarios of small-scale PV adoption under the two policy schemes of interest by assuming an annual increase in the Greek electricity retail price based on historical data. Additionally, studies in the literature also acknowledge that consumers are interested in boosting energy savings and reducing their bills; thus, preferences for SC-ST over NEM schemes are likely to be strongly incentivised in the future. However, while PV SC already seems attractive, electricity storage is still not a profitable solution owing to high costs and short lifetime. Only a sustained decrease in investment costs would lead to economically viable storage projects [28]. To this end, we use ATOM to explore the effectiveness of the suggested SC-ST scheme in driving investments in small-scale PV systems in Greece by assuming different feasible scenarios of decrease in storage investment costs. Finally, owing to the stochastic nature that typically characterises an ABM, we explore the expected effectiveness of the policy schemes under study- using the same values of the agent-related parameters- to validate the model's potential to quantify the uncertainty that is propagated to outcomes owing to its structure and parameters.

To develop ATOM, the initial framework of the Business Strategy Assessment Model (BSAM) [30,31], has been expanded and further developed, focusing on consumers, rather than power generators, as the unit of analysis. ATOM is part of the Technoeconomics of Energy Systems laboratory- TEESlab Modeling (TEEM) suite and was developed in the context of the EC-funded Horizon 2020 project "TRANSrisk[9]." The model serves as an entry point in technology adoption modelling by including a strong component of consumer- and policy-contingent scenario elements that correlate technology adoption with its value to consumers. The source code is written in Python programming language and,

[9] http://transrisk-project.eu/

therefore, runs in all three of the most widely used operating systems- Microsoft Windows, Apple OS X, and GNU/ Linux. Overall, our work bridges the gaps between research, development, and implementation contributing to the scientific literature by:

- Presenting a new ABM that specifies the values of the agent-related parameters under consideration, according to the plausibility of the model's results compared to historical data/ observations; further, we also assess all the main sources of uncertainty contributing to the total uncertainty of the model's outputs.
- Applying our ABM to explore scenarios of small-scale PV adoption in Greece, under the current NEM scheme and a proposed SC-ST support scheme. The novelty lies in bridging the disciplines of uncertainty analysis and ABM policy assessment, by showing how uncertainty in energy system modelling can influence effective policy design.
- Exploring the impact of electricity price and storage investment costs on PV adoption to highlight further policy relevant insights and support decision-making.

The remainder of this paper is organised as follows: **Section 3.2** presents, step by step, the methodological framework on which we relied to conceptualize and, thereafter, develop ATOM. **Section 3.3** presents the application of this framework to the geographic and socioeconomic context of Greece, to demonstrate the applicability of ATOM. **Section 3.4** reports the results of our forward-looking simulations, for the policy schemes under study, by exploring the impact of the retail price of electricity and storage costs on their effectiveness; further, we assess their performance for the same values of the agent-related parameters to capture how uncertainty is propagated to the model's outcomes owing to its structure and parameters. **Section 3.5** discusses key policy implications of our findings for potential end-users, as policymakers and practitioners. Finally, **Section 3.6** provides conclusions of our study and directions for future research.

3.2. Methodological framework

ATOM consists of three main modelling modules: (i.) a calibration module to define the set of the key parameters that govern the agents' behaviour and appropriate value ranges based on historical data/ observations; (ii.) a SA module that allows to quantify and consider uncertainties that are related to the characteristics and the decision-making criteria of the agents rather than the more obvious ones (e.g., technology costs, etc.) based on calibration results, and (iii.) a scenario analysis module to explore, given historical data/ observations, the plausible behaviour of the potential adopters in the geographic and socioeconomic contexts under study, for policy schemes of interest (i.e., forward-looking simulations). **Figure 3.1** below presents an overview of the five main methodological steps for conceptualising, and thereafter, developing these modules. In the sections below, each one of these methodological steps is presented and explained in more detail.

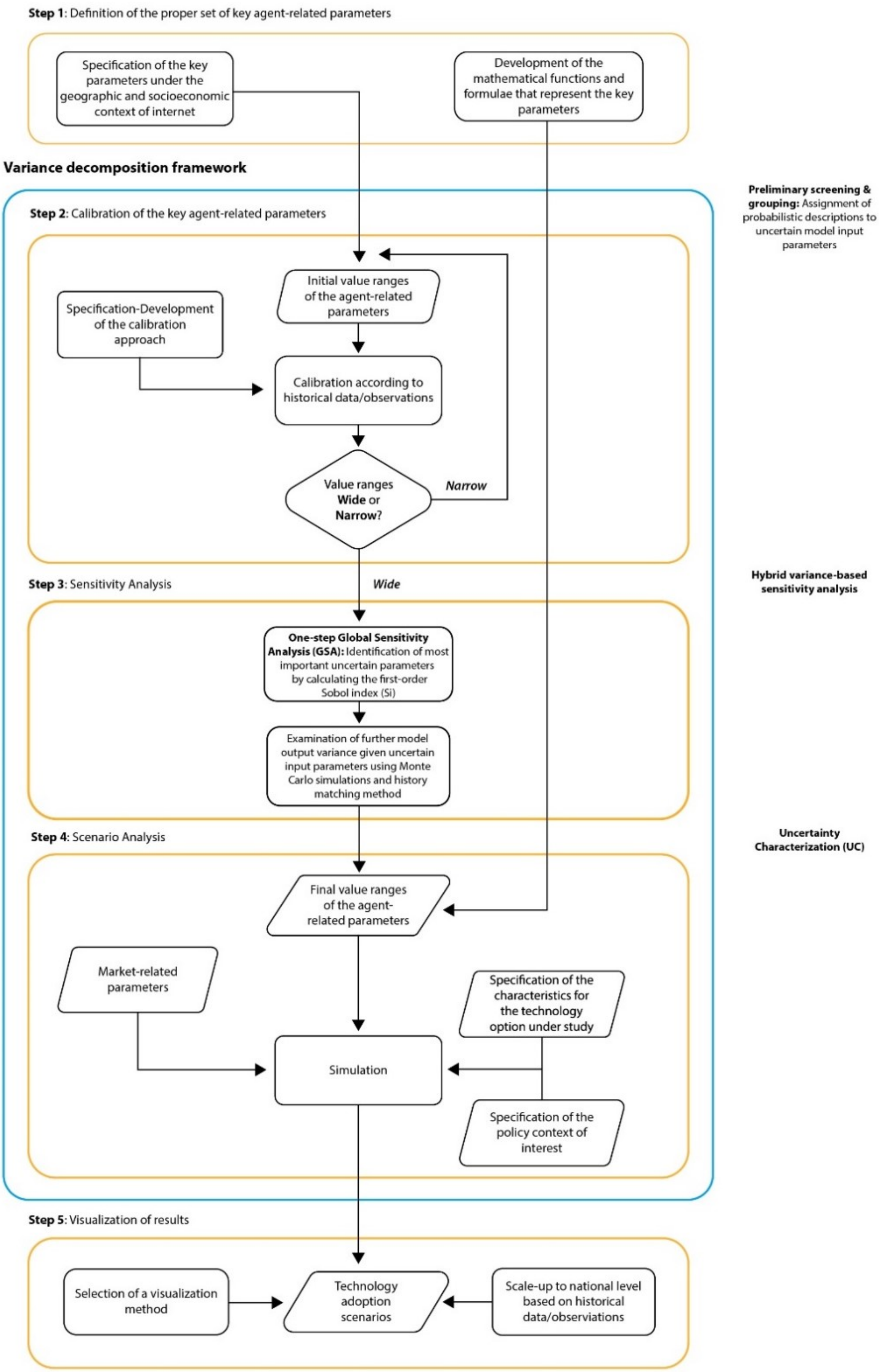


Figure 3.1. Methodological framework used to develop ATOM.

3.2.1. Step 1: Definition of the proper set of key agent-related parameters

As **Step 1**, we need to properly define the set of the key agent-related parameters that govern the agents' behaviour and decision-making process, besides shaping their propensity to invest in the technology under study. Scientific literature acknowledges that various factors should be considered when exploring the decision of consumers to adopt RES technologies [31]; existing studies report lack of awareness (e.g., financial, market, technical, etc.) [32], past market failures, social feasibility and sociocultural characteristics [33], and individual desire for greater energy autonomy [34]. Additionally, the economic driver seems to be crucial [8,32]. Considering prior studies, we define the set of key parameters that characterise the behaviour of the agents, that is, homeowners who, in each simulated time-period, either purchase or reject the technology under study. Typically, to build a quantitative model one needs to describe the relationships between model variables using mathematical equations with deterministic values. As a result, we develop the respective mathematical functions and formulae that represent these key parameters to generate arithmetic values of acceptable ranges. These ranges result from **Steps 2** and **3**, as described below.

3.2.2. Step 2: Calibration of the key agent-related parameters

As **Step 2**, the initial values of the agent-related parameters are set and the calibration approach to specify the appropriate ranges of these values is developed. The process of calibration allows us to quantify and consider uncertainties that are related to the behaviour and decision-making criteria of agents. Calibration in ATOM takes place on the basis of the concept of emulators, and, more specifically, of Gaussian process (GP) emulators, as they are typically a probabilistic approximation of an ABM. The probabilistic nature of emulators makes them ideal for the quantification of the uncertainty regarding their estimations, as well as the way the parametric uncertainty of the model gets reflected in its results. The model is then calibrated using historical data/ observations for the technology under study and for the geographic and socioeconomic context of interest, assuming that future uncertainty of parameter values implies that historical variations are representative for the future, as follows:

1. Preliminary value ranges of each agent-related parameter are chosen arbitrarily, with the goal of fitting a GP emulator to a reasonably large input space.
2. The GP emulator is fitted on the results from several parameter combinations simulated in ATOM. The parameter combinations are the input data and the model's results are the output data for the GP emulator.
3. To generate the input data, preliminary ranges for the value of each parameter are derived, and then, ATOM is run for 150 different parameter combinations. These initial combinations are chosen using a maximin Latin hypercube design (LHD) to fill the entire input space by maximising the minimum distance between the points generated.
4. At the end of the calibration, if the value ranges are too narrow, the user should revisit them, while, if they are wider than necessary, SA is necessary to test if, and for which parameters, this is true.

3.2.3. Step 3: Sensitivity analysis

SA aims to quantify the importance of uncertain parameters by explaining which of the n features of an input dataset $X = \{x_j, j = 1, \cdots, n\}$ are most responsible for the uncertainty in the model's results (i.e., y). Note that X denotes the set of the agent-related parameters, x_j denotes the parameters, and n is the total number of parameters. Our approach builds on the idea of variance-based sensitivity analysis (Sobol method), which is a form of Global Sensitivity Analysis (GSA) [26,27]. In particular, we use an one-step GSA and, then, we address further parametric uncertainty by using the history matching method [35], as described below. For a more detailed presentation on calibration and uncertainty quantification based on the concept of GP emulators we refer to Papadelis and Flamos (2018) [36].

1. We restrict the value ranges of the parameters that have only a small impact on the uncertainty of the model's outputs. Thus, the initial dataset X becomes $X' = \{x_j', j = 1, \cdots, n'\}$.

2. For each feature $j = 1,2, \cdots, n'$ in the remaining set of parameters X', we split X' into two parts (i.e., sets): the first one includes the selected feature and the other, which includes the remaining ones, is denoted by $EX' = (x_j', X_{-j})$.

3. We assess the sensitivity of y to the uncertainty regarding x_j' through the expected reduction in the variance of y, if the true value of x_j' is learnt. To calculate the expected reduction in variance, we use the mathematical formula provided by Saltelli et al., (2010) [37]:

$$V_{x_j'}\left(E\left(y \mid x_j'\right)\right) = \frac{1}{N}\sum_{i=1}^{N}\left\{f(B)_i\left(f\left(A_B^{(j)}\right)_i - f(A)_i\right)\right\}$$

where A and B are independent $N \times n'$ matrices that contain samples of the model's inputs.

4. To produce these matrices, we apply a Sobol sequence [37]. Sobol sequences are designed to cover the unit hypercube with lower discrepancy than completely random sampling. The index j runs from 1 to n', while the index j runs from 1 to N, where N is the number of input samples. The term $f(A)_i$ represents the i^{th} element of the vector that is the output of the GP emulator when evaluated at $X_*' = A$. The term $A_B^{(j)}$ represents a matrix where column j comes from matrix B and all other columns come from matrix A. The matrices A and B can be generated from a Sobol sequence of size $N \times 2 \cdot n'$, where A is the left half of the sequence and B is the right half.

5. Given $V_{x_j'}\left(E\left(y \mid x_j'\right)\right)$, we compute the first order sensitivity coefficient S_j that captures the main effect of x_j on y, as:

$$S_j = \frac{V_{x_j'}\left(E\left(y \mid x_j'\right)\right)}{V(y)} \in [0, 1]$$

6. Finally, we address further uncertainty in the model by using the history matching method, which has been successfully applied across a wide range of scientific fields, including calibration of ABMs [38]. A central concept of the method is the quantification of the major uncertainties that have an impact on the calibration process. To do so, we use the approach presented by Kennedy and O'Hagan (2001) [39], which works by excluding those subsets of the parameter space that are unlikely to provide a good match between model's outputs and observed reality (i.e., historical data/ observations). As the plausible space becomes smaller, emulators become smoother and more accurate, allowing us to zoom into the parameter space that we explore. As a result, the implausible parameter values are excluded in iterations known as "waves," and new GP emulators are built after each "wave."

Finally, while the Sobol method can be applied directly to the full parameter set, if the number of uncertain parameters is large, the computational cost can be prohibitive. The novelty of our approach, thus, lies in using the concept of emulators, as significantly faster approximations of the actual model, which allows us to employ Monte Carlo sampling methods that would be otherwise prohibitively expensive in terms of computational resources.

3.2.4. Step 4: Scenario analysis

Predictive "what-if" scenario analysis is used as a subsequent step in an ABM framework to provide insights on more specific questions posed to the model and make comparisons among two or more situations for quantifying the differences. Market-related parameters of the model are set according to past or existing conditions related to the geographic and socioeconomic context of interest. Accordingly, the characteristics of the technology under study and the policy context are specified. This step concludes with explorative forward-looking simulations focusing on system evolution through interactions between the agents, as a sequence of events and responses, and can be used to explore whether policy instruments lead to desirable results. Agent-related parameter values fixed within a model run are varied between runs, based on calibration results, to derive plausible technology adoption scenarios and to explore uncertainty propagation through the variance of the model's outputs. This step also allows for UC (i.e., aleatory or epistemic) [25,26].

3.2.5. Step 5: Visualisation of results

Finally, the projections of the adoption scenarios are scaled-up at national level by using historical data and past observations. The simulation outcomes are then visualised using error bars to graphically represent the "cone of uncertainty," indicating how uncertainty propagates to the model's outputs as the projection horizon moves further into the future.

3.3. Application to the PV sector in Greece

Literature findings acknowledge that mainly because of its geographic location (i.e., high solar irradiation levels), Greece is an attractive market choice for both small-scale PV owners and suppliers, including novel PV technologies, such as the organic photovoltaic (OPV) systems [40,41]. During the past decade, small residential PV systems in Greece have gained investors' attention, mainly owing to the profitable FiT scheme and simplified installation procedures that have been introduced by the special programme for the deployment of PV on buildings and roofs (Ministerial Decree OG B1079/4.6.2009) [42,43]. However, in 2013, the demand for new PV investments in Greece diminished owing to the drastic reduction of the tariffs and the imposition of a retroactive levy. These retroactive cuts to the FiT prices shook the confidence of investors in the stability of the expected revenues [44,45]. The latter brought changes in the regulatory framework of Greece with an NEM scheme taking the place of the effective, but very generous FiT scheme. This new scheme was legislated in 2014 by the Government Gazette Issue B'3583/31.12.2014 and came into effect by mid-2015 [46].

Scientific studies acknowledge that a NEM support scheme must be considered in combination with flexibility measures to maximise SC in residential buildings. Declining PV costs, along with rising retail prices and the phasing out of the FiT scheme, have made PV SC a more financially attractive choice for consumers than exporting to the grid. Such flexibility measures mainly refer to the further deployment of automated control technologies and electricity storage; further, they facilitate the large-scale integration of electricity from variable RES with the existing power system [47]. A particular focus is placed on the joint operation of SC with battery storage because it is the latest trend in small-scale PV systems [28]. Building on these insights, we apply the methodological steps, presented in **Section 3.2** above, to demonstrate the applicability of ATOM by extrapolating the dynamics of small-scale PV adoption among Greek consumers, under the current NEM scheme and a proposed SC-ST scheme. The model simulates scenarios of PV adoption among a small number of agents, that is, 1,000 homeowners, who decide to purchase or reject a small-scale PV installation in each simulated time-period.

3.3.1. Agent-related parameters for PV adoption

Considering prior knowledge and relevant insights from existing studies, we defined a proper set of agent-related parameters. **Figure 3.2** below presents the key parameters that govern the agents' behaviour in our application.

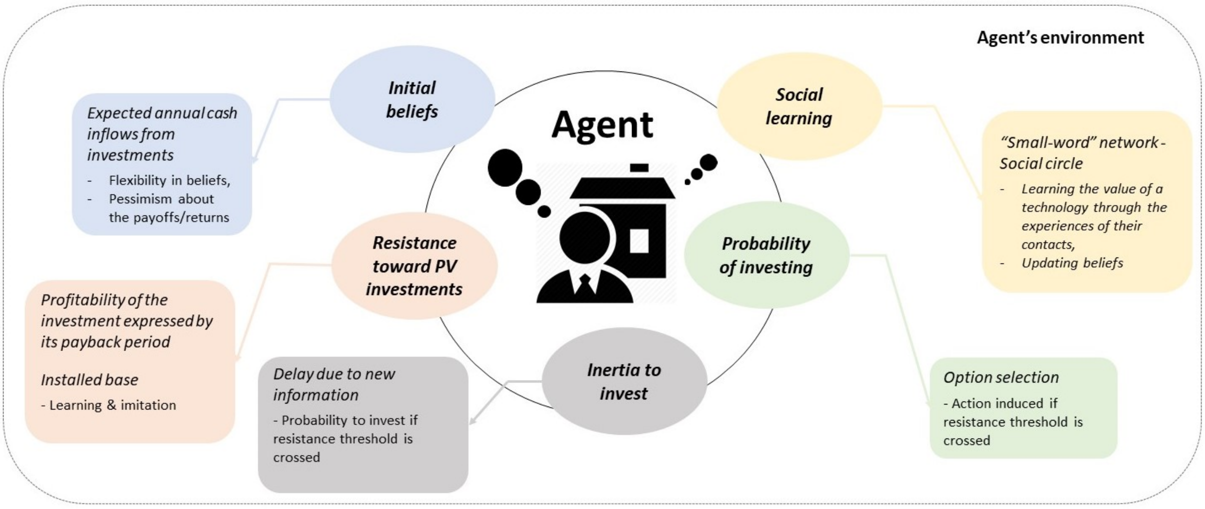


Figure 3.2. Set of agent-related parameters used for the application under study.

Initial beliefs

Each agent has an initial private belief about the expected annual cash inflows from investing in a PV system of 300 Wpeak. This belief is expressed as a Gaussian distribution with a mean value μ^{CF} and precision ρ^{CF}. Low values of ρ^{CF} reflect flexibility in beliefs (i.e., little evidence is sufficient to shift the agent's beliefs) and low values of μ^{CF} reflect pessimism about the payoffs of the investment. As a result, high values of μ^{CF} and low values of ρ^{CF} denote willing to invest agents, while low values of μ^{CF} and high values of ρ^{CF} denote risk-averse agents. The initial beliefs of each agent are randomly drawn from two global probability distributions, one for the mean value μ^{CF} and the other for the precision ρ^{CF}, while the value ranges of the parameters of both distributions need to be set through calibration.

Social learning

Young (2009) provides the following definition of social learning: "*People adopt [the innovation] once they see enough empirical evidence to convince them that [the innovation] is worth adopting, where the evidence is generated by the outcomes among prior adopters. Individuals may adopt at different times, due to differences in their prior beliefs, amount of information gathered, and idiosyncratic costs*" [48]. To capture the effects of social learning, each agent receives information from the agents in its social circle that have already invested in PV. This information concerns the actual profitability of their investments so far and is used to update the agent's beliefs. This is equivalent to updating a Gaussian prior, given a new observation. Accordingly, each agent has a social circle. This condition is modelled as a "small-world" network, which is a type of mathematical graph. The number of the connections per node is kept low; this is due to the fact that, despite people relating to a lot of other people (e.g., through social media, etc.), investment decisions tend to be influenced by a smaller circle. Stephenson and Carswell (2012) note that, while each household has distinct circumstances that may lead to such a decision, a common driver is knowing about the experience a house that had a similar change and, thus, having a point of comparison and/ or having the encouragement of family or friends [49].

Resistance toward PV investment

Agents are characterised by their resistance toward investing in solar PV. Resistance is defined as a weighted sum of two parameters:

a. The profitability of the investment expressed in terms of its payback period; thus, the larger the profitability the shorter the payback period, the lower the resistance. We assume that agents are able to use their beliefs regarding the expected cash inflows to estimate the profitability of investing. Given the fact that the agents' beliefs are expressed probabilistically, we can calculate the following z_i values, where $i = 1,2,\cdots,n$, represents the years after the simulation:

$$z_i = \frac{\mu^{CF} \cdot \sum_t^i \left(\frac{1}{(1+d)^t}\right) - capex}{\frac{i}{\rho^{CF}}} \cdot N(0,1),$$

where capex is the capital expenditure and d is the discount rate. z_i gives us the probability that the (discounted) payback period of the investment is equal to i. Assuming that all agents evaluate an investment based on when it will have paid itself back with probability 90%, this formula gives us the respective payback period i.

b. The difference between the total number of agents in the simulation and the number of those who have already invested in PV. The smaller the difference, the larger the installed base; and the larger the installed base, the smaller is the resistance. Baranzini et al., (2017) provide evidence that both learning and imitation are important components of the social contagion required for the adoption of solar PV. By making attitude toward PV a function of the installed base, we aim to capture the imitation (i.e., social influence) aspect [50].

The weights of this sum are derived from a global probability distribution; its parameters are regarded as agent-related parameters and their value ranges of whom need to be set through calibration.

Probability of investing

Agents have a threshold value for their resistance parameter. When the latter dips under the threshold value, action could be induced, but not necessarily so. For the calibration phase, we assumed that when agents decide to invest in a PV system, its size is given by the empirical probability distribution that was derived from the available historical data/ observations, as presented in **Figure 3.3**.

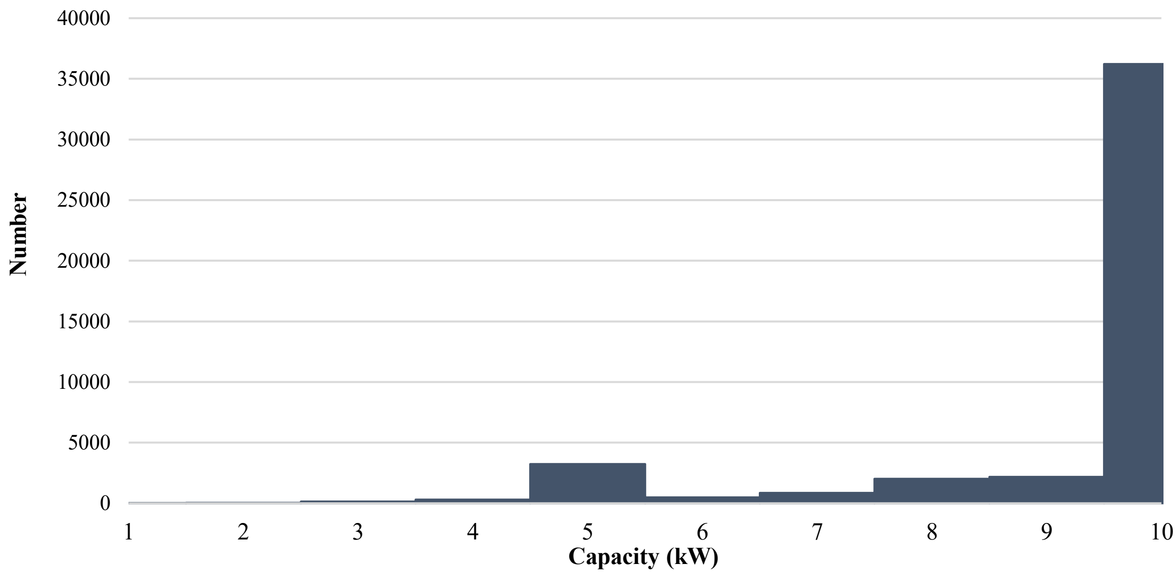


Figure 3.3. Size distribution of grid connection requests for small-scale PV systems during the period 2009-2013 in Greece, when the feed-in-tariff scheme was operational.

Note that the model used for the forward-looking simulations differs from the one used for calibration in the following ways:

- Available options: When the agents decide to invest in solar PV, they can choose one from a limited set of options, all of which are available to all the agents. These options concern the size of the PV system installed, i.e., 2.4 kWpeak, 4.8 kWpeak, and 9.6 kWpeak.
- The option selection rule: If more than one option is favourably evaluated by an agent, the selection is based on the SoftMax rule (i.e., normalised exponential function), and the probability of investing in option j is related to the agent's resistance to it, r_j, as $P(j) = \frac{e^{-r_j}}{\sum_k e^{-r_k}}$.

Inertia to invest

Young (2009) notes that inertia is the simplest reason why innovations take time to diffuse, as people delay acting on new information [48]. Accordingly, inertia has been included in the model by defining a global parameter (i.e., same value for all agents in the model) that represents the probability of any agent actually investing, if its resistance threshold is crossed. However, inertia is kept constant during calibration. The reason is that the inertia parameter controls the scale of the model. Changing its value, without changing the total number of the simulated agents, affects, at the end of the simulated period, the ratio of the number of adopters to the number of all simulated agents; this introduces non-identifiability into the model.

The initial value ranges of the agent-related parameters were set arbitrarily, as presented in **Table 3.1**.

Table 3.1. Initial value ranges and description of the agent-related parameters used for the application under study.

a/a	Parameter	Description	Initial Ranges	
			Min	Max
1.	Initial beliefs	The shape parameter of the global distribution that assigns μ^{CF} to each agent in the model.	100	250
2.		The shape parameter of the global distribution that assigns ρ^{CF} to each agent in the model.	10	50
3.	Social learning	The scale parameter of the global distribution that assigns μ^{CF} to each agent in the model.	10	50
4.		The scale parameter of the global distribution that assigns ρ^{CF} to each agent in the model.	5	20
5.	Resistance toward PV investments	The shape parameter of the global distribution that assigns the weight of the profitability to each agent's resistance.	0.5	5
6.		The scale parameter of the global distribution that assigns the weight of the profitability to each agent's resistance.	0.1	1
7.		The shape parameter of the global distribution that assigns the weight of the installed base to each agent's resistance.	0.5	5
8.		The scale parameter of the global distribution that assigns the weight of the installed base to each agent's resistance.	0.1	1
9.	Probability of investing	The shape parameter of the global distribution that assigns each agent's threshold value for their resistance parameter.	10	30
10.		The scale parameter of the global distribution that assigns each agent's threshold value for their resistance parameter.	5	10
11.	Inertia to invest	The inertia parameter was kept constant during calibration.	0.01	

3.3.2. Calibration based on historical data/ observations

ATOM was calibrated using the historical data/ observations for the small-scale PV capacity addition that took place during 2009-2013, which was the period of the largest PV addition in Greece. Calibration data corresponds to past market conditions (i.e., prices for small-scale PV systems and tariffs) and requests for grid connections. Since the available data for capacity addition was aggregated into records of MW per month, we have used data for the requests for grid connections; the records for these requests are available upon individual requests made to the Greek Regulatory Authority for Energy (RAE). The dataset is presented in **Figure 3.4**. As is evident by the plot, the demand for new PV investments in Greece fell in 2013 because of the drastic reduction in tariffs and the imposition of a retroactive levy.

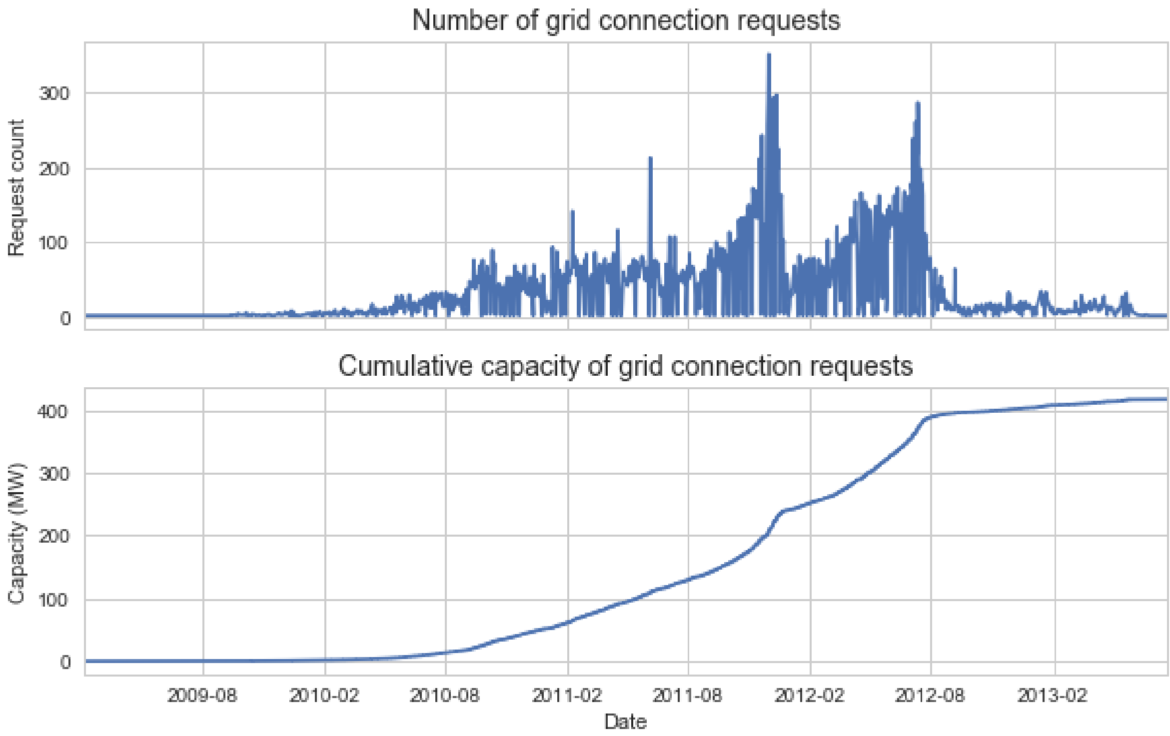


Figure 3.4. Aggregated capacity of grid connection requests for small-scale PV systems and capacity achieved in Greece during the period 2009-2013, when the feed-in-tariff scheme was operational.

Since the scale of PV capacities achieved by the model cannot be compared with the scale of the actual PV capacities achieved in the Greek power market (owing to the small number of the simulated agents, compared to the potential adopters in Greece), corresponding PV capacity pathways were scaled to the [0,1] range. This allowed the comparison of the simulated pathways with the scaled pathways of the actual PV investments during the calibration period. Calibration was conducted assuming that the model represents reality well if it can replicate the historical growth rates of PV installations. In other words, calibration looked for similar shapes of the cumulative PV capacity curve, while the scale was inevitably different. At the same time, calibration only based on the shape of the simulated pathways creates a problem of non-identifiability, and, thus, we needed a final target to use as a point of reference. To this end, the median of the capacities achieved at the end of the simulated period was mapped to the value of 1 during the scaling, and input data was normalised. Model results were split into four periods: **1.** mid-2010; **2.** end-2010; **3.** end-2011; and **4.** end of the simulation period. Four GP emulators were fitted to the respective results; the hyperparameters of each estimator were obtained by using maximum likelihood estimation (MLE).

3.3.3. Sensitivity analysis

GSA reveals that the parameters responsible for the greatest portion of the model's output variance are (**Figure 3.5**): **(1)** The shape parameter of the global distribution that assigns each agent's threshold value for their resistance parameter, **(2)** The shape parameter of the global distribution that assigns the weight of the profitability to each agent's resistance, and **(3)** The shape parameter of the global distribution that assigns μ^{CF} to each agent in the model. Final value ranges of the agent-related parameters are presented in **Table 3.2**.

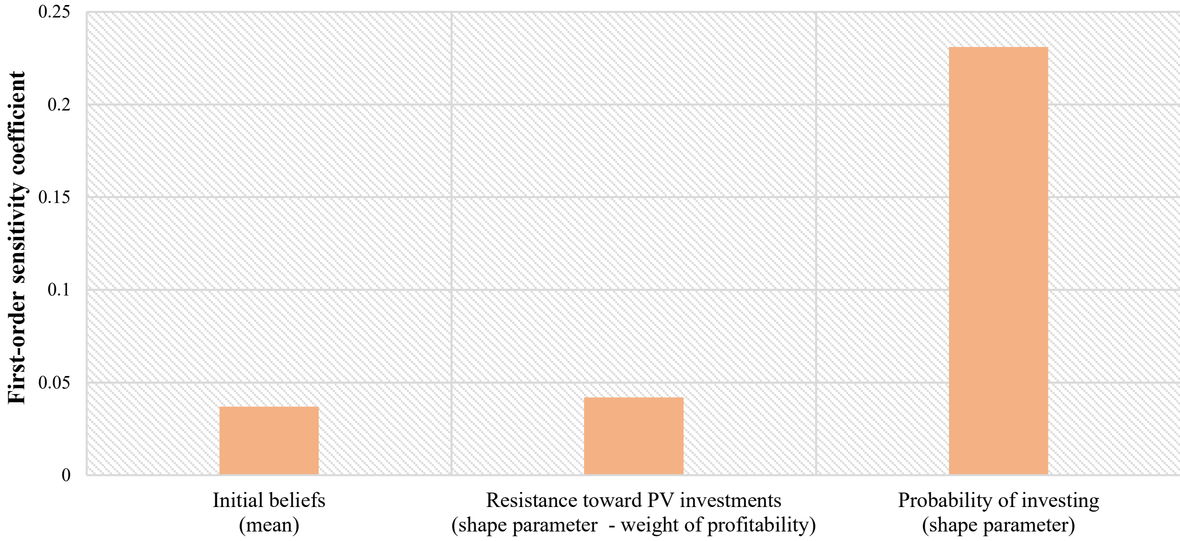


Figure 3.5. Sensitivity analysis results: Agent-related parameters with a value of first order sensitivity coefficient greater than the threshold value of 0.02. The threshold value has derived similarly to the study presented by Papadelis and Flamos (2018) [39].

Table 3.2. Final value ranges and description of the agent-related parameters used for the application under study.

a/a	Parameter	Description	Final Ranges	
			Min	**Max**
1.	Initial beliefs	The shape parameter of the global distribution that assigns μ^{CF} to each agent in the model.	181	192
2.		The shape parameter of the global distribution that assigns ρ^{CF} to each agent in the model.	15	45
3.	Social learning	The scale parameter of the global distribution that assigns μ^{CF} to each agent in the model.	10	48
4.		The scale parameter of the global distribution that assigns ρ^{CF} to each agent in the model.	5.8	20
5.	Resistance toward PV investments	The shape parameter of the global distribution that assigns the weight of the profitability to each agent's resistance.	1.9	3
6.		The scale parameter of the global distribution that assigns the weight of the profitability to each agent's resistance.	0.1	1
7.		The shape parameter of the global distribution that assigns the weight of the installed base to each agent's resistance.	0.5	4.7
8.		The scale parameter of the global distribution that assigns the weight of the installed base to each agent's resistance.	0.1	0.94
9.	Probability of investing	The shape parameter of the global distribution that assigns each agent's threshold value for their resistance parameter.	11.6	19.6
10.		The scale parameter of the global distribution that assigns each agent's threshold value for their resistance parameter.	5	9.7
11.	Inertia to invest	The inertia parameter was kept constant during calibration.	0.01	

3.3.4. Scenario analysis

For the scenario analysis, we set the market-related parameters based on past and existing conditions. Additionally, the characteristics of the PV technology and the respective generation and consumption profiles are specified according to historical data/ observations. Regarding the policy context of our scenarios, recent studies have already assessed the profitability of PV adoption under different NEM or SC-ST support schemes, mainly by using technoeconomic models; a few studies have only explored these issues under an ABM spectrum. However, to the best of our knowledge, no study so far has explored the effectiveness of such schemes using an ABM in the case of Greece. To this end, we apply

ATOM to explore the plausible behaviour of the potential PV adopters in Greece under these two policy schemes of interest. Furthermore, the rationale for supporting electricity SC by subsidising residential storage is twofold: **i.** The benefits of NEM for consumers come from lower consumption charges because of netting, and lower transmission/ distribution charges because of less electricity absorbed from the grid. Increasing SC brings the same benefits, and **ii.** SC can help decreasing the frequency and magnitude of peak generation events that stress the distribution network.

On the other hand, electricity prices affect the financial rationale of using NEM, or SC-based PV applications, because of their variation over the life cycle of PV systems. Although NEM and SC support schemes are becoming increasingly attractive to homeowners of all income groups, return on investment remains highly dependent on the unpredictability of electricity retail charges, increasing, thereby, uncertainty for rate payers [29]. To address this topic, we supplement our scenario analysis by exploring PV adoption assuming a progressive increase in the Greek retail price, as suggested by recent historical data/ observations. Finally, many studies acknowledge that consumers have an interest in increasing their energy savings and reducing their bills, and, thus, preferences for SC-ST over NEM schemes are expected to be widely incentivised in the future. Results from technoeconomic studies show that PV SC is already an attractive option, but electricity storage is not a profitable solution, as, for the time being, batteries are still expensive, and, despite technology progress, their lifetime remains short. Only a sustained decrease in their costs would lead to economically viable storage projects [28,51]. Nykvist and Nilsson (2015) mention that the cost of lithium-ion battery packs witnessed an 8% annual decrease between 2007 and 2014 [52]. As a result, to explore how a further decrease in storage costs affects the effectiveness of a potential SC-ST scheme in driving investments in small-scale PV in Greece, we use ATOM assuming six different plausible scenarios of annual decrease in storage investment costs.

Market-related parameters

Costs of small-scale PV systems, installed on roofs and buildings, were taken according to the trend suggested by the historical prices presented in **Table B.1** in **Appendix B**. In addition, we assume that consumers pay the most common residential tariff (i.e., "G_1" tariff) of the Public Power Corporation S.A. The price charged varies according to the total amount of electricity consumed during the netting period [53]. The different charges under the "G_1" tariff are summarised in **Table B.2** in **Appendix B**.

Solar PV generation modelling

We assume that all simulated agents will choose the same reference technology for their solar panels. The characteristics of the reference technology and installation are: **(i.)** Capacity: 300 Wpeak, **(ii.)** PV for utility system applications Test Condition (PTC) rating: 280.5 Wpeak, **(iii.)** Surface azimuth: South, and **(iv.)** Surface tilt: 30°. For the PV panel assumed, the same annual power generation profile was used for all the simulated years. For the calculation of this profile, a site-specific solar radiation dataset was retrieved from the Copernicus Atmosphere Monitoring Service (CAMS) radiation service. The dataset corresponds to 2016 hourly radiation at the location (38°, 23.8°). The total solar irradiance incident on the reference module is visualised in **Figure B.1** in **Appendix B**. The PV panel power generation was calculated using the Sandia PV Array Performance Model (SAPM). SAPM uses the PV panel's cell temperature to calculate its current-voltage curve, which is affected by the incident irradiance and weather conditions such as air temperature and wind speed. Data for the ambient air temperature and the wind speed at the location of interest was retrieved from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) web service. Finally, to calculate the Direct Current (DC) to Alternate Current (AC) conversion losses, we assumed a reference inverter with weighted efficiency of 96%.

Electricity load modelling

Along with the PV generation, electricity demand profiles are also necessary to model the energy inflows at the residential level. To do so, we used historical data and assumptions for the case of a typical Greek residential building. More specifically, it was assumed that all agents consume 3,750 kWh per year, which is the mean annual consumption of electrical power per household in Greece [54]. This consumption amount was used to scale down the data on the hourly total electricity demand in Greece for the year 2016; this helped to derive a daily profile for an "average" consumer. This daily profile was split into three seasonal profiles [55], to account for the effects of weather and temperature on electricity demand (**Figure 3.6)**.

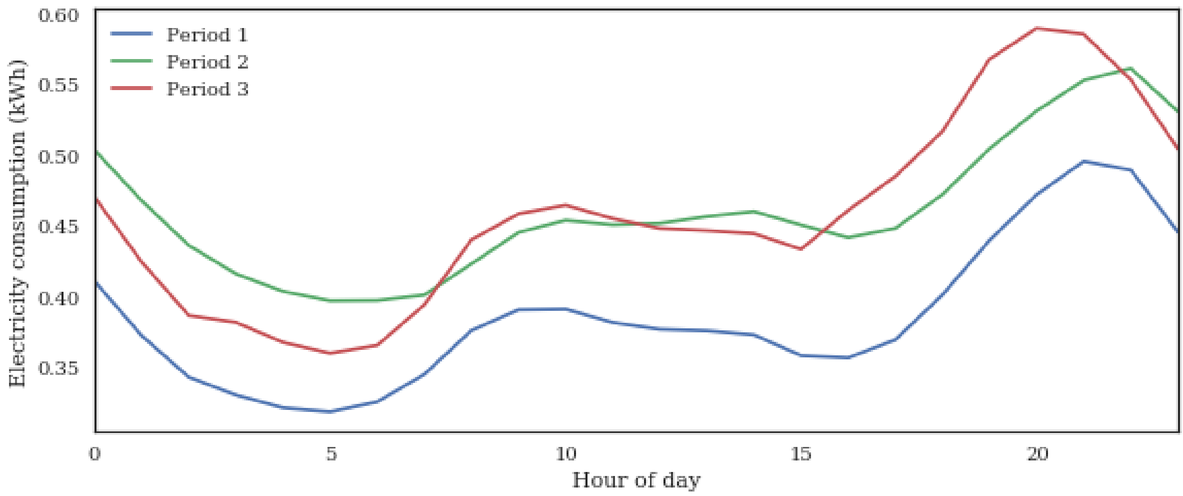


Figure 3.6. Mean daily electricity demand profiles assumed for the "average" household in Greece. The daily profile is split into three seasonal profiles, to account for the effects of weather and temperature on electricity demand: **Period 1 (mild weather):** April, May, October, and November; **Period 2 (hot weather):** June to September; and **Period 3 (cold weather):** December to March.

Policy scenarios

The NEM support scheme currently operational

The main provisions of the current NEM scheme in Greece, which are relevant to our study, are [53]:

- The amount charged under the competitive electricity consumption tariffs is the difference between the electricity inflow and outflow (i.e., net energy), if this difference is positive.
- The netting is done every four months, which is the billing period for residential tariffs. The excess electricity is transferred to the next billing period in the form of renewable energy credits (RECs). The transfer continues in all subsequent billing periods until the end of the year. After the end of the year, there is no compensation for any electricity surplus.
- The consumer is charged for the total amount of electricity consumed (i.e., both electricity absorbed from the grid and the fraction of the electricity generated onsite that is self-consumed) and for the "other utility services."
- The transmission and distribution charges are based only on the amount of the electricity absorbed from the grid.
- Consumers pay the special duty for reduction of gas emissions (ETMEAR) only on the electricity absorbed from the grid.

The expected benefits from investing P_{resid}^{total} (€), at the end of each netting period are calculated according to the following formula. Note that the first term increases with an increase in PV generation, only up to matching the total energy consumption of the agents, while the second term increases with an increase in SC, or by better matching demand with available PV generation.

$$P_{resid}^{total} = C_{grid} \cdot \min(E_{PV}, E_{resid}) + C_{PV} \cdot E_{resid_{PV}},$$

where:

- C_{grid}: Charges for the total amount of electricity consumed $\left(\frac{€}{kWh}\right)$;
- C_{PV}: Charges for the total amount of electricity absorbed from the PV panel $\left(\frac{€}{kWh}\right)$;
- E_{PV}: The total amount of electricity generated by the PV panel (kWh);
- E_{resid}: The total residential demand for electricity (kWh); and
- $E_{resid_{PV}}$: The total amount of electricity consumed from the PV panel (kWh).

A proposed SC-ST support scheme

Typically, the shorter the netting period is (i.e., daily or hourly), the closer a NEM scheme is to pure SC [1]; so, in this case, there is no reason to continue offering the NEM option because it is actually a form of storage service [56]. As a result, we assumed a support policy that does not remunerate excess generation, but subsidises the 25% of the initial storage investment cost according to the following formula [57]:

$$s_B = CAP_{PV} \cdot \min\left\{\frac{0.25 \cdot C_{0,B}}{CAP_{PV}}, 500\right\},$$

where:

- s_B is the subsidy payment (€);
- CAP_{PV} is the peak power capacity of the solar PV system (kW); and
- $C_{0,B}$ is the initial battery investment cost $\left(\frac{€}{kWh}\right)$.

Note that such a subsidy programme, which supports residential storage, has been recently prolonged in Germany by promising a payment depending on the size of the PV module and the initial investment cost of the storage [57]. Following Waffenschmidt (2014), we assumed a sizing of 1-to-1 for storage capacity to PV peak power [58]. For the storage system, according to the study presented in [57], we assumed an initial investment cost ($C_{0,B}$) of 800 €/kWh, and an expected lifetime of 3,000 equivalent full cycles. For the storage dispatch model, we used the SC optimisation algorithm presented in [59], with the storage capacity being dispatched in an optimum way to maximise SC. The benefits P_{resid}^{total} (€) from investing in the proposed SC-ST scheme are calculated according to the following formula:

$$P_{resid}^{total} = C_{grid} \cdot (E_{resid} - E_{grid}) + C_{PV} \cdot E_{resid_{PV}},$$

where:

- C_{grid}: Charges for the total amount of electricity consumed $\left(\frac{€}{kWh}\right)$;
- C_{PV}: Charges for the total amount of electricity absorbed from the PV panel $\left(\frac{€}{kWh}\right)$;
- E_{resid}: The total residential demand for electricity (kWh);
- E_{grid}: The total amount of electricity absorbed from the grid (kWh); and
- $E_{resid_{PV}}$: The total amount of electricity consumed from the PV panel (kWh).

Impact of the retail price of electricity on small-scale PV adoption

The current NEM scheme in Greece seems to favour prosumers at the expense of regular customers, since, by allowing a yearly netting period, the prosumer can offset the PV energy produced with that consumed at different times, thereby, abolishing the role of the grid- an asset for whose services, maintenance, and development all consumers pay [53]. This may lead to an increase in the retail price of electricity to counterbalance the revenue losses of the grid operator. Additionally, Nikas et al., (2018) indicated that a SC-ST support scheme, similar to the one presented in this chapter, could force Greek generators to bid higher prices for their capacity, leading to an increase in the retail price of electricity [60]. To address the impact of the retail price of electricity on the effectiveness of the current NEM scheme and the proposed SC-ST scheme, we assume that retail charges will evolve as they did during the past seven years. **Figure 3.7** below presents this evolution for household consumers in Greece, over the period 2010-2017. By observing data, a total increase of 60% for our forward-looking simulations seems to be a logical assumption.

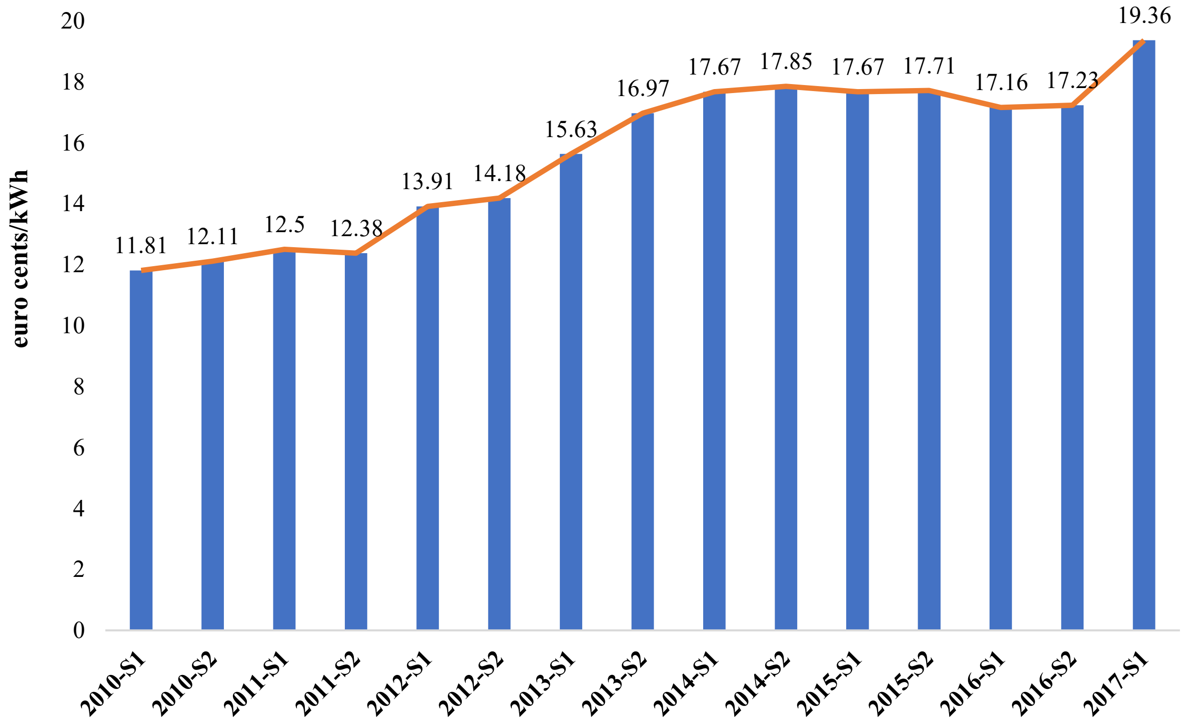


Figure 3.7. Evolution of the electricity price for household consumers in Greece from 2010 to 2017 (semi-annual data as acquired from [61]).

Impact of storage investment costs on small-scale PV adoption

We explore the impact of storage costs on the effectiveness of the SC-ST support scheme under study in driving investments in small-scale PV in Greece. To do so, we come up with six plausible scenarios of annual rate of decrease in investment costs. The scenarios under study are presented in **Table 3.3**. For each scenario, we run ATOM for the case that the retail price of electricity remains unaffected, as well as that it increases according to the trend suggested by historical data/ observations. As our intention is to quantify the impact of the expected decrease in storage costs on PV capacity addition, we compute the average value- from the different plausible sets of the agent-related parameters- of the PV capacity addition achieved.

Table 3.3. Six scenarios of annual decrease in storage investment costs based on the technology breakthroughs expected in the near future.

Scenarios	Annual rate of decrease (%)
SC1	5
SC2	6
SC3	7
SC4	8
SC5	9
SC6	10

3.3.5. Quantifying structural and parametric uncertainty

Because of the stochastic nature that typically characterises an ABM, we explore the expected effectiveness of the policy schemes, and the different cases under study, for the same values of the agent-related parameters. Our goal is to validate the model's potential to capture the uncertainty that is propagated to outcomes owing to its structure and parameters, for each case under study. To do so, we generated a set of plausible values for the agent-related parameters, as presented in **Table B.3** (**Appendix B**). Note that the mean value of the agents' initial beliefs regarding the profitability of the new policy schemes (i.e., μ^{CF}) is different than the corresponding value under the FiT scheme; this is because it is assumed that under the new policy regime agents' perceptions are affected by experience and past failures. For these values of the agent-related parameters, we run ATOM 25 times for all the cases presented in **Table 3.4**. For the cases "*SC-ST-3*" and "*SC-ST-4*," the annual decrease rate of storage investment costs is assumed to be the mean value of the six scenarios presented in **Table 3.3**.

Table 3.4. Six cases of the same values of the agent-related parameters to test the model's ability to capture uncertainty that is propagated to modelling outcomes owing to its structure and parameters.

a/a	Name	Description
1.	**"NEM-1"**	New PV capacity addition expected from the current NEM scheme, assuming no change in the retail price of electricity
2.	**"NEM-2"**	New PV capacity addition expected from the current NEM scheme, assuming a total increase of 60% in the retail price of electricity
3.	**"SC-ST-1"**	New PV capacity addition expected from the proposed SC-ST scheme, assuming no change in the retail price of electricity
4.	**"SC-ST-2"**	New PV capacity addition expected from the proposed SC-ST scheme, assuming a total increase of 60% in the retail price of electricity
5.	**"SC-ST-3"**	New PV capacity addition expected from the proposed SC-ST scheme, assuming an annual decrease of 7.5% in storage costs and no change in the retail price of electricity
6.	**"SC-ST-4"**	New PV capacity addition expected from the proposed SC-ST scheme, assuming an annual decrease of 7.5% in storage costs, and a total increase of 60% in the retail price of electricity

3.4. Results

All simulations were performed for 25 different sets of plausible values of the agent-related parameters, according to calibration results, to represent 25 different, but realistic behavioural profiles, from willing to invest, to risk-averse consumers. This way, we are able to capture behavioural and parametric uncertainty related to small-scale PV adoption. The projections for the new PV capacity addition during 2018-2025 were scaled up to the national level by using historical data and observations from the period that the FiT scheme was operational in Greece. Note that the blue dashed line in the figures below corresponds to the PV capacity addition that the FiT scheme achieved during the period 2009-2013.

3.4.1. Expected effectiveness of the NEM scheme in driving investments in small-scale PV in Greece

Not many studies in the scientific literature evaluate the effectiveness of the current NEM scheme in Greece. Those that do so, apply technoeconomic models to assess its profitability, but they do not make projections about the expected PV capacity addition [1,29,46,47,53]. To the best of our knowledge, this is the first time that a scientific study explores the expected effectiveness of the NEM scheme currently operational in terms of new PV capacity addition in Greece by using an ABM. As indicated in **Figure 3.8**, ATOM shows that the expected PV capacity addition from the current NEM scheme during 2018-2025 is positive, with the average expected capacity addition estimated at around 300 MW. However, it is evident that the scheme is not as efficient as the previous FiT scheme, with the most optimistic scenario (i.e., consumers willing to invest) showing that it will take at least seven years to achieve the same PV capacity addition that the FiT scheme achieved during the period 2009-2013. Additionally, results show a total range of aleatoric uncertainty of almost 225 MW, which, according to GSA results, implies that the scheme's effectiveness is closely related to the most uncertain agent-related parameter, namely the probability of investing. Total uncertainty is also influenced by consumers' resistance towards investing, which is shaped by consumers' beliefs about the profitability of the investment.

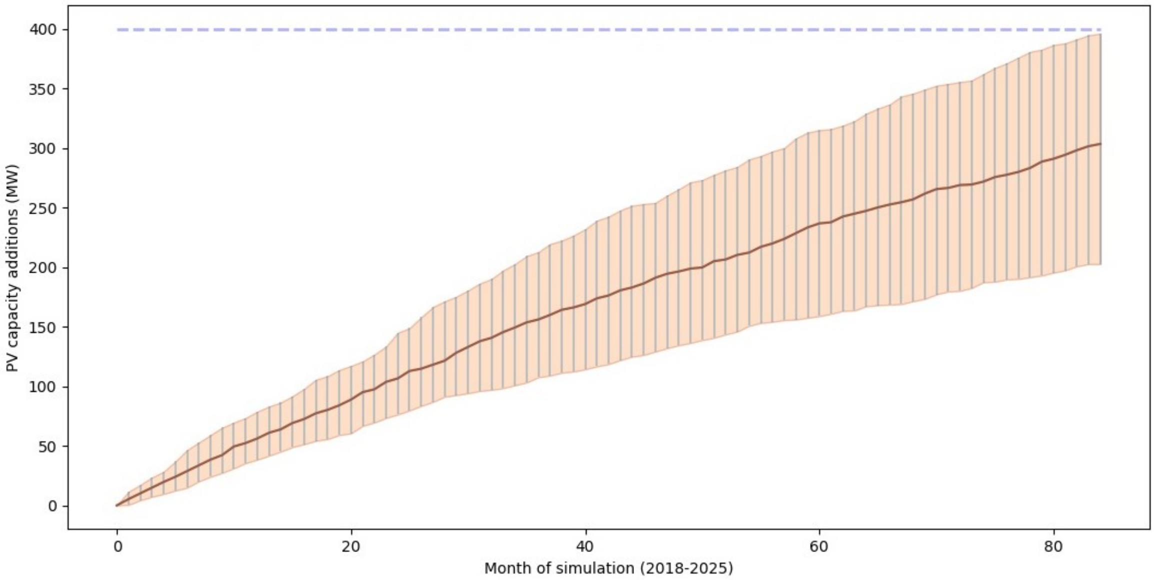


Figure 3.8. Simulation results on the PV capacity addition expected from the net-metering scheme currently operational in Greece over 2018-2025, assuming no change in the retail price of electricity. The brown curve represents the average expected adoption, while upper and lower bounds represent adoption trends for willing to invest (i.e., optimistic scenarios) and risk-averse consumers (i.e., pessimistic scenarios) respectively. The blue dashed line represents the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

3.4.2. Expected effectiveness of a proposed SC-ST scheme in driving investments in small-scale PV in Greece

There are no scientific studies evaluating the expected effectiveness of a proposed SC-ST scheme in Greece. To the best of our knowledge, this is the first time that a study addresses this topic. As indicated by **Figure 3.9**, supporting residential electricity storage seems less effective than the NEM scheme, with the average expected PV capacity addition estimated at around 200 MW. Compared to the previous FiT scheme, a storage subsidy of 25% is clearly less efficient, with the most optimistic scenario suggesting that it will take more than seven years to achieve the same PV capacity addition that the FiT scheme achieved. However, results show that aleatoric uncertainty, induced by the most uncertain agent-related parameters (i.e., probability of investing and resistance towards investing) is less compared to results for the NEM scheme. This means that probability of investing introduces less uncertainty to the total uncertainty of model outputs, and that consumers' resistance towards investing is shaped by clearer beliefs. Nevertheless, it is evident that the 25% subsidy is not sufficient to shift the consumers' beliefs about the profitability of the investment, and, thus, their resistance remains high.

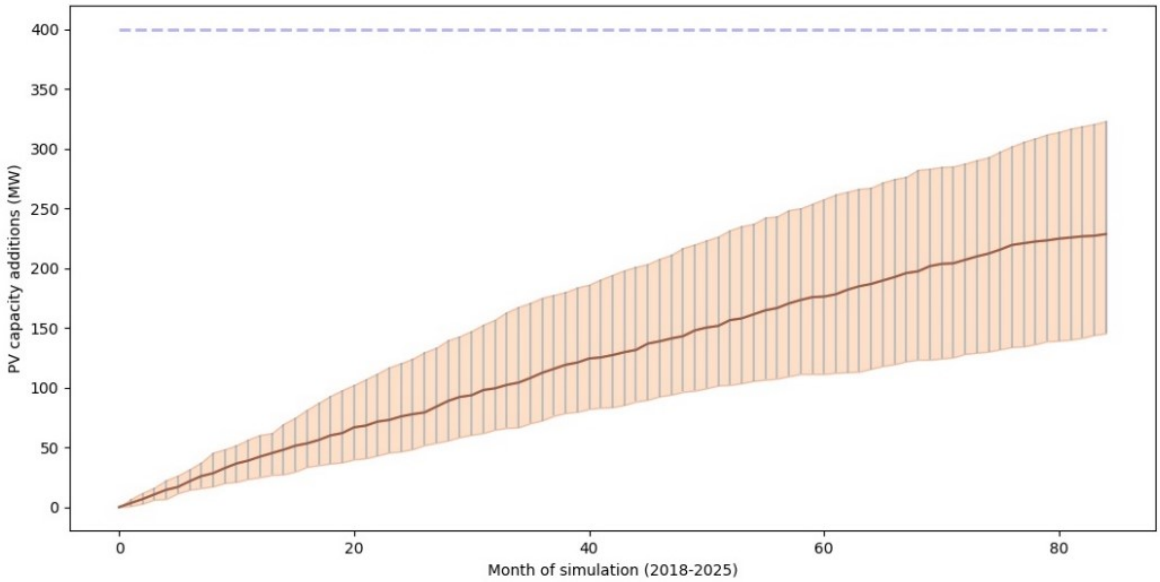


Figure 3.9. Simulation results on the PV capacity addition expected from a proposed self-consumption support scheme that subsidises residential storage (25% subsidy) in Greece over 2018-2025, assuming no change in the retail price of electricity. The brown curve represents the average expected adoption, while upper and lower bounds represent adoption trends for willing to invest (i.e., optimistic scenarios) and risk-averse consumers (i.e., pessimistic scenarios) respectively. The blue dashed line represents the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

3.4.3. Impact of an increase in retail charges on the effectiveness of the policy schemes under study in Greece

Assuming that the retail price of electricity in Greece will increase, our results indicate that the current NEM scheme can reach the target of additional 400 MW of PV capacity with more plausible combinations of the agent-related parameters (**Figure 3.10**). However, compared to the case wherein the retail price remains unchanged, the average improvement is not significant (i.e., 25MW), and it is evident that the new NEM scheme still remains less effective than the previous FiT scheme.

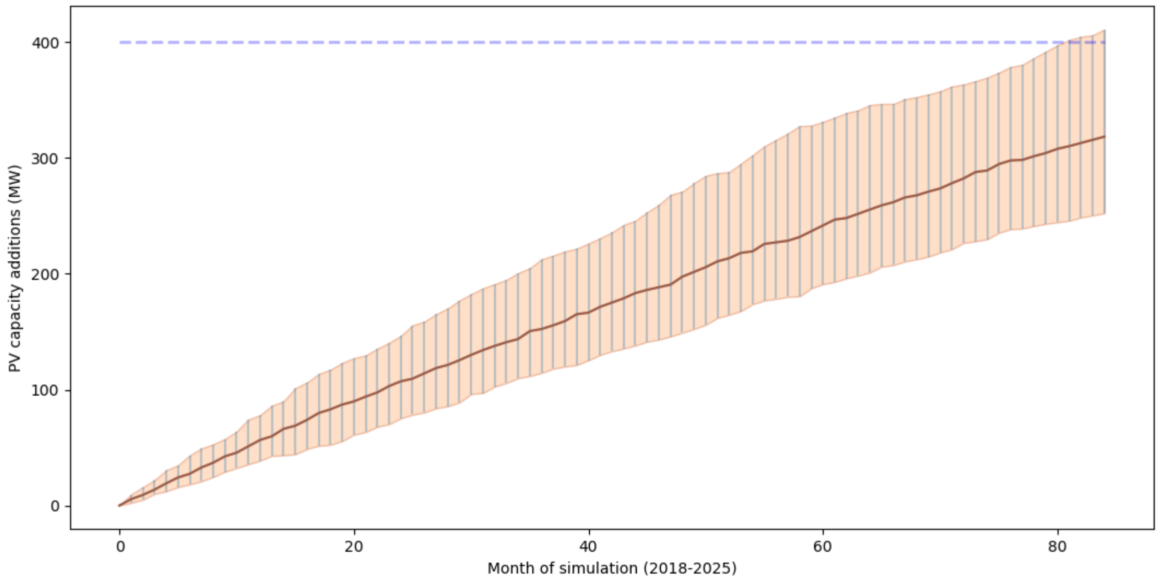


Figure 3.10. Simulation results on the PV capacity additions expected from the net-metering scheme currently operational in Greece over 2018-2025, if the retail price of electricity increases according to the trends of the past 7 years, as suggested by historical data/ observations. The brown curve represents the average expected adoption, while upper and lower bounds represent adoption trends for willing to invest (i.e., optimistic scenarios) and risk-averse consumers (i.e., pessimistic scenarios) respectively. The blue dashed line represents the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

An interesting finding, though, is that increasing the retail price of electricity makes the current NEM scheme more robust in terms of its effectiveness, by reducing behavioural uncertainty related to the agents' decision-making process. This was expected since an increase in the retail price could result in greater benefits for consumers who decide to become prosumers. Even the risk-averse consumers obtain a clearer and positive perception of the investment's profitability over the years. In contrast, increasing the retail price of electricity seems to have no significant effect on the effectiveness of the SC-ST support scheme. As visualised in **Figure 3.11**, the expected PV capacity addition and the uncertainty of the SC-ST support scheme remain almost at the same levels as those derived by assuming that the retail price remains unaffected. As the initial investment costs of storage are currently high, a subsidy of 25% is not enough to boost further investments, and even an increase in the retail price is not enough to shift consumers' beliefs and resistance.

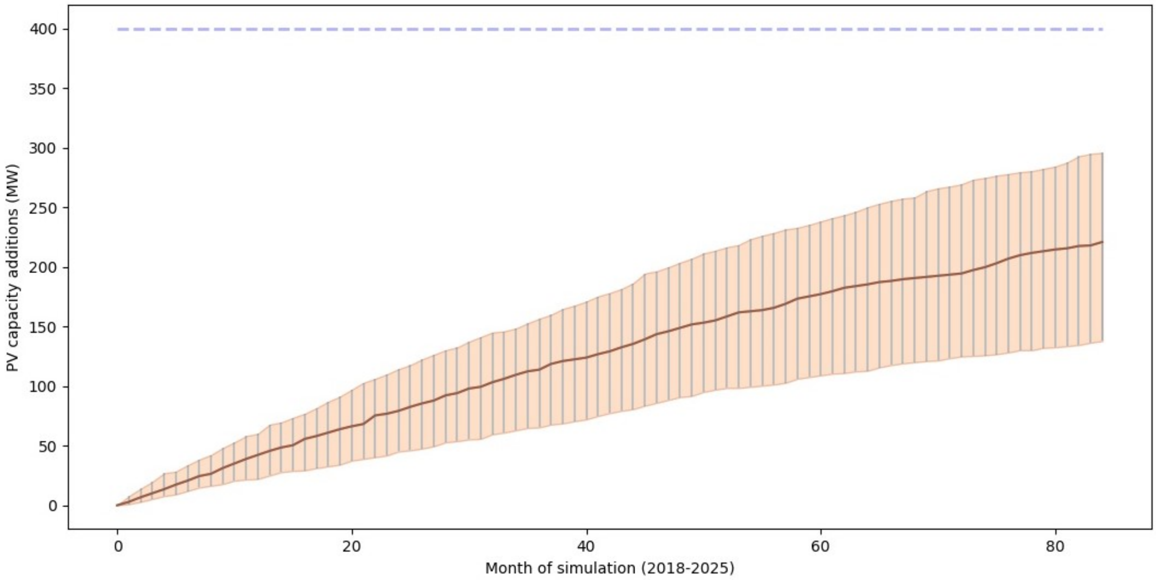


Figure 3.11. Simulation results on the PV capacity addition expected from a proposed SC-ST support scheme (25% subsidy) in Greece over 2018-2025, if the retail price of electricity increases according to the trends of the past 7 years, as suggested by historical data/ observations. The brown curve represents the average expected adoption, while upper and lower bounds represent adoption trends for willing to invest (i.e., optimistic scenarios) and risk-averse consumers (i.e., pessimistic scenarios) respectively. The blue dashed line represents the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

3.4.4. Impact of a decrease in storage costs on the effectiveness of the SC-ST support scheme under study in Greece

Our results show that an expected decrease in storage investment costs leads to greater PV capacity addition in Greece for the SC-ST scheme under study, irrespective of the retail price of electricity remaining fixed or increasing. As it becomes evident from both **Figure 3.12** and **Figure 3.13**, a steep decrease in battery costs (i.e., 8%, 9%, and 10% annual rates) can lead to significant improvements, with scenario "SC6" suggesting a 40% increase of the average expected PV capacity addition (i.e., more than 100 MW). This shows that the SC-ST support scheme under study could become slightly more effective than the current NEM scheme. On the other hand, lower annual rates of decrease in storage investment costs (i.e., 5%, 6%, and 7%) are not sufficient and lead to small increase in the expected PV capacity addition. Especially, for the case that the retail price of electricity increases, scenarios "SC1" and "SC2" show that the extra benefits from the decrease in costs are not sufficient to overcome the higher charges of electricity and, thus, the agents' perception about the profitability of the scheme remains unaffected (**Figure 3.9** and **Figure 3.11**). This is because they need to invest in storage of higher capacity and, therefore, of higher cost, to ensure a return on their expenditure.

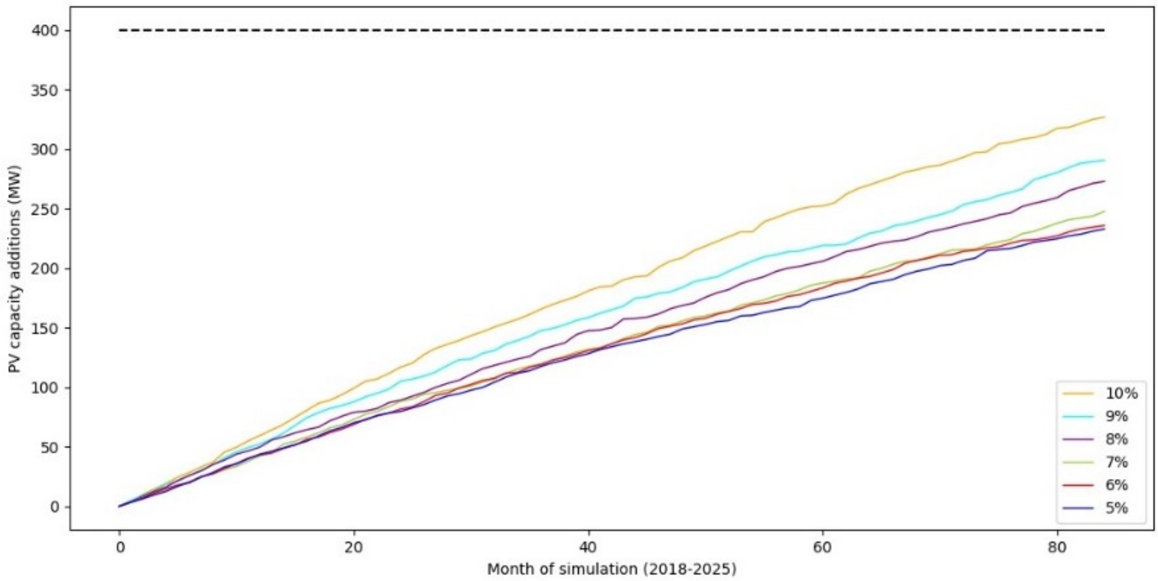


Figure 3.12. The impact of an expected decrease in storage investment costs on PV adoption in Greece over 2018-2025, if the retail price of electricity remains unchanged. The six curves correspond to six feasible scenarios of annual decrease in storage investment costs, while represent the expected adoption for the average consumer profile. The black dashed line represents the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

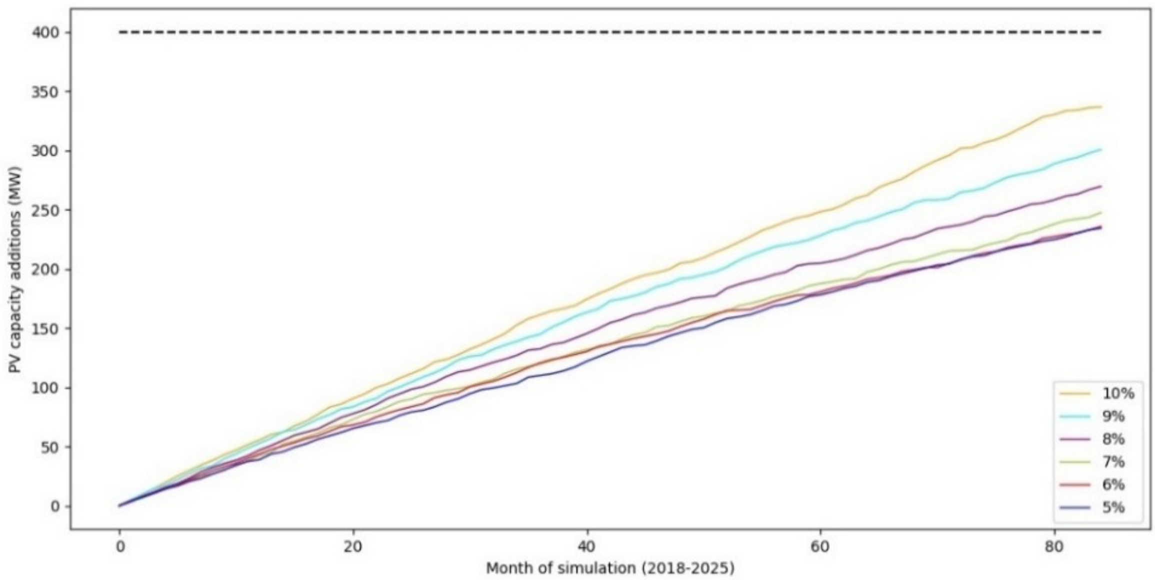


Figure 3.13. The impact of an expected decrease in storage investment costs on PV adoption in Greece over 2018-2025, if the retail price of electricity increases according to the trends of the past 7 years, as suggested by historical data/ observations. The six curves correspond to six feasible scenarios of annual decrease in storage investment costs, while represent the expected adoption for the average consumer profile. The black dashed line represents the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

3.4.5. Uncertainty propagation owing to the model's structure and parameters

Figure 3.14 demonstrates an indicative example of how structural and parametric uncertainty in ATOM can be quantified for each case under study. Our results show that for the NEM scheme, the model' structure introduces less uncertainty to its outcomes for the case that the retail price increases (i.e., "*NEM-2*"). For the cases "*SC-ST-1*" and "*SC-ST-2*", the model's structure seems to introduce almost the same amount of uncertainty to its outcomes. These findings validate the ability of ATOM to identify and characterise parametric uncertainties. In particular, the uncertainty that the electricity price parameter introduces to the expected PV capacity addition is characterised as epistemic, as by increasing the level of detail the total range of model uncertainty is reduced. Finally, an interesting finding is that the model's structure seems to add more uncertainty for the case "*SC-ST-4*" than the case "*SC-ST-3*", as it shows that increasing the level of detail for both the electricity price and the investment cost parameters, contributes more to the total uncertainty of the model's outputs. The latter implies that the effectiveness of the SC-ST scheme under study is more related to the investment cost parameter, rather the electricity price parameter.

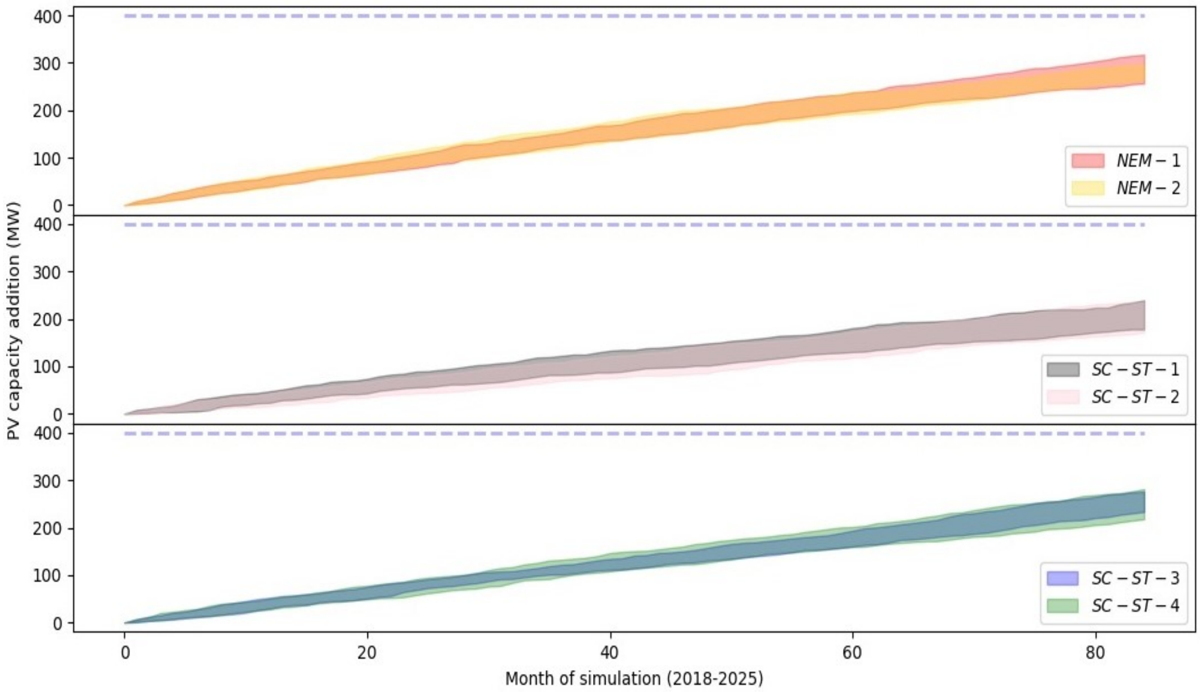


Figure 3.14. Uncertainty assessment of the performance of various policy schemes using the same values of the agent-related parameters to test the model's ability to capture uncertainty that is propagated to modelling outcomes owing to its structure and parameters. The dashed lines represent the total capacity addition that the feed-in-tariff scheme achieved during the period 2009-2013 in Greece.

3.5. Discussion

Although the application of modelling tools cannot result in a clear course of action as a "policy panacea," especially when simulating the future, ATOM can be of practical support to decision-makers, providing simplified answers to explorative "What-if" scenarios. Instead of using regression to extrapolate growth based on past trends, the model assesses the impact of different policy instruments through a more "real-world" process, addressing social and behavioural uncertainties that could characterise technology adoption in all spectrums of strategic energy planning. Considering the existing ambiguity in the PV market in Greece, for example, the appropriateness of ATOM as a valuable decision and support tool becomes evident, when modelling outcomes are translated to simplified policy-relevant answers that could support the further development of the PV sector. In particular, the national PV capacity targets for 2025 and 2030, as defined by the Ministry of Energy and Environment, are 5,500 MW and 6,900 MW respectively [62]. Assuming that the contribution of small-scale PV to the national capacity targets is about 14.5% (for about every 7 MW large-scale installation, 1 MW small-scale PV is installed), and based on historical data from the period 2016-2018 [63], the small-scale PV capacity target for 2025 can be defined as 417 MW. The latter is assumed considering that the revised national PV capacity target for 2020 is 3,300 MW and that the total PV capacity achieved until the end of 2017 was 2,624 MW [64]. The target trajectory for small-scale PV in Greece until 2030 is presented in **Figure 3.15**.

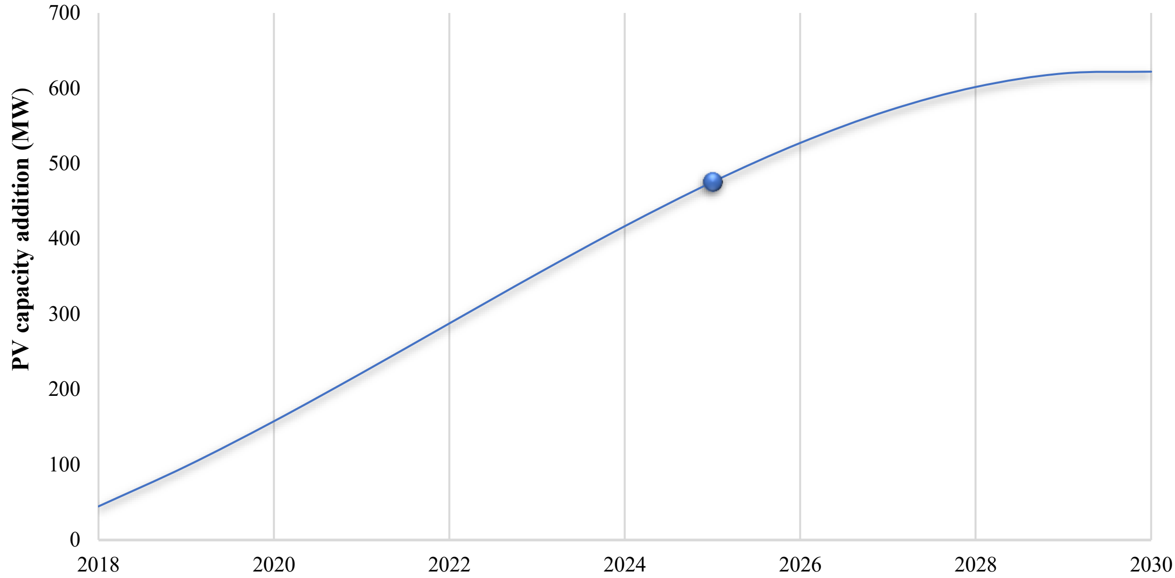


Figure 3.15. Trajectory of the small-scale PV capacity addition in Greece required for the achievement of the overall national PV capacity targets of 2030.

Our results, while acknowledging the determinant role of NEM provisions in the further growth of small-scale PV systems, show that the scheme, as currently implemented in Greece, is not capable of achieving the necessary capacity addition towards the national target of 2025. In particular, while the scheme could be successful until the end of 2021, it won't be able to reach the national target of 2025, even in the most optimistic of the modelling outcomes. This implies that policy contingency actions are required. Furthermore, by enabling variance decomposition and uncertainty characterisation our model show how uncertainties impact simulation results. This highlights the novelty of ATOM, which lies mainly in bridging the disciplines of uncertainty analysis and ABM policy assessment, by demonstrating how model uncertainty could influence effective policy design. For example, our results allowed us to identify the epistemic uncertainty that the electricity price parameter contributes to simulation outputs, indicating that the effectiveness of the NEM scheme in Greece is closely related to the retail price of electricity. In particular, simulation results indicated that an increase in the retail price, reduces total uncertainty in modelling outcomes, which is mainly introduced by modelling parameters, as the probability of investing, consumers' beliefs, and resistance towards investing. In policy terms, this is translated into a reduction of the behavioural uncertainty related to the effectiveness of the NEM scheme, especially for the case of risk-averse consumers, which implies that different sources of positive financial outcomes for consumers should be further investigated.

An increase in the retail price of electricity, therefore, while entailing an extra source of revenue that shifts consumers' beliefs and reducing their resistance towards investing, should be considered only in conjunction with appropriate policy provisions. Such provisions should focus on relieving vulnerable social groups and less fortunate-at risk of poverty- consumers from burdensome charges, as cross-subsidisation between prosumers and regular customers could distort the level-playing field and lead to an unfair competition. Efficient policymaking needs to explore more market-based NEM structures by introducing alternative pricing strategies. This will create stability, which will make the benefits of investing more explicit, providing extra motives for regular customers. Market-based structures applicable to the existing policy landscape in Greece, include exploring different netting policies (e.g., full netting with grid charges) and replacing transfer of surplus electricity in the form of RECs with the compensation of the excess electricity through realistic, market-based prices.

On the other hand, policies that promote SC have the potential to drive the uptake of storage technologies that could bring demand flexibility into the market and enable the integration of electricity from variable RES. Our results indicate that a proposed SC-ST scheme (25% subsidy), while being less effective than the current NEM scheme, creates less uncertainty in terms of its performance. Although the latter suggests that the success of a SC-ST scheme in Greece could be more robust, our results show that a subsidy of 25% is not enough to boost the further diffusion of small-scale PV towards the national targets of 2025. Additionally, it has been demonstrated that the effectiveness of a SC-ST in Greece is closely related to the investment cost parameter. This is another insight that would be missed in a standard ABM framework. Simulation outcomes indicate that significant technological breakthroughs are necessary for a 25% storage subsidy to become slightly more profitable than the current NEM scheme. In particular, our results suggest that investment costs should follow a steep learning curve of at least a 10% annual reduction until 2025. This implies that efficient policy measures promoting SC-ST should consider, along with ancillary benefits of SC (e.g., balancing the frequency and magnitude of peak generation events that stress the distribution network [65,66], etc.), high levels of subsidisation. Since the latter seems rather infeasible owing to implications of the existing economic recession in Greece, national policy planning should focus on new and sustainable business models that monetise the value of PV SC with storage. This will enable the design of regulatory frameworks that ensure clear incentives for consumers and new revenue collection practices for utilities.

3.6. Conclusions

In this chapter, we present ATOM, an agent-based model that has a strong component of consumer- and policy-contingent scenario elements that correlate technology adoption with its value to the consumers. To demonstrate its applicability, we used it to explore the evolution of the market share of small-scale PV (i.e., 1-10kWpeak) in Greece, under two different policy schemes of interest. Recent studies have already addressed the issue of PV adoption using an agent-based modelling framework in different geographic, socioeconomic, and policy contexts; this is because agent-based models, typically, provide a flexible framework to simulate the adoption decision-making process of the members of a heterogeneous social system. However, this flexibility comes with greater uncertainty, as modelling the decision-making process of agents often requires the inclusion of several criteria that introduce additional uncertainty to modelling results. To the best of our knowledge, existing models are deterministic and fail to capture uncertainties related to agency, with only the study presented by Pearce and Slade (2018) [21] quantifying the uncertainty introduced to their modelling outcomes. Uncertainty quantification is of paramount importance for modelling tools, especially when they are utilised for decision and support, and policymaking.

The originality and the novel contribution of our work is that ATOM, supported by a complete framework that consists of uncertainty and sensitivity analysis decision and support techniques, bridges the disciplines of uncertainty in agent-based modelling policy assessment, and can be a valuable tool in effective policy design. In particular, ATOM allows for obtaining realistic uncertainty bounds and splitting the total model output uncertainty in its major sources, based on a variance decomposition framework and an uncertainty characterisation method. Thus, by identifying and characterising the different types of uncertainty, the contribution of the main sources of uncertainty to the total uncertainty in modelling outcomes can be calculated. Additionally, by specifying the values of the agent-related parameters under consideration according to the plausibility of modelling outcomes, based on historical data/ observations, the model allows for handling behavioural uncertainty of the agents, by including the range of the different plausible behavioural scenarios in the variance of the results that they produce. However, incorporating uncertainty in existing energy models typically leads to heavy computational burdens, which limit the number of uncertain parameters that can be considered. Although uncertainty analysis is typically problem-specific, our work could be a valuable contribution to further modelling efforts. In particular, another novelty of our approach lies in using the concept of emulators, as significantly faster approximations of the actual model, allowing the employment of Monte Carlo sampling methods that would be otherwise prohibitively expensive in terms of computational resources.

As future research, ATOM will be applied to explore scenarios of PV adoption in different geographic and socioeconomic contexts around Europe, expanding its initial modelling framework to explore the effect of more agent-related parameters in PV adoption. Scientific literature, for example, reports that the attitude of Greek consumers toward installing small-scale PV systems varies according to their income and education level, and also seems to be correlated with their consumption profiles and demographic characteristics [53,67]. In addition, ATOM will be further developed to derive adoption scenarios for other technologies, such as electricity storage or smart-grid devices that increase demand flexibility. Finally, studies in the scientific literature suggest that policy measures must adapt to uncertain and continuously changing conditions [68,69]. Thus, a policy design process that utilises agent-based modelling should be structured around the concept of adaptability [70]. This means that, as new data on the actual decisions of the relevant actors is accumulated, the initial policy design should adapt in the same way as it adapts to changes in its environment. As a result, the authors intend to link ATOM with a modelling toolbox for adaptive policy pathways; thus, support policy measures for further technology adoption can adapt to uncertainties- generated by their assumptions and their environment- that may hinder their performance. This task could also build on the strengths of a stakeholder engagement strategy that provides a more comprehensive and detailed assessment of policy interventions. This could enable a more participatory policymaking approach that collaboratively explores policy needs and underlying model capability requirements, to improve policy decision usability.

Appendix B

Table B.1. Historical prices of small-scale PV systems during the period 2009-2013 in Greece, when the feed-in-tariff scheme was operational.

Year	Prices (€/Wpeak)
2010	4.0
2011	3.2
2012	2.4
2013	1.5

Table B.2. Competitive electricity consumption tariffs and other regulated charges under the current most common residential tariff (i.e., "G1" tariff) in Greece.

Consumption thresholds (kWh)	Tariff for electricity consumed (€/kWh)
0-2000	0.09460
>2000	0.10252

Consumption thresholds (kWh)	TSO charges (€/kWh)	DSO charges (€/kWh)	ETMEAR fee (€/kWh)	Other utility services (€/kWh)
0-1600	0.00527	0.0213	0.02477	0.00699
1601-2000				0.01570
2001-3000				0.03987
>3000				0.04488

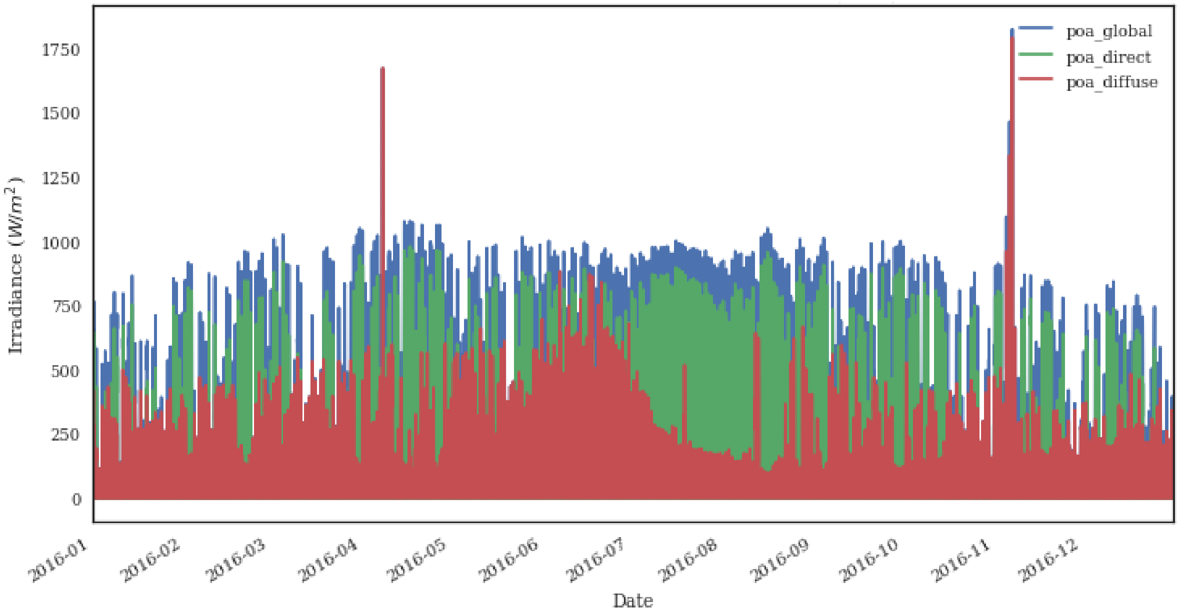


Figure B.1. Solar irradiance incident for the PV module assumed. The site-specific solar radiation dataset was retrieved from the Copernicus Atmosphere Monitoring Service (CAMS) radiation service. The dataset corresponds to 2016 hourly radiation for the coordinates of Greece (37.98°, 23.73°).

Table B.3. A random set of plausible values of the agent-related parameters to test the model's ability to capture uncertainty that is propagated to modelling outcomes owing to its structure.

a/a	Parameter	Description	Value
1.	Initial beliefs	The shape parameter of the global distribution that assigns μ^{CF} to each agent in the model.	450
2.		The shape parameter of the global distribution that assigns ρ^{CF} to each agent in the model.	39.68
3.	Social learning	The scale parameter of the global distribution that assigns μ^{CF} to each agent in the model.	35.72
4.		The scale parameter of the global distribution that assigns ρ^{CF} to each agent in the model.	17.20
5.	Resistance toward PV investments	The shape parameter of the global distribution that assigns the weight of the profitability to each agent's resistance.	2.04
6.		The scale parameter of the global distribution that assigns the weight of the profitability to each agent's resistance.	0.55
7.		The shape parameter of the global distribution that assigns the weight of the installed base to each agent's resistance.	3.53
8.		The scale parameter of the global distribution that assigns the weight of the installed base to each agent's resistance.	0.89
9.	Probability of investing	The shape parameter of the global distribution that assigns each agent's threshold value for their resistance parameter.	18.50
10.		The scale parameter of the global distribution that assigns each agent's threshold value for their resistance parameter.	7.36
11.	Inertia to invest	The inertia parameter was kept constant during simulation.	0.01

References

[1] Koumparou I, Christoforidis GC, Efthymiou V, Papagiannis GK, Georghiou GE. Configuring residential PV net-metering policies – A focus on the Mediterranean region. Renew Energy 2017;113:795–812. doi:10.1016/j.renene.2017.06.051.

[2] Michas S, Stavrakas V, Spyridaki N, Flamos A. Identifying Research Priorities for the further development and deployment of Solar Photovoltaics. Int J Sustain Energy 2019:276–96. doi:10.1080/14786451.2018.1495207.

[3] Lang T, Ammann D, Girod B. Profitability in absence of subsidies: A techno-economic analysis of rooftop photovoltaic self-consumption in residential and commercial buildings. Renew Energy 2016;87:77–87. doi:10.1016/j.renene.2015.09.059.

[4] Bertsch V, Geldermann J, Lühn T. What drives the profitability of household PV investments, self-consumption and self-sufficiency? Appl Energy 2017;204:1–15. doi:10.1016/j.apenergy.2017.06.055.

[5] De Boeck L, Van Asch S, De Bruecker P, Audenaert A. Comparison of support policies for residential photovoltaic systems in the major EU markets through investment profitability. Renew Energy 2016;87:42–53. doi:10.1016/j.renene.2015.09.063.

[6] Beck T, Kondziella H, Huard G, Bruckner T. Assessing the influence of the temporal resolution of electrical load and PV generation profiles on self-consumption and sizing of PV-battery systems. Appl Energy 2016;173:331–42. doi:10.1016/j.apenergy.2016.04.050.

[7] Yu HJJ. A prospective economic assessment of residential PV self-consumption with batteries and its systemic effects: The French case in 2030. Energy Policy 2018;113:673–87. doi:10.1016/j.enpol.2017.11.005.

[8] Sommerfeld J, Buys L, Vine D. Residential consumers' experiences in the adoption and use of solar PV. Energy Policy 2017;105:10–6. doi:10.1016/j.enpol.2017.02.021.

[9] MacAl CM, North MJ. Tutorial on agent-based modelling and simulation. J Simul 2010;4:151–62. doi:10.1057/jos.2010.3.

[10] Ringler P, Keles D, Fichtner W. Agent-based modelling and simulation of smart electricity grids and markets - A literature review. Renew Sustain Energy Rev 2016;57:205–15. doi:10.1016/j.rser.2015.12.169.

[11] Bonabeau E. Agent-based modeling: methods and techniques for simulating human systems. Proc Natl Acad Sci 2002;99:7280–7. doi:10.1073/pnas.082080899.

[12] Taylor R, Besa MC, Forrester J. Agent-Based Modelling: A Tool for Addressing the Complexity of Environment and Development Policy Issues. 2016.

[13] Nikolic I, Ghorbani A. A Method for Developing Agent-based Models of Socio-technical Systems. IEEE Int. Conf. Networking, Sens. Control (ICNSC), 2011, IEEE; 2011, p. 44–9.

[14] Zhang T, Nuttall W-J. Evaluating Government's Policies on Promoting Smart Metering Diffusion in Retail Electricity Markets via Agent-Based Simulation. J Prod Innov Manag 2011;28:169–86.

[15] Edmonds, B., Lucas P, Rouchier J, Taylor R. Human Societies: Understanding Observed Social Phenomena. In Simulating Social Complexity. In: Edmonds B, Meyer R, editors. Underst. Complex Syst., Berlin, Heidelberg: Springer; 2013, p. 709–748.

[16] Haringa DB. Microgeneration in the domestic sector in the Netherlands. Utrecht University (UU), 2010.

[17] Zhao J, Mazhari E, Celik N, Son YJ. Hybrid agent-based simulation for policy evaluation of solar power generation systems. Simul Model Pract Theory 2011;19:2189–205. doi:10.1016/j.simpat.2011.07.005.

[18] Robinson SA, Stringer M, Rai V, Tondon A. GIS-Integrated Agent-Based Model of Residential Solar PV Diffusion. 32nd USAEE/IAEE North Am. Conf. July 28-31, 2013, p. 1–19.

[19] Palmer J, Sorda G, Madlener R. Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation. Technol Forecast Soc Change 2015;99:106–31. doi:10.1016/j.techfore.2015.06.011.

[20] Adepetu A, Keshav S. Understanding Solar PV and Battery Adoption in Ontario: An Agent-based

Approach. Seventh Int. Conf. Futur. Energy Syst. e-Energy '16, ACM New York, NY, USA; 2016. doi:10.1145/2934328.2934333.

[21] Pearce P, Slade R. Feed-in tariffs for solar microgeneration: Policy evaluation and capacity projections using a realistic agent-based model. Energy Policy 2018;116:95–111. doi:10.1016/j.enpol.2018.01.060.

[22] Warmink JJ, Janssen JAEB, Booij MJ, Krol MS. Identification and classification of uncertainties in the application of environmental models. Environ Model Softw 2010;25:1518–27. doi:10.1016/j.envsoft.2010.04.011.

[23] Uusitalo L, Lehikoinen A, Helle I, Myrberg K. An overview of methods to evaluate uncertainty of deterministic models in decision support. Environ Model Softw 2015;63:24–31. doi:10.1016/j.envsoft.2014.09.017.

[24] Willems P. Model uncertainty analysis by variance decomposition. Phys Chem Earth 2012;42–44:21–30. doi:10.1016/j.pce.2011.07.003.

[25] Koppelaar RHEM, Keirstead J, Shah N, Woods J. A review of policy analysis purpose and capabilities of electricity system models. Renew Sustain Energy Rev 2016;59:1531–44. doi:10.1016/j.rser.2016.01.090.

[26] Moret S, Codina Gironès V, Bierlaire M, Maréchal F. Characterization of input uncertainties in strategic energy planning models. Appl Energy 2017;202:597–617. doi:10.1016/j.apenergy.2017.05.106.

[27] Mavromatidis G, Orehounig K, Carmeliet J. Uncertainty and global sensitivity analysis for the optimal design of distributed energy systems. Appl Energy 2018;214:219–38. doi:10.1016/j.apenergy.2018.01.062.

[28] Camilo FM, Castro R, Almeida ME, Pires VF. Economic assessment of residential PV systems with self-consumption and storage in Portugal. Sol Energy 2017;150:353–62. doi:10.1016/j.solener.2017.04.062.

[29] Nikolaidis AI, Milidonis A, Charalambous CA. Impact of fuel-dependent electricity retail charges on the value of net-metered PV applications in vertically integrated systems. Energy Policy 2015;79:150–60. doi:10.1016/j.enpol.2015.01.010.

[30] Papadelis S, Flamos A, Androulaki S. Setting the framework for a Business Strategy Assessment Model. Int J Energy Sect Manag 2012;6:488–517. doi:10.1108/17506221211281993.

[31] Kontochristopoulos Y, Michas S, Kleanthis N, Flamos A. Investigating the market effects of increased RES penetration with BSAM: A wholesale electricity market simulator. Energy Reports 2021;7:4905–29. doi:10.1016/j.egyr.2021.07.052.

[32] Luthra S, Kumar S, Garg D, Haleem A. Barriers to renewable / sustainable energy technologies adoption : Indian perspective. Renew Sustain Energy Rev 2015;41:762–76. doi:10.1016/j.rser.2014.08.077.

[33] Reddy S, Painuly JP. Diffusion of renewable energy technologies-barriers and stakeholders' perspectives. Renew Energy 2004;29:1431–47. doi:10.1016/j.renene.2003.12.003.

[34] Sen S, Ganguly S. Opportunities, barriers and issues with renewable energy development – A discussion. Renew Sustain Energy Rev 2017;69:1170–81. doi:10.1016/j.rser.2016.09.137.

[35] Yu, Hyun Jin Julie, Popiolek N. Challenges and opportunities of photovoltaic (PV) growth with self-consumption model. Proc. 38th Int. Assoc. Energy Econ. Int. Conf., Antalya (Turkey): 2015.

[36] Craig PS, Goldstein M, Seheult AH, Smith JA. Pressure Matching for Hydrocarbon Reservoirs: A Case Study in the Use of Bayes Linear Strategies for Large Computer Experiments. Case Stud. Bayesian Stat. Lect. Notes Stat., New York, NY: Springer; 1997, p. 37–93.

[37] Papadelis S, Flamos A. An application of calibration and uncertainty quantification techniques for agent-based models. In: Doukas H, Flamos A, Lieu J, editors. Underst. Risks Uncertainties Energy Clim. Policy - Multidiscip. Methods Tools a Low Carbon Soc. Springer B. Ser., Springer, Cham; 2019, p. 79–95. doi:https://doi.org/10.1007/978-3-030-03152-7_3.

[38] Saltelli A, Annoni P, Azzini I, Campolongo F, Ratto M, Tarantola S. Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Comput Phys Commun 2010;181:259–70. doi:10.1016/j.cpc.2009.09.018.

[39] Andrianakis I, Vernon IR, Mccreesh N, Mckinley TJ, Oakley JE, Nsubuga RN, et al. Bayesian History

Matching of Complex Infectious Disease Models Using Emulation : A Tutorial and a Case Study on HIV in Uganda. Plos Comput Biol 2015;11. doi:10.1371/journal.pcbi.1003968.

[40] Kennedy MC, O'Hagan A. Bayesian calibration of computer models. J R Stat Soc Ser B (Statistical Methodol 2001;63:425–64. doi:10.1111/1467-9868.00294.

[41] Chatzisideris MD, Laurent A, Christoforidis GC, Krebs FC. Cost-competitiveness of organic photovoltaics for electricity self-consumption at residential buildings: A comparative study of Denmark and Greece under real market conditions. Appl Energy 2017;208:471–9. doi:10.1016/j.apenergy.2018.03.019.

[42] Ramïrez FJ, Honrubia-Escribano A, Gï¿½mez-Lï¿½zaro E, Pham DT. Combining feed-in tariffs and net-metering schemes to balance development in adoption of photovoltaic energy: Comparative economic assessment and policy implications for European countries. Energy Policy 2017;102:440–52. doi:10.1016/j.enpol.2016.12.040.

[43] Kyritsis A, Voglitsis D, Papanikolaou N, Tselepis S, Christodoulou C, Gonos I, et al. Evolution of PV systems in Greece and review of applicable solutions for higher penetration levels. Renew Energy 2017;109:487–99. doi:10.1016/j.renene.2017.03.066.

[44] Anagnostopoulos P, Spyridaki NA, Flamos A. A "new-deal" for the development of photovoltaic investments in Greece? A parametric techno-economic assessment. Energies 2017;10:1173. doi:10.3390/en10081173.

[45] Papadelis S, Stavrakas V, Flamos A. What do capacity deployment rates tell us about the efficiency of electricity generation from renewable energy sources support measures in Greece? Energies 2016;9. doi:10.3390/en9010038.

[46] Flamos A. A sectoral micro-economic approach to scenario selection and development: The case of the greek power sector. Energies 2016;9:1–12. doi:10.3390/en9020077.

[47] Tselepis S. The PV market developments in Greece, net-metering study cases. Conf. 31st EUPVSEC, Hamburg: 2015.

[48] Kyritsis A, Roman E, Kalogirou SA, Nikoletatos J, Agathokleous R, Mathas E, et al. Households with Fibre Reinforced Composite BIPV modules in Southern Europe under Net Metering Scheme. Renew Energy 2017:1–10. doi:10.1016/j.renene.2017.09.068.

[49] Young HP. Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. Am Econ Rev 2009;99:1899–924. doi:10.1257/aer.99.5.1899.

[50] Stephenson J, Carswell P. Energy Cultures and Social Networks – influences on household energy behaviour. Energy Effic. Behav. Conf., Helsinki: 2012.

[51] Baranzini A, Carattini S, Peclat M. What Drives Social Contagion in the Adoption of Solar Photovoltaic Technology. 2017.

[52] Motors T. Powerwall - Lithium Battery n.d.

[53] Nykvist B, Nilsson M. Rapidly falling costs of battery packs for electric vehicles. Nat Clim Chang 2015;5:329–332. doi:10.1038/nclimate2564.

[54] Christoforidis GC, Panapakidis IP, Papadopoulos TA, Papagiannis GK, Koumparou I, Hadjipanayi M, et al. A model for the assessment of different Net-Metering policies. Energies 2016;9. doi:10.3390/en9040262.

[55] Dascalaki EG, Balaras CA, Kontoyiannidis S, Droutsa KG. Modeling energy refurbishment scenarios for the Hellenic residential building stock towards the 2020 & 2030 targets. Energy Build 2016;132:74–90. doi:10.1016/j.enbuild.2016.06.003.

[56] Christoforidis GC, Panapakidis IP, Papagiannis GK, Papadopoulos TA, Koumparou I, Hatzipanayi M, et al. Investigating net-metering variant policies: The case of Greece. 2015 IEEE 15th Int Conf Environ Electr Eng EEEIC 2015 - Conf Proc 2015:2023–8. doi:10.1109/EEEIC.2015.7165486.

[57] Eid C, Reneses Guillén J, Frías Marín P, Hakvoort R. The economic effect of electricity net-metering with solar PV: Consequences for network cost recovery, cross subsidies and policy objectives. Energy Policy

2014;75:244–54. doi:10.1016/j.enpol.2014.09.011.

[58] Goebel C, Cheng V, Jacobsen HA. Profitability of residential battery energy storage combined with solar photovoltaics. Energies 2017;10:1–17. doi:10.3390/en10070976.

[59] Waffenschmidt E. Dimensioning of decentralized photovoltaic storages with limited feed-in power and their impact on the distribution grid. Energy Procedia 2014;46:88–97. doi:10.1016/j.egypro.2014.01.161.

[60] Quoilin S, Kavvadias K, Mercier A, Pappone I, Zucker A. Quantifying self-consumption linked to solar home battery systems: Statistical analysis and economic assessment. Appl Energy 2016;182:58–67. doi:10.1016/j.apenergy.2016.08.077.

[61] Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-baltvilks J, et al. Barriers to and consequences of a solar-based energy transition in Greece. Environ Innov Soc Transitions 2018:1–17. doi:10.1016/j.eist.2018.12.004.

[62] Statista. Electricity prices for household consumers in Greece from 2010 to 2017, semi-annually (in euro cents per kilowatt-hour) 2018.

[63] Psomas S. Status and outlook of the Greek PV Market. Hell Assoc Photovolt Co 2018:1–14.

[64] Operator of RES and Guarantees of Origin. Renewable Energy Sources and Combined Heat and Power: Summary Information Sheet (In Greek). 2018.

[65] HELAPCO. Greek PV Market statistics - 2017. Hell Assoc Photovolt Co 2018:1–5.

[66] Diouf B, Pode R. Potential of lithium-ion batteries in renewable energy. Renew Energy 2015;76:375–80. doi:10.1016/j.renene.2014.11.058.

[67] Kyriakopoulos GL, Arabatzis G. Electrical energy storage systems in electricity generation : Energy policies , innovative technologies , and regulatory regimes. Renew Sustain Energy Rev 2016;56:1044–67. doi:10.1016/j.rser.2015.12.046.

[68] Tsantopoulos G, Arabatzis G, Tampakis S. Public attitudes towards photovoltaic developments: Case study from Greece. Energy Policy 2014;71:94–106. doi:10.1016/j.enpol.2014.03.025.

[69] Haasnoot M, Kwakkel JH, Walker WE, ter Maat J. Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. Glob Environ Chang 2013;23:485–98. doi:10.1016/j.gloenvcha.2012.12.006.

[70] Kwakkel JH, Haasnoot M, Walker WE. Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty. Environ Model Softw 2016;86:168–83. doi:10.1016/j.envsoft.2016.09.017.

[71] Spyridaki N-A, Banaka S, Flamos A. Evaluating public policy instruments in the Greek building sector. Energy Policy 2016;88:528–43. doi:10.1016/J.ENPOL.2015.11.005.

Chapter 4 - Empowering end-users

Nomenclature

Acronyms & abbreviations	
AC	Air-condition
BES	Building Energy System
DC	Direct current
DR	Demand-Response
DREEM	Dynamic high-Resolution dEmand-sidE Management
DSM	Demand-side management
EC	European Commission
EE	Energy efficiency
EEOS	Energy efficiency obligation scheme
EU	European Union
EPBD	Energy Performance Buildings Directive
HEP	Hourly electricity price
HVAC	Heating, Ventilation and Air-Conditioning
IWEC	International Weather for Energy Calculations
LP	Limiting price
MCAR	Missing completely at random
PID	Proportional-Integral-Derivative
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PV	Photovoltaic
RC	Resistance-Capacity
RES	Renewable energy sources
RL	Reinforcement learning
SARSA	State Action Reward (next)State (next)Action
SECH	Statistics on Energy Consumption in Households
SLG	Strategic Growth Load
SOC	State of Charge
SR	Spinning Reserve
SMP	System Marginal Price
TEEM	TEESlab Modeling
TEESlab	Technoeconomics of Energy Systems laboratory
TOU	Time-of-Use
TMY	Typical Meteorological Year

Parameters	
A	Surface
f_{act}	Fraction of the aperture area in the PV panel
G	Conductance
I_{CL}	Clothing insulation
M	Metabolic rate
γ	Discount factor
η	Efficiency

Indices & sets	
A_s	Action space
k	Index
S	State space
t	Index of time period

Variables	
I	Current
P	Power
R	Reward function
T	Temperature
T_{air}	Mean indoor air temperature
T_o	Mean outdoor air temperature
T_{rm}	Mean radiant temperature
T_{set}	Indoor temperature setpoint
TSI	Total solar irradiation
$T_{set,min}$	Minimum acceptable indoor temperature setpoint
$T_{set,normal}$	Normal indoor temperature setpoint
υ	Ambient air velocity
v	Voltage
π	Optimal RL policy
φ	Relative humidity

4. A modular high-resolution demand-side management model to quantify benefits of demand flexibility in the residential sector

Abstract

Increasing shares of renewable energy sources and managing total demand are considered pivotal for energy transitions that fundamentally re-envisage the electricity system. A key challenge of such transitions is integrating and absorbing increased shares of non-dispatchable renewable energy sources, without jeopardising the security and the reliability of the electricity system. To this end, key solutions include the introduction of demand-side management. However, so far, demand-side management modelling at the building sector has been proven challenging, as existing models are not flexible enough to incorporate a wide set of modelling features and guiding principles, while including all important aspects of end-use. This chapter presents a new dynamic high-resolution demand-side management model which brings together key features and guiding principles of demand-side management modelling. The novelty of the model lies mainly in its modularity, as the main modelling framework is decomposed into individual modules, hierarchically dependent on components embodying standards and design rules, allowing for multiple configurations and computational efficiency. To demonstrate its applicability the model was used to explore benefits of demand flexibility for consumers in the residential sector in Greece. Simulation results showed that the flexibility to increase self-consumption can be brought to the Greek electricity sector without a need for significant changes in the current market design, and for consumers to sacrifice thermal comfort and energy services.

Keywords: Smart home; Battery storage; RES generation; Demand-Response; Maintenance and control; Demand-side management.

4.1. Introduction

Current global climate targets implied by the Paris Agreement command low-carbon transitions that fundamentally re-envisage the electricity system. Although electricity decarbonisation is not the only action suggested by these transitions, it is argued that a "sooner-than-later" carbon-free electricity system will enable mitigation in other sectors and accelerate the transition to a low-carbon society [1]. Further deployment of renewable energy sources (RES) and reducing total demand are considered critical in decarbonising the electricity system [2]. However, one of the main challenges of a transition based on a high RES penetration is integrating these variable energy sources without jeopardising security, reliability, and resilience of the electricity system [3]. Key solution to this end include demand-side management (DSM), encompassing the entire range of management functions associated with directing demand-side activities, including programme planning, evaluation, implementation, and monitoring. Its main objective is to improve the energy system at the side of the end-user in terms of consumption and cost effectiveness [4]. Different aspects of DSM range from improving energy efficiency (EE) up to sophisticated real-time control of distributed energy resources through smart devices with incentives for promoting certain consumption/ production patterns [5]. By doing so, DSM adds significant economic value to all actors involved and interacting with each other in the modern energy network, while reduces carbon footprint of conventional generators at the same time [6].

According to the scientific literature the main aspects of DSM are: **(I)** EE, **(II)** Strategic Load Growth (SLG), **(III)** Demand-Response (DR), **(IV)** Time-of-Use (TOU), and **(V)** Spinning Reserve (SR) [5]. However, energy management concept changes from utility-driven control to one involving participation of end-use customers in determining prices and clearing the market [7]. As a result, categories such as SLG or SR seem outdated at the time being, with EE and DR being the most reliable, cost effective and efficient practices to affect the demand curve. On the other hand, while TOU tariffs are sent beforehand to allow the consumer to adapt to new prices, DR signals have a more direct impact on the behaviour and consumption patterns of the consumer [8]. Some studies acknowledge TOU as a subcategory of DR implying that both aspects aim at shifting the demand from peak to off-peak times. This reduces the fluctuations in demand curve and contributes to the efficiency of flexible conventional power plants. Essentially, both practices reward consumers for altering their consumption practices and routines [9]. Especially DR can shift consumption from times when energy is limited to times when it is abundant, for example times with high RES generation. DR schemes allow to manage local power consumption in response to supply conditions, such as high market prices, peak demand, or regulation signal. Thus, lower grid operating costs, increased system reliability and improved EE can be achieved [10].

Furthermore, regarding the future of power grids, it is often stated that residential end-users will play a more active role in the management of electric power supply and demand, transitioning from passive consumers to active co-providers called "prosumers" [11]. However, end-use products and services need to be considered for such a transition [12]. To this end, to foster their role and evaluate their impact into the future energy regime, modelling of user interaction and resource management needs to be considered first through DSM modelling exercises. Indicatively, DSM modelling can support electricity distribution network operators for modelling of network peak demand, demand aggregators for estimation of potential demand-side flexibility, government agencies for assessing incentive scheme costs, or electricity retailers for understanding the impact of different technology adoption upon their demand portfolio. Thus, accurate DSM modelling could be beneficial for testing DR schemes that are primarily offered to residential customers and could provide directions for the development of products and services related to the smart-grid paradigm.

4.2. Why a new model?

Especially in the residential sector, DSM modelling can be used for studying electric use patterns, EE concerns, and behavioural analysis of consumers. Typically, DSM modelling incorporates inputs such as building envelope characteristics, climate properties, occupancy and behavioural patterns, indoor temperature, characteristics of the end-use equipment and their flexibility, load or generation profiles in case of RES, and aggregation for a time period and validation. However, key aspects of DSM models include energy demand and management modelling, and hence, their structure is often characterised by the type of approach used for the energy demand aspect of end-use. Two main types of approaches have been developed towards this end: top-down and bottom-up. Top-down methods model residential electricity demand as a whole regarding its general characteristics, while bottom-up methods, aggregate load profiles. Bottom-up models are considered more precise in general as they enable the aggregation of various household types with different characteristics and information [13].

Mai and Chung (2016) present an energy model that focuses on thermal and simplified energy consumption modelling of a residential building. A predictive controller determines the optimal heating/ cooling strategy to minimise energy costs without violating temperature constraints, while the model also considers electricity price signals and the predictions of future disturbances. However, it does not consider technologies and systems that introduce flexibility [14]. Furthermore, the approach presented by Pradhan et al., (2016) builds the demand curve, based on historical data, while it formulates an optimisation problem for residential DR aiming at the minimisation of the total pricing, and preserving user convenience [15]. However, the model does not consider thoroughly either thermal comfort or flexibility provided by RES and storage installations. Similarly, Gottwalt et al., (2017) present a model of different devices for flexibility analysis, elaborating on an accurate representation of residential customers within a smart grid. The impact of RES and storage installations are not considered though [16].

Croce et al., (2017) present a fully distributed architecture to automatically control and implement distributed DR schemes in a community of smart buildings [17]. The model balances supply and demand, but it does not consider price signals from utility or storage for improving RES integration. Mahmoudi et al., (2017) proposes a statistical/ stochastic model to integrate the uncertainties of wind generation on the supply side and of roof-top solar photovoltaic (PV) on the demand side [18]. However, the model does not foresee the integration of battery storage and occupants' profiles. Martirano et al., (2017) present a Building Energy System (BES) model, managing both electric and thermal loads and improving the energy performance of the building through DR [19]. The model is based on sample data of energy consumption, it does not consider, though, electricity prices focusing on control loads for optimising consumption. On the other hand, Ren et al., (2017) present a BES model that includes RES and storage modelling, but it focuses only on a room [20]. The model proposes a multi-objective optimisation approach for enabling residential DR to optimise the system's economy and occupants' comfort by a synergetic dispatch of source-load-storage management systems integrated into the building.

Hu and Xiao (2018) present a hybrid model consisting of a control-oriented room thermal model and an air-condition (AC) inverter steady-state model, while optimal scheduling of indoor air temperature setpoints is formulated as a nonlinear programming problem to achieve low cost, thermal comfort, and peak power reductions [21]. However, the model focuses only on a room and except of AC units, no other loads are considered. Sivaneasan et al., (2018) present a DR management algorithm, enabling DR to overcome RES intermittency based on a thermal building model [22]. The proposed algorithm utilises a combination of AC and mechanical ventilation load reduction, priority-based load shedding, and battery energy storage for managing RES intermittency. Its main deficiency is the absence of occupants' profiles, price signals, and weather information leading to a simplified model. Finally, Alimohammadisagvand et al., (2018) study the effect of different DR strategies on energy consumption and costs from heating, also considering occupants' thermal comfort. The model considers quite a few shaping factors, but neglects cutting edge technologies or social implications [23].

It becomes apparent that most models in the scientific literature address DSM partially, or in a simplified manner, used most of the times for forecasting purposes. The main challenge of DSM models is being flexible enough, while at the same time including all important aspects of end-use. The key set of features and guiding principles of a DSM model to judge what should be incorporated and omitted, or simplified in the interests of computational efficiency, and in recognition of data availability limitations, can be summarised as follows:

- Bottom-up structure,
- Capability to be integrated with other models and be easily reused,
- Capability to produce outputs at a high resolution (i.e., one minute),
- Data requirements that are achievable such that the model can be self-contained,
- Seasonal variability to reflect the changing level of demand between winter and summer,
- Computational efficiency to simulate large numbers of buildings with the appropriate diversity of demand,
- Modular structure to reduce simulation complexity owing to the multidisciplinary nature and input data requirements,
- Considering occupant behaviour along with determination of end-use qualities to bridge the gap between statistical and engineering models,
- Inclusion of practical load control strategies that will allow price-based DR signals to enable the smooth operation of the smart grid paradigm,
- Capability to link the energy system to economic development and technological breakthrough (i.e., inclusion of alternative energy technologies or other energy carriers at a later date).

Considering the above, the main premise of this chapter was to develop a fully integrated dynamic high-resolution model embodying key features that are not found together in existing models. To this end, this chapter presents the **D**ynamic high-**R**esolution d**E**mand-sid**E** **M**anagement (DREEM) model, a hybrid bottom-up model that combines key features of both statistical and engineering models. The model serves as an entry point in DSM modelling in the building sector, by expanding the computational capabilities of existing BES models to assess the benefits and limitations of demand flexibility, primarily for consumers, and for other power actors involved. The novelty of the DREEM model mainly lies in its modularity, as its structure is decomposed into individual modules characterised by the main principles of component- and modular-based system modelling approach, namely "*the interdependence of decisions within modules*; *the independence of decisions between modules*; *and the hierarchical dependence of modules on components embodying standards and design rules*" [24].

This modular approach allows for more flexibility in terms of possible system configurations and computational efficiency towards a wide range of scenarios studying different aspects of end-use. It also provides the ability to incorporate future technological breakthroughs in a detailed manner, such as the inclusion of heat pumps, or electric vehicles, in view of energy transitions envisioning the full electrification of the heating and transport sectors. The latter makes the DREEM model competitive compared to other models in the field, since scientific literature acknowledges that there are limitations to how much technological detail can be incorporated without running into computational and other difficulties [25].

The model also supports the capability of producing output for a group of buildings and could also serve as a basis for modelling domestic energy demand within the broader field of urban, national, or regional energy system analysis. The DREEM model is part of the Technoeconomics of Energy Systems laboratory- **TEE**Slab **M**odeling (TEEM) suite and was developed in the context of the EC-funded Horizon 2020 project "TRANSrisk[10]." In this study, the applicability of the model is demonstrated by exploring benefits of demand flexibility for consumers and other power actors in the residential sector in Greece. Note that, although its applicability is demonstrated in the case of Greece, the DREEM model can be configured and used for different geographical and socioeconomic contexts to fill-in knowledge gaps from an international and cross-country perspective. Overall, the novel contribution of this work to the scientific literature is mainly twofold:

- Developing a DSM model that, based on the strengths of object-oriented programming and equation-based system modelling approaches [26], is: **(I)** input–output free (all modelling components are declarative in nature, as opposed to the traditional procedure), **(II)** modular, **(III)** hierarchical (enable incremental modelling, i.e., models can consist of sub-models in multiple levels) with control capabilities, which helps in managing the complexity of large systems, **(IV)** universal (model definition in a generic form), **(V)** able to provide more realistic representations of the dynamic systems, **(VI)** able to integrate occupants' behaviour along with determination of end-use qualities, and policies supporting RES, and **(VII)** able to allow for faster development and simulation.
- Developing and testing via simulation control strategies the coordination of electricity storage and smart thermostats towards increasing the consumption of RES electricity. The novelty lies in combining electricity storage with smart thermostat capabilities, considering that the flexibility potential of the latter has primarily been used so far for increasing EE in buildings.

The remainder of this paper is organised as follows: **Section 4.3** presents, step by step, the methodological framework on which the DREEM model was developed. **Section 4.4** presents the application of this framework to the geographical and socioeconomic context of Greece, to demonstrate the applicability of the DREEM model. **Section 4.5** reports simulation results, while discusses implications of modeling findings for key end-users and policymakers. Finally, **Section 4.6** provides conclusions and shapes directions for future research.

4.3. Model description

The DREEM model consists of multiple components, each of which is composed of additional modules. The overall architecture of the model, as visualised in **Figure 4.1**, makes it flexible to be adapted, modified, and extended in the future. All the modules of the model were developed using the "Buildings" library [27], which is an open-source, freely available Modelica library for building energy and control systems. Modelica is an equation-based, object-oriented modelling language for the simulation of dynamic systems [28], and has been used in several studies and applications for the design and the simulation of various BES and control systems [29–32]. Alongside to the Modelica models, Python scripts have been developed to model parts of the "Demand-Response" and "Control strategies" components, and to enable the interface with the Dymola simulation environment. **Table 4.1** provides a short description of each component, along with its individual modules.

[10] http://transrisk-project.eu/

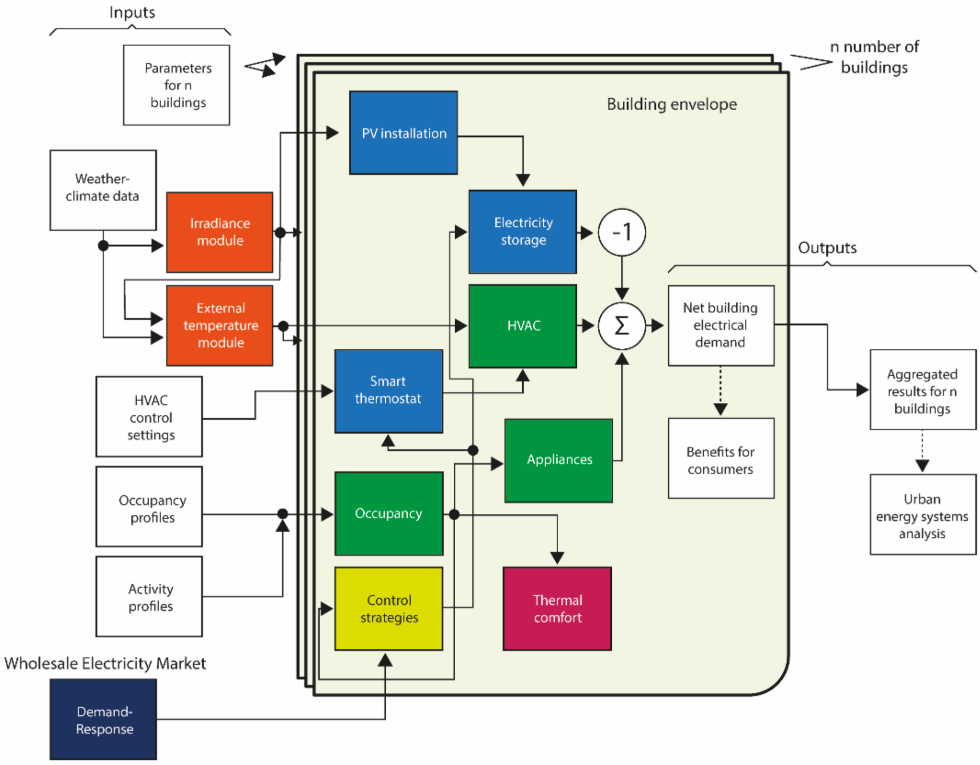


Figure 4.1. Overall architecture of the DREEM model as it currently stands.

Table 4.1. Hierarchical structure of the DREEM model: Short description of the main components and modules.

Components	Modules	Description
C1: Weather/ Climate	-	This single-module component is responsible for generating climatic boundary conditions. It reads weather data from the respective files and then provides them to the other components, where and when necessary.
C2: Building envelope	-	This single-module component models different building typologies with the corresponding characteristics, properties, and heat conduction elements.
C3: Electricity demand	C3M1: Occupancy	This module defines and sets the parameters for the behaviour and the activities of the occupants by generating and storing default patterns, such as for the case of a residential building: wake-up times and arrival times from work, washing and cooking hours, etc. An uncertainty variable is available to make the person more stochastic. Also, active occupancy modelling is enabled to account for the "sharing of appliances" effect.
	C3M2: Appliances	This module is responsible for generating energy demand profiles from appliances, using statistics describing their total mean daily energy demand and associated power use characteristics, including steady-state consumption, or typical use cycles, as appropriate. The "Occupancy" module considers when specific appliances are likely to be used.
	C3M3: Heating, Ventilation, and Air-Conditioning	This module is responsible for heating, ventilation, and air-conditioning inside the building, according to the "Smart thermostat" module's input data and signals.
C4: Thermal comfort	-	This single-module component is responsible for determining, based on international standards, appropriate thermal conditions and temperature ranges that result in thermal satisfaction of occupants.
C5: Flexibility management	C5M1: Photovoltaic installation	This module contains information about the orientation of the roof to determine the PV generation based on the position of the sun and recorded irradiation data for the location of interest.
	C5M2: Electricity storage	This module contains models that represent different energy storages. It takes as an input the power that should be stored in/ extracted from the storage. The "Control strategies" component is responsible so that only a reasonable amount of power is exchanged, and that the state of charge remains between the appropriate ranges.
	C5M3: Smart thermostat	This module is responsible for the heating, ventilation and air-conditioning control system. By receiving the indoor temperature as a measured signal and, based on the

		difference of set and measured temperature, it sends signals to the "HVAC" module to yield the heat and ventilation flows inside the building.
C6: Demand-Response	-	This single-module component simulates DR mechanisms that motivate the consumers to respond to real-time price-based signals.
C7: Control strategies	-	This single module component is responsible for the energy management supervision strategy that, given the time-shifting events of demand and the occupancy signals, aims at achieving energy savings and cost-effectiveness.

4.3.1. C_1: Weather/ Climate

Seasonal variability to reflect on the changing level of demand between winter and summer is an important aspect of DSM modelling, often omitted, or addressed in an oversimplified manner by existing models in the field. The DREEM model addresses thoroughly this issue compared to other approaches through the inclusion of a single-module component dedicated to generating accurate climatic boundary conditions based on historical weather data. To do so, this component uses Typical Meteorological Year (TMY) [33] weather data format and in particular the "TMY3" format [34]. The module is then configured to provide a common set of irradiance and temperature data for the geography under study, with the respective irradiance and temperature profiles having appropriate time-diversity to enable higher resolution.

4.3.2. C_2: Building envelope

Modelling and simulation of the dynamic thermal behavior of buildings is a particularly challenging area [35]. There are various well-established and sophisticated packages dedicated to this task, which have been widely used for detailed studies of specific individual buildings under specific conditions (e.g., weather and occupancy profiles, etc.). However, adopting such models implies extremely detailed input data requirements and high discretisation, resulting in excessive computational runtimes [36]. To address such limitations and achieve computational efficiency, the DREEM model builds on the concept of "reduced (low)-order" modules that adequately represent building thermal dynamics for the purposes at hand [37]. Reduced-order thermal network modelling represents a thermal zone by thermal resistances and capacities (RC-network) [38], using the electrical circuit analogy, in which voltage is analogous to temperature and current is analogous to convective and radiative heat transfer. The respective module represent all main thermal masses of the building under study as four elements, accompanied with supportive features for consideration of solar radiation, as visualised and further described in **Appendix C.1**. The parameters for heat transfer coefficients, and thermal resistances and capacities, are determined using historical data and standards for the geographical context of interest.

4.3.3. C_3: Electricity demand

DSM is expected to introduce time-shifting of end-use demand, while micro-generation is expected to alter net demand profiles as seen by the supplier. To this end, accurate electricity demand modelling is an important prerequisite [39]. Bottom-up electricity demand models that use probabilistic methods to provide stochastic high-resolution data are typically a very useful tool for modelling end-use demand in buildings [40]. Recognising that it is not possible to predict the exact behaviour of individual occupants, or appliances, the aim of stochastic demand modelling is to provide simulated data, with the right statistics, suitable for the task at hand. A critical precursor, therefore, is considering exactly which statistics need to be included and which aspects need to be approximated. However, by including too much detail, existing models are often computationally intensive, requiring the collection and analysis of enormous amounts of input data, often not available [37]. Although more accurate and sophisticated demand profiles could be achieved, such a degree of detail is not required in the context of DSM modelling [41]. On the other hand, the "human dimension" is not to be neglected, as there is an increasing recognition of the value of integrating social and behavioural insights into models. A "fit-for-purpose" model, thus, is one that achieves a reasonable balance between model accuracy, data complexity, and computational efficiency [42]. The DREEM model builds on this concept, aiming at the generation of accurate and realistic electricity demand profiles, avoiding unnecessary complexity. This component uses a bottom-up approach with the spikiness of the load created by simulating the switching on/ off of individual appliances. The individual modules use many simplified assumptions to simulate various aspects of electricity demand (e.g., occupancy and occupants' behaviour, sharing of appliances, etc.), and focuses on a minimal set of easily obtainable parameters and statistics (such as from surveys or census data).

C_3M_1: Occupancy

This module uses household composition and occupancy patterns derived from historical and statistical data, based on the concept of fixed, a priori schedules [43]. Schedules are defined independently of the predicted conditions during the simulation, and they represent simplified and predictable activity scenarios according to day-types. Schedules derive either from standards or from observation-based statistically aggregated data and include deterministic rules, where actions are perceived as direct consequences of one or more drivers. One limitation to this approach, though, is that given their deterministic nature, schedules typically represent environments where the occupants' behaviour is always foreseeable and repeatable [42].

The DREEM model builds on the simplicity of this approach using a heuristic approach to address the limitation of repeatability. In particular, the module distinguishes three states of occupancy. States are described in terms of a combined state variable, which consists of a first digit describing the occupancy state (1 = "at home", 0 = "not at home") and a second digit describing the activity state (1 = "active", 0 = "not active"). In order to refine the modelling of the timing of electricity demand, a second mechanism, based on the occupants' activities, is used. Statistical data is used to create profiles, but in this case they are "activity profiles," which show people's tendencies. For example, people tend to do cooking activities around mealtimes. Thus, each activity has its own daily profile. Furthermore, a weighted stochastic function is applied for some days or hours of the day to make occupants more stochastic in terms of their activity profiles (e.g., after-work/ school activities, etc.).

The next step is to link these activities to appliances. For example, watching television will obviously require a television to be in use, etc. The latter ensures that appliances are activated at appropriate times of day without need for detailed appliance usage statistics. For accurate demand modelling it is also important to account for the sharing of appliances and lighting. Sharing is dependent on the number of active occupants in a house at a given time and also on the appliance type in question, as the load profile very much depends on the occupancy pattern [44]. Thus, electronic equipment is activated, when appropriate, using a probability function, which depends on the active number of inhabitants. Each person that changes its state to active can trigger a device to be turned on, and in that event a random value between 0.7 and 1.3 is selected as weight for its power consumption. The resulting weighted consumption time series is scaled in magnitude to match the annual power consumption for electronics. As soon as a person leaves the house again, there is a probability that such a device turns off again. Finally, the module distinguishes between weekdays and weekends and holidays (i.e., no occupancy), and ensures that no appliances are left on when nobody is at home, except from individual freezers/ refrigerators and routers.

C_3M_2: Appliances

This module builds on the simplicity of engineering methods, determining the relationships between end-uses and electricity demand, to estimate the final electricity consumption of the building under study. Engineering methods rely on information of the building characteristics and end-uses themselves to calculate consumption based on power ratings and use characteristics. Consequently, one strength of this technique is the ability to model new technologies solely based on their traits. Additionally, the

"Distributions" technique utilises distributions of appliance ownership and use with common appliance ratings to calculate consumption of each end-use [13]. End-uses are specified in the "Occupancy" module, which feeds this module with turn on/ off and TOU data. The product of appliance ownership, appliance use, appliance rating, and the inverse of appliance efficiency, results in the electricity consumption. This bottom-up approach has the capability of determining the total consumption of the building without relying on historical data.

C3M3: Heating, Ventilation, and Air-Conditioning

Heating, ventilation, and air-conditioning (HVAC) systems plays a vital role in DSM modelling [45]. As a result, compared to monolithic approaches of existing models, addressing the topic of end-use in an integrated top-down way, the operation of the HVAC system is separately handled by this individual module, also allowing for the further inclusion of technologies that enable demand flexibility, as smart thermostats. Typically, different modelling approaches require different levels of user skills, resolution and details, and different levels of user customisation capability. Higher explicitness in system representation requires more knowledge about the system because of the increasing number of parameters for system specification, often difficult to obtain as they are not supplied by manufacturers. Additionally, higher explicitness implies more intensive computational requirements, which makes the analysis of the results more complicated. However, most design techniques do not require detailed system modelling, as final consumption can be estimated by using simpler modelling approaches. As a result, a conceptual system representation becomes sufficient when only load predictions are considered and/ or energy saving options are investigated [46]. This module builds on the advantages of such an approach (e.g., lower user expertise required, less input data, less intense computations, easier results analysis, etc.) by modeling the HVAC system as a split AC unit for electric space heating/ cooling, along with an electric pump for indoor ventilation and infiltration. This module is controlled by the "Smart thermostat" module that allows the HVAC system to properly operate and to provide adequate services, adjusting the control variables to meet the required setpoint in spite of disturbances and considering the dynamic system's characteristics.

4.3.4. C_4: Thermal comfort

A large proportion of the energy consumed in buildings is used for thermal comfort and, thus, having a good understanding of its implications is imperative for accurate modelling [47], especially when studying aspects of energy poverty. However, to the best of the authors' knowledge, most of the models in the field do not include the thermal comfort topic under their scope. Thermal comfort is defined as "*that condition of mind that expresses satisfaction with the thermal environment*" and has a great influence on the productivity of indoor building occupants [48]. Dissatisfaction may be caused by warm or cool discomfort of the body, or by unwanted heating/ cooling [49]. Addressing modelling gaps, this single-module component is responsible for determining, based on international standards, appropriate indoor thermal conditions and temperature ranges that result in thermal satisfaction of the occupants based on the "DIN EN ISO 7730" [50], "ASHRAE 55" [51], and "EN 15251" [52] standards. It builds on the Fanger approach [53], using the characteristic numbers "Predicted Mean Vote (PMV)" and "Predicted Percentage of Dissatisfied (PPD)" to compute thermal comfort of occupants. The PMV index was selected, as it works well in AC applications and not naturally ventilated buildings [47].

Typically the PMV index is based on a theoretical model combined with the results from experiments and is written as a function of four environmental variables (temperature, T; relative humidity, φ; mean radiant temperature, T_{rm}; air velocity, υ), and two individual parameters (metabolic rate, M; clothing insulation, I_{CL}) [54]. Metabolic rate represents the heat generated within the body (met, 1met equals to 58.2 W/m^2 and is said to be the metabolomic rate of a seated person at rest) [55].

The module receives as input the activity profiles of the occupants at each time step and sets the metabolic rate, for simplification purposes, to the value of the most thermally discomfort person. Furthermore, clothing mediates convective, as well as radiative and evaporative heat exchange, and in the assessment standards this effect is solely incorporated by the basic thermal insulation value I_{CL} (clo is a unit used to express the thermal insulation provided by garments and clothing ensembles, with 1 clo=0.155 $m^2 \cdot K/W$). The component receives signal from the simulation calendar regarding the time of the year and respectively sets clothing insulation profiles based on tables with insulation values of sample clothing ensembles, as derived from the "ASHRAE 55" standard. Finally, for the PPD index the categorisation presented by the European EN 15251 standard is followed and further expanded by adding a supplementary subcategory, as presented in **Table 4.2**.

Table 4.2. Applicability of the thermal comfort categories of the EN 15251 standard as adapted in the context of this study (source: [52]).

Thermal state of the body as a whole			
Category	**PPD (%)**	**PMV**	**Explanation**
I	<6	-0.2 < PMV < +0.2	High level of expectation: recommended for spaces occupied by very sensitive and fragile persons with special requirements like handicapped, sick children, elderly persons, etc.
II	<10	-0.5 < PMV < +0.5	Normal level of expectation: used for new buildings and renovations.
III	<15	-0.7 < PMV < +0.7	Acceptable, moderate level of expectation: used for existing buildings.
IV			
(a)	<20	-1 < PMV < +1	Marginal level of expectation: values that should only be accepted for a very limited part of the day.
(b)	>20	PMV < -1 or PMV > +1	Inacceptable level of expectation: values outside the criteria for the above categories, that should only be accepted for a very limited part of the year.

4.3.5. C_5: Flexibility management

One of the main drawbacks of existing models is their inability to link the energy system to economic developments and technological breakthroughs. The DREEM model addresses this issue in a structured way for each application at hand. In particular, this component uses a bottom-up approach that initially specifies for each building under study the available flexible devices and technologies, synchronising their operation with the configurations of the occupants, where necessary, as obtained from the "Occupancy" module. The "Occupancy" module is used to create consistent profiles for the devices, meaning that devices requiring user interaction can only change their state when a person is at home. For flexible devices the usage patterns are generated using the household configuration and it is guaranteed that the start/ end times are synchronised with the occupancy profiles. At this version the DREEM model focuses on the inclusion of technologies as PV installations and electricity storage (i.e., batteries), and devices as smart thermostats and energy management control systems. The operation of this component's modules is controlled by the "Control strategies" component.

C_5M_1: Photovoltaic installation

This module models a simple small-scale PV installation (i.e., up to 10kWpeak) with orientation. The module takes as an input the direct and diffuse solar radiation, as derived from the "Weather/ Climate" component, based on historical irradiance data for the geography of interest, and the location and the orientation of the PV panel, specified by the surface tilt, latitude, and azimuth. The complete possible monthly energy yield of the PV installation is calculated during simulation and the power generated P_{PV} is computed as $P_{PV} = A \cdot f_{act} \cdot \eta \cdot TSI$, where A is the panel area, f_{act} is the fraction of the aperture area, η is the panel efficiency, and TSI is the total solar irradiation, which is the sum of direct and diffuse irradiation. This power is equal to $P_{PV} = v \cdot I$, where v is the voltage across the panel and i is the current that flows through the panel. Access-energy produced has to be fed into the electric grid and thus, a grid synchronisation is necessary.

C_5M_2: Electricity storage

This module takes as an input the power P_{bat} that should be stored in the battery ($P_{bat} > 0$), or that should be extracted from the battery ($P_{bat} < 0$), as generated from the "PV installation" module. It uses a fictitious conductance G, such that $P_{bat} = v \cdot I$ and $I = v \cdot G$, where v is the voltage difference across the pins and I is the current at the positive pin. The main output of the module is the state of charge (SOC) of the battery. While the module does not enforce the SOC to be between zero and one, each time it crosses this range, a warning will be written to the simulation log file. The module also does not limit the current through the battery, and it is linked to the "Control strategies" module, which provides appropriate control so that only a reasonable amount of power is exchanged and that the SOC remains between appropriate ranges.

C_5M_3: Smart thermostat

Typically, the performance of HVAC systems can be improved through optimised supervisory control strategies that adjust temperature setpoints to improve the operating efficiency [56]. Building heating/cooling control by condition means control with respect to indoor temperature [46], with the respective control systems being either time controllers (occupancy-based controllers), or condition-based controllers [57]. This module builds on both approaches, modelling the HVAC control system as a typical arrangement of a thermostat and a timer. The thermostat is modelled as a typical Proportional-Integral-Derivative (PID) process controller, which receives the indoor temperature as a measured signal and, based on the difference of set and measured temperature, sends signal to the "HVAC" module to yield the necessary heat flow, which is then injected into the building as convective heat flow. However, tuning a PID controller is an important issue, as improper choice of the gains can make the whole system unstable [57]. To do so, the "Good Gain" method, a simple experimental method, which can be used on a real process (without any knowledge about the process to be controlled), or simulated system, was used [58]. Finally, a hysteresis element is also included in this module to allow the indoor air temperature to vary from the setpoint and always be kept within predetermined minimum and maximum levels, as derived from the "Thermal comfort" component.

4.3.6. C_6: Demand-Response

DR schemes offered to residential customers, providing directions for the development of products and services related to the smart-grid paradigm, are considered integral part of DSM modelling. However, most of the existing approaches deal with this topic in an isolated manner, usually exploring implications for the electricity market, and often omitting key aspects and features of end-use. The DREEM model addresses this gap, by bringing together all important aspects of end-use with a DR modelling framework that builds on the concept of time-based DR methods. Time-based DR methods are considered the most effective DSM strategies, because their inherent characteristics are more suitable to the "real-world" unsteady and fluctuating energy consumption patterns [8]. This component simulates DR mechanisms as derived through: **(i).** considering Hourly Electricity Prices (HEPs) and a Limiting Price (LP), and **(ii).** a more "real-world" situation, in which a central planner that attempts to maximise flexibility value by issuing DR signals, is assumed. This entity learns the optimal policy that maximises its revenues through an optimisation approach based on Reinforcement Learning (RL) theory. Although RL theory has already been used to address the topic of DR [59], to the best of our knowledge, this is the first time that a model, which brings together all the guiding principles of DSM modelling, uses machine learning to illustrate the decision-making framework and solve the dynamic pricing problem in a hierarchical electricity market that considers both service provider's profit and consumer's costs.

C_6M_1: Hourly Electricity Prices

The electricity prices are different at each pricing period and this price variation, compared to a constant benchmark (i.e., LP), is used to issue DR signals. HEPs are fed in the module as historical market data for the geographical context of interest, while the LP is selected from a set of plausible constant values, as presented in similar literature studies [60].

C_6M_2: A "real-world" situation

RL techniques provide insights of how agents may optimise their control of an environment. For successful implementation in complex realistic situations, agents must derive efficient representations of the environment and learn from past experience to handle new situations [61]. This module considers tasks in which the agent interacts with an environment through a sequence of observations, actions, and rewards. The goal of the agent is to select actions through an optimal policy that maximises cumulative future reward. The RL agent (i.e., central planner) interacts with the environment (i.e., day-ahead market and households) over time. At each time step t (i.e., each hour), the agent receives a state s_t in a state space S, and selects an action a_t from an action space A_s, following a policy π (a_t| s_t), which simulates the agent's behaviour (i.e., mapping from state s_t to actions a_t). The agent then receives a scalar reward (or penalty) r_t according to the value of its action and transitions to the next state s_{t+1} according to the environment dynamics and the reward function $R(s,a)$. This approach is episodic, with the process continuing until the agent reaches a terminal state and then it restarts (i.e., next episode). The return $R_t = \sum_{k=0}^{\infty} \gamma^k \cdot r_{t+k}$ is the discounted, accumulated reward with a discount factor $\gamma \in (0,1]$. The agent intends to maximise the expectation of such long-term return from each state and the problem is set up in discrete state and actions spaces. The output of the RL algorithm is a value function, which is the prediction of the expected, accumulative, discounted, future reward, measuring how good each state, or each state-action pair is.

4.3.7. C_7: Control strategies

Finally, an important aspect of DSM modelling, often omitted by existing models, or addressed in an isolated manner, is the inclusion of practical load control strategies that will allow price-based DR signals, towards the smooth operation of the smart-grid paradigm. To address this modelling need, the DREEM model includes a whole component responsible for the energy management supervision strategy towards the achievement of energy savings and cost-effectiveness. In general, supervisory control systems are high-level controllers that allow complete consideration of the system's characteristics and interactions among all elements and their associated variables [46]. This component builds on the concept of rule-based control strategies, such as presented in previous studies [62]. The suggested control algorithm is heuristic and uses the minimum and normal indoor temperature setpoints, the indoor temperature of the building, and the SOC of the storage. The algorithm controls the operation of the HVAC system and the PV and storage installations and regulates the temperature setpoints for space heating/ cooling and the storage charging/ discharging. The indoor air temperature is generally maintained at a constant setpoint that allows thermal comfort during occupied periods, while the control strategy provides proper setpoints for minimum energy use, without jeopardising thermal comfort. The proposed changes to setpoints are made by increasing, or decreasing the indoor air temperature setpoint by small, fixed values to achieve further energy savings, while respecting thermal comfort of the occupants. The algorithm also allows for considering DR events to enable better energy savings for consumers through DSM supervision. The main advantages of such control strategies are that they: **(i).** use the dynamic, or time-dependent increment change of controller setpoints in response to any significant change in outdoor conditions or thermal loads by considering the dynamic interaction of several factors, such as indoor and supply air temperature, and **(ii).** require neither a detailed multi-zone variable air volume model, nor an optimisation algorithm.

4.4. Case study

In this section the applicability of the DREEM model is demonstrated for the geographical and socioeconomic context of Greece. Located in Southern Europe, Greece is a transcontinental country, strategically located at the crossroads of Europe, Asia, and Africa, with a diverse geographical landscape and a large potential in RES (i.e., high solar irradiation levels), which makes it an attractive market choice for both small-scale PV owners and suppliers [63]. Furthermore, due to its numerous islands, electricity interconnection of the islands with the mainland remains a continuous challenge, with the non-interconnected islands mainly depending on conventional generation units. As a result, Greece makes a reasonable selection for a decarbonised vision of an electricity sector that also relies on decentralised generation and storage. The parameterisation of the individual components/ modules of the DREEM model is presented in the next sections, along with key data inputs/ outputs, to explore the energy performance of a single-family residence in the city of Athens, for one-year period (i.e., 1/1-31/12 2020), by testing the following two scenarios:

1. **Business-As-Usual ("SC1"):** The family consumes energy according to their daily needs, maintaining indoor temperature at comfort levels.
2. **Flexibility through provision of services to the grid ("SC2"):** The family invests in solar PV and electricity storage installations, and in a smart thermostat and an advanced control device that regulates the dwelling's energy performance, while complying, if possible, to dynamic market-based DR signals. The suggested control function ensures that RES self-consumption and thermal comfort of consumers are not compromised. As a result, the potential for additional revenue and benefits through the provision of services to the grid is evaluated.

Additionally, the DREEM model allows for seasonal simulations to account for the effects of weather and temperature on electricity demand as in [64]. The three typical seasonal profiles considered to present simulation results are: **(I). Period 1 (mild weather):** April, May, October, and November, **(II). Period 2 (hot weather):** June to September, and **(III). Period 3 (cold weather):** December to March.

4.4.1. Weather/ Climate data

The International Weather for Energy Calculations (IWEC) weather data is used [65]. The data on weather conditions were accumulated by recording an 18-year period (1982-1999) in Athens region. The data consists of location information, as latitude, longitude, and the time zone relative to Greenwich Mean Time, along with detailed hourly data of temperature, relative humidity, wind speed and direction, solar direction and radiation, etc. The annual temperature profile for the city of Athens as generated by the model is presented in **Appendix C.2**. The average annual temperature is estimated at 18.8^{o}C.

4.4.2. Building envelope & properties

The building envelope under study is a detached house, modelled as a thermal zone with four elements for exterior walls, interior walls, floor plate, and roof, with two windows with double glazing. The floor area of the building is 81m^2 and its height is 3.2m. Specifications of the building envelope and properties of different elements are set according to the specifications of the Greek Energy Performance Buildings Directive (EPBD), or "KENAK" regulation [66], as defined in the guidelines of the Technical Chamber of Greece (TEE-TCG) [67]. The properties are summarised in **Appendix C.3**, and the U-values of each structure element is less than the maximum requirements set by the TEE-TCG.

4.4.3. Domestic occupancy and energy demand modelling

A typical Greek nuclear (conjugal) family is assumed, consisting of two working parents and two children; one school-aged child (6-11 years old) and one adolescent (12-18 years old). For their occupancy profiles, fixed typical schedules were adopted. These schedules were not distinguished between seasonal profiles, as typically parents' working hours, or children's school hours, are not differentiated between summer and winter. On the other hand, these schedules were differentiated between weekdays and weekends, while it was assumed that all the family members were out of their residence for family vacations for one week during Christmas and Easter, and for two weeks during summer. Finally, a weighted stochastic function was applied for some days and evening hours to account for some after-work/ school activities (e.g., sports, arts, outdoor education, extracurricular activities, etc.). Higher weight values were chosen for the case of weekends, as typically people tend to do such activities when they do not work. Activity profiles showing occupants' tendencies were also created to account for the types of end-use and for sleeping. These profiles were also distinguished between weekdays and weekends as people tend to do more housekeeping activities during weekends.

Furthermore, all European Union (EU) Member States participate in community statistical programmes, part of which is the "Development of detailed statistics on energy consumption in households (SECH)." The SECH survey aimed at collecting data and valuable information on the household energy consumption, on the type of final energy, and on the sources of energy used from the households, compared with demographic and economic characteristics. To the best of our knowledge, this survey is the most recent one for the residential sector in Greece. More details on the questionnaire design, respondent targeting and quota sampling are provided in the respective report [68]. The appliances in the model were configured using the SECH 2012-2013 survey data (**Appendix C.4**), describing their mean total daily energy demand and associated power use characteristics, including steady-state consumption, or typical use cycles as appropriate, along with ownership levels. For missing values, a regression imputation analysis for Missing Completely At Random (MCAR) data was performed [69]. Additionally, activity profiles and end-uses for appliances were specified according to the statistics and the occupancy profiles and were distinguished between working days and weekends.

4.4.4. Thermal comfort: Acceptable indoor temperature setpoints

One of the key findings from various field studies on adaptive thermal comfort is the correlation between the mean indoor air temperature (T_{air}) and the prevailing mean outdoor air temperature (T_o). To define the indoor temperature setpoints that maintain thermal comfort for Period 1, a recent adaptive model, as developed by de Dear and Brager, especially used for HVAC applications, was considered [70]. On the other hand, to define the acceptable ranges of indoor air temperature for Period 2 and Period 3, the correlation between PMV values and indoor temperatures was studied in a similar way with the one presented in previous scientific studies [71]. Both periods were simulated to determine the critical PMV values (minimum and maximum) and indoor temperatures, and the values obtained were used to find the linear trendline of PMV as a function of the indoor air temperature. The linear trendlines were then used to determine the acceptable ranges of indoor temperature setpoints, by inserting lower and upper limits of PMV values, as presented in the respective categories in **Table 4.2**, into the equations of the linear trendlines. Minimum PMV values are defined for heating, while maximum for cooling. **Appendix C.5** presents the linear trendlines of indoor air temperatures for Period 2 and Period 3. The ranges of the acceptable indoor temperature setpoints for all periods under consideration are presented in **Table 4.3**.

Table 4.3. Acceptable indoor air temperature ranges for the building envelope under study.

Period 1									Period 2	Period 3
April		May		October		November		Category	Min-Max T_{air} (°C)	
T_o	T_{air}	T_o	T_{air}	T_o	T_{air}	T_o	T_{air}	I	22.9 - 24.6	21.7 – 22.6
								II	22.3 - 25.1	21.2 – 23.0
15.24	22.90	19.85	23.38	18.84	23.26	14.49	22.83	III	22.0 - 25.5	20.8 – 23.4
								IV(a)	21.5 - 26.0	20.2 – 23.9

4.4.5. Photovoltaic and storage installations

Following Waffenschmidt 2014, a sizing of 1-to-1 for storage capacity to PV peak power was assumed [72], with a typical capacity for a small residential stationary storage selected (i.e., 5kWpeak) as stated in [73], with nominal voltage of 12 volts. Since storing power from the grid is out of the context of the case study presented, Direct Current (DC) storage is a suitable choice, as it is typically applied when the primary aim is to store solar energy directly from the PV panels and use it during peak loads. Additionally, DC storage is lower cost, enabling retrofit in existing infrastructure, and it leverages existing PV inverter technology.

4.4.6. Demand-Response: Real-time price-based signals

Building on the "real-world" approach, the state space of the problem at hand is defined as a three-variable vector $S = [s_1, s_2, s_3]$, where s_1 corresponds to the System Marginal Price (SMP), s_2 to the demand forecast for each household, and s_3 to the actual demand of each household. For the initial values of the state variables, historical data of 2015 for the Greek day-ahead market was used, to start the algorithmic solution from a realistic starting point in terms of the market signals that could be issued. The initial values of the state variables are visualised in **Appendix C.6**, and were scaled down to the average consumer level using the mean annual consumption of electrical power per household in Greece (i.e., 3,750 kWh) [74].

Additionally, it was also assumed that the agent buys electricity in SMP based on the day-ahead market and charges the consumers according to the most common residential tariff (i.e., "G_1" tariff) of the Public Power Corporation S.A. in Greece. The price charged varies according to the total amount of electricity consumed during the billing period [75] and the different charges are summarised in **Appendix C.6**. Finally, it was assumed that the agent has to choose the optimal action to maximise its profits from the action space $A = [a_1, a_2, a_3, a_4, a_5]$, which corresponds to "No Signal" (a_1), "Signal 1: Shift total demand by ≥5%" (a_2), "Signal 2: Shift total demand by ≥10%" (a_3), "Signal 3: Shift total demand by ≥15%" (a_4), and "Signal 4: Shift total demand by ≥20%" (a_5). To do so, a Python implementation of the SARSA (**S**tate **A**ction **R**eward (next)**S**tate (next)**A**ction) algorithm was developed, as adapted [76] and further presented in **Appendix C.6**.

4.4.7. Control supervision

Load shifting is one of the main DR manners, as DR schemes can be more beneficial, if suppliers can increase the value of the maximum shiftable load [77]. The control algorithm assumes that occupants comply with the DR signals, if active at home, shifting energy demand related to appliances to the next hour they are active, and a DR event is not signalled. **Figure 4.2** depicts the flowchart of the supervisory control strategy implemented in the context of the case study presented, and further explained in **Appendix C.7**. Note that T_{set} is the indoor temperature setpoint, $T_{set,normal}$ is the normal indoor temperature setpoint, and $T_{set,min}$ is the minimum acceptable indoor temperature setpoint.

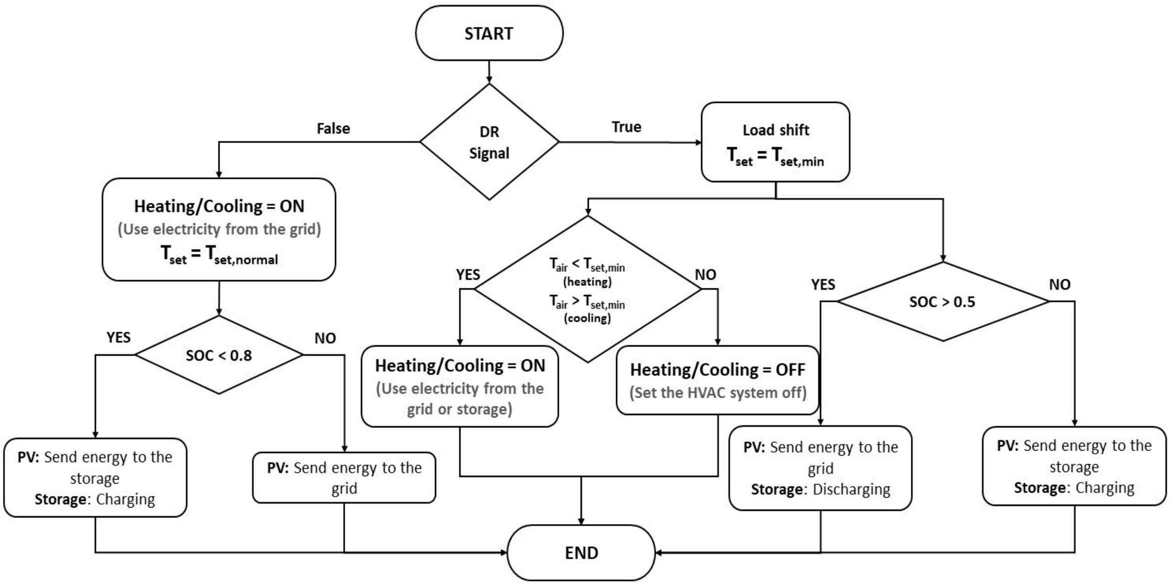


Figure 4.2. Flowchart of the Momentary Control Algorithm used in the context of the case study presented as implemented by the "Control strategies" component.

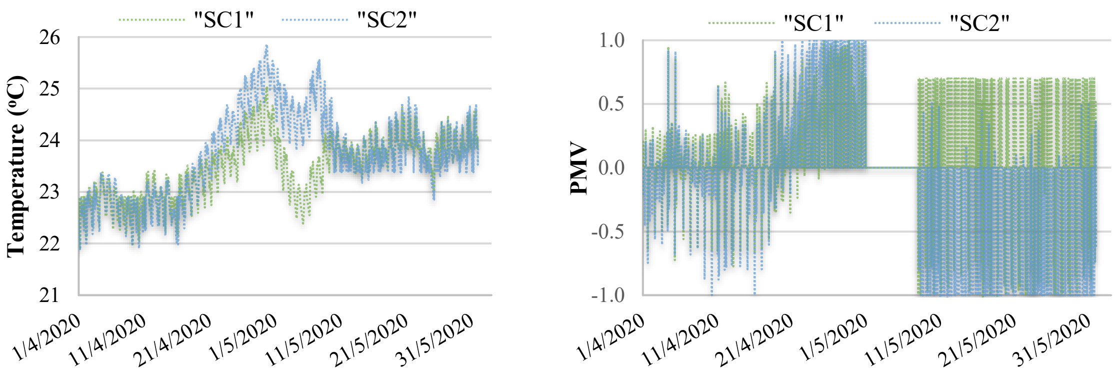
Example simulation outputs of the DREEM model for indicative single weekdays and weekend days in winter and summer are presented in **Appendix C.8**.

4.5. Results and discussion

Figure 4.3, **Figure 4.4**, **Figure 4.5**, **Figure 4.6**, and **Figure 4.7** present simulation results for both the scenarios "SC1" and "SC2" and for all seasonal profiles considered. Additionally, **Table 4.4** summarises quantified benefits of demand flexibility for consumers in the residential sector in Greece, if they invest in PV and storage installations, along with smart devices (i.e., smart thermostat and energy management control system), while motivated to comply with dynamic DR signals ("SC2"). All simulations for each scenario and seasonal profile under study were performed using a Python interface with the Dymola environment (version 2018 FD01) on a standard PC with an Intel ® Core ™ i7- 6700U CPU @ 2.70 GHz and 8.0 GB RAM, with an average running time of 60.8 seconds. The latter shows the potential of the DREEM model to allow for fast simulations of complex, large systems, bringing together all the key aspects and guiding principles of DSM and BES modelling. Detailed simulation results for both the scenarios under study and all the three seasonal profiles considered are presented in **Appendix C.9**.

4.5.1. Period 1- Mild weather

a.



b.

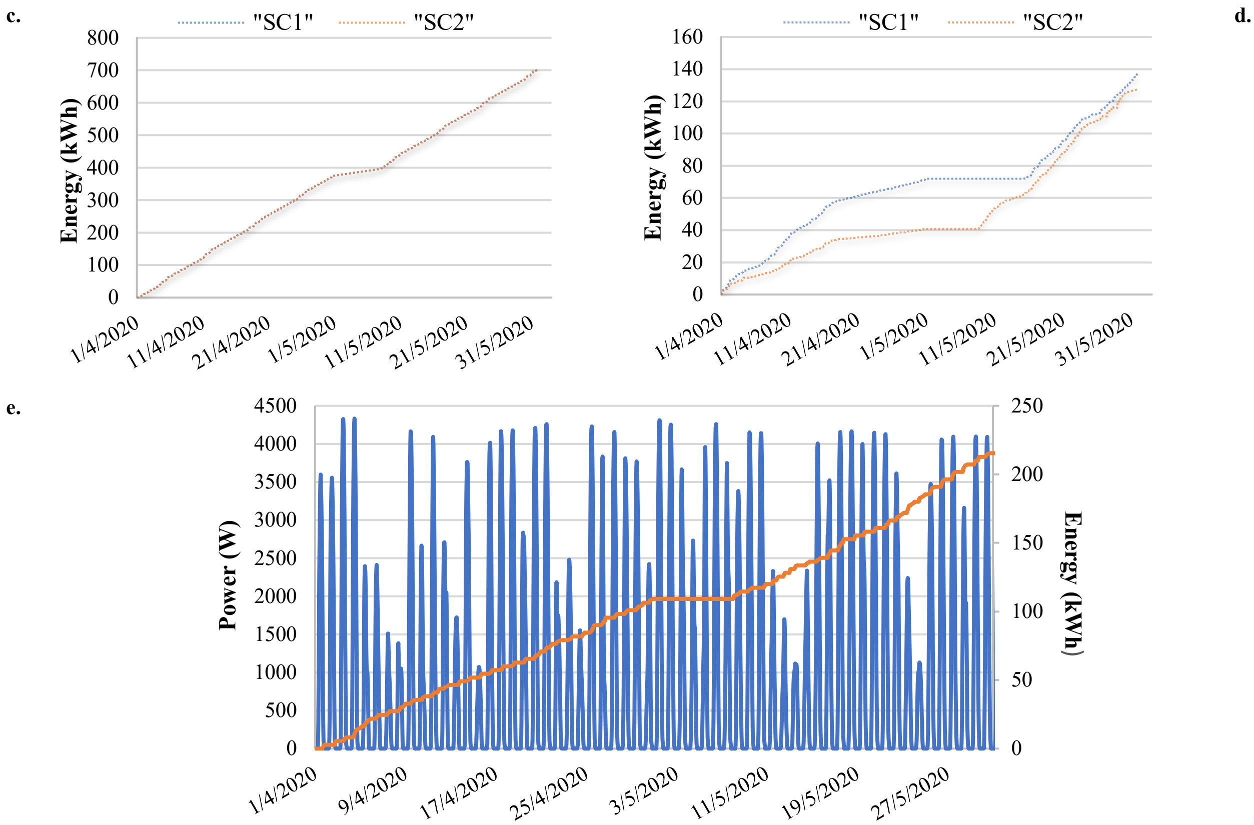
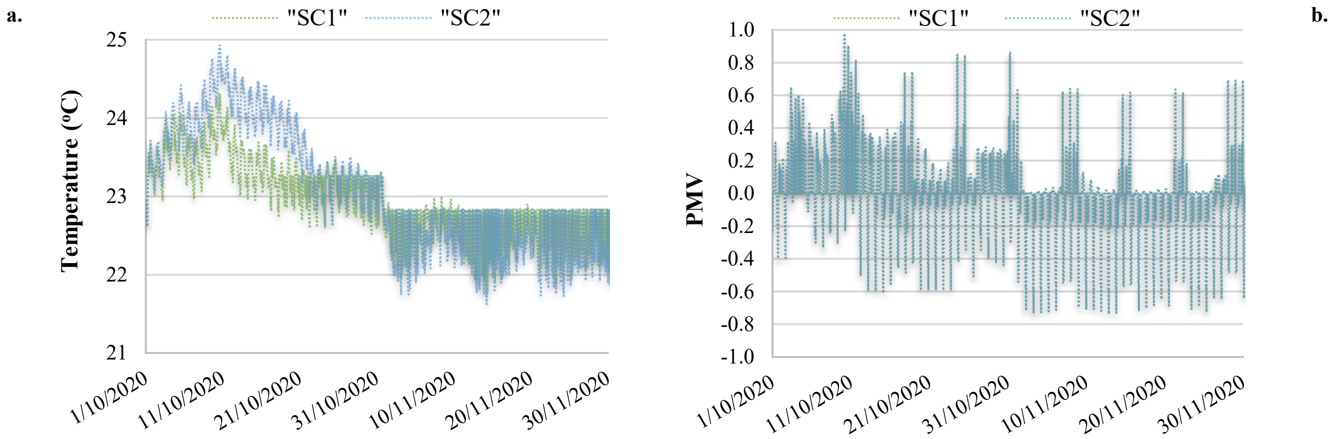


Figure 4.3. Simulation outcomes for the period April-May 2020, for both scenarios under study. **a.** Indoor temperature (°C), **b.** PMV-index of thermal comfort, **c.** Cumulative energy consumption (kWh) of appliances, **d.** Cumulative energy consumption (kWh) of the HVAC system, and **e.** Solar power (W) generation and energy (kWh) self-consumption owing to the PV-battery installations for the scenario "SC2."



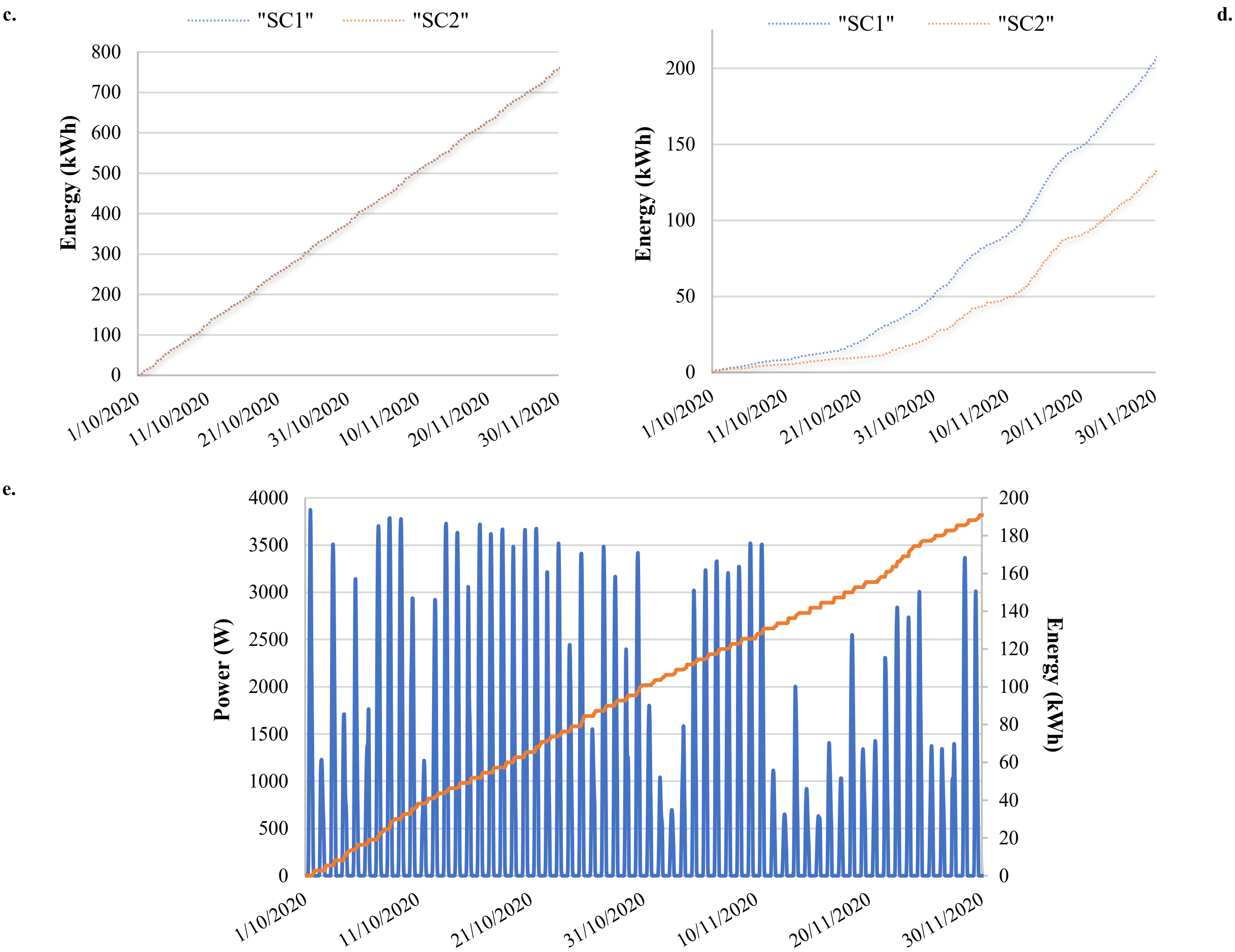
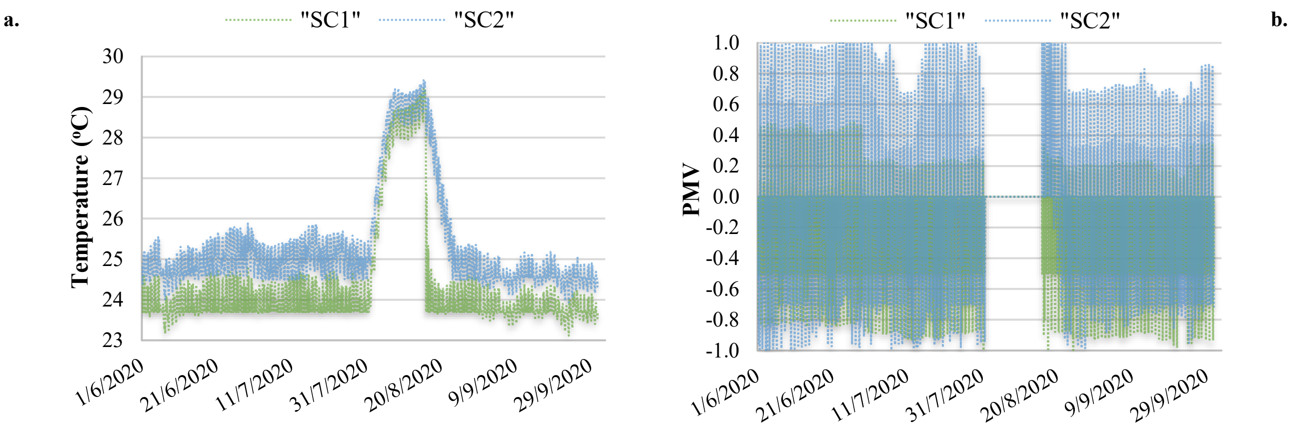


Figure 4.4. Simulation outcomes for the period October-November 2020, for both scenarios under study. **a.** Indoor temperature (°C), **b.** PMV-index of thermal comfort, **c.** Cumulative energy consumption (kWh) of appliances, **d.** Cumulative energy consumption (kWh) of the HVAC system, and **e.** Solar power (W) generation and energy (kWh) self-consumption owing to the PV-battery installations, for the scenario "SC2."

4.5.2. Period 2- Hot weather



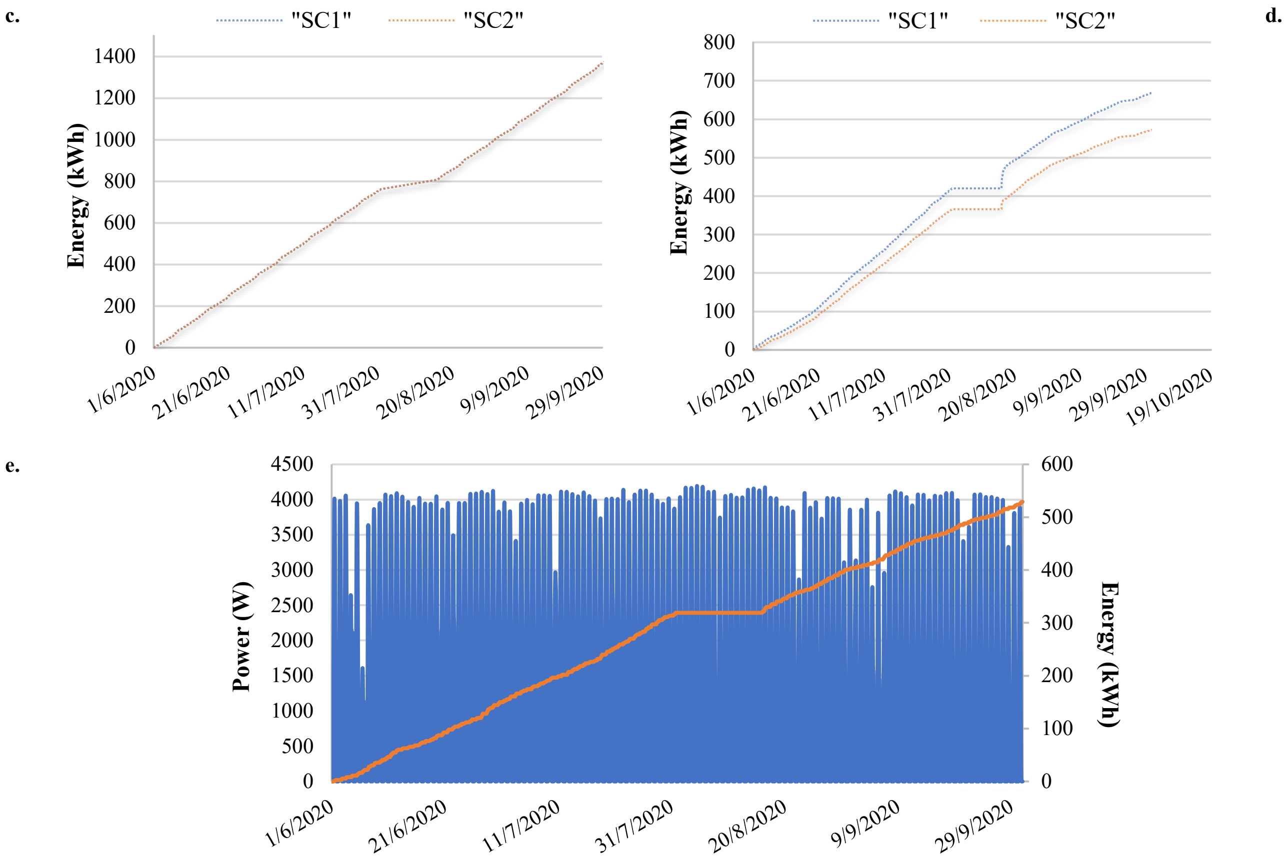
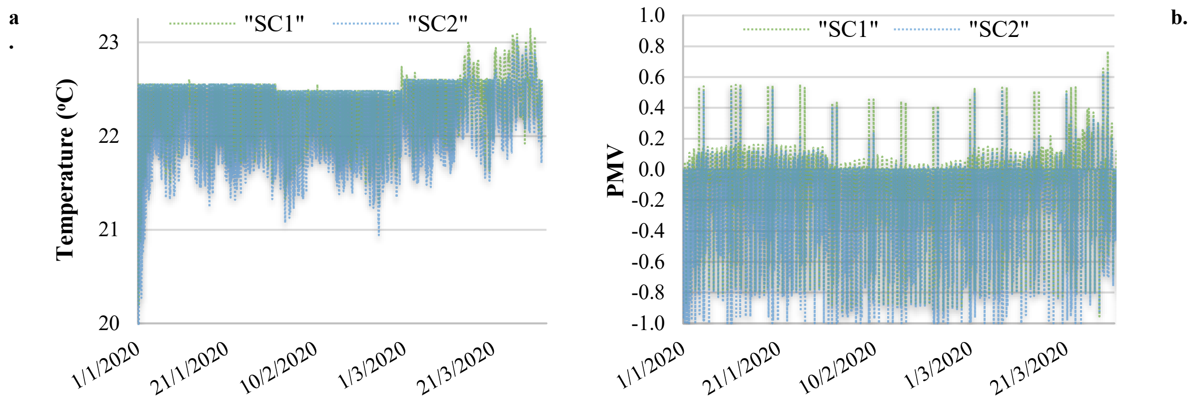
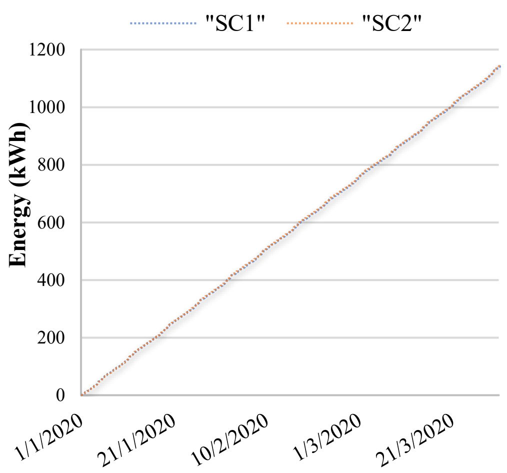


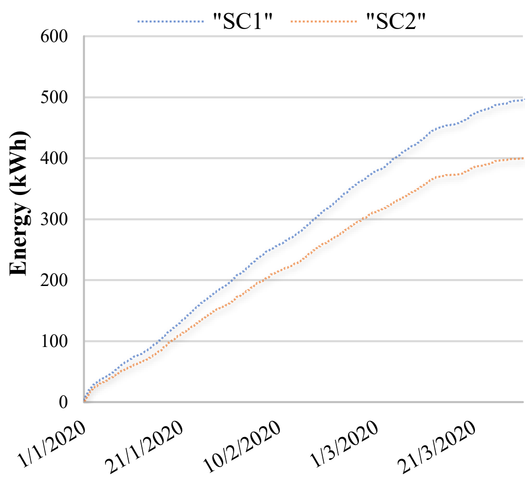
Figure 4.5. Simulation outcomes for the period June-September 2020, for both scenarios under study. **a.** Indoor temperature (ºC), **b.** PMV-index of thermal comfort, **c.** Cumulative energy consumption (kWh) of appliances, **d.** Cumulative energy consumption of the HVAC system (kWh), and **e.** Solar power generation (W) and energy self-consumption (kWh) owing to the PV-battery installations, for the scenario "SC2."

4.5.3. Period 3- Cold weather



c.





d.

e.

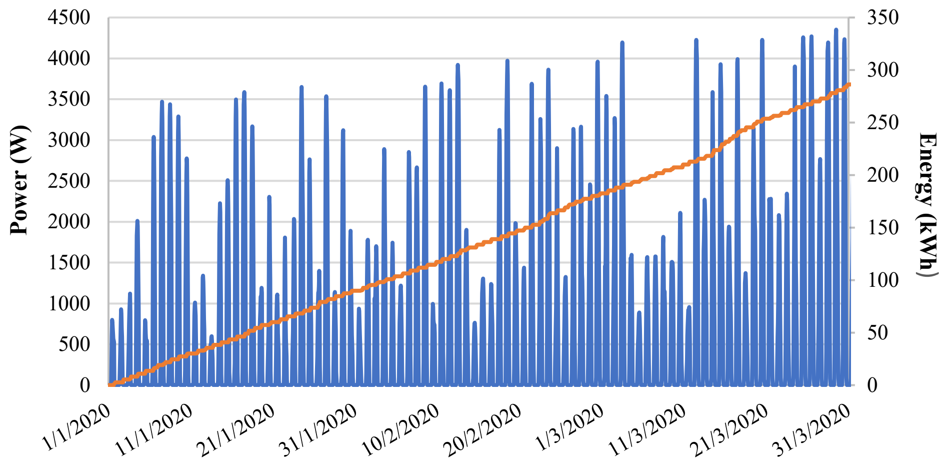
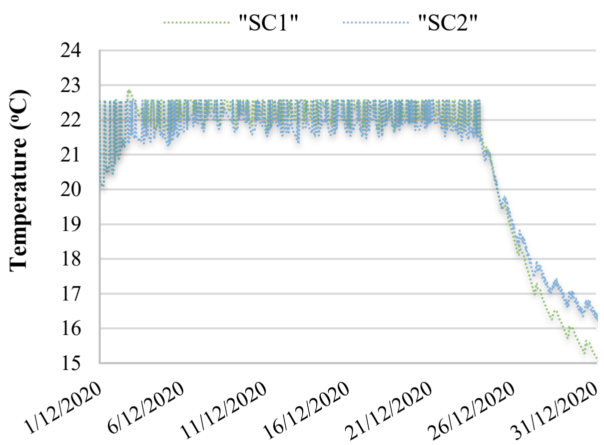
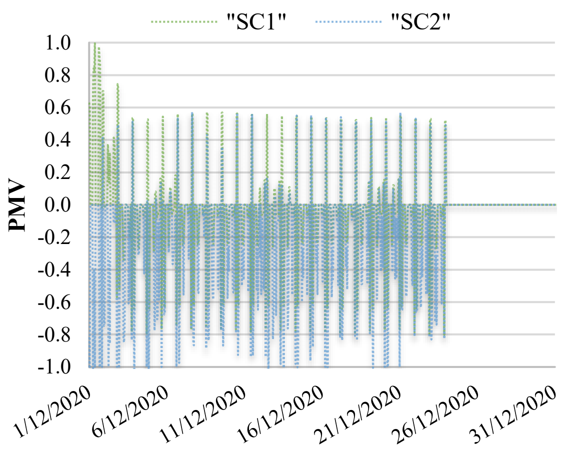


Figure 4.6. Simulation outcomes for the period January-March 2020, for both scenarios under study. **a.** Indoor temperature (ºC), **b.** PMV-index of thermal comfort, **c.** Cumulative energy consumption (kWh) of appliances, **d.** Cumulative energy consumption of the HVAC system (kWh), and **e.** Solar power generation (W) and energy self-consumption (kWh) owing to the PV-battery installations, for the scenario "SC2."

a.





b.

c. d.

e.

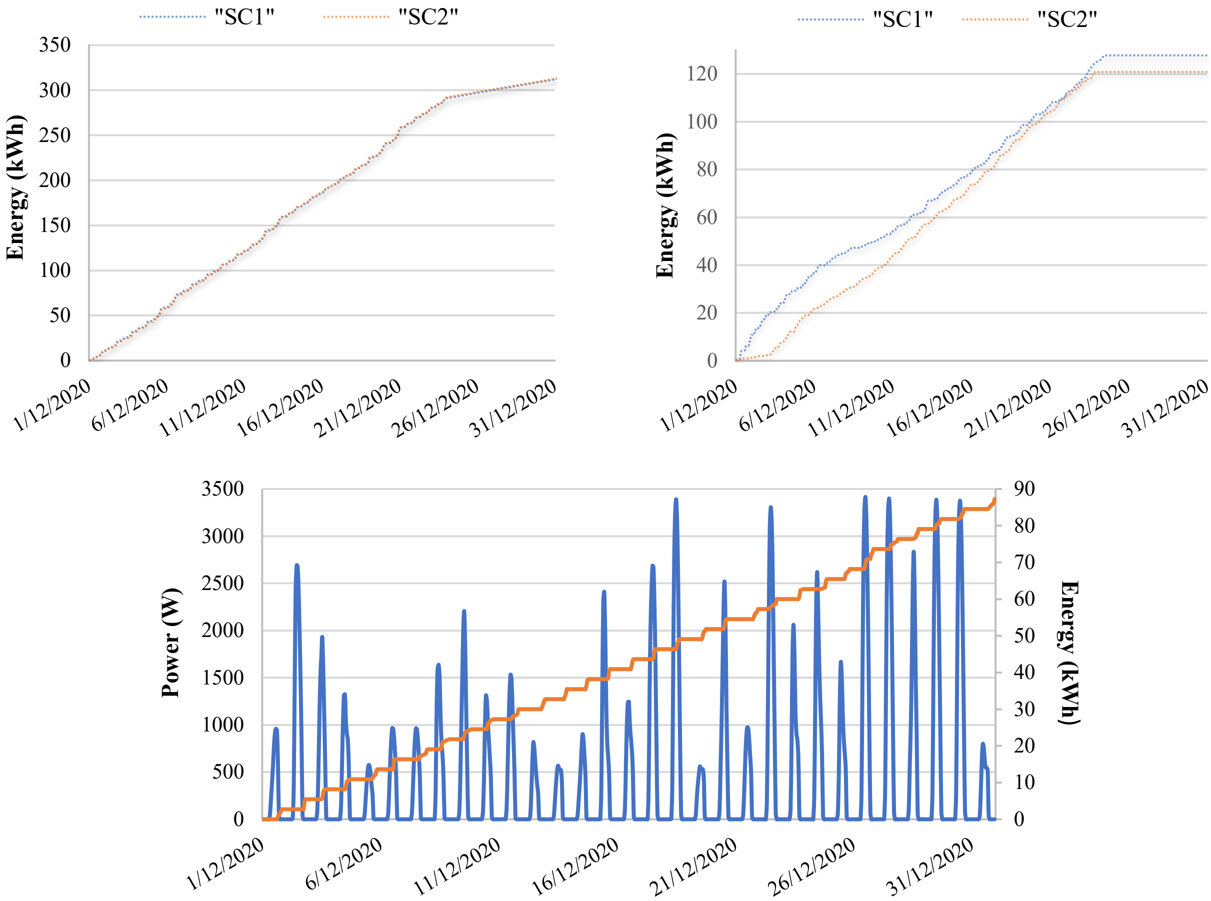


Figure 4.7. Simulation outcomes for the period of December 2020, for both scenarios under study. **a.** Indoor temperature (ºC), **b.** PMV-index of thermal comfort, **c.** Cumulative energy consumption (kWh) of appliances, **d.** Cumulative energy consumption of the HVAC system (kWh), and **e.** Solar power generation (W) and energy self-consumption (kWh) owing to the PV-battery installations, for the scenario "SC2."

Simulation results for the scenario "SC1" showed that the total annual electricity consumption for the case under study is 5,969.3 kWh. Assuming that consumers pay the "G_1" tariff, annual competitive electricity charges are €1,098.1. Considering the model's energy demand forecasting it becomes apparent at a first glance that there is a certain deviation between the final consumption as derived from the DREEM model, and the average annual electricity consumption per household in Greece (i.e., 3,750 kWh). However, this should be considered with the fact that the DREEM model focuses on electric space heating/ cooling systems, supporting recent trends in energy demand emerging out of the electrification of the heating sector. Considering that households in Greece still use oil as the primary energy source for main space heating systems, and that the total mean annual electricity consumption for space heating/ cooling per household is estimated at 112.5 kWh and 150 kWh respectively [74], simulation results shed light in full electrification scenarios of heating/ cooling in the Greek residential sector.

In particular, for a building envelope constructed post 2010 in the Climatic Zone B in Greece, which is considered highly energy efficient, full electrification of heating is estimated at 975.4 kWh, while full electrification of cooling is estimated at 669.1 kWh. This means that the full electrification of both heating and cooling is estimated at a total of 1,382 kWh of extra annual electricity consumption. Subtracting this amount of energy, the total electricity demand forecast, as derived from the DREEM model is 4,587.3 kWh, which is closer to the annual average demand in Greece. However, results from the SECH 2012-2013 survey data [68] reveal that the average number of occupants per households in the Greek residential sector is almost two and a half persons. Considering that the current study focused on a four members family (15.83% according to the statistical data), it is obvious that the DREEM model, while not developed solely for this purpose, forecasts electricity demand adequately.

Table 4.4. Quantified benefits of demand flexibility and self-consumption for consumers in the residential sector in Greece, for the building envelope under study.

Total Energy Savings (kWh)					**Total Financial Savings (€)**				
Period 1		**Period 2**	**Period 3**		**Period 1**		**Period 2**	**Period 3**	
Ap-My	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**	**Ap-My**	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**
228.3 (27.14%)	266.3 (27.18%)		386.0 (23.41%)	88.4 (20.13%)			-		
497.3 (27.31%)		626.0 (30.43%)	475.6 (22.78%)		91.9 (31.23%)		179.7 (45.08%)	143.8 (35.57%)	
		1,598.9 (26.80%)					**416.4 (37.86%)**		

On the other hand, results from scenario "SC2" indicated that, if the family under study invested in solar PV and storage installations, along with smart thermostat and energy management control system infrastructure, and agreed to a dynamic DR regime, total annual electricity consumption would be 4,365.8 kWh. In this case competitive electricity charges would be €681.9, while energy savings of 1,603.8 kWh and financial savings of €416.4 could be achieved. In summary, modelling findings indicate that PV self-consumption with storage and other infrastructure combined with dynamic market DR signals, could bring significant savings to consumers, mainly due to less electricity absorbed from the grid. This is also validated by literature studies acknowledging that the effect of load shifting is more effective if combined with PV self-consumption due to the diurnal cycle of PV and the fact that many shiftable load follow the same diurnal cycle pattern [78].

However, literature studies acknowledge that PV self-consumption can be fundamentally negative for power suppliers [79]. Especially for the case of Greece, Nikas et al., (2019) showed that allowing PV self-consumption with storage in the residential sector could force generators to bid higher prices for their capacity, leading to an increase in the retail price of electricity. This way generators and suppliers could counterbalance revenue losses owing to self-consumption and the limited flexibility of the current Greek electricity market [2]. These results highlighted a consequential risk that must be incorporated into future policymaking, as this development could expose vulnerable social groups and customers to burdensome charges. The study concluded that policymakers in Greece should support smart self-consumption, triggered by measures that have a broader view of the system's state, and activated based on price signals. Additionally, successful DR depends mainly on the capabilities of end-users in altering their loads with a favourable manner for both the power suppliers and themselves [80].

To this end, results from the RL algorithm (**Figure 4.8**) showed that occupants, during the one-year period of simulation, could comply with the 75.06% of the total signals issued, altering their demand and adjusting thermostat setpoints to less comfortable levels, with a favourable manner for both the supplier and them. In particular, simulation results showed that supporting smart self-consumption in Greece through dynamic price signals allows the electricity supplier to counterbalance revenue losses due to self-consumption by a margin of 13.15%, which, given the charges assumed, equals to €33/ household per annum. Scaling up at a national level, this is equivalent to a total offset in the range of €239 to €256 million.

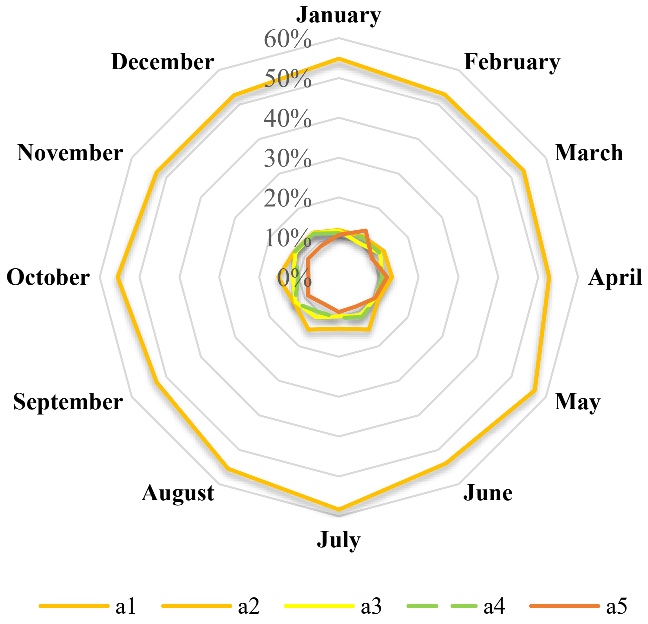


Figure 4.8. Quantification of the optimal demand-response policy according to the reinforcement learning algorithm.

On the other hand, simulation results also showed that promoting the full electrification of heating/ cooling in the Greek residential sector could lead to an extra annual electricity consumption of 1,382 kWh. This extra amount of electricity sold to consumers could bring the supplier an additional annual revenue of €266.24 per household, which scaling up at a national level is equivalent to a total profit in the range of €1.92 to €2.06 billion. These estimations are rather conservative, considering that the building envelope under study is considered highly energy efficient, and shall be further explored for all the residential building typologies in Greece. However, they provide strong evidence, that by promoting smart self-consumption, along with the electrification of the heating sector in Greece, revenue losses could be offsetted, and considerable profits for the energy supplier could be achieved. As a result, further revenue opportunities for energy suppliers could also rise through the promotion of electrical smart building-scale technologies that allow energy savings, coupled with electricity generation from RES. This is also acknowledged by scientific literature suggesting a strong technoeconomic viability when integrating smart AC systems with solar PV generation [81].

While findings of this chapter suggest that a shift to a decentralised vision of a low carbon future electricity system in Greece, where consumers generate and store clean energy locally, and are motivated to comply with DR signals, is a "win-win" situation for all actors involved, an important implication should be highlighted. Part of this future electricity infrastructure will be only developed if consumers are willing to invest in technological capabilities. Before consumers choose to expose themselves to bilateral dynamic electricity price contracts with their suppliers, they should first pursue the technological capabilities that enable demand flexibility. Considering that it is unlikely for consumers to invest in new technological capabilities having flexibility of the electricity system as their primary goal, it is reasonable to assume that consumers may only invest according to a value stemming from increased proportion of the self-produced electricity that they consume. While technological infrastructure is already available, though, business models and regulatory innovation are needed in order to find ways to maximise the value of the technological capabilities, as well as to monetise them, to compensate consumers. This is also acknowledged by recent studies in the scientific literature [82].

The current European regulatory framework leads to conditions where business models do not bring the full value of demand-side capabilities, even when the latter are already there, due to conflicts between the interests of consumers and market actors [83]. Given that in modern energy systems technological innovation will continuously pose new challenges to existing regulatory frameworks, innovation in regulation should be as important as regulating innovation [84]. As a result, efficient policymaking around Europe should explore “game-changer” business models that incentivise all involved actors to incorporate demand flexibility into the markets that can valorise it.

For starters, the proposed business models and applications should not require significant changes in the current regulatory framework, or in the current operation of the power market. As findings in this study indicated, a reasonable start for EU Member States is focusing on the benefits from integrating demand flexibility into the retailing operations of the utilities. Demand flexibility can be a valuable resource for suppliers when they manage their (physical) open position. Especially in view of a high-RES market design compatible with the EU Target Electricity Model [85], demand flexibility can supplement their trades to minimise the costs of short-term electricity procurement.

Another potential starting point could also be the EE obligation schemes (EEOS) recently introduced, especially in countries where awareness and maturity regarding energy savings and services market is relatively improved [86]. The maturity of the energy service market can be benefited by such schemes, since they usually operate as a driver to generators and suppliers for further business development, rather than obstacles, also inducing cost reduction of penalties for non-compliance with the EEOs.

Especially in Greece, building on the modelling outcomes of this chapter, policymaking should focus on promoting small-scale PV with technologies as battery storage or smart thermostats. Considering the existing ambiguity in the PV market in Greece [87], such an infrastructure could generate additional sources of revenue for consumers, which could counterbalance the phase out of the previous feed-in-tariff (FiT) scheme [88]. In particular, policy efforts should focus on more market-based structures by avoiding cross-subsidisation, along with appropriate promotion campaigns that will inform consumers on the benefits of self-consumption and its influence on their electricity bill. This should be evaluated along with the fact that electricity storage manufacturers are promising revolutionary progress regarding cost reductions in the coming years [89], and that PV self-consumption can balance the frequency and magnitude of peak generation events that stress the distribution network [90].

Furthermore, observing thermal comfort of occupants for each period under study, it is evident that the PMV index is constantly inside the range [-1,1], which according to the PPD index indicate an acceptable maximum discomfort level of 20%. The latter results from the fact that the DREEM model includes a detailed “Thermal Comfort” component, allowing to predict in advance the comfort ranges for each period and building typology under study. By allowing control algorithms to coordinate with such a component and smart devices as smart thermostats, simulation results indicated that consumers could achieve cost-effectiveness and energy savings without significant sacrifices on thermal comfort or other energy services. This partially contradicts literature studies acknowledging that DR control strategies realised in a passive manner through temperature setpoint adjustments, result in unacceptable indoor environment that impair occupants’ performance [80]. Considering that the Momentary Control Algorithm implemented in this study is not the best practice, more nuanced and advanced algorithmic approaches can be explored, revealing the full potential of the rule-based control strategies.

Overall, simulation results show the potential of the DREEM model to quantify benefits of demand flexibility, primarily for consumers in the residential sector, and energy providers, embodying key capabilities that are not found together in existing models. The distinguished features of the model make it competitive, compared to existing work in the field, as it provides dynamic high-resolution simulation results for a whole year period in less than 5 minutes, rather than one day period [91], a limited period (i.e., 15-20 days) [92], or a specific period of time [93], while allowing:

- The optimal control of HVAC systems in response to real-time price-based DR signals, also considering seasonal variability to reflect the changing level of demand between winter and summer, rather than focusing on a single period [94].
- To bring together all important aspects of DSM and BES modelling, achieving in parallel optimal trade-offs among electricity costs, thermal comfort, and peak power reductions in a dynamic electricity environment, rather than only focusing on individual aspects of end-use [95].
- To test different enabling technologies (e.g., energy storage, energy management control systems, etc.) in response to price-based DR signals, rather than only focusing on the most commonly studied case of PV self-consumption [96].

4.6. Conclusions

Considering the future of power systems, it is often stated that residential end-users will play a more active role in the management of electric power supply and demand and that they are expected to shift from passive consumers to active co-suppliers called “prosumers.” To foster the role and evaluate their impact, products and services for end-users need to be thoroughly considered through accurate Demand-Side Management modelling. The main challenge of modelling exercises is providing the necessary flexibility to incorporate a wide set of modelling features and guiding principles, while at the same time include all important aspects of end-use. However, existing models address Demand-Side Management partially or in a simplified manner, used most of the times for forecasting purposes. In this chapter, the Dynamic high-Resolution dEmand-sidE Management (DREEM) model, which serves as an entry point in Demand-Side Management modelling in the building sector, was presented. The model expands the computational capabilities of existing models to assess the benefits and limitations of demand flexibility, primarily for consumers, and for other power actors involved.

The novelty of the DREEM model lies mainly in its modularity, as its structure is decomposed into individual modules characterised by the main principles of component- and modular-based system modelling approach. This approach allows for more flexibility in terms of possible system configurations and computational efficiency, exploring all the important aspects of Demand-Side Management accurately. The latter provides the ability to incorporate future technological breakthroughs in a detailed manner, without running into computational and other modelling difficulties, avoiding limitations related to how much technological detail can be incorporated into the model. It also provides the capability of producing output for a group of buildings, serving as a basis for modelling domestic energy demand within the broader field of urban energy system analysis. To demonstrate the capabilities of the model and its applicability, it was used to explore benefits of demand flexibility for consumers in the residential sector in Greece, considering scenarios of decentralisation and full electrification of heating and cooling.

Simulation results showed that promoting a synergistic co-operation between the power supplier and the prosumer could lead to significant cost reductions and energy savings, paving the way towards “game-changer” business models that capture new value on the supply side by coupling it to the demand side. These outcomes have already been presented in two EC-funded events, during November 2018, namely: "TRANSrisk Policy Lunch-Paris in Practice: Understanding the Risks and Uncertainties" in Brussels, and "TRANSrisk & SET-Nav Regional Workshop: Decarbonising our energy system-Transformation pathways, policies, and markets, with spotlight on Greece" in Athens. During these events, relevant stakeholders from the field validated the potential of the DREEM model as a useful decision support tool that provides fast answers to “What-if” scenarios. Especially policy experts and practitioners highlighted its usefulness in the further development of business models that will increase the value of the technological infrastructure required towards a high RES and decentralised power system. As a result, taking advantage of the model’s capability to be integrated with other models and be easily re-used, the authors intend to develop, and further explore such business models, by linking the DREEM model with the Agent-based Technology adOption Model (ATOM) [97] to explore adoption scenarios of relevant technological infrastructure (e.g., small-scale PV, residential storage, Information and Communication Technologies, etc.) towards a European decentralised electricity system.

Furthermore, considering the modular structure of the DREEM model and the wide range of functionalities that allows, it could be used to explore decarbonisation scenarios of the European building stock. Such scenarios could enable the evaluation of the performance and replicability potential of different energy efficiency measures, also focusing on aspects of energy poverty that have not been thoroughly addressed so far in the scientific literature. In particular, modelling exercises could evaluate the performance of conventional and innovative energy efficiency measures in terms of their long-term energy savings, sustainability, risk, and return of investment. Such an evaluation would focus on assessing the potential benefits of each measure at a disaggregated (households-neighbourhood) level, providing utilities with valuable and actionable insights. As the DREEM model also allows for greater sophistication, with the integration of complex dynamics of the building stock transformations into the modelling process, it provides the capability to adopt a more interdisciplinary approach, encompassing the inclusion of socioeconomic and demographic factors. Thus, customer profiles as well as the particularities of energy poor households per country, will also be considered to tailor the measures and maximise their impact.

Building on this idea, and considering developments on the smart-grid paradigm, the DREEM model will also be coupled with a computational monetary framework [98] that uses the energy currency concept [99] to promote incentive schemes, which, by using energy as a monetary entity, raise public awareness on the dependence of energy consumption to individual behaviour. Such a study could shed light on how such schemes, promoting concepts of "Peer-to-Peer" energy trading and economy [100], could result in the mitigation of the energy consumed by local electricity distribution systems. Important behavioural implications could be derived from this endeavour, along with a structured policy framework that could motivate people to regulate their energy consumption as a way to financially benefit from obtaining energy saving practices.

Finally, public engagement and trust requires greater openness from researchers whose work is meant to suggest implications to end-users from the field of policy and practice, shaping policy strategies towards climate change mitigation [101]. To this end, supporting efforts around Europe towards open model development [102], the DREEM model will be made publicly available. Associate source code, datasets, and detailed documentations, along with suitable open licenses to enable the model's use, modification, and republication, will be distributed through existing public channels. This effort will be further motivated and assisted in the context of the EC-funded Horizon 2020 project "SENTINEL[11]," which aims at developing a modelling framework in support of the transition to a low-carbon energy system in Europe, enhancing public transparency, scientific reproducibility, and open-source development.

[11] https://sentinel.energy/

Appendix C

Appendix C.1

The DREEM model builds on the concept of reduced-order thermal network modelling, using the electrical circuit analogy, in which voltage is analogous to temperature (T) and current is analogous to convective (Q_{Conv}) and radiative (Q_{Rad}) heat transfer.

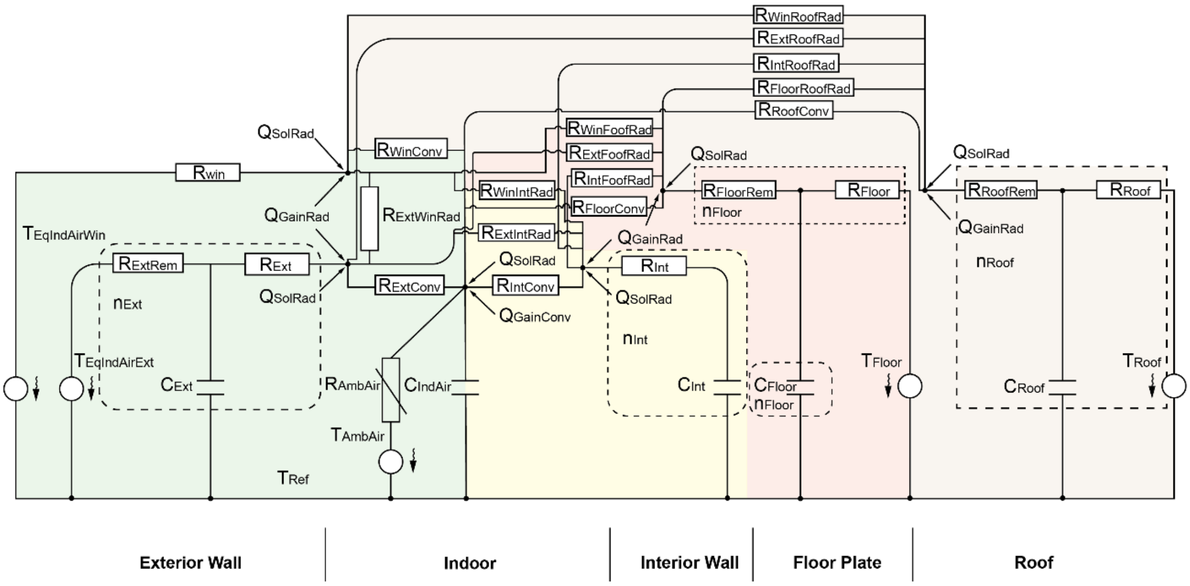


Figure C.1. RC-network representing all the main thermal masses of the building envelope in the DREEM model.

1. The “Exterior Wall” (shorthand: Ext**)** element contributes to heat transfer to the ambient and is parameterised by the length of the RC-chain (nExt) and the vector of capacities (CExt[nExt]), connected via the vector of resistances (RExt[nExt] and remaining resistances RExtRem) to the ambient (shorthand: AmbAir) and indoor air (shorthand: IndAir). This element also considers radiation transmission through windows (shorthand: Win).
2. The “Internal Wall” (shorthand: Int**)** element distinguishes between internal thermal masses and exterior walls. Given that internal masses are applicable to adiabatic conditions, this element allows for considering the dynamic behaviour induced by internal heat storage. The element is parameterised by the length of the RC-chain (nInt) and the vectors of capacities (CInt[nInt]) and resistances (RInt[nInt]).
3. The “Floor” (shorthand: Floor) element allows for considering long-term effects that dominate the excitation of floors and typically differ from the excitation of exterior walls. The element is parameterised by the length of the RC-chain (nFloor) and the vectors of the capacities (CFloor[nFloor]) and resistances (RFloor[nFloor] and remaining resistances RFloorRem).
4. The addition of the “Roof” (shorthand: Roof) element leads to a finer resolution of the dynamic behaviour of the heat transfer in the building, as roofs typically exhibit the same excitations as exterior walls but have different coefficients of heat transfer owing to their orientation. The element is parameterised by the length of the RC-chain (nRoof) and the vectors of capacities (CRoof[nRoof]) and resistances (RRoof[nRoof] and remaining resistances RRoofRem).
5. Finally, the ambient air temperature (shorthand: AmbAir) and solar irradiance (shorthand: Sol) are derived from the “Weather/ Climate” component, while casual heat gains (shorthand: Gain) within the building are derived from the “HVAC” and “Occupancy” modules, respectively.

Appendix C.2

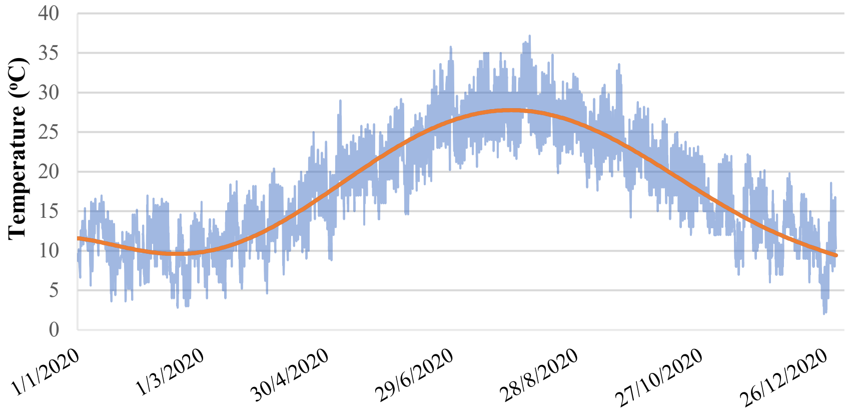


Figure C.2. Annual dry bulb air temperature profile for the city of Athens during 2020, as generated by the DREEM model.

Appendix C.3

Table C.1. Properties and U-values of the different structure elements for the building envelope under study.

Structure Elements	Surface A (m²)	U-values (W/m²·K)	Maximum U-value allowed (W/m²·K) - Zone B	Total solar heat transmittance (g)
Ext wall	28.8	0.27	0.5	-
Roof	81	0.095	0.45	-
Floor	81	0.095	0.45	-
Windows	3	2.8	3	0.46
	Thermal bridges	**l_i (m)**	**Ψ_i (W/m·K)**	
	"ΕΞΓ-11"	12.8	-0,20	
	"Δ-28"	36	+0,10	
	"ΔΠ-11"	36	+0,65	
	"ΠΡ-4"	36	+0,50	
	"Λ-14"	6	+0,05	
	"AK-14"	8	+0.30	
	"AK-14"	8	+0.30	

The mean U-value of the building envelope under study can be calculated by **Eq. (C.3.1)**:

$$U_m = \frac{\sum_{j=1}^{n} A_j \cdot U_{j.} \cdot b + \sum_{i=1}^{v} l_i \cdot \Psi_{i.} \cdot b}{\sum_{j=1}^{n} A_j} \leq U_{m,max} \left(\frac{W}{m^2 \cdot K}\right) \quad \textbf{(C.3.1)}$$

- U_m is the mean heat transfer coefficient of the building envelope (W/m²·K),
- $U_{m,max}$ is the maximum mean heat transfer coefficient allowed for the building envelope (W/m²·K),
- n is the number of the structure elements of the building envelope (-),
- v is the number of thermal bridges occurred at junctions between two surfaces A_j of the building envelope (-),
- A_j is the total surface of each structure element of the building envelope (m²),
- U_j is the heat transfer coefficient of each structure element *j* of the building envelope (W/m²·K),
- l_i is the total length of thermal bridges occurred at junctions between two surfaces A_j of the building envelope (m),

- Ψ_i is the linear heat loss coefficient of thermal bridges occurred at junctions between two surfaces A_j of the building envelope (W/m·K),
- b is a correction factor for each structure element of the building envelope (-).

The maximum mean heat transfer coefficient allowed for the building envelope $U_{m,max}$ is calculated according to specification of the TEE-TCG using the ratio of total exterior surface and total volume of the building $\frac{A}{V}$. According to the **Eq. (C.3.1)**: $\mathrm{U_m} = 0.61 < 0.73 = \mathrm{U_{m,max}}\ \left(\frac{A}{V} > 1\right)$.

Appendix C.4

Table C.2. Weekly energy consumption from appliances based on the SECH 2012–2013 survey data in Greece.

Appliances	**Ownership Rate** (%)	**Nominal Power** (W)	**Time-Of-Use (TOU)** (days/week)	**Time-Of-Use (TOU)** (hours/day)	**Weekly consumption** (kWh/week)
Cooking					
Hobs	91.82	1,600	1.56	1.92	4.77
Electric cooker with oven	86.89	2,150	2.86	3.21	19.75
Microwave oven	33.33	1,150	2.13	1.03	2.51
Toaster	61.80	1,300	2.52	0.20	0.66
Coffee maker	36.91	1,100	2.32	1.00	2.55
Water boiler	31.41	1,250	1.79	1.00	2.23
Cooker hoods	89.64	108	1.56	1.89	0.32
Lighting					
Incandescent lamp (x6)	80.54	80	7.00*	3	1.68
LED lamp (x2)	4.75	10	7.00*	2	0.14
Night light (x1)	95.01	1	7.00*	8	0.06
Other appliances					
Fridge-freezer	80.57	150	7.00	24.00	25.20
Dishwasher	29.02	1350	3.09	0.52	4.95
Washer (without tumble dryer)	94.30	500	2.46	0.50	1.76
Iron	94.98	1000	1.82	0.31	2.15
Vacuum cleaner	78.06	450	2.19	0.21	0.67
Color-television set	99.03	100	7.00	5.19	3.63
DVD or VCR	37.05	40	2.51	0.39	0.11
Stereo	30.59	24	4.21	1.00	0.17
Computer (e.g., desktop, laptop, tablet, etc.)	41.84	300	3.06	0.53	1.10
Peripheral devices (e.g., printer, scanner, etc.)	13.91	50	0.56	0.13	0.05
Internet devices (e.g., printer, scanner, etc.)	38.21	10	7.00	24.00	1.68
Video game consoles	6,36	160	3.73	0.77	0.86
Charger: mobile phone charger	99.36	1	6.58	1.27	0.08

* Values that were assumed as the respective field was not included in the survey.

Appendix C.5

Typical seasonal activity and clothing levels, and air velocity values were assumed for the average consumer according to the ASHRAE standard. For the activity levels, the following values were selected: **a.** 1.0 met (which is equal to the energy produced per unit surface area of a seated person at rest), **b.** 1.2 met (standing and relaxed), and **c.** 1.7 met (walking in the office and cooking). In terms of clothing, the following insulation levels were selected: **1. Period 2:** 0.36 clo (walking shorts, short-sleeve shirt), 0.54 clo (knee-length skirt, short-sleeve shirt, panty hose, sandals), and 0.61 clo (trousers, long-sleeve shirt), **2. Period 3:** 0.96 clo (trousers, long-sleeve shirt, suit jacket), 1.14 clo (trousers, long-sleeve shirt, suit jacket, T-shirt), and 1.30 clo (trousers, long-sleeve shirt, long-sleeve sweater, T-shirt, suit jacket, long underwear bottoms).

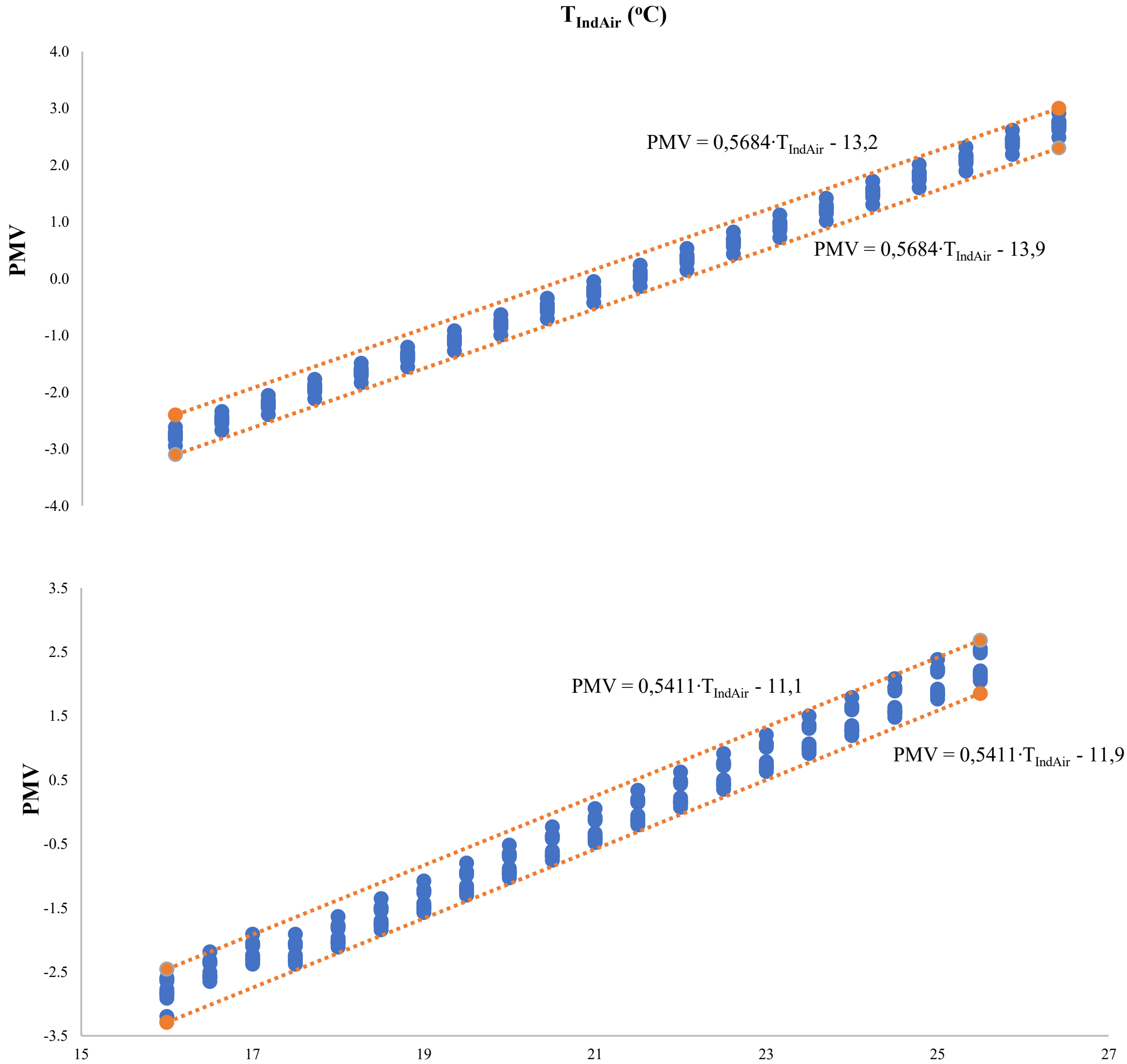


Figure C.3. Defining minimum and maximum linear lines of indoor temperature setpoints for Period 2 and Period 3 for the building envelope under study.

Appendix C.6

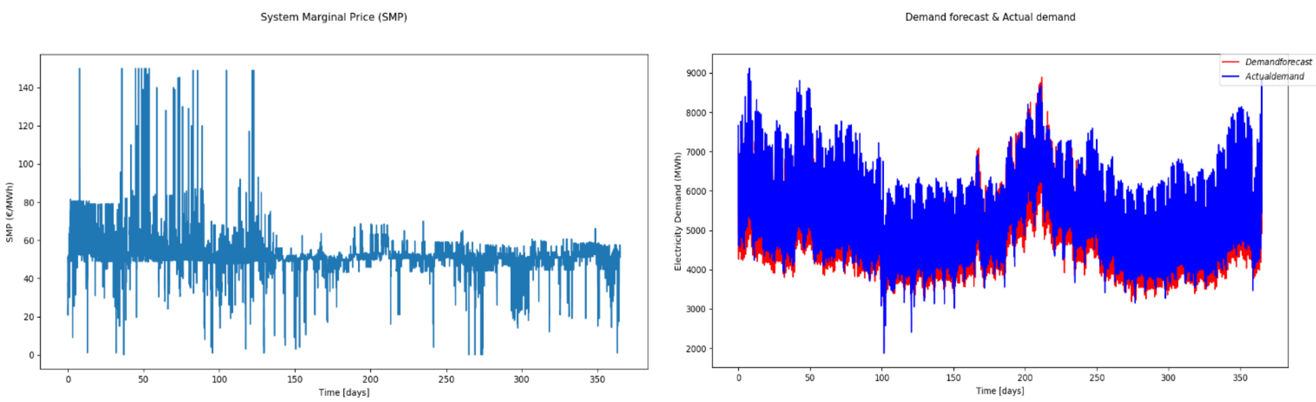


Figure C.4. Historical data of 2015, for the Greek day-ahead market: a. System Marginal Price (SMP), b. Total demand forecast and actual demand.

Table C.3. Competitive electricity consumption tariffs and other regulated charges under the "G1" scheme.

Consumption thresholds (kWh)	Tariff for electricity consumed (€/kWh)
0-2000	0.09460
>2000	0.10252

Consumption thresholds (kWh)	TSO charges (€/kWh)	DSO charges (€/kWh)	ETMEAR fee (€/kWh)	Other utility services (€/kWh)
0-1600				0.00699
1601-2000	0.00527	0.0213	0.02477	0.01570
2001-3000				0.03987
>3000				0.04488

Table C.4. SARSA algorithm: pseudocode as adapted from Sutton and Barto (2017) [89].

Output: action value *Q*

Initialise *Q* arbitrarily, e.g., to 0 for all states, set action value for terminal states as 0
initialise state *s* ← historical data
until *Q* converges
  for each *episode* **do**
    for *each step of episode, state s is not terminal* **do**
      a ← action for *s* derived by *Q*, e.g., *ϵ-greedy*
      take action *a*, observe *r*, *s′*
      a′ ← action for *s'* derived by *Q*, e.g., *ϵ-greedy*

$$Q(s,a) \leftarrow Q(s,a) + a \cdot [r + \gamma \cdot Q(s',a') - Q(s',a')]$$

      $s \leftarrow s'$, a $\leftarrow a'$
    End
  end
  state *s* ← simulation results

SARSA is an on-policy control method to find the optimal policy with the update rule $Q(s,a) \leftarrow Q(s,a) + a \cdot [r + \gamma \cdot Q(s',a') - Q(s',a')]$. From an optimal action value function, the optimal policy is derived. The algorithmic solution is recursive with the state variables s_2 and s_3 taking the values of the simulation results at the end of each iteration, until the value function (i.e., Q-value) converges with a predetermined accuracy. The state variable s_1 remains the same for each iteration. Then, the optimal policy that maximises the agent's reward is derived.

Appendix C.7

At each hour t_h, using **Eq. (C.7.1)**, the Momentary Control Algorithm assumes that the energy demand is equal to:

$$E_{app\_load}^{t_h} = E_{app\_load,0}^{t_h} + DR^{t_h - 1} \quad \textbf{(C.7.1)}$$

where $E_{app\_load,0}^{t_h}$ is the original energy demand at time interval t_h, and DR^{t_h-1} is the energy shifted from the previous hour. The constraint of DR^{t_h-1} is expressed using **Eq. (C.7.2)**:

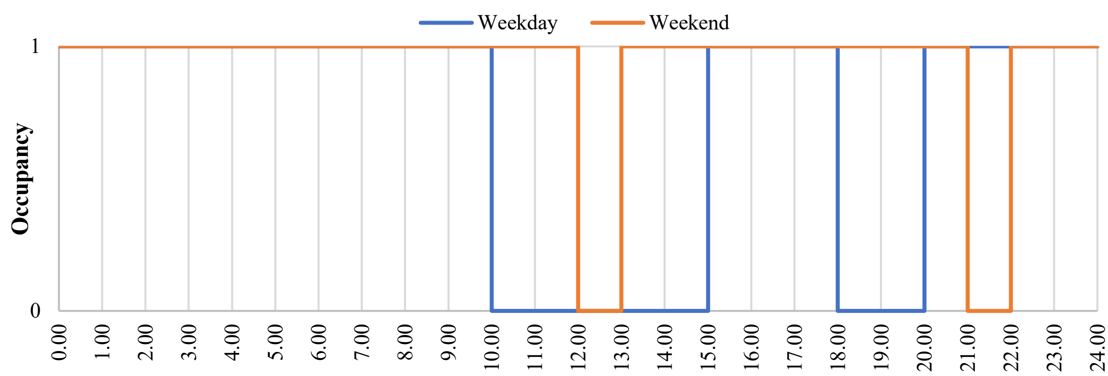
$$DR^{t_h-1} \geq -DR_{max}^{t_h-1} \quad \textbf{(C.7.2)}$$

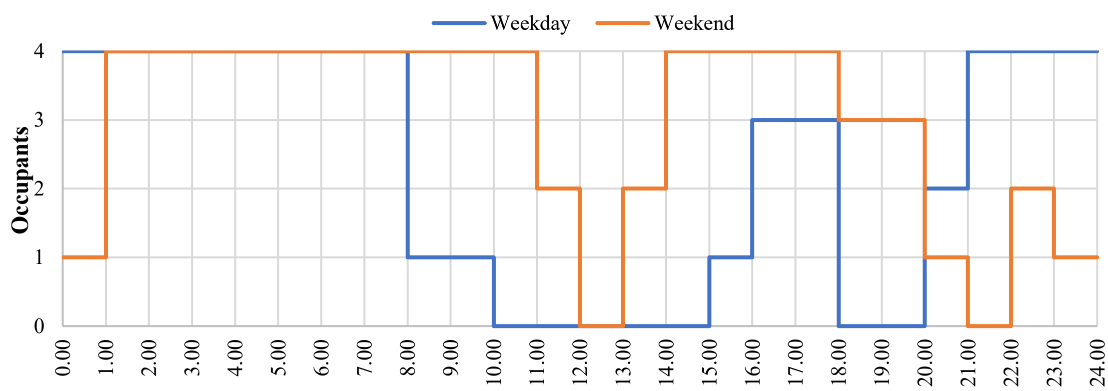
where $DR_{max}^{t_h-1}$ is the maximum deferrable energy load that can be shifted as suggested by the results of the RL algorithm. When it comes to the energy needs of the occupants related to the appliances they use, load shedding is out of scope of the current study, as the initial premise is that occupants don't need to sacrifice neither thermal comfort nor energy services. At the end of the simulation period (i.e., N), the total deferrable load related to the use of appliances must satisfy **Eq. (C.7.3)**:

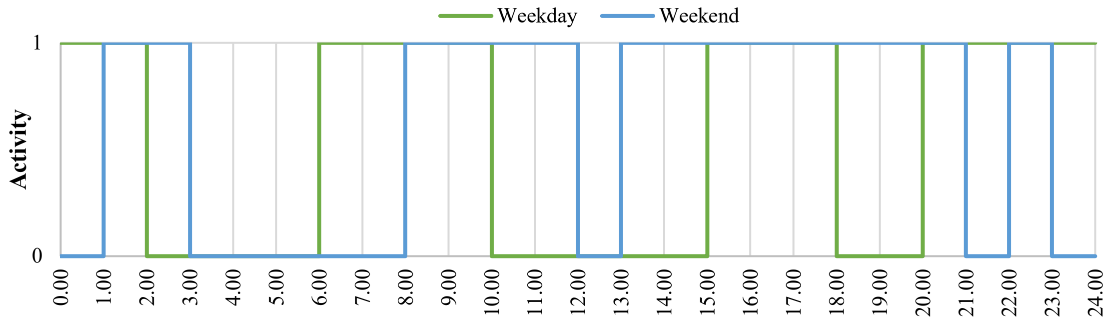
$$\sum_{t=1}^{N} DR^{t_h} = 0 \tag{C.7.3}$$

Furthermore, if a DR event is not signalled, the HVAC system is turned on (using electricity from the grid) and a normal temperature setpoint (i.e., **Category I** or **II**, **Table 4.2**) is used for space heating/ cooling. If the battery is not fully charged (i.e., SOC less than 80%), then the solar power generated charges the storage, else, if the storage is fully charged, then the solar power generated is fed to the grid. If a DR event is signalled, then the algorithm sends signal to the occupant to shift the energy demand for the next one hour and uses a minimum temperature setpoint for space heating/ cooling (i.e., **Category III** or **IV**(a), **Table 4.2**). During a DR event, the control algorithm checks the indoor temperature of the building and the storage's SOC. If the indoor temperature of the building is less than the minimum temperature setpoint (heating), or more than the minimum temperature setpoint (cooling), then the HVAC system is turned on (using electricity from the grid or storage), otherwise it is turned off (i.e., the indoor temperature is considered acceptable and will be balanced through natural convention). Additionally, if the storage is semi-charged (i.e., SOC more than 0.5), then it is discharged and the solar power generated is fed to the grid, otherwise it charges the storage. Finally, while a continuous operation of the HVAC system throughout the day could easily satisfy thermal comfort, it could also lead to unnecessary energy overconsumption as the occupancy is intermittent. Therefore, during unoccupied times and periods the HVAC system is turned off.

Appendix C.8






Weekday
Weekend
Activity
1
0
0.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
9.00
10.00
11.00
12.00
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22.00
23.00
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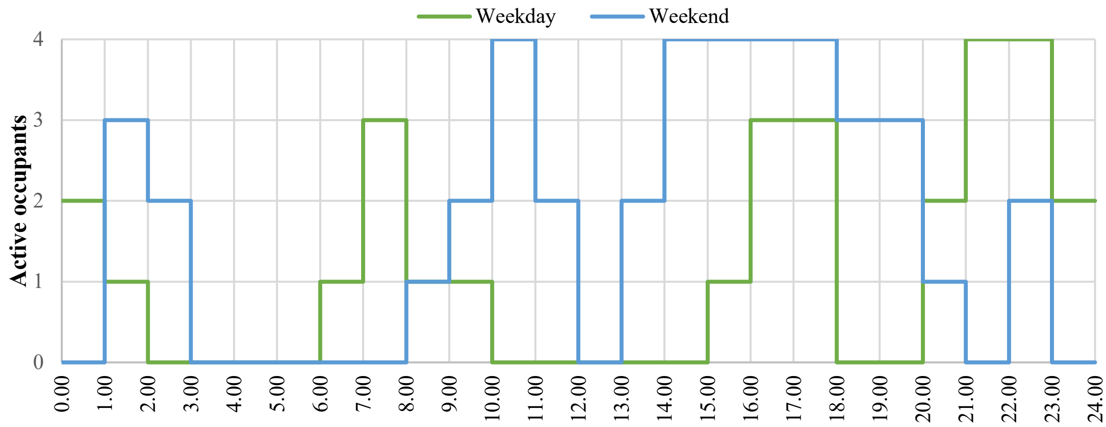
Weekday
Weekend
Active occupants
4
3
2
1
0
0.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00
8.00
9.00
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11.00
12.00
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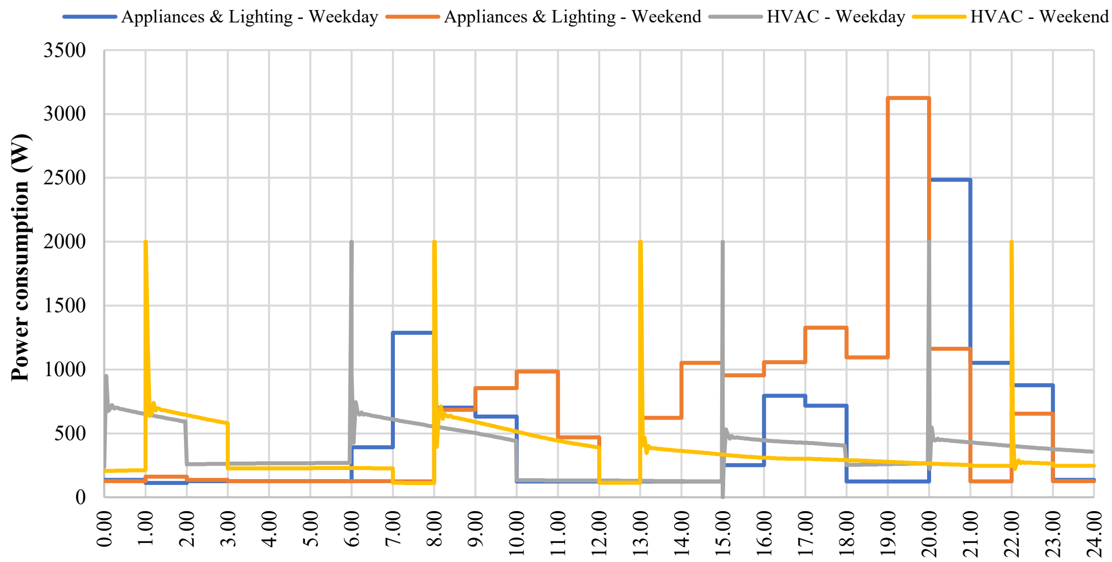
22.00
23.00
24.00


Appliances & Lighting - Weekday
Appliances & Lighting - Weekend
HVAC - Weekday
HVAC - Weekend
Power consumption (W)
3500
3000
2500
2000
1500
1000
500
0
0.00
1.00
2.00
3.00
4.00
5.00
6.00
7.00
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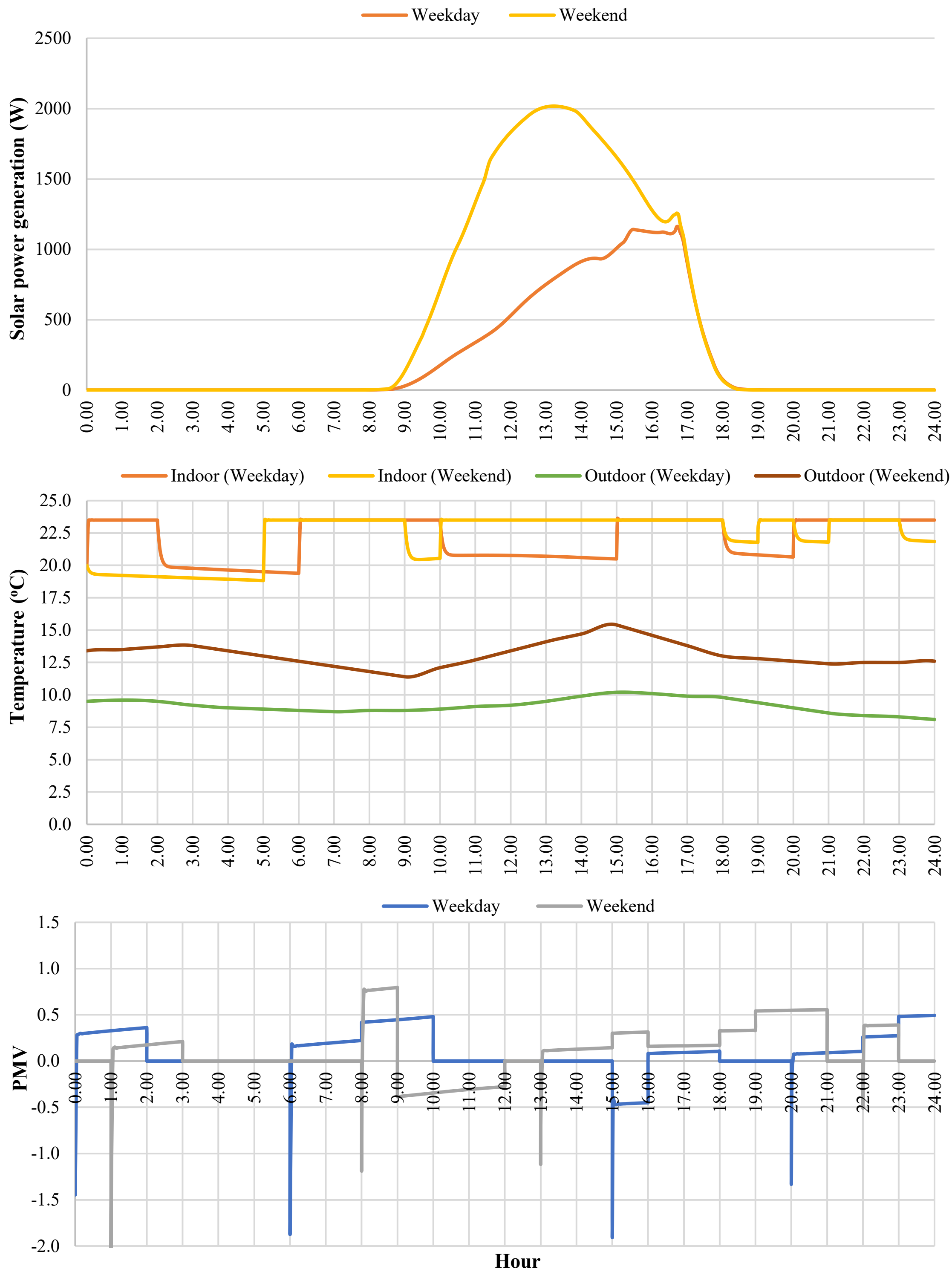
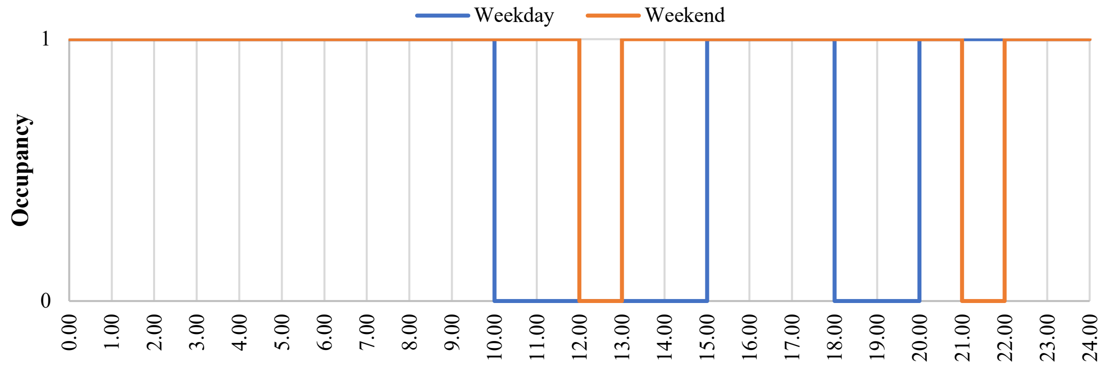
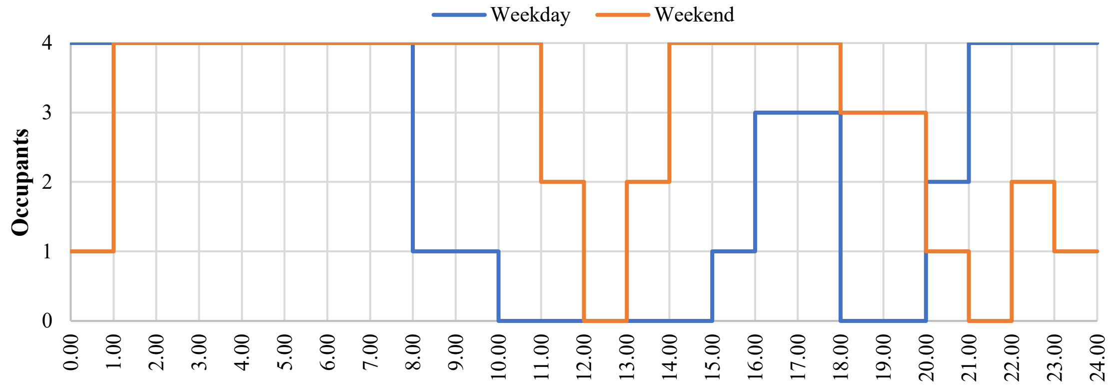
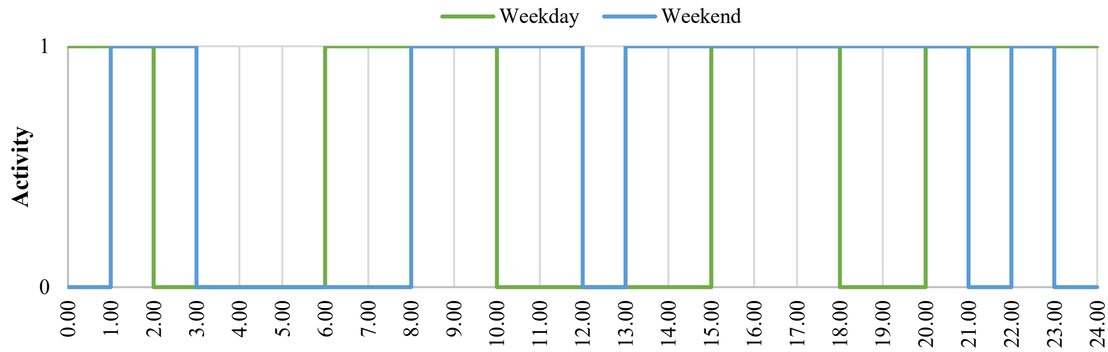
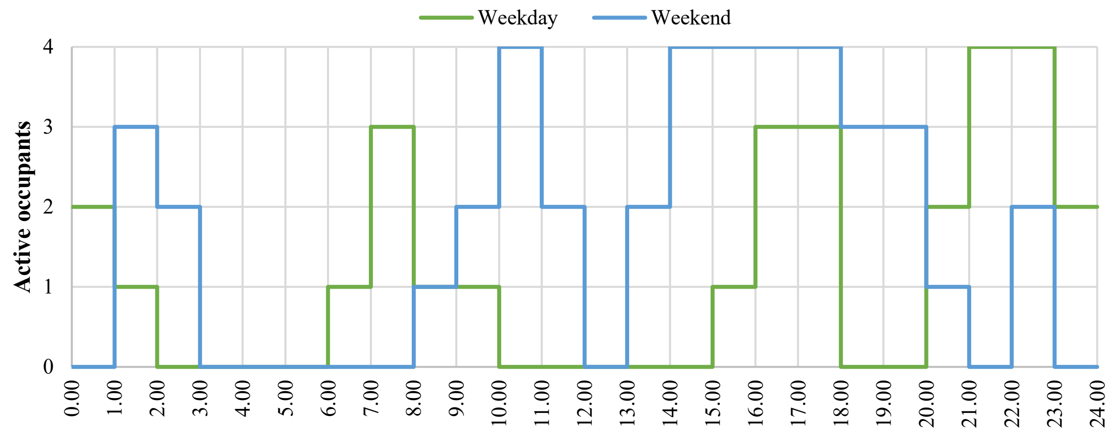


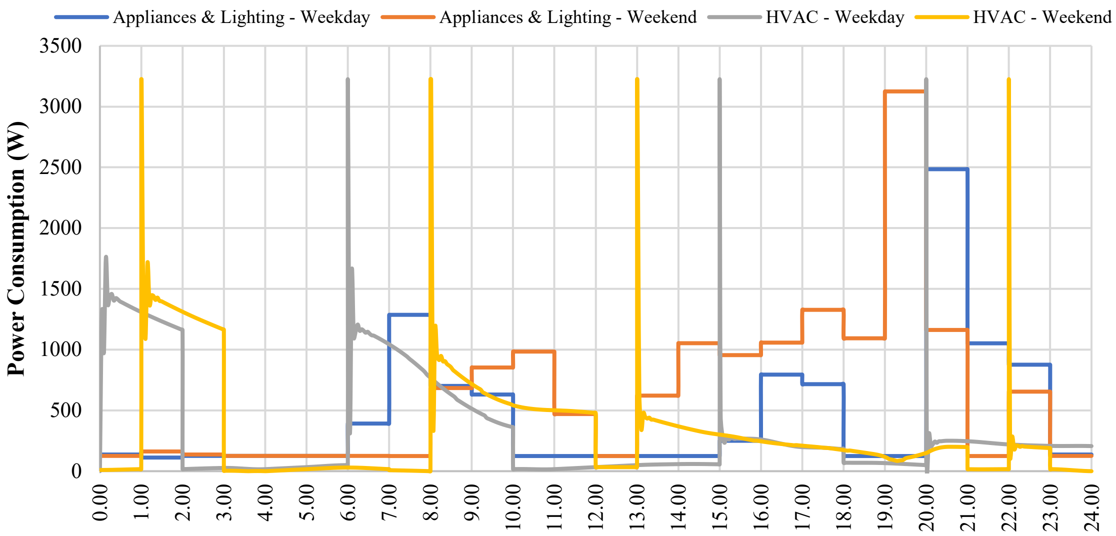
Figure C.5. Example simulation outputs of the DREEM model for indicative single weekdays and weekend days in winter.

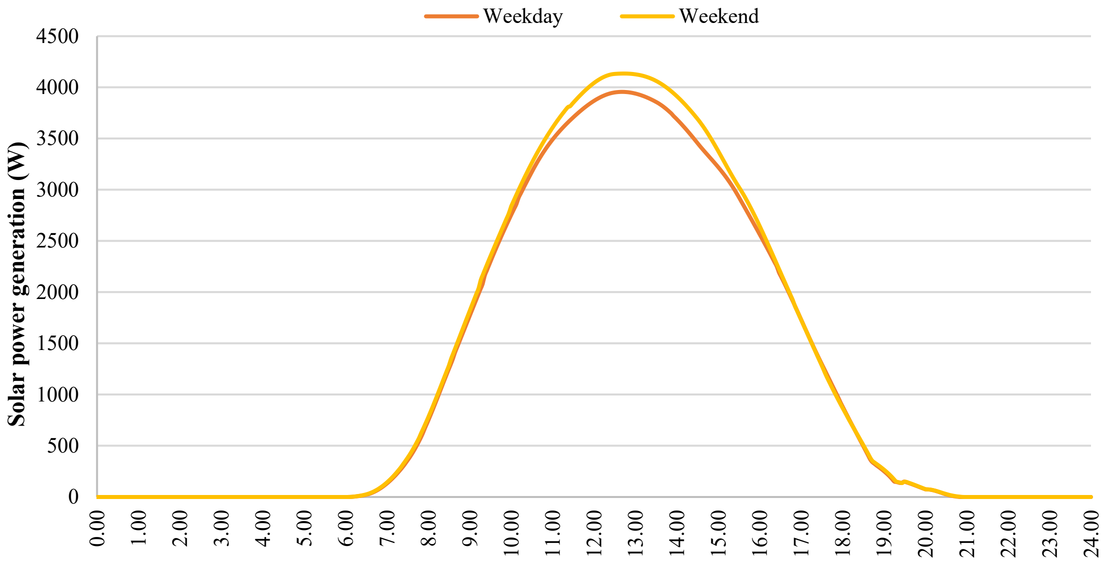

Weekday
Weekend
Occupancy
1
0
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00

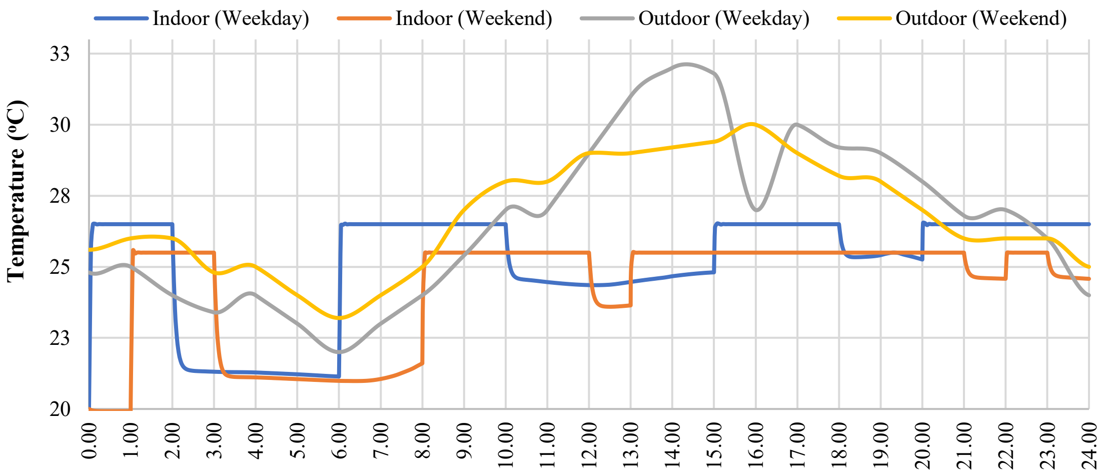

Weekday
Weekend
Occupants
4
3
2
1
0
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00


Weekday
Weekend
Activity
1
0
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00


Weekday
Weekend
Active occupants
4
3
2
1
0
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00


Appliances & Lighting - Weekday
Appliances & Lighting - Weekend
HVAC - Weekday
HVAC - Weekend
Power Consumption (W)
3500
3000
2500
2000
1500
1000
500
0
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00


Weekday
Weekend
Solar power generation (W)
4500
4000
3500
3000
2500
2000
1500
1000
500
0
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00


Indoor (Weekday)
Indoor (Weekend)
Outdoor (Weekday)
Outdoor (Weekend)
Temperature (ºC)
33
30
28
25
23
20
0.00 1.00 2.00 3.00 4.00 5.00 6.00 7.00 8.00 9.00 10.00 11.00 12.00 13.00 14.00 15.00 16.00 17.00 18.00 19.00 20.00 21.00 22.00 23.00 24.00

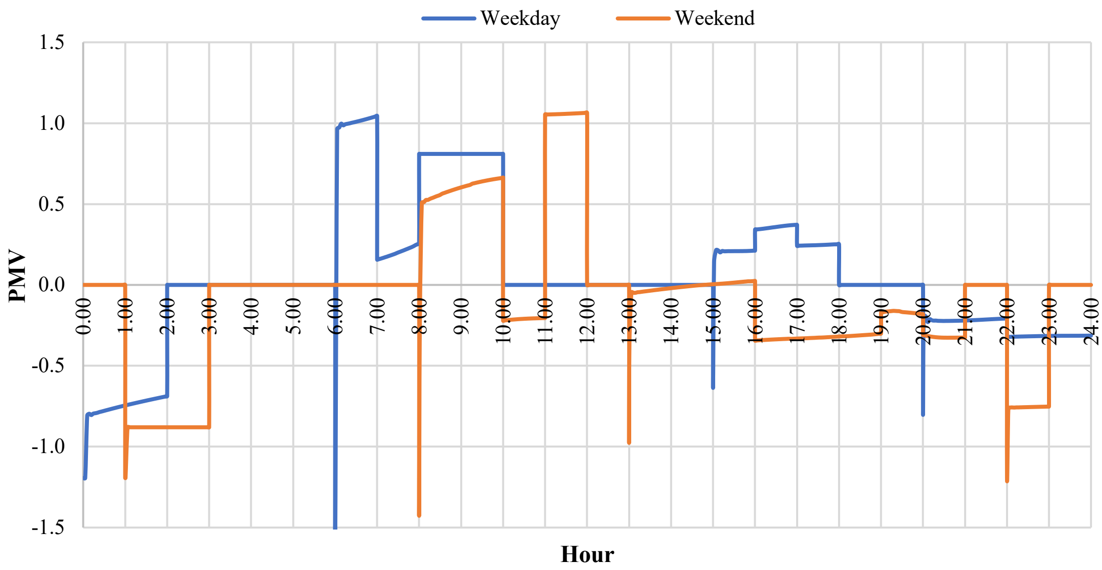


Figure C.6. Example simulation outputs of the DREEM model for indicative single weekdays and weekend days in summer.

Appendix C.9

Table C.5. Detailed simulation results for both the scenarios “SC1” and “SC2,” and all the three seasonal profiles considered.

		“SC1”					**“SC2”**				
		Period 1		**Period 2**	**Period 3**		**Period 1**		**Period 2**	**Period 3**	
		Ap-My	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**	**Ap-My**	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**
Energy consumption (kWh)	Appliances	703.7	768.5		1,149.8	314.9	703.7	768.5		1,149.9	314.9
		1,472.2		1,387.9	1,463.6		1,472.2		1,387.9	1,463.6	
	HVAC	137.6	211.1		498.9	127.8	127.5	135.7		401.9	120.9
		348.7		669.1	626.7		263.2		572.2	522.8	

	“SC2”				
	Period 1		**Period 2**	**Period 3**	
	Ap-My	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**
Energy savings - setpoints adjustment (kWh)	10.1 (7.34%)	75.4 (35.72%)		97 (19.47%)	6.9 (5.39%)
	85.5 (24.5%)		96.9 (14.48%)	103.9 (16.58%)	
	286.3 (17.41%)				
Energy savings - PV-storage self-consumption (kWh)	218.2 (25.93%)	193.6 (19.77%)		289.1 (17.53%)	87.3 (19.87%)
	411.8 (22.62%)		529.1 (25.72%)	376.4 (18.04%)	
	1,317.3 (22.09%)				

	“SC1”					**“SC2”**				
	Period 1		**Period 2**	**Period 3**		**Period 1**		**Period 2**	**Period 3**	
	Ap-My	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**	**Ap-My**	**Oc-No**	**Jn-Se**	**Ja-Ma**	**De**
Total electricity	841.3	979.6		1,648.7	442.7	613.0	710.6		1,262.7	348.5

consumed from the grid (kWh)	1,820.9	2,057.0	2,091.4	1,323.6	1,431.0	1,611.2
		5,969.3			**4,365.8**	
Total cost of electricity (€)	294.3	398.5	404.3	202.4	218.8	260.5
		1,098.1			**681.7**	

References

[1] Michas S, Stavrakas V, Spyridaki N-A, Flamos A. Identifying Research Priorities for the further development and deployment of Solar Photovoltaics. Int J Sustain Energy 2019;38. doi:10.1080/14786451.2018.1495207.

[2] Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-baltvilks J, et al. Barriers to and consequences of a solar-based energy transition in Greece. Environ Innov Soc Transitions 2018:1–17. doi:10.1016/j.eist.2018.12.004.

[3] Schlachtberger DP, Becker S, Schramm S, Greiner M. Backup flexibility classes in emerging large-scale renewable electricity systems. Energy Convers Manag 2016;125:336–46. doi:10.1016/j.enconman.2016.04.020.

[4] Lampropoulos I, Kling WL, Ribeiro PF, Van Den Berg J. History of demand side management and classification of demand response control schemes. IEEE Power Energy Soc Gen Meet 2013:1–5. doi:10.1109/PESMG.2013.6672715.

[5] Palensky P, Dietrich D. Demand side management: Demand response, intelligent energy systems, and smart loads. IEEE Trans Ind Informatics 2011;7:381–8. doi:10.1109/TII.2011.2158841.

[6] Albadi MH, El-Saadany EF. Demand Response in Electricity Markets: An Overview. 2007 IEEE Power Eng Soc Gen Meet 2007:1–5. doi:10.1109/PES.2007.385728.

[7] Yu L, Li YP, Huang GH, An CJ. A robust flexible-probabilistic programming method for planning municipal energy system with considering peak-electricity price and electric vehicle. Energy Convers Manag 2017;137:97–112. doi:10.1016/j.enconman.2017.01.028.

[8] Su H, Zio E, Zhang J, Chi L, Li X, Zhang Z. A systematic data-driven Demand Side Management method for smart natural gas supply systems. Energy Convers Manag 2019;185:368–83. doi:10.1016/j.enconman.2019.01.114.

[9] Borsche T, Andersson G. A review of demand response business cases. IEEE PES Innov Smart Grid Technol Conf Eur 2015;2015-Janua:1–6. doi:10.1109/ISGTEurope.2014.7028916.

[10] Shariatzadeh F, Mandal P, Srivastava AK. Demand response for sustainable energy systems: A review, application and implementation strategy. Renew Sustain Energy Rev 2015;45:343–50. doi:10.1016/j.rser.2015.01.062.

[11] Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy 2016;1:16032. doi:10.1038/nenergy.2016.32.

[12] Geelen D, Reinders A, Keyson D. Empowering the end-user in smart grids: Recommendations for the design of products and services. Energy Policy 2013;61:151–61. doi:10.1016/j.enpol.2013.05.107.

[13] Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renew Sustain Energy Rev 2009;13:1819–35. doi:10.1016/j.rser.2008.09.033.

[14] Mai W, Chung CY. Model predictive control based on thermal dynamic building model in the demand-side management. IEEE Power Energy Soc Gen Meet 2016;2016-Novem:1–5. doi:10.1109/PESGM.2016.7741437.

[15] Pradhan V, Balijepalli VSKM, Khaparde SA. An effective model for demand response management systems of residential electricity consumers. IEEE Syst J 2016;10:434–45. doi:10.1109/JSYST.2014.2336894.

[16] Gottwalt S, Gärttner J, Schmeck H, Weinhardt C. Modeling and valuation of residential demand flexibility for renewable energy integration. IEEE Trans Smart Grid 2017;8:2565–74. doi:10.1109/TSG.2016.2529424.

[17] Croce D, Giuliano F, Tinnirello I, Galatioto A, Bonomolo M, Beccali M, et al. Overgrid: A Fully Distributed Demand Response Architecture Based on Overlay Networks. IEEE Trans Autom Sci Eng 2017;14:471–81. doi:10.1109/TASE.2016.2621890.

[18] Mahmoudi N, Shafie-khah M, Saha TK, Catalão JPS. Customer-driven demand response model for facilitating roof-top PV and wind power integration. IET Renew Power Gener 2017;11:1200–10. doi:10.1049/iet-rpg.2016.0752.

[19] Martirano L, Habib E, Parise G, Greco G, Manganelli M, Massarella F, et al. Demand Side Management in Microgrids for Load Control in Nearly Zero Energy Buildings. IEEE Trans Ind Appl 2017;53:1769–79. doi:10.1109/TIA.2017.2672918.

[20] Ren H, Wang F, Zhou L, Liu X, Catalao JPS, Talari S, et al. Multi-Objective Optimization Model of Source–Load–Storage Synergetic Dispatch for a Building Energy Management System Based on TOU Price Demand Response. IEEE Trans Ind Appl 2017;54:1017–28. doi:10.1109/tia.2017.2781639.

[21] Hu M, Xiao F. Price-responsive model-based optimal demand response control of inverter air conditioners using genetic algorithm. Appl Energy 2018;219:151–64. doi:10.1016/j.apenergy.2018.03.036.

[22] Sivaneasan B, Kandasamy NK, Lim ML, Goh KP. A new demand response algorithm for solar PV intermittency management ☆. Appl Energy 2018;218:36–45. doi:10.1016/j.apenergy.2018.02.147.

[23] Alimohammadisagvand B, Jokisalo J, Sirén K. Comparison of four rule-based demand response control algorithms in an electrically and heat pump-heated residential building. Appl Energy 2018;209:167–79. doi:10.1016/j.apenergy.2017.10.088.

[24] Pereverza K, Pasichnyi O, Kordas O. Modular participatory backcasting: A unifying framework for strategic planning in the heating sector. Energy Policy 2019;124:123–34. doi:10.1016/j.enpol.2018.09.027.

[25] Nikas A, Doukas H, Papandreou A. A Detailed Overview and Consistent Classification of Climate-Economy Models. In: Doukas H, Flamos A, Lieu J, editors. Underst. Risks Uncertainties Energy Clim. Policy Multidiscip. Methods Tools a Low Carbon Soc., Springer, Cham; 2018, p. 1–54. doi:10.1007/978-3-030-03152-7.

[26] Wetter M, Haugstetter C. Modelica versus TRNSYS–A comparison between an equation-based and a procedural modeling language for building energy simulation. Second Natl. IBPSA-USA Conf. Cambridge, MA August 2-4, 2006 Model., vol. 11, 2006, p. 262–9.

[27] Wetter M. Co-simulation of building energy and control systems with the building controls virtual test bed. J Build Perform Simul 2011;4:185–203. doi:10.1080/19401493.2010.518631.

[28] Wetter M. Modelica-based modelling and simulation to support research and development in building energy and control systems. J Build Perform Simul 2009;2:143–61.

[29] Zuo W, Wetter M, Tian W, Li D, Jin M, Chen Q. Coupling indoor airflow, HVAC, control and building envelope heat transfer in the Modelica Buildings library. J Build Perform Simul 2016;9:366–81. doi:10.1080/19401493.2015.1062557.

[30] Bünning F, Sangi R, Müller D. A Modelica library for the agent-based control of building energy systems. Appl Energy 2017;193:52–9. doi:10.1016/j.apenergy.2017.01.053.

[31] Lauster M, Remmen P, Fuchs M, Teichmann J, Streblow R, Müller D. Modelling long-wave radiation heat exchange for thermal network building simulations at urban scale using Modelica. Proc. 10th Int. Model. March 10-12, 2014, Lund, Sweden, 2014, p. 125–33. doi:10.3384/ecp14096125.

[32] Wetter M, Bonvini M, Nouidui TS. Equation-based languages - A new paradigm for building energy modeling, simulation and optimization. Energy Build 2016;117:290–300. doi:10.1016/j.enbuild.2015.10.017.

[33] Cebecauer T, Suri M. Typical Meteorological Year Data: SolarGIS Approach. Energy Procedia 2015;69:1958–69. doi:10.1016/j.egypro.2015.03.195.

[34] Wilcox S, Marion W. Users Manual for TMY3 Data Sets. Technical Report. 2008.

[35] Zhao F, Lee SH, Augenbroe G. Reconstructing building stock to replicate energy consumption data. Energy Build 2016;117:301–12. doi:10.1016/j.enbuild.2015.10.001.

[36] Lauster M, Teichmann J, Fuchs M, Streblow R, Mueller D. Low order thermal network models for dynamic simulations of buildings on city district scale. Build Environ 2014;73:223–31. doi:10.1016/j.buildenv.2013.12.016.

[37] Mckenna E, Thomson M. High-resolution stochastic integrated thermal – electrical domestic demand model. Appl Energy 2016;165:445–61. doi:10.1016/j.apenergy.2015.12.089.

[38] Harish VSKV, Kumar A. Reduced order modeling and parameter identification of a building energy system model through an optimization routine. Appl Energy 2016;162:1010–23. doi:10.1016/j.apenergy.2015.10.137.

[39] Richardson I, Thomson M, Infield D, Clifford C. Domestic electricity use: A high-resolution energy demand model. Energy Build 2010;42:1878–87. doi:10.1016/j.enbuild.2010.05.023.

[40] McKenna E, Krawczynski M, Thomson M. Four-state domestic building occupancy model for energy demand simulations. Energy Build 2015;96:30–9. doi:10.1016/j.enbuild.2015.03.013.

[41] Hoogsteen G, Molderink A, Hurink JL, Smit GJM. Generation of Flexible Domestic Load Profiles to Evaluate Demand Side Management Approaches. 2016 IEEE Int. Energy Conf. (ENERGYCON), 4-8 April, Leuven, Belgium: IEEE; 2016. doi:10.1109/ENERGYCON.2016.7513873.

[42] Gaetani I, Hoes PJ, Hensen JLM. Occupant behavior in building energy simulation: Towards a fit-for-purpose modeling strategy. Energy Build 2016;121:188–204. doi:10.1016/j.enbuild.2016.03.038.

[43] Yao R, Steemers K. A method of formulating energy load profile for domestic buildings in the UK. Energy Build 2005;37:663–71. doi:10.1016/j.enbuild.2004.09.007.

[44] Richardson I, Thomson M, Infield D. A high-resolution domestic building occupancy model for energy demand simulations. Energy Build 2008;40:1560–6. doi:10.1016/j.enbuild.2008.02.006.

[45] Wang F, Li K, Duić N, Mi Z, Hodge BM, Shafie-khah M, et al. Association rule mining based quantitative analysis approach of household characteristics impacts on residential electricity consumption patterns. Energy Convers Manag 2018;171:839–54. doi:10.1016/j.enconman.2018.06.017.

[46] Trčka M, Hensen JLM. Overview of HVAC system simulation. Autom Constr 2010;19:93–9. doi:10.1016/j.autcon.2009.11.019.

[47] Yang L, Yan H, Lam JC. Thermal comfort and building energy consumption implications - A review. Appl Energy 2014;115:164–73. doi:10.1016/j.apenergy.2013.10.062.

[48] Alimohammadisagvand B, Alam S, Ali M, Degefa M, Jokisalo J, Sirén K. Influence of energy demand response actions on thermal comfort and energy cost in electrically heated residential houses. Indoor Built Environ 2017;26:298–316. doi:10.1177/1420326X15608514.

[49] Du P, Zheng LQ, Xie BC, Mahalingam A. Barriers to the adoption of energy-saving technologies in the building sector: A survey study of Jing-jin-tang, China. Energy Policy 2014;75:206–16. doi:10.1016/j.enpol.2014.09.025.

[50] DIN EN ISO 7730. Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria 2005.

[51] Taleghani M, Tenpierik M, Kurvers S, Van Den Dobbelsteen A. A review into thermal comfort in buildings. Renew Sustain Energy Rev 2013;26:201–15. doi:10.1016/j.rser.2013.05.050.

[52] CEN Ce. CEN Standard EN15251. In: Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics 2007.

[53] Fanger PO. Thermal comfort: Analysis and applications in environmental engineering. Danish Tech Press 1970.

[54] Luo M, Wang Z, Ke K, Cao B, Zhai Y, Zhou X. Human metabolic rate and thermal comfort in buildings: The problem and challenge. Build Environ 2018;131:44–52. doi:10.1016/j.buildenv.2018.01.005.

[55] Havenith G, Holme I. Personal Factors in Thermal Comfort Assessment Clothing Properties and Metabolic Heat Production Pdf Free Ebook Download From Bellsouthpwp.Net. Energy Build 2002;34.

[56] Nassif N, Moujaes S. A cost-effective operating strategy to reduce energy consumptionin a HVAC system. Int J Energy Res 2008;32:543–558. doi:10.1002/er.1364.

[57] Dounis AI, Caraiscos C. Advanced control systems engineering for energy and comfort management in a building environment-A review. Renew Sustain Energy Rev 2009;13:1246–61. doi:10.1016/j.rser.2008.09.015.

[58] Haugen F. The good gain method for simple experimental tuning of PI controllers. Model Identif Control 2012;33:141–52. doi:10.4173/mic.2012.4.3.

[59] Lu R, Hong SH, Zhang X. A Dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach. Appl Energy 2018;220:220–30. doi:10.1016/j.apenergy.2018.03.072.

[60] Alimohammadisagvand B, Jokisalo J, Kilpeläinen S, Ali M, Sirén K. Cost-optimal thermal energy storage system for a residential building with heat pump heating and demand response control. Appl Energy 2016;174:275–87. doi:10.1016/j.apenergy.2016.04.013.

[61] Volodymyr M, Koray K, David S, Andrei AR, Joel V, Marc GB, et al. Human-level control through deep reinforcement learning. Nature 2015;518:529–533. doi:10.1038/nature14236.

[62] Ruusu R, Cao S, Manrique Delgado B, Hasan A. Direct quantification of multiple-source energy flexibility in a residential building using a new model predictive high-level controller. Energy Convers Manag 2019;180:1109–28. doi:10.1016/j.enconman.2018.11.026.

[63] Chatzisideris MD, Laurent A, Christoforidis GC, Krebs FC. Cost-competitiveness of organic photovoltaics for electricity self-consumption at residential buildings: A comparative study of Denmark and Greece under real market conditions. Appl Energy 2017;208:471–9. doi:10.1016/j.apenergy.2018.03.019.

[64] Christoforidis GC, Panapakidis IP, Papagiannis GK, Papadopoulos TA, Koumparou I, Hatzipanayi M, et al. Investigating net-metering variant policies: The case of Greece. 2015 IEEE 15th Int Conf Environ Electr Eng EEEIC 2015 - Conf Proc 2015:2023–8. doi:10.1109/EEEIC.2015.7165486.

[65] ASHRAE. International Weather for Energy Calculations (IWEC Weather Files) Users Manual and CD-ROM 2001.

[66] Spyridaki NA, Ioannou A, Flamos A, Oikonomou V. An ex-post assessment of the regulation on the energy performance of buildings in Greece and the Netherlands—a cross-country comparison. Energy Effic 2016;9:261–79. doi:10.1007/s12053-015-9363-1.

[67] Technical Chamber of Greece. Technical Directive 20701-1: National Specifications of Parameters for Calculating the Energy Performance of Buildings and the Issue of the Energy Performance Certificate. 2017.

[68] Hellenic Statistical Authority E. Development of detailed statistics on Energy consumption in Households-2011/2012. Quality Report. Hellenic Statistical Authority; 2013.

[69] Crambes C, Henchiri Y. Regression imputation in the functional linear model with missing values in the response. J Stat Plan Inference 2019;201:103–19. doi:10.1016/j.jspi.2018.12.004.

[70] de Dear RJ, BragerG.S. Developing an adaptive model of thermal comfort and preference. ASHRAE Trans 1998;104:145–67.

[71] Brennan L, Owende P. Biofuels from microalgae-A review of technologies for production, processing, and extractions of biofuels and co-products. Renew Sustain Energy Rev 2010;14:557–77. doi:10.1016/j.rser.2009.10.009.

[72] Waffenschmidt E. Dimensioning of decentralized photovoltaic storages with limited feed-in power and their impact on the distribution grid. Energy Procedia 2014;46:88–97. doi:10.1016/j.egypro.2014.01.161.

[73] Pfeifer A, Dobravec V, Pavlinek L, Krajačić G, Duić N. Integration of renewable energy and demand response technologies in interconnected energy systems. Energy 2018;161:447–55. doi:10.1016/j.energy.2018.07.134.

[74] Dascalaki EG, Balaras CA, Kontoyiannidis S, Droutsa KG. Modeling energy refurbishment scenarios for the Hellenic residential building stock towards the 2020 & 2030 targets. Energy Build 2016;132:74–90. doi:10.1016/j.enbuild.2016.06.003.

[75] Christoforidis GC, Panapakidis IP, Papadopoulos TA, Papagiannis GK, Koumparou I, Hadjipanayi M, et al. A model for the assessment of different Net-Metering policies. Energies 2016;9. doi:10.3390/en9040262.

[76] Sutton RS, Barto AG. Reinforcement Learning: An Introduction (2nd Edition, in preparation) 2017.

[77] Vahid-Pakdel MJ, Nojavan S, Mohammadi-ivatloo B, Zare K. Stochastic optimization of energy hub operation with consideration of thermal energy market and demand response. Energy Convers Manag 2017;145:117–28. doi:10.1016/j.enconman.2017.04.074.

[78] Salpakari J, Mikkola J, Lund PD. Improved flexibility with large-scale variable renewable power in cities through optimal demand side management and power-to-heat conversion. Energy Convers Manag 2016;126:649–61. doi:10.1016/j.enconman.2016.08.041.

[79] Eyre N, Darby SJ, Grünewald P, McKenna E, Ford R. Reaching a 1.5C target: Socio-technical challenges for a rapid transition to low carbon electricity systems. Philos Trans R Soc A Math Phys Eng Sci 2017:1–20.

[80] Yan C, Xue X, Wang S, Cui B. A novel air-conditioning system for proactive power demand response to smart grid. Energy Convers Manag 2015;102:239–46. doi:10.1016/j.enconman.2014.09.072.

[81] Novaes Pires Leite G de, Weschenfelder F, Araújo AM, Villa Ochoa ÁA, Franca Prestrelo Neto N da, Kraj A. An economic analysis of the integration between air-conditioning and solar photovoltaic systems. Energy Convers Manag 2019;185:836–49. doi:10.1016/j.enconman.2019.02.037.

[82] Li K, Liu L, Wang F, Wang T, Duić N, Shafie-khah M, et al. Impact factors analysis on the probability characterized effects of time of use demand response tariffs using association rule mining method. Energy Convers Manag 2019;197. doi:10.1016/j.enconman.2019.111891.

[83] Wolisz H, Punkenburg C, Streblow R, Müller D. Feasibility and potential of thermal demand side management in residential buildings considering different developments in the German energy market. Energy Convers Manag 2016;107:86–95. doi:10.1016/j.enconman.2015.06.059.

[84] Rubino A. Network charges in a low CO2 world. Nat Energy 2018;3:255–6. doi:10.1038/s41560-018-0115-2.

[85] Newbery D, Pollitt, Michael G, Ritz RA, Strielkowski W. Market design for a high-renewables European electricity system. Renew Sustain Energy Rev 2018;91:697–707. doi:10.1016/j.rser.2018.04.025.

[86] Capgemini. Energy efficiency EU directive and its impacts on Utilities business models 2011:4.

[87] Papadelis S, Stavrakas V, Flamos A. What do capacity deployment rates tell us about the efficiency of electricity generation from renewable energy sources support measures in Greece? Energies 2016;9. doi:10.3390/en9010038.

[88] Papadelis S, Flamos A. An application of calibration and uncertainty quantification techniques for agent-based models. In: Doukas H, Flamos A, Lieu J, editors. Underst. Risks Uncertainties Energy Clim. Policy - Multidiscip. Methods Tools a Low Carbon Soc. Springer B. Ser., Springer, Cham; 2019, p. 79–95. doi:https://doi.org/10.1007/978-3-030-03152-7_3.

[89] Camilo FM, Castro R, Almeida ME, Pires VF. Economic assessment of residential PV systems with self-consumption and storage in Portugal. Sol Energy 2017;150:353–62. doi:10.1016/j.solener.2017.04.062.

[90] Kyriakopoulos GL, Arabatzis G. Electrical energy storage systems in electricity generation : Energy policies , innovative technologies , and regulatory regimes. Renew Sustain Energy Rev 2016;56:1044–67. doi:10.1016/j.rser.2015.12.046.

[91] Wang A, Li R, You S. Development of a data driven approach to explore the energy flexibility potential of building clusters. Appl Energy 2018;232:89–100. doi:10.1016/j.apenergy.2018.09.187.

[92] Hu M, Xiao F, Jørgensen JB, Li R. Price-responsive model predictive control of floor heating systems for demand response using building thermal mass. Appl Therm Eng 2019;153:316–29. doi:10.1016/j.applthermaleng.2019.02.107.

[93] Pallonetto F, Oxizidis S, Milano F, Finn D. The effect of time-of-use tariffs on the demand response flexibility of an all-electric smart-grid-ready dwelling. Energy Build 2016;128:56–67. doi:10.1016/j.enbuild.2016.06.041.

[94] Adhikari R, Pipattanasomporn M, Rahman S. An algorithm for optimal management of aggregated HVAC power demand using smart thermostats. Appl Energy 2018;217:166–77. doi:10.1016/j.apenergy.2018.02.085.

[95] Neves D, Pina A, Silva CA. Comparison of different demand response optimization goals on an isolated microgrid. Sustain Energy Technol Assessments 2018;30:209–15. doi:10.1016/j.seta.2018.10.006.

[96] Stavrakas V, Papadelis S, Flamos A. An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers. Appl Energy 2019;255:113795. doi:10.1016/j.apenergy.2019.113795.

[97] Marinakis V, Doukas H. An advanced IoT-based system for intelligent energy management in buildings. Sensors (Switzerland) 2018;18. doi:10.3390/s18020610.

[98] Sgouridis S, Kennedy S. Tangible and fungible energy : Hybrid energy market and currency system for total energy management . A Masdar City case study. Energy Policy 2010;38:1749–58. doi:10.1016/j.enpol.2009.11.049.

[99] Zhang C, Wu J, Zhou Y, Cheng M, Long C. Peer-to-Peer energy trading in a Microgrid. Appl Energy 2018;220:1–12. doi:10.1016/j.apenergy.2018.03.010.

[100] Pfenninger S. Energy scientists must show their workings. Nature 2017;542:393. doi:10.1038/542393a.

[101] Morrison R. Energy system modeling : Public transparency , scienti fi c reproducibility , and open development. Energy Strateg Rev 2018;20:49–63. doi:10.1016/j.esr.2017.12.010.

Chapter 5 - Discussion and conclusions

Nomenclature

Acronyms & abbreviations			
ABM	Agent-based model/ Agent-based modelling	FiT	Feed-in-tariff
ATOM	Agent-based Technology adOption Model	GHG	Greenhouse gas
CO_2	Carbon dioxide	H2020	Horizon 2020 Research Programme
DR	Demand-Response	KPI	Key performance indicator
DREEM	Dynamic high-Resolution dEmand-sidE Management	PV	Photovoltaic
DSM	Demand-side management	RES	Renewable energy sources
EC	European Commission	RES-E	Electricity generation from RES
EEOS	Energy efficiency obligation scheme	TEEM	TEESlab Modelling
EU	European Union	TEESlab	Technoeconomics of Energy Systems laboratory
EUS	Energy union strategy		

5. Discussion and conclusions

This Chapter summarises results and discusses key findings of the dissertation thesis, while reflecting on implications for end-users from the fields of policy and practice. It also summarises the contribution of the thesis to fields of research and academia, and energy system modelling. It concludes with limitations of the thesis and concrete suggestions for further research.

5.1. Conclusions

The European Commission's (EC's) energy union strategy (EUS) stresses out the importance of putting "*citizens at the core*" of the energy transition and envisions a Europe where "*citizens take ownership of the energy transition, benefit from new technologies to reduce their bills, participate actively in the market, and where vulnerable consumers are protected*." Increasing the European Union's (EU's) climate ambition is expected to lead to the complete transformation of the current energy system by investing in feasible and innovative technological options and by empowering end-users/ citizens and including them in the energy transition.

Considering the latter, this dissertation thesis builds on the premise that the shift to a more decentralised vision of a low-carbon energy system in Europe, where end-users (consumers/ citizens) take ownership of the energy transition, benefit from new technologies to reduce their bills, and actively participate in the market, implies that part of the necessary infrastructure will be only developed if end-users are willing to invest in/ pursue the technological capabilities required. However, considering that it is unlikely for end-users to invest in new technological capabilities having the support (e.g., flexibility, etc.) of the energy system as their primary goal, it is reasonable to assume that they may only invest according to a value stemming from increased proportion of the self-produced energy that they consume.

Furthermore, supporting the EU's climate vision, energy system models have been at the heart of the EU's climate and energy scenarios, assisting policymakers to unpack and face challenges and uncertainties related to the deep transformation that the energy system goes under. However, the new ambitions set by the European "Green Deal" require better adapted modelling tools for addressing the challenges and uncertainties of the upcoming energy transition, also reflecting, as precisely as possible, on the concerns, needs and demands of stakeholders interested in, and affected by, the European climate and energy policies.

Scientific support to climate action though the use of energy system models is not only about exploring capacity of "*what*", in terms of policy and outcome, but also about assessing feasibility and desirability, in terms of "*when*," "*where*," and especially for "*whom*." Without the necessary behavioural and societal transformations, the world faces an inadequate response to the climate crisis challenge. This could result from poor uptake of low-carbon technologies, continued high-carbon intensive lifestyles, or economy-wide rebound effects.

Considering the latter, this dissertation thesis acknowledges that, while energy system models tools, which also consider behavioural aspects of the different end-uses, are key to understanding future profile shapes of the upcoming transition, so far, the potential of these models is underrated and inadequately explored. Especially when it comes to demand-side, new modelling tools, including all important aspects of end-use, while also considering behavioural and societal aspects of the energy transition, are needed.

In this context, this dissertation thesis identified two main research gaps:

I. While the technological infrastructure required for the transition to a more decentralised low-carbon energy system in Europe, where end-users actively participate to the energy transition, is already available, we are still lacking business models and regulatory innovations to find ways to maximise the value of the technological capabilities as well as to monetise them, in order to compensate end-users.

II. While energy system models have assisted policymaking in Europe so far, the new trends and paradigms of the energy transition, as also dictated by the recent policy developments in the EU, we are still lacking modelling features and architectures that will be able support the assessment of the product-service offerings and regulatory innovations needed to empower end-users to actively participate to the energy transition.

In this context, the key objective of this thesis is to contribute to the scientific literature by improving understanding on the **(i.)** interactions between the key characteristics of end-users' behaviour and how it affects investment decisions, and on the **(ii.)** specific benefits of different technological capacities for engaging residential end-users and incentivising household-level changes towards energy autonomy. To meet this objective, we developed two new energy system models to analyse and model the effects of innovative regulatory designs and product-service offerings that could incentivise residential end-users to actively participate in the energy transition and invest in demand flexibility.

The overall work of this thesis has been presented through a set of successive research chapters, as following:

- **Chapter 1 - Introduction to the PhD thesis:** Emphasis on the weaknesses and gaps of existing energy system models and on how they should be further enhanced to be able to support efficient policymaking for the transition to climate neutrality by 2050 in the EU.
- **Chapter 2 - Analysing policy effects:** Development of an analytical framework that facilitates the systematic exploration of the impact that policy measures have on the electricity system and its components.
- **Chapter 3 - Understanding technology adoption:** Development of a new agent-based modelling (ABM) framework (ATOM), which apart from exploring the expected effectiveness of technology adoption under regulatory designs of interest, allows to consider and explicitly quantify the uncertainties that are related to agents' preferences and decision-making criteria (i.e., behavioural uncertainty).
- **Chapter 4 - Empowering end-users:** Development of a new dynamic high-resolution bottom-up demand-side management model (DREEM) that combines key features of both statistical and engineering models and serves as an entry point in demand-side management (DSM) modelling in the building sector.

Taken as a whole, the aforementioned research chapters constitute stand-alone yet successive steps of an integrated framework (**Chapter 1**), which demonstrates how energy system modelling can be used in support of the assessment of novel product-service offerings and innovative regulatory designs that empower end-users to participate to the energy transition and incentivise demand flexibility. The applicability and usefulness of this integrated framework has been demonstrated for the case of Greece, ultimately supporting and further informing the decision-making process of planning and (re)designing more effective policy instruments, by: **a.** quantifying the impact that the feed-in-tariff (FiT) scheme had on the energy system and its components during the period 2009-2013, **b.** exploring the effectiveness of alternative (to the previous FiT scheme) regulatory designs, as net-metering and self-consumption schemes, towards the adoption of scall-scale photovoltaic (PV) systems by residential end-users and the achievement of the national targets of 2025, and **c.** assessing benefits and limitations of demand flexibility for residential end-users if they invested in technological capabilities as small-scale PV and battery storage systems, smart thermostats, energy management systems, and demand-response (DR) functionalities.

5.2. Summary of results and discussion of key findings

This dissertation thesis focus on how to improve energy system models in support of policy planning and regulatory designs that put end-users at the centre of attention, empowering them to participate more actively to the upcoming energy transition, and incentivising them to invest in technological capabilities that increase demand flexibility. This section summarises the results of the dissertation thesis and discusses the key findings and the contributions with regard to the overarching research question and the three thematic research questions that were defined. The central research question of this dissertation thesis is:

How could energy system models be used to evaluate the adoption of regulatory designs and product-service offerings that empower end-users and incentivise demand flexibility in support of low-carbon energy systems?

To answer this overarching research question, the thesis was structured around three main pillars (Figure 1.1), namely: **(i). Policy**, **(ii). Technology**, and **(iii). End-users**. These three pillars shaped the overall flowchart of the thesis (Figure 1.2) and allowed us to decompose the overarching research question into the three following thematic research questions (**$RQ_{1\text{-}3}$**):

RQ_1	*How did the regulatory design of the past affect the transition to a low-carbon energy system?*
RQ_2	*How could alternative regulatory designs incentivise end-users to invest in technological infrastructure for the transition to a low-carbon energy system?*
RQ_3	*How could new regulatory designs and novel product-service offerings incentivise end-users to invest in technological infrastructure for the transition to a low-carbon energy system?*

Based on these thematic questions, our aim was threefold: **1.** *to identify key features and architectures that could contribute to more efficient modelling of innovative paradigms for the transition to low-carbon energy systems*, **2.** *to assess how regulatory designs of the past have performed so far in terms of affecting the energy system and its components*, and **3.** *to assess the potential of alternative regulatory designs to incentivise residential end-users to participate more actively to the energy transition by investing in novel product-service offerings that could increase demand flexibility*. These thematic research questions (**$RQ_{1\text{-}3}$**) have been analysed in one or more of the previous chapters (**Sections 2-4**).

5.2.1. Reflecting on the thematic research questions of the dissertation thesis

To demonstrate the usefulness and the applicability of the research work that was conducted under this thesis, we used as a testing ground the case of Greece. Located in Southern Europe, Greece is a transcontinental country, strategically located at the crossroads of Europe, Asia, and Africa, with a diverse geographical landscape and a large potential in renewable energy sources (RES) (i.e., high solar irradiation levels), which makes it an attractive market choice for both small-scale PV owners and suppliers. Furthermore, due to its numerous islands, electricity interconnection of the islands with the mainland in Greece remains a continuous challenge, with the non-interconnected islands depending mainly on conventional generation units. Finally, it presents a very recent case of a radical change in the planning of the energy system development, as in the second half of 2019, Greece took the political decision of phasing-out lignite-fired power plants in a short time horizon- initially by 2028, while recently it has been decided that the phasing-out of lignite will take place by 2025. As a result, Greece makes an interesting case study for a decarbonised vision of an electricity sector, which relies on decentralised generation and storage through the active participation of end-users.

In **Section 1.4**, we also provided the geographic and socioeconomic context of the dissertation thesis by introducing the reader to the main specifications of the energy transition by 2030 and 2050 in Greece, and by describing how each thematic research question has been adapted and answered for the case under study. Below we summarise results and discuss key findings of the thesis, applying each thematic research question in the case of Greece.

RQ_1 How did the regulatory design of the past affect the transition to a low-carbon energy system?

Over the period 2009 to 2013, RES in Greece have been treated as a special type of market participant, mainly owing to their non-dispatchable nature. During this period, electricity generation from RES (RES-E) has been compensated based on a FiT scheme, which was necessary for the investment initiation, not only in the country, but also in many national electricity systems across Europe. Despite the remarkable boom, as RES penetration progressively reached large-scale, and given the economic recession in Greece, market prices were distorted, and market efficiency was downgraded. This was also the case in several other EU Member States. As a result, and in spite of the learning progress of the past years, governments and regulatory agencies remain still uncertain about the regulatory framework necessary to incorporate larger shares of RES into the generation mix of a country or region.

While most studies on the regulatory design of RES-E support mechanisms focus on assessing the efficiency of the different alternatives, there is a knowledge gap on how these mechanisms affect the performance of the energy market. In view of a high-RES market design compatible with the EU Target Electricity Model, regulatory efforts need to include in their scope the interaction between the market and RES-E sector. To this end, quantitative assessment studies filling knowledge gaps on the market effect of RES-E support mechanisms, either at a national or at an EU level, are of paramount importance.

Although the FiT scheme is almost in the past in Greece, **Chapter 2** focused on the ex-post assessment of the scheme to identify the main drivers and interactions that governed the major monetary flows and causal relationships within the wholesale electricity market, over the period 2009 to 2013.

To do so, we developed an analytical framework that facilitate the systematic exploration of the impact that policy measures have on the electricity system and its components. Our framework was built on the premise that assessing how a policy measure affects the performance of the energy market requires the quantification of both the benefits and the costs attributed to it. By exploring the monetary flows in the electricity market, one adopts a holistic view, which can provide insights on the interactions between different components of the benefits and costs, as well as on the possible conflicts or alliances between the involved actors of the system. As a result, government officials and consultants in the policy community can gain a clearer perspective on how to devise a roadmap of least resistance for a policy measure to attain its goals. Given that, while European RES targets have been set, governance of RES-E support beyond 2020 at an EU level remains undefined, **Chapter 2** contributes to the scientific literature by paving the way for a more comprehensive, detailed, and better-structured analysis of RES-E policy design than what currently prevails.

Our results indicated that the share of wind RES-E achieved by the FiT scheme, owing to the displacement of conventional generators, had a positive environmental impact, highlighting a reduction trend of carbon dioxide (CO_2) emissions. Understanding and analysing emission trends can contribute to the effective design of policies and practices targeting the achievement of the existing climate goals. However, the large-scale penetration of RES-E alone, does not necessarily imply a more environmental-friendly energy generation approach. Increasing the shares of RES-E in Greece is a step to the right direction; an efficient low-carbon transition though, also requires the inclusion of an appropriate regulatory framework designed to consider factors associated with the adverse impacts of the early stages in the life cycle of RES.

In addition, our work explicitly quantified the emission savings attributed to the FiT scheme, decoupled from issues of economic growth. From this aspect, policy priority for breaking the connection between economic growth and greenhouse gas (GHG) emissions is vital to establish a stable RES support framework and a safe environment for investors.

On the other hand, while our results indicated that the capacity of the wind RES-E generation achieved by the FiT scheme in Greece did not compromise the reliability of the electricity system, compared to historical data available, this was almost 70% less than the total PV capacity achieved over the period under study. The latter, derived mainly from the fact that the FiT scheme in Greece made it extremely challenging to determine the appropriate RES-E remuneration levels, led to a regulatory failure and market asymmetry at the end of 2013. As a result, since then, the existing market structure and mechanisms are unable to incentivise long-term investments and support the long-term growth of infrastructure. Considering that the country is still in financial distress, special attention must be paid to policy measures that do not undermine market competitiveness.

As a result, to avoid similar rebound effects in the long-term, decision-makers should envision a more adaptive policymaking process, which, based on the concept of key performance indicators (KPIs), will allow for contingency planning, by monitoring cost reductions owing to technological progress and learning effects, controlling the profit margin of prosumers, and limiting public expenses and burdensome charges.

RQ_2. How could alternative regulatory designs incentivise end-users to invest in technological infrastructure for the transition to a low-carbon energy system?

Since the FiT scheme, and although regulatory efforts in Greece to reach the standards of other European markets that experienced a transition from a high FiT status to a market-based environment have been put in place, with a net-metering scheme legislated in 2014 and into effect since mid-2015, progress in Greece still remains slow. In this context, **Chapter 3** focused on the assessment of alternative regulatory designs that could incentivise end-users to invest, once again, in PV systems. In particular, our work focused on exploring the effectiveness of two alternative (to the FiT scheme) and more market-oriented regulatory designs- the existing net-metering scheme and of a self-consumption scheme that subsidises battery storage systems- in empowering residential end-users to invest in small-scale PV systems (i.e., 1-10kWpeak).

However, a good estimation of end-users' expected response to specific policy measures is of paramount importance in the design of effective schemes for the adoption of innovative energy technology such as PV systems, as their decision-making process is influenced by a multitude of factors, as, indicatively, grid access fees, revenues from excess electricity, e.g., tariff-based or no compensation, etc., the geographical character of the compensation, i.e., only onsite or virtual compensation allowed, the maximum timeframe for compensation, e.g., real-time, hours, up to a year, etc., the availability of dynamic pricing contracts, etc. In this context, ABM techniques provide an appropriate framework to model such private adoption decisions. However, the models currently in use often fail to capture uncertainties related to agency and their ability to replicate reality.

In order to address this drawback, in **Chapter 3**, we developed and presented a new agent-based technology adoption model (ATOM) that is supported by a complete framework for parameter estimation and uncertainty quantification based on historical data/ observations. The novelty of ATOM lies in obtaining realistic uncertainty bounds and splitting the total model output uncertainty in its major contributing uncertainty sources. The usefulness and applicability of ATOM was demonstrated by exploring the evolution of the market share of small-scale PV systems in Greece under the two regulatory designs of interest for the period 2018-2025, i.e., to evaluate the potential of achieving the national targets of 2025 in the context of the national energy transition to 2030.

Although the application of modelling tools cannot result in a clear course of action as a "policy panacea," especially when simulating the future, ATOM can be of practical support to decision-makers, by providing simplified answers to explorative "What-if" scenarios. Instead of using regression to extrapolate growth based on past trends, the model assesses the impact of different policy instruments through a more "real-world" process, addressing social and behavioural uncertainties that could characterise technology adoption in all the different spectrums of strategic energy planning. Considering the existing ambiguity of the PV market in Greece, for example, the appropriateness of ATOM as a valuable decision and support tool becomes evident when modelling outcomes are translated into simplified policy-relevant answers that could support the further development of the PV market.

In particular, the national PV capacity targets for 2025 and 2030, as recently defined by the Ministry, are 5,500 MW and 6,900 MW respectively [1]. Assuming that the contribution of small-scale PV to the national capacity targets is about 14.5% (for about every 7 MW large-scale installation, 1 MW small-scale PV is installed) according to historical data from the period 2016-2018 [2], the small-scale PV capacity target for 2025 can be defined as 417 MW. The latter is assumed considering that the revised national PV capacity target for 2020 is 3,300 MW and that the total PV capacity achieved until the end of 2017 was 2,624 MW [3]. **Figure 5.1** presents the target trajectory for small-scale PV in Greece until 2030. Our results, while acknowledging the determinant role of net-metering provisions in the further growth of small-scale PV systems, showed that the scheme, as currently implemented in Greece, is not capable of achieving the necessary capacity addition towards the national target of 2025. In particular, while the scheme could be successful until the end of 2021, it won't be able to reach the national target of 2025, even in the most optimistic scenarios. This implies that policy contingency actions are required.

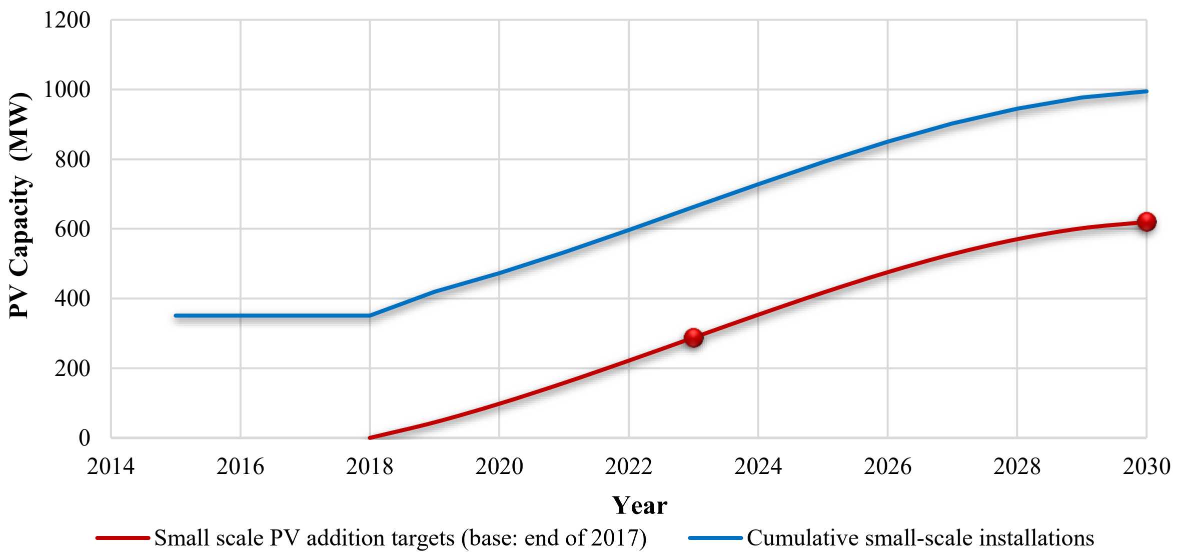


Figure 5.1. Indicative trajectory of small-scale PV capacity addition in Greece towards the national PV capacity targets of 2025 and 2030. Source: [1].

Furthermore, by enabling variance decomposition and uncertainty characterisation, ATOM showed how uncertainties impact simulation results. This highlights the novelty of the model, which lies mainly in bridging the disciplines of uncertainty analysis and ABM in policy assessment, by demonstrating how modelling uncertainty could influence effective policy design. For example, our results allowed to identify the epistemic uncertainty that the electricity price parameter contributes to simulation outputs, indicating that the effectiveness of the net-metering scheme in Greece is closely related to the retail price of electricity. In particular, simulation results indicated that an increase in the retail price, reduces the total uncertainty in the modelling outcomes, which is mainly introduced by parameters, as the probability of investing, end-users' beliefs and resistance towards investing. In policy terms, this is translated into a reduction of the behavioural uncertainty related to the effectiveness of the net-metering scheme, especially for the case of risk-averse end-users, which implies that different sources of positive financial outcomes for end-users should be further investigated.

An increase in the retail price, therefore, while entailing an extra source of revenue that shifts consumers' beliefs and reducing their resistance towards investing, should be considered only in conjunction with appropriate policy provisions. Such provisions should focus on relieving vulnerable social groups and less fortunate-at risk of poverty- consumers/ citizens from burdensome charges, as cross-subsidisation between prosumers and regular customers could distort the level-playing field and lead to an unfair competition. Efficient policymaking needs to explore more market-based net-metering structures by introducing alternative pricing strategies. This will create stability, which will make the benefits of investing more explicit, providing extra motives for regular customers. Market-based structures applicable to the existing policy landscape in Greece, include exploring different netting policies (e.g., full netting with grid charges, etc.), and replacing transfer of surplus electricity in the form of renewable energy credits, with the compensation of the excess electricity through realistic, market-based prices.

On the other hand, policies that promote self-consumption have the potential to drive the uptake of storage technologies, which could bring demand flexibility into the market and enable the integration of electricity from variable RES. Our results indicated that the suggested self-consumption scheme (subsidising the investment cost of residential battery storage systems by 25%), while being less effective than the current net-metering scheme, creates less uncertainty in terms of its performance. Although the latter suggests that the success of such a self-consumption scheme in Greece could be more robust, our results showed that a subsidy of 25% is not enough to boost the further diffusion of small-scale PV towards the national targets of 2025.

Additionally, it has been demonstrated that the effectiveness of such a self-consumption scheme in Greece is closely related to the investment cost parameter. This is another insight that would be missed in a standard ABM framework. Simulation outcomes indicated that significant technological breakthroughs are necessary for a 25% storage subsidy to become slightly more profitable than the current net-metering scheme. In particular, our results suggest that investment costs should follow a steep learning curve of at least a 10% annual reduction until 2025. This implies that efficient policy measures promoting self-consumption with storage should consider, along with ancillary benefits of self-consumption (e.g., balancing the frequency and magnitude of peak generation events that stress the distribution network, etc.), high levels of subsidisation. Since the latter seems rather infeasible owing to implications of the existing economic recession in the post-COVID era, national policy planning in Greece should focus on new and sustainable business models that monetise the value of PV self-consumption with storage. This will enable the design of regulatory frameworks that ensure clear incentives for end-users and new revenue collection practices for utilities.

RQ_3. How could new regulatory designs and novel product-service offerings incentivise end-users to invest in technological infrastructure for the transition to a low-carbon energy system?

Chapter 3 leaves us with an important implication; in order to incentivise residential end-users in Greece to invest in the technological infrastructure necessary for increasing demand flexibility capabilities, national policymaking needs to focus on new and sustainable business models that will monetise the value of this infrastructure and on novel regulatory frameworks that will create clear incentives for end-users. **Chapter 4** builds on the premise that both solutions need to acknowledge one simple fact; that although such business models and regulatory designs could indeed incentivise residential end-users to participate more actively to the energy transition, they won't be that impactful if they conflict with the interests of the other actors of the energy market, as for example, the retailing operations of the utilities.

This latter is highlighted by recent studies in the scientific literature, acknowledging that PV self-consumption can be fundamentally negative for power suppliers [4]. Especially for the case of Greece, scientific studies have shown that allowing PV self-consumption with storage in the residential sector, could force suppliers to bid higher prices for their capacity, leading to an increase in the retail price of electricity. This way utilities could counterbalance revenue losses owing to self-consumption and the limited flexibility of the current Greek electricity market [5]. Such results highlight a consequential risk that must be incorporated into future policymaking, as this development could expose vulnerable social groups and customers to burdensome charges. The study concluded that policymakers in Greece should support smart self-consumption, triggered by measures that have a broader view of the system's state, and activated based on price signals.

Additionally, successful DR schemes mainly depend on the capabilities of end-users in altering their loads with a favourable manner for both power suppliers and themselves [6]. The latter implies that only "win-win" situations that allow for the interests of all the involved energy market actors to be well-balanced have a real chance to succeed.

To this end, and considering all the above-mentioned, **Chapter 4** focused on the development of a business model, which could incentivise both residential end-users and market actors like utilities/ suppliers to invest in product-service offerings that could increase demand flexibility, through novel regulatory designs that allow and support smart self-consumption, activated based on dynamic DR price-based signals. However, to demonstrate the applicability and usefulness of such a business model, evaluation of the benefits for both sides through accurate quantification is needed.

To address this need, thus, in **Chapter 4**, we developed and presented a new Dynamic high-Resolution dEmand-sidE Management (DREEM) model, which is a hybrid bottom-up model that combines key features of both statistical and engineering models. DREEM serves as an entry point in DSM modelling in the building sector, by expanding the computational capabilities of the existing Building Energy Simulation models to assess the benefits and limitations of demand flexibility for residential end-users, primarily, and then for other energy market actors involved. The applicability of DREEM was demonstrated for the case of the residential sector in Greece, by evaluating a scenario where residential users invest in technological infrastructure as a solar PV and an electricity storage installation, a smart thermostat and an advanced control device that regulates the dwelling's energy performance, while complying, if possible, with market dynamic DR signals. As a result, the potential for additional revenue and benefits through the provision of services to the grid was evaluated.

Simulation results showed that PV self-consumption with storage and other smart infrastructure, combined with DR signals, could bring significant savings to residential end-users, mainly due to the less electricity absorbed from the grid. They also showed that supporting smart self-consumption in Greece through dynamic price-based signals allows the electricity supplier to counterbalance revenue losses due to self-consumption by a margin of 13.15%, which given the charges assumed equals to €33 per household annually. Scaling up at a national level, this is equivalent to a total offset in the range of €239 to €256 million. On the other hand, though, simulation results showed that promoting the full electrification of heating/ cooling in the Greek residential sector could lead to an extra annual electricity consumption of 1,382 kWh. This extra amount of electricity sold to consumers could bring the supplier an additional annual revenue of €266.24 per household, which scaling up at a national level is equivalent to a total profit in the range of €1.92 to €2.06 billion.

These findings provide strong evidence, that by promoting smart self-consumption, along with the electrification of the heating sector in Greece, revenue losses could be offsetted and considerable profits for the energy supplier could be achieved. As a result, further revenue opportunities for energy suppliers could also rise through the promotion of electrical smart building-scale technologies that allow energy savings, coupled with electricity generation from RES. However, while simulation results suggest that a shift to a decentralised vision of a future low-carbon electricity system in Greece, where residential end-users generate and store clean energy locally, and are motivated to comply with dynamic price-based signals, is a “win-win” situation for all actors involved, an important implication should be highlighted. Part of this future electricity infrastructure will only be developed if residential end-users are willing to invest in the technological capabilities presented.

Before residential end-users choose to expose themselves to bilateral dynamic electricity price contracts with their suppliers, they should first pursue the technological capabilities that enable demand flexibility. Considering that it is unlikely for residential end-users to invest in the new technological capabilities required having flexibility of the electricity system as their primary goal, it is reasonable to assume that they will only invest according to a value stemming from increased proportion of the self-produced electricity that they consume. To this end, while technological infrastructure is already available, business models and regulatory innovation are needed in order to find ways to maximise the value of the technological capabilities, as well as to monetise them, to compensate residential end-users.

However, the current European regulatory framework leads to conditions where business models do not bring the full value of demand-side capabilities, even when the latter are already there, due to conflicts between the interests of end-users and market actors. Given that in modern energy systems technological innovation will continuously pose new challenges to existing regulatory frameworks, innovation in regulation should be as important as regulating innovation. As a result, efficient policymaking around Europe should explore “game-changer” business models that incentivise all involved actors to incorporate demand flexibility into the markets that can valorise it.

For starters, the proposed business models and applications should not require significant changes in the current regulatory framework, or in the current operation of the power market. As our work indicated, a reasonable start for EU Member States is focusing on the benefits from integrating demand flexibility into the retailing operations of the utilities. Demand flexibility can be a valuable resource for suppliers when they manage their (physical) open position. Especially in view of a high-RES market design compatible with the EU Target Electricity Model, demand flexibility can supplement their trades to minimise the costs of short-term electricity procurement. Another potential starting point could also be energy efficiency obligation schemes (EEOs), especially in countries where awareness and maturity regarding energy savings and service market is relatively improved. The maturity of the energy service market can be benefited by such schemes, since they usually operate as a driver for generators and suppliers for further business development, rather than obstacles, also inducing cost reduction of penalties for non-compliance with EEOs.

Especially in the case of Greece, building on the modelling findings presented, policymaking should focus on promoting small-scale PV with technologies, as battery storage or smart thermostats. Considering the existing ambiguity of the PV market, such an infrastructure could generate additional sources of revenue for end-users, not only in the residential sector, which could counterbalance the phase out of the previous FiT scheme. In particular, policy efforts should focus on more market-based structures by avoiding cross-subsidisation, along with appropriate promotion campaigns that will inform end-users on the benefits of self-consumption and its influence on their electricity bill. This should be evaluated along with the fact that electricity storage manufacturers are promising revolutionary progress regarding cost reductions in the coming years, and that PV self-consumption can balance the frequency and magnitude of peak generation events that stress the distribution network.

5.2.2. Reflecting on the overarching research question of the dissertation thesis

After summing up the main findings for the thematic research questions, we return to the overarching research question of the thesis:

How could energy system models be used to evaluate the adoption of regulatory designs and product-service offerings that empower end-users and incentivise demand flexibility in support to low-carbon energy systems?

In **Figure 5.2**, we map the key issues (as those identified from the thematic research questions in the "Introduction" section) that the two energy system models developed address in order to answer to the overarching research question of the dissertation thesis according to their relevance to the three pillars on which this thesis builds, namely: **(i). Policy**, **(ii). Technology**, and **(iii). End-users** (Figure 1.1, **Section 1.3**).

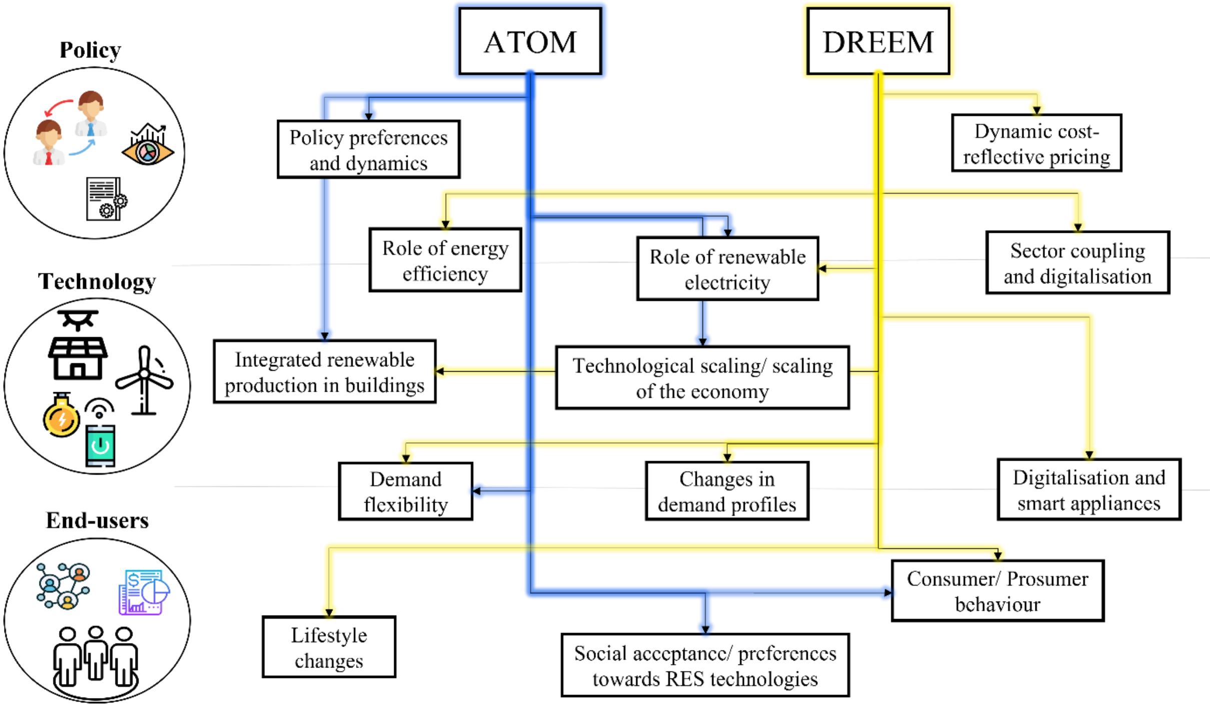


Figure 5.2. Mapping of the key issues that the two energy systems developed address to answer to the overarching research question of the dissertation thesis, also according to their relevance to each one of the three pillars on which the dissertation thesis builds.

We see that the two models developed are able to address all the important aspects related to product-service offerings and regulatory designs that could empower end-users to participate more actively to the energy transition by investing in technological capabilities that increase demand flexibility, while increase the understanding about policy effects, the role of technology adoption, and the decision-making behaviour of end-users. This was possible mainly because of the development of new modelling architectures, which, building on the inefficiencies of existing energy system models, bring together features, capabilities, and qualities, that existing models lack. The latter makes both ATOM and DREEM competitive compared to other models in the field, as they are able to address key issues of the energy transition to climate neutrality that most of the existing models are still not able to adequately address. This speaks of the contribution of the dissertation thesis to the field of energy system modelling (see **Section 5.3.1**).

Furthermore, the dissertation thesis does not only theoretically answer the overarching research question above, but it practically test the applicability and usefulness of the two new models in the case of Greece, considering real-life specifications of the upcoming energy transition. We showed how the two models can be used to evaluate the adoption of innovative product-service offerings, like PV and storage systems, smart-home technologies, DR services and novel regulatory designs, like net-metering, self-consumption, and dynamic cost-reflective pricing policies, could empower residential end-users in Greece to invest in the necessary capabilities that could increase demand flexibility. The latter makes both ATOM and DREEM useful decision and support tools that could provide fast answers to "What-if" scenarios and derive insightful implications for decision-makers.

The latter has also been validated by different policy experts, who were presented outcomes of the thesis during several EC-funded events the last three years, as, indicatively, the "*TRANSrisk Policy Lunch-Paris in Practice: Understanding the Risks and Uncertainties*" in Brussels, the "*TRANSrisk & SET-Nav Regional Workshop: Decarbonising our energy system- Transformation pathways, policies and markets, with spotlight on Greece*" in Athens, etc. Especially policy experts and practitioners in Greece have highlighted the usefulness of both models in the further development of business models that will increase the value of the technological infrastructure required towards a high RES and decentralised power system. This also speaks of the contribution of the dissertation thesis to the field of policymaking (see **Section 5.3.2**).

5.3. Overall contribution of the dissertation thesis

The overall contribution of this dissertation thesis is mainly summarised as follows: **1.** Contribution of the dissertation thesis to the field of energy system modelling, **2.** Contribution of the dissertation thesis to the field of policymaking, and **3.** Contribution of the dissertation thesis to the fields of research and academia.

5.3.1. Contribution of the dissertation thesis to the field of energy system modelling

Right from the "Introduction" section (**Section 1.1.3**), this dissertation thesis synthesised the key issues that energy system planners need to grapple with, and that modern energy system models need to accomplish for the transition to climate neutrality by 2050 in Europe (**Table 1.1**). We also reflected on "*how*" and "*why*" the existing framework of energy system models used for policy advice in the EU do an inadequate job at addressing these key issues; most of the existing energy system models are too coarse and do not acknowledge that a decarbonised energy system, and especially a climate-neutral one, will function very differently than the current system, leading to entirely different modelling requirements.

Accelerating the energy transition towards climate neutrality by 2050 in Europe requires that we develop a new set of energy system modelling tools, able to represent and analyse the drivers and barriers to complete decarbonisation, including decentralisation, a large-scale expansion of fluctuating renewable power leading to a vastly increased need for flexibility, sector coupling, including the electrification of mobility and heating, and the impacts of different market designs on the behaviour of energy sector actors. This often goes beyond improving the models' resolution as it fundamentally requires the development of a new modelling framework for the transition to climate neutrality.

In this context, thus, this dissertation thesis, acknowledging the existing gaps in the field of energy system modelling and the key issues that energy system planners are concerned with, has developed two new energy system models, one in the field of technology adoption/ diffusion ("Understanding technology adoption", 2nd pillar of the dissertation thesis) and one in the field of demand-side management ("Empowering end-users to invest in demand-flexibility capabilities", 3rd pillar of the dissertation thesis). Both ATOM and DREEM have been developed in the context of three EC-funded

Horizon 2020 projects, "CARISMA[12]," "TRANSrisk[13]," and "SENTINEL[14]," and are part of the Technoeconomics of Energy Systems laboratory (TEESlab) Modelling (TEEM) suite.

ATOM is developed in Python, while DREEM is mainly developed using the "Buildings" library [7], which is an open-source, freely available Modelica library for building energy and control systems. Modelica is an equation-based, object-oriented modelling language for the simulation of dynamic systems [8], and has been used in several studies and applications for the design and the simulation of various Building Energy Simulation and control systems [9–12]. Alongside to the Modelica models, Python scripts have been developed to model parts of the DR and control components of the model, and to enable the interface with the Dymola simulation environment. Since both models' source code is in open-source programming languages, they can both runs in all three of the most widely used operating systems- Microsoft Windows, Apple OS X, and GNU/ Linux.

Both ATOM and DREEM are new entries in their respective fields, and building on the inefficiencies of existing energy system models, seek to serve existing tools in a complementary way by addressing the key issues of energy transition that are presented in **Table 1.1**, as follows:

1. Decentralisation and variability in electricity supply

Representing a future infrastructure that includes large shares of decentralised RES and operates under a variety of objectives (e.g., self-consumption, cost minimisation, revenue maximisation through aggregation, etc.).

Both models are able to contribute toward this goal. In particular, ATOM, based on available historical data/ observations, is able simulate the adoption potential of different regulatory designs (e.g., FiT, net-metering, self-consumption, subsidisation schemes, etc.) that incentivise the inclusion of large shares of decentralised RES by different types of end-users, e.g., consumers/ citizens, utilities, other market actors, etc. Different constraints, e.g., technology costs, fuel prices, revenue calculation formulas, etc., concerning each time the operation of the market under study, e.g., PV market, wind market, etc., can be inserted into the model to achieve more realistic representations.

On the other hand, DREEM is able to model and simulate different configurations of decentralised energy systems that aim to achieve energy autonomy and sufficiency, and to evaluate benefits and limitations of each configuration, primarily for the end-users under study, e.g., consumers/ citizens, etc., and then for other market actors involved, e.g., utilities, suppliers, other market actors, etc. Different constraints e.g., cost minimisation, revenue maximisation through aggregation, can be inserted into the model.

2. Need for flexibility

Accurately representing the flexibility potential of RES and consumers/ prosumers (both capabilities and limitations) and simulating different strategies for the utilisation of this flexibility.

The issues of flexibility and prosumerism were two of the main motivating factors for the development of ATOM and DREEM, since existing models do an inadequate job in addressing these two topics. In particular, both models are able to simulate the adoption effectiveness of different strategies (i.e., technological infrastructure, practices, and regulatory designs) that aim to increase and utilise flexibility capabilities, e.g., net-metering, PV and battery storage systems, smart management and control systems, DR and other dynamic pricing schemes, energy communities, etc.

[12] http://www.carisma-project.eu/
[13] http://transrisk-project.eu/
[14] https://sentinel.energy/

3. Integration of energy sectors (electricity, heating/ cooling, and gas)

Putting demand at the centre of the system to model different energy carriers in a unified way (demand service).

This issue is also at the heart of DREEM as a DSM model, since a critical issue across all the energy system models is the need to balance supply and demand; energy demand is rarely a modelling outcome, but rather an exogenous input assumption, either as a static demand, or with some elasticity. When it comes to energy system modelling, the demand side is overly underrepresented and DREEM addresses this gap by modelling different energy carriers in the building sector, e.g., electricity, oil, natural gas, hydrogen, etc., in a unified way, also contributing to the evaluation of sector coupling, and by simulating energy demand at different temporal and spatial resolutions.

In addition, as the modelling structure of DREEM is modular, viz, it is decomposed into individual modules characterised by the main principles of component- and modular-based system modelling approach, it allows for more flexibility in terms of possible system configurations and computational efficiency, accurately representing all the important aspects of DSM. The latter provides the ability to incorporate future technological breakthroughs in a detailed manner without running into computational and other modelling difficulties, avoiding limitations related to how much technological detail can be incorporated into the model. It also provides the capability of producing output for a group of buildings, serving as a basis for modelling energy demand within the broader field of urban energy system analysis.

4. Short- and long-term market dynamics

Capturing the effect of short- to mid-term market effects on longer-term investment decisions and consumer behaviour.

The agent-based structure of ATOM provides a suitable framework to simulate the decision process of the members of a heterogeneous social system, based on members' individual preferences, behavioural rules, and communication within a social network. Thus, ATOM describes the micro-level behaviour of "agents" and allows the inclusion of considerable detail about their decisions and (inter-)actions, also providing an intuitive framework to consider the explicit characteristics of both technology and human behaviour.

On the other hand, also considering developments on the smart-grid paradigm, DREEM can be used for developing business models that promote incentive schemes, which by using energy as a monetary entity, raise public awareness on the dependence of energy consumption to individual behaviour. Thus, the model allows to explore important behavioural implications regarding structured policy frameworks that motivate people to regulate their energy consumption as a way to benefit financially from obtaining energy saving practices.

5. Social drivers/ constraints and societal reactions to energy trajectories

Capturing how societal actors interact and shape the energy future, including in far-from-cost-optimal ways, especially the way their strategies may co-evolve and how they react to energy system developments and create pressure to redirect policies and the overall energy trajectory.

ATOM has been developed in such a way to provide the user with flexibility in selecting the factors/ parameters that are assumed to moderate end-users' behaviour, according, each time, to the case of interest and the technological infrastructure under study. For example, scientific literature reports that the attitude of Greek consumers toward installing small-scale PV systems varies according to their income and education level, and also seems to be correlated with their consumption profiles and demographic characteristics [13]. To this end, the model allows to explore different behavioural and socioeconomic profiles and to implement socially-informed modelling exercises by reflecting on the decision-making process of different end-users' profiles, also focusing on societal actors or groups that face social/ economic marginalisation.

On the other hand, as DREEM allows for greater sophistication with the integration of complex dynamics of the building stock transformations into the modelling process, it also provides the capability to adopt a more interdisciplinary approach, encompassing the inclusion of socioeconomic and demographic factors. Thus, end-user profiles, as well as particularities of different social groups (e.g., vulnerable, underrepresented, etc.) can be considered each time to tailor the strategies under evaluation and maximise their impact.

6. Non-economic determinants and barriers (including financing-related issues) for the necessary investments

Accurately and explicitly representing the factors often dismissed as "non-economic factors."

Based on the aforementioned, ATOM is able to address aspects related to social acceptance and preferences towards RES technologies, local opposition against RES and energy infrastructure projects, citizen and community ownership, policy preferences and dynamics of adoption/ diffusion, and technological scaling and scaling of the economy in terms of how the speed of technology deployment affect the speed and direction of the energy transition. In addition, as DREEM allows for more interdisciplinary approaches, it is able to support the development of different business models that evaluate the investment potential in the technological infrastructure under study, also considering different demographics and profiles of the investing parties.

7. Uncertainty quantification

Capturing how societal actors interact and shape the energy future, including in far-from-cost-optimal ways, especially the way their strategies may co-evolve and how they react to energy system developments and create pressure to redirect policies and the overall energy trajectory.

This issue is also at the heart of ATOM, since one limitation of existing models is that they often fail to capture and quantify uncertainties related to agency (i.e., individuals or households, who make decisions independently). In order to address this drawback, ATOM allows to consider and explicitly quantify the uncertainties that are related to agents' preferences and decision-making criteria (i.e., behavioural uncertainty). In particular, the novelty of ATOM, compared to existing models, lies in obtaining realistic uncertainty bounds and splitting the total model output uncertainty in its major contributing sources, based on a variance decomposition framework and an uncertainty characterisation method, while accounting for structural uncertainty.

Thus, ATOM supports the definition of uncertainty ranges, considering the type (i.e., input, parametric and structural) and the nature of uncertainty (i.e., epistemic or aleatory), and how uncertainty propagates to the model outcomes over the planning time horizon. Variance decomposition is conducted in all the three main modules of ATOM (i.e., calibration, sensitivity analysis, and scenario analysis):

1. By allowing the user to select preliminary values for the agent-related parameters according to the plausibility of its results, based on historical data/ observations (goodness-of-fit statistics), the model captures input uncertainty (i.e., calibration module).
2. By deriving forward-looking simulations for different behavioural profiles (i.e., different set of agent-related parameters), from willing to invest to risk-averse end-users, ATOM captures parametric uncertainty (i.e., scenario analysis module).

3. Both types of uncertainty are then propagated through the model and their contribution to the total model's output variance is quantified. The rest uncertainty is assumed to be explained by the model's structure.

Uncertainty propagation for the agent-related parameters is done for each one of them, allowing calculation of the sensitivity of each parameter to the model output, in the context of a variance-based sensitivity analysis (Sobol method), and calculation of the relative contribution of the variance for each parameter to the total model output variance (i.e., sensitivity analysis module).

Finally, public engagement and trust requires greater openness from researchers whose work is meant to suggest implications to end-users from the field of policy and practice, shaping policy strategies towards climate change mitigation [14]. To this end, supporting efforts around Europe towards open-model development [15], the main products of this dissertation thesis, ATOM and DREEM, will be made publicly available. Associate source code, datasets, and detailed documentations, along with suitable open licenses to enable the model's use, modification, and republication, will be distributed through existing public channels. This effort is currently assisted in the context of the ongoing EC-funded Horizon 2020 projects "SENTINEL" and "ENCLUDE[15]," which aim at developing a modelling framework in support of the transition to a low-carbon energy system in Europe, enhancing public transparency, scientific reproducibility, and open-source development.

5.3.2. Contribution of the dissertation thesis to the field of policymaking

Apart from the technical contribution of this dissertation thesis, which applies mainly to the field of energy system modelling through the development of two new energy system models, this thesis also contributes to the field of policymaking. In particular, the application of the two models in the case of Greece and the interpretation of modelling findings raise a set of interesting insights that policymakers and practitioners should take into account. We summarise these policy insights at the EU and at the national level as follows, according to their relevance and their applicability:

Implications for policy and practice at the EU level

1. In view of a high-RES market design in line with the EU Target Model regulatory efforts need to expand their approach to carefully: **a.** review how the energy market performance is affected by the different support mechanisms both in the short- and the long-term, **b.** assess past and modern policy mechanisms to optimise market performance in both time horizons.
2. Although new legal mechanisms based on a combination of tax benefits and other incentives, as net-metering, feed-in-premiums and tenders, are currently considered regulatory designs that supported overcoming the difficulties of the post-FiT era in the EU and could raise, once again, end-users' willingness to participate more actively to the energy transition, the policy focus should be on closer-to-the-market self-consumption schemes that eliminate aspects of subsidisation and introduce more advanced market rules, like compensating end-users through dynamic cost-reflective pricing policies, e.g., real-time electricity prices, etc.
3. Although financial support is of substantial importance to incentivise new RES investments, it has to be designed in a way that does not result in public deficits or burdening costs for consumers. For example, while increasing the retail price of electricity in EU member states entails an extra source of revenue that could shift consumers' beliefs towards prosumerism, it should be considered only in conjunction with appropriate policy provisions. Such provisions should focus on relieving vulnerable social groups and less fortunate-at risk of poverty- consumers (i.e., regular

[15] https://encludeproject.eu/

customers of electricity) from burdensome charges, as cross-subsidisation between consumers and prosumers could distort the level-playing field and lead to an unfair competition.

4. The current EU regulatory design leads to conditions where business models do not bring the full value of demand-side capabilities. Given that in modern energy systems technological innovation will continuously pose new challenges to existing regulatory designs, innovation in regulation should be as important as regulating innovation. As a result, policymaking around the EU should explore "game-changer" business models that incentivise all involved actors to incorporate demand flexibility into markets that can valorise it. Such business models should not require significant changes in the existing regulatory environment. A reasonable start for Member States could be integrating demand flexibility into the retailing operations of the utilities. Another starting point could also be energy efficiency obligation schemes (EEOS), especially in countries where awareness and maturity regarding energy savings and energy service market are relatively improved since EEOS usually operate as a driver to generators and suppliers for further business development and cost reduction of penalties for non-compliance to EEOS.

Implications for policy and practice at the national level

1. For the energy transition in Greece to happen in a fair and socially just manner, with "*no one being left behind*," policymakers need to ensure that the regulatory environment adapts to the new situation in order to avoid legislative failures of the past. To avoid negative rebound effects as the ones of the FiT scheme in the long-term, decision-makers should envision a more adaptive policymaking process, which, based on the concept of KPIs, will allow for contingency planning, by monitoring cost reductions owing to technological progress and learning effects, controlling the profit margin of prosumers, and limiting public expenses and burdensome charges for consumers.
2. Considering that the financial distress of the last decade and the potential negative consequences that the COVID pandemic could have for the national economy, attention must be paid to policy measures that do not undermine market competitiveness. In this context, policy priority is needed for breaking the connection between economic growth and GHG emissions in order to establish a stable RES support framework and a safe environment for investors.
3. Policymakers need to explore more market-based net-metering structures by introducing alternative pricing strategies. This will create a stable environment, which will provide extra motives for regular customers to become prosumers. Such market-based structures applicable to the existing policy landscape in Greece include exploring different netting policies (e.g., full netting with grid charges, etc.), and replacing transfer of surplus electricity in the form of renewable energy credits with the compensation of the excess electricity through realistic, market-based (i.e., cost-reflective) prices.
4. Self-consumption is not yet regulated in Greece; however, considering the existing ambiguity of the PV market and the foreseen transformation of the national energy system, policy planning should focus on promoting PV self-consumption, along with storage systems and electrical smart building-scale technologies that allow energy savings, and business models that will monetise the value of this technological infrastructure. This will enable the design of regulatory designs that ensure clear incentives for consumers and new revenue collection practices for utilities. Promotion campaigns that will inform end-users on the benefits of self-consumption and its influence on their electricity bill are also required.
5. Although increasing the shares of RES in Greece is a step to the right direction, an efficient low-carbon transition also requires the introduction of appropriate regulatory designs that will consider factors associated with the adverse impacts of the early stages in the life cycle of RES.

5.3.3. Contribution of the dissertation thesis to the fields of research and academia

Contributing to the fields of research and academia, this thesis concludes with the publication of:

- Twelve (13) scientific articles in peer-reviewed journals, eleven (11) of which are in scientific journals with impact factor (IF), as also presented in **Table 5.1**.
- Ten (10) announcements in international peer-reviewed conferences.
- Fifteen (15) technical reports and other studies.

Table 5.1. List of peer-reviewed journals in which the PhD candidate has published scientific articles during the dissertation thesis.

Peer-reviewed journals	Publisher	IF*	Number of published scientific articles
Applied Energy	Elsevier BV	9.746	1
Energies	MDPI	3.004	2
Energy	Elsevier BV	7.147	1
Energy Conversion and Management	Elsevier BV	9.709	1
Energy Policy	Elsevier BV	6.142	2
Energy Research and Social Science	Elsevier BV	6.834	1
Environmental Innovation and Societal Transitions	Elsevier BV	9.680	1
International Journal of Sustainable Energy	Taylor & Francis	N/A	1
Open Research Europe	European Commission	N/A	1
Renewable & Sustainable Energy Reviews	Elsevier BV	14.982	1
Sustainability	MDPI	3.251	1

**As accessed on the 14th of December 2021.*

In addition, up until the time of the defence of this dissertation thesis, the candidate has an overall of 246 citations (213 excluding self-citations) and an h-index of 8 according to the "Scopus[16]" database, and an overall of 348 citations, an h-index of 9, and an i10-index of 9, based on the "Google Scholar[17]" database. For a more detailed presentation of the scientific publications and technical reports of the candidate, we refer the reader to **Appendix D**.

Finally, another contribution of the thesis to the field of research is that the methodological and modelling frameworks presented have laid the groundwork for new researchers that pursue their PhD thesis. In particular, the further development of both ATOM and DREEM is currently funded by several new EC-funded projects, namely: "IAMCOMPACT, "ENCLUDE," "ENPOR[18]," "ENSMOV[19]," "SENTINEL," and "SocialWatt[20]," which focus on different aspects of the energy system and the upcoming energy transition. The further development and application of the models in the context of these projects also shape the directions for further research of the dissertation thesis.

5.4. Limitations and prospects for further research

With the completion of this doctoral dissertation thesis, a series of thoughts and suggestions for further research, based on key limitations of the thesis, has been formed:

[16] Scopus Author Identifier: 56700348300
[17] https://scholar.google.gr/citations?user=mZ4MA4EAAAAJ&hl=el
[18] https://www.enpor.eu/el/
[19] https://ensmov.eu/
[20] https://www.socialwatt.eu/

- The analytical framework presented under **Chapter 2** provides a good starting point for analysing the relationship between wind and peak loads, which remains ambiguous over the years, as was also dictated by the respective patterns. However, while a static analysis like the one presented can provide useful insights, a dynamic analysis is also imperative, due to the fact that, as the RES-E penetration increases, the peak period of the residual load shifts toward hours that the RES-E generation has lower capacity factors. This results to a condition where, mainly owing to increased reserve requirements, increasing RES-E capacity has diminishing returns in terms of its value. As a result, further research should focus on expanding the presented framework so that it also incorporates the estimation of the possible deviations of the capacity values during different time periods in order to quantify the impact that limited data can have on the calculation results. Future studies can build on our work to assess the impact of newly introduced support mechanisms, as net-metering, or feed-in-premium, in different geographical and socioeconomic contexts across the EU.
- In terms of further research in the field of energy system modelling and future development of the ATOM (**Chapter 3**) and DREEM (**Chapter 4**) models, the following set of actions are proposed:
  - **ATOM**

    I. The presented version of ATOM has been developed so that is simulates adoption scenarios of small-scale PV systems. However, given the availability of historical data/ observations, the model can be easily expanded so that it simulates adoption scenarios for other technologies that increase demand flexibility, such as, for example, electricity storage, smart-grid devices, electric vehicles, etc.

    II. The current set of the agent-related parameters used by the model is technology specific, meaning that it has been selected, based on the most updated insights of the scientific literature, so that it matches adoption trends of small-scale PV systems. However, this module of ATOM will be expanded so that it brings together all relevant adoption parameters for a different set of technological options of interest, also considering the role of context. Scientific literature, for example, reports that the attitude of Greek consumers toward installing small-scale PV systems varies according to their income and education level, and also seems to be correlated with their consumption profiles and demographic characteristics. In this context, an extensive database will be developed so that the model is able to simulate technology adoption, taking into account the specifications of the technology and the context under study.

    III. The current version of the model focuses on the adoption of the technological infrastructure required in the context of the energy transition; however, mechanics and functions will be further expanded so that the model is able to simulate the further diffusion of social innovations and energy citizenship trends and paradigms that will be essential for the achievement of climate and energy targets, e.g., energy communities, ecovillages, low-carbon lifestyles, etc., by heterogeneous social ensembles of different profiles.
  - **DREEM**

    I. The presented version of DREEM has been developed with a focus on the residential sector, while the application under study only explored a specific residential building typology. The “Building envelope” component of the model will be expanded so that it is able to simulate all the different residential building typologies in the EU, based on the specifications provided by the "TABULA[21]" webtool and other reliable sources, so that the model is able to also account for energy efficiency scenarios. In addition, the model will be also expanded so that it simulates other building typologies apart from only residential buildings, e.g., public buildings, social housing, etc.

II. The "Electricity demand" component of the model will be further expanded and transformed into an "Energy demand" component to also compute heating demand from other types of fuels and technologies, like oil and natural gas boilers, biomass, hydrogen, etc., toward scenarios that foresee the decarbonisation of the heating sector. In addition, an EU database for different occupancy and activity profiles, along with traits of different appliances and devices, based on available survey and census data, will be developed, so that the model is able to simulate electricity demand in different geographical and socioeconomic contexts in the EU.

III. Finally, the "Flexibility management" component will be further expanded, so that it also simulates other technologies that can provide flexibility benefits to the grid, e.g., electric vehicles towards the electrification of the transport sector, etc.

- **Both models**

I. From a technical perspective, focus will be given on both models' continuous development in a modular way; both models' structure will be made up of independent, but interlinked individual components and modules, which will be characterised by the main principles of component- and modular-based system modelling approach. Inefficiencies of energy system models will be always under the microscope indicating areas of further improvements, as, e.g., ensuring both models' capability to be integrated with other models and be easily re-used, increasing geographic and/ or temporal resolution of the models, incorporating societal and behavioural parameters, having consumers/ citizens at the centre of the analysis, etc.

II. Over the past few years, stakeholders and other relevant end-users that have experienced the models via "hands-on" sessions, or demonstration of simulation results, have acknowledged the models' capacity to provide accurate answers to quick "what-if" scenarios. In this context, both models' further development will always be conducted in a participatory and co-creative manner, eliciting knowledge and preferences embedded on key stakeholders and other relevant actors. This will ensure a "people-centric" development approach, which will reflect on the different end-users' real-life and most updated needs. This will make both models relevant and useful in a meaningful way.

III. Especially policy experts and practitioners have highlighted both models' usefulness in the further development of business models that will increase the value of the technological infrastructure required towards a high-RES and decentralised power system. As a results, special focus will also be given to the development of the necessary interface protocols between the two models to explore adoption scenarios of relevant technological infrastructure towards a European decentralised system, also creating a set of algorithms that will enable the tracing of cascading uncertainties between the models.

IV. Finally, public engagement and trust requires greater openness from researchers whose work is meant to suggest implications to end-users from the field of policy and practice,

[21] https://webtool.building-typology.eu/#bm

shaping policy strategies towards climate change mitigation. To this end, supporting efforts around Europe towards open model development, both models will be made publicly available. Associate source codes, datasets, and detailed documentations, along with suitable open licenses to enable both models' use, modification, and republication, will be distributed through existing public channels. In this context, a strategic focus will be the creation of a community of users, who will get familiar with the models, also contributing to their further development, implementation to other geographical and socioeconomic contexts, etc.

- Finally, the applicability and usefulness of both models have only been demonstrated for the case of Greece and only for a very limited spectrum of the envisioned pathways and scenarios for the transition to 2030 and 2050. In this context, updated versions of both models will be used to simulate different scenarios and transition pathways (dictated by current policy ambitions and existing climate and energy targets) in Greece and other EU member states.
  - **ATOM**
    I. ATOM will be applied to explore scenarios of PV adoption in different geographical and socioeconomic contexts in the EU. In this context, the model will also be soft-linked to modelling toolboxes of qualitative and quantitative descriptions of social and political drivers and constrains of the energy transition. The main objective will be to provide empirically based insights on social and political aspects of the energy transition to improve the representation of these aspects in ATOM. Different ideal/ typical and distinct storylines that are based on transition theory and empirical observations of actual social/ political drivers and barriers in the EU energy transition will be explored, and quantitative, empirical data for a range of key social/ political parameters will be collected. Particular focus will be given to the selection of member states of different climatic regions, e.g., northern Europe, central Europe, southern Europe, etc., to reflect on how weather and climatic conditions specifically affect PV adoption.

    II. Furthermore, studies in the scientific literature suggest that policy measures must adapt to uncertain and continuously changing conditions. Thus, a policy design process that utilises agent-based modelling should be structured around the concept of adaptability. This means that, as new data on the actual decisions of the relevant actors is accumulated, the initial policy design should adapt in the same way as it adapts to changes in its environment. As a result, ATOM will be soft-linked with another in-house modelling toolbox, which focuses on the development of dynamic adaptive policy pathways; thus, support policy measures for further PV adoption towards the achievement of national targets in the EU can adapt to uncertainties- generated by their assumptions and their environment- that may hinder their performance. This exercise will also build on the strengths of a stakeholder engagement strategy that provides a more comprehensive and detailed assessment of policy interventions, towards a more participatory policymaking approach that collaboratively explores policy needs and underlying model capability requirements, to improve policy decision usability.
  - **DREEM**
    I. Considering the modular structure of the DREEM model and the wide range of functionalities that allows, it will be used to explore decarbonisation scenarios of the European building stock. Such scenarios could enable the evaluation of the performance and replicability potential of different energy efficiency measures. In

particular, modelling exercises could evaluate the performance of conventional and innovative energy efficiency measures in terms of their long-term energy savings, sustainability, risk, and return of investment. Such an evaluation would focus on assessing the potential benefits of each measure at a disaggregated (households-neighbourhood) level, providing utilities with valuable and actionable insights. As the DREEM model also allows for greater sophistication, with the integration of complex dynamics of the building stock transformations into the modelling process, it provides the capability to adopt a more interdisciplinary approach, encompassing the inclusion of socioeconomic and demographic factors. Thus, customer profiles as well as different household particularities will also be considered to tailor the measures and maximise their impact.

II. In this context, the primary focus of the model will be to evaluate the cost-effectiveness of different energy efficiency measures in the residential sector in Greece, also suggesting specific portfolio of measures and policy schemes that could contribute to the achievement of the 2030 national energy saving targets.

III. In addition, modelling exercises will also focus on the regional level, exploring and evaluating best energy mixture pathways in the residential sector, to be in line with 2050 national energy targets. Different regions of particular interest will be explored as, e.g., Attica region (where the city of Athens, capital of Greece, is), Central Macedonia region (where the city of Thessaloniki, the second larger city in Greece, is), the regions of Peloponnese and Western Macedonia, where natural gas infrastructure is currently under development to support the phase out of the lignite-fired power plants and a fair and just transition for the local municipalities, etc.

IV. Furthermore, considering developments regarding the smart-grid paradigm, the DREEM model will also be coupled with a computational monetary framework that uses the energy currency concept to promote incentive schemes, which, by using energy as a monetary entity, raise public awareness on the dependence of energy consumption to individual behaviour. Such a study could shed light on how such schemes, promoting concepts of "Peer-to-Peer" energy trading and economy, could result in the mitigation of the energy consumed by local electricity distribution systems. Important behavioural implications could be derived from this endeavour, along with a structured policy framework that could motivate people to regulate their energy consumption as a way to financially benefit from obtaining energy saving practices.

V. Finally, one basic indicator that is used for the identification of energy poor households in Greece is the energy poverty ratio, based on which, "*a household is considered energy poor if it is required to spend over 10% of its income on all domestic energy use…*" Furthermore, there are clear indications that a significant amount of energy consumed in residential buildings is used for thermal comfort. In this context, the DREEM model will be used to explore the correlation between thermal comfort, income, and energy poverty in Greece. The novelty of this application will mainly lie in using statistical data, the energy poverty ratio, and DREEM outputs, to identify energy poor households in the Greek residential sector, in accordance with their thermal comfort and income. DREEM will be used for the calculation of the energy consumption of the Greek residential sector for marginal cases of thermal comfort that are accepted for a very limited part of the day, according to different global standards, and an annual income threshold for each scenario will be calculated and compared against the expected annual income of each household.

Appendix D

Scientific articles published in peer-reviewed journals

1. **Tzani, D.**, **Stavrakas, V.**, **Santini, M.**, **Thomas, S.**, **Rosenow, J.**, **Flamos, A.**, Pioneering a performance-based future for energy efficiency: Lessons learnt from a comparative review analysis of pay-for-performance programmes. *Renew Sustain Energy Rev* 2022;158:112162. doi:10.1016/j.rser.2022.112162.
2. **Süsser**, **D.**, **Gaschnig**, **H.**, **Ceglarz**, **A.**, **Stavrakas**, **V.**, **Flamos**, **A.**, **Lilliestam**, **J.**, Better suited or just more complex? On the fit between user needs and modeller-driven improvements of energy system models. *Energy* 2022;239:121909. doi:10.1016/j.energy.2021.121909.
3. **Süsser, D., Ceglarz, A., Stavrakas, V., Lilliestam, J.,** COVID-19 vs. stakeholder engagement: the impact of coronavirus containment measures on stakeholder involvement in European energy research projects. *Open Res Eur 2021*;1:57. doi:10.12688/openreseurope.13683.1.
4. **Süsser, D., Ceglarz, A., Gaschnig, H., Stavrakas, V., Flamos, A., Giannakidis, G., Lilliestam, J.,** Model-based policymaking, or policy-based modelling? How energy models and energy policy interact, *Energy Research and Social Science 2021*, **75**: 101984. https://doi.org/10.1016/j.erss.2021.101984.
5. **Stavrakas, V., Kleanthis, N.; Flamos, A.,** An Ex-Post Assessment of RES-E Support in Greece by Investigating the Monetary Flows, and the Causal Relationships in the Electricity Market. *Energies 2020*, **13(17)**:4575, https://doi.org/10.3390/en13174575.
6. **Spyridaki, N.A., Stavrakas, V., Dendramis, Y., Flamos, A.,** Understanding technology ownership to reveal adoption trends for energy efficiency measures in the Greek residential sector. *Energy Policy 2020*;**140**. doi:10.1016/j.enpol.2020.111413.
7. **Michas, S., Stavrakas, V., Papadelis, S., Flamos, A.,** A transdisciplinary modeling framework for the participatory design of dynamic adaptive policy pathways. *Energy Policy 2020*;**139**. doi:10.1016/j.enpol.2020.111350.
8. **Stavrakas, V., Flamos, A.,** A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector. *Energy Convers Manag 2020*;**205**. doi:10.1016/j.enconman.2019.112339.
9. **Stavrakas, V., Papadelis, S., Flamos, A.,** An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers. *Appl Energy 2019*;**255**:113795. doi:10.1016/j.apenergy.2019.113795.
10. **Nikas, A., Stavrakas, V., Arsenopoulos, A., Doukas, H., Antosiewicz, M., Witajewski-Baltvilks, J., et al.,** Barriers to and consequences of a solar-based energy transition in Greece. *Environ Innov Soc Transitions 2019*;**35**:383–99. doi:10.1016/j.eist.2018.12.004.
11. **Michas, S., Stavrakas, V., Spyridaki, N.A., Flamos, A.,** (2019) Identifying Research Priorities for the further development and deployment of Solar Photovoltaics, *International Journal of Sustainable Energy*, **38:3**, 276-296, doi: 10.1080/14786451.2018.1495207.
12. **Stavrakas, V., Spyridaki, N.A., Flamos, A.,** Striving towards the Deployment of Bio-Energy with Carbon Capture and Storage (BECCS): A Review of Research Priorities and Assessment Needs. *Sustainability 2018*, **10**, 2206, https://doi.org/10.3390/su10072206.
13. **Papadelis, S., Stavrakas, V., Flamos, A.,** What Do Capacity Deployment Rates Tell Us about the Efficiency of Electricity Generation from Renewable Energy Sources Support Measures in Greece? *Energies 2016*, 9, **38**, https://doi.org/10.3390/en9010038.

Scientific articles currently under revision in peer-reviewed journals

1. **Chatterjee, S., Stavrakas, V., Oreggioni, G., Süsser, D., Staffell, I., Lilliestam, J., Molnar, G., Flamos, A., Ürge-Vorsatz, D.,** Existing tools, user needs and required model adjustments for energy demand modelling of a carbon-neutral Europe, under review in *Energy Research and Social Science (Elsevier BV)*.
2. **Kleanthis, N., Stavrakas, V., Ceglarz, A., Süsser, D., Schibline, A., Lilliestam, J., Flamos, A.,** Stakeholder perspectives on the critical issues and challenges of the European transition to climate neutrality in different geographical contexts, under review in *Energy Research and Social Science (Elsevier BV)*.

Working scientific articles to be soon submitted in peer-reviewed journals

1. **Süsser, D., Stavrakas, V., Martin, N., Talens-Peiró, L., Lilliestam, J., Gaschnig, H., Flamos, A., Madrid-López, C.,** Why sustainable energy pathways/models must consider environmental and social aspects of the energy transition, to be submitted in *Energy Research and Social Science (Elsevier BV)*.
2. **Tzani, D., Exintaveloni, D.S., Stavrakas, V., Flamos, A.,** Determining policy strategies for the development of energy efficiency Pay-for-Performance programmes in the European Union: A SWOT-AHP analysis. to be submitted in *Energy Policy (Elsevier BV)*.
3. **Papantonis, D., Burbidge, M., Tzani, D., Stavrakas, V., Bouzarovski, S., Flamos, A.,** Structural factors impacting energy efficiency policy implementation for the alleviation of energy poverty in the European Private Rented Sector, to be submitted in *Energy Research and Social Science (Elsevier BV)*.
4. **Spyridaki, N.A., Stavrakas, V., Flamos, A.,** What are the achievable energy efficiency potential for subsidies under Article 7 of the EED? A methodological framework and application in the Greek household sector, to be submitted in *Sustainability (MDPI)*.
5. **Pearce, B.B.J., Stavrakas, V., Tsopelas, I., Lieu, J., Ioannou, A., Dunphy, N.P., Xeakis, G., Falcone, G., Brenner-Fliesser, M., Matowska, G., Protopapadaki, C., Flamos, A.,** Energy citizenship for inclusive decarbonization: The need for an (inter-)transdisciplinary, mixed-methods assessment framework, to be submitted in *Environmental Innovation and Societal Transitions (Elsevier BV)*.

Announcements in international peer-reviewed conferences

1. **Süsser, D., Ceglarz, A., Stavrakas, V., Lilliestam, J.,** Model-based policymaking or policy-based modelling? On the interaction between energy modelling and energy policymaking, *Energy and Climate Transformations: 3rd International Conference on Energy Research & Social Science*, 20-23 June 2022, Manchester, United Kingdom.
2. **Papantonis, D., Burbidge, M., Tzani, D., Martini, E., Stavrakas, V., Flamos, A.,** Structural Factors Impacting Energy Efficiency Policy Implementation in the European Private Rented Sector, *Energy and Climate Transformations: 3rd International Conference on Energy Research & Social Science*, 20-23 June 2022, Manchester, United Kingdom.
3. **Pearce, BB.J., Dunphy, N., Falcone, G., Flamos, A., Ioannou, A., Lieu, J., Stavrakas, V.** (2021), Energy citizens for inclusive decarbonization- Operationalizing transdisciplinarity within the Horizon 2020 framework, *International Transdisciplinarity Conference 2021 (ITD21)*, 13-17 September, Zurich, Switzerland.
4. **Süsser, D., Madrid-Lopez, C., Stavrakas, V., Talens-Peiro, L.** (2021), Coupling socio-technical transitions with environmental impacts for a truly sustainable governance of energy systems, *5th International Conference on Public Policy (ICPP5)*, 5-9 July, Barcelona, Spain.

5. **Süsser, D., Ceglarz, A., Stavrakas, V.** (2021), Models as actors in policymaking: Does energy modelling enable ambitious climate and energy policies?, *5th International Conference on Public Policy (ICPP5)*, 5-9 July, Barcelona, Spain.
6. **Tzani, D., Stavrakas, V., Flamos, A.** (2020), Different portfolios of measures to improve energy efficiency in the residential sector in Greece towards the achievement of the 2030 targets, *6th International Conference on Smart Energy Systems (SESAAU 2020)*, 6-7 October, Aalborg, Denmark.
7. **Stavrakas, V., Tzani, D., & Flamos, A.** (2019). Future development of the European solar market towards decentralized renewable energy generation and storage: A cross-country comparative analysis. *14th Conference on Sustainable Development of Energy, Water and Environment Systems (SDEWES) Conference*, 1-6 October, Dubrovnik, Croatia.
8. **Stavrakas, V., Tzani, D., & Flamos, A.** (2019). Exploring the impact of demand-response actions on thermal comfort and energy cost in the residential sector in Greece. *14th Conference on Sustainable Development of Energy, Water and Environment Systems (SDEWES) Conference*, 1-6 October, Dubrovnik, Croatia.
9. **Stavrakas, V., Papadelis, S., & Flamos, A.** (2018). Achieving a low-carbon power system through empowering consumers to produce and store clean energy at the local level: The case of Greece. *7th International Symposium & 29th National Conference on Operational Research (HELORS) Conference*, 14-16 June, Chania, Greece
10. **Kontochristopoulos, I., Stavrakas, V., Papadelis, S., & Flamos, A.** (2015). A Python-implemented model to simulate electricity demand in the residential sector. *4th Student Conference of the Hellenic Operational Research Society (HELORS): Opportunities and Challenges within the economic crisis*, 17-18 December, Athens, Greece.

Technical reports & other studies

1. **Chatterjee, S., Stavrakas, V., Oreggioni, G., Staffell, I., Flamos, A., Ürge-Vorsatz, D.**, (2021). Integration of demand model results into system planning models. Deliverable 3.3. Sustainable Energy Transitions Laboratory (SENTINEL) project. European Commission. Central European University (CEU), Budapest, Hungary.
2. **Süsser, D., Pickering, B., Chatterjee, S., Oreggioni, G., Stavrakas, V., Lilliestam, J.**, (2021). Integration of socio-technological transition constraints into energy demand and systems models. Deliverable 2.5. Sustainable Energy Transitions Laboratory (SENTINEL) project. Potsdam: Institute for Advanced Sustainability Studies (IASS). DOI: 10.48481/iass.2021.030.
3. **Gaschnig, H., Süsser, D., Ceglarz, A., Stavrakas, V., Flamos, A., & Lilliestam, J.** (2021). Survey questionnaire and results on user needs for energy models for the European energy transition, related to Süsser et al. (2021) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5040378.
4. **Madrid-Lopez, C., Süsser, D., Stavrakas, V., Lilliestam, J., Flamos, A., Talens-Peiro, L., & Martin, N.** (2021). Model development to match ENVIRO, QTDIAN and ATOM to user needs. Deliverable 2.4. Sustainable Energy Transitions Laboratory (SENTINEL) project. (Version 1). Zenodo. https://doi.org/10.5281/zenodo.4912687.
5. **Stavrakas, V., Ceglarz, A., Kleanthis, N., Giannakidis, G., Schibline, A., Süsser, D., Lilliestam, J., Psyrri, A., & Flamos, A.** (2021). Case specification and scheduling. Deliverable 7.1. Sustainable Energy Transitions Laboratory (SENTINEL) project. Zenodo. https://doi.org/10.5281/zenodo.4699518.

6. **Chatterjee, S., Oreggioni, G., Stavrakas, V., Aryandoust, A., Ürge-Vorsatz, D., Staffell, I., & Flamos, A.** (2021). Model development to match models to the user needs. Deliverable 3.2. Sustainable Energy Transitions Laboratory (SENTINEL) project.
7. **Bachner, G., Khanna, T., Kleanthis, N., Mayer, J., Michas, S., Sgarlato, R., & Stavrakas, V.** (2021). Model Improvements Report. Deliverable 5.2. Sustainable Energy Transitions Laboratory (SENTINEL) project.
8. **Gaschnig, H., Süsser, D., Ceglarz, A., Stavrakas, V., Giannakidis, G., Flamos, A., Sander, A., Lilliestam, J.** (2020): User needs for an energy system modeling platform for the European energy transition. Deliverable 1.2. Sustainable Energy Transitions Laboratory (SENTINEL) project, Potsdam: Institute for Advanced Sustainability Studies (IASS), 149 p.
9. **Süsser, D., Ceglarz, A., Gaschnig, H., Stavrakas, V., Giannakidis, G., Flamos, A., Sander, A., Lilliestam, J.** (2020): The use of energy modelling results for policymaking in the EU. Deliverable 1.1. Sustainable Energy Transitions Laboratory (SENTINEL) project, Potsdam: Institute for Advanced Sustainability Studies (IASS), 53 p.
10. **Santini, M., Tzani, D., Thomas, S., Stavrakas, V., Rosenow, J., & Celestino, A.** (2020). Experience and Lessons Learned from Pay-for-Performance (P4P) pilots for Energy Efficiency. Zenodo. https://doi.org/10.5281/zenodo.3887823.
11. **Stavrakas, V., Nikas, A., Papadelis, S., Siskos, L., Doukas, H., & Flamos, A.** (2018). A final brief of 14 country case studies, Deliverable 3.3, Chapter 7. Transition Pathways and Risk Analysis for Climate Change Mitigation and Adaptation Strategies (TRANSrisk) project.
12. **Michas, S., Stavrakas, V., Papadelis, S., Flamos, A., Antosiewicz, M., Witajewski-Baltvilks, J.** (2018). Toolboxes for adaptation and mitigation policy pathways, Deliverable 7.3. Transition Pathways and Risk Analysis for Climate Change Mitigation and Adaptation Strategies (TRANSrisk) project.
13. **Stavrakas, V., Papadelis, S., Flamos, A.** (2018). Identifying Innovation Policy Options in Transition Pathways: Achieving a low-carbon power system through empowering consumers to produce and store clean energy at the local level: the case of Greece, Deliverable 6.4, Chapter 3. Transition Pathways and Risk Analysis for Climate Change Mitigation and Adaptation Strategies (TRANSrisk) project.
14. **Koretsky, Z., Stefan, B., Núñez Ferrer, J., Alessi, M., Spyridaki, N.A., Stavrakas, V., et al.** (2017). Report on the knowledge gaps about key contextual factors. Deliverable 6.3. Coordination and Assessment of Research and Innovation in Support of climate Mitigation Options (CARISMA) project.
15. **Stavrakas, V., Michas, S., Spyridaki, N.A., Papadelis, S., Kontochristopoulos, I., Flamos, A.** (2017). Report on identifying research needs for climate change mitigation technology options. Deliverable 4.1. Coordination and Assessment of Research and Innovation in Support of climate Mitigation Options (CARISMA) project.

References

[1] Ministry of Environment and Energy. National Energy and Climate Plan of Greece. 2019.

[2] Operator of RES and Guarantees of Origin. Renewable Energy Sources and Combined Heat and Power: Summary Information Sheet (In Greek). 2018.

[3] HELAPCO. Greek PV Market statistics - 2017. Hell Assoc Photovolt Co 2018:1–5.

[4] Eyre N, Darby SJ, Grünewald P, McKenna E, Ford R. Reaching a 1.5C target: Socio-technical challenges for a rapid transition to low carbon electricity systems. Philos Trans R Soc A Math Phys Eng Sci 2017:1–20.

[5] Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-baltvilks J, et al. Barriers to and consequences of a solar-based energy transition in Greece. Environ Innov Soc Transitions 2018:1–17. doi:10.1016/j.eist.2018.12.004.

[6] Yan C, Xue X, Wang S, Cui B. A novel air-conditioning system for proactive power demand response to smart grid. Energy Convers Manag 2015;102:239–46. doi:10.1016/j.enconman.2014.09.072.

[7] Wetter M. Co-simulation of building energy and control systems with the building controls virtual test bed. J Build Perform Simul 2011;4:185–203. doi:10.1080/19401493.2010.518631.

[8] Wetter M. Modelica-based modelling and simulation to support research and development in building energy and control systems. J Build Perform Simul 2009;2:143–61.

[9] Zuo W, Wetter M, Tian W, Li D, Jin M, Chen Q. Coupling indoor airflow, HVAC, control and building envelope heat transfer in the Modelica Buildings library. J Build Perform Simul 2016;9:366–81. doi:10.1080/19401493.2015.1062557.

[10] Bünning F, Sangi R, Müller D. A Modelica library for the agent-based control of building energy systems. Appl Energy 2017;193:52–9. doi:10.1016/j.apenergy.2017.01.053.

[11] Lauster M, Remmen P, Fuchs M, Teichmann J, Streblow R, Müller D. Modelling long-wave radiation heat exchange for thermal network building simulations at urban scale using Modelica. Proc. 10th Int. Model. March 10-12, 2014, Lund, Sweden, 2014, p. 125–33. doi:10.3384/ecp14096125.

[12] Wetter M, Bonvini M, Nouidui TS. Equation-based languages - A new paradigm for building energy modeling, simulation and optimization. Energy Build 2016;117:290–300. doi:10.1016/j.enbuild.2015.10.017.

[13] Tsantopoulos G, Arabatzis G, Tampakis S. Public attitudes towards photovoltaic developments: Case study from Greece. Energy Policy 2014;71:94–106. doi:10.1016/j.enpol.2014.03.025.

[14] Pfenninger S. Energy scientists must show their workings. Nature 2017;542:393. doi:10.1038/542393a.

[15] Morrison R. Energy system modeling : Public transparency , scienti fi c reproducibility , and open development. Energy Strateg Rev 2018;20:49–63. doi:10.1016/j.esr.2017.12.010.