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Survey of the use of AI in the Maritime Industry

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Abstract

The link between human and technology is very strong and getting stronger everyday. The Artificial intelligence also seems to be like new in the history of technology but surprisingly someone can see that started to established the early 90s. AI is here to help people to make their lives better and easier. AI is getting to be part of big companies as integral tool even for making decision. If the AI along with human intelligence going to cooperated combined then the humanity is going to be see incredible results. And this is the main scope of this research, to show how the people put AI in their life and use it as tool in order to achieve the best for their everyday professional life and their company's interest. Although the shipping companies delayed to add AI for their favour, the last decade this changed, trying to build even unmanned ships sailing totally automatic with the help of AI and this seems to be only the beginning for cooperation of this industry and AI.

Keywords:

AI
ARTIFICIAL INTELLIGENCE
MARITIME INDUSTRY
AI MARITIME INDUSTRY

Περίληψη

Ο δεσμός μεταξύ ανθρώπου και τεχνολογίας είναι πολύ ισχυρός και δυναμώνει καθημερινά. Η τεχνητή νοημοσύνη φαίνεται επίσης να είναι σαν καινούργια στην ιστορία της τεχνολογίας, αλλά παραδόξως κάποιος μπορεί να δει ότι άρχισε να καθιερώνεται στις αρχές της δεκαετίας του '90. Το AI είναι εδώ για να βοηθήσει τους ανθρώπους να κάνουν τη ζωή τους καλύτερη και ευκολότερη. Η τεχνητή νοημοσύνη γίνεται μέρος μεγάλων εταιρειών ως αναπόσπαστο εργαλείο ακόμη και για τη λήψη αποφάσεων. Εάν η τεχνητή νοημοσύνη μαζί με την ανθρώπινη νοημοσύνη συνεργαστούν, τότε η ανθρωπότητα θα δει απίστευτα αποτελέσματα. Και αυτό είναι το κύριο αντικείμενο αυτής της έρευνας, για να δείξει πώς οι άνθρωποι βάζουν την τεχνητή νοημοσύνη στη ζωή τους και τη χρησιμοποιούν ως εργαλείο προκειμένου να επιτύχουν το καλύτερο για την καθημερινή τους επαγγελματική ζωή και το συμφέρον της εταιρείας τους. Αν και οι ναυτιλιακές εταιρείες καθυστέρησαν να προσθέσουν τεχνητή νοημοσύνη προς όφελός τους, την τελευταία δεκαετία αυτό άλλαξε, προσπαθώντας να κατασκευάσουν ακόμη και μη επανδρωμένα πλοία που πλέουν εντελώς αυτόματα με τη βοήθεια της τεχνητής νοημοσύνης και αυτό φαίνεται να είναι μόνο η αρχή για τη συνεργασία αυτής της βιομηχανίας και της τεχνητής νοημοσύνης.

Λέξεις κλειδιά:

ΤΕΧΝΗΤΗ ΝΟΗΜΟΣΥΝΗ, AI, ΝΑΥΤΙΚΗ ΒΙΟΜΗΧΑΝΙΑ,

Contents

1. Introduction 8
1.1 Evolution of Shipping 8
1.2 Maritime Market and New Technologies 10
1.3 Digital Transformation 11
1.4 Artificial Intelligence in Shipping 12
2. Theoretical Background 14
2.1 Intelligence 14
2.2 Artificial Intelligence 14
2.3 Separating artificial from natural intelligence 16
2.3.1 Classical and computational artificial intelligence 16
2.3.2 Turing test 16
2.4 Areas of artificial intelligence 17
2.4.1 Problem solving 17
2.4.2 Proof of Theorems 17
2.4.4 Artificial-Computer Vision 18
2.4.5 Machine Learning 18
2.4.6 Action Planning and Scheduling 18
2.4.7 Autonomous Robots 19
2.5 Machine Learning 19
2.6 Machine Learning Techniques 21
2.6.1 Supervised Learning 21
2.6.2 Unsupervised Learning 24
2.6.3 Clustering 24
2.6.4 Reinforcement Learning 25
3. AI in the Maritime Industry 26
3.1 Companies developing A.I. in shipping 26
3.1.1 METIS 26
3.1.2 Signal Ocean 27
3.1.3 DeepSea Technologies 27
3.2 Investigation of Algorithmic Applications in Shipping 28
3.2.1 Object Recognition 28
3.2.2 Autonomous Navigation 28
3.2.3 Trip Planning Optimization 28
3.2.4 Maintenance Forecasting and Energy Performance Management 28

3.2.5 Fare Control 29
3.2.6 Maritime Communications 29
3.2.7 Improving Safety at Sea 29
4. Applications 29
4.1 Autonomous Vessel and Digital Maritime Technology 29
4.2 Autonomy in the transport sector 31
4.3 Differences between conventional, remote-controlled and autonomous ships 32
4.4 Technical development and testing 33
4.4.1 AAWA 34
4.4.2 MUNIN 34
4.4.3 Revolt 35
4.4.4 Yara Birkeland 35
4.5 Theoretical Approach to Neural Networks in Autonomous Navigation 36
4.5.1 Maritime transport 36
4.5.2 First steps for autonomous movement 37
4.5.3 Autonomous navigation system functions and neural networks 37
4.6 Estimation of Shipbuilding Costs using ANN 40
4.6.1 ABC System 41
4.6.2 ABC system implementation using ANN 41
4.7 Fuel consumption and malfunction prediction using artificial intelligence programs 44
5. Other Advanced Shipping Technologies 4.0 46
5.1 Big Data Analysis 46
5.2 Internet of Things 47
5.3 Autonomous Vehicles and Robotics 48
5.4 Virtual and Augmented Reality 49
5.5 Digital Security and Blockchain 51
6. Big Data in Maritime Industry 52
6.1 Data types and data sources in shipping 52
6.2 E-navigation System 53
6.3 Green shipping and ship performance 55
6.4 Challenges 56
6.4.1 Data quality and integration 56
6.4.2 Data consolidation 57

6.4.3 Available Equipment 57
7. Conclusions 58
References 60

1. Introduction

Shipping is the backbone of the global economy. The first voyage for commercial purposes took place in the Mesolithic Age, 8000 BC, in the Aegean Sea (Maritime Museum, 2024), and today 90% of global trade takes place by sea with ships carrying more than 11 billion tonnes of goods annually (ICS, 2024).

Maritime trade allows for imports and exports on an intercontinental level, which shape the conditions for the existence of free trade and the ability to obtain both raw materials and manufactured goods from developed, transition and developing economies.

It is a well-founded industry that is continuously strengthening and expanding, according to the analysis of the United Nations Conference on Trade and Development data for the last 5 years (UNCTAD, 2024). Merchant ships increased by 7.1% in number and 14.3% in capacity from 2016 to 2020. In January 2020, the global fleet approached 2.1 billion tonnes in capacity, 81 million more than the previous year. Remarkably, 15 countries manage 80% of the global fleet with Greece - 17.7%, Japan - 11.4%, China - 11.2%, Singapore - 6.7% and Hong Kong - 4.9% at the top.

According to indicative statistics for the year 2018, the total value of the European Union's transactions involving 47% of exports and 55% of imports amounted to €2,006 billion, showing the largest increase compared to air and land transport (Europa, 2019). The preference for maritime transport is not accidental; it is also due to economic and environmental factors. It is known to offer the lowest cost but also leaves the smallest environmental footprint by having the lowest carbon dioxide (CO_2) emissions per ton of product (ICS, 2024).

Considering the size of the industry, the frequency and value of transactions, the creation of added value and the continuous trend towards expansion, it is safe to conclude that merchant shipping will continue to define the global economy in the future.

1.1 Evolution of Shipping

Shipping is evolving; wood, rowing and sails have been replaced by steel and engines and in recent years, digitalization has entered shipping with new perspectives. The history of shipping can be divided into three main revolutionary periods. The first is the transition from sailing ships to steamships in the 19th century. At the beginning of the 20th century, steam engines were replaced by diesel engines, electric motors and other types of internal combustion engines. The third technological revolution occurred in the 1970s and introduced computers on board ships with the installation of sensors, displays for real-time data display, satellite communication and control systems and other advanced technology systems that facilitated the daily life of seafarers and supported high-quality ship maintenance.

The fourth technological revolution is underway and is based on Big Data analysis and Artificial Intelligence. Artificial Intelligence has accelerated technological developments to the extent that there have been rapid upgrades and extraordinary cost reductions. However, the shipping industry always seems reluctant to adopt innovative technologies as even today, information on demand and supply is communicated via emails or personal contacts, while daily tasks and cost-benefit calculations are done manually. It is worth exploring the reasons why such a powerful industry with a future has hesitated to adopt sophisticated technological tools to coordinate its processes more efficiently and maximize its profit.

The shipping ecosystem shows increased complexity in the way it operates, as it is an intermediate market in which three parties interact with different roles and purposes. Shipping companies either own a fleet of ships or take over the commercial management of other ship owning companies. It is commonly accepted that ships can bring a high profit, but their risk as expensive assets with high maintenance costs - such as fuel, crew, repairs - even on days when they are unused, should not be ignored. Therefore, ship owners want to ensure maximum employment of their ships in conjunction with maximum revenue (Signal Group, 2020).

On the other side of any deal there are the shippers who control the commodities globally and aim to secure the right ship at the ideal time to transport their cargoes (Signal Group, 2020). Deals in shipping are coordinated by brokers, who gather a large amount of data from ship owners and shippers, based on which they pursue profitable deals. Their success is based on the accuracy of the information they provide (Signal Group, 2020). Transactions worth millions are based on personal relationships, intense negotiations and private information that fund a network coordinated by brokers.

It is estimated that a modern ship generates more than 20 gigabytes of data on a daily basis (Marine Digital, 2020), which comes from various sources and is often in non-standard formats. Data can be categorized based on the method of collection, manually or automatically. Each ship maintains information on crew, supplies, and the cargo it carries. In addition, there is the captain's log, the ship's log and the daily report to record the internal and external status of the ship. At the same time, ports and channels complete reports on the vessel's stay, loading or unloading of the goods and costs. Finally, insurance companies and certification bodies have their own databases on injuries and accidents. Since 2004, all ships have been required to produce electronic data. Through the AIS (Automatic Identification System) (IMO, 2024) and coastal and space radars, data on the position of the ship, its speed and direction are collected. Sensor data for monitoring crew health, fuel consumption, equipment use and wear and tear are also becoming increasingly widespread. Accordingly, huge amounts of data are being generated in real time and the key characteristics of Big Data, defined by Doug Laney in 2001: volume, velocity and variety.

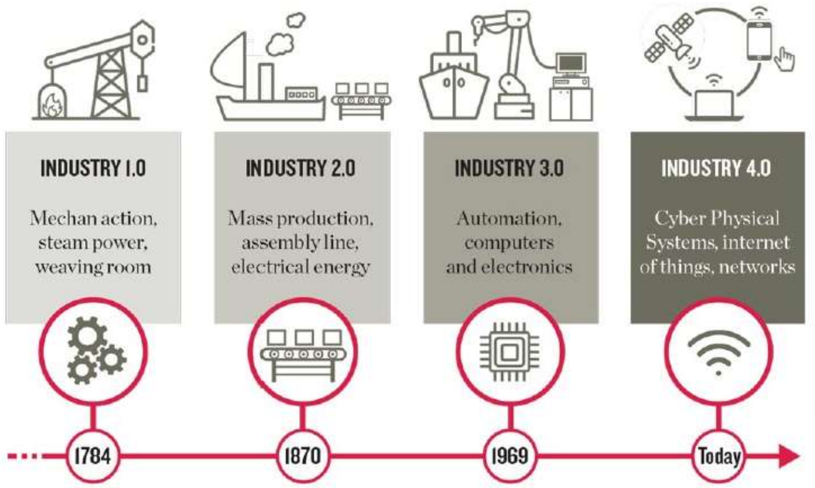


Figure 1.1. Chronological evolution of the shipping industry (Bureauveritas, 2024).

1.2 Maritime Market and New Technologies

Shipping is directly affected by events that cannot be accurately predicted such as adverse weather conditions, increased demand in certain countries, canal traffic, environmental legislation leading to repairs (such as IMO 2020), economic blockades of certain countries, a war, a pandemic or an accident. For example, the tanker industry experienced a significant upturn with the onset of the COVID-19 crisis, due to lower oil prices and higher exports from major producers, as shown in Figure 1.2. In the long term, however, lower air and road transport demand, and effectively lower oil consumption, will hurt the industry for at least 15 months (BIMCO, 2024). Market levels are shaped by the supply and demand for ships across regions of the world. This makes the market volatile and makes it difficult to plan strategy and make fleet allocation decisions. A significant number of volatile factors need to be taken into account and although AI can greatly support the process, it cannot replace human instinct and adaptation to different, unpredictable conditions.

Digital culture cannot be achieved instantaneously, as it is a process of transformation, a new approach. The prospect of a neutral, open digital environment for secure, easy and real-time information exchange is great and shipping companies are already starting to embrace it. In particular, AI enables scalability, ensuring that smarter decisions can be made faster and more accurately. Companies that recognize the industry shift are incorporating technological solutions minimizing risk and financial losses. With the adoption of AI technologies, in the future the entire ecosystem will enter a new era of growth.

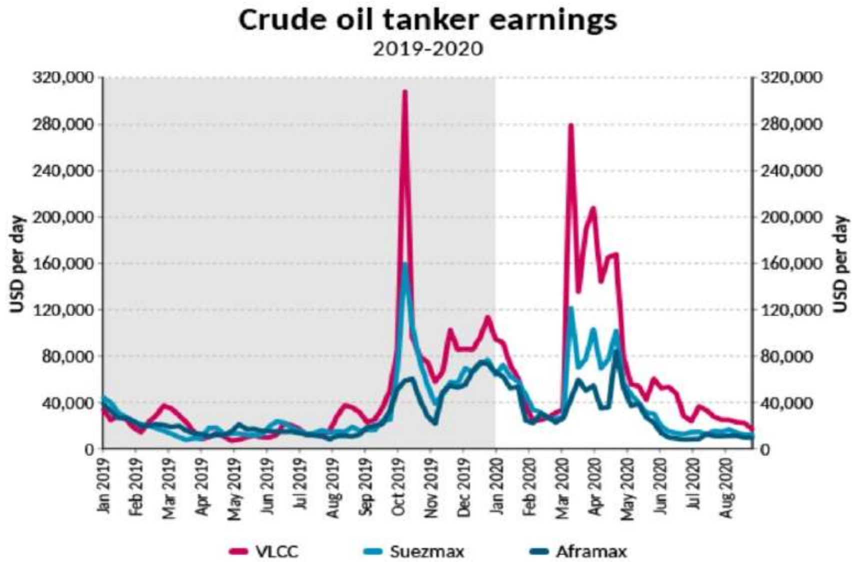


Figure 1.2. Crude oil tanker revenues, 2019-2020.

1.3 Digital Transformation

The requirements and challenges identified at every stage from planning and optimal implementation to the safe completion of the transport of a cargo have led to the digitization of the industry and the application of advanced technologies. Regarding the dynamics of value creation in a shipping company, general economic reporting models (Stopford, 2009) describe three key variables that contribute to value creation: (a) the revenues received from chartering/operating the ship, (b) the cost of operating the ship, and (c) how the business is financed. Such costs include the cost of operating the vessel, voyage costs, capital costs (which depend on how the vessel is financed) and the cost of transporting cargo. The general incidence of such costs is approximately 45% for both operating costs and voyage costs, and the remaining 10% for capital costs. The competitive advantage of Shipping 4.0 is value creation through advanced analytics. As organizations become digitized their analytical capabilities will evolve into predictive capabilities. Until recently, the monitoring functions of each ship subsystem were analyzed in an unstructured way by people with rudimentary analytical knowledge. This makes it difficult to detect important features and prevents the full exploitation of information to create added value.

Artificial intelligence applications tend to fill this gap. AI is expected to support sailing and navigation with minimal external intervention, as well as the handling of hazardous and emergency events, reducing the dependence on human intervention that can be negatively affected by lack of skills or situational awareness.

1.4 Artificial Intelligence in Shipping

The major challenge now facing the maritime industry is the integration of intelligent artificial intelligence tools for the proactive monitoring and management of its assets (ships, engines, etc.) through Information and Communication Technology (ICT), with a primary focus on wear and tear monitoring and prediction, and secondarily on fault detection and diagnosis, as well as fuel consumption prediction.

Artificial intelligence (AI) is a promising strategy used to address a variety of issues such as engineering, medicine, information technology and many other applications (Data Mining, 2011). A characteristic of AI is that AI algorithms rely on the availability of a large amount of data for their training but do not require a physical understanding of the system for which they are developed (Yusri et al., 2018). Moreover, when sufficient training data exists, the majority of algorithms can develop the requested predictive models (Ineza Havugimana et al., 2023).

After the first and second wave of AI algorithm development in the 1970s and 2000s, respectively, we are now in the middle of a third wave (Makridakis, 2017). There were many challenges that contributed to the development of AI algorithms to solve problems related to the proper operation of a machine. The biggest challenges are the prediction, tuning and optimization of the nonlinear and complex phenomena occurring inside an internal combustion engine. Examples of phenomena occurring inside an engine are the variations of temperatures and pressures inside the cylinder, the corresponding variations of the fluids in the engine's networks (oil, oil, fresh and seawater cooling), and the combustion products such as the amount of emitted pollutants (Ineza Havugimana et al., 2023).

In other words, we can obtain a large amount of information from an engine in terms of speed, torque, fuel injection and consumption, pressure, load, temperature and much more. The best way to manage the huge amount of data to get the most out of it is to use artificial intelligent algorithms.

As shown in Figure 1.3, we are already in the era of the 4th Industrial Revolution, or Industry 4.0. Industry 4.0 refers to a generation of industrial activities characterized by smart systems and web-based solutions. Industry 4.0 is characterized by cyberphysical systems (CPS) and intelligent factories (or intelligent ships when referring to shipping) based on the concept of the "Internet of Things" (IoT) (Galar and Kumar, 2017). Cyberphysical systems or embedded systems are integrated electronic or digital components that monitor and control physical devices. These systems communicate through a network that is usually based on Internet technology, creating an Internet of Things (IoT) ("Advanced Manufacturing and Automation V," 2016).

One of the application areas of Industry 4.0 that is of particular interest to shipping is maintenance in the form of self-learning and intelligent systems that have the ability to predict failures and make accurate diagnoses. Another area that is also of great interest to shipping is the development of intelligent systems for predicting fuel consumption. These systems, in order to accurately extract information, have high requirements in terms of access to data and the quality of this data, and therefore need to use multiple data sources to ensure their reliability.

AI-related data are generated, collected, and processed at different levels by different information technology (IT) systems, e.g. enterprise resource planning (ERP) system for business operations, supervisory control and data acquisition (SCADA) system for process operations, computerized maintenance management system (CMMS) and condition monitoring (CM) system for maintenance operations, and safety instrumented systems for safety-related operations.

With the current level of technology, it is relatively easy and affordable to combine the information provided by these systems. The purpose of these systems is to develop predictive models for both maintenance management and fuel consumption (Galar and Kumar, 2017).

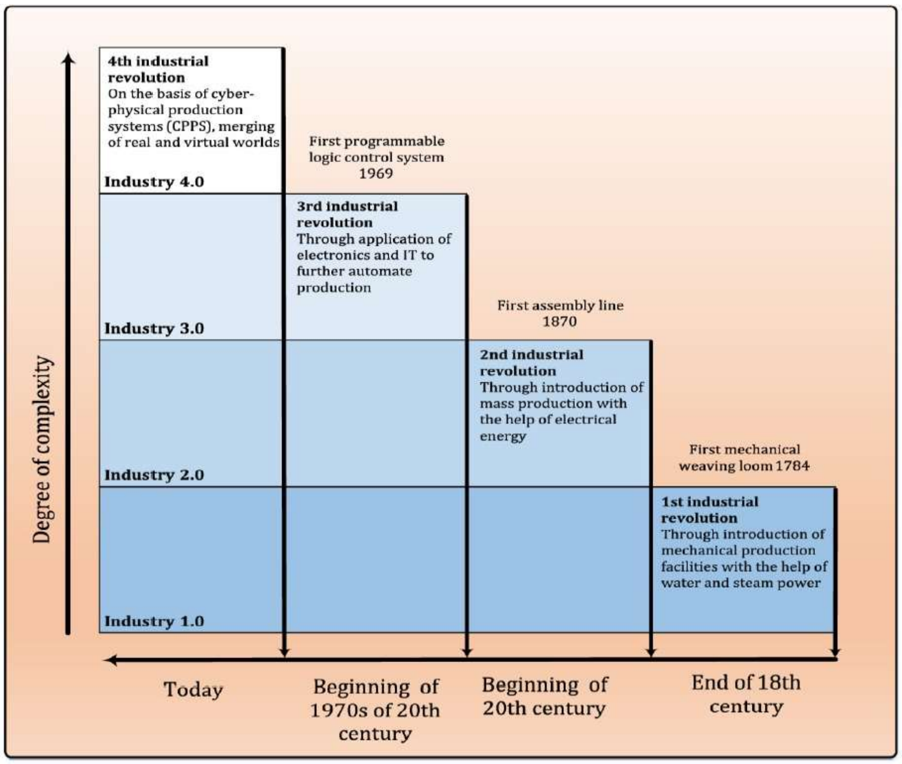


Figure. 1.3 Definition of Industry 4.0 (Deloitte, 2014).

Artificial intelligence, sensor technology, 3D printing, robotics, drones and nanotechnology are some examples of technologies that accelerate industrial processes and make them more agile by combining cyber-physical systems and IoT. Many of these technologies are not new but emerged some 20 or 30 years ago, but recent rapid increases in computing power ("Moore's Law," 2023) and cost reductions make them now suitable for industrial use (Deloitte, 2023). Moore's Law is named after Intel co-founder Gordon Moore because of an observation he made, in 1965, about the number of transistors in an electronic circuit. According to this law, every 18 to 24 months the density of integrated circuits in an electronic circuit doubles. This increase implies a significant technological development and has contributed to the development of more powerful, faster and more efficient computer systems.

2.1 Intelligence

According to Vergherakis (2015), "intelligence is a set of mental functions that we use to cope with new situations and solve problems, drawing on previous experiences". The theory of multiple intelligence was proposed by Howard Gardner (2000) where he expands the definition of intelligence and describes seven different types of mental abilities:

1. Linguistic Intelligence: It is the advantage that characterizes those who are very good at handling language, poetry, grammar, writing and reading such as writers, philosophers etc.

2. Logical-mathematical Intelligence.

3. Spatial intelligence: It is the perceptual ability to create a mental model of a space and then manipulate and operate in it. For example, sailors, engineers, decorators, architects, artists (painters, sculptors) are likely to have developed spatial intelligence.

4. Musical intelligence: is the intelligence that characterizes musicians, composers, etc.

5. Somatomotor intelligence: It is the kind of intelligence that creates a great dancer, athlete, sculptor etc.

6. Interpersonal Intelligence: The ability to understand and work with other people. Most likely this type is exhibited in good realtors, salespeople, teachers, etc.

7. Intrapersonal Intelligence: The ability to understand oneself, to use one's abilities successfully. Such people can succeed in almost any area related to themselves.

2.2 Artificial Intelligence

Various definitions of artificial intelligence have been formulated. They classify them into four categories that approach AI from different perspectives in terms of its goal: (Vlachavas et. al., 2006)

1. Systems that think like humans

2. Systems that think rationally

3. Systems that act like humans

4. Systems that act rationally (Russell and Norvig, 2005)

From the above four categories, a more general definition of AI can be derived, which could be as follows: Artificial Intelligence is the field of computer science that deals with the design and implementation of programs that can mimic human cognitive abilities, thus displaying characteristics that we usually attribute to human behavior, such as learning, problem solving, natural language understanding, problem solving, etc. (Vlachavas et. al., 2006).

There are many disciplines that contribute techniques and ideas to AI. Some of them are psychology, philosophy, linguistics, neuroscience, computer science as well as engineering.

Neurology: is the discipline that deals with the nervous system and in particular the study of the brain. We know that the brain is made up of nerve cells or neurons. In 1929 Hans Berger invented the electroencephalograph, when the measurement of intact brain activity began. The development of magnetic resonance imaging of brain function gives scientists detailed images of brain activity, allowing measurements that show interesting correlations with ongoing processes. A very important conclusion that emerges from this is that the brain creates a collection of cells that can lead to thought and cognition, specifically we are referring to cognition.

Psychology: According to the science of psychology, the brain works like a device that processes information. From 1920 to 1960, psychology was strongly influenced by the behaviorism movement led by John Watson. The basic premise of this theory is that the acquisition of knowledge and learning is the result of the dependencies between the stimuli that an individual receives from his or her environment and his or her responses to those stimuli. That is, an individual's behavior is shaped and controlled by environmental factors. Computational modelling led to the creation of cognitive science and it is now accepted among psychologists that "a cognitive theory should resemble a computer program" (Anderson, 1980).

Linguistics: (Modern) linguistics was created around the same time as artificial intelligence. They developed together, sharing a common area, that of computational linguistics. It soon became apparent that understanding language was a more complex problem than it seemed. To understand language, it is not enough to understand the structure of sentences, but it is also necessary to understand the subject and the context (Russell and Norvig, 2005).

Computer science: The success of artificial intelligence is due to two factors: intelligence and computers. Computer science provides the necessary tools so that modern programs, such as software and programming languages, can be written (Russell and Norvig, 2005).

Philosophy: The philosopher Aristotle was the first to formulate a set of laws about cognition. In particular, he identified a kind of syllogism, i.e. a system of reasoning that allowed one to produce conclusions given some initial assumptions. Later in more modern times Gottfried Wilhelm Leibniz wanted to mechanize syllogism. Thus he tried to create a language with which all human knowledge could be expressed (Nilsson, 2010).

2.3 Separating artificial from natural intelligence

For any phenomena we can distinguish the real ones from the fake ones. We can also distinguish the natural from the artificial. Natural means that it is created by nature while artificial means that it is produced by humans. So artificial intelligence can be interpreted as the opposite of real intelligence. Of course we cannot have fake intelligence. If an agent behaves intelligently, it is intelligent. So artificial intelligence will be intelligence that has been created artificially. It is also determined by external behavior and this was the motivation for creating a test for intelligence known as the Turing test (Poole and Mackworth, 2010).

2.3.1 Classical and computational artificial intelligence

We distinguish between two approaches to artificial intelligence - classical and computational artificial intelligence. Classical intelligence has to do with the simulation of human intelligence. The way it approaches it is by using systems and algorithms using symbols. Classical intelligence is also based on the understanding of mental processes. Computational intelligence is based on imitating biological processes. For example, such processes are the way the brain works as well as the process by which species evolve (Vlachavas et. al., 2006).

2.3.2 Turing test

The Turing test is a way of testing whether a machine has the ability to think. It was invented by Alan Turing. The test is carried out with a woman, a man and an examiner in three different rooms and neither is allowed to see the other. The rooms are soundproofed, but each person has a video so that they can communicate.

This test is designed for the examiner to find out which of the two people is the man and which is the woman by using various questions to them as a basis and the answers they give. However, the man and the woman are not obliged to tell the truth, which they both know in advance that they can also lie. In particular, the man is encouraged to lie frequently and to whatever extent he wants and is intended to mislead the examiner. Obviously this makes the examiner's job more difficult and there is a possibility that he may come to the wrong conclusions. But the test is not completed until the examiner decides which room the man is in and which room the woman is in. But what happens if the man is replaced by a smart computer programmed like him? If the machine is "stupid", then the examiner will draw correct conclusions more often. But if the machine is "smarter" than the man, then the examiner will have to be wrong more often (Gibilisco, 1994).

In fact, Turing predicted that by the year 2000, it would be possible to develop an artificial intelligence that could fool 30% of respondents after just five minutes of conversation. The first program to pass this test is considered ELIZA, which was started in 1976 by American programmer Joseph Weisenbaum, ELIZA managed to convince Weisenbaum's secretary that she was talking to him.

2.4 Areas of artificial intelligence

Artificial intelligence is a synthesis of methods, models, tools and systems that borrow from, but at the same time integrate and specialise in four different scientific areas:

1. Cognitive Sciences such as Philosophy, Psychology, Logic, Cybernetics,

2. Mathematical Science and in particular Model and Proof Theory, Mathematical Logic, Mathematical Logic, Operations Research

3. The broader scientific area of computer science as the main product of artificial intelligence is the experienced systems, intelligent information systems, proofs of theorems, etc.

4. Control theory and automata and in collaboration with biotechnology, which propose the development of intelligent systems at the hardware level (hardware, neural networks) (Panagiotopoulos and Anastasakis, 2012).

2.4.1 Problem solving

When we attempt to solve a problem, we must first define it and then design an algorithm that solves it by having several choices of actions available to it at each step and deciding which one to choose. For a problem to be given as an input to an algorithm, it must first be explicitly formulated and then defined in a suitable way to be an input to the algorithm (Georgoulis, 2015).

2.4.2 Proof of Theorems

Artificial intelligence and mathematics have always had a symbiotic relationship. Every aspect of AI has its mathematical roots. Efforts to improve computational logic have led to new results in mathematical logic; using artificial intelligence we have the ability to carry out problem solving and proof of theorems. We include both logical and analogical reasoning in the proof of theorems (Greenberg, 2000).

2.4.3 Natural Language Processing

Natural language processing is done in three stages:

1. Syntactic analysis

2. Semantic analysis

3. Pragmatic analysis

The most common errors that a sentence can present and thus prevent its recognition are spelling errors and in order to deal with them we use error correction algorithms. Natural language processing has many applications such as information extraction, construction of electronic dictionaries, and machine translation (Jurafsky and Martin, 1999).

2.4.4 Artificial-Computer Vision

Artificial vision, also called computer vision, is the branch of artificial intelligence that tries to give computers and other machines (such as robots) the ability to see. Vision in a physical being is used to distinguish objects, find food and generally perceive the outside world. With the development of technology, artificial vision may soon be a complement to biological vision (Learned-Miller, 2011).

2.4.5 Machine Learning

Machine learning is the creation of models or patterns from a data set that has a computer system as its source. Based on the type of each problem we have developed various machine learning techniques and we distinguish two types of machine learning.

1. Supervised learning.

2. Unsupervised learning. The system learns from the generation of patterns (Vlachavas et. al., 2006).

2.4.6 Action Planning and Scheduling

Scheduling creates a problem that occurs in the majority of industrial applications. It is the process in which we assign resources to tasks with data, criteria and some constraints within a certain time frame. Scheduling has a very important role in industrial applications. In order to solve problems of this kind we make use of appropriate algorithms.

2.4.7 Autonomous Robots

Autonomous robots are robots that have the ability to act on their own without the need for someone to operate or control them. This type of robot is programmed to respond to external stimuli. One feature is that it has a sensor for detecting obstacles. This way, whenever it encounters an obstacle, it changes direction. Of course, some of the more advanced robots use "stereo vision" which enables them to see the world around them and even their software has the ability to classify various objects as well as calculate what distance they are in relation to the robot. Today robots can navigate in various environments.

2.5 Machine Learning

An important branch of AI is machine learning or machine learning (ML). ML is based on the idea that computer systems have the ability to be trained at a rapid rate through specific data and furthermore have the ability to correctly identify developing patterns and relationships that are created between a specific set of data (Tsaganos et al., 2020). Machine learning aims to enable machines to perform their tasks skillfully using intelligent software in order to enable them to make decisions with minimal human intervention.

Machine learning techniques, which will be developed later in the chapter, form the backbone of the intelligent software used to develop machine intelligence (Mohammed et al., 2016). In general, ML, for training the system in question, is based on observations and measurements derived from a pool of data, as mentioned earlier, which, combined with already recorded data, which have been analysed, ultimately lead to the training of the system (Mohammed et al., 2016).

ML techniques depend Thus machine learning is directly related to another important discipline, the database discipline, thus being intertwined with terms such as Knowledge Discovery from Data (KDD), data mining and pattern recognition (Mohammed et al., 2016).

ML, then, involves the study of algorithms and statistical models used by computer systems to gradually improve their performance on a particular task or function over time (Tsaganos et al., 2020). ML-based methods have been widely applied in recent years to many scientific and engineering problems (Lary et al., 2016). Machine learning involves the following five (5) steps of performing a task (Russell et al., 2010; Tsaganos et al, 2020):

- Collecting data

- Preparing data

- Training models

- Evaluating models

- Improving performance

The three main machine learning techniques are supervised learning, unsupervised learning and reinforcement learning (Russell et al., 2010; Tsaganos et al., 2020), as shown in Figure 2.1 (Rajbanshi, 2021). In Figure 2.1 we also observe the different types per ML technique as well as the machine learning algorithms corresponding to each type.

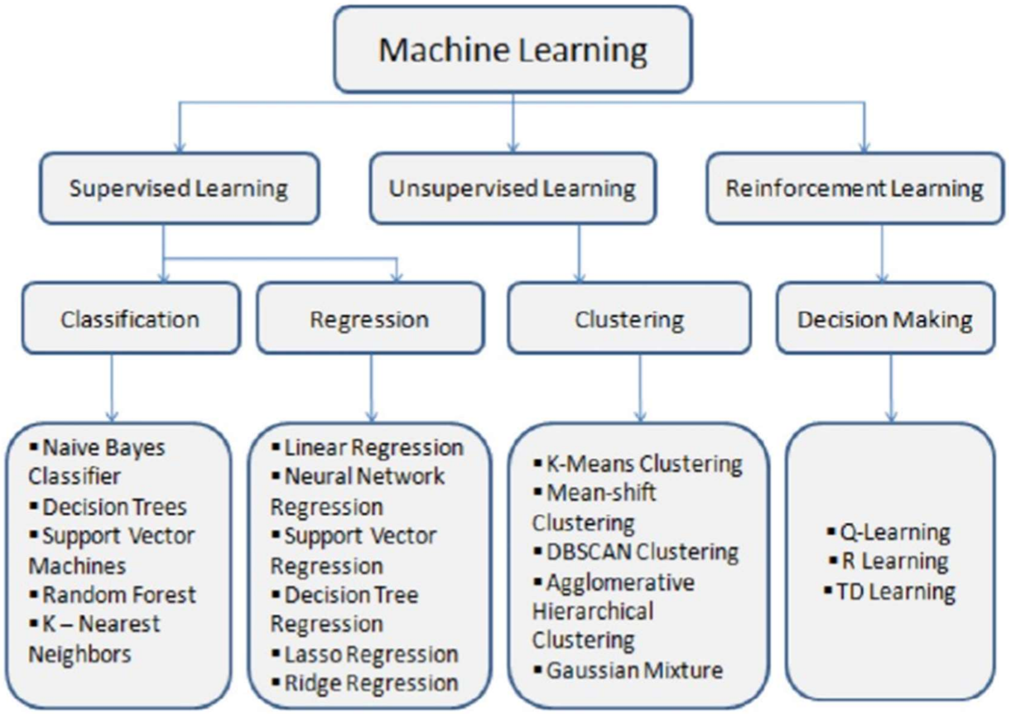


Figure 2.1 The main branches of machine learning (Rajbanshi, 2021).

Supervised learning is divided into two groups of algorithms, classification algorithms and regression algorithms (Rajbanshi, 2021). Classification algorithms include Naive Bayes Classifiers (Naive Bayes Classifier), Decision Trees (Decision Trees), SVM (Support Vector Machines), Random Forests (Random Forest) and kNN (k - Nearest Neighbors) (Russell et al., 2010; Tsaganos et al, 2020). regression algorithms include simple linear regression, multiple linear regression, multinomial regression, decision tree regression, random forest regression and ensemble methods (Russell et al, 2010; Tsaganos et al., 2020).

Unsupervised learning consists of clustering algorithms such as k-means clustering, hierarchical clustering and others (Rajbanshi, 2021; Russell et al, 2010). Finally, reinforcement learning is based on decision making algorithms i.e. the final outcome is derived each time from the interaction of the system with the environment in which it operates. Examples of such algorithms are Q-learning, R-learning and TD learning algorithms (Mohammed et al., 2016; Rajbanshi, 2021).

The further development of intelligent systems, through ML tools, is also of great interest for the shipping industry. The integration of intelligent systems in ships has application both in optimizing fuel consumption and preventing imminent malfunctions (Psaraftis, 2019). Over time, AI will make ships more efficient, safer and their systems easier to use (Tsaganos et al., 2020). ML will be the pillar to make fully autonomous ships a reality in the future (Dalaklis et al., 2018).

Furthermore, the use of AI will provide ship crews with a better understanding of both the internal and external environment of the ship. This will be achieved by correlating the data obtained through the ship's existing systems, both from the propulsion plant sensors and from sensors monitoring external factors (e.g. anemometer, GPS speed, etc.).

The ever-increasing demand for more data on conducting safe navigation, combined with the digitalisation of the shipping industry, is directly linked to significant technical challenges (Dalaklis et. al., 2018). AI and ML will play a dominant role in solving the problem of managing the huge amount of data generated from the operation of ships of shipping companies, thus providing solutions that will have a significant impact on the sustainability of the shipping industry (Tsaganos et al., 2020).

2.6 Machine Learning Techniques

As mentioned in the previous subchapter, machine learning is divided into three main categories of learning techniques (Figure 2.1). Supervised learning, unsupervised learning and reinforcement learning. Each of these techniques can be implemented through different algorithms. In the remainder of this section, the three categories of machine learning techniques will be briefly analysed and the main methods of each technique will be discussed.

2.6.1 Supervised Learning

In supervised learning the available data have "labels" about their desired outcome. That is, the algorithms accept as input the values of only a portion of the data set, which for this case is the training data (Russell et al., 2010). The algorithms learn from a labeled data set to generate expected predictions in response to new data (Rajbanshi, 2021). In this case, that is, the algorithms know where the input data are mapped to i.e. what the expected outcome will be in other words (Mohammed et al., 2016).

The results (output) of the input data are also referred to as output data. The goal of supervised learning is to train the algorithm on a rule based on which it will be able to match the inputs with their outcomes (the outputs) in order that when new data is input, the algorithm will be able to predict with the highest reliability and accuracy the outcome of the new input data.

For the most part, the evaluation of the output is performed by supervisors who are human, but it is not excluded that the evaluation is also assigned to machines. However, human judgments are more accurate than their machine counterparts, which has been demonstrated through research (Mohammed et al., 2016) where error rates on data evaluated by machines are much higher than their human counterparts.

As already mentioned, supervised learning is divided into two groups of algorithms, classification algorithms and regression algorithms (Mohammed et al., 2016). A brief description of the two methods on which these categories of algorithms are based will follow.

Regression

Regression is a statistical method used to analyse the correlation that occurs between two or more variables in order to predict one variable based on the others (Rajbanshi, 2021). For a regression model to be meaningful, there must be a linear correlation between the variables under consideration. This means that the variation in the value of one variable will correspondingly cause some variation in the value of the other variable.

In the simplest scenario, where there are two variables, one is called the dependent variable (Y) and the other is called the independent variable (X). The linear correlation between the variables allows us to predict the values of the dependent variable (Y) if the values of the independent variable (X) are known (Mohammed et al., 2016). Similarly, a regression model can be generalized to include more than two variables, denoted by "n".

Despite the attempt to accurately predict the values of variable Y, this is practically impossible due to the presence of "random error", i.e. due to the presence of uncontrolled (random) factors that affect the regression model. This random error (e) prevents the accurate prediction of the dependent variable Y for a given value of the independent variable X or for multiple values of other variables X1, X2, ..., Xn. In order to evaluate regression methods, specific statistical coefficients are used which, depending on their value, indicate the accuracy achieved by the predictive model in question.

Classification

Classification is a supervised machine learning technique that aims to classify data into predefined categories, which can be two or more. Classification is part of the supervised learning technique because the algorithm is trained on the basis of the existing data, which includes the classes to which the observations belong.

Then, the algorithm, is trained so that it assigns these observations to the classes based on the values of certain attributes (Rajbanshi, 2021). After training, the algorithm is able to predict the class for the new data based on the attribute values, thus trying to provide as accurate and reliable predictions as possible (Kesavaraj and Sukumaran, 2013).

The goal in the classification method is to take an input vector x and classify it into one of N distinct classes Cn, where n = 1, ... , N. In the most common scenario, the classes are considered separated, such that each input is assigned to a single class (Bishop, 2006).

Artificial Neural Networks models

Artificial Neural Networks (ANNs) are part of the supervised learning technique. ANN's are mathematical, algorithmic, software models inspired by their biological counterparts and which allow complex nonlinear relationships between the response variable and its inputs to be performed (Bishop, 2006; Russell et al., 2010).

An artificial neural network consists of basic units, called neurons (Lazakis et al., 2018). The goal of ANNs is to mimic the way biological neurons communicate in order to process inputs to produce an output. Neurons form a network that responds to stimuli from other neurons in the network (Russell et al., 2010). Figure 2.2 represents a neural network with multiple neurons. We observe that the neurons in the input layer activate the neurons in the hidden layer, in which a computation is performed depending on the inputs, which then activate the neuron in the output layer where the response is the requested output (Bishop, 2006). In short, each layer of hidden neurons receives input from the immediately preceding layers and generates outputs which act as inputs for the immediately following layers.

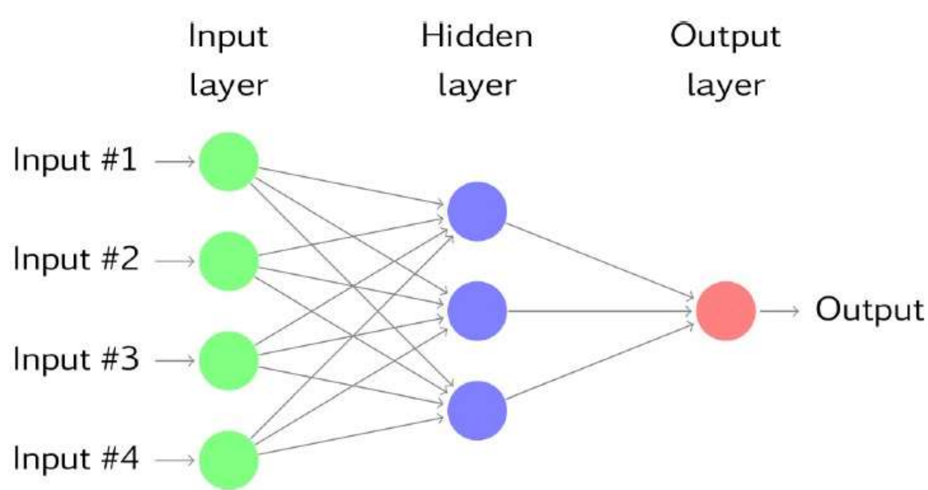


Figure 2.2: Neural network with four inputs and a hidden layer with three hidden neurons.

The 'signal' passed between neurons consists of a real number and the output of each neuron is determined by a non-linear function, which is the sum of its inputs. The connections between neurons are often referred to as edges (Bishop, 2006). Neurons and edges usually have some weighting which is adjusted during the learning process. The role of each gravity is to either enhance or reduce the strength of the signal generated at any given time in a connection. The inputs to each neuron (or node) are therefore combined using a linear combination. Subsequently, the result is modified based on a nonlinear function before being output. Each ANN must be trained several times using different random starting points each time, with the results averaged (Moreira et al., 2021). The number of hidden layers and the number of nodes in each hidden layer must be determined in advance.

Finally, ANNs are adopted to address problems related to the functional diagnosis of systems. The goal is to develop an automated diagnostic program that is able to learn from historical repair data, requiring minimal human intervention, and provide accurate diagnostic guidance. The characteristic of ANN's is the fact that they can establish correlations between faults and repair actions without requiring a full understanding of the complex operation of a system (Bishop, 2006; Moreira et al., 2021; Russell et al., 2010).

2.6.2 Unsupervised Learning

Unlike supervised learning, the central idea of unsupervised learning is based on finding a correlation between data without the existence of labels on the data. Unsupervised learning aims to categorize data without knowing in advance what to look for (Russell et al., 2010).

In unsupervised learning we have no supervisors or training data but only data without labels. The idea is for the algorithm to identify a hidden association between these data (Mohammed et al, 2016). The algorithm is then trained on a label-free dataset and tries to reach an inference by extracting on its own common features between data, data repetitions and existing patterns (Rajbanshi, 2021).

The most common method in unsupervised learning is clustering, i.e., detecting potentially useful groups of input data (Russell et al., 2010). A brief description of this method follows below.

2.6.3 Clustering

The clustering technique belongs to the category of unsupervised learning. In this method, a dataset is analyzed by having as a criterion the similarity that occurs between observations of a set of characteristics (Mohammed et al., 2016).

The main objective of the method is to form "clusters" or groups of observations that show the highest degree of similarity. To be considered successful, the clustering method aims for high homogeneity within each group of observations and significant differentiation between observations belonging to different groups (Ezugwu et al., 2022). There are two main categories of clustering methods (Ezugwu et al., 2022):

- Hierarchical methods, which are subcategorized into divisive and agglomerative methods.

- Non-hierarchical methods.

The most well-known measures for evaluating clustering models are the following:

- Silhouette Coefficient.

- Davies - Bouldin Index.

- Davies-Bouldouldin Index (Davies-Bouldin Index).

2.6.4 Reinforcement Learning

The reinforcement learning method is based on exploiting the observations collected due to the interaction of the program with the environment in order to maximize the benefit and minimize the risk (Mohammed et al., 2016). In order to produce intelligent programs (or agents), reinforcement learning follows the following steps:

- Input data is obtained from the agent.

- Then the agent uses a decision function to perform an action.

- After the required action is performed, the agent receives a reward or reinforcement from the environment.

- The information obtained as a result of the agent's action regarding the reward is stored.

Using the stored information, the agent, achieves the optimal decision making

3. AI in the Maritime Industry

The use of artificial intelligence (AI) in the shipping industry has brought significant improvements in several areas, such as route optimization, risk prediction and prevention, and reduced operating costs. AI enables the analysis of vast amounts of data from sensors, surveillance systems and satellite imagery, helping shipping companies make better and more strategic decisions. For example, AI algorithms can predict weather conditions and recommend optimal routes, reducing fuel use and limiting environmental impact. In addition, AI is helping to improve safety through early warning systems for potential hazards such as collisions and breakdowns. Also, automating processes through AI reduces the need for human intervention in simple but time-consuming tasks, boosting productivity and efficiency. Overall, AI is driving the shipping industry in a greener, safer and more profitable direction.

3.1 Companies developing A.I. in shipping

3.1.1 METIS

Metis is a high-tech company with experience in the shipping industry, specializing in the development of innovative solutions for the global shipping industry. A significant part of its solutions is achieved through the development of Artificial Intelligence and Machine Learning technologies. The company's goal is to ensure an integrated and reliable data collection, processing and analysis process providing useful and reliable information to a shipping company's executives. In addition to Artificial Intelligence and Machine Learning technologies, it also uses Cloud, Smart Devices and wireless network technologies, offering the ability to monitor and update on the operation of its ships in real-time, without the intervention of the individual crew.

Metis is essentially a virtual personal assistant that can be used by shipping executives. It can run non-stop 24/7 and monitors every ship of a shipping company, recording thousands of readings and data from them. It also has the ability to receive data from third-party systems, such as the weather conditions in the area where each ship is located. Metis' innovation gives shipping companies the advantage of having at their disposal accurate forecasts, such as for example the exact predicted fuel consumption, taking into account the weather conditions that the ship will encounter depending on its course, and all its characteristics (such as the actual engine performance), until its next destination. This facilitates the work of the shipping company, resulting in increased productivity and better control of operating costs, such as fuel consumption costs.

3.1.2 Signal Ocean

Signal Ocean's platform uses the B2B SaaS (Software as a Service) model developed with modern technology methods such as Artificial Intelligence and cloud computing. It provides a continuous stream of data and information to support decision making by shipping companies. The user, through a user friendly environment consisting of dynamic lists and computational tools, is able to monitor data of shipping markets in real time, thus facilitating the user to make appropriate decisions more efficiently and faster. From the early stages of its implementation, several of the largest shipping companies were quick to use this platform. Executives are able to quickly see the total and capacity of ships available in any part of the globe and the cargoes that are looking for a carrier, as well as the daily rates that the customer can offer and the rates that their competitors are agreeing to. It not only assesses the huge amount of information available but also the points at which each shipping company is strong, depending for example on the profile of its fleet and its network of contacts and acquaintances.

3.1.3 DeepSea Technologies

DeepSea Technologies is a Greek company with founders Roberto Koustas and Konstantinos Kyriakopoulos since 2017. Mr. Kustas studied at Oxford and Mr. Kyriakopoulos at Cambridge, both of them applied next generation technologies in the shipping industry that they knew well. "We saw that we had both the will and the knowledge to bring a change to the shipping industry" (Koustas, 2020).

DeepSea's platform operation has the ability to collect data from ships around the world in real time. Utilising Machine Learning technology the system can evaluate the collected data resulting in very quickly identifying any problems and recommending actions to optimise ship performance, leading to cost reduction. The Deepsea platform was initially started to be tested on Danaos Corp. ships in 2017. Other shipping companies soon followed suit. Nowadays, the Deepsea platform has been adopted by hundreds of companies where its customers include some of the largest multinationals. Today Deepsea employs around 45 employees with the vast majority of them located in Greece, while maintaining offices in the UK and Cyprus.

3.2 Investigation of Algorithmic Applications in Shipping

Artificial Intelligence, and more specifically Machine Learning, enables the use of intelligent algorithms to evaluate data and provide logical guidance to potential problems in shipping and maritime transport. In this section, we address specific problems that multiple academic publications focus on.

3.2.1 Object Recognition

Several machine learning algorithms specialise in image recognition and processing. A key application is object recognition at sea, whether it is another ship or an obstacle, through normal or satellite images (Mishra, 2021).

3.2.2 Autonomous Navigation

Smooth navigation depends on the ability of the system to detect and avoid collision and attachment hazards. We observe that in this class of problems, Reinforcement Learning has application in creating a simulation environment for model training (Gao and Shi, 2020) (Shi and Liu, 2020).

3.2.3 Trip Planning Optimization

Machine learning can enhance the internal planning and execution of the journey. More specifically, improved estimations, ship speed control and course planning are key parameters to optimize the implementation of a voyage. AI can help both in finding the optimal route from a point A to a point B based on historical data, but also generate valid real-time predictions of a ship's course (Wen et. al., 2020; Yongfeng et. al., 2021).

3.2.4 Maintenance Forecasting and Energy Performance Management

Maintenance and repair work on a ship, such as underwater hull cleaning or propeller polishing, is costly and time-consuming. Anticipating these needs can lead to more efficient planning of such operations.

Techniques that collect data from ship engines to estimate fuel consumption can manage noisy sensor data and lead to improved accuracy in predictions (Agamy et. al., 2020; Han et. al., 2021).

3.2.5 Fare Control

A more accurate picture of vessel occupancy and cargo supply supports the offer of more realistic prices in a negotiation (Munim and Schramm, 2021; Kamallmam et. al, 2020).

3.2.6 Maritime Communications

AIS transmission is now mandatory for every vessel to facilitate its immediate tracking and data collection. Applications have been developed to detect anomalies and irregularities in signal transmission. In addition, land-sea communications are facing difficulties and hence there is a need for optimal use of available resources and networks (Lionis et. al., 2021; Yang and Shen, 2020).

3.2.7 Improving Safety at Sea

Techniques related to the detection, understanding, assessment of obstacles, ships and even piracy or other potential risks can significantly improve safety at sea. In addition, the implementation of environmental regulations and green technology can be more easily controlled (Kaloop et. al., 2021; Karetnikov and Sazonov, 2021).

4. Applications

4.1 Autonomous Vessel and Digital Maritime Technology

Throughout human history, all tasks performed by the human hand have tended to be replaced by the development of technology and technological achievements. The major achievements that human kind has experienced and changed the course of world history are known as technological-industrial revolutions. This term, refers to the major changes that occur in technology and the industrial organization of production, causing changes in the living conditions, working conditions, and economic wealth of a society. (Dombrowski, 2014).

The First Industrial Revolution is known to have begun in England in the mid-18th century, when a very important technology, the steam engine, was invented, which transformed most of the work from agricultural to industrial. In the late 19th century, and after technological developments had already affected most countries in the world, the Second Industrial Revolution followed with the use of electricity and the increase in steel and iron production around the world. At the same time at that time, mass production and the assembly line appeared for the first time as solutions to increase productivity resulting in a better quality of life. Technological development brought the invention of the microchip in 1971 which is considered the starting point of the Third Industrial Revolution. Through the invention of computer technology, production became more automated, productivity increased even more and labour costs decreased.

The vision of the Fourth Industrial Revolution (Industry 4.0) is based on the previous digital revolution, but it has three key features that differentiate it from the previous one. Artificial intelligence, the huge amount of data (Big Data) and the much greater computing power of modern computers. With artificial intelligence being its main feature. The main goal of development and research in the field of artificial intelligence is to automate intelligent behaviors, information gathering, critical thinking ability, communication, planning, learning, manipulation and perception.

In factory systems, Industry 4.0, combines smart digital technology, big data and machine learning to create a connected network that aims to better manage both production and the supply chain. In such a network, humans and robots can be complementary to each other, taking advantage of the benefits of their combination. A key element to achieve this purpose is CPS (cyber physical systems) technology, which has the potential to create a functionally integrated relationship by connecting the physical world and digital reality (Dombrowski, 2014).

While all companies operating today are different, they all face a common challenge such as the need to collect and access information in real-time, across processes, products, people and partners. The so-called Fourth Industrial Revolution, already heavily influencing the daily life of people on land, is taking its first steps in shipping as well.

Developing technologies such as the Internet of Things (IoT), Cloud Computing, Big Data, and robotics have the potential to change the ways in which ships can be designed, built and operated in the future. One example is, automated simulations will be used to mirror our physical world in a virtual model, which is already being used in many design processes, helping to intelligently design a ship. The Internet of Things will be able to be used to connect objects in the physical world that have a virtual representation to the Internet, allowing them to communicate and interact with each other (Dombrowski, 2014).

Cloud computing and Big Data analytics will be used to make real-time decisions and collect and evaluate data from various sources within and outside the company if necessary during the business plan planning process and trip and route optimization (Saldivar, 2017).

For the shipping industry, therefore, technological innovations are strongly related to the digitisation of data related to the ship, its operations and the shipping company's offices ashore, in order to create value by processing it. It is important to note that, the main idea of the maritime industry 4.0 (marine 4.0) is to combine the sum of all these technologies and allow them to work together (Lambrou, 2017). Ships, ports, cargo and shipping operations will be connected via the internet, thanks to the rapid development of ITC information and communication technology in order to organise and control processes efficiently in real time. Increased connectivity, digitisation of data and automation of processes through advanced sensors and intelligent systems are paving the way for the creation of the so-called smart ship. The smart ship concept covers a wide range of possibilities from predictive maintenance, performance optimisation, decision support tools, increased automation and robotics to the most talked about in shipping circles, unmanned ship operation (Lambrou, 2017).

The main incentive for the creation of unmanned ships, which is the first important step towards a smart ship, apart from reducing operating costs, is to increase overall efficiency and safety in shipping. As unmanned ships can be operated either completely autonomously or remotely controlled, i.e. by remote control from the control centre ashore, it is only a matter of time before a fully autonomous ship is created, according to shipping experts. As we know, ships have already been built which operate by remote control, but they are still in the experimental stage. For example, in August 2018 Wartsila successfully piloted a ship in the North Sea for hours under remote control from its facility in San Diego, California, 8,000 kilometres away.

Of course, the vision of the major players in the autonomous ship industry, such as Rolls-Royce, is not just to build an unmanned ship controlled from land, but to create a fully autonomous ship that can make transatlantic voyages (AAWA, 2016).

4.2 Autonomy in the transport sector

Autonomous vehicles have their roots in research on artificial intelligence that began in the late 1950s. However, the more systematic developments started around 1980 and have continued at a different scale from that 7 era until today (Rodseth and Burmeister, 2012).

In the last decade, thanks to huge advances in computer science that allow environment perception, route planning and real-time vehicle control, the implementation of an autonomous navigation system for a ship is technically possible. Most researchers use levels of autonomy to describe the degree of autonomy of a machine. Autonomy levels are classified according to the famous Thomas Sheridan scale (Theunissen, 2014). This scale performs a ten-level categorization, starting from level one, where the human is responsible for all decisions, and ending at level ten, where the system is fully autonomous and acts on its own. Although technically operating a system at a high level of autonomy may be feasible, legislative issues, reliability requirements of an autonomous operation and certification challenges may be reasons to limit the authority of such a system, and the decision-making level of the vehicle may be limited to level five.

The possibility of building unmanned ships and marine vessels in general has been around for years. For example, the US Navy has already developed small vessels that operate with some degree of autonomy (Burmeister, 2014). The first actions were military in nature, but drones can certainly be used for a wide variety of purposes and objectives. Nowadays, many countries make use of unmanned submarines for the purpose of underwater mapping, mineral prospecting, scientific marine research, oil pipeline repair, ship and port maintenance, cable laying and wreck examination. As a result of rapid technological developments in recent years and the experience gained from the operation of small and medium USVs, ambitions are evolving to create unmanned commercial vessels capable of performing transatlantic voyages.

4.3 Differences between conventional, remote-controlled and autonomous ships

Unmanned commercial ships are one of the latest projects in maritime technology and many large organisations and companies around the world are exploring its potential use and development. The lack of human factors is not the only difference between conventional ships and autonomous ships. The important difference between the two is that crew members and the captain are responsible for making, managing and executing decisions. Unmanned ships can "make decisions" by combining remote control, and automation.

Nowadays, most of the conventional ships operate in "often unmanned spaces", as many systems such as those in the engine rooms have been highly automated. At the same time, a ship's navigation functions also have a level of automation as most ships have advanced anti-collision radar (ARPA). But also common automation systems such as autopilot and systems such as Long Range Identification and Tracking (LRIT) or Automatic Identification System (AIS) are used to gather information from the ship's environment. However, a crew is required to monitor its operations and perform maintenance tasks (Mogens, 2017). We use the term "automation" for the processes that enable the ship to perform certain operations and have the ability to choose between alternative strategies without human control. That is, an 'automated' ship simply has comparatively more advanced automation systems than a 'conventional' ship, which have the ability to complete certain functions without human interaction (Rodseth and Burmeister, 2012).

Autonomous ships have a level of self-management and automation that is the result of the application of advanced technology and automation, aimed at implementing some form of self-governance. An autopilot, which may still be quite advanced, does not have autonomy under this condition (Rodseth and Nordahl, 2017). A limited autonomous ship has the ability to operate automatically in most cases while having a default option to solve common problems, such as avoiding collisions. There are also set limits on the options it is able to use in order to solve problems, for example its arrival time and maximum deviation from the planned route (Rodseth and Nordahl, 2017).

A fully autonomous ship, in contrast, can handle all situations on its own. It operates using advanced computer systems and sensor technology and does not need human interaction. This is an alternative that is realistic for short-distance actions in a controlled environment. Since no constraints are defined, a system of this type could be called "intelligent" and has complete freedom to take actions and take from phases within its expertise and we cannot know in advance what the results of its decision will be (Rodseth and Burmeister, 2012).

A remote-controlled ship is a ship that is controlled remotely, namely from a control centre located ashore. All actions performed by it follow a planned sequence but are characterized by a high degree of automation as the system is expected to operate safely on its own (Rodseth and Nordahl, 2017). In the event of any unexpected event or when an automatic operation is completed it will request human intervention. Staff at the onshore control centre should always be available to intervene and initiate remote control where necessary. In order to adopt a common direction in the categorization of MASS, the IMO has proposed four degrees of autonomy (IMO in MSC 99, 2018):

1. Ships with automated processes and advanced decision support functions and on-board crew who control all shipboard systems and operations. 2. Ships which are controlled and operated by remote control from a remote location, with the crew still on board.

3. Ships which are controlled and operated by remote control from a remote location, but no crew is on board.

4. Ships which are completely autonomous and can handle all situations without the need for human intervention.

4.4 Technical development and testing

Currently, the EU has several R&D projects aimed at developing and building self-propelled ships and a Japanese consortium has recently emerged with similar objectives. However, extensive real-world testing is necessary to ensure the normal operation of the embedded system and the minimum safety and reliability requirements of future autonomous vessels.

In early 2016, Finland established the DIMECC to connect companies involved in the construction of autonomous vessels. After years of research, the companies involved already have some technical solutions. DIMECC created a test area for autonomous and unmanned vessels in Finland, called Jaakonmeri Test Area. The Jaakonmeri Test Area is open to anyone in the world to test relevant technologies. The purpose of creating this area is to accelerate the process of developing autonomous ships worldwide.

4.4.1 AAWA

The AAWA (Advanced Autonomous Waterborne Applications) project is a Finnish 6.6-million-euro project funded by the Finnish Funding Agency for Technology and Innovation (Tekes) to study preliminary specifications and designs. It is necessary for the realization of autonomous ships. (AAWA, 2016) To achieve this goal, it brought together ship designers, equipment manufacturers, research institutes and key members of the maritime industry. Rolls-Royce, the leader of the AAWA consortium, stated that it is interested in building a system that can remotely control autonomous ships. At the same time, he said: "There will not be fully autonomous or remotely controlled ships, but a mixture of the two, depending on the type and operation of each vessel." The current technology required to build autonomous ships is feasible but the challenge is to make the technology reliable and profitable" (AAWA, 2016).

As part of the project, the ship control system already in use will be integrated into the satellite communication network and the ground system will be integrated into the existing communication technology so that the ship will have autonomous control. Finferries will support the project by providing the 65-metre-long vessel Stella, which will be used to test sensors under various operational and climatic conditions. ESL Shipping will study the impact of autonomous ships in the short sea sector and best practices to ensure cyber security. In the short term, this will involve building tugs that can be remotely controlled from a nearby control center onshore. But in the long term, Rolls-Royce envisages the establishment of a control center, with 7 to 14 employees, which will be able to monitor and control an entire commercial fleet in every part of the world.

4.4.2 MUNIN

Maritime Unmanned Navigation Intelligence in Networks (MUNIN) is a research project carried out between 2012 and 2015 with a budget of €3.8 million. It is jointly funded by the EU and eight partners with different scientific and industrial backgrounds to investigate the technological, economic and legal viability of autonomous vessels. The premise is that "unmanned ships can autonomously advance in intercontinental navigation with at least the same safety and efficiency as manned ships" (MUNIN, 2013).

The vision of MUNIN was to develop a platform with the first systems of an autonomous vessel, which firstly, will have the ability to steer the ship in an autonomous way and secondly, an operator in a control center, remote from the ship, ashore, will be able to gain control of the ship at any time. Speaking to (Newsweek magazine) Newsweek, Ornulf Jan Rodseth, director of the Norwegian research institute Marintek (which is involved in MUNIN), said the project has set short and long-term goals. The short-term goal has to do with the possibility of reducing the number of crews to one or two people, with most operations being carried out from a remote center located ashore. The long-term goal is about creating fully automated, unmanned ships that he believes will eliminate all types of maritime accidents. But full autonomy for a merchant ship is something difficult to achieve in the near future, the research carried out may benefit maritime transport in the short term by providing improved navigation systems.

4.4.3 Revolt

ReVolt is a project by DNV GL, which involves the construction of a container ship, which is 60 meters long and has a capacity of 100 TEU and an average speed of 6 knots. Instead of using conventional fuels, this vessel runs on a 3,000 kWh battery, reducing operating costs by not using (conventional) fuels and minimizing the number of high maintenance parts on board. The vessel has the ability to travel 100 nautical miles before the battery needs to be recharged. There is also the possibility that the energy required to charge its batteries may be generated from renewable energy sources, which also leads to reduced carbon dioxide emissions. With an estimated lifetime of 30 years, this ship compared to a diesel-powered ship is likely to generate a profit of USD 34 million. In order to test this ship, a 1 in 20 scale model has actually been built. DNV GL started testing the ReVolt in the third quarter of 2015. DNV GL manufactures sensors, cameras and radars to monitor the ship's environment, together with NTNU (Norwegian University of Science and Technology) and Kongsberg Maritime.

4.4.4 Yara Birkeland

In 2017, Norwegian companies Yara International and Kongsberg announced that they are developing a 100 to 150 TEU autonomous container ship that will not emit any gaseous pollutants. The ship is named after Yara founder and pioneer Kristian Birkeland and will be the world's first fully electric container ship. Kongsberg provides high-tech systems and solutions for commercial transport, aerospace, oil and gas, and is responsible for developing and providing all the technologies needed to operate the ship.

It is estimated that the vessel can replace up to 40,000 000 diesel-powered trucks, reducing NOx and CO2 emissions while making the roads on which these trucks travel safer. The vessel will operate within 12 nautical miles of the coast (Norwegian territorial waters) and between three ports in southern Norway. The distances between the ports range from 7 nautical miles to 30 nautical miles. As the ship will transport the products on a well-defined route from Yara's production facility in Brevik to a facility in Larvik, Norway, it will greatly simplify preparation (Komianos, 2018).

4.5 Theoretical Approach to Neural Networks in Autonomous Navigation

Shipping is the building block of the global economy and has been growing rapidly in recent years. 90 % of the world's goods are transported by sea (Grote et. al., 2016). The main objective of every ship's mission is to complete it safely by seeking to prevent accidents. However, it is worth noting that most of the accidents that occur are due to the human factor. This has led to the creation of systems that either support the proper operation of a ship or take over its autonomous navigation.

4.5.1 Maritime transport

The International Maritime Organization (IMO) in 1972 created the International Collision Avoidance Regulation (ICR) which sets out the maritime traffic code. It clearly and comprehensively defines the required actions to be taken by two ships when they are on a collision course and, more generally, in situations that may lead to undesirable consequences. The following is a description of three indicative rules of the ICAS (Lyoulis, 2013):

1) Rule 15 states that of two ships crossing their courses, the one on the right has priority.

2) Rule 16 refers to the obligation of each guarding ship to make conspicuous any change of course or speed so that it is immediately perceptible to the guarding ship and at the same time maintain a constant safe distance between them. It is worth noting that no safe distance is specified, nor is there a single way of avoiding a collision. To the collision avoidance action resulting from rule 15, the options of stopping the escaping ship or even reversing it can be added.

3) Rule 17 states that the escaping ship must maintain a smooth motion and steady heading during collision avoidance actions.

The above rules shall be varied in each case where the guarding ship fails to perform its role either through weakness or through misjudgement. In such cases the protected ship must necessarily act appropriately. As can be seen, the avoidance of a collision is not carried out in a unique way, as different actions are likely to be taken in environments with similar conditions. According to IMO Regulation A.893, each ship is required to be provided with a detailed voyage plan before departure, which includes information for the entire voyage and methodologies for any problems that may arise. However, compliance with this plan is not always possible. By way of example, when two ships A and B are on a collision course, if A is the sentinel then it must necessarily deviate from its course.

As can be seen, any autonomous navigation system must obey the International Collision Avoidance Regulation. Although the ICOS does not contain the concept of uniqueness for the actions that must take place in maritime traffic, it can be the starting point for making decisions that facilitate dealing with dynamic environments.

4.5.2 First steps for autonomous movement

The autonomous movement of a ship is based on the ability to perceive and interpret the environment. The algorithms currently used in autonomous ship navigation use machine learning models and have evolved from the development of simpler approaches whose discovery was a feat of science. A typical example is Artificial Potential Fields (APFs) where the motion environment is considered a dynamic field where the ship receives a positive load and is attracted to the destination position which receives a negative load (Naeem et. al., 2016). At the same time, any point of distress receives a positive load and is repelled. However, in cases of multiple avoidance points, the repulsion from them can create endless cycles making it impossible to approach the final destination.

Also a method that has been used to find a safe vessel course is Voronoi diagrams consisting of points in the plane called nodes. Specifically, for each node a region is created that includes the points that are closer to it than to all other nodes.

4.5.3 Autonomous navigation system functions and neural networks

An autonomous navigation system includes all those parts that allow information from the environment to be collected and used for decision-making. These parts facilitate or replace traditional navigation methods, enabling safe movement of the vessel and supporting functions such as determining and monitoring the vessel's status, automated course planning, collision avoidance, detection of unusual behavior and identification of nearby vessels. The combination of the above is a complex process and is supported by both machine and deep learning methods. The following is a brief overview of the above functions. Determining and monitoring the state of a ship is crucial for autonomous navigation and relies on systems that evaluate the available data to make decisions and define voyage specifications such as the possibility of full autonomy of movement or the presence of a human crew. By analyzing all the parameters, decisions are taken that will largely determine the smooth operation of the ship.

The course planning system is a useful and necessary tool for the autonomous navigation system that allows the determination of the optimal course of a ship towards a destination with a view to avoiding dangerous points and completing the voyage safely. It is based on the collection of data to map the environment in which the ship is to move and the use of this data to determine the course. Data collection is carried out using appropriate sensors. Each maritime expedition has a predefined plan which defines elements such as the distance of the voyage, the time of its completion, the speed of movement, the expected weather conditions, etc. In cases where deviations from this schedule occur, it is necessary to find the causes of the unusual behavior. The sooner they are identified, the quicker the issues can be addressed while ensuring again the safety of the journey. Particularly useful is an information exchange system between ships where the intentions and actions of each vessel are known. This system is called the Automatic Identification System (AIS) and helps to identify the environment in which a ship is moving.

A collision between two or more ships is one of the main risks in maritime transport. Such accidents can occur both on the high seas and in confined areas such as ports. Incorrect instructions from a ship's command center, crew inattention and adverse weather conditions are common causes of a collision. The use of AI applications in the navigation of a ship ensures the formal application of safe navigation rules by reducing the scope for human error. In maritime transport, collision avoidance is determined by the ICS. When studying the corresponding rules, it can be seen that they vary according to the size and the ability of the ships involved to change direction. Therefore, any autonomous navigation system has to detect and take into account the type of a ship. Moving on, we focus on some of the machine and deep learning applications used by autonomous navigation systems with neural networks as a common reference point. Neural networks allow the processing of data collected by the ship's sensors in order to gain knowledge and make decisions.

4.5.5 Locating the species of a ship using CNN

Of particular interest are Convolutional Neural Networks in identifying the type of ship. Its identification is done through photographs that are input to a CNN and categorized into classes. Each class corresponds to a different category of ship. Figure 4.1 shows the operation of a CNN for identifying the type of a ship.

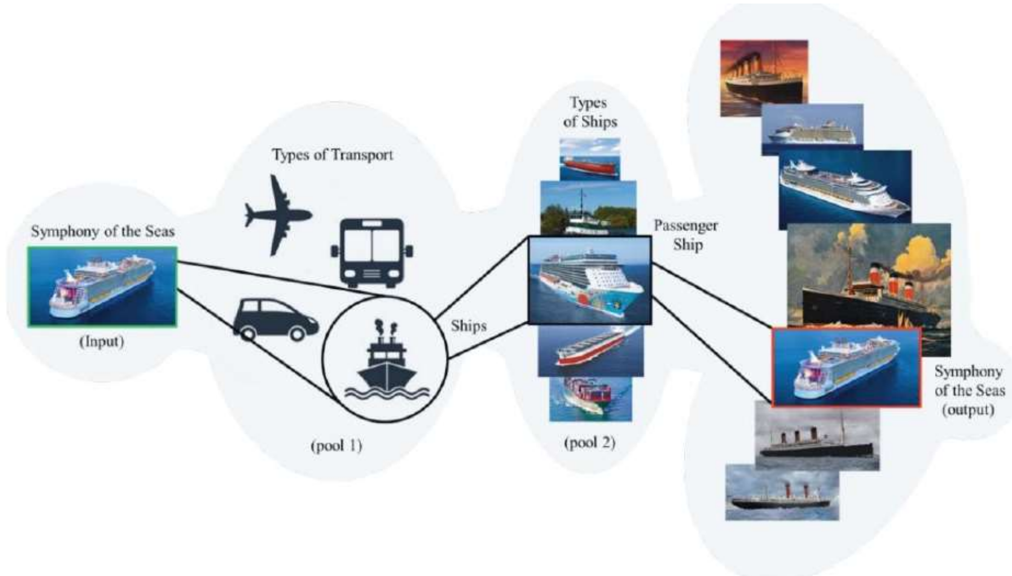


Figure 4.1: CNN to identify the species of a ship (Bm et. al., 2019).

The performance of these networks is based on their successful training and, by extension, on the availability of appropriate training data. The collection of these is therefore a priority for any research team. However, in ship identification and categorization, the collection of suitable photographs representing the different types of ships is not an easy task. The difficulty in approaching marine vehicles to obtain such photographs and their diversity make it difficult to categorize them into groups-classes. Also, the identification of a particular type of ship through photographs is significantly affected by the variations in lighting and angle of view of the corresponding photograph. Considering the large amount of data required, the necessity of finding methods that circumvent the above difficulties by allowing efficient network training is crucial.

An interesting solution that takes advantage of feeding a network with ready-made training data that is widely applicable and can train the network in identifying general features from input images is implemented by Zhenzhen, Baojun, Lindo & Zhen (Zhenzhen et. al., 2019). The motivation for using this method is the behavior of modern CNN models where, especially at the first layer, they seem to extract similar features that are not necessarily related to the type of objects to be categorized. This learning transfer action, of course, does not replace the necessity of having specialized photographs through which to identify the specific features that will determine the final categorization of ships into classes. However, it is an interesting proposal that both facilitates and speeds up the training process. In this implementation, the identification and discrimination of the different types of ships is carried out at two levels, coarse grained and fine grained. In the first, each ship is identified and assigned to one of three classes:

1. Aircraft carriers

2. Warships

3. Civil ships

If it is of Warship type, the second level categorization follows, where it is further assigned to one of the following 5 classes:

1. Coastal Combat Ships

2. Shipyard Transport Ships

3. Amphibious Assault Ships

4. Submarines

5. Destroyers

Two CNNs are used, each of which is a variant of the well-known AlexNet and GoogleNet models, adapting their structure to the requirements for the identification of the type of a ship. The aim is to categorize ships into the classes defined at the first and second levels. Their training is based on feeding ready-made training data of a general nature, obtained from the ImageNet platform, and using two small datasets constructed manually by the researchers themselves. The first one contains photos of ships belonging to the first level classes and the second one contains photos of ships belonging to the second level classes. To evaluate the performance, the original AlexNet and GoogleNet models are trained simultaneously without using the ready-made training data but only with the two datasets.

It follows that supporting CNNs with the ready-made training data brings immediate results. After the required training period to stabilize the extracted estimates, both networks show improved performance for both first-level and second-level categorization. As a benchmark, the performance of the original AlexNet and GoogleNet networks without transfer learning is used as a comparison. It is worth noting that the increased performance is achieved without substantial additional cost.

4.6 Estimation of Shipbuilding Costs using ANN

Building a ship is a complex and time-consuming process in which many processes take place simultaneously. Each such construction follows strict protocols designed to ensure the creation of safe structures. Due to its large size, the construction of each ship is carried out in stages and relies on the cooperation of many different disciplines. From the gathering of the necessary raw materials, the availability of the appropriate technological equipment to the final stage of welding the hull of the ship, a multitude of processes are required to be completed using clear and predefined methods. It is easy to see the need to record the costs of each such construction in order to correlate them with the corresponding revenues. Such information can be used in many ways and is certainly essential for the optimal operation of any shipyard.

However, the way of recording and monitoring the costs associated with the construction of a ship is not unique. In this respect it is worth noting that in order for the recording of costs to be meaningful, both direct and indirect costs must be taken into account. In particular, indirect costs such as the need for appropriate facilities and electricity, accounting and the necessary periodic maintenance of machinery should be calculated and allocated to each product of an undertaking in a proportionate manner and not equally since each product is differentiated from the others. Therefore, for the construction of a ship, the necessary parameters that influence and determine the size of these indirect costs must be taken into account.

For example, the electricity requirements for the construction of a small-scale ferry versus the construction of a cruise ship allowing transatlantic voyages are clearly different. Thus, we conclude that the geometrical characteristics of a ship have to be taken into account. Furthermore, in a multi-product production series, the first of these is usually the most costly, so it must be priced accordingly.

4.6.1 ABC System

One system of calculating indirect costs in the production of a product that is of particular interest is Activity Base Costing (ABC), which takes into account the variation in the cost of producing each product. In a company using such a costing system, concepts such as costs per unit of production or costs per hour appear. Thus, unlike traditional costing methods, the ABC system calculates the actual consumption of resources for each product.

The use of such a system, although it entails additional costs, is cost-effective in large productions and complex constructions. This is because by calculating the indirect costs for each production process, the appropriate information is now available to evaluate how the firm operates (Mahal & Hossain, 2015). Essentially, an accurate record is made between the benefits and costs of each product. This link can be used to prioritize products in terms of their profitability, making it possible to target production and also to adjust it based on the data offered by the ABC system. Thus, the detailed mapping of the operation of the business facilitates its evaluation and allows the identification of undesirable phenomena and losses, contributing to its economic longevity.

4.6.2 ABC system implementation using ANN

Here follows the description of an interesting implementation that models the operation of an ABC system based on a neural network (Urkmez et. al., 2008). The objective is to estimate the indirect costs that occur during the construction of a ship. This calculation starts by recording the parameters that affect the production process and constitute the input of the neural network. These parameters are divided into:

1) Manufacturing parameters that include the name of the shipyard, the type of ship and the order number

2) Geometric parameters that relate to the geometric characteristics of each ship and include the total length, length between perpendiculars, maximum width, height and maximum draught

3) Capacity parameters that include the capacity of the ship, the capacity of the engine that determines its power and the maximum speed of the ship

The training of the network is based on data collected from three shipyards for twenty-two ships in total (Urkmez et. al., 2008). From this data, parameters from the eighteen ships were used to train the network. The neural network shown in Figure 4.2 has two hidden layers where intermediate calculations are performed.

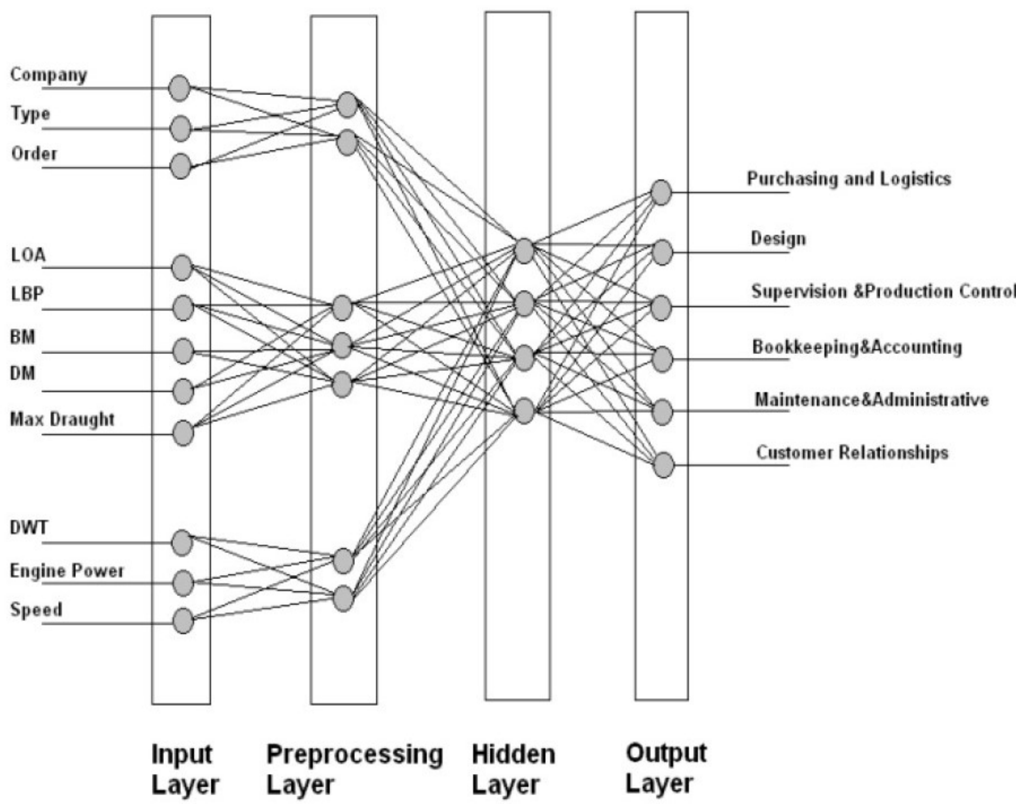


Figure 4.2. ANN implementing ABC (Urkmez et. al., 2008).

The network output includes 6 neurons, each of which corresponds to one of the following categories of indirect outputs:

• Purchasing & logistics

• Design

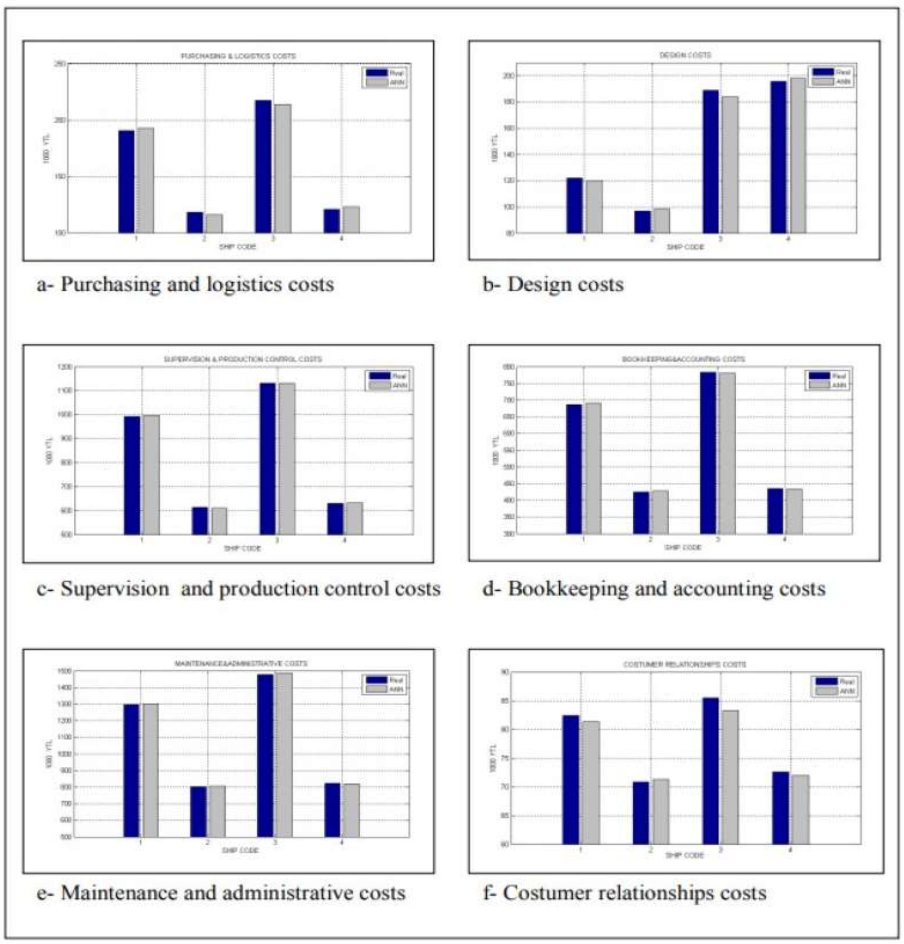
• Supervision & Production control

• Bookkeeping & Accounting

• Maintenance & Administrative

• Customer relationships

Upon completion of the training, the neural network was used to calculate the indirect costs in the construction of the four remaining ships. The values of the network inputs and outputs as well as the actual outputs are available (Urkmez et. al., 2008). The charts presented in Figure 4.3 compare the costs estimated by the neural network with the actual values for each of the aforementioned categories. The performance of the neural network is particularly encouraging. In conclusion, the application of this neural network for estimating the costs of a shipyard appears to be effective as the maximum error recorded between the estimated and actual costs was 2.53 %.



a- Purchasing and logistics costs

b- Design costs

c- Supervision and production control costs

d- Bookkeeping and accounting costs

e- Maintenance and administrative costs

f- Costumer relationships costs

Figure 4.3: Error presentation for ANN estimates (Urkmez et. al., 2008).

4.7 Fuel consumption and malfunction prediction using artificial intelligence programs

The main objective of every shipping company is the efficient operation of its ships in order to reduce operating costs and increase profitability. This direction is of interest to many players in the shipping industry, such as ship managers, shipping regulators and policy makers. The efficient operation of a ship, as mentioned above, has substantial economic implications which are expressed through factors such as reduced fuel consumption and reduced maintenance costs. The problem of estimating the fuel consumption of a ship is multi-dimensional as, in addition to the operation of the main engine, it depends on parameters affecting the overall resistance of the ship such as weather (e.g. wave height, sea currents, wind strength), draught and speed of the ship, hull, propeller and axial system fouling.

The process of planned maintenance of a machine or a component is one of the most critical processes that take place on a ship and aims at the proper and uninterrupted operation of a system. This process should be carefully planned and scheduled in detail by every shipping company. Ships, which are the main assets of shipping companies, are particularly affected by the problem of failure of a material or system. Each ship consists of a set of systems (propulsion, power, navigation, etc.) which, over time, may fail. A failure can lead to highly complex situations such as ship refueling or long-term repairs, which bring significant economic consequences to a shipping company (Cipollini et al., 2018).

Each system is designed for a specific life cycle, which can often be influenced by various factors such as the raw materials used, estimated working hours and environmental conditions (Takata et al., 2004). The wear and tear of individual components of the system will at some point require repair or replacement, resulting in the system having to be taken out of service to perform scheduled maintenance or repair work (Peng et al., 2010).

Artificial intelligence is an important tool in solving the problems of predicting fuel consumption and preventing imminent malfunctions through predictive maintenance. AI programs developed to address these problems are based on machine learning algorithms. In addition, to achieve these objectives, it is necessary to develop appropriate models that take into account various variables, of the problems under consideration, which show correlation between them and are then analysed. The derivation of such a model that can accurately predict the ship's performance under different operating profiles (operation under specific draught, operation under specific engine loading, sailing with propulsion limitation due to failure, etc.) and under different weather conditions can help in determining the optimal operating profiles of the ship and thus in predicting fuel consumption (Gkerekos et al., 2019).

The existence of such a model could help to identify performance patterns that deviate from the optimal operational profile. Also, such a model could indicate the potential underperformance of various systems and/or subsystems of the ship (Cipollini et al., 2018b). Various attempts to model ship operating conditions have been reported in the literature, ranging from approaches based on model testing with a combination of data, to the development of machine learning (ML) models based solely on the use of data (Gkerekos et al., 2019).

Machine learning is defined as the process of computer programming to optimise a specific performance criterion based on virtual data (e.g. training) or previous experience (Gkerekos et al, 2019). Machine learning problems are usually classified into supervised and unsupervised problems. In the case of supervised learning, the goal of the algorithm is to utilize the input data for training and in combination with the given target (output) to generate a mapping that returns a relevant target value for the new observations. In unsupervised problems, the examples used to train the algorithm only include input values and the goal of the algorithm is to provide some image or value for that input.

Data is extracted through automated data logging and monitoring (ADLM) systems, which are capable of extracting information from huge volumes of raw data. Machine learning models, although more computationally expensive, offer the advantage of providing results tailored to specific hull shapes (e.g. flat hull ships, V-shaped hulls, catamarans, etc.), sailing conditions and main engine operation as well as to a specific ship operation profile (Gkerekos et al., 2019).

In summary, when it comes to predicting fuel consumption, AI can analyze data collected from sensors on board, such as speed, sea state and engine status. This process will lead to an optimization of fuel management and consequently to a reduction in the operating costs of the ship in question. In addition, AI algorithms can, after collecting and processing data, automatically adjust the engine and navigation system settings to the user's desired operating model, taking into account the conditions and requirements of the voyage, in order to achieve fuel savings (Gkerekos et al., 2019).

As far as the maintenance of the ship's systems is concerned, AI techniques can continuously monitor the condition of components and systems and detect anomalies in their operation. Based on this monitoring, operating models will be derived and the deviation from them will enable preventive maintenance or maintenance based on the operating status in order to avoid failures (Cipollini et al., 2018).

In conclusion, the introduction of AI techniques in shipping can have significant benefits both in predicting fuel consumption and in preventing imminent malfunctions. Impending malfunctions refer to operating conditions that deviate from the intended operation of a machine or system and which, if not addressed immediately, can lead to unpleasant situations such as the failure of a component or even the total destruction of a machine, with the consequences mentioned at the beginning of this section. It is important to mention that artificial intelligence can help the crew of a ship by providing them with real-time information and advice on the operation of the propulsion plant. The ultimate goal is for the system operators to make decisions that will lead to the optimum operation of the installation, as appropriate, in order to save fuel and avoid malfunctions.

5. Other Advanced Shipping Technologies 4.0

Shipping 4.0 technologies combined offer even more powerful and complete solutions. Artificial Intelligence is inextricably linked to Large Scale Data Analysis, Interconnectivity, Robotics, Virtual and Augmented Reality and Digital Security.

5.1 Big Data Analysis

The term Big Data, which emerged in 2001, was used to describe data sets so large and complex that traditional software cannot process them. Today, the focus is on harnessing them and generating value for understanding the world and making decisions (Mirovic et. al., 2018). In order to qualify as big data, at least the following characteristics must be satisfied (Marken, 2021):

1) Volume: the abundance and extent of data collected and stored;

2) Velocity: the rate of data production from different sources;

3) Variety: different types and forms of data.

4) Veracity: accurate and quality data.

5) Value: monetary value from derived data.

In shipping, large amounts of different types of data are produced. More specifically, it is data:

■ fuel costs, transit times, wages, insurance that determine profit

■ weather conditions, traffic delays and port traffic (volatile data to be transmitted in real time and collected by sensors and GPS services)

■ location, speed, direction, ship's draft from the automated identification system (AIS)

■ networks along the coast via radio range

■ specialized instruments, such as wave radar, oil spill detectors, high precision navigation inertial sensors

■ ship condition monitoring and detection of hazardous conditions by physical systems of modern ships such as control systems, torque-controlled winches, sophisticated dynamic positioning systems, new navigation systems

■ to monitor existing regulations by advanced environmental sensors

This data is collected from multiple devices and stored with different formatting. Accuracy and validity in the systems can be at high levels. However, there is the possibility of incorrect measurement or human input of information and therefore due diligence and cleansing of these is required before they are analyzed. As a result, they can be exploited to provide important information on ship performance and navigation.

5.2 Internet of Things

It is imperative that shipping companies have timely information on the condition of the ship and the conditions in the area where they are moving or docked. IoT technology makes tracking and logging much easier and possible in real time (tovima, 2024). Consequently, it minimizes the response and communication time between land and sea, which benefits risk and cost reduction. The concept of applying the Internet of Things at sea was developed to harmonize and digitize information and modernize the maritime industries by the United Nations International Maritime Organization (IMO) under the name of eNavigation. This technology is based on Machine Type Communication.

Over the last decade, the International Maritime Organization has been promoting the Automatic Identification System (AIS) introduced by the International Telecommunication Union to identify ships, report their position and monitor them. Although the data exchange capability is becoming limited and the integrated architectural framework to deal with all maritime applications and interconnection services is becoming obsolete, the Automatic Identification System can be considered as a first maritime machine-to-machine communication system. The figure below graphically illustrates a conceptual architecture of a Thing Interconnection Network. We observe that there are only wireless solutions, satellite and terrestrial communication networks as well as infrastructure and specific communication topologies (Zhang et. al., 2020).

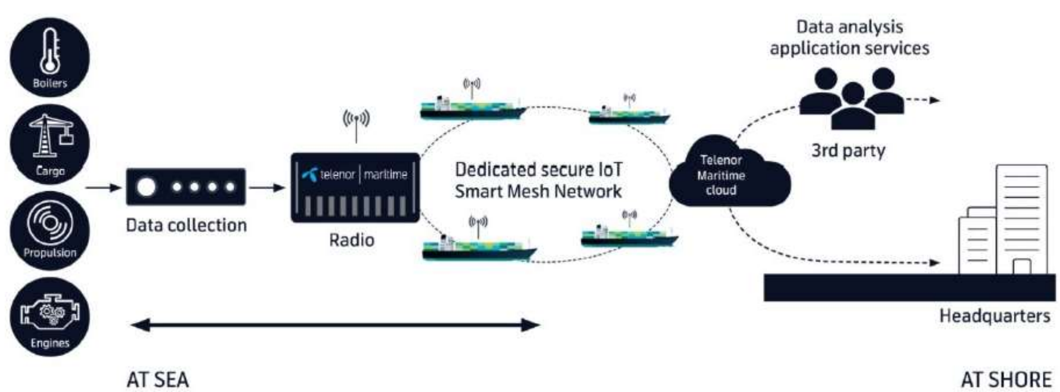


Figure 5.1. Interconnection of Things (www.telenormaritime.com)

Interconnectivity represents the broader concept of connecting physical objects to facilitate real-time communication between sensors that provide real-time data transmission from a device back to a receiver. Specifically, in shipping it enables gain in system performance, simplifies the management of complex transportation and supply chain systems, including both technical, operational and coordination efficiencies. In addition, the Interconnection of Things includes satellite technology and telematics that can significantly improve navigation, security, remote monitoring and maintenance, communication and environmental performance (Sanchez et. al., 2019).

Commercial shipping is starting to adopt the idea of autonomous ships and is already implementing smart navigation systems, and the usability of this technology is therefore increasing. In this context, another extremely useful application of IoT concerns safer navigation. For example, in channels where there is a risk of collision in case of unclear instructions or incorrect handling and consequently information about the depth, the situation along the passage, the ships sailing on the perimeter as well as advice on the course to follow based on appropriate computational predictions is required (Latifov, 2019).

5.3 Autonomous Vehicles and Robotics

The epitome of the technological revolution is the construction of autonomous drones that are monitored and controlled entirely by land-based operators. Since shipping is a commercial business, a key criterion is the economic benefit of such technology.

According to Baltic Exchange, crew accounts for about 57% of the total operational costs of a medium oil tanker (Lines, 2020). Reducing the number of personnel on board will also result in a significant reduction in costs, although new jobs will be created. In theory, removing some of the crew from the ship and monitoring remotely reduces safety issues. Furthermore, according to Rolls-Royce Marine's Vice President of Innovation, Oskar Levander, an unmanned vessel can save up to 15% of the fuel used to keep the crew alive at sea (Futurenautics, 2024). Saving such a large proportion of fuel, which accounts for 60-70% of costs, will not only make ships more efficient, but also greener. While progress towards ship autonomy is constantly being achieved, there are significant limitations in achieving fully autonomous ships, as theoretical calculations are not always applicable in the real world where external and unpredictable factors influence.

It is important to define the concept of autonomy. An indicative categorization concerns the following six distinct levels (LR, 2016):

1) Level 0 Manual ship handling

All actions and decision making are performed manually by a human. The person in charge may be on board or ashore and give instructions by radio transmitter. Note that systems may have a level of autonomy. For example, engine control, gauges, wind direction are not decision support.

2) Level 1 On-board decision support

Actions are performed by a human but based on a decision support tool that presents options to the system administrator, suggests route planning (course, cruising speed) or provides data such as charts. The administrator has the possibility to modify course and speed whenever necessary.

3) Level 2 On-board and off-board decision support

Ship-level actions are again taken by a human operator while the decision support tool can receive data from on-board and off-board systems.

4) Level 3 Autonomous decision making and execution in human presence

Shipboard decisions and actions are taken by the information system based on data from on-board or off-board sensors autonomously with human supervision. Decisions of high importance shall be implemented in such a way that a human being can intervene and modify them. The system monitors the operation of the ship and accepts the orders before they are executed.

5) Level 4 Autonomous decision making under monitoring

Decisions are made and executed by the information system which takes into account risks and their impacts as soon as they appear through sensors, processes and evaluates the data and executes the optimal solution. The manager is informed when the uncertainty for the decision exceeds a certain threshold (Neofitou, 2020). Autonomous monitoring and control can come from on-board or shore-based systems. It is possible for the ship's crew to override the autonomous/control system.

6) Level 5 Full autonomy

Decisions are made and executed by the information system, after it has calculated scenarios and assessed impacts and risks. The system acts on the basis of the analyses and response options, taking into account the specific characteristics of the environment. Data about the environment and corresponding past typical events that may be repeated feed machine learning algorithms. Control of ship systems (e.g. software operating parameters) is possible without crew authorization. It is not possible for the ship's crew to override the autonomous/control system (LR, 2017).

Protecting the oceans and seas is a key concern of the International Maritime Organization (IMO), while ensuring that regulations keep pace with technological developments. The exercise to determine the safety and environmentally sound operation of Maritime Autonomous Surface Ships (MASS), which started in 2017, was completed in May 2021 (IMO, 2021).

5.4 Virtual and Augmented Reality

Virtual Reality (VR) is the technology that provides almost real and/or believable experiences in a synthetic or virtual way, while Augmented Reality (AR) enhances the real world by including computer-generated information (Shen and

Shirmohammadi, 2008). Augmented Reality (AR) technology is becoming one of the main digital tools of Industry 4.0.

There are already obvious applications of spatial intelligence with environmental data as well as machine diagnostic information allowing visualization and aiming at automating crew tasks such as inspections, remote surveys, maintenance and expert assistance. This technology can provide improved situational awareness and decision support.

More specifically, based on qualitative research conducted among maritime employees on the potential of this technology (Musleh, 2021), the following can be summarized:

■ Easier identification of pipelines and wiring and their utility

■ Assistance during machinery maintenance with instructions and suggested steps

■ Check and checklist inspections where the supervisor is not required to type as the report is verbally recorded

■ Real-time video recording and statistical analysis from sea to shore

■ Remote assistance from the offices / IT and Technical department

Virtual reality (VR) technology uses cameras with built-in depth, 3D and motion sensors, which, by combining the data and using intelligent algorithms, allow the creation of video that can be rendered in 3D and used for visual inspection, maintenance or ship security purposes. The system allows all information to be displayed on screens in front of the user's eyes, directly improving their knowledge and understanding of the environment around the ship (Sherman and Craig, 2018).

An additional challenge that can be addressed with Virtual Reality (VR) technology is the need for constant familiarization with new technological equipment and training of the crew, especially the engineers. The creation of training software using specially configured equipment can support the review of the installation and operation of a machine prior to ordering from suppliers. In addition, this technology provides the possibility of interactive measurement, analysis and training from anywhere.

According to research conducted on students at the Maritime Academy of Asia and the Pacific (MAAP) during their main engine training, the group that joined the virtual reality program compared to the group that followed the traditional training method showed significantly improved performance.

This is also due to Virtual Reality's ability to introduce the crew to an engaging learning experience that leads to more effective knowledge acquisition and retention (Buenaobra et. al., 2018). Hybrid Reality, which combines the real and digital worlds, is applied to ship design by upgrading the process and converting 2D drawings into 3D drawings. From the initial design stage, architectural errors can be identified that will bring about a revision of the design avoiding unnecessary development costs and production time delays (Cebollero and Sanchez, 2016). At this stage, it is also vital to consider different design alternatives, especially in complex projects where information needs to be constantly reviewed, analyzed and verified.

It is also possible to present the product to customers – ship owners in order to make decisions and pay attention to details that may not always be foreseen before the start of construction. Multiple users - engineers, designers, project managers - can be in the same simulation at the same time and interact on the virtual ship (Mes, 2018).

5.5 Digital Security and Blockchain

Blockchain is a distributed ledger technology; each member has access to its information and a secure trace of all shipments. The network provides secure interaction and identity protection for users thanks to cryptography. This system is more accurate as it allows all members to be monitored simultaneously in real time. This implies that port authorities, ship managers and shippers can improve the supply chain by monitoring all the progress (Lexology, 2024).

Indicative applications in shipping:

■ Traceability and fuel quality assurance

The inability to reliably track, trace and ensure the origin and quality of fuel is partly due to the existing documentation process in the oil industry, which uses paper reports. A system based on blockchain technology can improve the tracking of fuel origin and quality with data collected throughout the oil supply chain. This data will be accessible by those organizations that need to verify product compliance with regulations or insurance policies.

■ Maritime transport monitoring

Shipping transactions are generally time-consuming and costly. The shipping industry relies heavily on traditional ways of doing business, including reliance on forms and documents. Transactions involve exporters, importers, port and customs authorities, financiers who often require written documentation and physical inspection of documents, resulting in high costs and incomplete information. Blockchain could eliminate the need for a central broker/coordinator as a standalone clearing system if properly integrated with IoT devices. The ability to keep all documents in one secure and accessible - by all stakeholders - place will also reduce the cost of audits.

■ Smart contracts and payments

The current payment process in shipping is relatively inefficient compared to other sectors. There is a strong lack of automation in invoicing, which is often completed by bank transfers and cheques, particularly in small and medium-sized shipping companies. Blockchain is technology intended for applications in more efficient validations and payments, enabling a decentralized and seamless platform for managing remittances with speed and reliability. Despite the benefits of its use, blockchain technology is relatively immature, still developing and presents risks. Startups have been established to evaluate the stability of the technology, however, they face ongoing challenges in terms of scalability, interoperability, data management, standards and uncertainty with respect to government regulations (Yang, 2019).

6. Big Data in Maritime Industry

The previous section gave several definitions of what Big Data means. In shipping, however, a clear definition does not exist. This is for two reasons: on the one hand there are many stakeholders, such as port operators, shipbuilders, charter brokers, insurance companies, and many others, and on the other hand data collection systems and digital sensors are constantly growing. Always considering the stakeholders, Big Data in shipping includes data of ship performance, freight costs, weather, labor costs, oil costs, navigation systems, cargo data (Koga, 2015).

6.1 Data types and data sources in shipping

There are different types of data in shipping:

1) Navigation data: includes data on the position of the ship, its speed, its course. They are usually collected using technologies such as GPS, AIS, Radar,

2) Ship performance data: Include data on fuel consumption, engine performance, speed, and other data on the operation of the ship

3) Weather data: Includes measurements such as wind speed and direction, wave height, temperature, rainfall, and other data that can affect the operation of the ship. The main sources of weather data are weather stations and satellites.

4) Load data: This includes data on the type, weight and volume of the cargo being carried, as well as information on its condition and handling requirements.

5) Port data: includes data on port operations, such as the movement of ships in the port and the handling of cargo. Usually these data are collected by the port authorities.

6) Regulatory data: Include data on compliance with shipping-related regulations, such as exhaust emissions

Two of the most important data sources in shipping are the Voyage Data Recorder (VDR) and the Automatic Identification System (AIS).

AIS is a system originally created to avoid collision between ships and which allows the exchange of digital signals between ships on the VHF frequency. The data that is mutually exchanged with other ships is:

1) The ship's identity (IMO number)

2) The type of cargo

3) The port of departure and port of call

4) The speed

5) The position

6) Data from the Vehicle Traffic System VTS (Pallikaris, 2018).

The main purpose of VDR is to provide data for analysis in case of an accident. For this reason, the International Maritime Organisation (IMO) has made it compulsory to equip all passenger ships, and other vessels over 3000 gross tonnage, with VDRs. This system is similar to the recorders used in airplanes to collect flight data. The VDR is connected to other devices where all the information from each voyage is stored in digital format. The data recorded through the VDR is:

1) The ship's position

2) The digital course information,

3) The Radar and ECDIS images

4) Various other sensors that equip the ship

5) The status of the steering gears and their response to the master's commands

6) The conversations inside the bridge

7) The bridge's communication with the ship's devices operating on VHF frequency

8) Various alarms/warnings related to the ship's status (Pallikaris, 2018).

It is obvious that with so many data sources, there are great opportunities to exploit them for the benefit of shipping. It is also obvious that this exploitation is multi-dimensional, with applications relating to the ship and its better performance, which in turn leads to a more environmentally friendly operation of the ship. Safety and autonomous ships are two further examples. Finally, smart ports, for example the port of Hamburg in Germany uses a cloud based analytics tool called SmartPort Logistics. This system records different types of data, such as ship positions, bridge height and width, and scheduled routes. Through this system, the port employees know when the ships are expected to dock at the port, and correspondingly the cargo carriers know when the cargo is expected to be unloaded (Pallikaris, 2018).

The above examples of applications will be analyzed in this thesis. To these will be added the challenges brought by digitalization in shipping, Big Data and the use of artificial intelligence.

6.2 E-navigation System

In 2006 the IMO adopted a plan to develop modern electronic shipping, also known as e-navigation. The definition of e-navigation is 'the harmonious collection, integration, exchange, presentation and analysis of all shipping-related information on board ship and ashore. All this process is carried out exclusively by electronic means to improve navigation and all related safety-related maritime services, the procedures for the prevention of safe navigation and the protection of the marine environment' (IMO).

The aim of this project is to improve navigation and reduce errors, contributing to the improvement of safe navigation by taking into account hydrographic, meteorological and geographical information and risks. At the same time, to facilitate the congestion of ships when necessary, to allow the exchange of data between ships, land-based vessels, to allow immediate response to accidents and to allow the search and rescue of victims. All this of course providing global coverage, consistency in standards and regulations and global compatibility in equipment.

All of the above are mentioned to show that there are similarities and differences between e-navigation and Big Data. The main difference is that the data generated by e-navigation is not used for the purpose of research to develop new methods that may benefit shipping. e-navigation focuses mainly on safety, and uses real-time data.

Of greater interest, however, is how e-navigation can contribute to the use of Big Data. According to the Strategic Implementation Plan (SIP), there are four stages (out of eighteen listed) that can be associated with the use of Big Data (IMO, 2018). These are:

1) Investigate the best way to automate data collection internally on board to better generate reports including static and dynamic information;

2) Develop guidelines for software quality assurance;

3) Develop guidelines on how to achieve improved reliability and resilience of PNT (Position, Navigation, Timing) systems on board by integrating with external systems;

4) Develop a common maritime data structure.

The automation of data collection will allow for efficient collection and storage of ship voyage data. Software quality assurance demonstrates the need for reliability of software that collects data. The reliability of PNT systems has to do with one of the main characteristics of Big Data, veracity. Finally, the existence of a common data structure is very important, since it will allow easy movement of the data. All these are interrelated with Big Data and its applications.

To date, there are projects that have used e-Navigation, such as EfficienSea, MONALISA, ACCSEAS, SESAME and STM. MONALISA, for example, wants to contribute to efficient, safe and environmentally friendly maritime transport. This is achieved through the development, demonstration and dissemination of innovative e-navigation services to the maritime industry, which can lay the foundations for future international growth. Ensuring the quality of hydrographic data for the main navigation areas in Swedish and Finnish waters in the Baltic Sea contributes to improving safety and optimising ship routes (IALA, 2024).

6.3 Green shipping and ship performance

Climate change is a major challenge for shipping. There is now pressure to reduce fuel consumption and greenhouse gas emissions, which is becoming an imperative for change. By green shipping, we mean the use of sustainable practices aimed at reducing its impact on the environment. Shipping accounts for around 3% of greenhouse gas emissions (Lloyds, 2021).

The International Maritime Organization (IMO), in 2018 introduced a first strategy to reduce greenhouse gases, aiming to reduce them by 50% by 2050 compared to 2008, and improve energy efficiency by 40% by 2030, working towards 70% by 2050 (IMO, 2018). Also, from 1 January 2023, all ships will be required to calculate the Existing Existing Energy Efficiency Index (EEXI) in order to measure their energy efficiency as well as to start collecting data for reporting the CII Carbon Intensity Indicator. The Carbon Intensity Index essentially refers to the overall environmental footprint of each ship. Shipowners are asked to calculate the carbon burden, which in turn will allow the ship to be classified into one of five scoring categories. Which category each ship falls into is something that will be calculated each year, with the aim of being at least in category C in the long term. Should the ship be in one of the categories D (for 3 consecutive years) or E, then there should be a plan to improve this position. According to a report by Finnish technology firm Wärtsilä, more than 80% of bulk carriers and container ships will be in the lowest Carbon Intensity Index category if no action is taken (Clayton, 2014).

The two main ways to reduce GHGs from shipping are on the one hand to improve energy efficiency, which will also lead to better fuel consumption, and on the other hand to introduce new, alternative fuels, which will have a much lower, or even zero, environmental footprint.

At present, however, only 15% of the world's fleet has the capacity to convert to these fuels. The use of Big Data, and by extension artificial intelligence (AI), offers an opportunity for a digitally driven reduction in emissions.

According to Ricardo Energy and Environment, strategies that include digital optimization can deliver a 38% reduction in greenhouse gas emissions (Inmarsat, 2021). Another study, carried out by KPMG, states that digitally-based ship voyage planning can lead to a 15% reduction in fuel and energy (KPMG, 2021).

As is clear from the above, one of the ways that can lead to a reduction in carbon dioxide and greenhouse gas emissions is the optimization of the ship's route (ship weather routing). This optimization can be achieved by analyzing data from different sources, for example weather data, sea currents, fuel consumption. All these data can be collected from weather stations, satellites, meters and sensors on board the ships. Of course, this is not an easy process. Given that each ship is unique in terms of its behavior, no advanced ship routing system can perform such a precise analysis to achieve the optimal routing without the side effect of wasting fuel. Winds, waves and currents, combined with the speed and pollution of the ship's hull and other factors make the equation very difficult. However, if we could use this equation in any way, it would give another perspective on how we can achieve our goal. So the question that arises is how to solve the above equation. Many attempts have been made in the past, ranging from sea trials extracting complex statistics, to 3D modelling 3D modelling, with some of them wrong from the start, very accurate or even limited in scope. The accuracy of the optimization model we want to achieve is also of great importance. For example, a model with 80% accuracy, while in the past it might have been considered a good model, today it would not have the impact we would like to have, simply because it does not capture the actual performance of the ship in enough detail to achieve less fuel consumption and therefore a reduction in carbon dioxide and greenhouse gas emissions.

6.4 Challenges

Despite the great opportunities created by the use of Big Data, its use has created enormous challenges, some of which are common to all the industries that use it. These challenges include data quality, data collection, storage and transport, but the challenges are not limited to these. They also have to do with technology, competition, security and the expertise of the people who have to manage them. Certainly, however, these challenges can be divided into specific categories:

1) Technological challenges

2) Security challenges

3) Human resource challenges

4) Data governance

Technological challenges cover a wide range of challenges including data integration, data quality and the tools used to collect and process data.

6.4.1 Data quality and integration

The quality of the data, their reliability, their availability are key components for their further processing and use for the extraction of results. The quality of data requires pre-processing, and this is perhaps the most important step for knowledge discovery in databases. Incomplete values, outliers, inconsistencies in the data are common problems in data collection. Missing values occur when there are no values for some of the characteristics being measured. This may be due to equipment malfunction, inconsistencies in other recorded data that may have led to their deletion or non-registration. Outliers may also occur due to problems with the measurement equipment. Data inconsistencies occur when data from different sources are not the same. Different units of measurement, different representation, changes and corrections to data from only one source can lead to inconsistencies. It is noteworthy that most data scientists spend 75% 80% cleaning the data so that any analysis can lead to reliable results/information.

As can be seen from the above, data quality is extremely important. The main factors that pose a risk to quality are network outages, and/or system failure or malfunction. Furthermore, manual data entry is a major source of errors. At the same time, the difficulty presented by the many different sources is not negligible, and the integration of data from many sources is a huge challenge not only for shipping, but for all industries.

6.4.2 Data consolidation

Data integration aims to combine data from multiple sources into a single destination. The greatest benefit of consolidation is that it creates a comprehensive view of the sources. In shipping, data integration between sensors is essential, as it is a way to ensure that there are no blind spots and that small objects can be detected. Also, while some of the more mature sensors (such as GNSS and AIS) have established data standards, other types of sensors are still adapting, resulting in standards that are less well defined.

Another parameter to consider at this point is the frequency of the data. It is necessary to ensure that this is good, so that it gives a complete picture of the situation to enable real-time decision-making.

It is also important that any new system developed for data collection has compatibility with other systems, in order to reduce data sources, or data processing to make it compatible where possible. IMO member states are trying to share a unified data format, a common structure, to be used in electronic navigation. According to the SIP (IMO, 2014), it is expected that data providers adopt 'recognized IMO data standards such as the IHO's S100'. S100 is a hydrographic data standard that conforms to the standards set by the International Organization for Standardization (ISO) and IMO has adopted it as a unified format for electronic navigation (Koga, 2015).

6.4.3 Available Equipment

Finally, it is obvious that because data is stored, processed and analyzed through tools, it is imperative to ensure the availability of powerful tools. In other words, the performance or even the achievement of big data usage directly depends on the capability of the tools involved. The volume of data generated in shipping is enormous. From sensor and navigation data, to cargo and weather data, and storing it can exhaust existing storage space, which is costly. This is currently being addressed with storage on cloud platforms. Also, the fact that data comes in different formats. Creating uniform data standards is necessary to simplify consolidation efforts. This practically means that there should so that there is a standardized system of information exchange in sensors and communication protocols. The relationship between tools and innovation is proportional: the better the tool, the more innovation. Each company develops or invests in the development of the relevant equipment and technology on the basis of the principles of market competition.

7. Conclusions

It is now clear that AI affects every aspect and sector of shipping with its respective advantages and disadvantages. Further development requires (a) exploiting the opportunities in the environment to reduce the weaknesses of the technology and (b) using the strengths to address the potential risks.

In particular, the high costs of research and development can be covered by investment capital from shipping companies that want to keep up with modern shipping. At the same time, the economic and environmental impact can become an incentive for the adoption of AI tools even by more traditional ship owners. Automation of processes, digitalization of training and reduction of human error will contribute to easier and more efficient crew training. The high cost of installing new equipment and sensors on board will be more than offset by the reduction in costs, maintenance costs and accidents. The rapidly growing size of the market for innovative software applications in shipping will force the creation of legislative and regulatory frameworks as well as the development of digital security since transactions will be carried out electronically.

The solutions offered by AI contribute fundamentally to more informed, immediate and intelligent decision-making. In each area, tools offer either to analyze the situation and provide an indication or suggestion or to predict a future situation based on history. For the most part, the models support human decisions with the ultimate goal of training them to a degree that will lead to the implementation of the autonomous ship. In the shipping sector, models for short-term forecasting of supply and demand, as well as ship inflow and outflow in such a volatile market can be instrumental in achieving outperformance relative to the competition.

Most applications and reports, however, refer to the monitoring of mechanical systems as well as the energy efficiency of ships. The early and accurate detection of a technical problem, the indication for maintenance as well as the finding of sub-optimal ship behavior provide the necessary knowledge for the ship's technical manager to prepare properly and perform the necessary actions in a planned and cost-effective manner. Optimal routing based on ocean, weather, restrictive areas as well as real-time ship traffic is also the focus of both academic research and commercial software applications.

At the academic level, a lot of research is being done on ship safety, including crew monitoring for accidents, reinforcement training of artificial intelligence models for collision avoidance as first efforts towards autonomous navigation, but also recognition of other ships or obstacles through image processing.

At present, these algorithms as tools are also advisory. In the future, the following areas could be further explored and developed:

■ Broadening the range of tools and applications considered to fully capture technological progress in the maritime sector. The introduction of more tools in this survey may lead to the development of more discernible trends or even to the opposite conclusion, i.e. that some of the trends that appeared to exist may turn out to be statistically insignificant.

■ Evaluation of the performance and accuracy of models and application technology. Benchmarking between tools that aim to solve a group of problems can bring out their strengths. The difficulty to be overcome in commercial applications concerns corporate competition. However, this study can be strengthened at the academic level.

■ Study the impact of digital transformation on work organization practices. The digitalization of processes as well as office-to-ship communication tends to modify the daily life of employees. It would be of particular interest to record the changes in the work of both the ship's crew and the other parties involved (port authorities, charterers, brokers, ship owners, banks). As well as measuring the willingness of less and more familiar shipping companies to adopt a new technology.

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