ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Τμήμα Ψηφιακών Συστημάτων

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ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

του

ΠΥΘΑΓΟΡΑ Π. ΚΑΡΑΜΠΙΠΕΡΗ

Πειραιάς, 2011

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Η διατριβή υποβάλλεται για την κάλυψη των απαιτήσεων απόκτησης Διδακτορικού Διπλώματος

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Πυθαγόρας Π. Καραμπιπέρης

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UNIVERSITY OF PIRAEUS

Department of Digital Systems

DECISION MODELS IN ADAPTIVE EDUCATIONAL HYPERMEDIA SYSTEMS

A Thesis

Presented to

The Academic Faculty

by

PYTHAGORAS P. KARAMPIPERIS

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Pythagoras P. Karampiperis

PhD Candidate

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to my family

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Λέξεις Κλειδιά:

Μοντέλα Αποφάσεων, Προσαρμοστικά Εκπαιδευτικά Συστήματα Υπερμέσων, Έμπειρα Συστήματα Κανόνων, Εκπαιδευτικές Τεχνολογίες, Μαθησιακά Αντικείμενα, Εκπαιδευτικά Μεταδεδομένα,, Μοντελοποίηση Εκπαιδευομένων, Μοντέλα Προσαρμοστικότητας, Αξιολόγηση Απόδοσης, Αλγόριθμοι Βελτιστοποίησης.

Keywords:

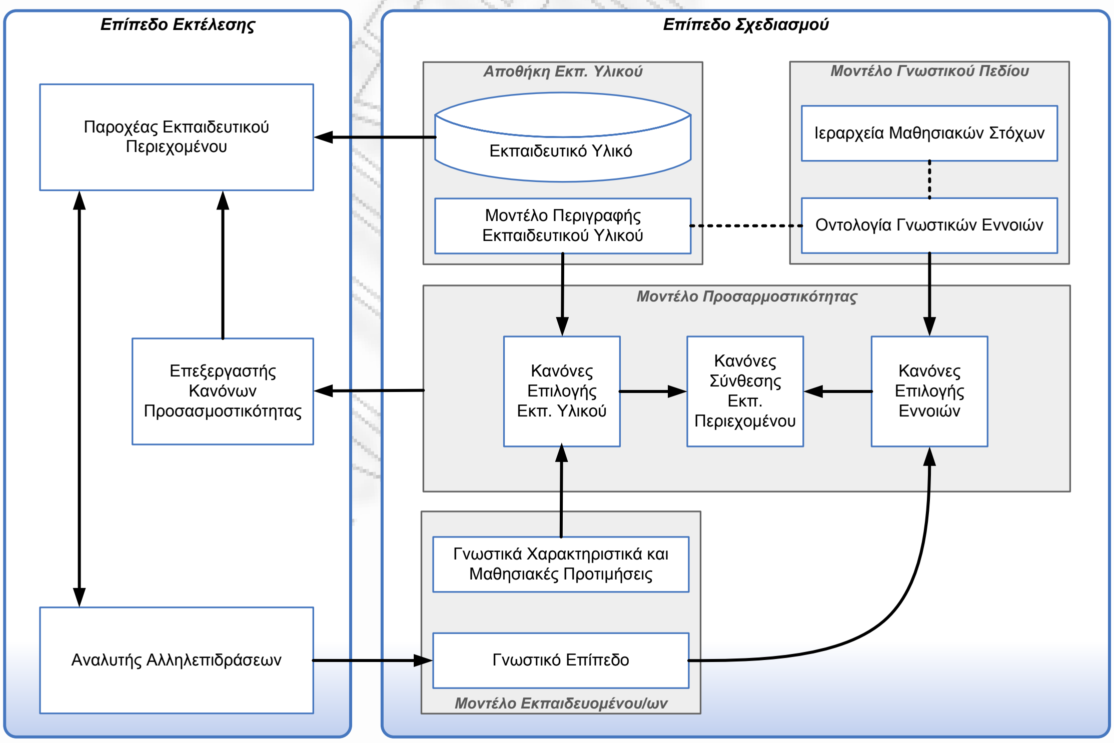
Decision Models, Adaptive Educational Hypermedia, Rule-based Expert Systems, Learning Technologies, Learning Objects, Learning Object Metadata, Learner Modeling, Adaptation Models, Performance Evaluation, , Optimisation Algorithms.

Extended Summary (in Greek)

A. Ορισμός Προβλήματος

Τα προσαρμοστικά εκπαιδευτικά συστήματα υπερμέσων (Adaptive Educational Hypermedia Systems) είναι συστήματα τεχνολογικά υποστηριζόμενης εκπαίδευσης που προσαρμόζουν το παρεχόμενο εκπαιδευτικό περιεχόμενο στις ειδικότερες εκπαιδευτικές ανάγκες του κάθε εκπαιδευομένου ή ομάδας εκπαιδευομένων [1], [2], [3].

Η κεντρική λειτουργική μονάδα των συστημάτων αυτών είναι το Μοντέλο Προσαρμοστικότητας (Adaptation Model) [4], [5], όπως παρουσιάζεται στην Εικόνα 0.1. Το μοντέλο προσαρμοστικότητας τυπικά αποτελείται από ένα σύνολο κανόνων [6], [7], στόχος των οποίων είναι ο καθορισμός του τρόπου επιλογής εκπαιδευτικού υλικού (resource selection) από μία αποθήκη ή συλλογή εκπαιδευτικού υλικού και του τρόπου σύνθεσής του (resource sequencing) ως ενιαίο εκπαιδευτικό περιεχόμενο, προσαρμοσμένο στις ιδιαίτερες εκπαιδευτικές ανάγκες ενός εκπαιδεύομενου ή ομάδας εκπαιδευομένων.



Εικόνα 0.1: Γενικευμένη Αρχιτεκτονική Προσαρμοστικών Εκπαιδευτικών Συστημάτων Υπερμέσων

Σύμφωνα με τη βιβλιογραφία, κεντρική υπόθεση κατά το σχεδιασμό προσαρμοστικών εκπαιδευτικών συστημάτων υπερμέσων, και ειδικότερα του μοντέλου προσαρμοστικότητας αυτών, είναι η ύπαρξη ικανών ειδικών εκπαιδευτικού σχεδιασμού (instructional designers) οι οποίοι μπορούν να ορίσουν ρητώς και με σαφήνεια τους κανόνες προσαρμοστικότητας [8]. Κάτι τέτοιο όμως είναι αρκετά δύσκολο να συμβεί, αφού θα απαιτούσε από ένα ειδικό εκπαιδευτικού σχεδιασμού όχι μόνο τη γνώση κατάλληλου εκπαιδευτικού σχεδιασμού, αλλά και των λεπτομερειών υλοποίησης των μοντέλων με βάση τα οποία πρέπει να οριστούν οι κανόνες προσαρμοστικότητας (Μοντέλο Εκπαιδευομένων, Μοντέλο Περιγραφής Εκπαιδευτικού Υλικού και Μοντέλο Γνωστικού Πεδίου) [6].

Επιπρόσθετα, βασικό μειονέκτημα της χρήσης κανόνων για την περιγραφή του μοντέλου προσαρμοστικότητας είναι ότι απαιτεί το σχεδιασμό ενός υπερβολικά μεγάλου και πολύπλοκου συνόλου κανόνων, με αποτέλεσμα να είναι εξαιρετικά δύσκολος τόσο ο εκ των προτέρων ορισμός του, όσο και η συντήρηση/ανανέωσή του κατά την διάρκεια της εκτέλεσης (runtime) [9], [10]. Η δυσκολία καθορισμού των απαιτούμενων κανόνων οφείλεται στα προβλήματα που επιφέρει η πιθανή επικάλυψη μεταξύ των κανόνων, ή/και η ανεπάρκεια των κανόνων αυτών [11].

Προς τούτο, από τη σχετική βιβλιογραφία αναγνωρίζεται ως ανοιχτό θέμα η *ανάπτυξη κατάλληλων μεθόδων/τεχνικών που να επιτρέπουν τον αυτόματο ορισμό των κανόνων προσαρμοστικότητας* [12], [13] με βάση την πρακτική που ακολουθείται από διαφορετικές κοινότητες εκπαιδευτικής πρακτικής (Communities of Educational Practice) [14].

Επιπρόσθετα, στη βιβλιογραφία έχουν προταθεί διάφορες τεχνικές που επιτρέπουν είτε την προσαρμοστική επιλογή εκπαιδευτικού υλικού [15], είτε την προσαρμοστική σύνθεση εκπαιδευτικού περιεχομένου [16], [17], χωρίς ωστόσο να υπάρχει ένα *ενιαίο πλαίσιο αξιολόγησης της επίδοσης των τεχνικών αυτών*. Πιο συγκεκριμένα, ως μετρικές αξιολόγησης χρησιμοποιούνται είτε γενικές μετρικές από το πεδίο εξαγωγής πληροφορίας (Information Extraction), που όμως δεν λαμβάνουν υπ' όψιν τις ιδιαιτερότητες του υπό εξέταση προβλήματος, είτε μετρικές που είναι αυστηρά εφαρμόσιμες στις προτεινόμενες τεχνικές [18].

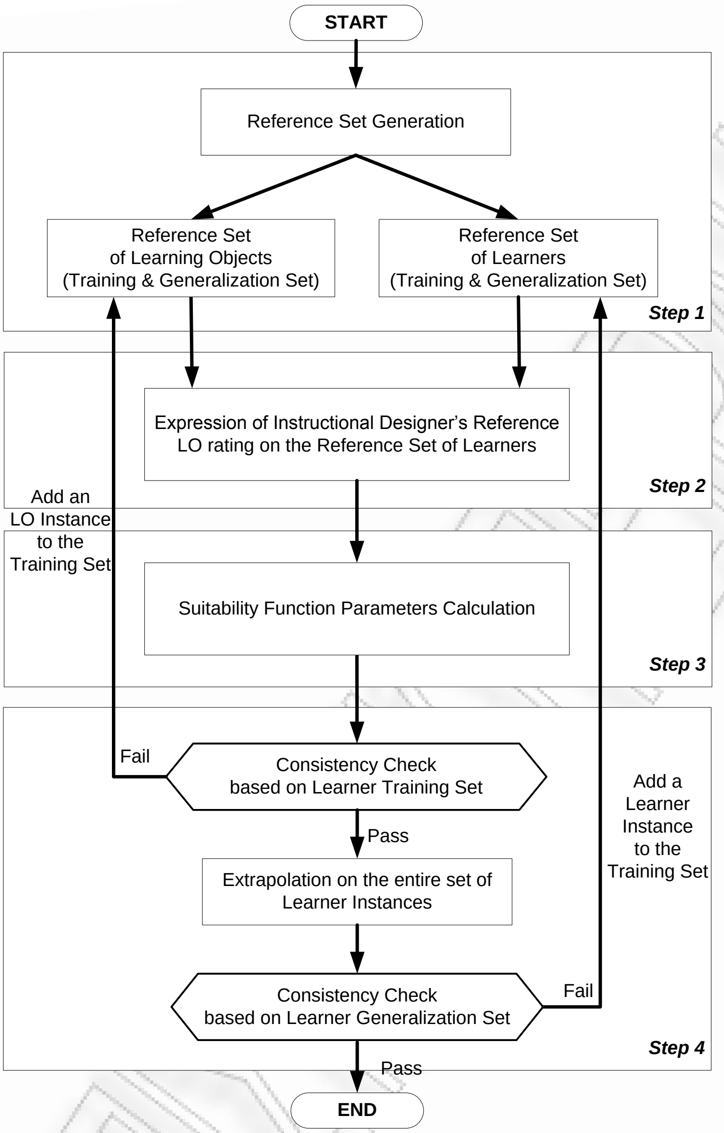
Β. Περιγραφή Αποτελεσμάτων Έρευνας

Η διδακτορική αυτή διατριβή ασχολείται με θέματα που αφορούν στην *προσαρμοστική επιλογή εκπαιδευτικού υλικού*, στην *προσαρμοστική σύνθεση εκπαιδευτικού περιεχομένου*, καθώς και στην σχεδίαση ενός *πλαισίου αξιολόγησης της επίδοσης μεθόδων/τεχνικών αυτόματου ορισμού κανόνων προσαρμοστικότητας*. Πιο συγκεκριμένα:

Μοντέλα Αποφάσεων Προσαρμοστικής Επιλογής Εκπαιδευτικού Υλικού

Βασικός στόχος της ερευνητικής προσπάθειας σε αυτή την κατεύθυνση ήταν η δημιουργία ενός μοντέλου αποφάσεων το οποίο μιμείται τον τρόπο με τον οποίο ένας ειδικός εκπαιδευτικού σχεδιασμού επιλέγει το κατάλληλο εκπαιδευτικό υλικό από μια αποθήκη ψηφιακού εκπαιδευτικού υλικού για έναν συγκεκριμένο εκπαιδευόμενο του οποίου τα χαρακτηριστικά (User Profile) γνωρίζει. Η υλοποίηση ενός τέτοιου μοντέλου αντικαθιστά τους κανόνες επιλογής υλικού (Content Selection Rules) που εντάσσονται στο μοντέλο προσαρμοστικότητας (Adaptation Model) ενός παραδοσιακού προσαρμοστικού συστήματος ηλεκτρονικής μάθησης (βλέπε Εικόνα 0.1).

Πιο συγκεκριμένα, αναπτύξαμε ένα μοντέλο απόφασης το οποίο εκτιμά την καταλληλότητα ενός μαθησιακού αντικειμένου (learning object) για έναν εκπαιδευόμενο υποθέτοντας ότι γνωρίζουμε τα χαρακτηριστικά του εκπαιδευομένου. Το αποτέλεσμα είναι μια συνάρτηση, που καλείται *συνάρτηση καταλληλότητας* (suitability function), η οποία συσχετίζει τα χαρακτηριστικά ενός μαθησιακού αντικειμένου (τα οποία αποτυπώνονται στο Μοντέλο Περιγραφής Εκπαιδευτικού Υλικού) με τα χαρακτηριστικά ενός εκπαιδευόμενου (τα οποία αποτυπώνονται στο Μοντέλο Εκπαιδευομένου) και αντιστρόφως, και μας επιτρέπει την εύρεση του καταλληλότερου μαθησιακού αντικειμένου για ένα συγκεκριμένο εκπαιδευόμενο από ένα σύνολο μαθησιακών αντικειμένων.



Εικόνα 0.2: Διαδικασία δημιουργίας Συνάρτησης Καταλληλότητας

Η προτεινόμενη μέθοδος δημιουργίας της συνάρτησης καταλληλότητας αποτελείται από τα εξής βήματα (όπως παρουσιάζονται στην Εικόνα 0.2):

– *Βήμα 1: Δημιουργία Συνόλων Αναφοράς*

  Το πρώτο βήμα για την δημιουργία της συνάρτησης καταλληλότητας περιλαμβάνει την δημιουργία ενός συνόλου αναφοράς μαθησιακών αντικειμένων καθώς και εκπαιδευομένων, μέσω της χρήσης των αντίστοιχων μοντέλων περιγραφής τους. Για κάθε μία περίπτωση δημιουργούμε δύο σύνολα δεδομένων, το πρώτο εξ αυτών καλείται *σύνολο εκπαίδευσης* (Training Set) και θα χρησιμοποιηθεί για τον υπολογισμό των παραμέτρων της συνάρτησης καταλληλότητας, ενώ το δεύτερο καλούμενο ως *σύνολο γενίκευσης* (Generalisation Set), θα χρησιμοποιηθεί για τον έλεγχο της γενίκευσης της συνάρτησης καταλληλότητας. Κάθε μαθησιακό αντικείμενο του συνόλου αναφοράς προσδιορίζεται από ένα μοναδικό προσδιοριστή της μορφής LO_i και χαρακτηρίζεται από n στοιχεία $g^{LO_i}=(g_1^{LO_i},g_2^{LO_i},\ldots,g_n^{LO_i})$ του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού. Στον Πίνακα 0.1, παρουσιάζονται αναλυτικά τα στοιχεία του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού που χρησιμοποιήσαμε για τις προσομοιώσεις μας. Τα στοιχεία αυτά είναι υποσύνολο του διεθνούς προτύπου περιγραφής μαθησιακών αντικειμένων IEEE Learning Objects Metadata (IEEE LOM) [19].

Πίνακας 0.1: Στοιχεία Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού

IEEE LOM Category	IEEE LOM Element	Explanation
General	Structure	Underlying organizational structure of a Learning Object
	Aggregation Level	The functional granularity of a Learning Object
Educational	Interactivity Type	Predominant mode of learning supported by a Learning Object
	Interactivity Level	The degree to which a learner can influence the aspect or behaviour of a Learning Object.
	Semantic Density	The degree of conciseness of a Learning Object
	Typical Age Range	Developmental age of the typical intended user.
	Difficulty	How hard it is to work with or through a Learning Object for the typical intended target audience.
	Intended End User Role	Principal user(s) for which a Learning Object was designed, most dominant first.
	Context	The principal environment within which the learning and use of a LO is intended to take place.
	Typical Learning Time	Typical time it takes to work with or through a LO for the typical intended target audience.
	Learning Resource Type	Specific kind of Learning Object. The most dominant kind shall be first.

Ομοίως, κάθε προφίλ εκπαιδευομένου του συνόλου αναφοράς προσδιορίζεται από ένα μοναδικό προσδιοριστή της μορφής L_j και χαρακτηρίζεται από m στοιχεία $u^{L_j}=(u_1^{L_j},u_2^{L_j},\ldots,u_m^{L_j})$ του Μοντέλου Εκπαιδευομένων (Learner Model). Στον Πίνακα 0.2, παρουσιάζονται αναλυτικά τα στοιχεία του Μοντέλου Εκπαιδευομένων που χρησιμοποιήσαμε για τις προσομοιώσεις μας. Τα στοιχεία αυτά είναι υποσύνολο του διεθνούς μοντέλου περιγραφής εκπαιδευομένων IMS Learner Information Package (IMS LIP) [20].

Τα σύνολα δεδομένων αναφοράς, παράγονται τυχαία, κατά τρόπο ώστε να έχουν κανονική κατανομή (normal distribution) στο εύρος τιμών του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού και κανονική λογαριθμική κατανομή (lognormal distribution) στο εύρος τιμών του Μοντέλου Εκπαιδευομένου.

Πίνακας 0.2: Στοιχεία Μοντέλου Εκπαιδευομένων

Learner Model Element	IMS LIP Element	Explanation
Learning Style	Accessibility/Preference/typename	The type of cognitive preference
	Accessibility/Preference/prefcode	The coding assigned to the preference
Modality Preference	AccessForAll/Context/Content	The type of modality preference
Knowledge Level	QCL/Level	The level/grade of the QCL
	Activity/Evaluation/noofattempts	The number of attempts made on the evaluation.
	Activity/Evaluation/result/interpretscope	Information that describes the scoring data
	Activity/Evaluation/result/score	The scoring data itself.

– *Βήμα 2: Διαβάθμιση του Συνόλου Αναφοράς Μαθησιακών Αντικειμένων*

Για κάθε προφίλ εκπαιδευομένου του συνόλου εκπαίδευσης (Training Set), ζητάμε από τον ειδικό εκπαιδευτικού σχεδιασμού να ορίσει την σειρά προτίμησης των μαθησιακών αντικειμένων που υπάρχουν τόσο στο σύνολο εκπαιδεύσεως όσο και στο σύνολο γενίκευσης (Generalisation Set). Επιπρόσθετα, για κάθε προφίλ εκπαιδευομένου του συνόλου γενίκευσης, ζητάμε από τον ειδικό εκπαιδευτικού σχεδιασμού να ορίσει την σειρά προτίμησης των μαθησιακών αντικειμένων που υπάρχουν στο γενίκευσης.

– *Βήμα 3:Υπολογισμός Παραμέτρων Συνάρτησης Καταλληλότητας*

Σε αυτό το βήμα ορίζουμε ένα πρόβλημα βελτιστοποίησης το οποίο σαν στόχο έχει τον υπολογισμό των παραμέτρων της συνάρτησης καταλληλότητας κατά τρόπο ώστε να προσεγγίζει τις επιλογές του εκπαιδευτικού ειδικό εκπαιδευτικού σχεδιασμού για τα σύνολα εκπαίδευσης.

Πιο συγκεκριμένα, για κάθε προφίλ εκπαιδευόμενου L_j ορίζουμε ως συνάρτηση μερικής καταλληλότητας (marginal suitability function) του στοιχείου g_k του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού, μια συνάρτηση που εκφράζει πόσο σημαντικό είναι το στοιχείο g_k όταν υπολογίζουμε την καταλληλότητα ενός μαθησιακού αντικειμένου LO_i για το συγκεκριμένο εκπαιδευόμενο L_j. Η συνάρτηση αυτή εκφράζεται από τον τύπο: $s_{g_k}^{L_j}(g_k^{LO_i}) = a_{g_k}^{L_j} + b_{g_k}^{L_j} g_k^{LO_i} \exp(-c_{g_k}^{L_j} g_k^{LO_i\,2})$, όπου $g_k^{LO_i}$ είναι η τιμή του στοιχείου g_k του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού για το μαθησιακό αντικείμενο LO_i. Ο υπολογισμός των παραμέτρων $a_{g_k}^{L_j} \in R,\ b_{g_k}^{L_j} \in R,\ c_{g_k}^{L_j} \in R$, για όλα τα στοιχεία g_k του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού, οδηγεί στον υπολογισμό της συνάρτησης καταλληλότητας για το συγκεκριμένο εκπαιδευόμενο L_j, σύμφωνα με τον τύπο: $S^{L_j}\left(g^{LO_i}\right)=\frac{1}{n}\sum_{k=1}^{n} s_{g_k}^{L_j}(g_k^{LO_i})$.

Χρησιμοποιώντας τη σειρά προτίμησης των μαθησιακών αντικειμένων του συνόλου εκπαίδευσης (Training Set) για το εκπαιδευόμενο L_j, ορίζουμε τις διαφορές καταλληλότητας $\Delta^{L_j}=(\Delta_1^{L_j},\Delta_2^{L_j},\ldots,\Delta_{q-1}^{L_j})$, όπου q ο αριθμός των μαθησιακών αντικειμένων στο σύνολο εκπαίδευσης και $\Delta_l^{L_j}=S_{LO_l}^{L_j}-S_{LO_{l+1}}^{L_j}\geq 0$ η διαφορά προτίμησης μεταξύ δύο συνεχόμενων (subsequent) μαθησιακών αντικειμένων στη σειρά προτίμησης. Στη συνέχεια, για κάθε διαφορά προτίμησης ορίζουμε το σφάλμα *e*, ώστε $\Delta_l^{L_j}=S_{LO_l}^{L_j}-S_{LO_{l+1}}^{L_j}+e_l^{L_j}\geq 0$ και επιλύουμε το πρόβλημα βελτιστοποίησης: Ελαχιστοποίηση $\sum_{l=1}^{q-1}(e_l^{L_j})^2$ υπό τους περιορισμούς:

$$\left.\begin{array}{ll}\Delta_l>0 & \text{αν } S_{LO_l}^{Lj}>S_{LO_{l+1}}^{Lj}\\ \Delta_l=0 & \text{αν } S_{LO_l}^{Lj}=S_{LO_{l+1}}^{Lj}\end{array}\right\}\text{και } 0\leq s_{g_k}^{L_j}(g_k^{LO_i})\leq 1,\ \forall g_k$$

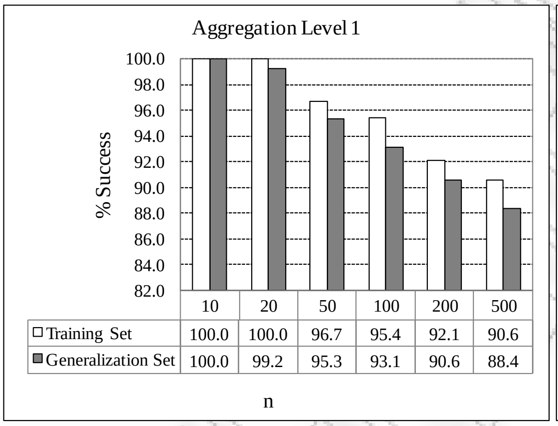
Με την επίλυση του παραπάνω προβλήματος βελτιστοποίησης, υπολογίζουμε τις παραμέτρους $a_{g_k}^{L_j}\in R,\ b_{g_k}^{L_j}\in R,\ c_{g_k}^{L_j}\in R$, για όλα τα στοιχεία g_k του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού. Το πρόβλημα αυτό επιλύεται κάνοντας χρήση κλασσικών μεθόδων μη-γραμμικού προγραμματισμού (ένα συνδυασμό της μεθόδου πολλαπλασιαστών Lagrange και μεθόδων συζυγών κατευθύνσεων).

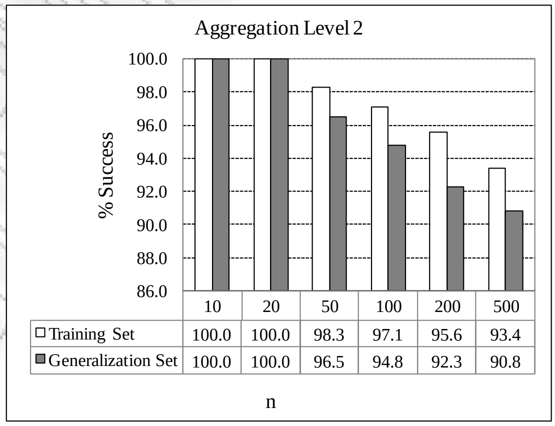
– *Βήμα 4: Έλεγχος Συνέπειας και Γενίκευση*

Σε αυτό το βήμα ελέγχουμε τη συνέπεια της συνάρτησης καταλληλότητας χρησιμοποιώντας την σειρά προτίμησης μαθησιακών αντικειμένων του συνόλου γενίκευσης για κάθε προφίλ εκπαιδευομένου του συνόλου εκπαιδεύσεως. Εάν τα αποτελέσματα δεν είναι ικανοποιητικά επεκτείνουμε το σύνολο εκπαιδεύσεως και επαναλαμβάνουμε τη διαδικασία των Βημάτων 2 και 3. Σε αντίθετη περίπτωση, χρησιμοποιώντας γραμμική παρεμβολή υπολογίζουμε τις παραμέτρους της συνάρτησης καταλληλότητας για όλους τους συνδυασμούς τιμών του μοντέλου εκπαιδευομένου, και ελέγχουμε την επιτυχία επιλογής χρησιμοποιώντας την σειρά προτίμησης μαθησιακών αντικειμένων του συνόλου γενίκευσης για κάθε προφίλ εκπαιδευομένου του συνόλου γενίκευσης.

Προκειμένου να μελετήσουμε την ικανότητα προσαρμοστικής επιλογής εκπαιδευτικού υλικού του προτεινόμενου μοντέλου, πραγματοποιήθηκαν προσομοιώσεις επιλογής από ένα σύνολο προσομοιωμένων μαθησιακών αντικειμένων.

Πιο συγκεκριμένα, προσομοιώσαμε 15 διαφορετικές περιπτώσεις επιλογών προτίμησης μαθησιακών αντικειμένων από αντίστοιχους ειδικούς εκπαιδευτικού σχεδιασμού, θεωρώντας ως μοντέλο προτίμησης αντίστοιχες συναρτήσεις της βιβλιοθήκης CUTE (Constrained and Unconstrained Testing Environment, http://hsl.rl.ac.uk/cuter-www/index.html). Με βάση αυτά τα μοντέλα προτίμησης κατασκευάσαμε 100 διαφορετικές σειρές προτίμησης (η κάθε μία εκ των οποίων αντιστοιχεί σε ένα διαφορετικό προφίλ εκπαιδευομένων), αποτελούμενες από 500 μαθησιακά αντικείμενα, για κάθε προσομοιωμένο ειδικό εκπαιδευτικού σχεδιασμού. Τις πρώτες 50 τις χρησιμοποιήσαμε για την εκπαίδευση του προτεινόμενου μοντέλου, ενώ τις υπόλοιπες 50 για τον έλεγχο της γενίκευσης.





Εικόνα 0.3: Ενδεικτικά Πειραματικά Αποτελέσματα Προσαρμοστικής Επιλογής Εκπαιδευτικού Υλικού

Στην Εικόνα 0.3, παρουσιάζονται ενδεικτικά πειραματικά αποτελέσματα από τις προσομοιώσεις αυτές. Πιο συγκεκριμένα παρουσιάζεται η ποσοστιαία επιτυχία ορθής επιλογής μαθησιακών αντικειμένων σε σχέση με το ζητούμενο αριθμό μαθησιακών αντικειμένων (n). Καθόσον η πολυπλοκότητα σύνθεσης (granularity) ενός μαθησιακού αντικειμένου επηρεάζει την ικανότητα επιλογής ενός εκπαιδευτικού ειδικό εκπαιδευτικού σχεδιασμού, τα αποτελέσματα δίνονται για δύο βασικές κατηγορίες μαθησιακών αντικειμένων σε σχέση με το επίπεδο συνάθροισής τους (aggregation level). Σύμφωνα με το διεθνές πρότυπο περιγραφής μαθησιακών αντικειμένων IEEE Learning Objects Metadata (IEEE LOM), το επίπεδο συνάθροισης ενός μαθησιακού αντικειμένου εκφράζει την πολυπλοκότητα σύνθεσης αυτού και παίρνει τις τιμές “1” όταν το μαθησιακό αντικείμενο αποτελείται από μια μόνο ψηφιακή πηγή και “2” όταν πρόκειται για σύνθετες συλλογές ψηφιακών πηγών.

Δεδομένου ότι για ένα μόνο προφίλ εκπαιδευομένου, οι διαφορετικοί τύποι μαθησιακών αντικειμένων, που προκύπτουν από τον συνδυασμό των δυνατών τιμών των στοιχείων του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού (Πίνακας 0.1), υπολογίζονται πάνω από 900.000, είναι σχεδόν μη ρεαλιστική η υπόθεση ότι ένας ειδικός εκπαιδευτικού σχεδιασμού είναι ικανός να ορίσει σε ένα τυπικό προσαρμοστικό εκπαιδευτικό σύστημα υπερμέσων το πλήθος των κανόνων εκείνων που να καλύπτουν όλες τις περιπτώσεις.

Τα πειράματα που διεξήχθησαν, έδειξαν ότι η χρήση του προτεινόμενου μοντέλου οδηγεί σε ακριβείς αποφάσεις επιλογής Εκπαιδευτικού Υλικού, με ποσοστό επιτυχίας πάνω από 80%, όταν ζητείται από τον ειδικό εκπαιδευτικού σχεδιασμού ο καθορισμός της σειράς προτίμησης 10 μαθησιακών αντικειμένων για 50 διαφορετικές περιπτώσεις προφίλ εκπαιδευομένων, δηλαδή ο καθορισμός 500 συνολικά συνδυασμών, και συνεπώς παρουσιάζει πλεονεκτήματα σε σχέση με την παραδοσιακή προσέγγιση της χρήσης κανόνων.

Τα αποτελέσματα αυτής της έρευνας έχουν δημοσιευτεί στο διεθνές περιοδικό “Journal of Interactive Learning Research” σε ειδικό τεύχος με θέμα “Computational Intelligence in Web-Based Education” [P6] και έχουν παρουσιαστεί σε 2 διεθνή συνέδρια (3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems [P11] και IASTED Conference on Web Based Education WBE 2004 [P13]) και σε 1 εθνικό συνέδριο (4th Hellenic Conference with International Participation on ICT in Education [P14]).

Σε συνέχεια της ερευνητικής προσπάθειας για την ανάπτυξη μοντέλων προσαρμοστικής επιλογής εκπαιδευτικού υλικού, και προκειμένου να μειώσουμε τις απαιτήσεις του προτεινόμενου μοντέλου επιλογής σε σχέση με τη ζητούμενη πληροφορία από ένα ειδικό εκπαιδευτικού σχεδιασμού, μελετήθηκε η ικανότητα δυναμικής εξέλιξης του προτεινόμενου μοντέλου αποφάσεων.

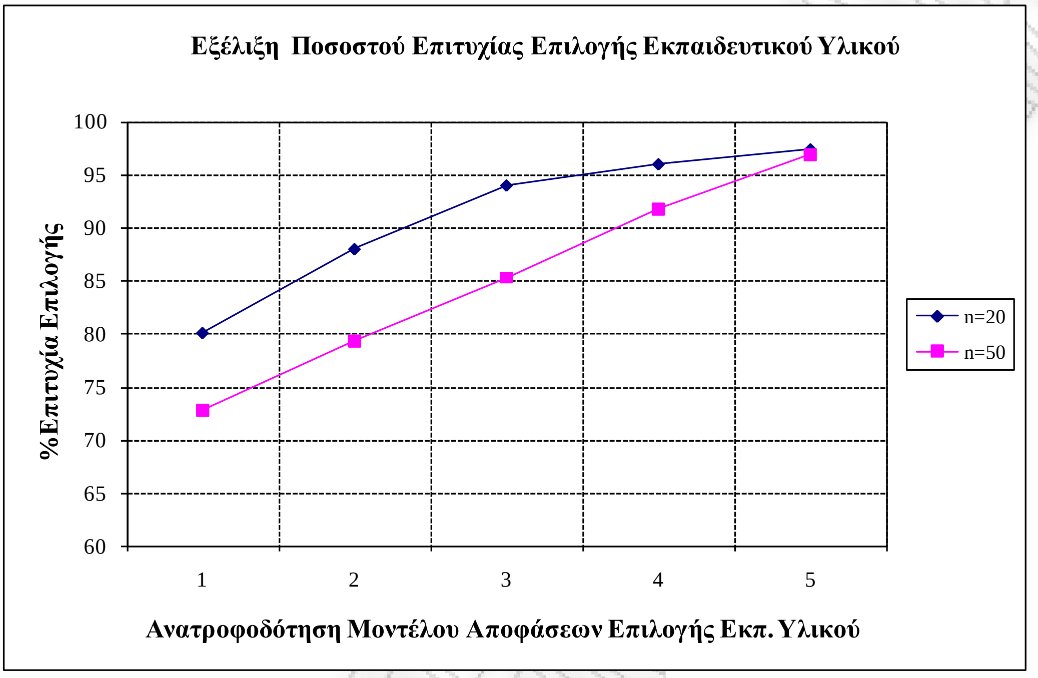
Προς τούτο, επεκτείναμε το προτεινόμενο μοντέλο αποφάσεων επιλογής εκπαιδευτικού υλικού ώστε να κάνει χρήση του μοντέλου εκτίμησης Cognitive Trait Model (CTM) των γνωστικών χαρακτηριστικών (cognitive characteristics) ενός εκπαιδευόμενου. Το μοντέλο αυτό, που έχει προταθεί από τους Kinshuk και Lin [21], με βάση παλαιότερες αποφάσεις επιλογών εκπαιδευτικού υλικού, έχει τη δυνατότητα εκτίμησης των γνωστικών χαρακτηριστικών Working Memory Capacity και Inductive Reasoning Skill και ως αποτέλεσμα προτείνει συγκεκριμένες τιμές για τα στοιχεία InteractivityType, InteractivityLevel, SemanticDensity και Difficulty του Μοντέλου Περιγραφής Εκπαιδευτικού Υλικού, του προς επιλογή εκπαιδευτικού υλικού. Η χρήση του CTM είχε σαν στόχο αφενός τον περιορισμό των διαστάσεων του προβλήματος βελτιστοποίησης που ορίζουμε και αφετέρου την ανατροφοδότηση του μοντέλου αποφάσεων επιλογής εκπαιδευτικού υλικού, ώστε εξελικτικά να βελτιώνει την επιτυχία επιλογής.

Προκειμένου να μελετήσουμε την ικανότητα δυναμικής εξέλιξης του προτεινόμενου μοντέλου αποφάσεων με βάση την εκτίμηση των γνωστικών χαρακτηριστικών ενός εκπαιδευόμενου, πραγματοποιήθηκαν προσομοιώσεις επιλογής από ένα ευρύ σύνολο προσομοιωμένων μαθησιακών αντικειμένων. Πιο συγκεκριμένα, με βάση τα προσομοιωμένα μοντέλα προτίμησης ειδικών εκπαιδευτικού σχεδιασμού, που χρησιμοποιήσαμε για τα προηγούμενα πειράματά μας, κατασκευάσαμε 20 διαφορετικές σειρές προτίμησης, αποτελούμενες από 50 μαθησιακά αντικείμενα, για κάθε προσομοιωμένο ειδικό εκπαιδευτικού σχεδιασμού. Τις πρώτες 10 τις χρησιμοποιήσαμε για την εκπαίδευση και γενίκευση του προτεινόμενου μοντέλου, ενώ τις υπόλοιπες 10 για τη μέτρηση της δυναμικής εξέλιξης του προτεινόμενου μοντέλου αποφάσεων.

Στην Εικόνα 0.4, παρουσιάζονται ενδεικτικά πειραματικά αποτελέσματα από τις προσομοιώσεις αυτές. Πιο συγκεκριμένα παρουσιάζεται η ποσοστιαία επιτυχία ορθής επιλογής (selection success) μαθησιακών αντικειμένων σε σχέση με το ζητούμενο αριθμό μαθησιακών αντικειμένων (n) και τις ανατροφοδοτήσεις του μοντέλου αποφάσεων επιλογής εκπαιδευτικού υλικού από το μοντέλο εκτίμησης CTM.

Τα πειράματα που διεξήχθησαν, έδειξαν ότι (α) η χρήση του προτεινόμενου μοντέλου οδηγεί σε ακριβείς αποφάσεις επιλογής εκπαιδευτικού υλικού, με ποσοστό επιτυχίας πάνω από 70%, τόσο για σχετικά μικρό αριθμό ζητούμενων μαθησιακών αντικειμένων (n=20), όσο και για σχετικά μεγάλο αριθμό (n=50), όταν ζητείται από τον ειδικό εκπαιδευτικού σχεδιασμού ο καθορισμός της σειράς προτίμησης 50 μαθησιακών αντικειμένων για 10 διαφορετικές περιπτώσεις προφίλ εκπαιδευομένων, (β) το προτεινόμενο μοντέλο έχει τη δυνατότητα δυναμικής εξέλιξης όταν συνδυαστεί με το μοντέλο εκτίμησης CTM, με αποτέλεσμα οι αποφάσεις επιλογής να είναι ακριβέστερες όσο ανατροφοδοτείται από το CTM.

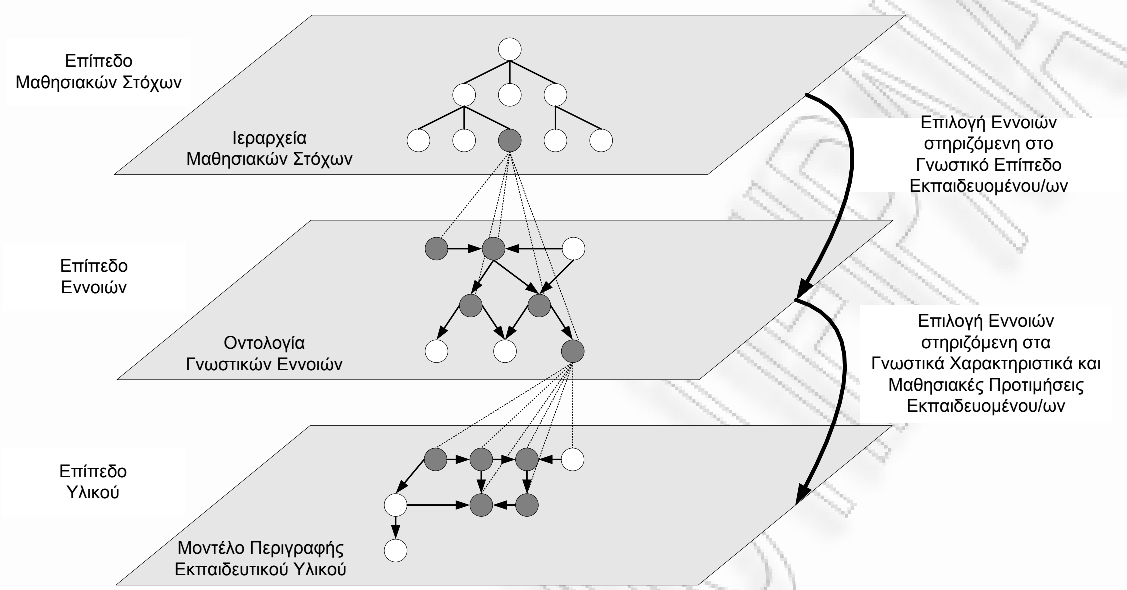
Τα αποτελέσματα της έρευνας αυτής, έχουν δημοσιευτεί στο διεθνές περιοδικό "Innovations in Education and Teaching International" [P3].



Εικόνα 0.4: Ενδεικτικά Πειραματικά Αποτελέσματα Δυναμικής Εξέλιξης Προσαρμοστικής Επιλογής Εκπαιδευτικού Υλικού

Προσαρμοστική Σύνθεση Εκπαιδευτικού Περιεχομένου

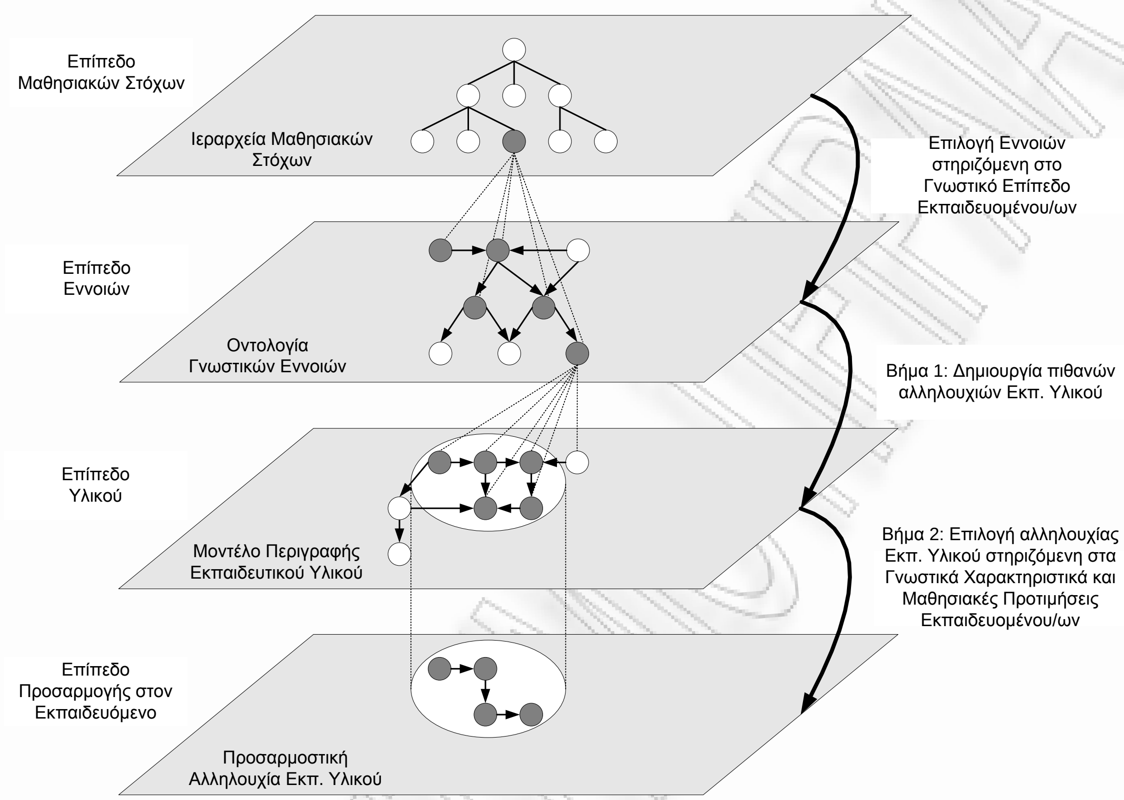
Βασικός στόχος της ερευνητικής προσπάθειας σε αυτή την κατεύθυνση ήταν η δημιουργία ενός μοντέλου αποφάσεων για τη προσαρμοστική σύνθεση εκπαιδευτικού περιεχομένου χωρίς την απαίτηση της χρήσης κανόνων. Πιο συγκεκριμένα, η ερευνητική προσπάθεια επικεντρώθηκε στην επέκταση του μοντέλου αποφάσεων επιλογής εκπαιδευτικού υλικού, ώστε με βάση την πληροφορία που περιέχεται στο Μοντέλο Περιγραφής Υλικού (Resource Description Model), στο Μοντέλο Εκπαιδευομένου (Learner Model) και στο Μοντέλο Περιγραφής του Γνωστικού Πεδίου (Domain Model) ενός προσαρμοστικού εκπαιδευτικού συστήματος υπερμέσων (βλέπε Εικόνα 0.1), να λαμβάνονται αποφάσεις σύνθεσης εκπαιδευτικού περιεχομένου. Σύμφωνα με τη διεθνή βιβλιογραφία, τα παραδοσιακά προσαρμοστικά εκπαιδευτικά συστήματα υπερμέσων, συνθέτουν εκπαιδευτικό περιεχόμενο στηριζόμενα σε κανόνες σύνθεσης που υλοποιούν μια διαδικασία δύο βημάτων [6], [9]. Πρώτα παράγουν μια αλληλουχία εννοιών κατά τρόπο ώστε να καλύπτεται ο εκπαιδευτικός στόχος του εκάστοτε εκπαιδευόμενου και στη συνέχεια επιλέγουν το κατάλληλο εκπαιδευτικό υλικό από μια Αποθήκη Εκπαιδευτικού Υλικού για κάθε μια έννοια ξεχωριστά (Εικόνα 0.5).



Εικόνα 0.5: Γενικευμένη Διαδικασία Σύνθεσης Εκπαιδευτικού Περιεχομένου σε Προσαρμοστικά Εκπαιδευτικά Συστήματα Υπερμέσων

Λόγω των προβλημάτων που επιφέρει η πιθανή επικάλυψη μεταξύ των κανόνων προσαρμοστικότητας, ή/και η ανεπάρκεια των κανόνων αυτών, ενδέχεται η αλληλουχία εκπαιδευτικού υλικού (resource sequence) που παράγεται να μην είναι συνεχής. Για να ξεπεράσουμε το πρόβλημα αυτό, επεκτείναμε τη γενικευμένη διαδικασία σύνθεσης εκπαιδευτικού περιεχομένου, κατά τρόπο ώστε πρώτα να παράγονται όλες οι πιθανές συνεχείς αλληλουχίες διαθέσιμου εκπαιδευτικού υλικού που καλύπτουν τον εκπαιδευτικό στόχο του εκάστοτε εκπαιδευόμενου, και ύστερα να επιλέγεται από αυτές η καταλληλότερη. Αναλυτικά τα προτεινόμενα βήματα προσαρμοστικής σύνθεσης εκπαιδευτικού περιεχομένου παρουσιάζονται στην Εικόνα 0.6.

Αξίζει να σημειωθεί ότι, για την επιλογή της κατάλληλης αλληλουχίας εκπαιδευτικού υλικού για τον εκάστοτε εκπαιδευόμενο, χρησιμοποιούμε το μοντέλο επιλογής εκπαιδευτικού υλικού και πιο συγκεκριμένα τη συνάρτηση καταλληλότητας που αναπτύξαμε στο προηγούμενο ερευνητικό στάδιο. Η συνάρτηση αυτή χρησιμοποιείται για να βαθμονομήσει τον κάθε κόμβο της αλληλουχίας. Το αποτέλεσμα της διαδικασίας αυτής είναι βαθμονομημένοι κατευθυνόμενοι γράφοι (directed weighted graphs) που εκφράζουν όλα τα δυνατά μονοπάτια του εκάστοτε εκπαιδευομένου για την επίτευξη ενός μαθησιακού στόχου. Για την επιλογή του καταλληλότερου μονοπατιού (αλληλουχίας εκπαιδευτικού υλικού) χρησιμοποιούμε αλγορίθμους συντομότερου μονοπατιού (shortest path algorithms).



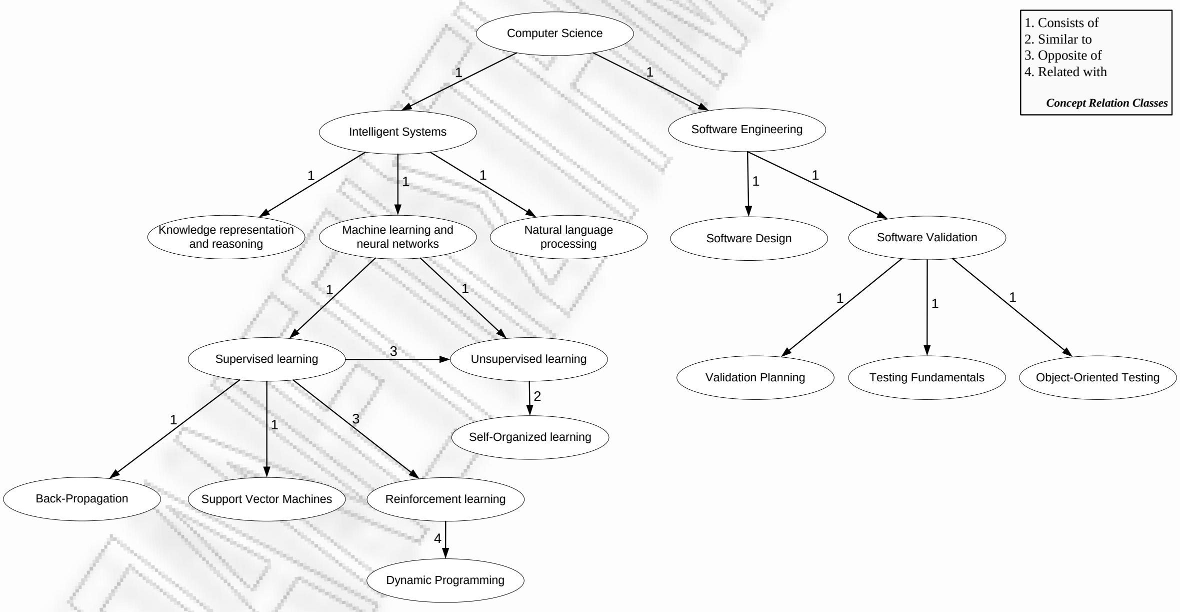
Εικόνα 0.6: Προτεινόμενη Διαδικασία Σύνθεσης Εκπαιδευτικού Περιεχομένου

Προκειμένου να μελετήσουμε την ικανότητα προσαρμοστικής σύνθεσης εκπαιδευτικού υλικού του προτεινόμενου μοντέλου, πραγματοποιήθηκαν προσομοιώσεις σύνθεσης από ένα ευρύ σύνολο προσομοιωμένων μαθησιακών αντικειμένων. Πιο συγκεκριμένα, ως Μοντέλο Περιγραφής Εκπαιδευτικού Υλικού χρησιμοποιήσαμε υποσύνολο του διεθνούς προτύπου περιγραφής μαθησιακών αντικειμένων IEEE Learning Objects Metadata (IEEE LOM), που παρουσιάστηκε στον Πίνακα 0.1. Ως Μοντέλο Εκπαιδευομένων χρησιμοποιήσαμε υποσύνολο του διεθνούς μοντέλου περιγραφής εκπαιδευομένων IMS Learner Information Package (IMS LIP) , που παρουσιάστηκε στον Πίνακα 0.2. Για την δημιουργία του Μοντέλου Γνωστικού Πεδίου χρησιμοποιήσαμε το προτεινόμενο Πρόγραμμα Σπουδών Επιστήμης Πληροφορικής της ACM (ACM Computing Curricula 2001 for Computer Science) [22]. Πιο συγκεκριμένα με βάση το πρόγραμμα σπουδών αυτό δημιουργήσαμε μια Οντολογία Γνωστικών Εννοιών, αποτελούμενη από 950 έννοιες (topics) οργανωμένες σε 132 ενότητες (units) και 14 θεματικές περιοχές (areas), όπως παρουσιάζεται στον Πίνακα 0.3.

Πίνακας 0.3: Θεματικές Περιοχές Οντολογίας Γνωστικών Εννοιών

Area	Units	Topics
Discrete Structures	6	45
Programming Fundamentals	5	32
Algorithms and Complexity	11	71
Architecture and Organization	9	55
Operating Systems	12	71
Net-Centric Computing	9	79
programming languages	11	75
Human-Computer Interaction	8	47
Graphics and Visual Computing	11	84
Intelligent Systems	10	106
Information Management	14	93
Social and Professional Issues	10	46
Software Engineering	12	85
Computational Science	4	61
TOTAL	**132**	**950**

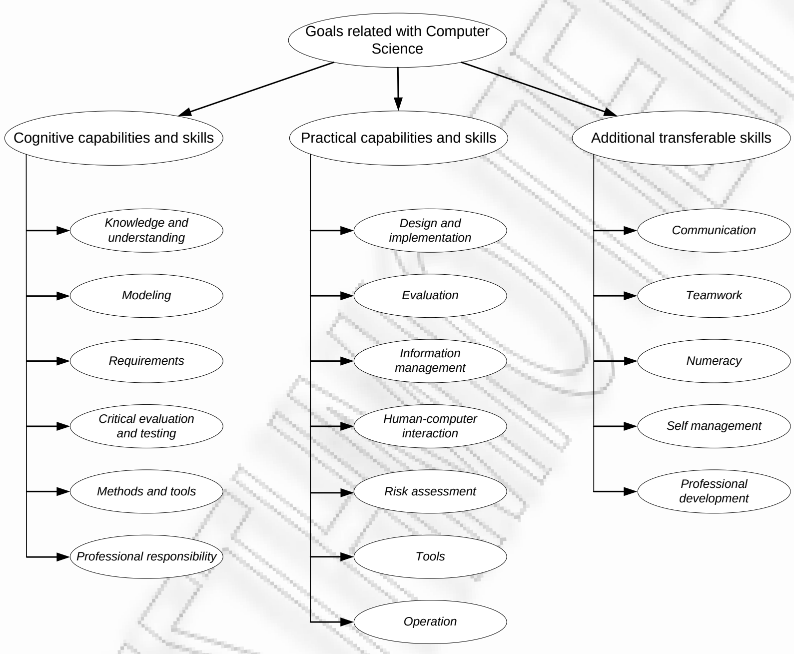
Στην Εικόνα 0.7, παρουσιάζεται τμήμα της Οντολογίας Γνωστικών Εννοιών που χρησιμοποιήσαμε στα πειράματά μας.



Εικόνα 0.7: Τμηματική Απεικόνιση Οντολογίας Γνωστικών Εννοιών

Επιπλέον, με βάση το πρόγραμμα σπουδών της ACM, καθορίσαμε την Ιεραρχεία Μαθησιακών Στόχων που παρουσιάζεται στην Εικόνα 0.8.

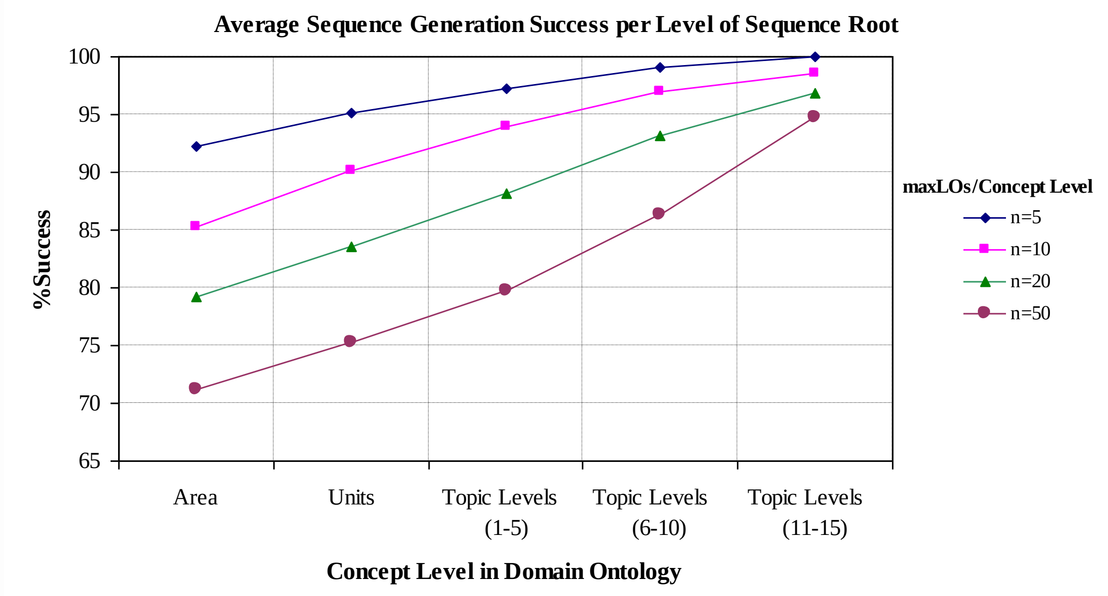
Για τον υπολογισμό της συνάρτησης καταλληλότητας κατασκευάσαμε 10 διαφορετικές σειρές προτίμησης, αποτελούμενες από 50 μαθησιακά αντικείμενα, για κάθε προσομοιωμένο ειδικό εκπαιδευτικού σχεδιασμού. Τις πρώτες 5 τις χρησιμοποιήσαμε για την εκπαίδευση της συνάρτησης καταλληλότητας, ενώ τις υπόλοιπες 5 για τον έλεγχο της γενίκευσης. Για το έλεγχο του προτεινόμενου μοντέλου σύνθεσης εκπαιδευτικού περιεχομένου δημιουργήσαμε ένα σύνολο 142.500 προσομοιωμένων μαθησιακών αντικειμένων, που αντιστοιχεί σε 150 μαθησιακά αντικείμενα για κάθε μία έννοια της Οντολογίας Γνωστικών Εννοιών, καθώς και ένα σύνολο 20 προφίλ εκπαιδευόμενων κατά τρόπο ώστε να έχουν κανονική κατανομή στο εύρος τιμών του Μοντέλου Εκπαιδευομένων.



Εικόνα 0.8: Ιεραρχεία Μαθησιακών Στόχων

Την επιτυχία ορθής σύνθεσης (learning object sequence generation success) την μετρήσαμε συγκρίνοντας τις παραγόμενες αλληλουχίες μαθησιακών αντικειμένων για 10 τυχαία επιλεγμένα προφίλ εκπαιδευομένων για κάθε επίπεδο εννοιών στην Οντολογία Γνωστικών Εννοιών, με τις αναμενόμενες αλληλουχίες μαθησιακών αντικειμένων βάση των προσομοιωμένων μοντέλων προτίμησης ειδικών εκπαιδευτικού σχεδιασμού. Στην Εικόνα 0.9, παρουσιάζονται ενδεικτικά πειραματικά αποτελέσματα από τις προσομοιώσεις αυτές. Πιο συγκεκριμένα παρουσιάζεται η ποσοστιαία επιτυχία ορθής σύνθεσης (sequence generation success) μαθησιακών αντικειμένων σε σχέση με το ζητούμενο αριθμό μαθησιακών αντικειμένων (n), καθώς και με επίπεδο εννοιών στην Οντολογία Γνωστικών Εννοιών.

Τα πειραματικά αποτελέσματα δείχνουν ότι η χρήση του προτεινόμενου μοντέλου οδηγεί σε ακριβείς αποφάσεις σύνθεσης εκπαιδευτικού περιεχομένου, με ποσοστό επιτυχίας πάνω από 70%, τόσο για σχετικά μικρό αριθμό ζητούμενων μαθησιακών αντικειμένων (n=5), όσο και για σχετικά μεγάλο αριθμό (n=50), όταν ζητείται από τον ειδικό εκπαιδευτικού σχεδιασμού ο καθορισμός της σειράς προτίμησης 10 μαθησιακών αντικειμένων για 50 διαφορετικές περιπτώσεις προφίλ εκπαιδευομένων.



Εικόνα 0.9: Ενδεικτικά Πειραματικά Αποτελέσματα Προσαρμοστικής Σύνθεσης Εκπαιδευτικού Περιεχομένου

Τα αποτελέσματα αυτής της έρευνας, έχουν ήδη δημοσιευτεί στο διεθνές περιοδικό "Educational Technology & Society" [P5], στο βιβλίο "Web-Based Intelligent e-Learning Systems: Technologies and Applications" [P4] και έχουν παρουσιαστεί σε 3 διεθνή συνέδρια (6th IEEE International Conference on Advanced Learning Technologies [P9], 4th IEEE International Conference on Advanced Learning Technologies [P10] και 3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems [P12]). Στο συνέδριο 4th IEEE International Conference on Advanced Learning Technologies [P10], η εργασία τιμήθηκε με το βραβείο Best Paper Award.

Σχεδίαση και Εφαρμογή Πλαισίου Αξιολόγησης

Βασικός στόχος της ερευνητικής προσπάθειας σε αυτή την κατεύθυνση ήταν ο σχεδιασμός ενός πλαισίου αξιολόγησης της επίδοσης μεθόδων/τεχνικών αυτόματου ορισμού κανόνων προσαρμοστικότητας. Πιο συγκεκριμένα:

Ως μετρική της επιτυχίας ορθής επιλογής (selection success) προτείνουμε τη χρήση της μετρικής: $\text{Selection Success (\%)} = 100 * \left(\frac{\textit{correct ranked Learning Objects selected}}{\textit{requested Learning Objects}} \right)$.

Παρόλο που η μετρική αυτή είναι όμοια με την μετρική υπολογισμού της ακρίβειας (precision) σε συστήματα εξαγωγής πληροφορίας (Information Extraction) και ορίζεται από τη σχέση: $\text{Precision} = \left(\frac{Number\ of\ Correct\ Items\ Selected}{Number\ of\ retrieved\ Items} \right)$, στην πράξη η προτεινόμενη μετρική είναι καταλληλότερη για την αξιολόγηση προσαρμοστικής επιλογής σε προσαρμοστικά εκπαιδευτικά συστήματα υπερμέσων.

Βασικός στόχος των συστημάτων αυτών είναι η αποφυγή σε δεδομένη χρονική στιγμή παροχής προς τους εκπαιδευομένους μεγάλου όγκου πληροφορίας, αφού σε αντίθετη περίπτωση θα ενίσχυαν γνωστικά προβλήματα αντί να τα θεραπεύουν, λόγω του προβλήματος της γνωσιακής υπερφόρτωσης (cognitive overload). Ως αποτέλεσμα, τα υποσυστήματα προσαρμοστικής επιλογής εκπαιδευτικού υλικού υλοποιούν μια πολιτική επιλογής περιορισμένης ποσότητας εκπαιδευτικού υλικού.

Συνεπώς, στην πράξη ο αριθμός των επιλεχθέντων μαθησιακών αντικειμένων δεν ξεπερνά τον αριθμό των επιθυμητών προς επιλογή μαθησιακών αντικειμένων, που σημαίνει ότι η προτεινόμενη μετρική είναι αυστηρότερη από την μετρική της ακρίβειας (precision), ενώ υπολογίζει με μεγαλύτερη ακρίβεια την επίδοση επιλογής και στις περιπτώσεις όπου ο αριθμός των επιλεχθέντων μαθησιακών αντικειμένων είναι μικρότερος από τον αριθμό των επιθυμητών προς επιλογή μαθησιακών αντικειμένων.

Ως μετρική της επιτυχίας ορθής σύνθεσης (learning object sequence generation success) προτείνουμε τη χρήση της μετρικής: $\text{Success (\%)} = 100 * \left(\frac{1}{2} + \frac{N_{concordant} - N_{discordant}}{n(n-1)} \right)$, όπου $N_{concordant}$ είναι τα εναρμονισμένα ζεύγη (concordant pairs) μαθησιακών αντικειμένων στις συγκρινόμενες αλληλουχίες, $N_{discordant}$ τα μη εναρμονισμένα ζεύγη (discordant pairs) και n ο αριθμός των μαθησιακών αντικειμένων σε κάθε μία από τις συγκρινόμενες αλληλουχίες.

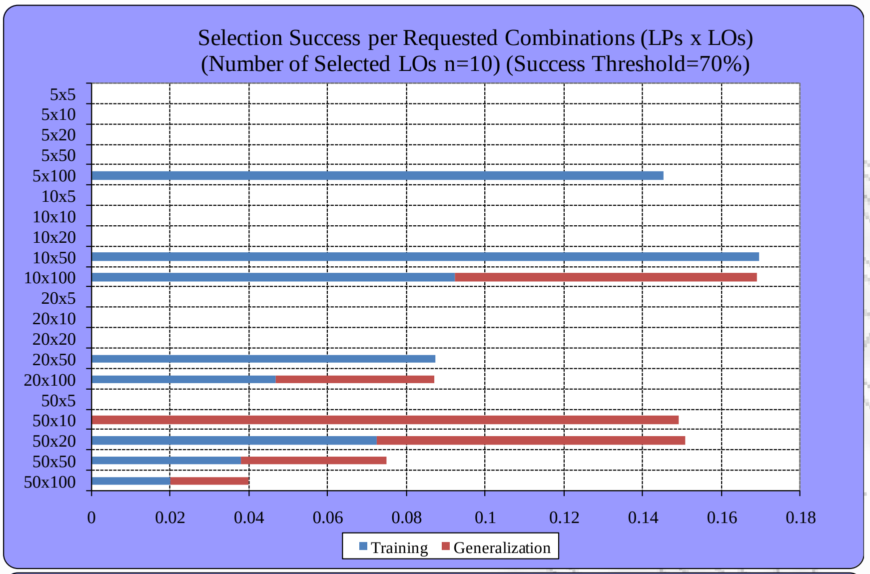
Η μετρική αυτή προκύπτει με κανονικοποίηση της μετρικής Τ του Kendall, στο εύρος τιμών [0,100] ούτως ώστε η πλήρης ταύτιση των συγκρινόμενων αλληλουχιών να οδηγεί σε μέγιστη επίδοση, ενώ η πλήρης δυσαρμονία σε μηδενική. Στόχος κατά την εφαρμογή της μετρικής αυτής είναι η σύγκριση των παραγόμενων αλληλουχιών μαθησιακών αντικειμένων, με πρότυπες αλληλουχίες που προκύπτουν είτε από τον απευθείας καθορισμό τους από έναν ειδικό εκπαιδευτικού σχεδιασμού, είτε μέσω της προσομοίωσης του μοντέλου προτίμησης ενός ειδικού εκπαιδευτικού σχεδιασμού.

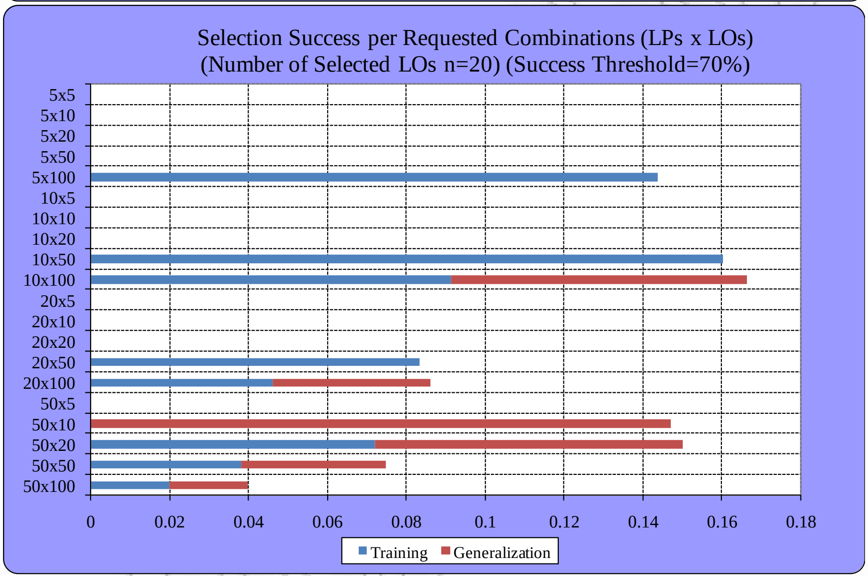
Το προτεινόμενο πλαίσιο αξιολόγησης, εφαρμόστηκε πειραματικά με στόχο την ανίχνευση των βέλτιστων παραμέτρων των προτεινόμενων μοντέλων προσαρμοστικής επιλογής εκπαιδευτικού υλικού και προσαρμοστικής σύνθεσης εκπαιδευτικού περιεχομένου, ώστε αφενός να ελαχιστοποιούνται οι απαιτήσεις των μοντέλων αυτών σε σχέση με τη ζητούμενη πληροφορία από έναν ειδικό εκπαιδευτικού σχεδιασμού, και αφετέρου να παρουσιάζουν μέγιστη επίδοση.

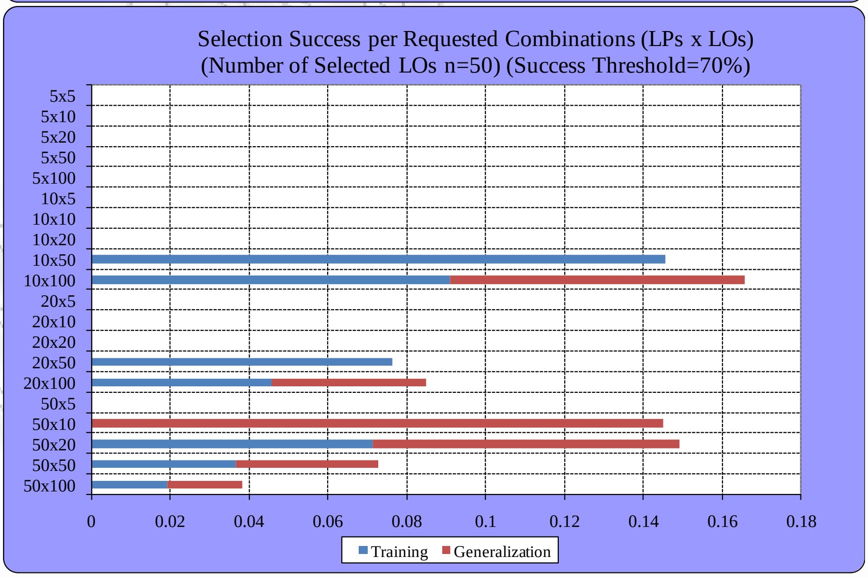
Προς τούτο, υπολογίστηκε ο λόγος της επίδοσης προς την απαίτηση πληροφορίας από έναν ειδικό εκπαιδευτικού σχεδιασμού. Η απαίτηση πληροφορίας είναι ισοδύναμη με τον αριθμό των ζητούμενων συνδυασμών αντιστοίχησης μαθησιακών αντικειμένων (Learning Objects - LOs) με προφίλ εκπαιδευομένων (Learner Profiles - LPs). Στην Εικόνα 0.10, παρουσιάζονται ενδεικτικά πειραματικά αποτελέσματα από τις προσομοιώσεις αυτές. Πιο συγκεκριμένα παρουσιάζεται ο λόγος της ποσοστιαίας επιτυχίας ορθής επιλογής (selection success) μαθησιακών αντικειμένων προς τον αριθμό των απαιτούμενων συνδυασμών μαθησιακών αντικειμένων με προφίλ εκπαιδευομένων (LOs x LPs).

Ως στόχος κατά την εκτέλεση των πειραμάτων τέθηκε η ικανοποίηση της συνθήκης: $\text{Selection Success} \geq 70\%$, και συνεπώς στα γραφήματα της Εικόνας 0.10, παρουσιάζονται μόνο οι περιπτώσεις όπου ξεπερνούν το παραπάνω κατώφλι επίδοσης. Στα γραφήματα αυτά, για κάθε μια περίπτωση συνδυασμού (LOs x LPs) παρουσιάζεται ο λόγος της επίδοσης προς την απαίτηση πληροφορίας τόσο κατά τη φάση εκπαίδευσης (training) του αλγορίθμου προσαρμοστικής επιλογής εκπαιδευτικού υλικού, όσο και κατά τη φάση ελέγχου γενίκευσης (generalisation).

Τα πειραματικά αποτελέσματα δείχνουν ότι το μέγιστο λόγο επίδοσης προς την απαίτηση πληροφορίας από έναν ειδικό εκπαιδευτικού σχεδιασμού, τον πετυχαίνουμε όταν ο αριθμός των ζητούμενων συνδυασμών αντιστοίχησης μαθησιακών αντικειμένων είναι: (50 βαθμονομημένα μαθησιακά αντικείμενα για τις περιπτώσεις 10 προφίλ εκπαιδευομένων) ή (10 βαθμονομημένα μαθησιακά αντικείμενα για τις περιπτώσεις 50 προφίλ εκπαιδευομένων). Παρόλο που και στις δύο περιπτώσεις ο αριθμός των ζητούμενων συνδυασμών είναι ίδιος (και ισούται με 500 συνδυασμούς), η χρήση τους παρουσιάζει τελείως διαφορετικά χαρακτηριστικά.







Εικόνα 0.10: Ενδεικτικά Πειραματικά Αποτελέσματα Επίδοσης Προσαρμοστικής Επιλογής Εκπαιδευτικού Υλικού προς τον Όγκο της Ζητούμενης Πληροφορίας από έναν Ειδικό Εκπαιδευτικού Σχεδιασμού

Στην πρώτη περίπτωση φαίνεται να έχουμε πολύ καλό λόγο επίδοσης προς την απαίτηση πληροφορίας κατά τη φάση εκπαίδευσης του αλγορίθμου προσαρμοστικής επιλογής εκπαιδευτικού υλικού, ενώ κατά την φάση ελέγχου γενίκευσης η απόδοση δεν ξεπερνά το κατώφλι επίδοσης που θέσαμε. Ο αλγόριθμος προσαρμοστικής επιλογής εκπαιδευτικού υλικού παρουσιάζει σε αυτή την περίπτωση overfitting στα δεδομένα εκπαίδευσής του. Αντίθετα, στην δεύτερη περίπτωση φαίνεται να έχουμε πολύ καλό λόγο επίδοσης προς την απαίτηση πληροφορίας κατά τη φάση ελέγχου γενίκευσης του αλγορίθμου προσαρμοστικής επιλογής εκπαιδευτικού υλικού, ενώ κατά την φάση εκπαίδευσης η απόδοση δεν ξεπερνά το κατώφλι επίδοσης που θέσαμε. Από τα παραπάνω, είναι προφανές ότι η δεύτερη περίπτωση είναι καταλληλότερη για την εφαρμογή του προτεινόμενου μοντέλου προσαρμοστικής επιλογής εκπαιδευτικού υλικού.

Η εφαρμογή λοιπόν του προτεινόμενου πλαισίου αξιολόγησης, μπορεί να οδηγήσει σε χρήσιμα συμπεράσματα τόσο στη μέτρηση της επίδοσης μεθόδων/τεχνικών αυτόματου ορισμού κανόνων προσαρμοστικότητας, όσο και στην εύρεση των βέλτιστων παραμέτρων για την εφαρμογή τους.

Τα αποτελέσματα αυτής της έρευνας, έχουν ήδη δημοσιευτεί στο βιβλίο “Intelligent and Adaptive Learning Systems: Technology Enhanced Support for Learners and Teachers ” [P2], έχουν παρουσιαστεί στο διεθνές συνέδριο 9th IEEE International Conference on Advanced Learning Technologies (ICALT 2009) [P8], ενώ έχουν υποβληθεί ως κεφάλαιο στο βιβλίο “Intelligent and Adaptive Educational-Learning Systems: Achievements and Trends” [P1] και στο διεθνές συνέδριο 4th International Conference on Intelligent Interactive Multimedia Systems and Services (KES-IIMSS 2011) [P7].

Publications based on this Thesis

In total, five (5) already published papers in International Journals/ Books and seven (7) papers in Scientific Conferences, with more than 130 citations.

International Journal Papers/ Book Chapters

[P1]. P. Karampiperis and D. Sampson, "Performance Evaluation of Decision-based Content Selection and Sequencing Approaches in Adaptive Educational Hypermedia Systems", in A. P. Ayala (Ed.), *Intelligent and Adaptive Educational-Learning Systems: Achievements and Trends*, Springer, (submitted for publication), January 2011

[P2]. D. Sampson and P. Karampiperis, "Decision Models in the Design of Adaptive Educational Hypermedia Systems", in Sabine Graf, Fuhua Lin, Kinshuk and Rory McGreal (Eds), *Intelligent and Adaptive Learning Systems: Technology Enhanced Support for Learners and Teachers*, IGI Global, 2011

[P3]. P. Karampiperis, T. Lin, D. Sampson and Kinshuk, "Adaptive Cognitive-based Selection of Learning Objects", International Journal on *Innovations in Education and Teaching International* (ISSN 1470-3300), vol. 43 (2), pp. 121-135, Taylor & Francis, May 2006, [*3 Citations*].

[P4]. P. Karampiperis and D. Sampson, "Automatic Learning Object Selection and Sequencing in Web-Based Intelligent Learning Systems", in Zongmin Ma (Ed.), *Web-Based Intelligent e-Learning Systems: Technologies and Applications* (ISBN 1-59140-729-3), Chapter III, pp. 56-71, Information Science Publishing, December 2005, [*11 Citations*].

[P5]. P. Karampiperis and D. Sampson, "Adaptive Learning Resources Sequencing in Educational Hypermedia Systems", *Educational Technology & Society Journal* (ISSN 1436-4522), vol. 8(4), pp. 128-147, October 2005, [*65 Citations*].

[P6]. P. Karampiperis and D. Sampson, "Adaptive Learning Object Selection in Intelligent Learning Systems", Journal of *Interactive Learning Research*, Special Issue on *Computational Intelligence in Web-Based Education* (ISSN 1093-023X), vol. 15(4), pp. 389-409, AACE Press, November 2004, [*11 Citations*].

International Conference Papers

[P7]. P. Karampiperis and D. Sampson, "Performance Evaluation of Adaptive Content Selection in AEHS", in Proc. of the 4th International Conference on Intelligent Interactive Multimedia Systems and Services (KES-IIMSS 2011), Piraeus, Greece, July 2011, (submitted for publication).

[P8]. P. Karampiperis and D. Sampson, "Evaluating the Performance of Adaptive Learning Objects Selection and Sequencing in Adaptive Educational Hypermedia Systems", in Proc. of the 9th IEEE International Conference on Advanced Learning Technologies (ICALT 2009), ISBN: 978-0-7695-3711-5, pp. 316-318, Riga, Latvia, IEEE Computer Society, July 2009.

[P9]. P. Karampiperis and D. Sampson, "Adaptive Learning Objects Sequencing for Competence-Based Learning", in Proc. of the *6th IEEE International Conference on Advanced Learning Technologies* (ICALT 2006), ISBN: 0769526322, pp. 136-138, Kerkrade, The Netherlands, IEEE Computer Society, July 2006, [*7 Citations*].

[P10]. P. Karampiperis and D. Sampson, "Adaptive Instructional Planning Using Ontologies", in Proc. of the *4th IEEE International Conference on Advanced Learning Technologies* (ICALT 04), ISBN: 0769521819, pp. 126-130, Joensuu, Finland, (*BEST PAPER AWARD*), IEEE Computer Society, August 2004, [*37 Citations*].

[P11]. P. Karampiperis and D. Sampson, "Adaptive Hypermedia Authoring: From Adaptive Navigation to Adaptive Learning Support", in Proc. of the *3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems*, vol. 2, pp. 449-454, Eindhoven, Netherlands, TU/e Pub., August 2004, [*1 Citation*].

[P12]. P. Karampiperis and D. Sampson, "Using Ontologies for Adaptive Navigation Support in Educational Hypermedia Systems", in Proc. of the *3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems* in *International Workshop on Applications of Semantic Web technologies for E-Learning* (SW-EL 04), vol. 2, pp. 314-323, Eindhoven, Netherlands, TU/e Pub., August 2004, [*2 Citations*].

[P13]. P. Karampiperis and D. Sampson, "Knowledge Modelling for Adaptive Content Selection in Educational Hypermedia Systems", in Proc. of the *IASTED Conference on Web Based Education* (WBE 2004), ISBN: 0889864063, pp. 408-413, Innsbruck, Austria, ACTA Press, February 2004, [*1 Citation*].

National Conference Papers

[P14]. P. Karampiperis and D. Sampson, "Adaptive Learning Objects Selection in Intelligent Learning Systems", in Proc. of the *4th Hellenic Conference with International Participation on ICT in Education*, ISBN: 9608835925, vol. 1, pp. 719-728, Athens, Greece, New Technologies Pub., September 2004, [*1 Citation*].

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Abbreviations

AH	Adaptive Hypermedia
AEH	Adaptive Educational Hypermedia
AEHS	Adaptive Educational Hypermedia Systems
AHAM	Adaptive Hypermedia Application Model
AM	Adaptation Model
CPF	Concepts Path Graph
DC	Dublin Core
FOHM	Fundamental Open Hypermedia Model
HTN	Hierarchical Task Network
LIP	Learner Information Package
LO	Learning Object
LOM	Learning Object Metadata
LPG	Learning Paths Graph
LT	Learning Technologies
LTSA	Learning Technology Systems Architecture
OHP	Open Hypermedia Protocol
PAPI	Public and Private Information
QCL	Qualifications, Certifications and Licenses
RTE	Run-Time Environment
SCO	Sharable Content Object
SCORM	Sharable Content Object Reference Model
XML	Extensible Markup Language

Chapter 1. Introduction

1.1. Motivation and Problem Statement

Adaptive Educational Hypermedia Systems (AEHS) have been proposed as the underlying facilitator for personalized web-based learning with the general aim of personalizing learning experiences for a given learner [1], [2], [9], [23], [24].

Adaptive learning objects selection and sequencing is recognized as challenging research issues in adaptive educational hypermedia systems (AEHS) [25], [26], [27]. In order to adaptively select and sequence learning objects in AEHS, the definition of adaptation behaviour, referred to as Adaptation Model, is required [28].

In the literature, there exist several approaches aiming to support the design of these rules by providing either direct guidance to AEHS designers, such as the Authoring Task Ontology (ATO) [10] and the Adaptive Hypermedia Architecture (AHA) [29], [30], or semi-automatic mechanisms for making the rule design process less demanding, such as the Layered AHS Authoring-Model and Operators (LAOS) [31] and the Adaptive Course Construction Toolkit (ACCT) [32], [33].

However, still the design of adaptive educational hypermedia systems requires significant effort [9], since dependencies between educational characteristics of learning resources and learners characteristics are too complex to exhaust all possible combinations [34]. This complexity introduces several problems on the definition of the rules required [11], [35], namely:

- *Inconsistency*, when two or more rules are conflicting.
- *Confluence*, when two or more rules are equivalent.
- *Insufficiency*, when one or more rules required have not been defined.

The problems of inconsistency and insufficiency of the defined rule sets are responsible for generating conceptual “holes” to the produced learning resource sequence (learning path). This is due to the fact that, even if appropriate resources exist in the Media Space, the conflict between two or more rules (inconsistency problem) or the absence of a required rule (insufficiency problem), prevents the AEHS to select them and use them in the learning resource sequence. As a result, either less appropriate resources are used from the Media Space, or required concepts are not covered at all by the resulting sequence [11].

As already described, the most commonly used approach for the definition of content selection and sequencing rules is the direct definition. To support this process, a number of design tools have been proposed in the literature [36]. These systems require the Instructional Designer to have good knowledge of the parameters of the system that can be adapted, as well as the details of the User Model. Typical examples of these systems are the AHA [30], MOT [37], [38] and the ELM-ART [39].

Although these systems provide graphical environments for the definition of the content selection and sequencing rules and/or visual representation of the resulting learning/teaching scenario, still it is difficult for Instructional Designers to overcome the problems of inconsistency and/or insufficiency of the defined rules [9]. This is due to the fact that, on one hand, dependencies between educational characteristics of learning resources and learner cognitive characteristics and preferences are rather complex [40], [41], and on the other hand, it is difficult for an Instructional Designer to know the details of each User Model in use and the corresponding meaningful pedagogical adaptations required [40], since there exist several different models for each learner cognitive characteristic [42]. For example, only in the case that learning styles are used as the main adaptation parameter, there exist more than seventy different models in use [43].

The main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made due to insufficiency and/or inconsistency of the defined adaptation rule sets. To this end, in the literature, an alternative approach has been proposed that uses adaptation patterns [44], [45], [46] (or templates) that have been a priori defined by an Instructional Designer during the design phase of the AEHS. These patterns contain both the content selection and the sequencing rules of the Adaptation Model. Typical examples of these systems are MOT [37], [38] and ACCT [32], [33].

Although this approach provides a solution to the inconsistency problem, it does not tackle with the problem of insufficiency, since that would require a huge set of patterns, which is difficult to be a priori defined. The problem of defining adaptation rules is a combinatorial problem, which means that in order to design sufficient and consistent adaptation rule sets, all the combinations of the adaptation decision variables should be covered. However, these combinations can be millions [41], leading to huge rule sets that is difficult to author, manage and verify their sufficiency and/or consistency.

The main hypothesis of this thesis is that it is feasible to construct a semi-automated, decision-based approach, which generates a continuous decision function that estimates the desired AEHS response, aiming to overcome the problems of insufficiency and inconsistency in the AM of an AEHS.

1.2. Contribution to State of the Art

1.2.1. Adaptive Content Selection

The main objective of the research effort in this direction was to create a decision model that mimics the way an instructional designer selects the suitable teaching material from a Learning Object Repository, for a specific learner whose characteristics (User Profile) are known. The implementation of such a model replaces the content selection rules of the Adaptation Model of typical AEHS.

To achieve this, we proposed a decision model which estimates the suitability of a learning object for a learner assuming that we know the characteristics of the learner. The result is a function, called suitability function, which relates the characteristics of a learning object (which are reflected in the Educational Resource Description Model) with the characteristics of a learner (which are reflected in the Learner Model) and vice versa.

The results of this research activity have been published in the following scientific journals, books and international conferences:

1. P. Karampiperis and D. Sampson, "Adaptive Learning Object Selection in Intelligent Learning Systems", Journal of *Interactive Learning Research*, Special Issue on *Computational Intelligence in Web-Based Education* (ISSN 1093-023X), vol. 15(4), pp. 389-409, AACE Press, November 2004, [*11 Citations*].

2. P. Karampiperis and D. Sampson, "Adaptive Hypermedia Authoring: From Adaptive Navigation to Adaptive Learning Support", in Proc. of the *3rd*

International Conference on Adaptive Hypermedia and Adaptive Web-based Systems, vol. 2, pp. 449-454, Eindhoven, Netherlands, TU/e Pub., August 2004, [*1 Citation*].

3. P. Karampiperis and D. Sampson, "Knowledge Modelling for Adaptive Content Selection in Educational Hypermedia Systems", in Proc. of the *IASTED Conference on Web Based Education* (WBE 2004), ISBN: 0889864063, pp. 408-413, Innsbruck, Austria, ACTA Press, February 2004, [*1 Citation*].

4. P. Karampiperis and D. Sampson, "Adaptive Learning Objects Selection in Intelligent Learning Systems", in Proc. of the *4th Hellenic Conference with International Participation on ICT in Education*, ISBN: 9608835925, vol. 1, pp. 719-728, Athens, Greece, New Technologies Pub., September 2004, [*1 Citation*].

The next step of the research effort was to reduce the requirements of the proposed model for adaptive content selection in respect to the required design effort, by studying the dynamic evolution capacity of the model.

To this end, we investigated how the use of predictive models for learner characteristics could be used to improve the content selection success without increasing the required design effort. More precisely, we used the Cognitive Trait Model (CTM) [21], which estimates learner's cognitive characteristics and proposes specific values for the elements "of the Educational Resource Description Model.

The use of the CTM was aimed at both reducing the dimensions of the optimisation problem in hand and at providing feedback to the content selection model in order to evolutionary improve its effectiveness. The conducted experiments verify this hypothesis.

The results of this research activity have been published in the following scientific journal:

5. P. Karampiperis, T. Lin, D. Sampson and Kinshuk, "Adaptive Cognitive-based Selection of Learning Objects", International Journal on Innovations in

Education and Teaching International (ISSN 1470-3300), vol. 43 (2), pp. 121-135, Taylor & Francis, May 2006, [3 Citations].

1.2.2. Adaptive Content Sequencing

The main objective of the research effort in this direction was the development of a decision model for adaptive content sequencing, avoiding the use of adaptation rules. More precisely, we extended the decision model for adaptive content selection, so as to produce sequencing adaptation decision using information stored in the Educational Resource Description Model, the Learner Model and the Concept Domain Model.

In the proposed sequencing method, we replace the content selection rules defined in the Adaptation Model with a decision-making function that estimates the suitability of a learning resource for a specific learner by relating the educational characteristics of learning resources defined in the educational resource description model with the learner's cognitive characteristics and preferences stored in the Learner Model. This suitability function is used for weighting each connection of the Learning Paths Graph, a graph containing all possible learning paths based on the relation between the Learning Goals Hierarchy, the concepts of the Domain Concept Ontology and the learning resources contained in the Media Space.

From the weighted graph, we then select the most appropriate learning path for a specific learner (personalized learning path) by using a shortest path algorithm.

The results of this research activity have been published in the following scientific journals, books and international conferences:

6. P. Karampiperis and D. Sampson, "Automatic Learning Object Selection and Sequencing in Web-Based Intelligent Learning Systems", in Zongmin Ma (Ed.), Web-Based Intelligent e-Learning Systems: Technologies and Applications (ISBN 1-59140-729-3), Chapter III, pp. 56-71, Information Science Publishing, December 2005, [11 Citations].

7. P. Karampiperis and D. Sampson, "Adaptive Learning Resources Sequencing in Educational Hypermedia Systems", *Educational Technology & Society Journal* (ISSN 1436-4522), vol. 8(4), pp. 128-147, October 2005, [*65 Citations*].

8. P. Karampiperis and D. Sampson, "Adaptive Learning Objects Sequencing for Competence-Based Learning", in Proc. of the *6th IEEE International Conference on Advanced Learning Technologies* (ICALT 2006), ISBN: 0769526322, pp. 136-138, Kerkrade, The Netherlands, IEEE Computer Society, July 2006, [*7 Citations*].

9. P. Karampiperis and D. Sampson, "Adaptive Instructional Planning Using Ontologies", in Proc. of the *4th IEEE International Conference on Advanced Learning Technologies* (ICALT 04), ISBN: 0769521819, pp. 126-130, Joensuu, Finland, (*BEST PAPER AWARD*), IEEE Computer Society, August 2004, [*37 Citations*].

10. P. Karampiperis and D. Sampson, "Using Ontologies for Adaptive Navigation Support in Educational Hypermedia Systems", in Proc. of the *3rd International Conference on Adaptive Hypermedia and Adaptive Web-based Systems* in *International Workshop on Applications of Semantic Web technologies for E-Learning* (SW-EL 04), vol. 2, pp. 314-323, Eindhoven, Netherlands, TU/e Pub., August 2004, [*2 Citations*].

1.2.3. Evaluation Framework for Decision-based Approaches

The main objective of the research effort in this direction was to design a framework for assessing the performance of decision-based adaptive content selection and sequencing approaches.

This evaluation framework was applied in the case of our proposed approach for adaptive content selection and sequencing. The goal the evaluation in our case was twofold: first, to examine whether the proposed semi-automated decision based approach is capable of extracting decision models which replicate the Adaptation Model (AM) of existing AEHS; and second, to verify that our proposed approach is robust and can be applied in cases where large-scale adaptation rule sets are needed to describe the desired AEHS response.

The results of this research activity have been published in the following scientific books and international conferences:

11. D. Sampson and P. Karampiperis, "Decision Models in the Design of Adaptive Educational Hypermedia Systems", in Sabine Graf, Fuhua Lin,

Kinshuk and Rory McGreal (Eds), Intelligent and Adaptive Learning Systems: Technology Enhanced Support for Learners and Teachers, IGI Global, 2011

12. P. Karampiperis and D. Sampson, "Evaluating the Performance of Adaptive Learning Objects Selection and Sequencing in Adaptive Educational Hypermedia Systems", in Proc. of the 9th IEEE International Conference on Advanced Learning Technologies (ICALT 2009), ISBN: 978-0-7695-3711-5, pp. 316-318, Riga, Latvia, IEEE Computer Society, July 2009.

Moreover, the results of this research activity have been submitted to the following scientific books and international conferences.

13. P. Karampiperis and D. Sampson, "Performance Evaluation of Decision-based Content Selection and Sequencing Approaches in Adaptive Educational Hypermedia Systems", in A. P. Ayala (Ed.), Intelligent and Adaptive Educational-Learning Systems: Achievements and Trends, Springer, (submitted for publication), January 2011

14. P. Karampiperis and D. Sampson, "Performance Evaluation of Adaptive Content Selection in AEHS", in Proc. of the 4th International Conference on Intelligent Interactive Multimedia Systems and Services (KES-IIMSS 2011), Piraeus, Greece, July 2011, (submitted for publication).

1.3. Thesis Overview

This dissertation consists of seven chapters.

In Chapter 1 we outlined the main research questions and hypotheses.

In Chapter 2, we discuss issues related with the Adaptation Model design in AEHS focusing on the different approaches used in the literature for the definition of content selection and sequencing rules. Then, we discuss the different techniques used in decision-based approaches for adaptive educational hypermedia sequencing. Finally, we discuss the evaluation approaches used for measuring the performance in the design of the Adaptation Model of AEHS, focusing on semi-automatic decision-based approaches.

In Chapter 3, we discuss how the structural components of the generalized AEHS architecture fit to the architectural approach used in LT conformant learning platforms.

Then, we review the Learning Technology standards and specifications which can be used for facilitating the sharing of learner information and educational content in AEHS.

In Chapter 4, we present our proposed semi-automated decision based approach. The proposed methodology is based on an intelligent mechanism that attempts to construct a suitability function that maps learning object characteristics over learner characteristics and vice versa.

In Chapter 5, we present the evaluation methodology that will be used to verify our main hypothesis: that it is feasible to construct a semi-automated, decision-based approach, which generates a continuous decision function that estimates the desired AEHS response, aiming to overcome the problems of insufficiency and inconsistency in the AM of an AEHS.

In Chapter 6, we present the executed experiments for verifying our main hypothesis. These experiments follow the evaluation methodology presented in Chapter 5. The goal of this evaluation is twofold: first, to examine whether the proposed semi-automated decision based approach is capable of extracting decision models which replicate the Adaptation Model (AM) of existing AEHS; and second, to verify that our proposed approach is robust and can be applied in cases where large-scale adaptation rule sets are needed to describe the desired AEHS response.

Finally, in Chapter 7 we give a summary of the main results and indicate some directions for future research.

Chapter 2. State of The Art-Adaptive Educational Hypermedia

2.1. Introduction

In this chapter, we review the design approaches for the definition of the AM in AEHS and discuss a set of performance evaluation metrics proposed by the literature for validating the use of decision-based approaches.

The chapter is structured as follows: First, we discuss issues related with the Adaptation Model design in AEHS focusing on the different approaches used in the literature for the definition of content selection and sequencing rules. Then, we discuss the different techniques used in decision-based approaches for adaptive educational hypermedia sequencing. Finally, we discuss the evaluation approaches used for measuring the performance in the design of the Adaptation Model of AEHS, focusing on semi-automatic decision-based approaches, and discuss the conclusions that can be offered.

2.2. Definition of AEHS

Henze and Nejdl [6] provided a logical definition of AEHS introducing a quadruple (KS, UM, OBS, AM) with the following notation:

- the Knowledge Space (KS), that contains two sub-spaces. The first one, referred to as, the *Media Space* contains educational resources and associated descriptive information (e.g. metadata attributes, usage attributes etc.) and the second, referred to as, the *Domain Model* contains graphs that describe the structure of the domain knowledge in-hand and the associated learning goals.
- the User Model (UM), that describes information and data about an individual learner, such as knowledge status, learning style preferences, etc. The User Model contains two distinct sub-models, one for representing the learner's state of knowledge, and another one for representing learner's cognitive characteristics and learning preferences (such as learning style, working memory capacity etc.). This distinction is made due to the fact that the first model (*Learner Knowledge Space*) can be frequently updated based on the interactions of the learner with the AEHS. On the other hand, learner's cognitive characteristics and learning preferences are more static, having the same property values during a significant time period.

- the Observations (OBS) which are the result of monitoring learner's interactions with the AEHS at runtime. Typical examples of such observations are: whether a user has visited a resource, the amount of time spent interacting with a given resource, etc. Observations related with learner's behavior are used for updating the User Model.
- the Adaptation Model (AM), that contains the rules for describing the runtime behaviour of the AEHS. Typically, these rules include *Concept Selection Rules* which are used for selecting appropriate concepts from the Domain Model to be covered, *Content Selection Rules* which are used for selecting appropriate resources from the Media Space, as well as, *Sequencing Rules* which are used for generating appropriate learning paths (sequences of learning objects) for a given learner.

2.3. Adaptive Hypermedia Architectures

Several architectural approaches have been proposed by the literature aiming to model Adaptive Hypermedia. In this section, we review the main approaches proposed and conclude with a generalized architecture that is used by the current state-of-the-art AEHS.

2.3.1. Adaptive Hypermedia Application Model (AHAM)

The Adaptive Hypermedia Application Model (AHAM)[48], [49] builds upon the DEXTER model[50], that is, a common model for hypertext-based systems that was designed for general purpose adaptive web applications. The AHAM model refines the DEXTER model so as to be used for educational purposes.

DEXTER separates the components of a hypertext system into three major layers; the "Within Component Layer" which stores the contents of the domain, the "Storage Layer" which contains the structure (nodes and links) between objects in the component layer, and the "Runtime Layer" which presents the hypertext information to the user. The DEXTER model also includes an "Anchoring Layer" to allow addressing of individual chunks of data within the component layer, and a "Presentation Specification Layer" which provides the runtime layer with information on how to present specific hypertext components.

The AHAM extension to DEXTER allows it to support adaptive hypermedia applications by separating the storage layer into a Domain Model, a User Model and an Adaptation Model, as depicted in Figure 2.1.

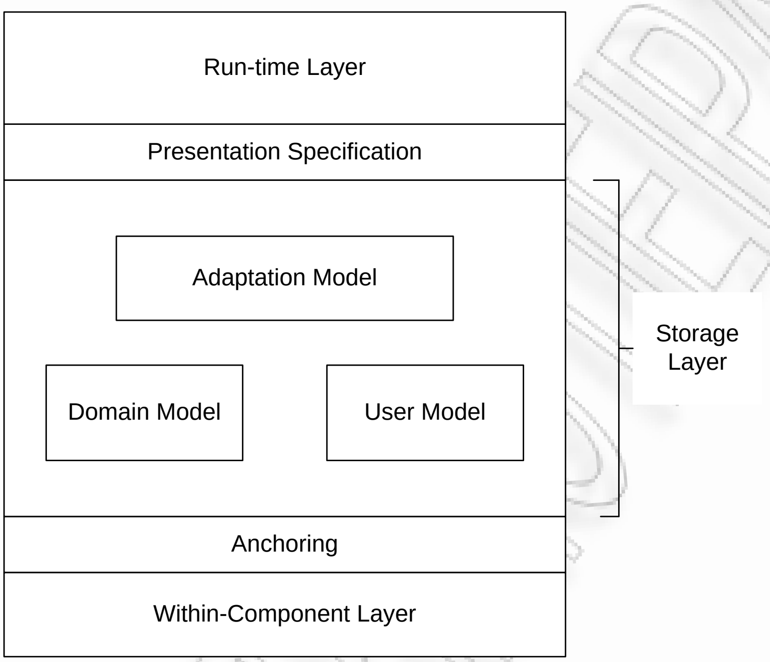

Figure 2.1: Adaptive Hypermedia Application Model (AHAM)

2.3.1.1. AHAM Hypermedia Structures

AHAM's domain model uses concept components to represent the abstract representation of an information item in an adaptive hypermedia domain. The structure of a concept is broken down into a set of attribute-value pairs, a sequence of anchors and a presentation specification.

To form a hypermedia space, concepts are arranged in a directed acyclic graph. Atomic concept components represent a single fragment of information and their anchors reference the physical information, while composite components use a "children" attribute to specify a sequence of smaller composite components or atomic concepts.

As in the Dexter model, the raw data (educational content) is stored in the within-component layer and all concept anchors reference the data in this layer. Presentation specifications determine how the particular data is to be displayed/ rendered.

2.3.1.2. AHAM Metadata

AHAM's metadata, in the form of attribute-value pairs can be associated with both atomic concepts and higher-level composite components. At the hypermedia structure level, these storage units provide a means for describing the relationship types between concepts. AHAM also specifies a user model, overlaid on top of the domain model, to determine factors and actions that affect the user. The user model is also a set of attribute-value pairs that can be used to represent user-specific metadata such as learner cognitive characteristics and preferences.

2.3.1.3. AHAM Adaptation Engine

To combine the hypermedia structure and metadata (or in AHAM terminology, the domain and user model) AHAM uses an adaptation model which contains a set of adaptation rules, and an interpreter (or engine) to process these rules.

Adaptation rules, written by a system designer, are stated in the form of event-condition-action clauses which provide the required mechanism to initialize the user model, update the user model and generate instances of adapted information.

2.3.2. Fundamental Open Hypermedia Model (FOHM)

Work at the University of Southampton, has concentrated on analyzing the fundamental components and structures of hypermedia systems. This work was part of the larger open hypermedia community which have developed formal models for representing the structure and associations that exist within the underlying components of hypermedia systems. To this end, a hypermedia model was developed, namely, the Fundamental Open Hypermedia Model (FOHM) [51].

FOHM was largely based on the prior work of the Open Hypermedia Protocol (OHP) [52] which was designed to provide a reference model and architecture for Open Hypermedia systems. OHP placed an emphasis on the different structures belonging to hypermedia domains and raised the issue of how context might affect such structures.

FOHM extended these ideas by developing a generalized model to represent the structure of these domains, and provided the facility to attach context and behavior information to the original OHP model.

While FOHM provides a theoretical hypermedia structure model, an engine, Auld Linky [53], is required to instantiate and process the model. Auld Linky stores a database of FOHM objects (in XML format) and responds to queries from client applications.

2.3.2.1. FOHM Hypermedia Structures

The primary structures in FOHM are the data item and the association. Following earlier hypertext models, data items are attached to associations using a process of reference, as depicted in Figure 2.2.

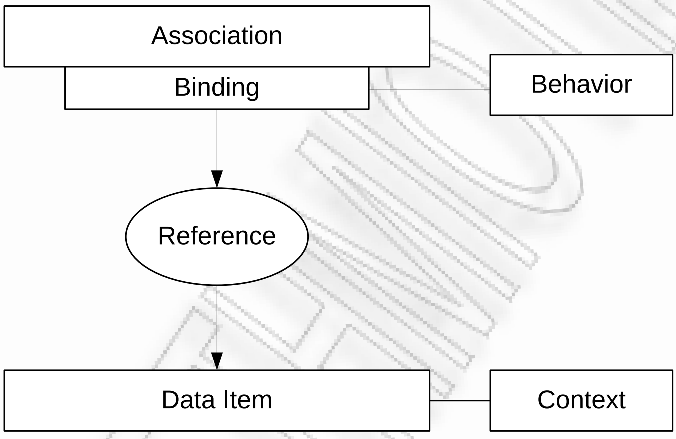

Figure 2.2: FOHM Object Structure

Data objects are components that encapsulate a piece of information. Associations are links that relate together data objects and other associations. By combining these structures together, FOHM can support complex hypermedia spaces. During FOHM's development, several common arrangements of FOHM objects have been identified.

“Tours” provide a sequential path across a set of objects, “Level's of Detail” are tours linking together increasingly detailed information and “Concepts” are associations that relate the same conceptual information using different presentation styles (i.e. handling different media representation of the same data).

2.3.2.2. FOHM Metadata

To enhance the modeling capacity of FOHM, two additional objects, context and behavior can be used as metadata/ annotation components. They are implemented using attribute-value pairs (in a similar manner to the attribute-value meta-data in AHAM).

Context objects provide a means of limiting, or scoping, the current "view" of the FOHM model. With this technique, a context object is attached to a FOHM query and it acts as a modifier, restricting the set of available FOHM objects that can be provided to the subset which have valid matching contexts.

In adaptive educational hypermedia, context objects are used to represent restrictions on user views of a domain, such as for representing the current level of user understanding in a given subject.

Behavior objects provide an event driven mechanism for specifying a set of actions. For example, a behavior object can be attached to the 'on traversal' event of an association (such as a standard hyperlink) to specify the changes to the state of the system after the user has activated the link.

In adaptive educational hypermedia, behavior objects are used to as a means of updating user models with new information based on the actions taken by the user.

2.3.2.3. FOHM Adaptation Engine

The engine component of FOHM is realized by Auld Linky. Auld Linky manages a hypermedia domain model marked up in XML as FOHM objects. When a client sends a personalization request to Auld Linky (in the form of a FOHM association query), Auld Linky analyses the domain model to find parts that match the query pattern and provides a personalized (adapted) view of the FOHM domain.

2.3.3. AEHS Generalized Architecture

The above presentation of AH models shows that although they follow different modeling approaches, they aim to address the same structural concerns, namely:

- the formulation of hypermedia spaces,
- the use of metadata to provide semantics for these spaces,
- the development of adaptation mechanisms to associate hypermedia structures with metadata.

However, there are some noticeable differences between these two models. FOHM, although it is flexible in structuring hypermedia objects, models only the adaptation mechanism. Moreover, this adaptation mechanism is directly defined over and associated with the content objects, which makes its application in adaptive educational hypermedia difficult. In AEHS, adaptation rules describe the runtime behaviour of the system representing the underlying pedagogical approach used by the AEHS. When these adaptation rules are distributed and defined explicitly over content objects, it is difficult for an Instructional Designer to author the required rule sets.

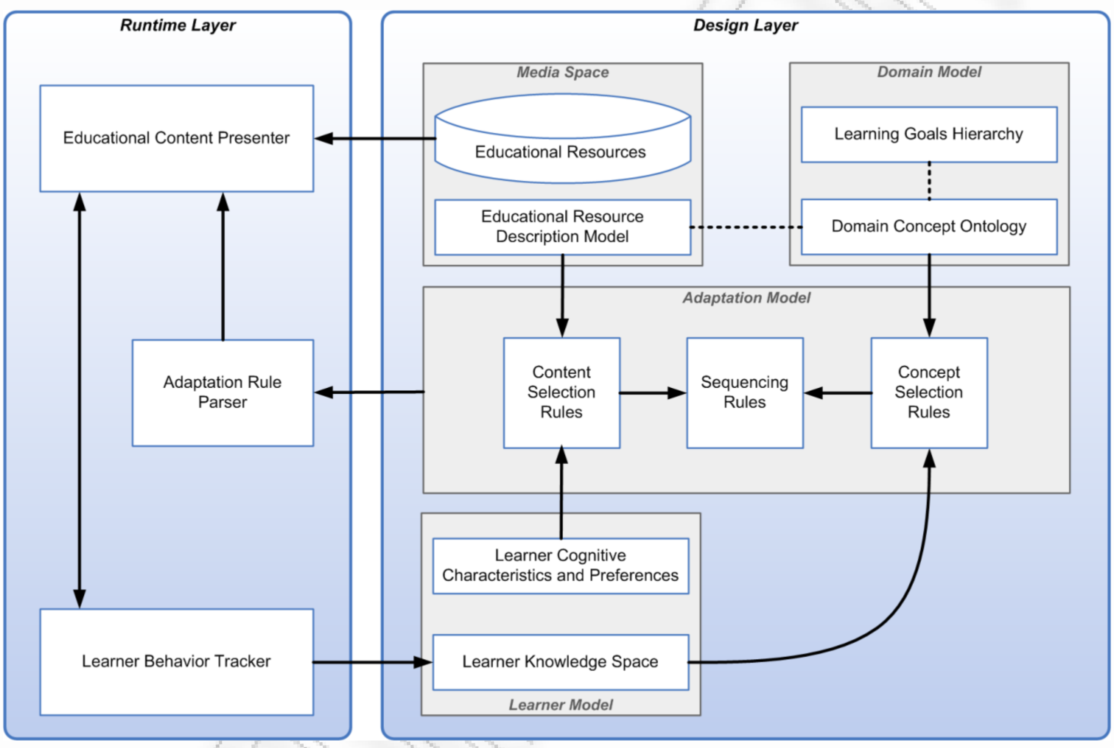

Figure 2.3: Generalized Architecture of Adaptive Educational Hypermedia Systems

On the other hand, AHAM cannot handle dynamically generated models or metadata at run time. AHAM has been designed to operate on predefined data models. This restriction was imposed to secure full knowledge of the adaptation rules at design time, and therefore, guarantee that all rules terminate, or at least identify those that do not. However this, limits the ability of any AHAM-based system to create annotations on hypermedia objects by users at runtime and then offer personalization services based on these metadata [54].

Current state-of-the-art adaptive educational hypermedia systems such as AHA [30], OntoAIMS [55], The Personal Reader [56], WINDS [57], ACCT [32], [33] follow an architectural approach that fully implements the core structural elements defined by Henze and Nejdl [6] in their AEHS definition [58].

This architecture is a variation of the AHAM model and consists of two main layers, namely, the *run-time layer* which contains the adaptation engine that performs the actual adaptation and the *design layer,* which stores information about the Media Space, the Domain Model, the User Model and the Adaptation Model. Figure 2.3 presents the generalized architecture of current state-of-the-art AEHS, illustrating the main components of this architecture and their interconnections. The dashed lines in this figure represent a logical connection between the linked models.

2.4. Design process of AEHS

According to the above mentioned generalized architecture the design process of an AEHS involves four key steps [4]:

- *Designing the Domain Model,* that is, the process of designing a hierarchy of learning goals, as well as, a concept hierarchy (Domain Concept Ontology) for describing the subject domain concepts. Depending on the domain, the application area, and the choice of the designer, concepts can represent bigger or smaller pieces of domain knowledge. The use of ontologies can significantly simplify the task of knowledge structuring by providing a standard-based way for knowledge representation [59]. Ontologies are specifications of the conceptualization and corresponding vocabulary used to describe a domain [60]. Ontologies typically consist of definitions of concepts relevant for the domain, their relations, and axioms about these concepts and relationships. For each learning goal specified in the Learning Goals Hierarchy, a set of associated concepts in the Domain Concept Ontology need to be specified. This information is used by the AEHS to determine which concepts need to be covered for reaching a specific learning goal.
- *Designing the User Model*, that is, the process of designing the Learner Knowledge Space, as well as, designing the model for learner's cognitive characteristics and preferences. For the design of the Learner Knowledge Space, there exist two main approaches, the *overlay modeling* [61] where the learner's state of knowledge is described as a subset of the Domain Concept Ontology and the *stereotype*

modeling [62], [63] where learners are classified into stereotypes inheriting the same characteristics to all members of a certain class.

- *Designing the Media Space*, that is, the process of designing the educational resource description model. This model describes the educational characteristics of the learning resources e.g. the learning resource type, or its difficulty, as well as structural relationships between learning resources e.g. if a resource requires another resource. For each learning resource contained in the Media Space a set of related concepts from the Domain Concept Ontology need to be specified. This information is used by the AEHS to determine if a specific learning resource covers a certain concept of the subject domain.
- *Designing the Adaptation Model* that is the process [64], [65] of defining (a) the *concept selection rules* which are used for selecting appropriate concepts from the Domain Model to be covered, (b) the *content selection rules* which are used for selecting appropriate resources from the Media Space, and (c) the *sequencing rules* which are used for generating appropriate “learning paths” (that is, sequences of learning objects) for a given learner.

After designing the AEHS by following the above mentioned steps, the adaptation engine (Adaptation Rule Parser in Figure 2.3), is responsible for interpreting the adaptation rules specified in the Adaptation Model in order to generate personalized learning paths. This process is called in the literature *adaptive educational hypermedia sequencing* [66], [67], [68].

Following the previous discussion on the systematic design of AEHS, one could identify three distinct design roles, namely:

- *The Domain Expert*, that is, the person who is responsible for defining the structure of the subject domain (Domain Concept Ontology), the structure of the Learner Knowledge Space, as well as, the concept selection rules of the Adaptation Model.
- *The Instructional Designer*, that is, the person who is responsible for defining the learner cognitive characteristics and preferences of the User Model, the structure of the educational resource description model, as well as, the adaptation rules of the Adaptation Model.

- *The Content Expert*, that is, the person who develops the learning resources and structures the Media Space by describing the produced learning resources using the educational resource description model.

Table 2.1: Role Participation in the design of AEHS models

	AEHS Models							
	Domain Model		Learner Model		Educational Resource Description Model	Adaptation Model		
Design Roles	Learning Goals Hierarchy	Domain Concept Ontology	Learner Characteristics & Preferences	Learner Knowledge Space		Concept Selection Rules	Content Selection Rules	Sequencing Rules
Domain Expert	X	X		X		X		
Instructional Designer	X		X		X		X	X
Content Expert					X			

In practice, these distinct roles do not operate independently, but, they cooperate for designing some of the system's models.

As presented in Table 2.1, the Domain Expert and the Instructional Designer need to work together for the definition of the Learning Goals Hierarchy, since learning goals are strongly related to the concept selection rules. Additionally, the Instructional Designer and the Content Expert need to work together for the definition of the educational resource description model, since, on one hand, this model is used for describing each learning resource developed by the Content Expert and, on the other hand, it is strongly related to the content selection and sequencing rules defined by the Instructional Designer.

Next section presents the current state-of-the-art tools for designing AEHS that implement the above mentioned abstract design model, focusing on the methods used for the definition of the content selection and sequencing rules in the Adaptation Model.

2.5. Adaptation Model Design in AEHS

Typically, adaptive educational hypermedia sequencing is based on two main processes, namely, the *concept selection process* and the *content selection process*. In the concept selection process, a set of learning goals from the Learning Goals Hierarchy is selected by the learner e.g. the AIMS [10], or in some cases by the designer of the AEHS e.g. INSPIRE [69]. For each learning goal, related concepts from the Domain Concept Ontology are selected. In the content selection process, learning resources for each concept are selected from the Media Space based on the content selection rules. Typical AEHS examples that utilize this process are the MOT [37], [38], the ApeLS [70], and the ELM-ART [39].

Figure 2.4 presents the typical abstract layers of adaptive educational hypermedia sequencing, demonstrating the connection of the above mentioned processes.

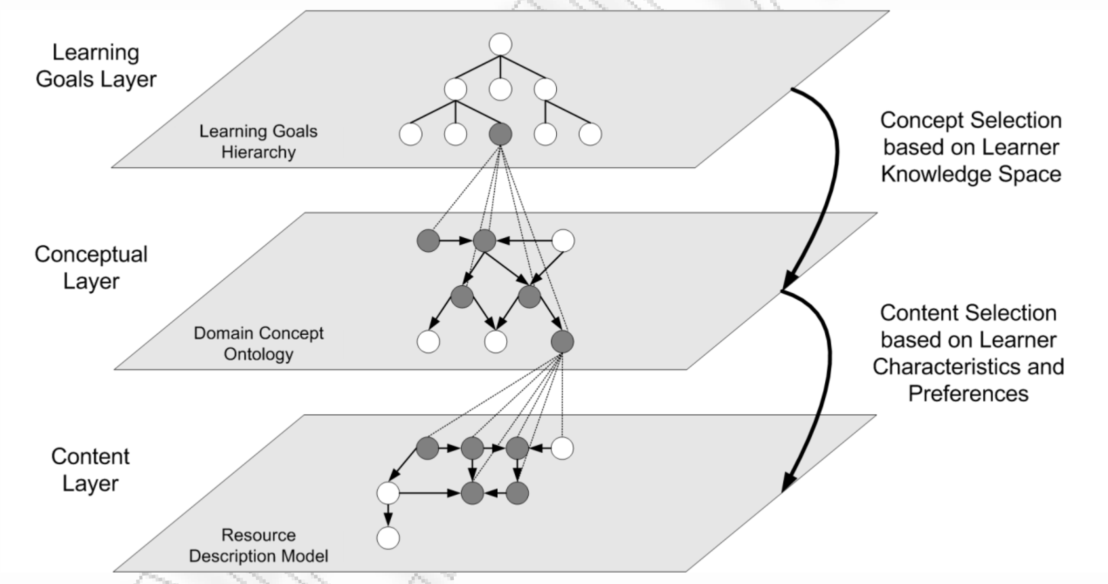

Figure 2.4: Typical Abstraction Layers of Adaptive Educational Hypermedia Sequencing

The most commonly used approach for the definition of content selection and sequencing rules by the AEHS Designers Team is the direct definition. In this approach, the content selection and sequencing rules are defined by the Instructional Designer during the design process and they are based on the elements of the User Model and the Resource Description Model, which is specified through the collaboration with the Content Expert.

To support this process, a number of design tools have been proposed in the literature. These systems require the Instructional Designer to have good knowledge of the parameters of the system that can be adapted, as well as the details of the User Model. Typical examples of these systems are the AHA [30], MOT [37], [38] and the ELM-ART [39].

Although these systems provide graphical environments for the definition of the content selection and sequencing rules and/or visual representation of the resulting learning/teaching scenario, still it is difficult for Instructional Designers to overcome the problems of inconsistency and/or insufficiency of the defined rules [9]. This is due to the fact that, on one hand, dependencies between educational characteristics of learning resources and learner cognitive characteristics and preferences are rather complex [40], [41], and on the other hand, it is difficult for an Instructional Designer to know the details of each User Model in use and the corresponding meaningful pedagogical adaptations required [40], since there exist several different models for each learner cognitive characteristic. For example, only in the case that learning styles are used as the main adaptation parameter, there exist more than seventy different models in use [43].

As already discussed, the main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made due to insufficiency and/or inconsistency of the defined adaptation rule sets. To this end, in the literature, another approach has been proposed that uses adaptation patterns [44], [45], [46] (or templates) that have been a priori defined by an Instructional Designer during the design phase of the AEHS. These patterns contain both the content selection and the sequencing rules of the Adaptation Model. Typical examples of these systems are MOT [37], [38] and ACCT [32], [33].

Although this approach provides a solution to the inconsistency problem, it does not tackle with the problem of insufficiency, since that would require a huge set of patterns, which is difficult to be a priori defined. The problem of defining adaptation rules is a combinatorial problem, which means that in order to design sufficient and consistent adaptation rule sets, all the combinations of the adaptation decision variables should be covered. However, these combinations can be millions [41], leading to huge rule sets that is difficult to author, manage and verify their sufficiency and/or consistency.

An alternative approach is the use of semi-automated decision based mechanisms [13], [17], [41], [47], which generate a continuous decision function that estimates the desired AEHS response. To achieve this, they use data from the implicit definition of sample adaptation rules and attempt to fit the response function on these data. This definition of implicit adaptation rules, is given in the form of model adaptation decisions, over which the adaptation response function should be fit. This approach overcomes both the problems of sufficiency and consistency; however it introduces decision errors that result from the decision function fitting errors during the machine learning process [41].

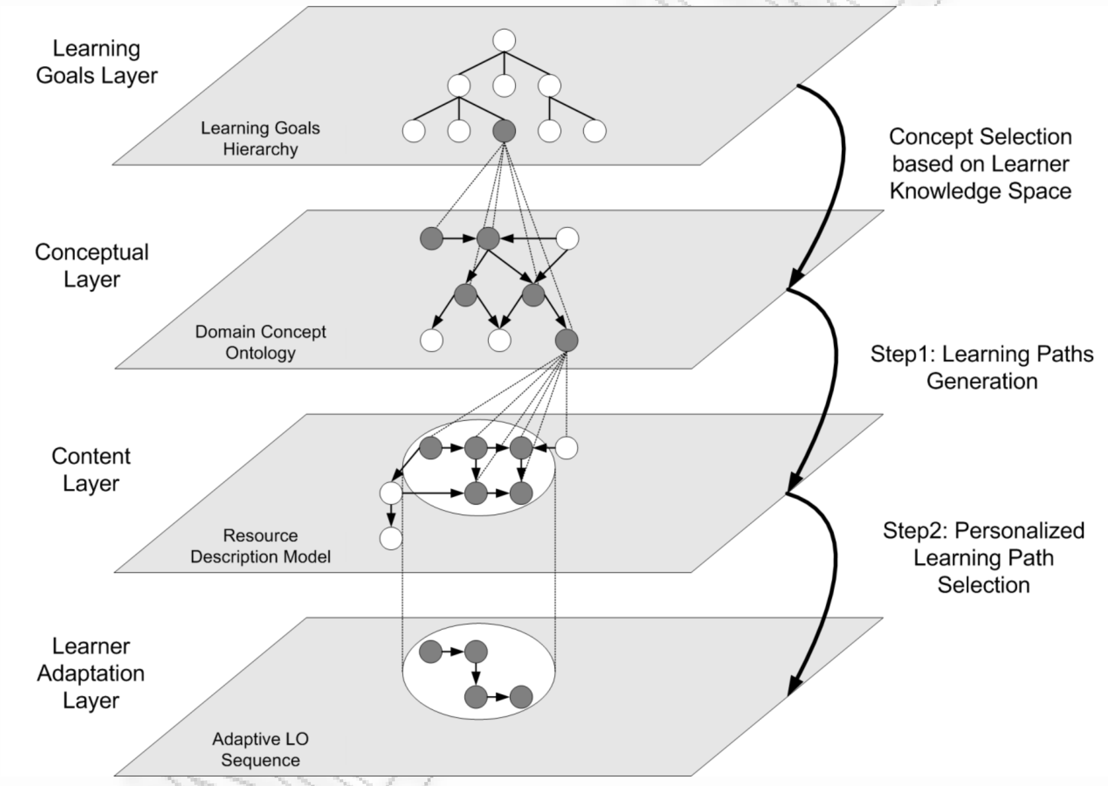

Figure 2.5: Abstraction Layers of Adaptive Educational Hypermedia Sequencing in Decision-based Approaches

Moreover, these approaches implement a variation of the above mentioned abstraction layers of adaptive educational hypermedia sequencing.

As already described AEHS that implement the direct rule definition approach use a two steps sequencing process. They first generate a sequence of concepts that matches the learning goal in hand, and then select learning recourses for each concept of the concept sequence. Due to the problems of inconsistency and insufficiency of the defined rule sets in the Adaptation Model, conceptual “holes” can be generated in the produced learning resource sequence.

To overcome this problem, decision-based approaches implement an alternative sequencing method. In this method, instead of generating the learning path by populating the concept sequence with available learning resources, first all possible sequences that match the learning goal in hand are generated and then the desired personalized learning path from the set of available paths is adaptively selected.

More precisely, the following two steps procedure is used:

- Step1: *Learning Paths Generation.* At this step a graph containing all possible learning paths based on the relation between the Learning Goals Hierarchy, the concepts of the Domain Concept Ontology and the learning resources contained in the Media Space, is generated. This graph is constructed as follows:

  Step1a: *Construction of the Concepts Path Graph.* The Concepts Path Graph (CPF) is a directed graph which represents the structure of the concepts of the Domain Concept Ontology that matches the learning goal in hand. The concepts contained in the CPF are selected based on the connection between the Learning Goals Hierarchy and the Domain Concept Ontology. The structure of the CPF is directly inherited by the structure of the Domain Concept Ontology. CPF is a simple directed graph, that is, a directed graph having no multiple nodes. This means that each concept is contained only once in the CPF. Additionally, CPF is an acyclic directed graph, that is, a directed graph containing no directed cycles. This means that in every possible concept sequence represented by the CPF, each concept has a unique existence.

  Step1b: *Construction of the Learning Paths Graph.* The Learning Paths Graph (LPG) is a directed graph which represents all possible learning paths (sequence of learning resources) that matches the learning goal in hand. To construct the LPG, for each concept of the CPF related learning resources are selected from the Media Space based on the connection between the Domain Concept Ontology and the Resource Description Model. Each node in the CPF is then replaced by the related set of learning resources retrieved from the Media Space. The structure of the learning resources set is directly inherited by the structure of the Media Space. The final graph is the Learning Paths Graph. Assuming that the Media Space does not contain circular references between learning resources, the LPG is again a simple acyclic directed graph. Although this assumption does not affect either the design of an AEHS, nor the sequencing methodology used in decision-based approaches, it is necessary for avoiding infinite learning paths.

- Step2: *Personalized Learning Path Selection.* At this step a personalized learning path is selected from the graph that contains all the available learning paths based on learner's attributes in the User Model. As a result, an additional layer (Figure 2.5) in the typical abstraction layers of adaptive educational hypermedia sequencing is introduced, namely the *Learner Adaptation Layer*. This additional layer is used for selecting the personalized learning path.

In decision-based adaptive content sequencing several approaches have been proposed by the literature. Their main difference is the approach used to select personalized learning paths in the Learner Adaptation Layer (step 2 of the abstraction layers of adaptive educational hypermedia sequencing). The most commonly used learning path selection techniques are the following:

– *Utility-based Learning Path Selection.* In this technique [17], [41] the Learning Paths Graph (step 1 of the abstraction layers of adaptive educational hypermedia sequencing) is weighted [71], [72] using a function which estimates the suitability/utility of each learning object contained in the graph for the targeted learner. Then, they apply a path discovery algorithm (typically a shortest path algorithm) in order to discover the sequence of learning objects contained in the weighted graph which maximises the overall utility, and thus, best matches the targeted learner. This technique is often called in the literature *preference-based sequencing based on weighted graphs*.

– *Similarity-based Learning Path Selection.* This technique uses a set of predefined sequences, typically modelled as a Petri-Net [73], associated with descriptions of the suitable targeted learner/s for each one of them [74]. The aim of the adaptive sequencing is to first identify the closest model sequence by measuring the similarity of the profile of the targeted learner with the learner profiles associated with each model sequence class, and then select the personalized learning path from the Learning Paths Graph which matches the model sequence, using either fuzzy rules directly defined by the instructional designer [74] or genetic algorithms [47], [75], [76].

2.5.1. Examples of decision-based AEHS

2.5.1.1. Utility-based Systems

2.5.1.1.1. PAIGOS

PAIGOS [77], [78], uses the Hierarchical Task Network planning [79] as a means to generate the available learning paths. In HTN-planning, the goal of the planner is to achieve a list of tasks, where each task is a symbolic representation of an activity to be performed. The planner formulates a plan by using methods to decompose the top tasks into smaller subtasks until primitive tasks are reached that can be carried out directly using operators.

Dynamic subtask expansion stops courseware generation at a level that specifies what kind of educational resources should be selected but does not specify which ones. The specific resources are selected at the time when the learner wants to use them. This allows generating a complete table of contents of the course while using up-to-date information for the selection of individual resources.

The selection of educational resources which populate the sequences of learning tasks is accomplished using a utility-based function which evaluates which learning object should be used for the targeted learner. However, this utility function is not dynamically updated, but is pre-authored by the instructional designer.

2.5.1.1.2. Software Organization Platform (SOP)

SOP [16] is an integrated courseware generation and knowledge management platform, supporting several KM functionalities such as experience management, requirements engineering, and project management.

SOP uses a utility-based decision model so as to adapt a learning space (a set of available learning paths) to individual learners. SOP's ultimate goal is to address the problem of closed corpus of AEHS, enabling them to use learning resources from real-world repositories, rather than resources specially designed to be served via the AEHS in hand. To this end, adaptation is not coupled to a fixed set of learning resources, but to types of learning space concepts. The system adapts and personalizes the learning space to the targeted learner. SOP's adaptation mechanism depends on contextual characteristics (i.e., individual, group), as well as, learner characteristics such as learning styles.

As in PAIGOS, this utility-based decision model is not dynamically updated, but is pre-authored by the instructional designer.

2.5.1.2. Similarity-based Systems

2.5.1.2.1. Personalized eLearning System (PeLS)

PeLS [75], implements an adaptive sequencing mechanism which uses genetic algorithms as the means to select the personalized learning path for the targeted learner. Genetic algorithms use information from a pre-testing phase and adapt the resulting sequence.

PeLS uses an agent-based architecture, consisting of:

- the learning interface agent, which provides the interaction interfaces with the learner,
- the pre-test and post-test process agent, which generates random testing items related to the learning goal in hand
- the learning path generation agent, which generates a personalized learning using the data collected from the pre-test phase,
- the adaptive navigation support agent, which executes the generated learning path,
- and the courseware management agent, which provide authoring facilities for instructional designers.

2.5.1.2.2. Standardized Course Generation Process (SCGP)

SCGP [74], aims to support the entire lifecycle of automatic courseware generation, from content authoring to content delivery. Thus, SCGP consists of a content authoring tool (called MEAT), which incorporates the automatic courseware generation algorithm, and a learning management system (called ANTS), which delivers the produced courses.

The auto-generated courses are conformant with the Sharable Content Object Reference Model (SCORM), however SCGP uses a Dynamic Fuzzy Petri Net model [80] to internally represent the course structure and the available learning paths.

SCGP uses model sequences, defined as Petri Nets, and using similarity measures estimates the closest model to the ideal for the targeted learner. Then, from ANT's repository of learning objects generates the learning path which matches the selected model sequence.

Next section presents the evaluation metrics proposed in the literature for evaluating the performance of decision-based adaptive content selection and sequencing and discusses them.

2.6. Performance evaluation in decision-based approaches

In this section, we focus on the performance evaluation metrics used in semi-automated decision-based approaches for adaptive content selection and sequencing. Performance evaluation in this context means measuring (a) how well a semi-automated approach fits the decision function to the provided model adaptation decisions (training data), and (b) how well this decision function responds to decision cases not known during the training process (generalization capacity). As a result, model adaptation decisions are divided into two sets: the training dataset, which is used for evaluating the performance during the training of the semi-automated approach, and the generalization dataset, which is used for measuring the generalization capacity of the approach. Performance evaluation is the comparison result between the expected system output and the estimated AEHS response over the above mentioned datasets.

2.6.1. Adaptive Content Selection

In adaptive content selection several approaches have been proposed by the literature. The most commonly used are the following:

– *Concept/Keyword-based Selection*. In these approaches, searching is performed based on a set of keywords, typically representing the desired concepts to be covered from the retrieved learning objects. In AEHS, these keywords are defined over the Domain Concept Ontology during the concept selection process, as already discussed. In this case, the ranking of learning objects is performed using a concept/keyword-based similarity formula [81], [82], which evaluates the relevance of each learning object, by comparing the desired concepts/keywords with the classification metadata used for describing the learning object in hand.

The main assumption of this approach is that the Domain Concept Ontology and the classification metadata used for the learning objects share the same concept/keyword terms. However, this is not always true, especially in domains where there exist a variety of classification models which use different terminology for describing a concept depending on the context of use, i.e. in the Medical domain there exist many classification systems such as Medical Subject Headings (MeSH) [83], the International Classification of Primary Care (ICPC) [84] etc. targeting different end-users. An alternative approach proposed by Kiu and Lee [85], uses unsupervised data-mining techniques for estimating the match between the desired concepts/keywords with the classification metadata used for describing the learning object in hand. This approach provides better results from the use of keyword-based similarity formula when different classifications models are used, but it requires significantly more time for the content selection process [85].

– *Preference-based Selection.* In these approaches, selection is performed based on the comparison of the learner profile in hand with the metadata description of the learning objects. In this case, the ranking of learning objects is performed using a preference score [7], [15], [86], which evaluates the utility/suitability of each learning object for the learner profile in hand.

In both techniques, the concept/keyword-based and the preference-based selection, general purpose evaluation metrics are used from the field of information extraction [18]. More specifically, precision and recall measures are applied in order to evaluate the effectiveness of the learning objects selection technique, in terms of accuracy and completeness respectively. *Precision* is the ratio of correct responses to the sum of correct and incorrect responses, and is defined by the following formula [15], [82]:

$$\text{Precision} = \left(\frac{Number\ of\ retrieved\ relevant\ LOs}{Number\ of\ retrieved\ LOs} \right)$$

Recall is the number of correct system responses divided by the sum of correct, incorrect and missing system responses, and is defined by the following formula [15], [82]:

$$\text{Recall} = \left(\frac{Number\ of\ retrieved\ relevant\ LOs}{Number\ of\ all\ relevant\ LOs} \right)$$

In order to have a single evaluation metric, *F-measure* is used, which is a weighted combination of recall and precision, and is defined by the following formula [82]:

$$\text{F - measure} = \left(\frac{2 * precision * recall}{precision + recall} \right)$$

However, we claim that these metrics are not suitable in the case of AEHS. This is due to the fact that AEHS implement a content selection strategy which limits the number of retrieved learning objects, aiming to restrict the amount of information provided to learners at a given time instance, due to the problem of learners' cognitive overload [39]. As a result, the precision should be measured not on the entire Media Space, but only on the desired sub-space which represent a set of the n most preferred learning objects, where n is the number of the desired learning objects. If not, the resulting precision would be higher or equal to the real one, since the number of retrieved learning objects is less or equal to the number of desired learning objects at a given time instance.

Moreover, since the resulting LO space is restricted, the recall measure should also be measured over the space of the n most relevant learning objects, and not over the space of all relevant learning objects. This introduces the need for an alternative evaluation metric in adaptive content selection. In [86], such an evaluation metric has been proposed as follows:

$$\text{Selection Success (\%)} = 100 * \left(\frac{correct\ ranked\ Learning\ Objects\ selected}{requested\ Learning\ Objects} \right)$$

Although this metric seems similar to the precision metric in information retrieval systems, its difference is critical. It evaluates the precision of selecting learning objects not on the entire space of the Media Space, but only on the desired sub-space, and also takes into consideration the ranking of the selection process. This means that the proposed metric is harder, since it measures the precision over a smaller value space.

2.6.2. Adaptive Content Sequencing

As already discussed, the most commonly used approaches in decision-based adaptive content sequencing are Utility-based sequencing and Similarity-based sequencing.

In both techniques, performance evaluation is measured by comparing the generated sequences of learning objects with model sequences defined either directly by the instructional designer, or via the use of simulated instructional designers' preference models, for a given learner profile [17], [47], [74].

A typical metric used for this purpose is the Euclidean distance between each pair of learning objects in the two sequences under comparison [87], [88]. This distance is called similarity and is defined by the following formula:

$$Similarity = \left\| g^{LO_A} - g^{LO_B} \right\| = \sqrt{\sum_{i=1}^{n} \left(g_i^{LO_A} - g_i^{LO_B} \right)^2},$$

where, LO_A and LO_B are the learning objects under comparison which belong respectively to the generated sequence and the model one, and n is the number of independent properties $g^{LO} = (g_1^{LO}, g_2^{LO}, \ldots, g_n^{LO})$ used in the Educational Resource Description Model for describing the educational resources of the Media Space (see also Figure 1).

However, this metric is not always accurate, since the Euclidean distance is calculated over the space defined by the learning object metadata (Educational Resource Description Model), and not over the instructional designer's preference space.

To clarify this, assume for example, that we have two learning object sequences produced by an AEHS, and that these sequences only differ in one of the learning objects included in them. In this case, the optimum sequence between these two would be defined by calculating the similarity of the learning objects which differ in these sequences, with the corresponding learning object of the model sequence.

Assume again, that the only difference of these learning objects in their corresponding metadata records is that the first one has difficulty equal to "1" and that the other one has difficulty equal to "3", whereas the learning object in the model sequence has difficulty equal to "2". In this case, the produced sequences will be equally similar to the model sequence, since their Euclidean distance from the model sequence is the same.

However, it is obvious that the first sequence will be easier and that the second one more difficult than the model one. For an instructional designer this difference may be critical, depending on the learner's knowledge level. This means that evaluating the sequencing performance only based on the metadata of the Resource Description Model without taking into consideration the instructional designer's preferences does not produce accurate results.

This introduces the need for an alternative evaluation metric in adaptive content sequencing, which measures the sequencing performance over the instructional designer's preference space. To achieve this, an evaluation metric, based on Kendall's Tau [89], which measures the match between two learning object sequences has been proposed [18], [41], as follows:

$$\text{Sequencing Success (\%)} = 100 * \left(\frac{1}{2} + \frac{N_{concordant} - N_{discordant}}{n(n-1)} \right),$$

where $N_{concordant}$ stands for the concordant pairs of learning objects and $N_{discordant}$ stands for the discordant pairs when comparing the generated learning objects sequence with a model one, and n is the number of learning objects in each sequence under comparison.

This metric is derived from Kendall's Tau, with scaling in the value space [0, 100], in such as way that two exactly similar sequences have 100% similarity measure and two completely disordered sequences have 0% similarity.

The Euclidean distance metric presented above, compares the learning object metadata of the generated sequences with the metadata of model sequences, whereas, the proposed metric compares the ordering of the learning objects in the generated sequences with those in the model sequences. This means that this measure is evaluated over the instructional designer's preference space rather than the metadata of the Resource Description Model.

2.7. Conclusion

Adaptive learning objects selection and sequencing is recognized as challenging research issues in AEHS. In order to adaptively select and sequence learning objects in AEHS, the definition of adaptation behaviour, referred to as Adaptation Model, is required.

Several efforts have been reported in literature aiming to support the Adaptation Model design by providing AEHS designers with either guidance for the direct definition of adaptation rules, or semi-automated mechanisms which generate the AM via the implicit definition of such rules.

The main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made. This is due to the fact that, even if appropriate resources exist in the Media Space, the absence of a required rule (insufficiency problem) or the conflict between two or more rules (inconsistency problem), prevents the AEHS to select and use them in the generated learning resource sequence. As a result, either less appropriate resources are used from the Media Space, or required concepts are not covered at all by the resulting sequence

The goal of the semi-automated, decision-based approaches is to generate a continuous decision function that estimates the desired AEHS response, aiming to overcome the above mentioned problem. To achieve this, semi-automated approaches use data from the implicit definition of sample adaptation rules and attempt to fit the response function on these data.

In this chapter, we reviewed the design approaches for the definition of the Adaptation Model in AEHS and discussed a set of performance evaluation metrics for validating the use of decision-based approaches.

Chapter 3. Integrating Learning Technologies in AEHS

3.1. Introduction

Currently, there are many educational content repositories which are intended to collect, share and reuse the dispersed learning resources and present the end-user a uniform interface to search, access and evaluate the resources, including the ARIADNE Knowledge Pool System (http://www.ariadne-eu.org/en/system), the Campus Alberta Repository of Educational Objects (CAREO) (http://www.careo.org), the U.S.-based Science, Mathematics, Engineering and Technology Education Digital Library (http://www.smete.org), the Educational Network Australia (http://www.edna.edu.au), the Gateway to Educational Materials (GEM) digital library (http://www.geminfo.org), the Scottish electronic Staff Development Library (SeSDL) (www.sesdl.scotcit.ac.uk), the LearnAlberta Portal (www.learnalberta.ca), the COLIS (www.edna.edu.au/go/browse/0), the Multimedia Educational Resource for Learning and Online Teaching (MERLOT) (www.merlot.org), the Universal Brokerage Platform for Learning Resources (www.educanext.org), the World Lecture Hall (www.utexas.edu/world/lecture/), the Globewide Network Academy (www.gnacademy.org), the McGraw-Hill Learning Network (MHLN) (www.mhln.com) and others. Most of them offer high quality resources in the form of learning objects [90] that are also metadata tagged [91].

Nevertheless, although the available content repositories offer high quality learning objects, and moreover, those objects are tagged using a common metadata schema (that is, the IEEE Learning Objects Metadata standard [19]), still reusing learning content among different AEHS remains an open issue [92].

Although, a wide variety of AEHS have been proposed in the literature such as AHA [30], OntoAIMS [55], The Personal Reader [56], WINDS [57], ACCT [32], [33], and PAIGOS [77], these systems are closed, self-contained systems that cannot be used as service components (*lack of reuse support*) [93], [94]. Additionally, due to their close architecture they face difficulties in supporting the variety of the required functionalities in a learning process since they cannot use external services (*lack of integration*). On the other hand, even if an open and scalable AEH environment has been implemented, the supported content has been designed to serve and support a specific pedagogical approach. As a result they are non-flexible in supporting different pedagogical approaches and they require extensive redesign effort in order to be used in different domains.

A possible solution to the above mentioned problem is the adoption of Learning Technologies (LT). Learning Technology standards and specifications are designed to facilitate the description, packaging, sequencing and delivery of educational content, learning activities and learner information [95].

The goal of LT is to facilitate interoperability between applications, providing uniform ways for representing educational content, learner information, as well as, uniform communication guidelines that can be used throughout the design, development, and delivery of learning content. Thus, enable educational content and learner information to be shared.

In this chapter, we discuss how the structural components of the generalized AEHS architecture, presented in Chapter 2, fit to the architectural approach used in LT conformant learning platforms. Then, we review the Learning Technology standards and specifications which can be used for facilitating the sharing of learner information and educational content in AEHS, and discuss the conclusions that can be offered.

3.2. Relation between AEHS Architecture and Learning Technologies

As already discussed, LT standards and specifications provide detailed guidelines for several aspects/ components of a learning system. The underlying driver for the development of these guidelines is the IEEE Learning Technology Systems Architecture (LTSA) standard [96].

This standard specifies an architecture for technology-enhanced learning systems that describes the high-level system design and the components of these systems, using a five-layer structure. The LTSA Layer 3 specifies the main components and interfaces in the architecture of learning systems. These components (shown in Figure 3.1) form a model that describes how the different entities in the learning system interact with each other.

There are three types of components defined in the LTSA Layer 3, namely:

– *Processes* (depicted as oval shapes in Figure 3.1) are the boundaries, services, inputs, and outputs of the learning system. Processes refer to users' and system components that cause changes in the state of the system.

– *Stores*. Two types of stores (represented as rectangular shapes in Figure 3.1) are described in the reference model. These relate to repositories of data that can be accessed by users using search, retrieval, and updating methods. In practice, the stores correspond to the system's database structures.

– *Flows* are described in terms of connectivity and the type of information exchanged. These are illustrated as arrowed lines between the processes and stores in Figure 3.1. Essentially, flows depict the interactions that take place between the various processes and stores of the LTSA system.

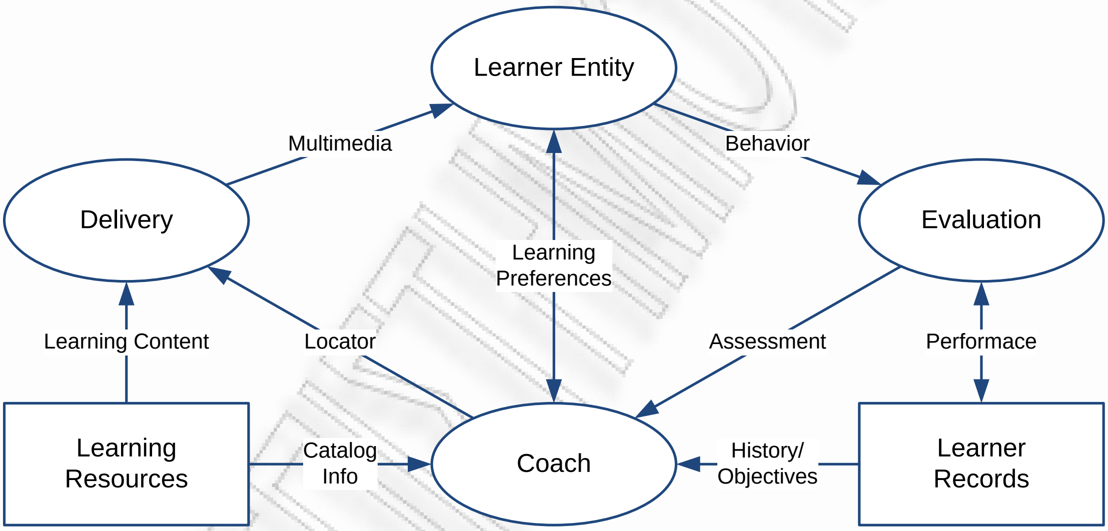

Figure 3.1: IEEE LTSA system components

In the LTSA reference architecture educational content is represented as a store called *learning resources* and the interaction of a learner with the content is represented as a flow called *multimedia*. This flow is a unidirectional flow from the delivery system to the learner. This means that interactions from the learner to the content are not supported by the reference architecture. Moreover, a process called *coach* represents an abstraction of a human teacher, or the adaptive behavior of a personalized educational system.

The interaction between the learner and the adaptive behavior of a personalized educational system is represented directly as a flow called *learning preferences* and indirectly through the process of *evaluation* and the *behavior* and *assessment* flows.

Sharable Content Object Reference Model (SCORM) [97] refines the IEEE LTSA reference architecture by specifying missing interactions. More precisely, SCORM provides a reference interaction model between a learner and learning content, and describes within a common technical framework the creation process of reusable learning content as "instructional objects", called *sharable content objects* (SCOs). SCORM describes that technical framework by providing a harmonized set of guidelines, specifications, and standards based on the work of several distinct e-learning specifications and standardization bodies. SCORM consists of three parts, namely:

– *Content Aggregation Model (CAM).* The SCORM CAM describes the content components used in a learning activity, how to package those components for exchange from system to system and how to describe those components to enable search and discovery. The CAM promotes the consistent storage, labeling, packaging, exchange and discovery of learning content. The SCORM CAM model contains information on Metadata, Content Structure and Packaging.

– *Run-Time Environment (RTE).* The purpose of the SCORM RTE is to provide a means for interoperability between SCOs and LMSs. SCORM provides the means for learning content to be interoperable across multiple learning systems regardless of the tools used to create the content. The three components of the SCORM RTE are *Launch, Application Program Interface* (API) and *Data Model.* Launch includes defining the relationship between learning systems and SCORM content such that all SCORM-conformant content is dependent upon a SCORM-conformant learning system to be delivered and displayed to the learner. The SCORM API provides a set of predefined methods for purposes of communication between a learning system and the SCOs it launches. The SCORM Run-Time Environment Data Model provides the data elements that can be used to "get" and "set" data from and to a learning system.

– *Sequencing and Navigation (SN).* The SCORM SN covers the essential learning system responsibilities for sequencing content objects during run-time and allowing SCOs to indicate navigation requests. The SCORM SN is based on the IMS Simple Sequencing (SS) Specification v1.0, which defines a method for representing the intended behavior of an authored learning activity such that any conformant learning system will be able to sequence discrete content components in a consistent way. It defines the required behaviors and functionalities that SCORM-conformant learning systems must implement to process sequencing information at runtime. More specifically, it describes the branching and flow of learning content in terms of an Activity Tree, based on the results of a learner's interactions with launched content objects and an authored sequencing strategy. The SCORM SN describes how learner-initiated and system-initiated navigation events can be triggered and processed, resulting in the identification of learning content for delivery.

Table 3.1: Relation between AEHS components and LT conformant architectures

<table>
<tr><th colspan="3"></th><th>IEEE LTSA</th><th>SCORM</th></tr>
<tr><td rowspan="9">AEHS Models</td><td rowspan="2">Domain Model</td><td>Learning Goals Hierarchy</td><td>Objectives (Flow)</td><td>-</td></tr>
<tr><td>Domain Concept Ontology</td><td>Catalog Info (Flow)</td><td>-</td></tr>
<tr><td rowspan="2">Learner Model</td><td>Learner Characteristics & Preferences</td><td>Learner Records (Store)</td><td>-</td></tr>
<tr><td>Learner Knowledge Space</td><td>Learner Records (Store)</td><td>-</td></tr>
<tr><td colspan="2">Educational Resource Description Model</td><td>Learning Resources (Store)</td><td>Content Aggregation Model</td></tr>
<tr><td rowspan="3">Adaptation Model</td><td>Concept Selection Rules</td><td>Coach (Process), Locator (Flow)</td><td>-</td></tr>
<tr><td>Content Selection Rules</td><td>Coach (Process), Locator (Flow)</td><td>-</td></tr>
<tr><td>Sequencing Rules</td><td>Coach (Process), Locator (Flow)</td><td>Sequencing and Navigation</td></tr>
</table>

Table 3.1 presents how the structural components of the generalized AEHS architecture, presented in Chapter 2, fit to the architectural approach used in LT conformant learning platforms.

From the above table, we can observe that although LTSA defines abstract representations that depend on the specific application in hand (e.g. the coach process), it can describe all the structural components of AEHS. This means that, for every aspect of AEHS relevant LT standards and/or specifications exist, that can serve as a mean to enable interoperability and reuse between models.

In this thesis, we focus on the LT standards/ specifications for modelling learner information, as well as, for describing educational content with metadata. Next sections, review these standards/ specifications.

3.3. LT standards for representing the Learner

3.3.1. Information in Learner Model

In AEHS, a Learner Model should contain information about the learner's domain knowledge prior to the use of the educational system, the learner's progress, preferences, interests, goals, and any other information related to the learner [61], [98]. Based on the dependence upon the subject domain, the information held in Learner Models could be divided into two major groups [1], [99]:

- *Domain specific information*: also named as knowledge model (KM), which represents a reflection of the learner's state and level of knowledge and skills in term of a particular subject domain.
- *Domain independent information*: may include learning goals, cognitive aptitudes, measures for motivation state, preference about the presentation method, factual and historic data, etc.

<u>Domain Specific Information</u>

The model of domain-specific information (knowledge model) represents a reflection of the learner's state and level of knowledge and skills in term of a particular subject. In relation to domain knowledge representation, learner knowledge models can be classified as follows [61]:

- *Scalar Models*. A scalar model is the simplest form of KM, and describes the level of learner's knowledge on the entire domain by means of a certain integral estimate such as a number ranging from 1 to 5.
- *Overlay Models*. If the entire domain model is made up of a set of knowledge elements or curriculum elements, the overlay model represents the learner knowledge as a subset of the domain model. A certain measure is assigned to each curriculum element based on the estimated learner's understanding on that element. The measure can be a scalar (an integer, or probability measure, or a flag such as initial, acquisition, assimilation or mastery) or a vector estimate.
- *Bug or Error Models*. Because overlay models cannot represent the errors that the learners made, the bug models or error models are developed to define and reflect the reasons of erroneous learner behaviours. The error models can be divided into perturbation models and differential models. *Perturbation models* assume one or more perturbations (misconceptions) exist for each curriculum element. The incorrect learner behaviours (errors) may be caused by the application of one of misconceptions in place of the related correct knowledge element. The learner knowledge is therefore represented by a union of a subset of the domain model and another subset of the misconception set with all misconceptions that the learner may have. *Differential models* capture misconceptions by only including the entities representing the differences between the expert knowledge and the learner's acquired knowledge.
- *Genetic Models*. Although both overlay models and error models represent the learners' knowledge states, they do not reflect the whole structure of domain knowledge. Genetic models represent the learner knowledge developing process from simple to complex and from special to general. The genetic model can be described by a genetic graph, and the nodes and the relationships between the nodes represent knowledge elements and their interactions.

Domain-specific information that may be stored in a Learner Model includes:

- Learner's *prior knowledge* about the domain

– *Records of learning behaviours* (number of lectures taken, number of helps asked, frequency of mistakes made while solving problems, reaction/answering time while solving problems, etc)

– *Records of evaluation /assessment* (qualitative and quantitative scores)

Domain Independent Information

A Learner Model also needs to cover a certain amount of domain-independent information in addition to the learner's current knowledge level. The domain-independent information about a learner may include cognitive aptitudes, measures for motivation state, preference about the presentation method, factual and historic data, etc.

– *Cognitive Aptitudes*. [21] and [100] identified a number of specific cognitive aptitudes in an overlay model besides learner's general attributes: General knowledge, Inductive reasoning skill, Working memory capacity, Procedural learning skill, Information processing speed, Associative learning skill, Reflectivity, and Risk-taking. In the overlay model the curriculum elements were classified as three types: *symbolic knowledge*, *procedural skill*, *conceptual knowledge*. The mastery of different types of curriculum elements was associated with one or more types of cognitive aptitudes.

– *Motivational States.* Motivation State is the force that drives the learner to engage in learning activities. The learner motivational state can be measured by a number of long-term and short-term parameters such as motivation, effort, attention, interest, distraction, persistence, etc. These parameters are in turn associated with other factors including knowledge level, readiness, complexity of topic, learning outcome, etc. [101] proposed a Learner Model that considered both learner motivation and knowledge states. The learner motivational state was represented in a Bayesian network.

– *Background and Experience.* Both background and experience information can be used as bases for deriving Learner Model parameters. *Background information* is about the learner previous experience that may have impact on learner learning achievement, such as profession, relevant work experience, perspectives etc.

Experience information is about how familiar the learner is with the learning environment. The learners who are quite familiar with the subject domain may be novices in using the educational systems and vice versa. This information is helpful in selecting appropriate adaptive navigation methods [102], [103].

– *Preferences.* The learners may have different preferences over a range of aspects of a learning environment. These preferences could be domain related or domain independent. Learner preferences are considered different from other information stored in Learner Models in that they cannot be deduced by the system. The learners have to inform the system directly or indirectly about those preferences. It is important for a web-based learning environment to present and organize learning content in the learner's preferred way. Individual learner preferences can also be accumulated to form group learner preferences in a group Learner Model. An important part of learner preferences is the learning style that is correlated with multiple intelligence: *Multiple Intelligence* [104] defines eight distinct intelligence forms stated as follows: Verbal/linguistic intelligence, Logical/mathematical intelligence, Visual/spatial intelligence, Musical/rhythmic intelligence, Bodily/kinaesthetic intelligence, Intra-personal intelligence, Interpersonal intelligence, and Naturalist intelligence. Gardner suggested that everyone possesses all above intelligence but in varying degrees, consequently a learner can show low ability in one domain area but high ability in another domain. Whereas, a *Learning Style* is defined as the unique collection of individual skills and preferences that affect how a learner perceives, gathers, and process learning content. Multiple Intelligence determines multiple learning styles. Just as every person has unique ways to see, hear or experience the world, every learner has different preferences for how, when, where and how often to learn knowledge.

- *Factual and Historic Data.* A Learner Model may also contain a number of factual and historic data about an individual learner such as name, age, parents, ID, past education, interests, etc. These are necessary for initializing an individual Learner Model.

3.3.2. IEEE P1484.2 (PAPI Learner)

Public and Private Information (PAPI) for Learners (PAPI Learner) is a standard effort aimed at providing the syntax and semantics of a Learner Model, including knowledge, learning styles, skills, abilities, records and personal information, all at multiple levels of granularity. This standard specifies the syntax and semantics of a "Learner Model", which characterizes a learner and his/her knowledge/abilities. This includes elements such as knowledge (from course to fine-grained), skills, abilities, learning styles, records, and personal information. The specification allows these elements to be represented in multiple levels of granularity, from a coarse overview, down to the smallest conceivable sub-element.

The working group for the Learner Model [P1848.2] has the following purposes:

- To enable learners to build lifelong personal Learner Models.
- To enable personalized instruction and effective instruction.
- To provide educational researchers with a standardized source of data.
- To provide a foundation for the development of additional educational standards, from a learner-centred learning focus.
- To provide architectural guidance to developers of learning environments.

The main architectural feature of the PAPI Learner standard is its logical division. It separates the security and the administration of several types of learner information (also called Profile Information):

- Personal information like name, address and social security number. It is not directly related to the measurement and recording of learner performance and is primarily concerned with administration. Usually this type of information is private and secure.
- Relations information, e.g., cohorts, classmates. This concerns the learner's relationship to other users of learning technology systems, such as teachers, practitioners, and other learners.
- Security information. This is concerned with the learner's security credentials, such as passwords, challenges/responses, private and public cryptographic keys, and biometrics.

– Preference information: useful and unusable I/O devices, learning styles and physical limitations. It describes preferences that may improve human-computer interactions.

– Performance information, like grades, interim reports, log books. This pertains to the learner's history, current work or future objectives and is created and used by learning technology components to supply enhanced learning experiences.

– Portfolio information: accomplishments, works and so on. This information is a representative collection of a learner's works or references to them that is intended to illustrate and justify the learner's abilities and attainments.

3.3.3. IMS Learner Information Package (LIP)

Another major standardization effort, the Learner Information Package (LIP), comes from the IMS, a consortium of institutions including government agencies, software developers, vendors, and training and education representatives. Version 1.0 of the IMS Learner Information Package Specification was released to the public in March 2001. The IMS LIP has partly been derived from the IEEE PAPI Learner.

The LIP specification provides a way of packaging learner information for exchange between disparate systems. It focuses on learner information, that is, the wide range of information that can be used by different systems to support the learner's activities. The semantics of the packages being exchanged may vary depending on the context; this is determined by the services participating in the exchange. Furthermore, learner information can be packaged from a variety of environments, not only human resources, learner information and learning management systems.

An important aspect of the implementation of the XML-based specification to note is that nearly all LIP elements are optional. Depending on needs, data can be packaged to match the basic LIP segment structure or to match the structure of information on either side of the exchange. Either approach is acceptable.

LIP can be used for individual learner information packaging (for example, a learner submitting his/her resume to an e-learning website) or for organizational exchange (both intra-organization, like data about employees, or extra-organization, like the certification of a learner's achievements to a third-party institution).

The data structures that form the core of the IMS LIP specification are briefly outlined below:

1. Accessibility – Data regarding the accessibility of learner's information as defined through:
    - Language: the definition of a learner’s language proficiencies.
    - Preference: the definition of a learner’s cognitive, physical and technological preferences.
2. Activity – The activity the learner is engaging in, comprising:
    - Learning activity reference: an external reference mechanism to the learning content.
    - Definition: the definition of the materials studied.
    - Product: the materials developed by the learners themselves.
    - Testimonial: statements attesting to the capabilities of the learner.
    - Evaluation: the results of the evaluations undertaken.
3. Affiliation – The learner’s professional affiliations and associated roles.
    - Competency – The competencies of the learner.
    - Goal – The learner’s goals and sub-goals.
4. Identification – The learner identification data. They comprise:
    - Formatted Name: the learner’s name, formatted.
    - Name: the learner’s name.
    - Address: the learner’s addresses.
    - Contact info: electronic-based contact information about the learner.
    - Demographics: demographics information about the learner.
    - Agent: the representatives permitted to act on behalf of the learner.
5. Interest – Hobbies and recreational interests of the learner.
6. Qcl – A description of the qualifications, certifications and various licenses of a learner.
7. Relationship – the set of relationships that are to be defined between the learner and their identification, accessibility, qualifications, competencies, goals, activities, interests, transcripts, security keys and affiliations.
8. Security key – the security-related information for the given learner.
9. Transcript – the transcripts that summarize the performance of the learner.

A full, detailed list of all LIP data elements would be of little interest. What is important is that the standard has been designed to be extensible, in order to accommodate any possible learner data.

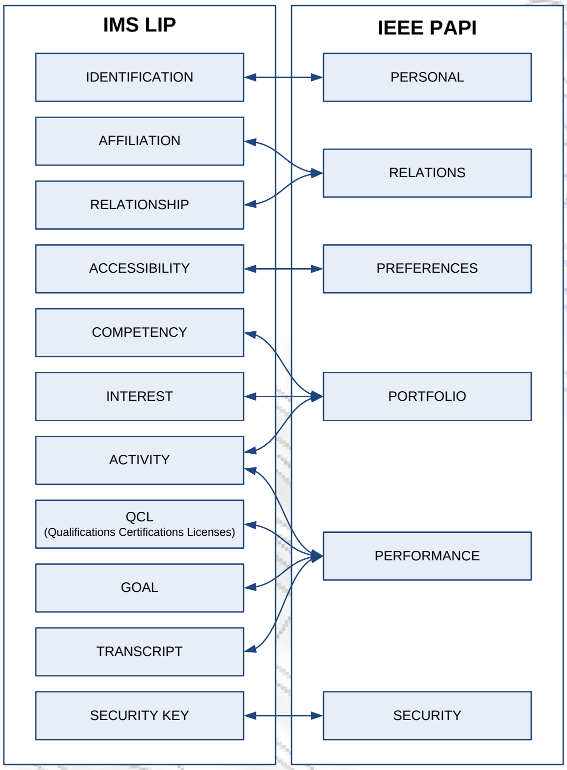

Figure 3.2: Relationship between the IMS LIP and the IEEE PAPI models

3.3.4. Relationship of the IEEE LTSC PAPI with the IMS LIP

As mentioned earlier, the IMS LIP work incorporated the IEEE PAPI specification. Figure 3.2 describes this relationship. An arrow in Figure 3.2 indicates the mapping between one data structure and another. Hence, data belonging to the IEEE PAPI personal group can be put in the identification IMS LIP data group when using the latter specification.

3.4. LT standards for representing Learning Resources

With the approval of the Learning Object Metadata (LOM) specification as a standard by the IEEE [19], learning object metadata models have achieved a stable common reference that provides designers and developers with a solid foundation for creating metadata infrastructures to meet the needs of educators and learners. Given the necessarily abstract nature of this standard, the task of adapting it to meet the specific and concrete needs of these stakeholders, requires interpretation, elaboration, extension, and in some cases, the specialization of both the syntax and semantics. Such processes lead to multiple elaborations and/or representations of the same standard, depending on the application (*application profiling*). This fact can affect interoperability between learning object repositories, and reusability of the stored learning objects. Hence, it identifies the need for learning object metadata (LOM) management infrastructures and environment that can support the twin goals of interoperability and reusability with the minimum human interference.

Today, the web community has embraced the collection and use of metadata to characterize and index educational resources, which lead to semantically more accurate retrieval of information. In the context of resource discovery, descriptive metadata is a characterization that aims to represent the intellectual content of the resource. Although several technologies exist for representing metadata e.g. the Resource Description Framework (RDF) and the Web Ontology Language (OWL), the most popular technology is still XML (eXtensible Markup Language) [105].

Learning resource metadata (LRM) are attracting increasing attention in this context, since they facilitate the description of learning resources, so that they can be easily retrieved [18]. A number of international efforts have been initiated during the past few years, aiming to define LRM specifications for the common description of educational resources. These specifications include fields that are considered necessary for the description of educational resources – such as the type of the resource (i.e. whether it is an experiment, simulation, questionnaire, assessment, etc), the target learner age, difficulty level, estimated learning time, etc – as opposed to "general purpose" meta-data standards (e.g. the Dublin Core), or standards that have been developed for different fields of knowledge (e.g. geo-spatial meta-data standards). The most well-known international LRM standardization initiatives are the IEEE LTSC, IMS, AICC, ARIADNE, and CEN / ISSS.

With the approval of the Learning Object Metadata (LOM) specification metadata models have achieved a stability and level of community requisite to their implementation in the form of application profiles [106] and supporting infrastructure. However, although a generally accepted standard for describing educational material

(IEEE Learning Object Metadata) exists, many educational metadata management systems are using other metadata models or previous versions of the IEEE standard; or even different translations of the IEEE LOM [107].

In this section we will present the main metadata models still in wide use, as well as, the most common application profiles used based on these models.

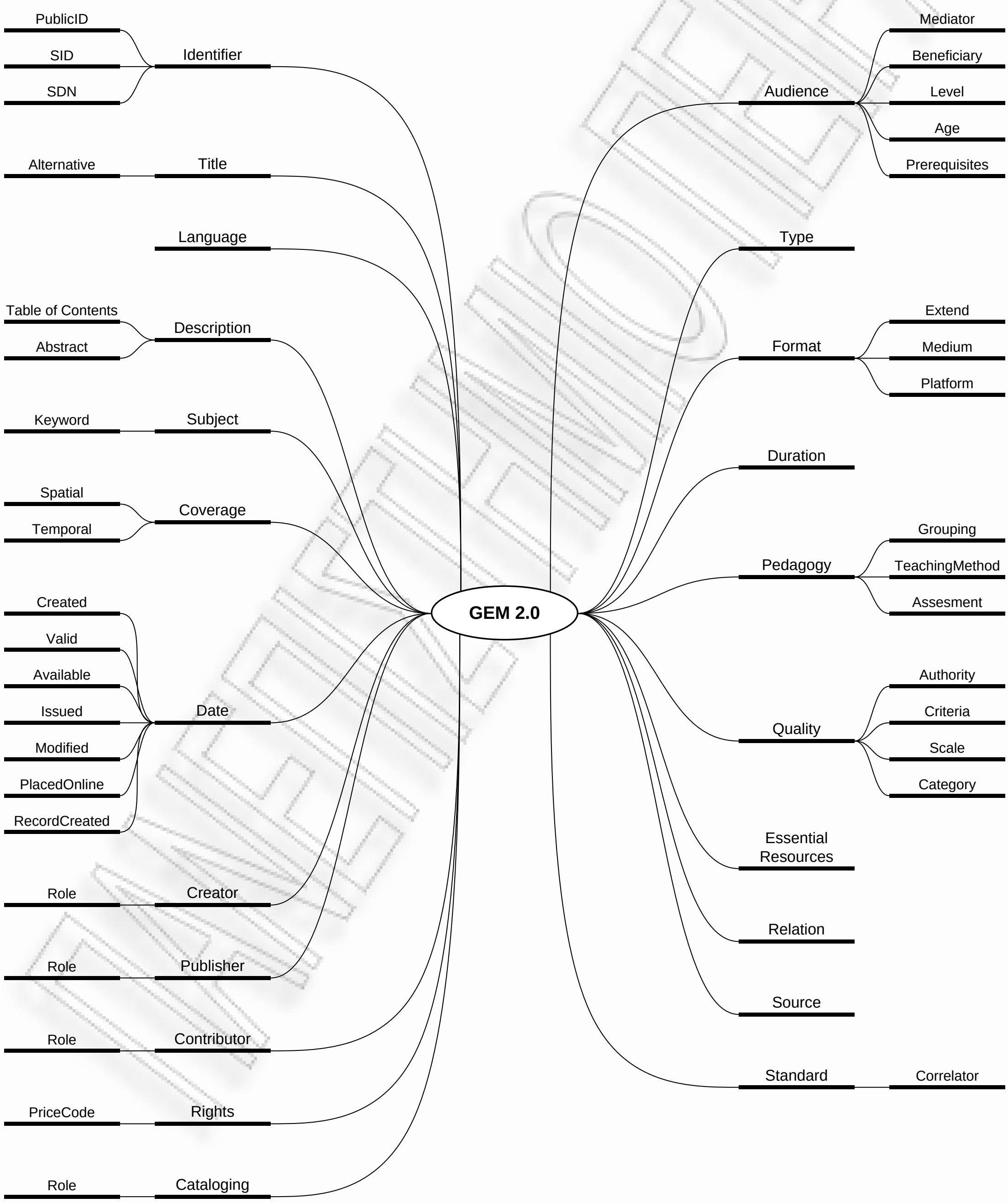

Figure 3.3: Generalized view of the structure of the GEM model

3.4.1. Gateway to Educational Materials (GEM) Model

The Gateway to Educational Materials (GEM) is sponsored by the U.S. Department of Education. GEM’s objective is to provide educators with quick and easy access to a number of educational resources found on various federal, state, university, non-profit, and commercial Internet sites. For this purpose GEM has defined a metadata model for describing learning resources.

The GEM metadata model is based on the Dublin Core model with the addition of education-specific elements. Figure 3.3 presents a generalized view of the structure of the GEM metadata model.

3.4.2. IEEE Learning Object Metadata (LOM) Standard

The IEEE Learning Technology Standards Committee (LTSC) has been providing for the development and maintenance of the Learning Object Metadata (LOM) standard since 1997. This process has been and continues to be an international effort with the active participation on the LOM Working Group by members representing more than 15 countries. This resulted in the first IEEE accredited standard to be completed by LTSC, the 1484.12.1 LOM data model standard. This is the first of a multi-part standard for Learning Object Metadata, which LTSC LOM is responsible for maintaining, developing and evolving. This responsibility is being fulfilled by current work on bindings of the data model standard and includes developing further versions of the data model standard. The IEEE LOM standard has been well received recognized and adopted internationally.

The elements of the IEEE LOM standard are organized in the following categories:

- Category *General*. This category groups the general information that describes a learning object as a whole.
- Category *Life Cycle*. This category describes the history and current state of a learning object and those entities that have affected the learning object during its evolution.
- Category *Meta-Metadata*. This category describes the metadata record itself (rather than the learning object that the metadata record describes).

- Category *Technical*. This category describes the technical requirements and characteristics of a learning object.
- Category *Educational*. This category describes the key educational or pedagogic characteristics of a learning object.
- Category *Rights*. This category describes the intellectual property rights and conditions of use for a learning object.
- Category *Relation*. This category defines the relationship between a learning object and other learning objects.
- Category *Annotation*. This category provides comments on the educational use of a learning object, and information on when and by whom the comments were created.
- Category *Classification*. This category describes where a learning object falls within a particular classification system.

Figure 3.4 presents a generalized view of the structure of the IEEE LOM standard metadata model.

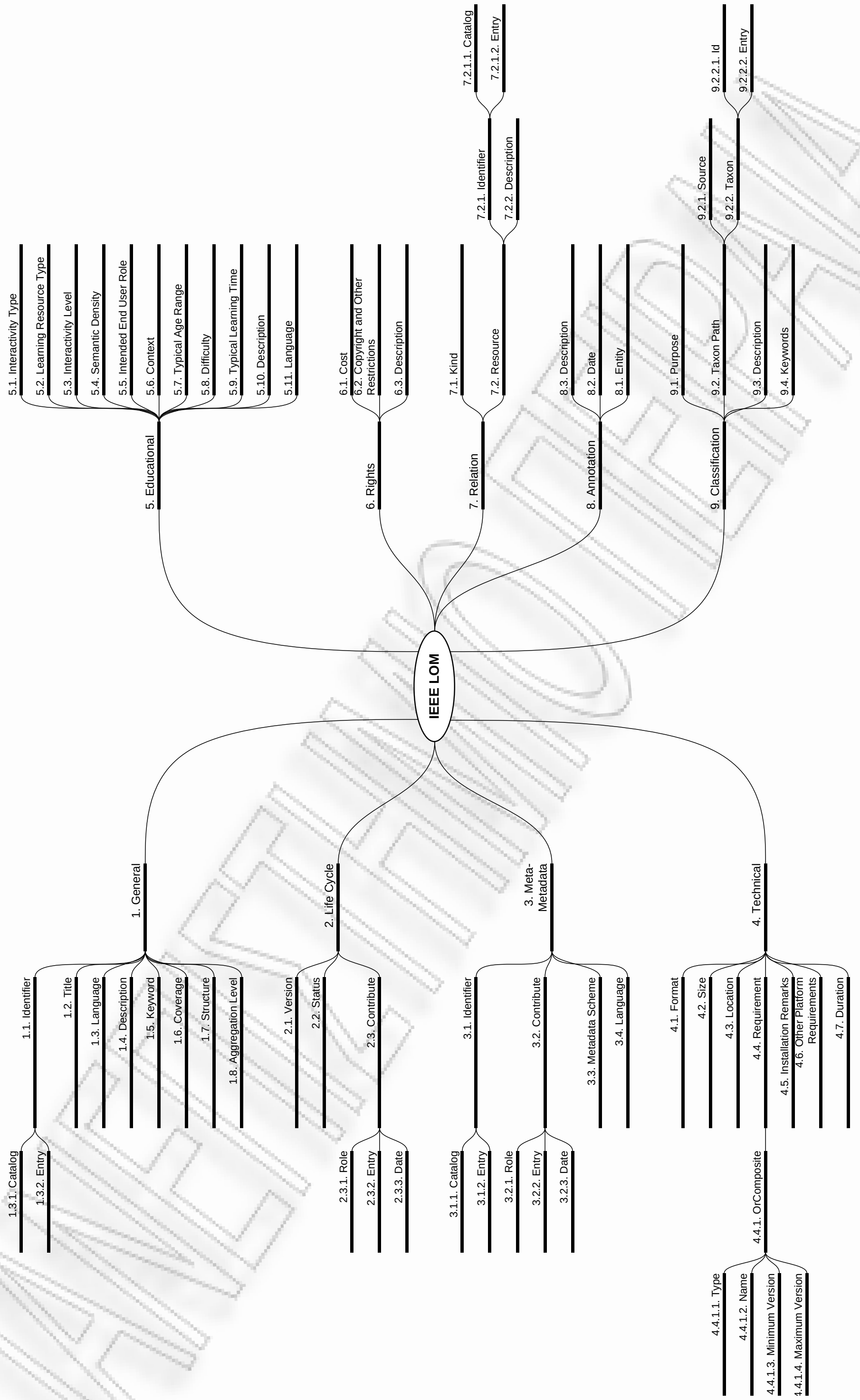

Figure 3.4: IEEE LOM elements

3.4.3. Learning Object Metadata Application Profiles

3.4.3.1. CanCore Application Profile

The CanCore Learning Object Metadata Application Profile (or simply CanCore) is a profiling initiative established in November 2000 to address asset management and resource discovery issues common to a number of e-learning projects sponsored by both federal and provincial governments. These include:

– the BELLE (Broadband-Enabled Lifelong Learning Environment) project, aiming to develop a prototype educational object repository.

– the POOL (Portal for Online Objects for Learning) project, aiming to develop a distributed learning content management infrastructure based on a peer-to-peer architecture.

– The CAREO (Campus Alberta Repository of Educational Objects) project, aiming to develop a searchable, Web-based collection of multidisciplinary teaching materials for educators across Alberta.

– The LearnAlberta Portal, aiming to provide modular, reusable learning resources integrated with provincial k-12 curricula and objectives.

The Canadian Core Metadata Application Profile, in short, is explicitly based on the elements and the hierarchical structure of the LOM standard, but it aims to reduce the complexity and ambiguity of this specification. The CanCore application profile consists of 8 main categories, 15 "placeholder" elements that designate sub-categories, and 36 "active" elements for which data are actively supplied in the process of creating a metadata record [108].

3.4.3.2. Celebrate Application Profile

The purpose of the CELEBRATE Metadata Application Profile is to support the exchange of information between learning object repositories. The metadata described in this application profile supports a variety of LO uses including management and discovery, as well as, the description of properties of individual LOs including educational attributes, digital rights and technical features.

The CELEBRATE Metadata Application Profile defines mandatory, recommended, and optional elements of the IEE LOM Data Model and extends it by defining new elements and new vocabularies. New elements are ‘Learning Principles’ in ‘Educational’ category and ‘CELEBRATE Digital Rights’ in ‘Rights’ category. New vocabularies have been defined for ‘Learning Resource Type’, ‘Intended End User Role’ and ‘Context’ in ‘Educational’ category and some refinements have been made to ‘Language’ value space and ‘Typical Age Range’ value space.

3.4.3.3. UK LOM Core Application Profile

The UK Learning Object Metadata Core (UK LOM Core) is an application profile of IEEE LOM, which is optimised for use by educational communities within the UK. The UK LOM Core consists of two components: a minimum required Core Element Set, and implementation Guidelines for all LOM elements plus additional Element Requirements.

The UK LOM Core is designed for use by metadata implementers (i.e. those who are creating applications for service and data providers that implement the LOM), application profile authors (i.e. those who are creating application profiles based on the LOM) and metadata creators (i.e. information professionals, resource authors, resource users, and others who contribute to a metadata record or instance). It is also envisaged that this document will be of relevance to those with a strategic interest in the creation of interoperable metadata (e.g. project managers, librarians, etc.).

The primary objective of the UK LOM Core is to increase the interoperability of metadata instances and application profiles within the UK educational community by:

- Promoting the appropriate use of LOM syntax and semantics,
- Defining the semantics of LOM data elements and advocating the use of common vocabularies, identifying a common core of elements that will provide an adequate description to facilitate general-purpose use and interoperability.

3.4.3.4. RDN/LTSN Application Profile

The primary purpose of this application profile to support learning object sharing between the UK Resource Discovery Network (RDN) and the UK Learning and Teaching Support Network (LTSN) services using the Open Archives Initiative Protocol for Metadata Harvesting (OAI-PMH). The RDN/LTSN application profile facilitates the following learning object discovery services:

- Advanced Searching via the use of learning object's title, description, keywords and author information stored in the metadata
- Filtering based on the publisher, the resource language, and the educational level.

3.5. Conclusions

Although the available content repositories offer high quality learning objects, still reusing learning content among different AEHS remains an open issue. Current AEHS are closed, self-contained systems that cannot be used as service components (*lack of reuse support*). Additionally, due to their close architecture they face difficulties in supporting the variety of the required functionalities in a learning process since they cannot use external services (*lack of integration*).

A possible solution to the above mentioned problems is the adoption of Learning Technologies (LT). Learning Technology standards and specifications are designed to facilitate the description, packaging, sequencing and delivery of educational content, learning activities and learner information.

The goal of LT is to facilitate interoperability between applications, providing uniform ways for representing educational content, learner information, as well as, uniform communication guidelines that can be used throughout the design, development, and delivery of learning content. Thus, enable educational content and learner information to be shared.

In this chapter, we discussed how the structural components of the generalized AEHS architecture fit to the architectural approach used in LT conformant learning platforms, and reviewed the Learning Technology standards and specifications which can be used for facilitating the sharing of learner information and educational content in AEHS.

Chapter 4. Proposed Adaptive Selection and Sequencing Method

4.1. Introduction

As already discussed in Chapter 2, in the literature there exist different approaches aiming to support the Adaptation Model design by providing AEHS designers with either guidance for the direct definition of adaptation rules, such as ATO [10], MOT [37], [38] and ACCT [32], [33], or semi-automated mechanisms which generate the AM via the implicit definition of such rules [16], [41], [74].

The main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made due to insufficiency and/or inconsistency of the defined adaptation rule sets [11], [109]. This is due to the fact that, even if appropriate resources exist in the Media Space, the absence of a required rule (insufficiency problem) or the conflict between two or more rules (inconsistency problem), prevents the AEHS to select and use them in the generated learning resource sequence. As a result, either less appropriate resources are used from the Media Space, or required concepts are not covered at all by the resulting sequence [11]. To this end, in the literature another approach has been proposed that uses adaptation patterns [44], [45], [46] (or templates) that have been a priori defined by an Instructional Designer during the design phase of the AEHS. These patterns contain both the content selection and the sequencing rules of the Adaptation Model. Typical examples of these systems are MOT [37], [38] and ACCT [32], [33].

Although this approach provides a solution to the inconsistency problem, it does not tackle with the problem of insufficiency, since that would require a huge set of patterns, which is difficult to be a priori defined. The problem of defining adaptation rules is a combinatorial problem, which means that in order to design sufficient and consistent adaptation rule sets, all the combinations of the adaptation decision variables should be covered. However, these combinations can be millions [41], leading to huge rule sets that is difficult to author, manage and verify their sufficiency and/or consistency.

An alternative approach is the use of semi-automated decision based mechanisms [13], [17], [41], [47], which generate a continuous decision function that estimates the desired AEHS response. To achieve this, they use data from the implicit definition of sample adaptation rules and attempt to fit the response function on these data. This definition of implicit adaptation rules, is given in the form of model adaptation decisions, over which the adaptation response function should be fit. This approach overcomes both the problems of sufficiency and consistency; however it introduces decision errors that result from the decision function fitting errors during the machine learning process [41].

In this chapter, we present our proposed semi-automated decision based approach. The proposed methodology is based on an intelligent mechanism that attempts to construct a *suitability function* that maps learning object characteristics over learner characteristics and vice versa.

4.2. Adaptive Learning Objects Selection

The proposed methodology does not depend on the metadata characteristics (attributes) used for learning objects and Learner Modeling, thus can be used for extraction of even complex pedagogy-related dependences. It is obvious that since characteristics/requirements like the domain are used for filtering, the dependencies produced are quite generic, depending only on the educational characteristics of the content and the cognitive characteristics of the learner. The selection methodology is generic, independent of the learning object and the learner characteristics used for the selection.

There exist many criteria affecting the decision of learning objects selection. Those criteria that lead to a straightforward exclusion of learning objects, such as the subject, the language and the media type, are used for filtering. The rest set of criteria such as the educational characteristics of learning objects are used for selection model extraction, since the dependencies of those criteria can model the pedagogy applied by the instructional designer, when selecting learning objects. Those criteria, due to the complexity of interdependencies between them, are the ones that cannot be directly mapped to rules from the instructional designer. Thus a semi-automated approach, like the proposed one, is needed.

In Table 4.1 and Table 4.2, we present examples of learning object and learner attributes respectively, derived from LT standards/ specifications as discussed in Chapter 3.

Table 4.1: Examples of Learning Object attributes derived from IEEE LOM standard

Selection Criteria	IEEE LOM Path	Explanation
General	LOM/General/Structure	Underlying organizational structure of a Learning Object
	LOM/General/Aggregation Level	The functional granularity (level of aggregation) of a Learning Object.
Educational	LOM/Educational/Interactivity Type	Predominant mode of learning supported by a Learning Object
	LOM/Educational/ Interactivity Level	The degree to which a learner can influence the aspect or behavior of a Learning Object.
	LOM/Educational/Semantic Density	The degree of conciseness of a Learning Object, estimated in terms of its size, span or duration.
	LOM/Educational/Typical Age Range	Age of the typical intended user. This element refers to developmental age and not chronological age.
	LOM/Educational/Difficulty	How hard it is to work with or through a Learning Object for the typical intended target audience.
	LOM/Educational/Intended End User Role	Principal user(s) for which a Learning Object was designed, most dominant first.
	LOM/Educational/Context	The principal environment within which the learning and use of a LO is intended to take place.
	LOM/Educational/Typical Learning Time	Typical time it takes to work with or through a LO for the typical intended target audience.
	LOM/Educational/Learning Resource Type	Specific kind of Learning Object. The most dominant kind shall be first.

Next, we present the algorithm for creating a suitability function that estimates the suitability of a learning object for a specific learner. We construct a suitability function with the assumption that the elements of the Learner Model are directly defined by the Instructional Designer and remain the same during the whole life cycle of the AEHS. To this end, before proceeding with the calculation of the suitability function, we assume that the learners' cognitive characteristics and preferences stored in the Learner Model, as well as, the structure of the Educational Resource Description Model have already been defined by the Instructional Designer.

Table 4.2: Examples of Learner attributes derived from IMS LIP specification

Selection Criteria	IMS LIP Path	Explanation	Usage Condition
Accessibility	LIP/Accessibility/Preference/typename	The type of cognitive preference	-
	LIP/Accessibility/Preference/prefcode	The coding assigned to the preference	-
	LIP/Accessibility/Eligibility/typename	The type of eligibility being defined	-
	LIP/Accessibility/Disability/typename	The type of disability being defined	-
Qualifications Certifications Licenses	LIP/QCL/Level	The level/grade of the QCL	LIP/QCL/Typename, LIP/QCL/Title and LIP/QCL/Organization should refer to a qualification related with the objectives of the learning goal
			LIP/QCL/date > Threshold
Activity	LIP/Activity/Evaluation/noofattempts	The number of attempts made on the evaluation.	LIP/Activity/Typename, LIP/Activity/status, LIP/Activity/units and LIP/Activity/Evaluation/Typename should refer to a qualification related with the objectives of the learning goal
	LIP/Activity/Evaluation/result/interpretscope	Information that describes the scoring data.	LIP/Activity/date > Threshold
	LIP/Activity/Evaluation/result/score	The scoring data itself.	LIP/Activity/Evaluation/date > Threshold

The process of creating the suitability function consists of the following steps, as shown in Figure 4.1:

Step1: Reference Sets Generation

The first step of the suitability calculation process includes the generation of the reference sets of learning objects and learners that will be used for calculating the suitability function. More precisely, we generate two sets of learning objects, namely, the *Learning Objects Training Set* (LOTS) and the *Learning Objects Generalisation Set* (LOGS), as well as, two sets of learners, namely, the *Learners Training Set* (LTS) and the *Learners Generalisation Set* (LGS). The two training sets (LOTS and LTS) are used for calculating the suitability function, and the two generalisation sets (LOGS and LGS) are used for evaluating the consistency of the produced suitability function.

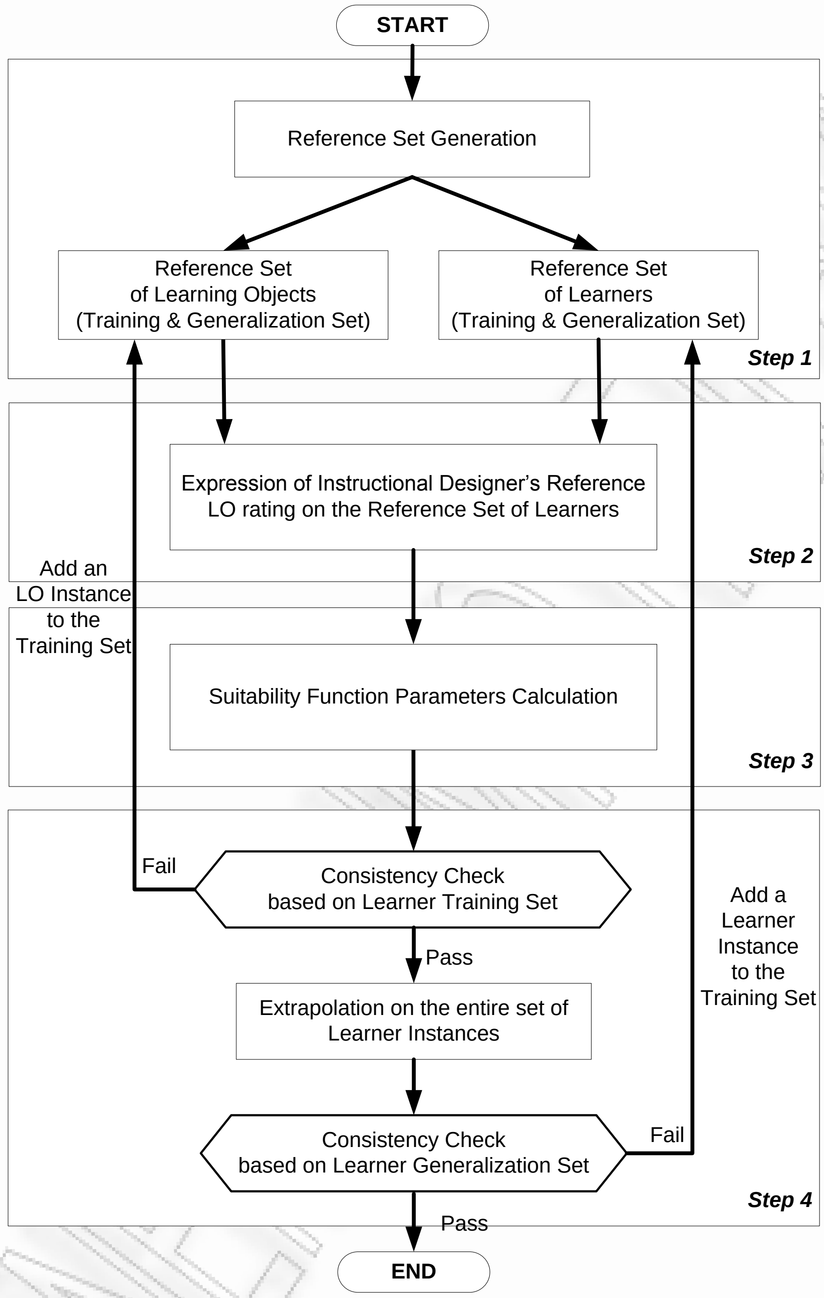

Figure 4.1: Workflow for generating the Suitability Function

Each one of the generated reference learning objects has a unique identifier of the form LO_i and is characterized by a set of n independent properties $g^{LO_i} = (g_1^{LO_i}, g_2^{LO_i}, \ldots, g_n^{LO_i})$ of the Educational Resource Description Model. Similarly, each one of the generated reference learners has a unique identifier of the form L_j and is characterized by a set of m independent properties $u^{L_j} = (u_1^{L_j}, u_2^{L_j}, \ldots, u_m^{L_j})$ of the Learner Model. The reference learning objects are randomly generated with normal distribution over the value space of each metadata element of the Resource Description Model. Similarly, the reference learners are randomly generated with normal distribution over the value space of each learner characteristic of the Learner Model.

Step2: *Reference LO rating by the Instructional Designer*

For each reference learner L_j contained in the LTS, we ask the Instructional Designer to define his/her preference rating of the reference learning objects contained in LOTS, as well as, to define his/her preference rating of the reference learning objects contained in LOGS. These preference ratings are expressed using two preference relations, namely, the strict preference relation and the indifference relation. A strict preference relation means that a learning object is preferred from another one and an indifference relation means that two learning objects are equally preferred. Additionally, for each reference learner L_j contained in the LGS, we ask the Instructional Designer to define his/her preference rating of the reference learning objects contained in LOGS.

Step3: *Suitability Function Parameters Calculation*

For a specific learner L_j we define as *marginal suitability function* of the Resource Description Model property g_k a function that indicates how important is a specific value of the property g_k when calculating the suitability of a learning resource LO_i for the learner L_j. This function has the following form (Karampiperis and Sampson, 2004):

$s_{g_k}^{L_j}(g_k^{LO_i}) = a_{g_k}^{L_j} + b_{g_k}^{L_j} g_k^{LO_i} \exp(-c_{g_k}^{L_j} {g_k^{LO_i}}^2)$, where $g_k^{LO_i}$ is the property value of learning object LO_i in the g_k element of the Resource Description Model and $a_{g_k}^{L_j} \in R,\ b_{g_k}^{L_j} \in R,\ c_{g_k}^{L_j} \in R$ are parameters that define the form of the marginal suitability function. The calculation of these parameters for all g_k properties of the Resource Description Model lead to the calculation of the suitability function for the learner L_j.

More precisely, for a specific learner L_j we define the *suitability function* as the aggregation of the marginal suitability functions for the learner Lj, as follows:

$S^{L_j}\left(g^{LO_i}\right)=\frac{1}{n}\sum_{k=1}^{n} s_{g_k}^{L_j}(g_k^{LO_i})$ with the following additional notation:

$s_{g_k}^{L_j}(g_k^{LO_i})$: Marginal suitability of the g_k element of the Resource Description Model, valued $g_k^{LO_i}$ for the learning object LO_i,

$S^{L_j}\left(g^{LO_i}\right)$: The global suitability of the learning object LO_i for the learner L_j.

If $S_{LO_1}^{Lj}$ is the global suitability of a learning object LO_1 and $S_{LO_2}^{Lj}$ is the global suitability of a learning object LO_2 for the learner L_j, then the following properties generally hold for the suitability function *S*:

$$\begin{array}{l} S_{LO_1}^{Lj} > S_{LO_2}^{Lj} \Leftrightarrow (LO_1)P(LO_2) \\ S_{LO_1}^{Lj} = S_{LO_2}^{Lj} \Leftrightarrow (LO_1)I(LO_2) \end{array},$$

where *P* is the strict preference relation and *I* the indifference relation in Instructional Designer's preference rating. These properties express that for a specific learner L_j, when a learning object LO_1 is preferred from another learning object LO_2, then the suitability function for LO_1 is greater than the suitability function for LO_2 and vise versa. Similarly, when two learning objects LO_1 and LO_2 have the same preference rating for a specific learner L_j, then they also have the same suitability function value.

Using the provided by the Instructional Designer preference rating of the reference learning objects contained in LOTS, for each reference learner L_j contained in the LTS, we define the *suitability differences* $\Delta^{L_j}=(\Delta_1^{L_j},\Delta_2^{L_j},\ldots,\Delta_{q-1}^{L_j})$ for the reference learner L_j, where q is the number of learning objects in the LOTS and $\Delta_l^{L_j}=S_{LO_l}^{L_j}-S_{LO_{l+1}}^{L_j}\geq 0$ the suitability difference between two subsequent learning objects in the rated LOTS. We then define an *error function e* for each suitability difference: $\Delta_l^{L_j}=S_{LO_l}^{L_j}-S_{LO_{l+1}}^{L_j}+e_l^{L_j}\geq 0$. We can then solve for each one of the learner instances L_j in the LTS the following constrained optimisation problem:

Minimize $\sum_{l=1}^{q-1}(e_l^{L_j})^2$ subject to the constraints: $\left.\begin{array}{ll}\Delta_l > 0 & \text{if } (\mathrm{LO}_l)P(LO_{l+1}) \\ \Delta_l = 0 & \text{if } (\mathrm{LO}_l)I(LO_{l+1})\end{array}\right\}$

and $0 \le s_{g_k}^{L_j}(g_k^{LO_i}) \le 1, \ \forall g_k$

By using Lagrange Multipliers [110], we can transform the above problem to an unconstrained optimisation problem, and solve it using typical non linear optimisation algorithms (e.g. conjugate gradient methods). For details on such methods the reader may refer to Appendix A.

This optimisation problem leads to the calculation of the values of the parameters a, b and c for each g_k property of the Resource Description Model over the instances of the LTS, that is, for each separate learner profile included in the LTS.

Step4: *Consistency Check and Extrapolation*

We then evaluate the consistency of the resulting suitability function, that is, the evaluation of how well the suitability function works for learning objects and/or learners that have not been used in the suitability function parameters calculation (step 3). To this end, we first use the provided by the Instructional Designer preference rating of the reference learning objects contained in LOGS, for each reference learner L_j contained in the LTS.

For a reference learner L_j, we estimate using the suitability function calculated in the previous step (step 3) the Instructional Designer's preference rating of each learning object contained in LOGS. We then compare the provided by the Instructional Designer preference rating with the estimated one. If the preference rating estimation of a learning object LO_i in LOGS is different than that provided by the Instructional Designer, we add the learning LO_i in the Learning Object Training Set (LOTS) and recalculate the suitability function parameters (step 3).

If the estimated and the provided preference ratings are the same, then we generalize the resulted suitability function from the LTS to all learners, by calculating the corresponding suitability values for every learner property $u_z^{L_j}$, using the following linear interpolation formula:

$$s_{g_k}^{L_j}\left(g_k^{LO_i}\right)=\begin{cases} s_{g_k}^{L_1}\left(g_k^{LO_i}\right), & if\ s_{g_k}^{L_1}\left(g_k^{LO_i}\right)=s_{g_k}^{L_2}\left(g_k^{LO_i}\right) \\ s_{g_k}^{L_1}\left(g_k^{LO_i}\right)+\dfrac{u_z^{L_j}-u_z^{L_1}}{u_z^{L_2}-u_z^{L_1}}\left[s_{g_k}^{L_2}\left(g_k^{LO_i}\right)-s_{g_k}^{L_1}\left(g_k^{LO_i}\right)\right], & if\ s_{g_k}^{L_2}\left(g_k^{LO_i}\right)>s_{g_k}^{L_2}\left(g_k^{LO_i}\right) \end{cases}$$

where L_1 and L_2 are the learners of the LTS closest (measured by Euclidean distance) to the learner L_j, $u_z^{L_1}$ and $u_z^{L_2}$ are the values of learner property u_z for learners L_1 and L_2 respectively, and $s_{g_k}^{L_1}$ and $s_{g_k}^{L_2}$ are the marginal suitability functions of the Resource Description Model property g_k for learners L_1 and L_2 respectively.

After the extrapolation on the entire set of learner instances, we evaluate again the consistency of the resulting suitability function, using the provided by the Instructional Designer preference rating of the reference learning objects contained in LOGS, for each reference learner L_j contained in the LGS. For a reference learner L_j, we estimate using the suitability function calculated in the previous step (step 3) the Instructional Designer's preference rating of each learning object contained in LOGS. We then compare the provided by the Instructional Designer preference rating with the estimated one. If the preference rating estimation for a learner L_j in LGS is different than that provided by the Instructional Designer, we add the learner L_j in the Learners Training Set (LTS) and recalculate the suitability function parameters (step 3).

4.3. Adaptive Learning Object Sequencing

As already described in Chapter 2, AEHS that implement the direct rule definition approach use a two steps sequencing process. They first generate a sequence of concepts that matches the learning goal in hand, and then select learning recourses for each concept of the concept sequence. Due to the problems of inconsistency and insufficiency of the defined rule sets in the Adaptation Model, conceptual "holes" can be generated in the produced learning resource sequence.

To overcome this problem, decision-based approaches implement an alternative sequencing method. In this method, instead of generating the learning path by populating the concept sequence with available learning resources, first all possible sequences that match the learning goal in hand are generated and then the desired personalized learning path from the set of available paths is adaptively selected.

In brief, this two steps procedure is the following:

Step1: *Learning Paths Generation.*

At this step a graph containing all possible learning paths based on the relation between the Learning Goals Hierarchy, the concepts of the Domain Concept Ontology and the learning resources contained in the Media Space, is generated.

Step2: *Personalized Learning Path Selection.*

At this step a personalized learning path is selected from the graph that contains all the available learning paths based on learner's attributes in the Learner Model.

In the proposed sequencing method, we replace the content selection rules defined in the Adaptation Model with a decision-making function that estimates the suitability of a learning resource for a specific learner by relating the educational characteristics of learning resources defined in the educational resource description model with the learner's cognitive characteristics and preferences stored in the Learner Model. This suitability function is used for weighting each connection of the Learning Paths Graph. From the weighted graph, we then select the most appropriate learning path for a specific learner (personalized learning path) by using a shortest path algorithm. Next, we present the methodology used for selecting the personalized learning path for a learner.

In order to be able to select from the Learning Paths Graph (LPG) the learning path that matches the characteristics and preferences of a specific learner, we need to add learner-related information to the LPG. This information has the form of weights on each connection of the LPG and represents the inverse of the suitability of a learning resource for the specific learner. This means that the higher value a weight in the LPG has, the less suitable the corresponding learning object in the sequence is for a specific learner.

For a specific learner Lj we define the weighting function for each directed connection (edge) of the Learning Paths Graph as $W^{L_j}\left(g^{LO_i}\right)=1-S^{L_j}\left(g^{LO_i}\right)\in[0,1]$, where $S^{L_j}\left(g^{LO_i}\right)$ is the global suitability for the learner L_j of the targeted learning object LO_i. in the edge.

After weighting the LPG using the weighting function, we need to find the most appropriate learning path for a learner. Since the weights in the LPG are calculated in such a way that the lower value they have the more suitable a learning object is, the calculation of the most appropriate learning path is equivalent to the calculation of the shortest path in the LPG. By relaxing the edges of the LPG according to a topological sort of its vertices (nodes of the graph), we can compute the shortest path.

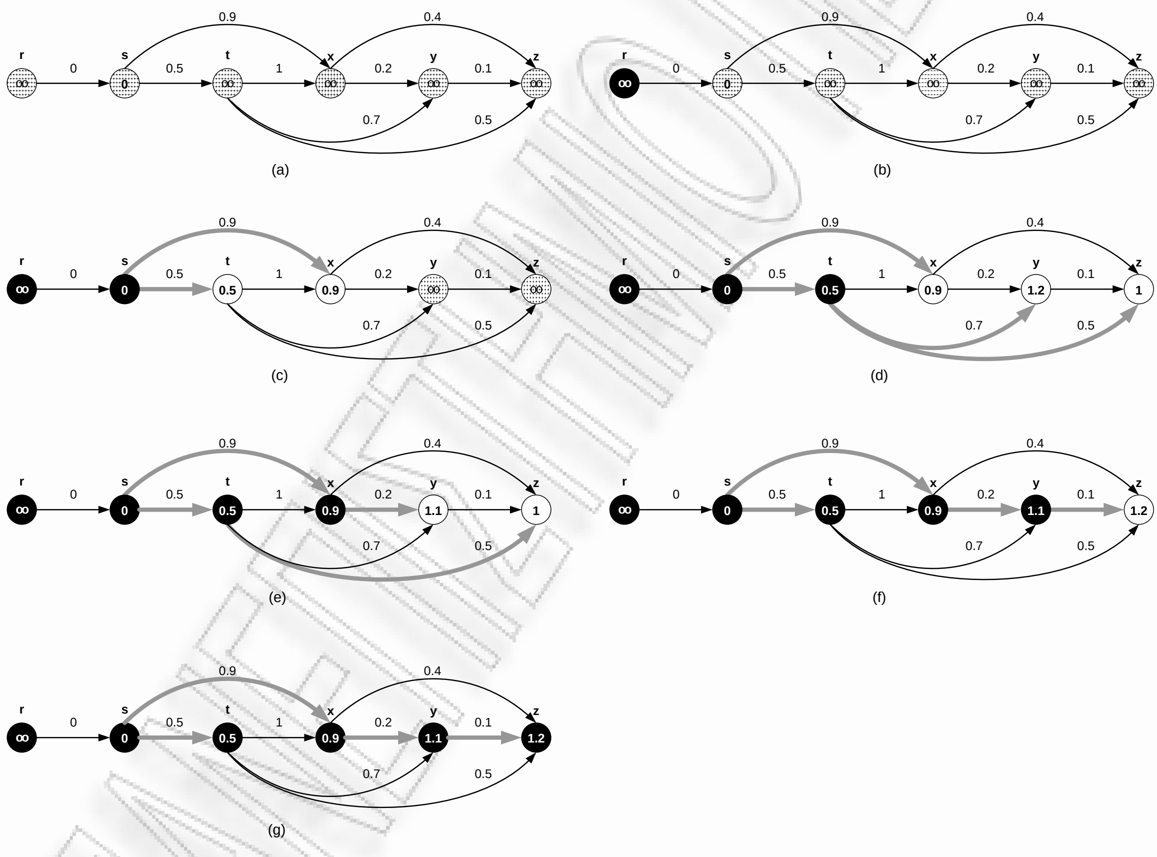

Figure 4.2: The execution of the algorithm for personalized learning path selection from the LPG. The d values are shown within the vertices, and shaded edges indicate the π values.

The algorithm starts by topologically sorting the LPG to impose a linear ordering on the vertices. If there is a path from vertex u to vertex υ, then u precedes υ in the topological sort (Figure 4.2a).

Let us call V the set of vertices contained in the LPG. For each vertex $\upsilon \in V$, we maintain an attribute d[υ] called shortest-path estimation, which is an upper bound on the weight of a shortest path from source s to υ. Additionally, for each vertex $\upsilon \in V$, we maintain an attribute $\pi[\upsilon]$ called shortest-path predecessor. We initialize the shortest-path estimates and predecessors using the following values: $\pi[\upsilon]$=NIL for all $\upsilon \in V$, $d[s]=0$, and $d[\upsilon]=\infty$ for $\upsilon \in V-\{s\}$ (Figure 4.2a). We make just one pass over the vertices in the topologically sorted order. As we process each vertex, we relax each edge that leaves the vertex. The process of relaxing an edge (u,υ) consists of testing whether we can improve the shortest path to υ found so far by going through u and, if so, updating $d[\upsilon]$ and $\pi[\upsilon]$. A relaxation step may decrease the value of the shortest-path estimate $d[\upsilon]$ and update υ's predecessor field $\pi[\upsilon]$ (Figure 4.2b-g).

The result of this process is the calculation of the shortest path in the LPG that corresponds to the sequence of learning objects that are most suitable for a specific learner L_j.

4.4. Conclusions

In order to adaptively select and sequence learning objects in AEHS the definition of the Adaptation Model is required. In the literature, there exist different approaches aiming to support the Adaptation Model design by providing AEHS designers with either guidance for the direct definition of adaptation rules, or semi-automated mechanisms which generate the AM via the implicit definition of such rules.

The main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made due to insufficiency and/or inconsistency of the defined adaptation rule sets.

An alternative approach is the use of semi-automated decision based mechanisms, which generate a continuous decision function that estimates the desired AEHS response. To achieve this, they use data from the implicit definition of sample adaptation rules and attempt to fit the response function on these data. This definition of implicit adaptation rules, is given in the form of model adaptation decisions, over which the adaptation response function should be fit. This approach overcomes both the problems of sufficiency and consistency; however it introduces decision errors that result from the decision function fitting errors during the machine learning process.

In this chapter, we presented our proposed semi-automated decision based approach. The proposed methodology is based on an intelligent mechanism that attempts to construct a suitability function that maps learning object characteristics over learner characteristics and vice versa. We claim that this method requires less effort by the instructional designer, since instead of defining a huge set of adaptation rules, only the designer's selection from a small set of learning objects over a reference set of learners is needed. The machine learning technique will try then to discover the dependence between learning object and learner characteristics that produce the same adaptation decisions as the instructional designer did.

Chapter 5. Evaluation Methodology

5.1. Introduction

As already discussed, the main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made due to insufficiency and/or inconsistency of the defined adaptation rule sets [11], [109].

In chapter 4, we presented our proposed semi-automated decision based approach. The proposed methodology is based on an intelligent mechanism that uses data from the implicit definition of sample adaptation rules and attempts to fit the response function on these data, using a suitability function that maps learning object characteristics over learner characteristics and vice versa.

We claim that this method requires less effort by the instructional designer, since instead of defining a huge set of adaptation rules, only the designer's selection from a small set of learning objects over a reference set of learners is needed. The machine learning technique will try then to discover the dependence between learning object and learner characteristics that produce the same adaptation decisions as the instructional designer did.

In this chapter, we present the evaluation methodology that will be used to verify our main hypothesis: that it is feasible to construct a semi-automated, decision-based approach, which generates a continuous decision function that estimates the desired AEHS response, aiming to overcome the above mentioned problems of insufficiency and inconsistency of the defined adaptation rule sets.

5.2. Evaluation Steps

The goal of this evaluation is twofold: first, to examine whether the proposed semi-automated decision based approach is capable of extracting decision models which replicate the Adaptation Model (AM) of existing AEHS; and second, to verify that our proposed approach is robust and can be applied in cases where large-scale adaptation rule sets are needed to describe the desired AEHS response.

To this end, the evaluation will be performed in two phases:

- *Phase A: Extracting the AM of existing AEHS.* In this evaluation phase, the Adaptation Model (AM) rules of existing AEHS will be used for generating sample adaptation decisions. These decisions have the form of combinations of learning objects mapped to learner profiles, and will be used to train the intelligent mechanism that fits the response function on these data. The goal of this phase is to examine whether the proposed semi-automated decision based approach is capable of extracting the decision model of the AEHS in hand. More specifically, we will try to extract the AM rules for content selection used in the INSPIRE [69], and the AHA [8], [29], [30], system.
- *Phase B: Scaling up the experiments.* As already discussed in Chapter 2, the problem of defining adaptation rules is a combinatorial problem, which means that in order to design sufficient and consistent adaptation rule sets, all the combinations of the adaptation decision variables should be covered. However, these combinations can be millions [41], leading to huge rule sets that is difficult to author, manage and verify their sufficiency and/or consistency. To this end, in order to keep the adaptation rule set human-maintainable, existing AEHS in the literature use few adaptation variables, typically 2 to 4 variables for describing learners' behaviour and 2 to 3 variables for describing educational content [111].

  The goal of this evaluation phase is to verify that our proposed approach is robust and can be applied in cases where large-scale adaptation rule sets are needed to describe the desired AEHS response. In order to do this, we will simulate the existence of an AEHS that uses as many adaptation variables as possible. These variables (learner profile properties and educational description model properties) will be selected from the elements of wide-spread Learning Technology standards, as discussed in Chapter 3. However, special attention was given in generating learner profiles and educational content metadata records that simulate real-life conditions. Details on how these datasets were generated are given in section 5.3.

  This evaluation phase can be divided in the following steps:

  - *Step B.1: Robustness Testing.* Before measuring the performance, it is important to investigate the robustness of our proposed approach. The scope of this testing phase is to check (a) that the optimisation problem in hand converges, and thus, is well-defined, and (b) that it is not dependent from the optimisation algorithm in use, and thus, the proposed approach is robust.

- *Step B.2: Assessment of Performance Evaluation Metrics.* An additional step is required to verify that the performance evaluation metrics presented in section 2.6 are suitable in the case of our proposed method for estimating the desired AEHS response (presented in Chapter 4). Our first goal is to evaluate these metrics, and then use these metrics in measuring the performance of our proposed decision-based approach. Our approach for adaptive content selection and sequencing uses (a) a preference-based learning objects selection mechanism based on the use of a suitability function, that estimates the utility of a given learning object for a given learner, and (b) a preference-based sequencing mechanism which uses the above mentioned suitability function for weighting the graph which represents all possible learning object sequences for a targeted learner, so as to discover the optimum learning path for a given learner.
- *Step B.3: Performance Evaluation.* The goal of this evaluation step is to validate the use and measure the performance of our decision-based approach for adaptive learning objects selection and sequencing in AEHS. Performance evaluation in this context means measuring (a) how well our semi-automated approach fits the decision function to the provided model adaptation decisions (training data), and (b) how well this decision function responds to decision cases not known during the training process (generalisation capacity). During this evaluation step, we will also examine the influence of the required design effort. In order to investigate the influence of the explicit combinations required from the instructional designer (which are directly equivalent to the design effort required) we will execute additional experiments measuring the selection success gain per number of requested combinations. This metric provides evidences about the trade-off that an instructional designer should make between the required effort and the improvement of the selection success rate. Moreover, during this evaluation step, we will investigate how the use of predictive models for

learner characteristics can be used to improve the content selection success without increasing the required design effort. More precisely, we will make use of the Cognitive Trait Model (CTM) [21]. This model, estimates learner's cognitive characteristics (and more precisely the Working Memory Capacity and the Inductive Reasoning Skill) and proposes specific values for the elements "InteractivityType", "InteractivityLevel", "SemanticDensity" and "Difficulty" of the Educational Resource Description Model. Thus, the use of CTM could reduce the dimensions of the optimisation problem.

5.3. Data Preparation

As described in Chapter 2, the adaptation model design is the process of defining (a) the concept selection rules which are used for selecting appropriate concepts from the *Domain Model* to be covered, (b) the content selection rules which are used for selecting appropriate resources from the *Media Space*, and (c) the sequencing rules which are used for generating appropriate learning paths (sequences of learning objects) for a given learner, based on learner's profile stored in the *Learner Model*. This means that before executing our experiments for measuring the performance of adaptive selection and sequencing of learning objects, we need to design (a) the Media Space, (b) the Learner Model, and (c) the Domain Model.

5.3.1. Designing the Media Space

In the first phase of the evaluation, we will extract the AM of the INSPIRE [69] and the AHA [8] system. The INSPIRE system uses two variables in the Educational Resource Description Model, namely, the Performance Level and the Learning Resource Type. On the other hand, the instructional rules introduced in the AHA system by Stash [112], [113] uses also two variables in the Educational Resource Description Model, namely, the Learning Resource Type and the Learning Resource Modality.

In the second evaluation phase, we simulate the existence of an AEHS where large-scale adaptation rule sets are needed to describe the desired AEHS response. To do so, we have used as Educational Resource Description Model a subset of the IEEE Learning Object Metadata standard elements [19], illustrated in Table 5.1. The Aggregation Level and the Relation/Kind elements are used for structuring the Media

Space and the Classification element is used for connecting learning resources with the concepts of the Domain Concept Ontology.

Table 5.1. Educational Resource Description Model used in Evaluation Phase B

IEEE LOM Category	IEEE LOM Element	Explanation
General	Structure	Underlying organizational structure of a Learning Object
	Aggregation Level	The functional granularity of a Learning Object
Educational	Interactivity Type	Predominant mode of learning supported by a Learning Object
	Interactivity Level	The degree to which a learner can influence the aspect or behavior of a Learning Object.
	Semantic Density	The degree of conciseness of a Learning Object
	Typical Age Range	Developmental age of the typical intended user.
	Difficulty	How hard it is to work with or through a Learning Object for the typical intended target audience.
	Intended End User Role	Principal user(s) for which a Learning Object was designed, most dominant first.
	Context	The principal environment within which the learning and use of a LO is intended to take place.
	Typical Learning Time	Typical time it takes to work with or through a LO for the typical intended target audience.
	Learning Resource Type	Specific kind of Learning Object. The most dominant kind shall be first.
Relation	Kind	Nature of the relationship between two Learning Objects

The Aggregation Level was used for classifying the available learning resources in two classes, namely, the raw media and the structured learning objects (Table 5.2. Each learning resource was tagged with a unique identifier depending on the aggregation level class that it belongs. For example, the identifier of learning resources with aggregation level 1 has the form of AG1:LOi, whereas, the identifier of learning resources with aggregation level 2 has the form of AG21:LOj, where i and j are the unique identifiers of the learning resources inside a specific aggregation class.

Table 5.2: Learning Objects' Aggregation Level according to IEEE LOM standard

IEEE LOM Element	Value Space	Description
General/Aggregation Level	1	The smallest level of aggregation, e.g. raw media data or fragments
	2	A collection of level 1 learning objects, e.g. a lesson chapter or a full lesson

In order to define the structure of learning resources at aggregation level 2 (that is, a collection of several learning resources at aggregation level 1) we have used the 'Relation' Category of the IEEE LOM standard. More specifically, in our simulations we have used eight types of relationships out the 12 predefined values at the Dublin Core Element Set [114], namely: "is part of" / "has part", "references" / "is referenced by", "is based on" / "is basis for", and "requires" / "is required by".

A partial view of the Media Space based on the use of the IEEE LOM Aggregation Level element and the Relation/Kind element is presented in Figure 5.1.

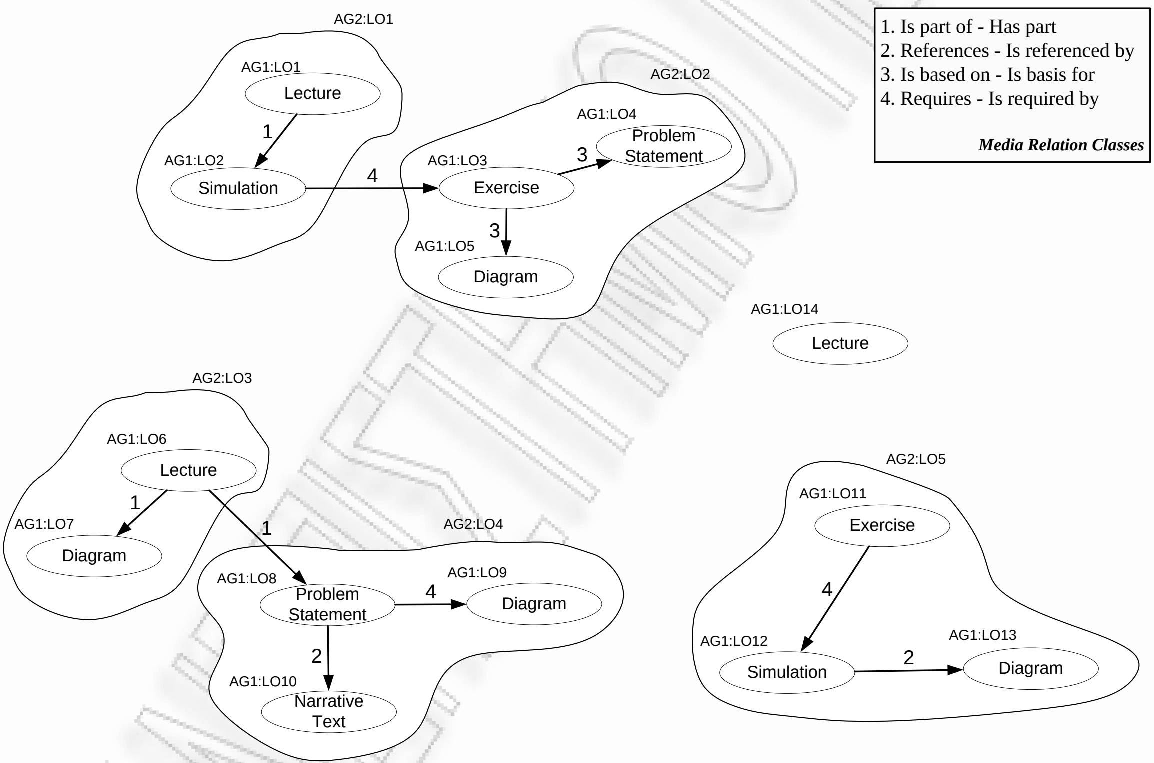

Figure 5.1: Partial View of Media Space Representation

Furthermore, for each learning resource included in the Media Space, a set of related concepts from the Domain Concept Ontology is specified using the Classification element of the IEEE LOM standard. This element describes the position of a specific learning object within a particular classification system and it is typically used in AEHS to determine if a specific learning resource covers a certain concept of the subject domain. Typical systems that used this approach are the Personal Reader [115], and the WINDS [57].

In the literature, several approaches exist that integrate the IEEE LOM metadata elements within domain concept ontologies [116], [117], [118],[119], [120]. The use of the classification element of the IEEE LOM standard, on one hand, models the connection between concepts of the Domain Concept Ontology and the learning resources, and on the other hand, enables the separation of the Educational Resource Description Model from the Domain Concept Ontology. This separation enables the use of separate metadata records for learning resources, thus, enabling the use of resources and associated metadata contained in external from the AEHS repositories.

In both evaluation phases, we need to simulate real-life conditions. This means that the simulated learning object metadata records should have a distribution over their value spaces similar to the metadata value distribution found in real-life learning object repositories.

Najjar and Duval [121], presented a statistical analysis of the actual use of IEEE LOM metadata elements in the ARIADNE learning object repository. The results were derived from analyzing the empirical data (usage logs) of 3,700 ARIADNE metadata instances. Table 5.3 shows the percentage of times each ARIADNE data element was filled in by indexers during the indexing process.

Table 5.3. Usage Percentage of Data Elements in ARIADNE Repository **[**121**]**

IEEE LOM Element	Value Provided (%)	Most used Vocabulary value (M)	% of M (filled-in)	%M among all cases
Aggregation Level	91.9	Lesson	92.7	85.2
Context	53.5	University Degree	69.7	37.2
Interactivity Level	53.2	Medium	67.7	36.1
Semantic Density	52.4	Medium	76.4	40.0
Difficulty Level	52.2	Medium	72.8	38.0
Restrictions	5.2	Contact Author	90	5.2
Source	1.3	-	-	-
Version Information	7.0	-	-	-
Description	11.2	-	-	-
OS Version	0.5	-	-	-
Installation Remarks	24.3	-	-	-
Other Constraints	0.15	-	-	-

From the data shown in Table 5.3, we notice that only one data element is almost always used: the Aggregation Level element. Other elements are used in about 50 % of the descriptions and the rest are rarely used in the indexing process. For the values of data elements, we can see that indexers often use just one value.

As a result, in order to simulate in our experiments the metadata of a real-world repository, we will generate metadata records with normal distribution over the metadata elements value space, simulating that not all metadata elements and their corresponding vocabulary terms are used equally. Normal distribution is a continuous probability distribution that is often used to describe random variables that tend to cluster around a single mean value.

5.3.2. Designing the Learner Model

In the first phase of the evaluation, we will extract the AM of the INSPIRE [69] and the AHA [8] system. The INSPIRE system uses two variables in the Learner Model, namely, the Learner's Knowledge Level and the Learner's Learning Style. On the other hand, the instructional rules introduced in the AHA system by Stash [112], [113] uses also two variables in the Learner Model, namely, the Learner's Learning Style and the Learner's Modality Preference.

In the second evaluation phase, we simulate the existence of an AEHS where large-scale adaptation rule sets are needed to describe the desired AEHS response. To do so, for the design of the Learner Model in our simulations, we have used an overlay model [61] for representing the Learners Knowledge Space and a stereotype model [62] for representing learners' preferences. More precisely, for the learners' knowledge level we assume the existence of a related certification for each node of the Learners Knowledge Space, the evaluation score in testing records and the number of attempts made on the evaluation. For modelling of learners' preferences we use learning styles according to Honey and Mumford model [122], as well as modality preference information consisting of four modality types, namely, the visual modality, the textual modality, the auditory modality and any combination of the three modality preferences [123]. Each element of the Learner Model was mapped to the IMS Learner Information Package specification [20], as shown in Table 5.4.

In order to simulate in our experiments the profiles of real learners we generated profile records using truncated standard lognormal distribution with [sigma]=1 and reduced by factor 1/5. This distribution is often used in the literature for simulating learner behaviour [124].

Table 5.4. Learner Model used in Evaluation Phase B

Learner Model Element	IMS LIP Element	Explanation
Learning Style	Accessibility/Preference/typename	The type of cognitive preference
	Accessibility/Preference/prefcode	The coding assigned to the preference
Modality Preference	AccessForAll/Context/Content	The type of modality preference
Knowledge Level	QCL/Level	The level/grade of the QCL
	Activity/Evaluation/noofattempts	The number of attempts made on the evaluation.
	Activity/Evaluation/result/interpretscope	Information that describes the scoring data
	Activity/Evaluation/result/score	The scoring data itself.

5.3.3. Designing the Domain Model

In this thesis we focus on content selection and sequencing rules, thus, we assume that the results of the concept selection process are apriori known. To this end, for the definition of the subject domain concepts, we chose a well structured curriculum, that is, the ACM Computing Curricula for Computer Science [22], and we extracted an ontology consisting of 950 topics organized in 132 units and 4 areas (see Table 5.5).

Table 5.5: Subject Domain Concepts covered in the Ontology

Area	Units	Topics
Discrete Structures	6	45
Programming Fundamentals	5	32
Algorithms and Complexity	11	71
Architecture and Organization	9	55
Operating Systems	12	71
Net-Centric Computing	9	79
programming languages	11	75
Human-Computer Interaction	8	47
Graphics and Visual Computing	11	84
Intelligent Systems	10	106
Information Management	14	93
Social and Professional Issues	10	46
Software Engineering	12	85
Computational Science	4	61

The use of ontologies for structuring the Domain Concept Ontology is commonly used in AEHS, since it provides a standard-based way for knowledge representation [125], [126], [127]. A partial view of the concept hierarchy in the domain ontology in use is shown in Figure 5.2.

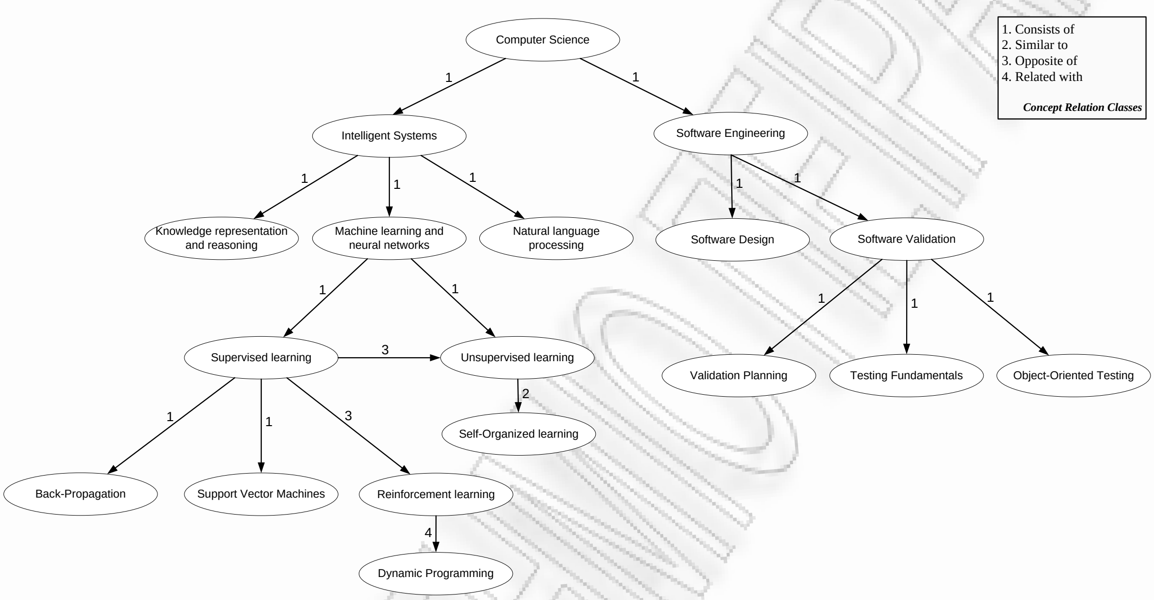

Figure 5.2: Partial View of Concept Hierarchy in the Domain Concept Ontology in use

For the description of the relations between the subject domain concepts we used four classes of concept relationships, as shown in Figure 5.2, namely:

- "Consists of", this class relates a concept with its sub-concepts
- "Similar to", this class relates two concepts with the same semantic meaning
- "Opposite of", this class relates a concept with another concept semantically opposite from the original one
- "Related with", this class relates concepts that have a relation different from the above mentioned

Furthermore, for the definition of the Learning Goals Hierarchy in our simulations, we have used again the ACM Computing Curricula for Computer Science, which defines for each subject domain concept associated learning objectives [22]. From this list of learning objectives we have created a Learning Goals Hierarchy which is presented in Figure 5.3. We then associated each topic of the 950 topics included in the Domain Concept Ontology in use with at least one node of the generated Learning

Goals Hierarchy, so as to provide a connection between learning goals and concepts of the particular Domain Concept Ontology in hand.

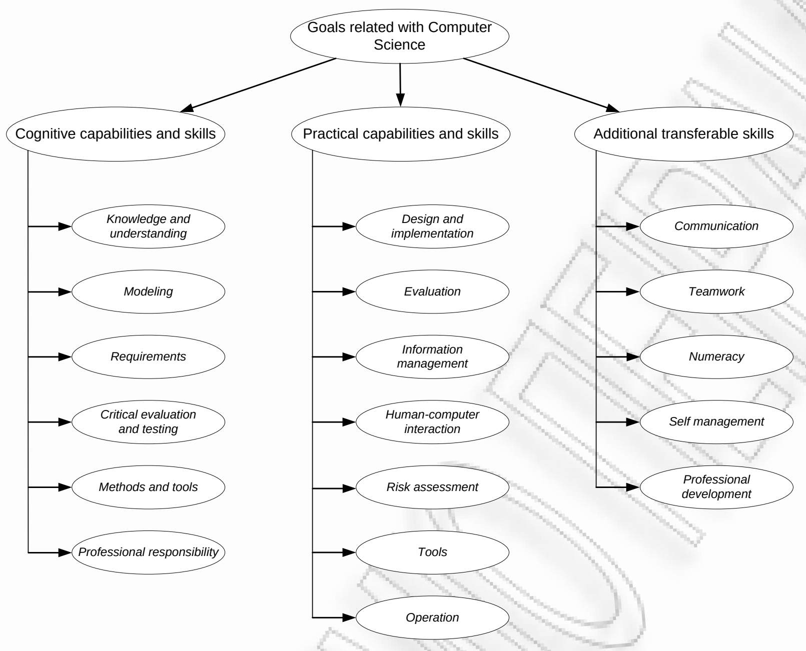

Figure 5.3: Learning Goals Hierarchy (ACM Computing Curricula for C.S.)

5.3.4. Simulating the AM of an AEHS

The goal of our experiments is to validate the use and measure the performance of our decision-based approach for adaptive learning objects selection and sequencing in AEHS. Performance evaluation in this context means measuring (a) how well our semi-automated approach fits the decision function to the provided model adaptation decisions (training data), and (b) how well this decision function responds to decision cases not known during the training process (generalisation capacity).

As a result, we need to produce model adaptation decisions for both learning object selection and sequencing and compare them with the corresponding response of our decision-based approach. Some of these model adaptation decisions will be used for training our method, and some will be used for measuring its' generalisation capacity.

In the first evaluation phase, the Adaptation Model (AM) rules of an existing AEHS are used for generating sample adaptation decisions. In the second evaluation phase, we need to simulate the existence of an AEHS that uses as many adaptation variables as possible. Since such an AEHS does not exist, we will simulate model adaptation decisions via the use of simulated instructional designers' preference models. These models have been selected in such a way that the preference surface is complex, thus, it would be a difficult task for the decision based algorithm to fit the training data.

To achieve this, we use as an instructional designers' preference model a multi-variable function, with 18 variables (k). These variables model the eleven (11) elements of the Educational Resource Description Model in use (that is, the elements used from the "General" and the "Educational" IEEE LOM categories) and the seven (7) elements of the Learner Model in use [10]. We assume that the response of this function expresses the utility of a given learning object for a given learner profile (preference-based selection problem), and also we use this function for weighting the graph which represents all possible learning object sequences for a targeted learner (preference-based sequencing problem).

In our experiments, we simulate the preference models of fifteen (15) instructional designers, using the functions presented in Appendix B. In Chapter 4, we have defined the suitability/utility function $S^{L_j}\left(g^{LO_i}\right)$ of a learning object LO_i for the learner L_j as a function which varies from 0 to 1. This means that before we can use the functions presented in Appendix B as instructional designers' preference models, we need to scale them in the same value space. The normalisation formula that we use for this purpose is the following:

$F_{(f_{(x)})} = \frac{f_{(x)}^2}{1+f_{(x)}^2}$, where $f_{(x)}$ is the testing function. This formula, scales $f_{(x)} \in \Re$ to a new function $F_{(x)} \in [0,1)$, where $F_{(f_{(x)}=0)} = 0$, and $\lim_{f_{(x)} \to \pm\infty} F_{(f_{(x)})} = 1$.

For evaluating the performance in the problem of adaptive learning objects selection, we have generated a set of 1.000 learning object metadata records and a set of 100 learner profiles. For evaluating the performance in the problem of adaptive learning objects sequencing, we have generated a set of 142.500 learning object metadata records (that is, 150 simulated learning objects for each one of the 950 topics of the Domain Concept Ontology) and a set of 100 learner profiles.

In each experiment, 50% of the available learning objects metadata records, randomly selected, were used for algorithmic training and the rest 50% for measuring the generalisation, that is, the estimation capacity, of the algorithm. Similarly, in each experiment 50% randomly selected of the available learner profiles were used for algorithmic training and the rest 50% for measuring the generalisation of the algorithm.

5.4. Conclusions

As already discussed, the main drawback of the direct definition of adaptation rules is that there can be cases during the run-time execution of AEHS where no adaptation decision can be made due to insufficiency and/or inconsistency of the defined adaptation rule sets [11], [109].

The goal of the semi-automated approaches is to generate a continuous decision function that estimates the desired AEHS response, overcoming the above mentioned problem [86]. To achieve this, they use data from the implicit definition of sample adaptation rules and attempt to fit the response function on these data. Although such approaches bare the potential to provide efficient Adaptation Models, they still miss a commonly accepted framework for evaluating their performance.

In this chapter, we presented an evaluation methodology for performance evaluation of decision-based semi-automated approaches. The application of this methodology in the case of our proposed approach is presented in the next Chapter.

Chapter 6. Experiments

6.1. Introduction

In this chapter, we present the executed experiments for verifying our main hypothesis: that it is feasible to construct a semi-automated, decision-based approach, which generates a continuous decision function that estimates the desired AEHS response, aiming to overcome the above mentioned problems of insufficiency and inconsistency of the defined adaptation rule sets. These experiments follow the evaluation methodology presented in Chapter 5.

The goal of this evaluation is twofold: first, to examine whether the proposed semi-automated decision based approach is capable of extracting decision models which replicate the Adaptation Model (AM) of existing AEHS; and second, to verify that our proposed approach is robust and can be applied in cases where large-scale adaptation rule sets are needed to describe the desired AEHS response.

6.2. Extracting the AM of existing AEHS

6.2.1. The INSPIRE Case Study

Our first experiment was the application of our decision-based approach for extracting the Adaptation Model (AM) of the INSPIRE system [69]. To this end, we simulated the AM of INSPIRE and produced sample adaptation rules in the form of combinations of learning objects mapped to learner profiles, and applied the methodology presented in Chapter 4, so as to extract the AM. The INSPIRE system uses two variables from the Learner Model (namely, the Learner’s Knowledge Level and the Learner’s Learning Style) and two variables from the Educational Resource Description Model (namely, the Performance Level and the Learning Resource Type), for performing content adaptation decisions according to Table 6.1.

Figure 6.1, presents the INSPIRE’s AM dependencies of the Learning Style and Learning Resource Type in the LO utility space, whereas Figure 6.2 presents the same dependencies of the produced AM when our decision based approach is applied. From these figures we can observe that the produced adaptation model is a super class of the INSPIRE’s AM, since it contains more adaptation rules (dependencies between learning object and learner characteristics). Moreover, we can observe that the produced AM has a continuous contour in the Utility Space, which means that this AM has the ability to always propose learning objects.

Table 6.1: INSPIRE Adaptation Model Rules

Learner Attributes		**Proposed Learning Objects**	
Knowledge Level	Inadequate	Performance Level	Remember
	Mediocre)	Performance Level	Use
	Advanced	Performance Level	Find
	Proficient	Performance Level	(Not defined)
Learning Style	Activist	Learning Resource Type	Activity-oriented
	Reflector	Learning Resource Type	Example-oriented
	Theorist	Learning Resource Type	Theory-oriented
	Pragmatist	Learning Resource Type	Exercise-oriented

In [69] the authors recognise as a problem when designing the INSPIRE system, the required effort for producing learning objects which cover all the combinations introduced by the INSPIRE Adaptation Model Rules. This is due to the fact that the INSPIRE adaptation rules does not cover all the combinations of the free variables value space, e.g. what happens when a learner has Knowledge Level equal to “Advanced” and Learning Style equal to “Theorist”, but no Theory-oriented learning object with Performance Level equal to “Find” exist in the LO repository. In this case, the INSPIRE system fails to provide a response, whereas by using our proposed decision based approach, the INSPIRE would respond with a suboptimal solution which would select the LO with the maximum utility for the given learner from the available ones.

After the above experiment, the research question was to investigate if the proposed decision based approach has the capacity of extracting the Adaptation Models of other existing AEHS. To this end, we examined the case of the AHA system [8], which is presented in next section.

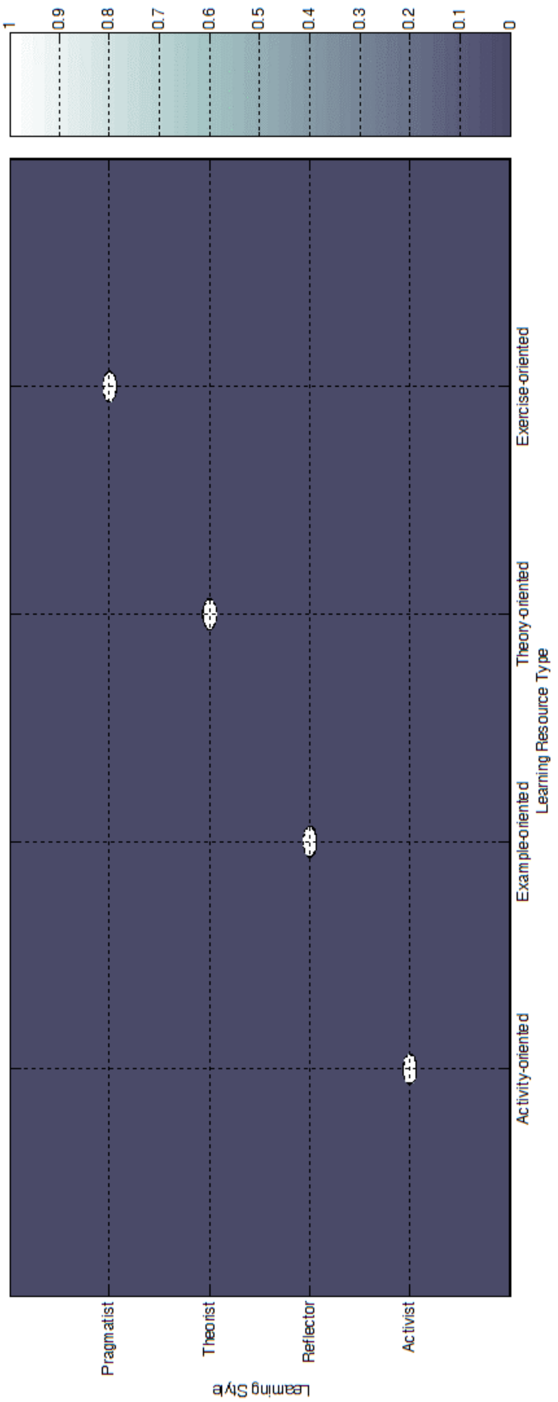

Figure 6.1: INSPIRE: Learning Style and Learning Resource Type Utility Space

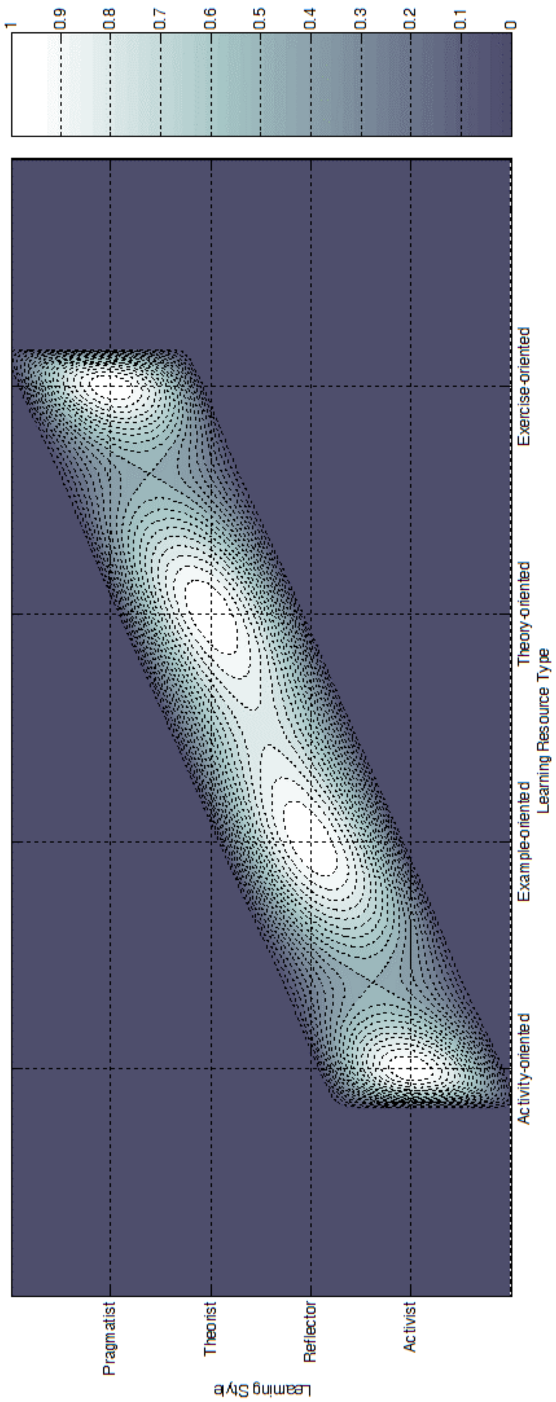

Figure 6.2: Generated Learning Style and Learning Resource Type Utility Space from INSPIRE

6.2.2. The AHA Case Study

The second experiment was the application of our decision-based approach for extracting the Adaptation Model (AM) of the AHA system [8], [29], [30], and more precisely the instructional rules introduced by Stash [113].

To this end, we simulated the AM of AHA and produced sample adaptation rules in the form of combinations of learning objects mapped to learner profiles, and applied the methodology presented in Chapter 4, so as to extract the AM. The content selection rules introduced by Stash [113] in the AHA system use two variables from the Learner Model (namely, the Learner's Modality Preference and the Learner's Learning Style) and two variables from the Educational Resource Description Model (namely, the Learning Resource Modality and the Learning Resource Type), for performing content adaptation decisions according to Table 6.2.

Table 6.2: AHA Content Selection Rules

<table>
<tr><th>Strategy #1</th><td colspan="3">Verbalizer vs. Imager Style</td></tr>
<tr><th colspan="2">Learner Attributes</th><th colspan="2">Proposed Learning Objects</th></tr>
<tr><td rowspan="3">Modality Preference (VERBvsIM)</td><td>VERBvsIM <= 30</td><td>Learning Resource Modality</td><td>Image</td></tr>
<tr><td>30 < VERBvsIM < 70</td><td>Learning Resource Modality</td><td>(No preference)</td></tr>
<tr><td>70 <= VERBvsIM</td><td>Learning Resource Modality</td><td>Text</td></tr>
<tr><th>Strategy #2</th><td colspan="3">Activist vs. Reflector Style</td></tr>
<tr><th colspan="2">Learner Attributes</th><th colspan="2">Proposed Learning Objects</th></tr>
<tr><td rowspan="2">Learning Style</td><td>Activist</td><td>Learning Resource Type</td><td>Preference Order:
1. Activity
2. Example
3. Explanation
4. Theory</td></tr>
<tr><td>Reflector</td><td>Learning Resource Type</td><td>Preference Order:
1. Example
2. Explanation
3. Theory
4. Activity</td></tr>
</table>

Figure 6.3, presents the dependencies of the Learner's Modality Preference and Learning Resource Modality in the LO utility space, in the case of AHA's "Verbalizer

vs. Imager Style" strategy, whereas Figure 6.4 presents the same dependencies of the produced AM when our decision based approach is applied.

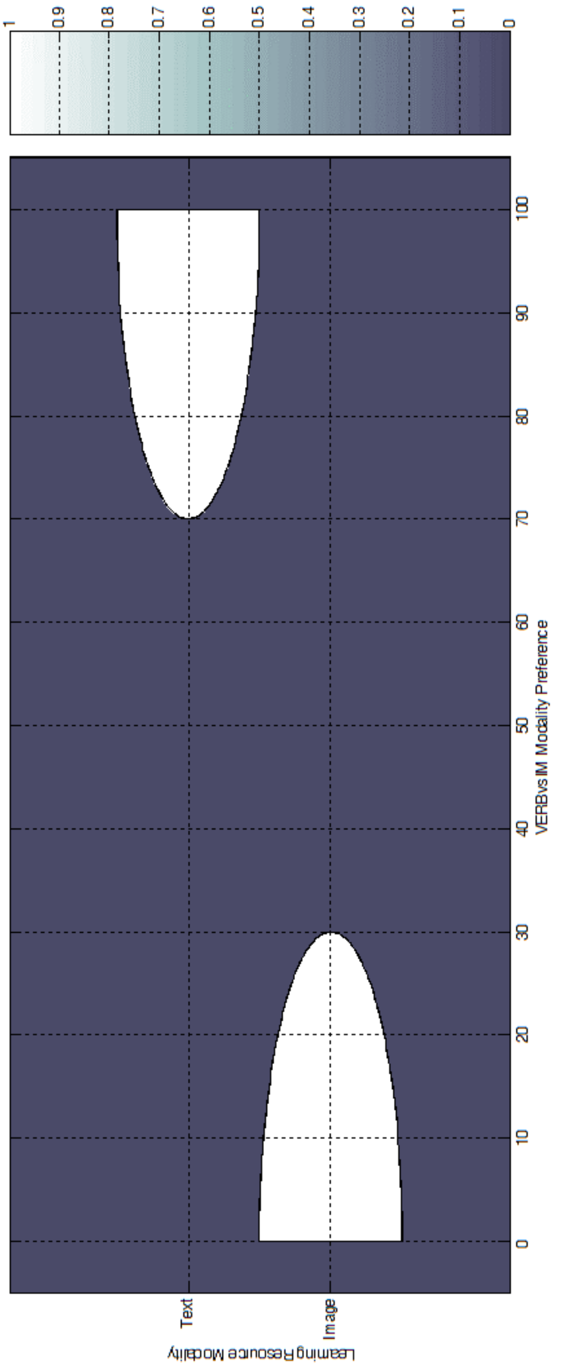

Figure 6.3: AHA Verbalizer vs. Imager Style Content Selection Strategy Utility Space

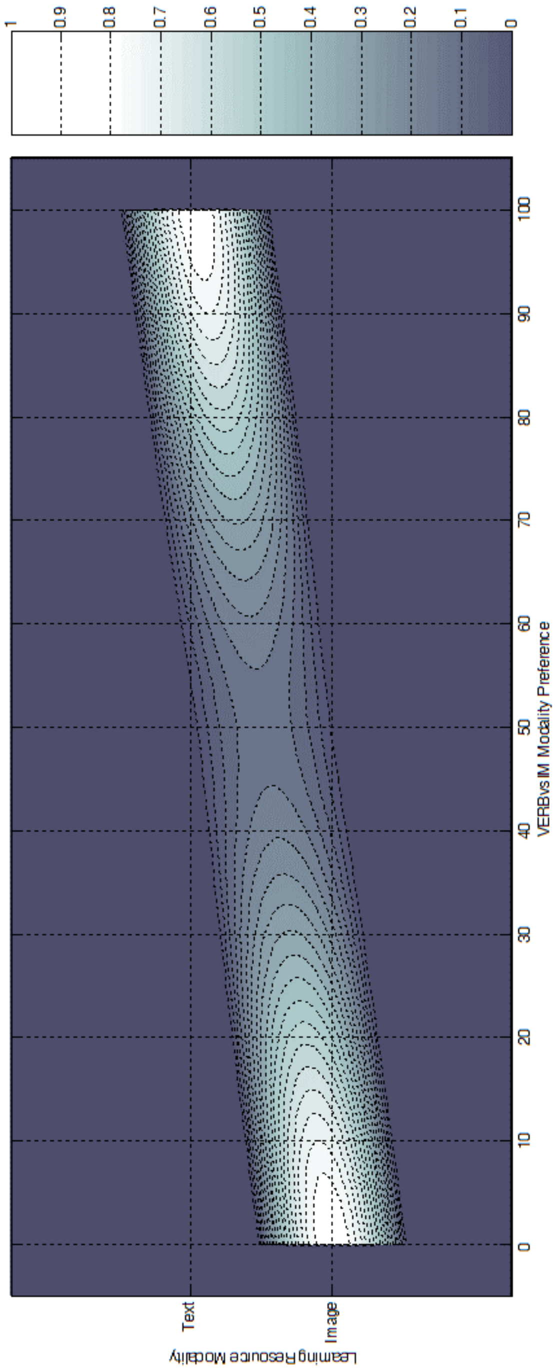

Figure 6.4: Generated Verbalizer vs. Imager Style Content Selection Strategy Utility Space

Moreover, Figure 6.5, presents the dependencies of the Learner's Learning Style and Learning Resource Type in the LO utility space, in the case of AHA's "Activist vs. Reflector Style" strategy, whereas Figure 6.6 presents the same dependencies of the produced AM when our decision based approach is applied.

From these figures we can again observe that the produced adaptation models are super classes of the AHA's AM, since they contain more adaptation rules (dependencies between learning object and learner characteristics).

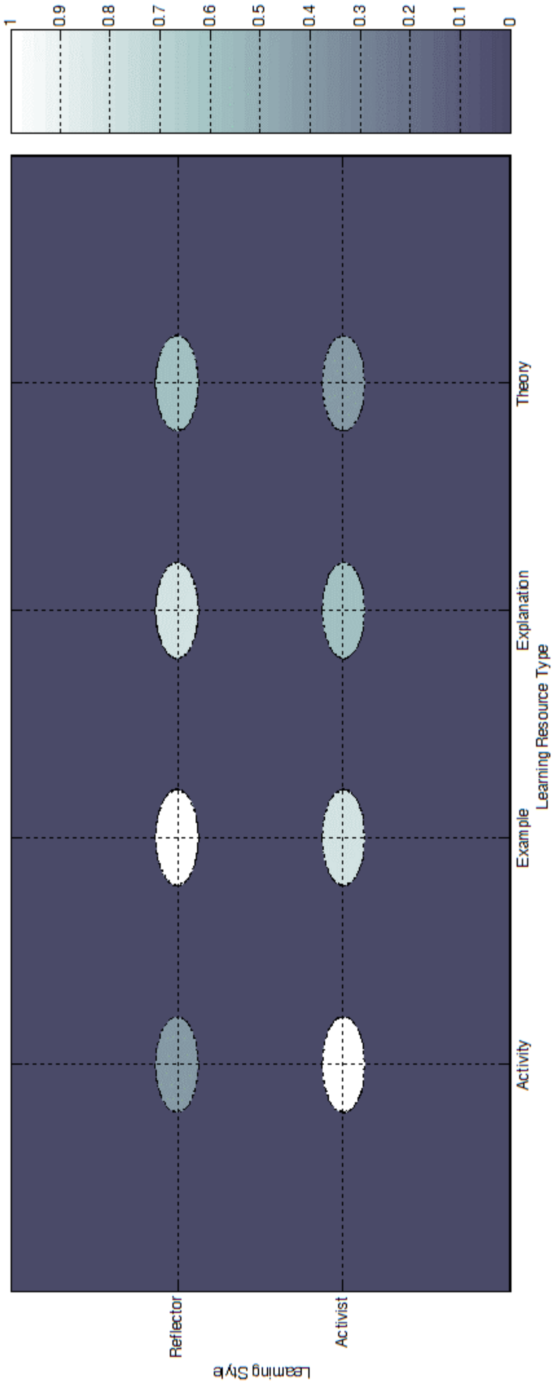

Figure 6.5: AHA Activist vs. Reflector Style Content Selection Strategy Utility Space

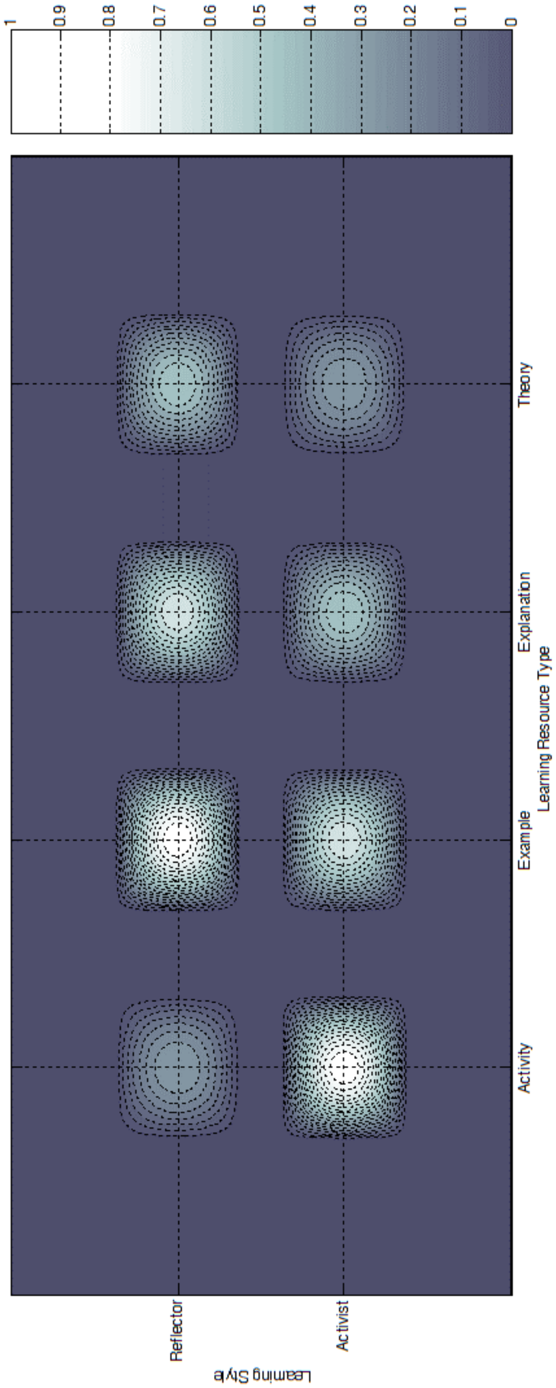

Figure 6.6: Generated Activist vs. Reflector Style Content Selection Strategy Utility Space

After the above experiment, the research question was to investigate if the proposed decision based approach has the capacity of learning more complex Adaptation Models, consisting of many free variables (such as the adaptation variables presented in Table 5.1 and Table 5.4), with complex preference surfaces, thus, it would be a difficult task for the decision based algorithm to fit the training data.

6.3. Scaling-up the Experiments

6.3.1. Robustness Testing

Before applying the proposed performance evaluation metrics it is important to investigate the robustness of our proposed approach. The scope of this testing phase is to check (a) that the optimisation problem in hand converges, and thus, is well-defined, and (b) that it is not dependent from the optimisation algorithm in use, and thus, the proposed approach is robust.

To this end, we have used four optimisation algorithms, namely, the Polak-Ribiere (OP #1) , the Accelerated Steepest Descent (OP #2), the DFP (OP #3) and the BFGS (OP #4) algorithm (for details see Appendix A), as well as, four neural networks trained using also the above mentioned optimisation algorithms respectively, for all the simulated instructional designers' preference model cases.

Since, the algorithmic training time is critical in AEHS where the Adaptation Model is dynamically updated during the execution phase, in the robustness testing we have also measured the training time of each algorithm/neural network used.

In order to be transparent from the machine used for the execution of the optimisation problem, the training time for each algorithm/neural network was measured in 10^7 machine cycles. A machine cycle is the time period, during which, one machine instruction is fetched from machine's memory and executed. The training time of an algorithm measured in machine cycles is always the same, independently from the machine used to execute the optimisation problem, and is given by the formula:

$$MC = \frac{TrainingTime \times \left(ClockRate / 10MHz \right)}{ClocksPerInstruction}$$

The comparison of the training time when different optimisation algorithms are applied provides evidences about the appropriate algorithm for the optimisation problem in hand.

Figures 6.7 to 6.18 present analytic experimental results for robustness testing experiments, when using as instructional designers' preference model, the model defined using the Rosenbrock, the Rastrigin, the Schwefel and the Griewangk testing functions (see also Appendix B).

Each figure presents (a) the cost function, which represents the mean %error in the calculation of the suitability/utility function, per algorithm iteration, (b) the cost function per machine cycles required, (c) the gradient of the cost function, which is used as the algorithmic training stop criterion, per algorithm iteration, and (d) the gradient of the cost function per machine cycles required.

In each case, we used different settings regarding the accuracy of the applied Line Search algorithm (see also Appendix Section A.2) and the use of Direction Reset (see also Appendix Section A.3.1.2). From Figures 6.7 to 6.18 we can observe the following:

- When using Conjugate gradient methods (Polak-Ribiere), the algorithmic training time – in terms of machine cycles – is lower than with the use of second order methods (DFP and BFGS) in most cases, whereas the BFGS algorithm is faster than the DFP.
- The Accelerated Steepest Descent converges similarly to the Polak-Ribiere algorithm, only when Direction Reset is not used.
- When Direction Reset is used Polak-Ribiere convergences faster, since it avoids cases where the directions $s^{(k)}$ are close to orthogonal to the first derivative $g^{(k)}$.
- The use of accurate Line Search (σ=0.9) increases the required computational effort, without improving the convergence. However, it reduces the overall algorithmic iterations.
- In most cases, solving the optimisation problem defined in Section 4.2 using non-linear solvers requires less machine cycles, than using a Neural Network, even with the same algorithm for neurons' weight calculation.

In all cases, the optimisation problem converges independently from the optimisation algorithm in use. However, the optimal (faster) configuration to be used in the rest experiments is the use of the Polak-Ribiere algorithm with reset and line accuracy (σ=0.1).

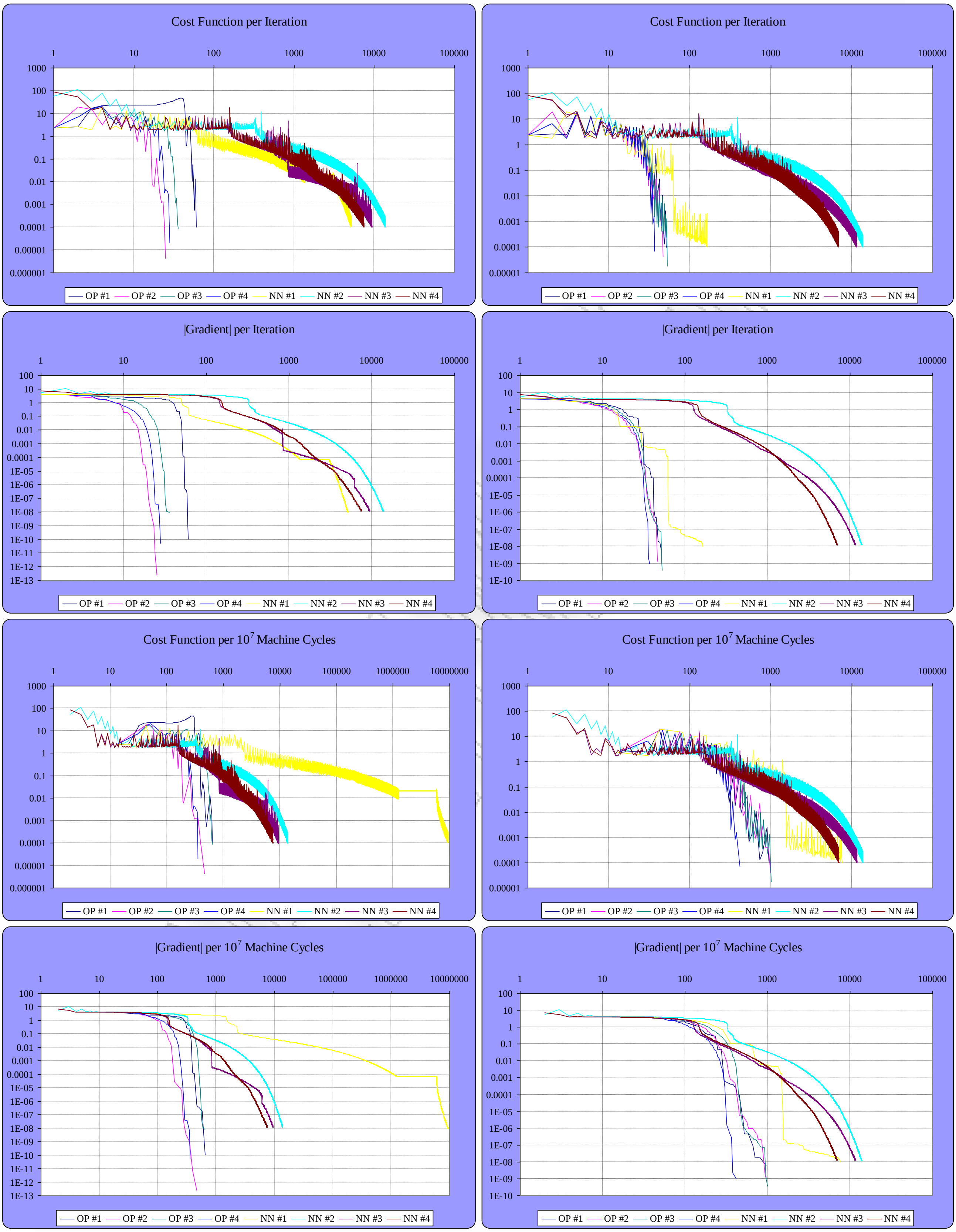

Figure 6.7: Robustness Testing Results using Rosenbrock testing function – Line Search Accuracy (σ=0.1) – (left column without Reset, right column with Reset)

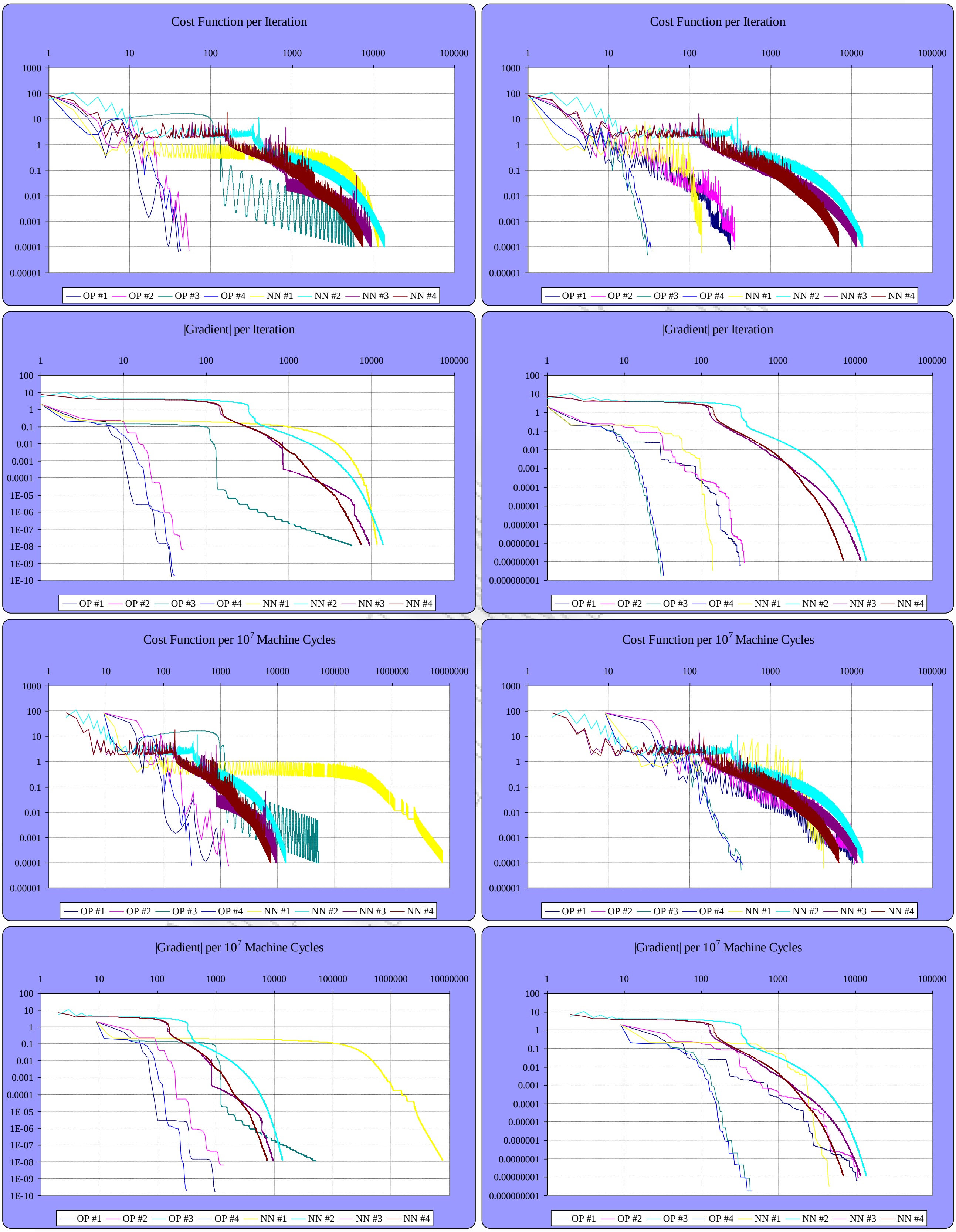

Figure 6.8: Robustness Testing Results using Rosenbrock testing function – Line Search Accuracy (σ=0.5) – (left column without Reset, right column with Reset)

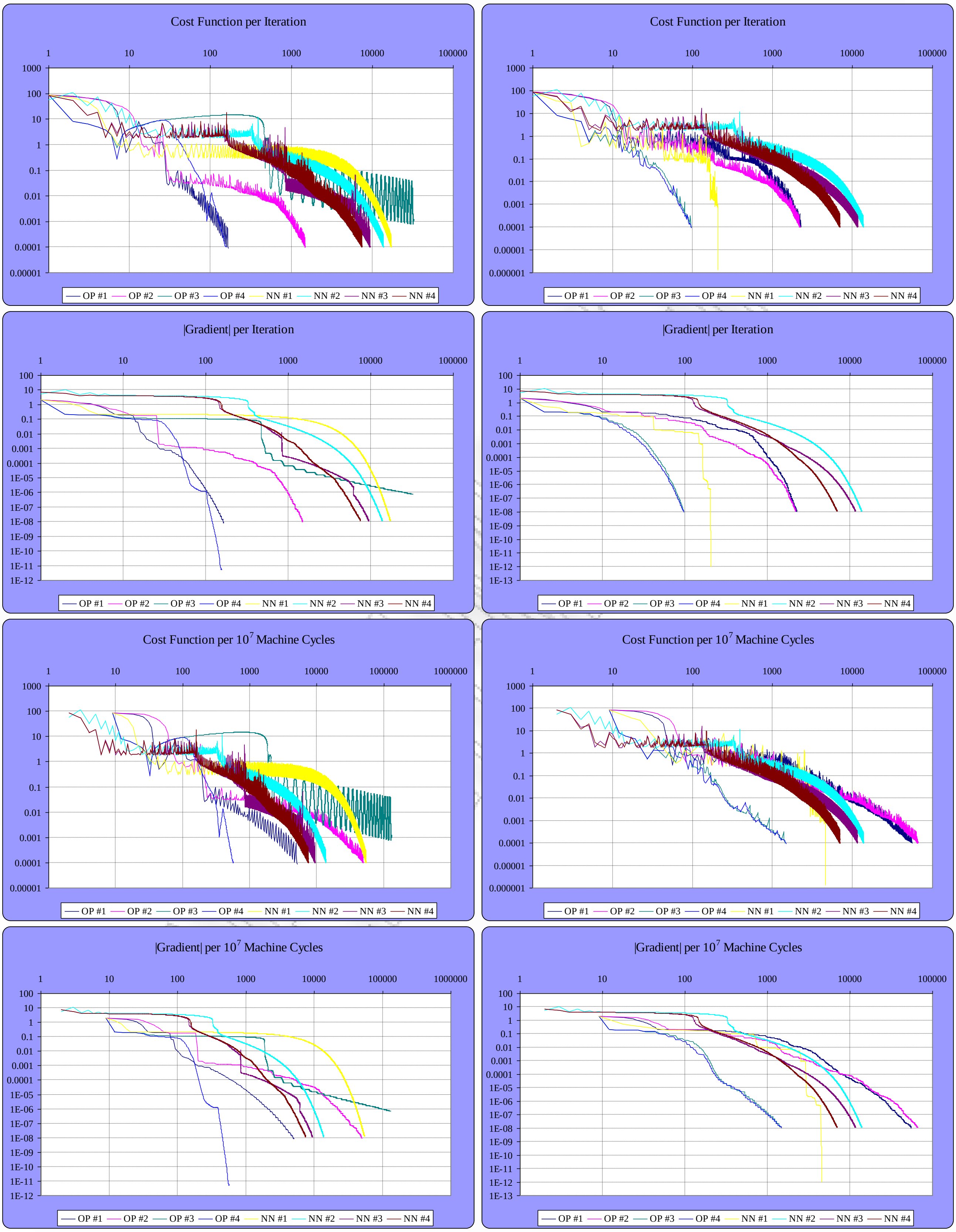

Figure 6.9: Robustness Testing Results using Rosenbrock testing function – Line Search Accuracy (σ=0.9) – (left column without Reset, right column with Reset)

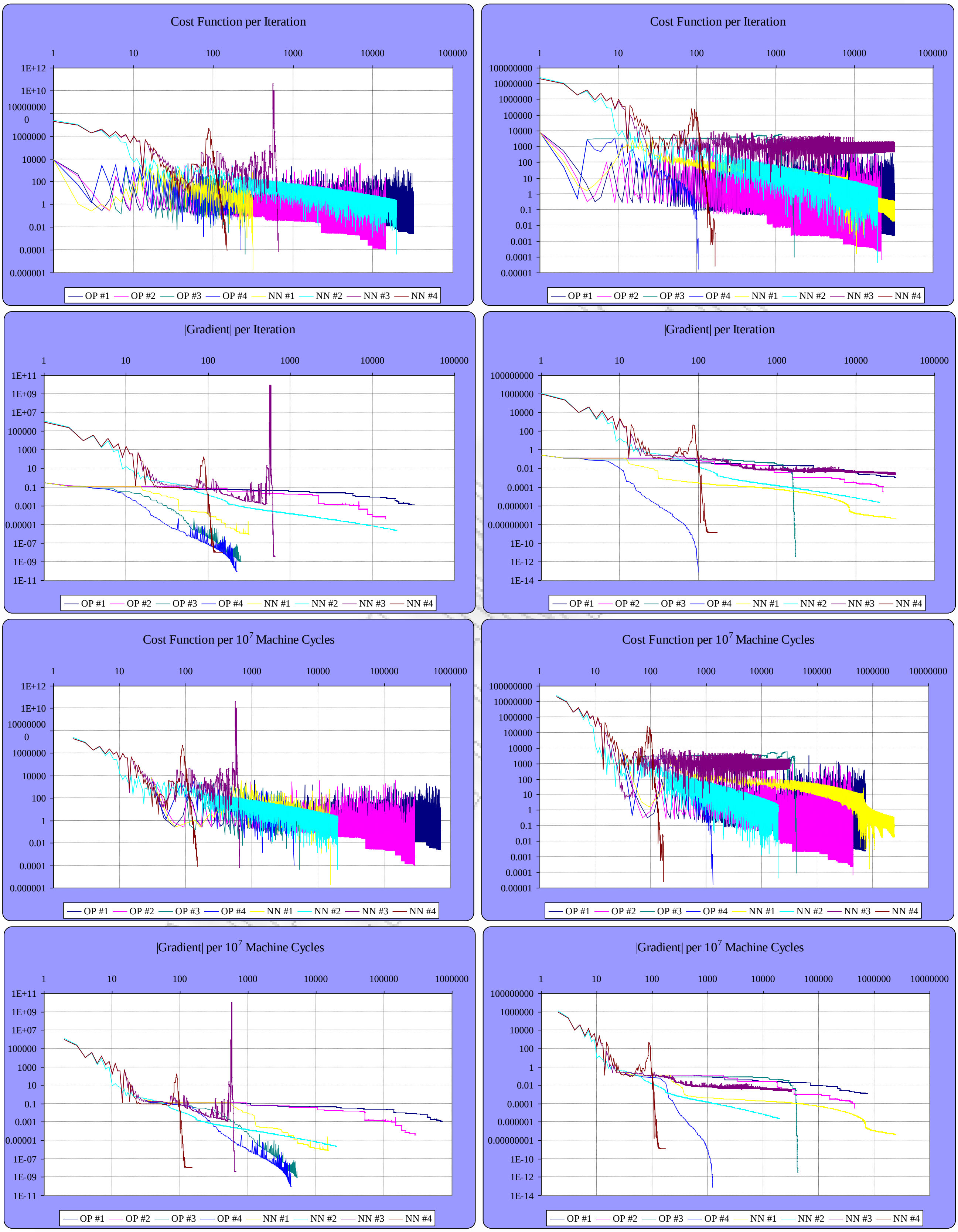

Figure 6.10: Robustness Testing Results using Rastrigin testing function – Line Search Accuracy (σ=0.1) – (left column without Reset, right column with Reset)

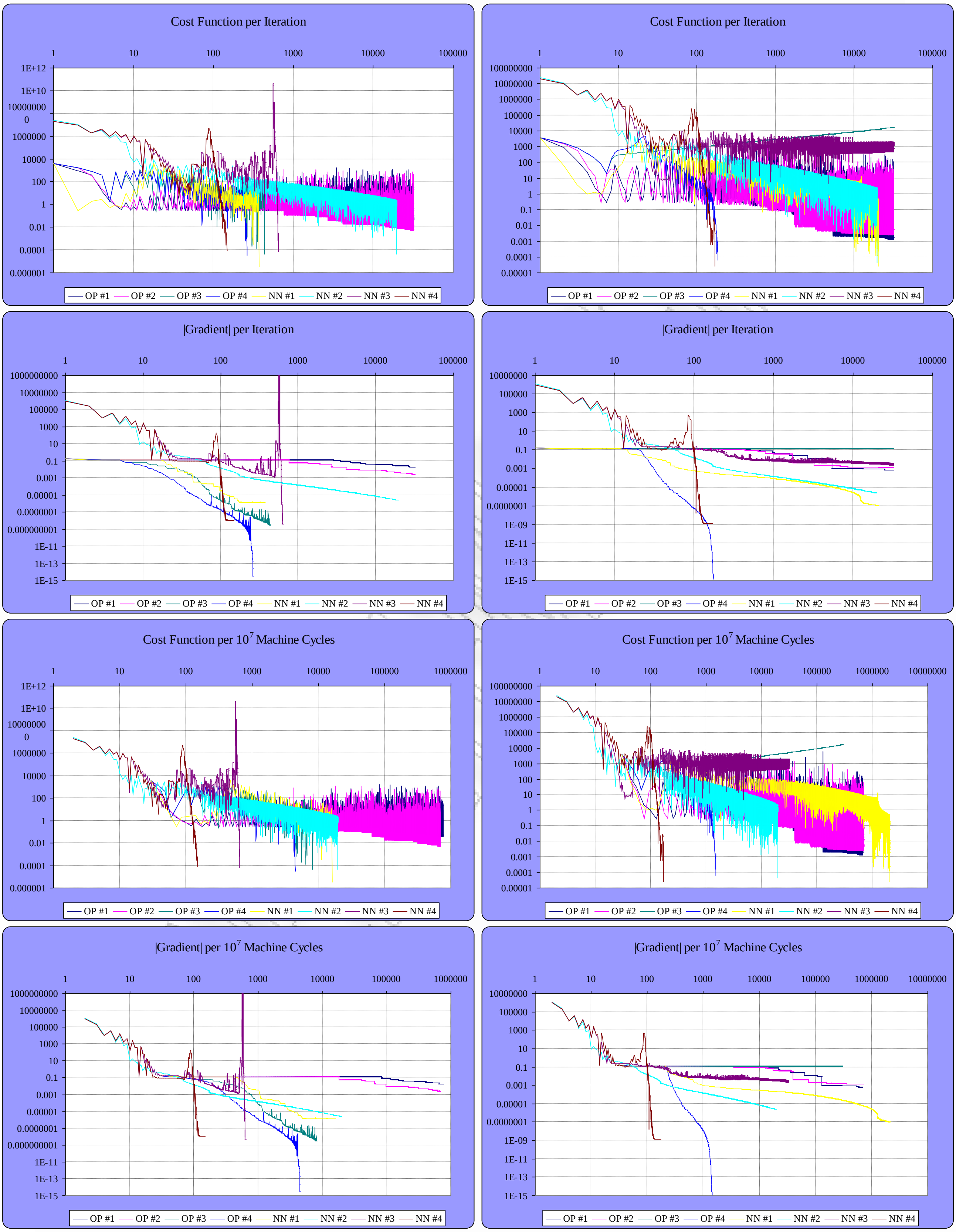

Figure 6.11: Robustness Testing Results using Rastrigin testing function – Line Search Accuracy (σ=0.5) – (left column without Reset, right column with Reset)

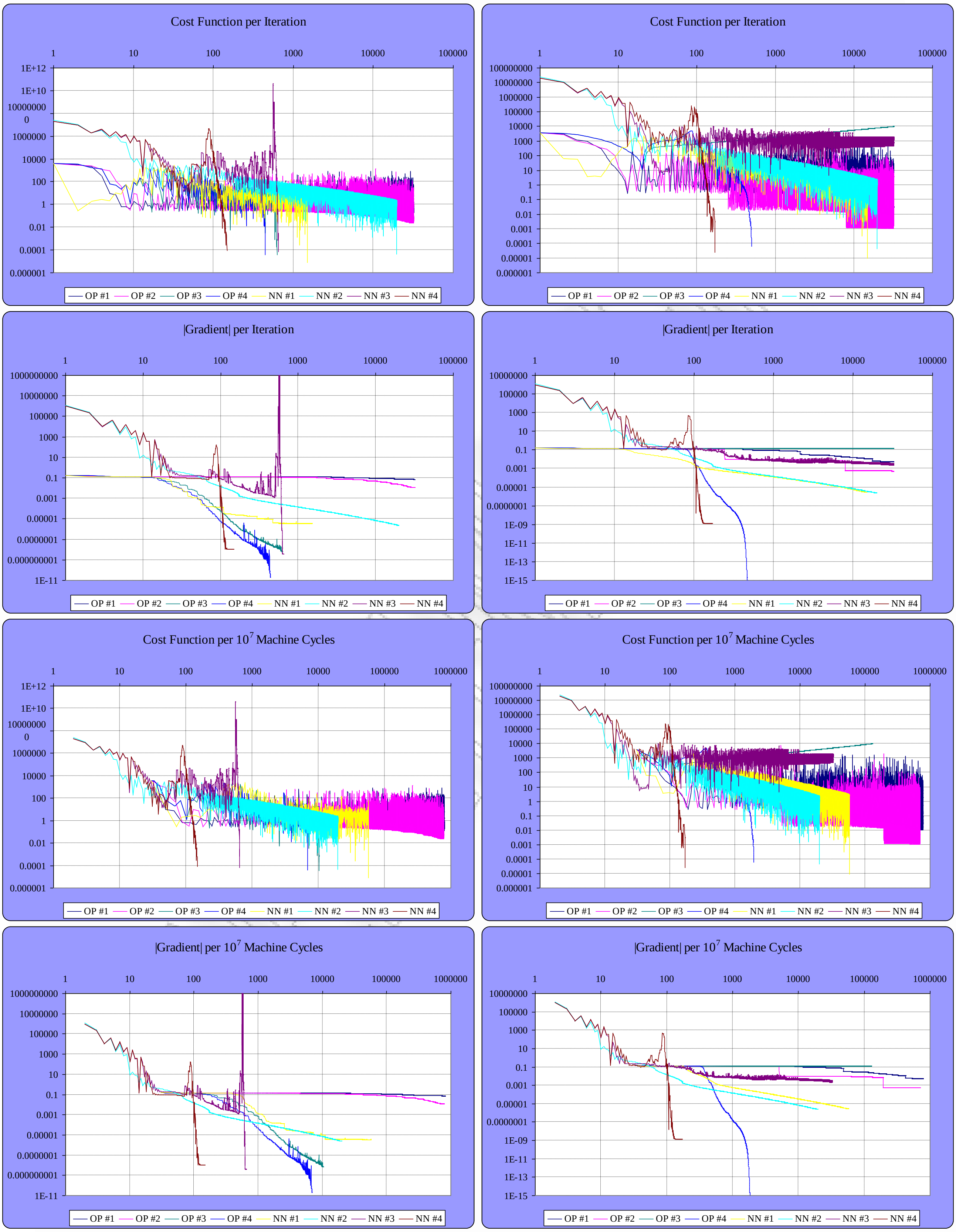

Figure 6.12: Robustness Testing Results using Rastrigin testing function – Line Search Accuracy (σ=0.9) – (left column without Reset, right column with Reset)

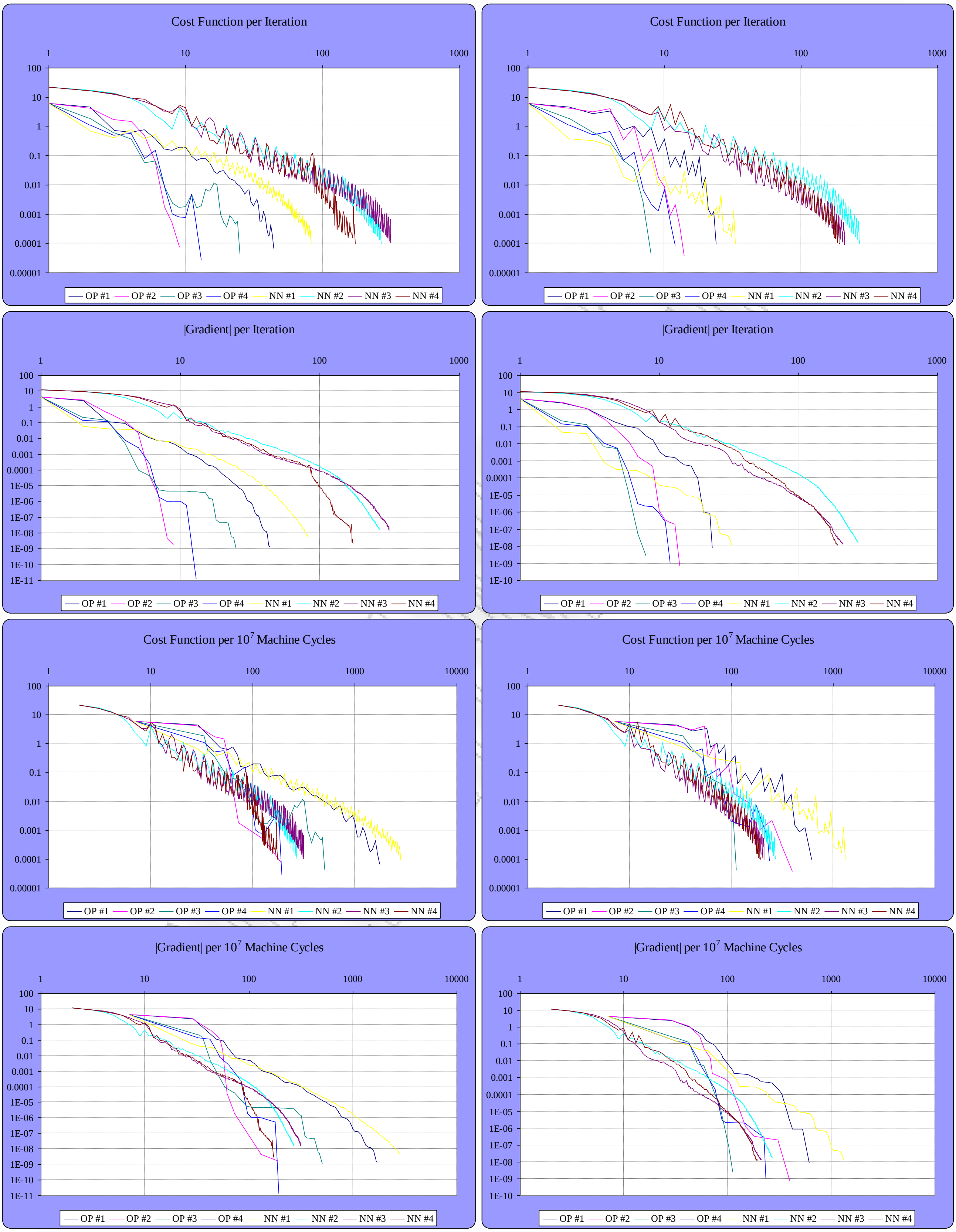

Figure 6.13: Robustness Testing Results using Schwefel testing function – Line Search Accuracy (σ=0.1) – (left column without Reset, right column with Reset)

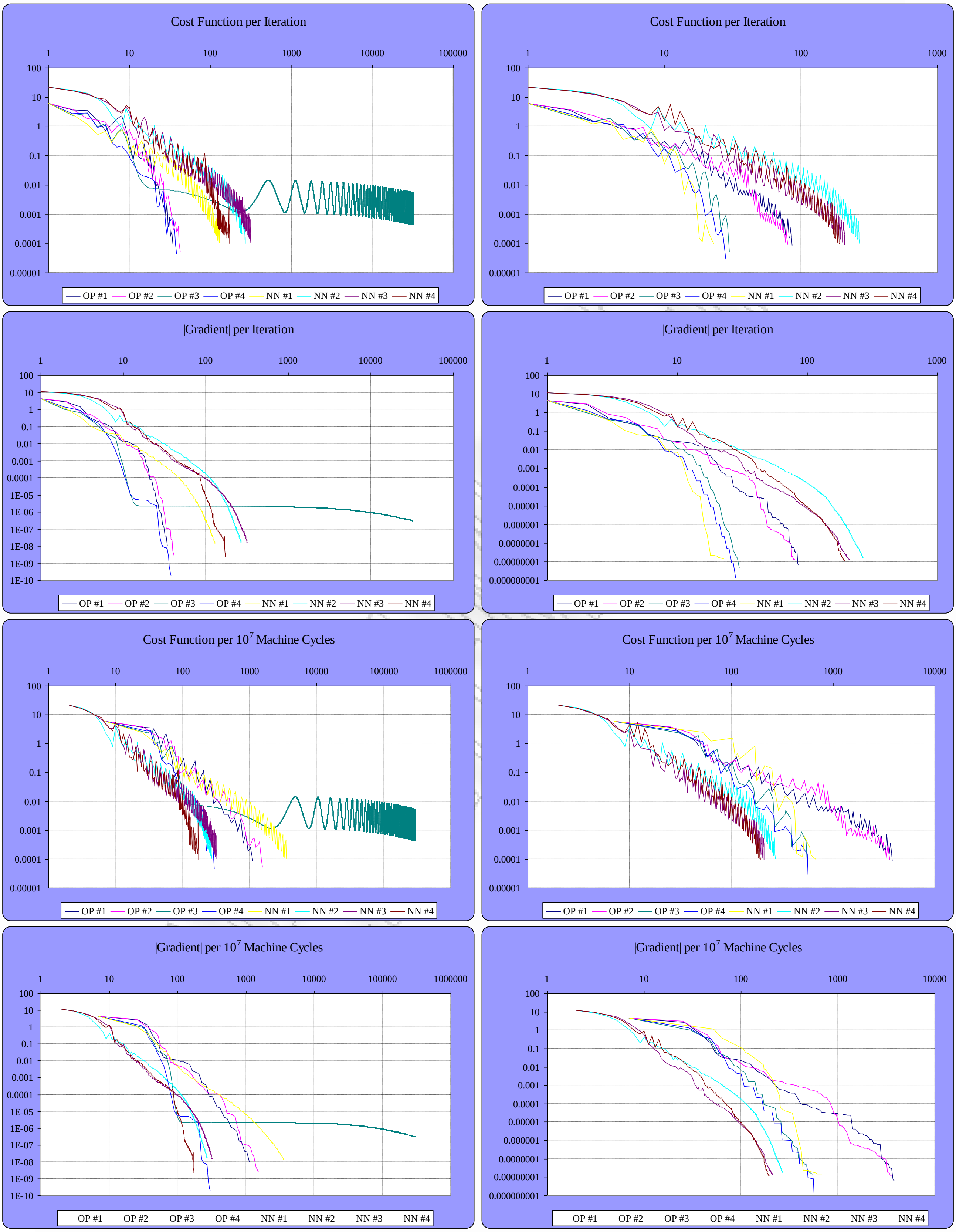

Figure 6.14: Robustness Testing Results using Schwefel testing function – Line Search Accuracy (σ=0.5) – (left column without Reset, right column with Reset)

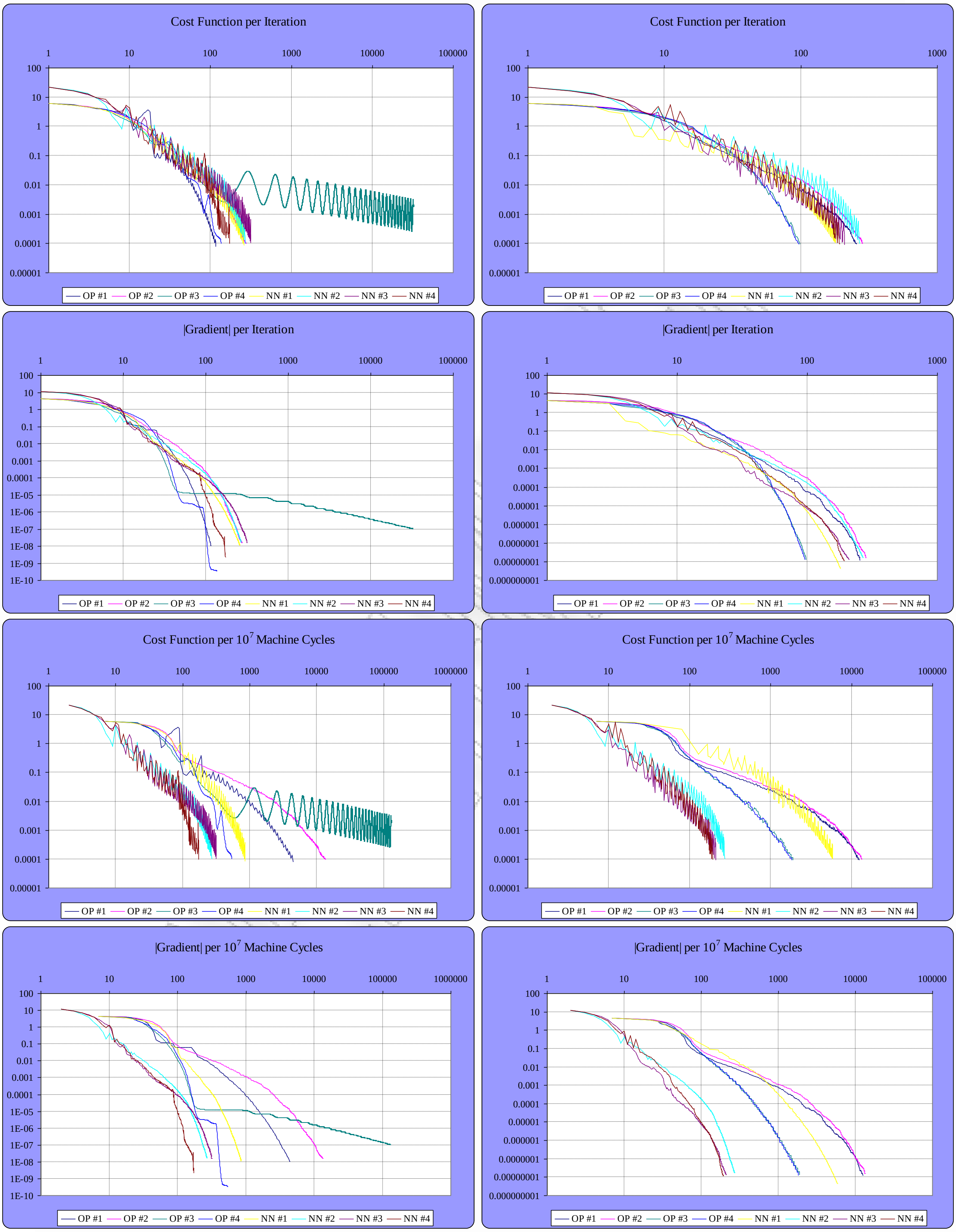

Figure 6.15: Robustness Testing Results using Schwefel testing function – Line Search Accuracy (σ=0.9) – (left column without Reset, right column with Reset)

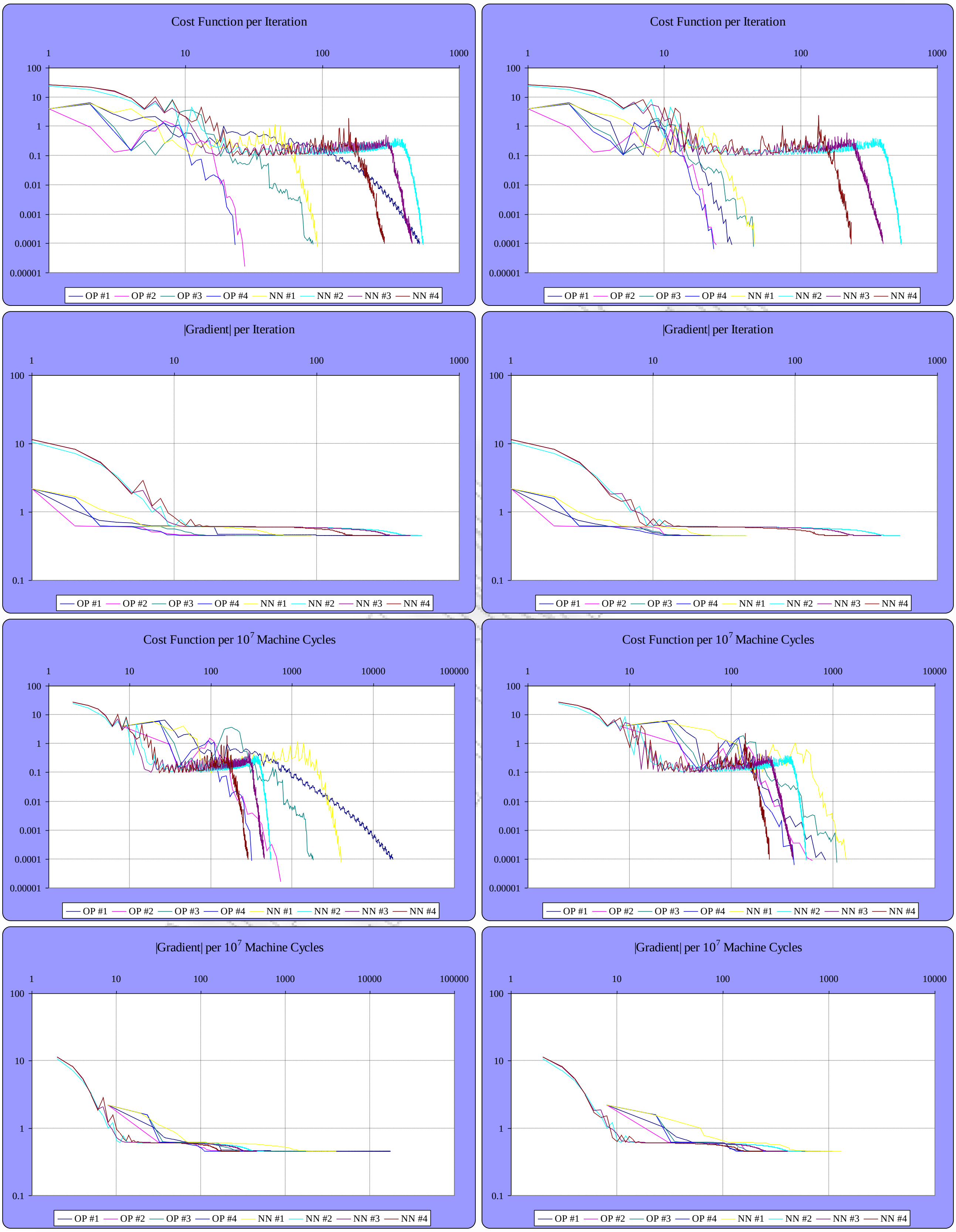

Figure 6.16: Robustness Testing Results using Griewangk testing function – Line Search Accuracy (σ=0.1) – (left column without Reset, right column with Reset)

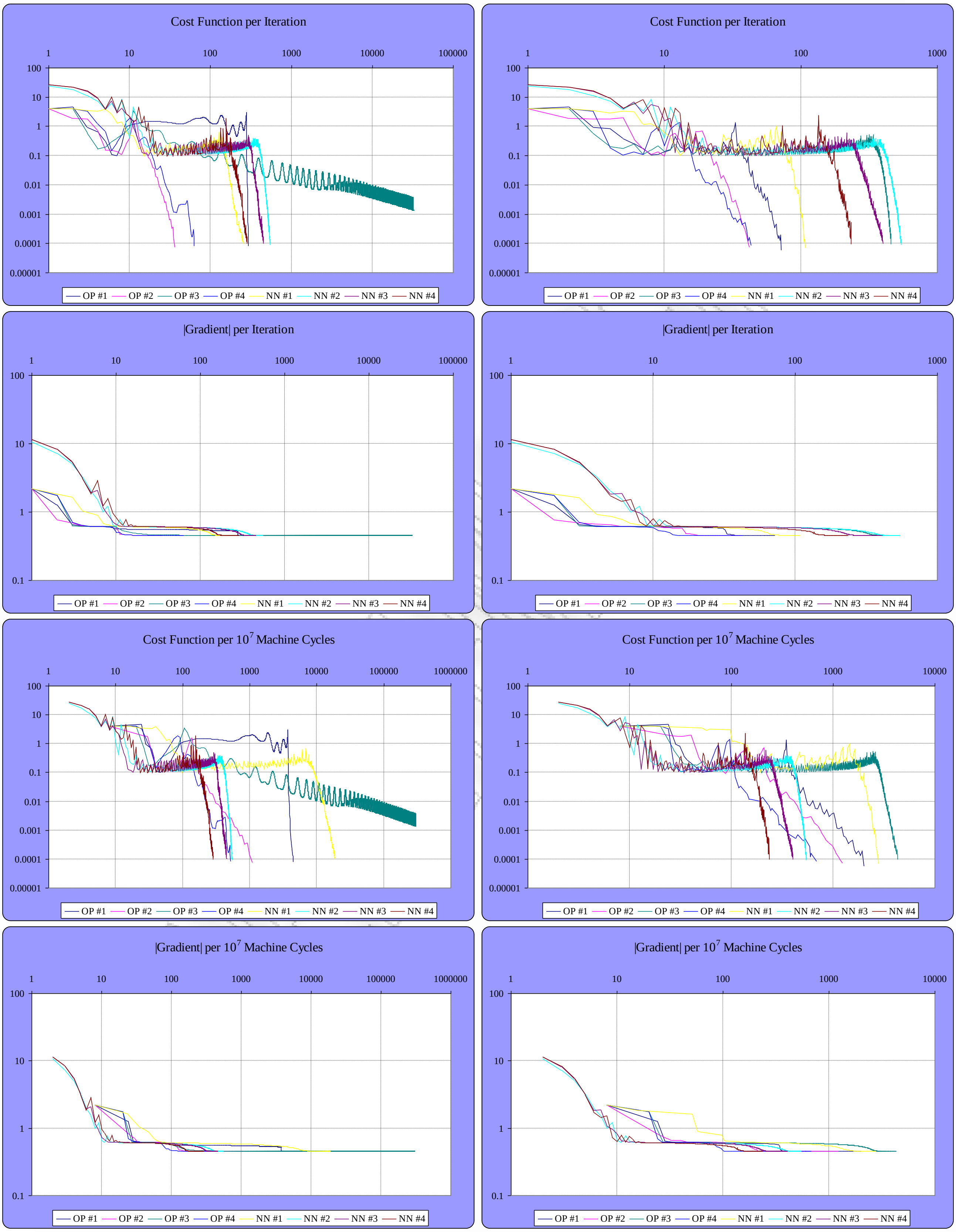

Figure 6.17: Robustness Testing Results using Griewangk testing function – Line Search Accuracy (σ=0.5) – (left column without Reset, right column with Reset)

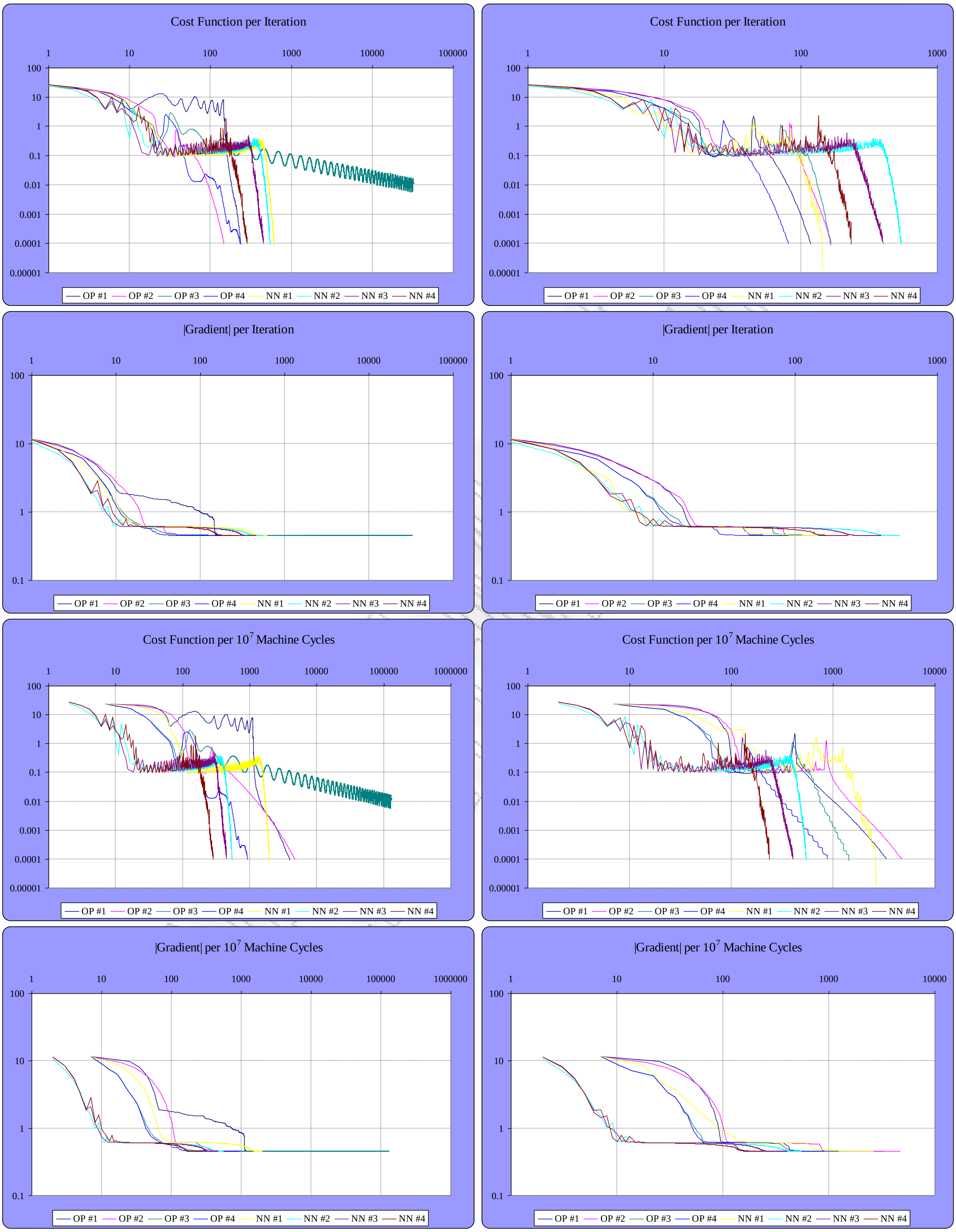

Figure 6.18: Robustness Testing Results using Griewangk testing function – Line Search Accuracy (σ=0.9) – (left column without Reset, right column with Reset)

6.3.2. Assessment of Performance Evaluation Metrics

In our experiments, we have applied the performance evaluation metrics presented in section 2.6 in the case of our proposed method for estimating the desired AEHS response (presented in Chapter 4). Our first goal is to evaluate these metrics, and then demonstrate the use of these metrics in measuring the performance of our proposed decision-based approach.

Our semi-automated approach for adaptive content selection and sequencing uses (a) a preference-based learning objects selection mechanism based on the use of a suitability function, that estimates the utility of a given learning object for a given learner, and (b) a preference-based sequencing mechanism which uses the above mentioned suitability function for weighting the graph which represents all possible learning object sequences for a targeted learner, so as to discover the optimum learning path for a given learner.

In order to compare the performance evaluation metrics presented in section 2.6, we evaluate the performance using randomly generated datasets which serve as model adaptation decisions and vary in size. The size of these datasets depends on the number of ranked learning objects for a given number of learner profiles. In real conditions, these rankings would be requested from an instructional designer. In our experiments, these rankings are the result of the application of the simulated instructional designers' preference models presented in Appendix B.

As already described, the datasets were divided into two subsets: the training dataset, which was used for algorithmic training and for evaluating the performance during the training process, and the generalisation dataset, which was used for measuring the generalisation capacity of the algorithm. Each experiment was executed 100 times using a randomly selected instructional designers' preference model.

Figure 6.19 presents average selection performance results during algorithmic training, when using different simulation parameters regarding the number of learner profiles and the number of learning object metadata records used. In each experiment, the selection performance was measured when using different values of the parameter n (varying from 10 to 500), which expresses the maximum number of requested learning objects from the Media Space.

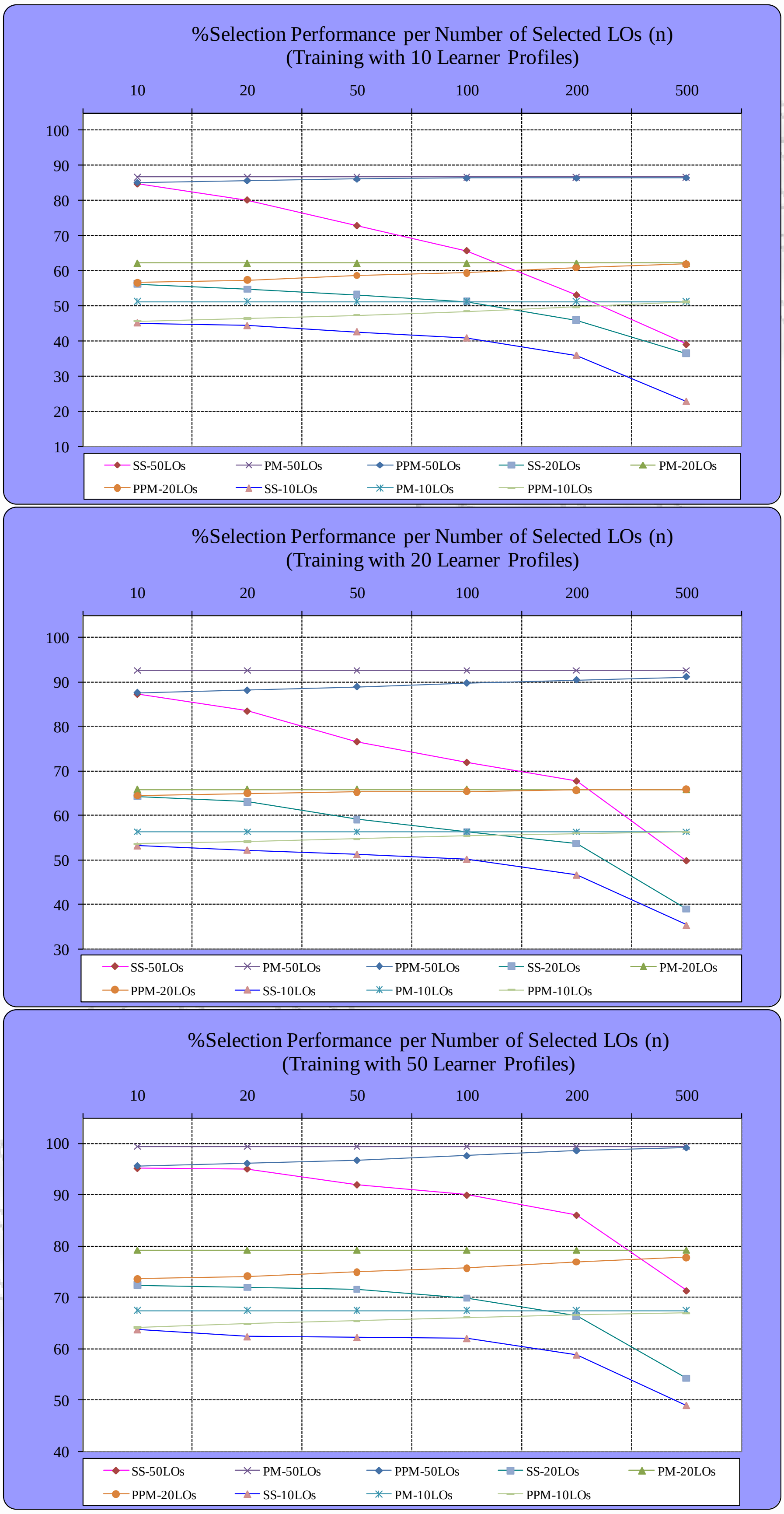

Figure 6.19: Adaptive Content Selection Performance Evaluation Metrics – Training Results

In Figure 6.19 the performance evaluation was measured using the typical Precision Metric (PM) as presented in section 2.6, the proposed alternative metric for Selection Success (SS), as well as, by applying the PM metric only on the desired sub-space of the Media Space (Partial Precision Metric, PPM).

From these results we observe the following:

a) Precision when measured with PM metric is independent from the maximum number of requested learning objects from the Media Space (selection space), as well as, from the ranking of the selected learning objects.

b) Precision when measured with PPM metric is independent from the ranking of the selected learning objects, but depends on the volume of the selection space.

c) The PPM metric tends to be equal to the PM metric when the selection space becomes bigger (n increases).

d) Performance evaluation using the PM metric is higher or equal to the performance when using the PPM metric. Also performance evaluation using the PM metric is higher or equal to the performance when using the SS metric.

e) The SS metric tents to be lower as the searching space increases, whereas PPM metric becomes higher as the searching space increases. This is due to the fact that, when the searching space increases the probability of introducing ranking errors also increases. Since the PPM metric is not dependent by the ranking of the selected learning objects, the PPM metric behaves differently from the SS metric.

The same observations apply also when measuring the generalisation capacity, as depicted in Figure 6.20. These observations verify the hypothesis that by definition the SS metric is harder than the PM or the PPM metric, which means that in the case of AEHS, where the ranking of the selected learning objects is critical, the SS metric should be used.

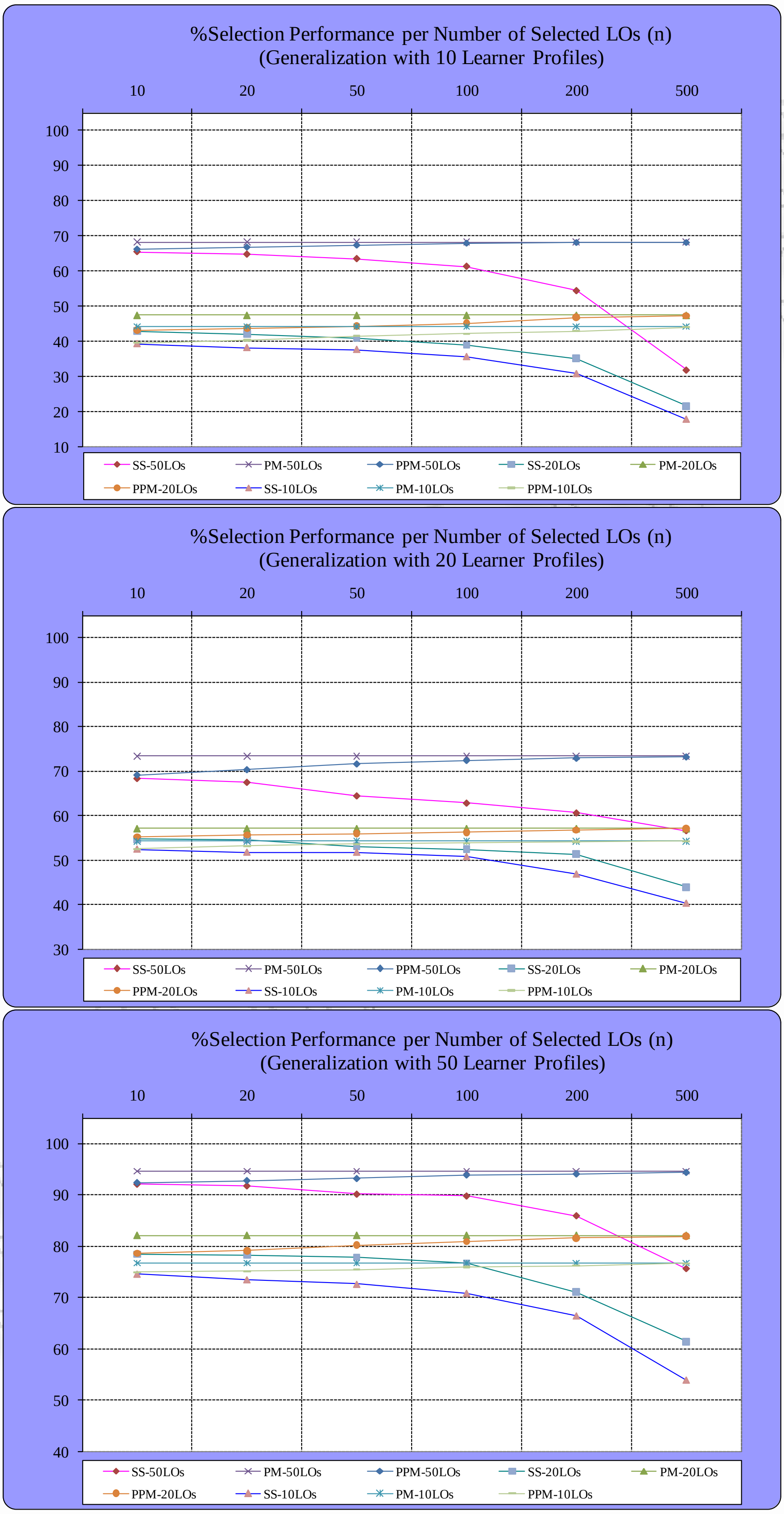

Figure 6.20: Adaptive Content Selection Performance Evaluation Metrics – Generalisation Results

6.3.3. Performance Evaluation

6.3.3.1. Adaptive Learning Object Selection

The goal of this evaluation step is to validate the use and measure the performance of our decision-based approach for adaptive learning objects selection. Performance evaluation in this context means measuring (a) how well our semi-automated approach fits the decision function to the provided model adaptation decisions (training data), and (b) how well this decision function responds to decision cases not known during the training process (generalisation capacity).

We evaluate the performance using randomly generated datasets which serve as model adaptation decisions and vary in size. The size of these datasets depends on the number of ranked learning objects for a given number of learner profiles. In real conditions, these rankings would be requested from an instructional designer. In our experiments, these rankings are the result of the application of the simulated instructional designers' preference models presented in Appendix B. As already described, the datasets were divided into two subsets: the training dataset, which was used for algorithmic training and for evaluating the performance during the training process, and the generalisation dataset, which was used for measuring the generalisation capacity of the algorithm. Each experiment was executed 100 times using a randomly selected instructional designers' preference model.

Figure 6.21 presents average selection performance results, when using constant Learner Profiles input, whereas, Figure 6.22 presents average selection performance results, when using constant Learning Objects per Learner Profile in use. In each experiment, the selection performance was measured when using different values of the parameter n (varying from 10 to 500).

From these results we observe that the selection success depends on the requested learning objects from the Media Space (n), as well as the number of the learning objects and learner instances used for algorithmic training. Additionally, for the same number of requested objects and the same number of learner profiles used, using more learning object metadata records produces higher selection success rates. Accordingly, for the same number of requested objects and the same number of learning object metadata records used, using more learner profiles produces higher selection success rates.

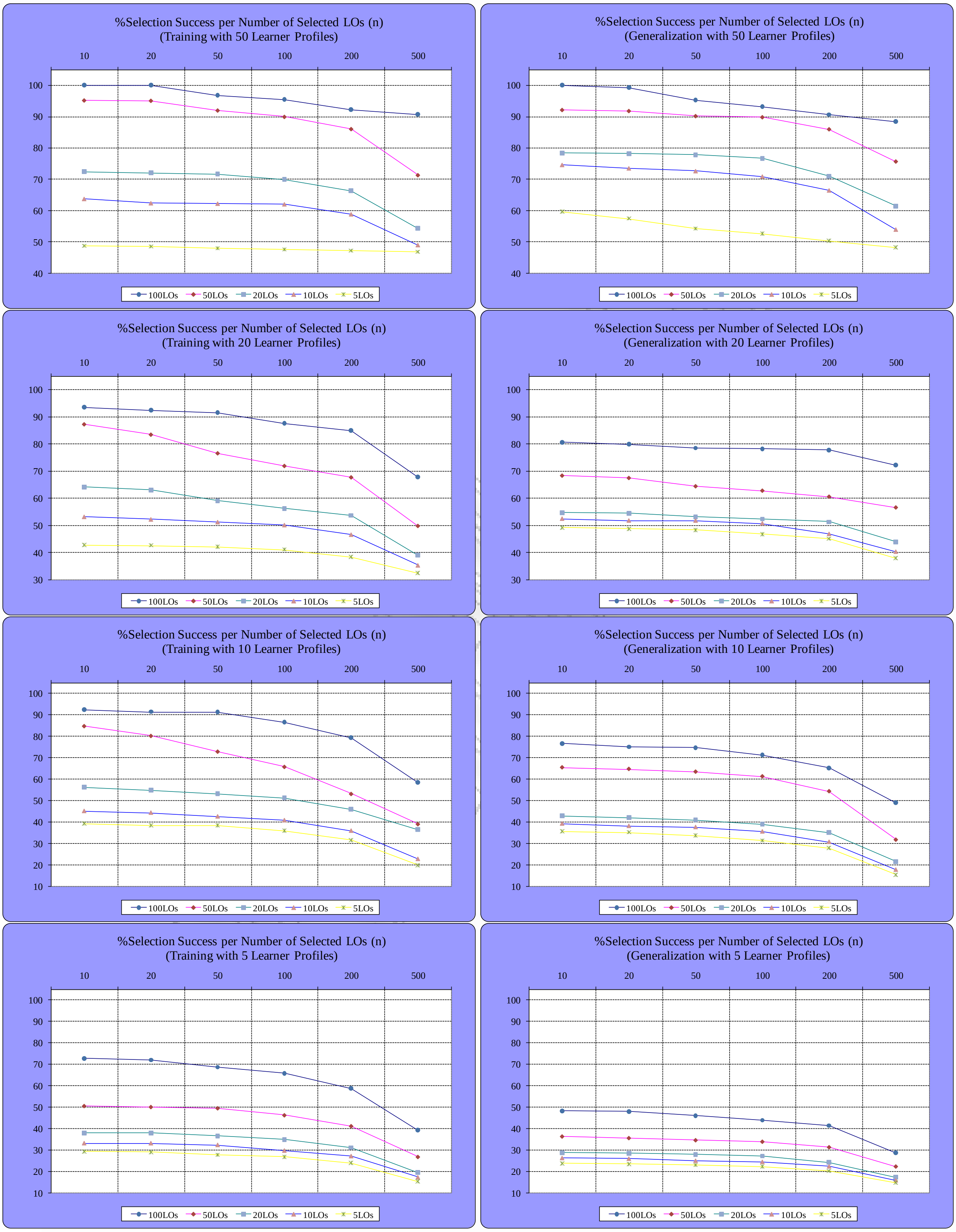

Figure 6.21: Adaptive Selection Success based on LPs input (left column: Training Results, right column: Generalisation Results)

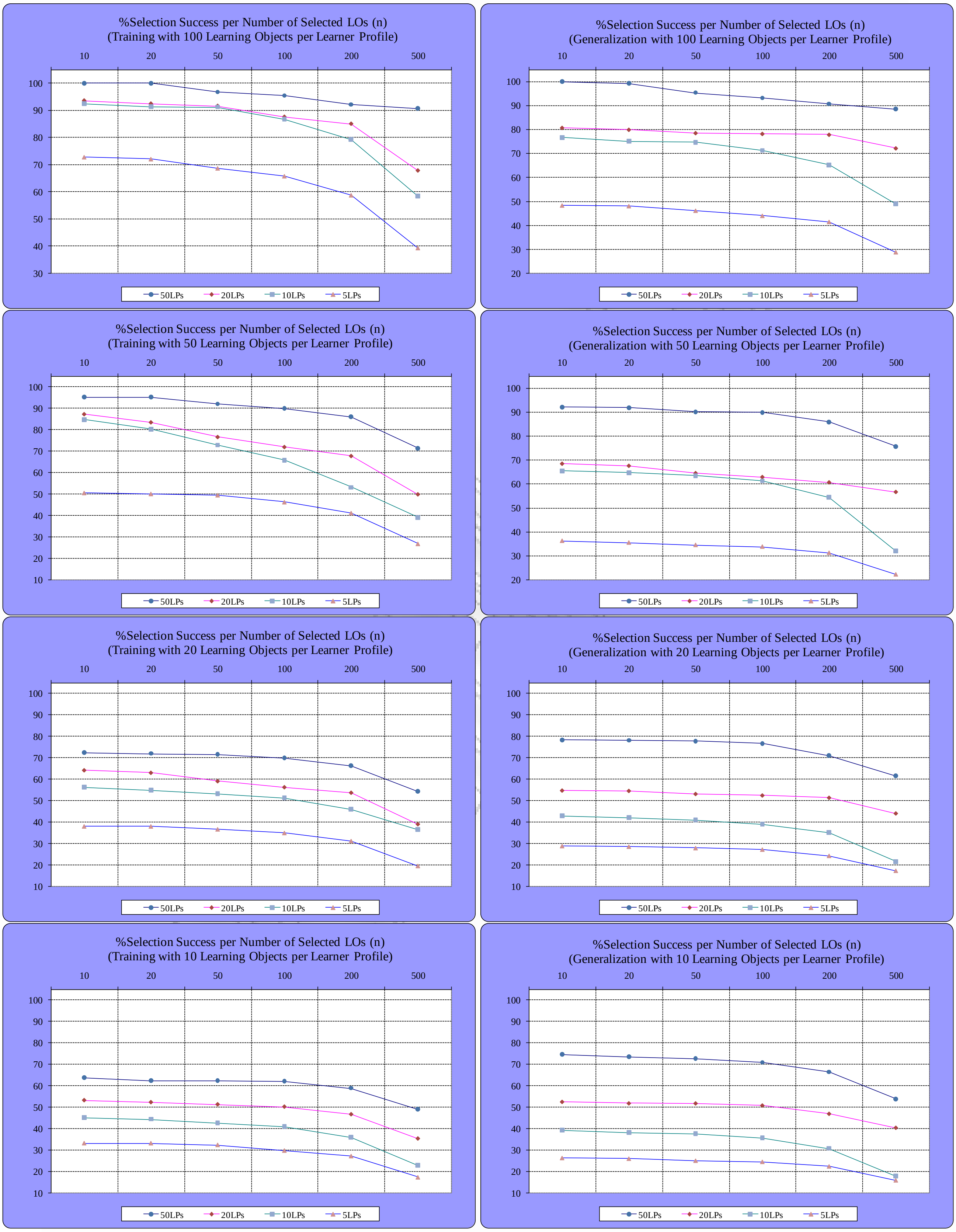

Figure 6.22: Adaptive Selection Success based on LOs input (left column: Training Results, right column: Generalisation Results)

More analysis on the results presented in Figures 6.21 and 6.22 shows that, when the desired number of learning objects (n) is relatively small (less than 20), the selected learning objects by the decision model are close to those the instructional designer would select (with success rate over 70%), when using an input set consisting of more than 500 combinations of learning objects mapped to learner profiles (calculated as the multiplication of the learning objects with the learner profiles used).

6.3.3.1.1. Investigating the influence of the required design effort

In order to investigate the influence of the explicit combinations required from the instructional designer (which are directly equivalent to the design effort required) we have executed additional experiments measuring the selection success gain per number of requested combinations. This metric provides evidences about the trade-off that an instructional designer should make between the required effort and the improvement of the selection success rate.

Figures 6.23 to 6.25 present simulation results of the design trade-off for combinations of learning object metadata records with learner profiles, with selection success over a given threshold, for different values of the desired number of learning objects (n).

From these results we observe that using a configuration of 500 combinations (which means classifying 50 learning object metadata records over 10 learner profiles or vice versa) the gain in the selection success rate is higher than using configurations with more combinations.

The machine learning algorithm uses input knowledge in order to generate a continuous decision function that estimates the desired AEHS response. This knowledge comes in the form of combinations of learning objects mapped to learner profiles. When more input knowledge is provided, the machine learning algorithm fits better the response function on these data. However, there is a limitation in this process, that is, if the algorithm is fed with too many input data, then it will over fit the response function over these data, losing its generalisation capacity.

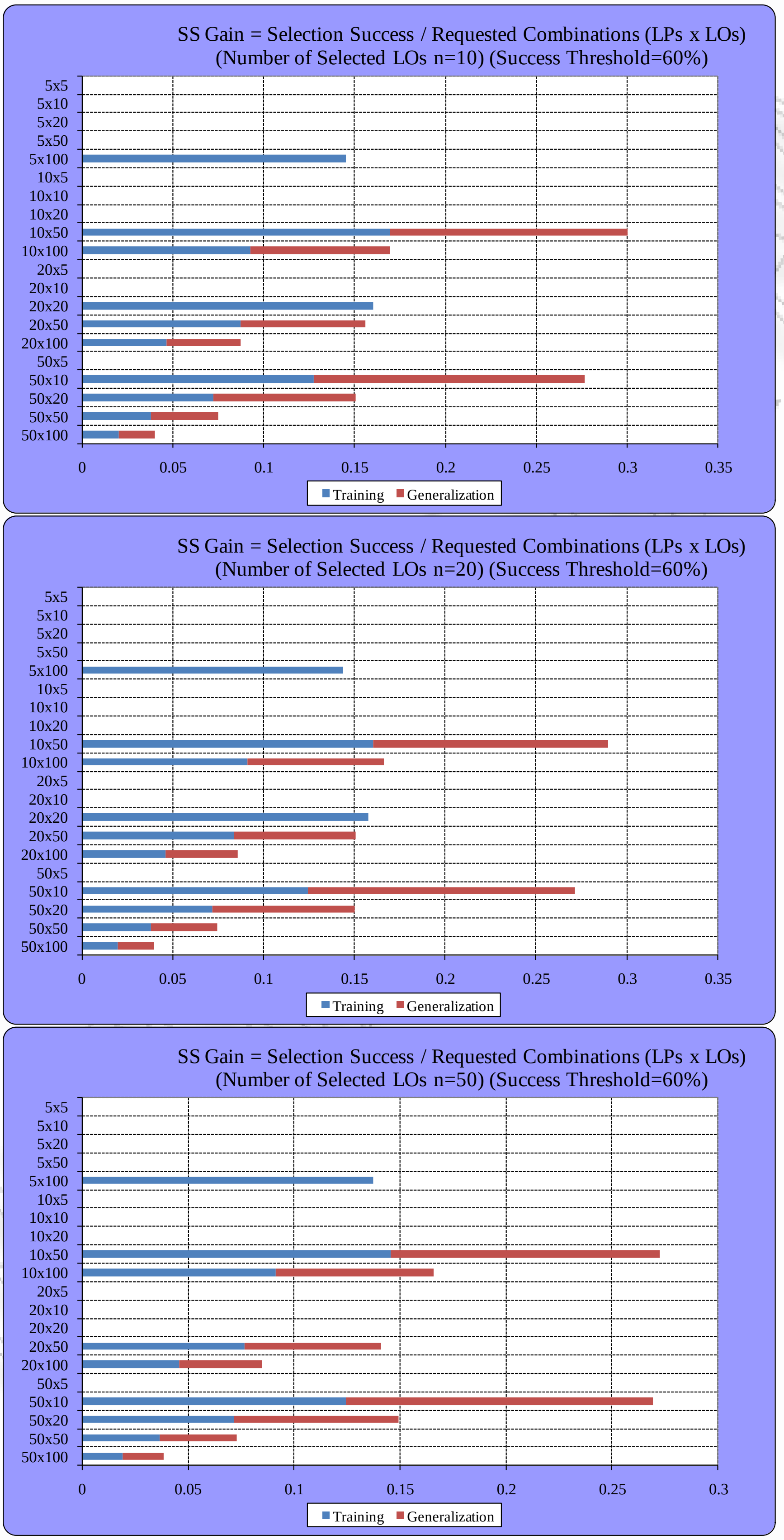

Figure 6.23: Adaptive Selection Success Gain per Requested input Combinations – Threshold=60%

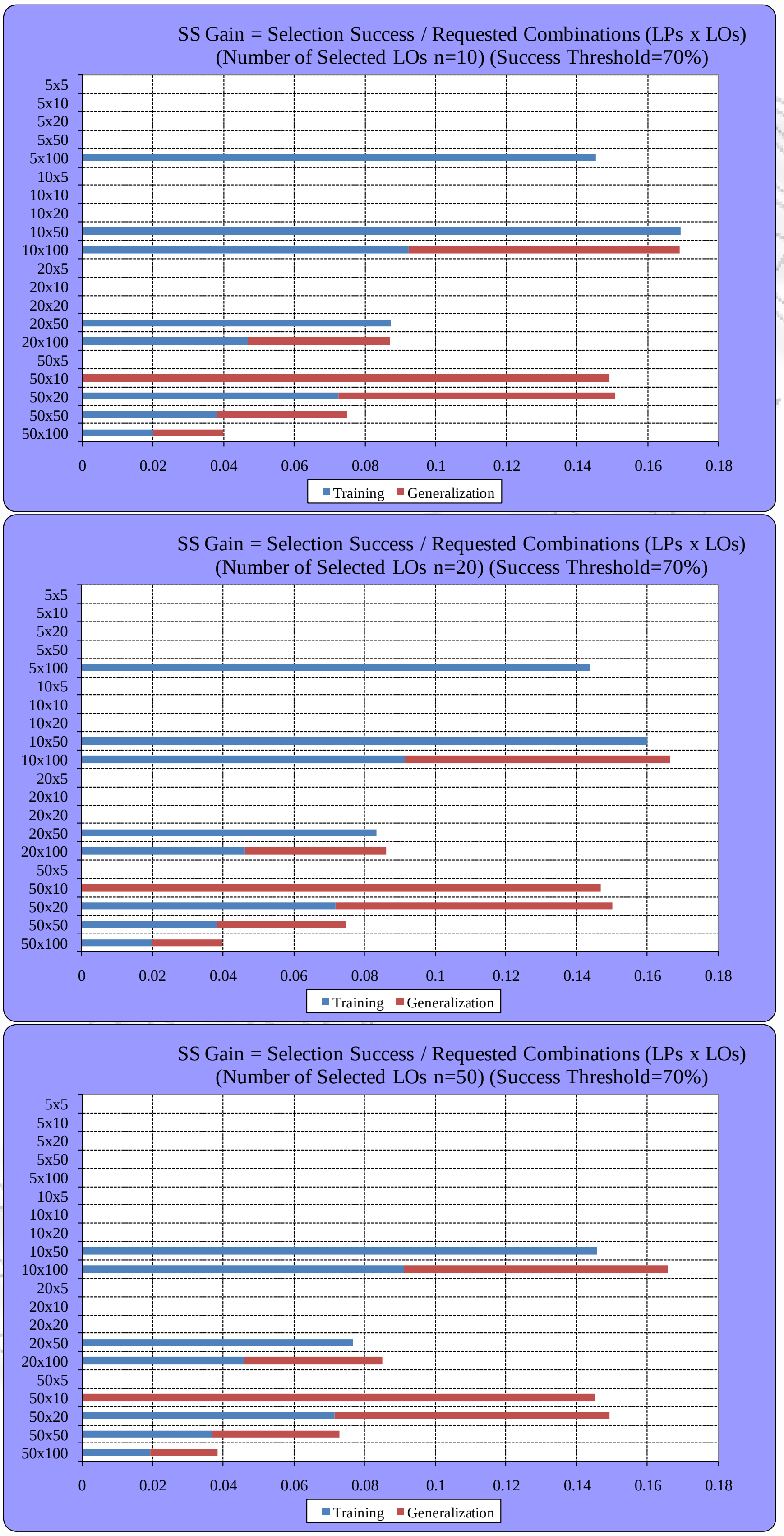

Figure 6.24: Adaptive Selection Success Gain per Requested input Combinations – Threshold=70%

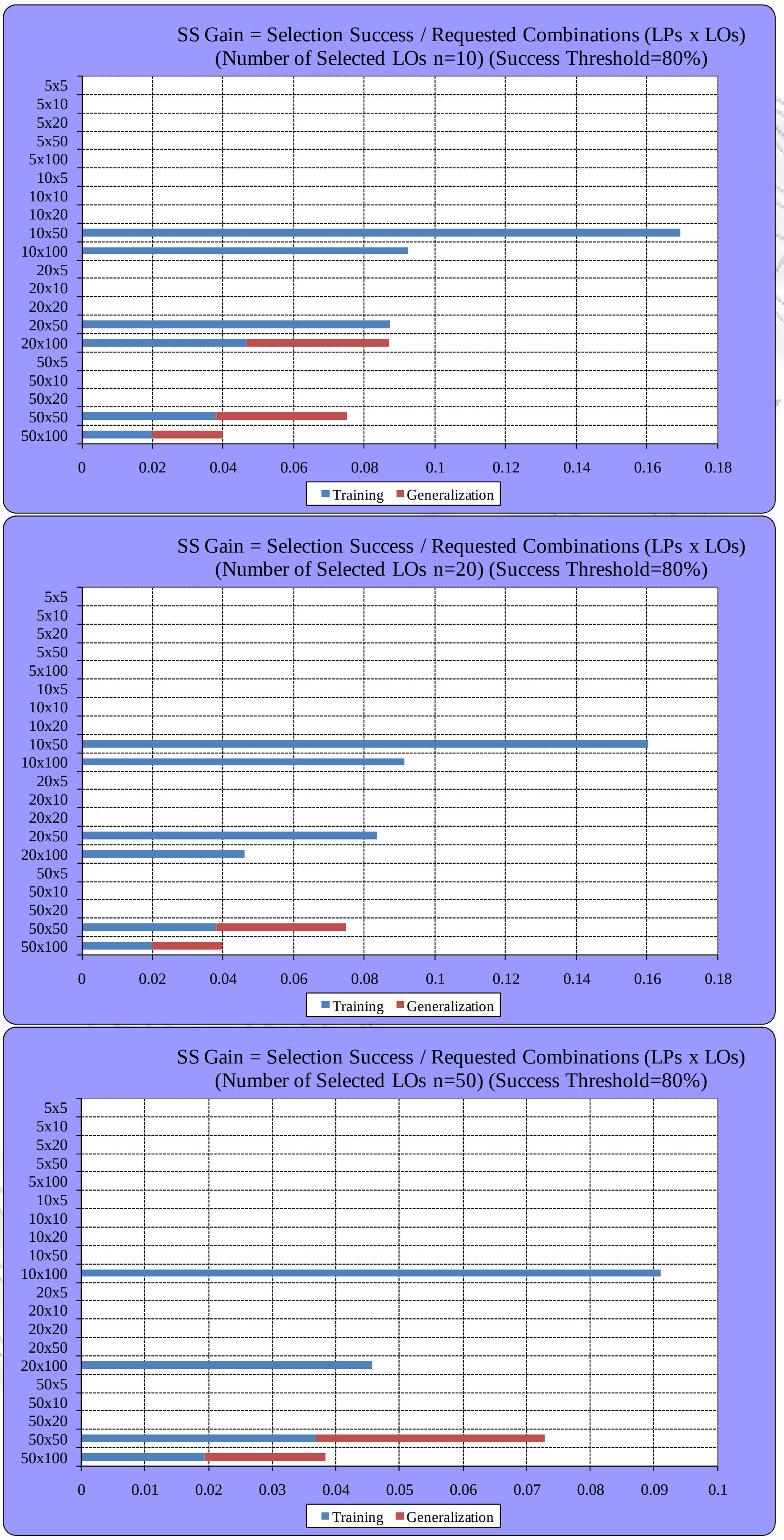

Figure 6.25: Adaptive Selection Success Gain per Requested input Combinations – Threshold=80%

Furthermore, we can observe that using the combination of 10 learning object metadata records classified over 50 learner profiles leads to higher gain in the generalisation success rate, whereas, using the opposite combination, that is, 50 learning object metadata records classified over 10 learner profiles, leads to better results during the algorithmic training.

This is due to the fact that our decision based approach uses an interpolation method over the learning objects metadata space and an extrapolation mechanism over the learner profile space. This means that our approach learns from learning object sequences associated with known learner profiles and generalizes its results to the unknown learner profiles. Thus, using combinations with more learning objects leads to higher success rates during the training process, whereas, using combinations with more learner profiles leads to higher success rates during the generalisation process.

As a result, in order to minimize the required design effort and at the same time to maximize the selection success rate, the combination of 10 learning object metadata records classified over 50 learner profiles would be preferred. However, from Figure 6.21 we can observe that using this configuration, the generalisation selection success varies from 75% (when n=10) to 68% (when n=200).

6.3.3.1.2. Using CTM to reduce the searching space

After the above experiment, the research question was how to refine the decision model, so as to improve the selection success without increasing the required design effort. To this end, we extended the decision model to make use of the Cognitive Trait Model (CTM) [21].

This model, estimates learner's cognitive characteristics (and more precisely the Working Memory Capacity and the Inductive Reasoning Skill) and proposes specific values for the elements “InteractivityType”, “InteractivityLevel”, “SemanticDensity” and “Difficulty” of the Educational Resource Description Model. Thus, the use of CTM reduces the dimensions of the optimisation problem.

Table 6.3 and Table 6.4 present the proposed values from the CTM model based on the estimation of learner's Working Memory Capacity and Inductive Reasoning Ability, respectively.

Table 6.3: CTM proposed values based on Working Memory Capacity

Working Memory Capacity	Low	High
InteractivityType	Expositive	Active
InteractivityLevel	Very low, low	Very high, high
SemanticDensity	Very low, low	Very high, high
Difficulty	Very easy, easy	Very difficult, difficult

Table 6.4: CTM proposed values based on Inductive Reasoning Ability

Inductive Reasoning Ability	Low	High
InteractivityType	Expositive	Active
InteractivityLevel	Very low, low	Very high, high
SemanticDensity	---	---
Difficulty	Very easy, easy	Very difficult, difficult

In our experiments, we used the recommendations of the CTM model as an iterative input in the process of estimating the suitability/utility of a given learning object for a given learner profile. More precisely, in each iteration we calculate the parameters of the utility/suitability estimation function, then we filter the searching space (Media Space) based on the recommendations of the CTM model and finally, refine/optimise the parameters of the utility/suitability estimation function using the reduced LO searching space.

Figures 6.26 and 6.27 present simulation results of the evolution of the generalisation selection success per iteration of the above mentioned process. From these results, we observe that each iteration leads to higher selection success.

Moreover, we observe that this increment is not linear and it is not dependent from the selection success of the previous iteration. This is due to the fact that each iteration filters the decision space decreasing the free variables of the optimisation problem. As a result, the problem of generating a continuous decision function that estimates the desired AEHS response becomes easier. Thus, since no extra input is required from the instructional designer, the use of CTM improves the performance of the decision model for adaptive learning objects selection, without affecting the required design effort.

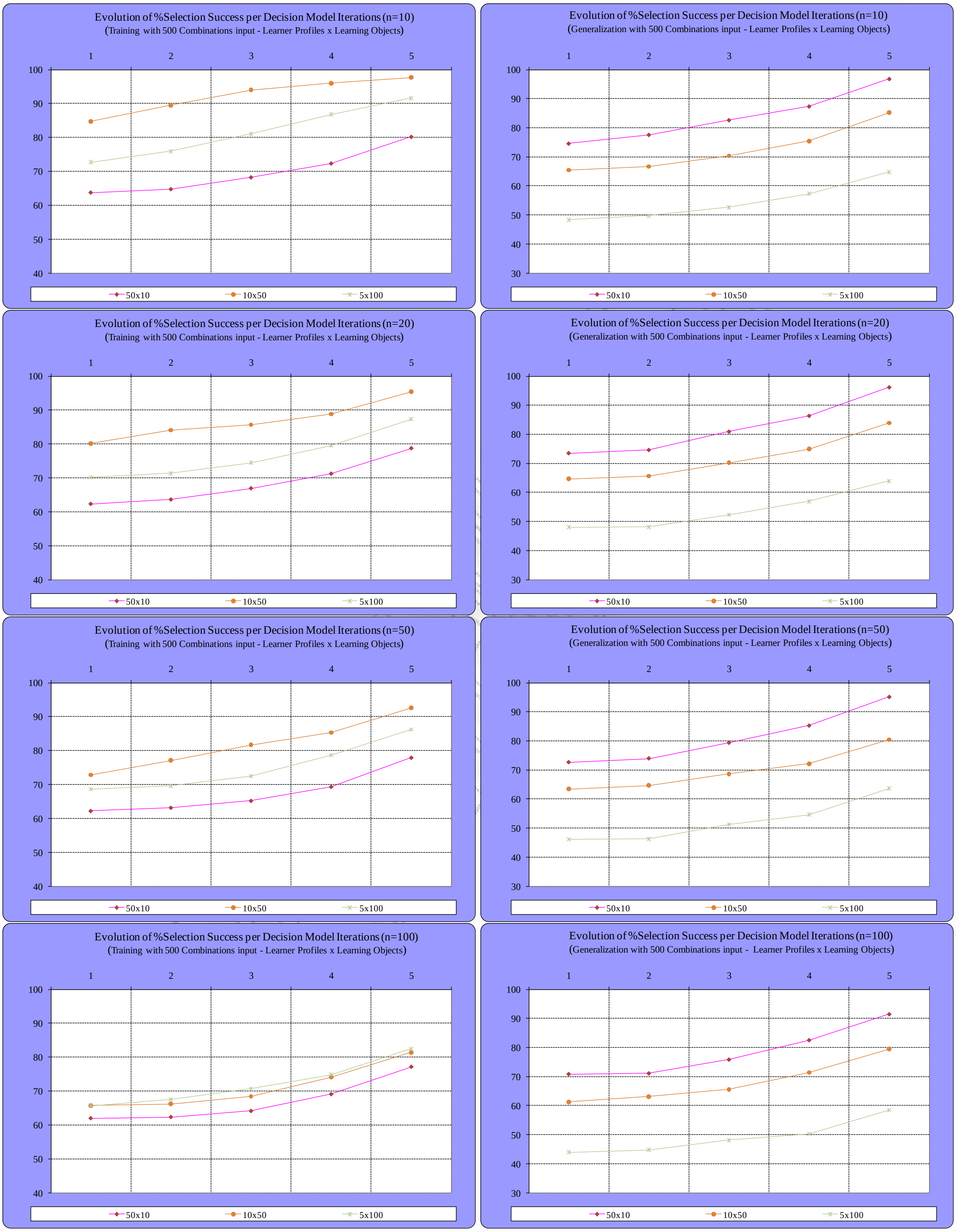

Figure 6.26: Selection Success Evolution by the iterative use of CTM (500 LP x LO input combinations) (left column: Training Results, right column: Generalisation Results)

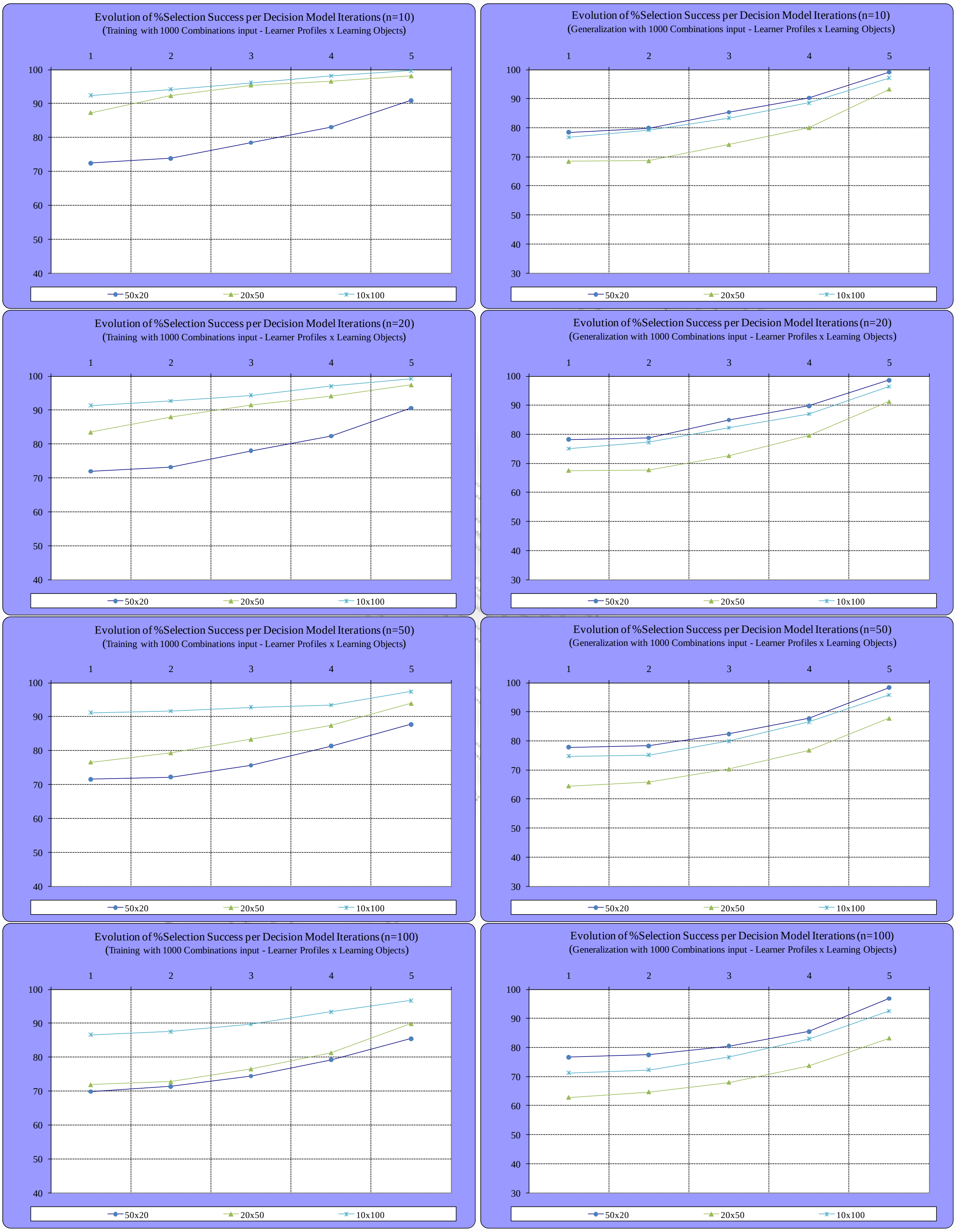

Figure 6.27: Selection Success Evolution by the iterative use of CTM (1000 LP x LO input combinations) (left column: Training Results, right column: Generalisation Results)

The simulation results demonstrate that when the CTM model is used, an improvement in the selection performance is achieved. However, this improvement depends on (a) the structure of the Media Space and (b) the complexity of the learning objects preference surface of the instructional designer.

6.3.3.2. Adaptive Learning Object Sequencing

The adaptive sequencing performance was evaluated by comparing the resulting learning object sequences with reference sequences for 50 different cases over the concept hierarchy of the Domain Ontology (10 randomly selected learner instances per concept level). Evaluation results are presented in Figure 6.28, presenting the success of our sequencing method for different cases of maximum requested number of learning objects (n) per concept level.

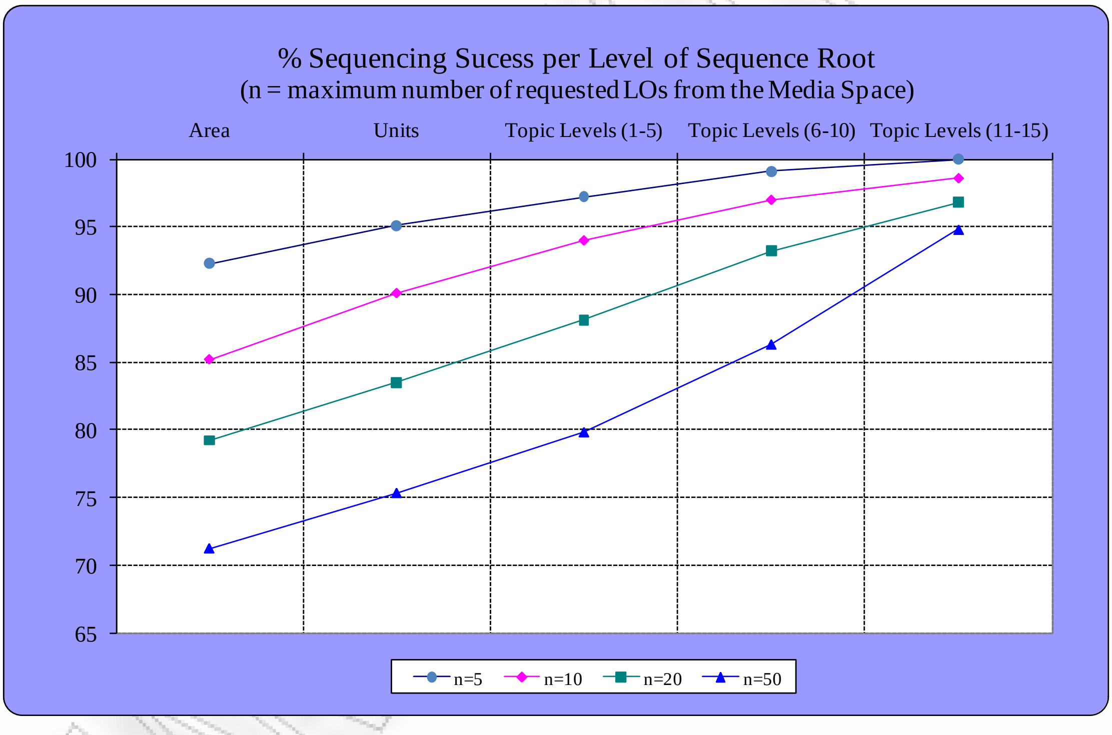

Figure 6.28: Performance results of Adaptive Content Sequencing

In Figure 6.28, the different concept levels express the depth in the Domain Ontology of the root concept in the desired sequence. For example, topic levels (1-5) correspond to concepts in the Domain Ontology with depth between one and five. These concepts are included in a Unit (see also Table 5.5 in Section 5.3.3) and they possibly include topics with depth greater than five, depending on the structure of the Domain Ontology.

From these results we observe that the success rate of the resulting learning object sequences is influenced by the concept levels that the end sequence covers, as well as the maximum number of requested learning objects from the Media Space (n).

For the same number of maximum requested learning objects from the Media Space (n), the higher level the sequence root is, the longer would be the resulted sequence introducing more sequencing mismatches.

These observations introduce two main design principles that should be followed in order to successfully generate personalized learning paths, namely:

– The Content Expert of an AEHS should design the Media Space by creating structured learning resources (with Aggregation Level equal to 2) rather than raw media. This internal structuring, on one hand, enables the AEHS to select less (but more aggregated) learning resources, and on the other hand, increases the probability of generating meaningful learning paths since less decisions about the structuring of the learning resources are taken by the AEHS.

– The end-user of an AEHS should request an adaptive web-based course covering the minimum needed parts of the Domain Concept Ontology, in order for avoiding the generation of huge sequences that introduce mismatches.

In order to investigate in more detail these mismatches, we have evaluated the selection success on two different sub sets of the Learning Objects Estimation Set. The first data set contains learning object metadata records with aggregation level 1 (raw media) and the second data set contains learning object metadata records with aggregation level 2 (structured learning objects), as defined in Table 5.2 (Section 5.3.1). Figure 6.29 presents average simulation results for learning objects selection.

From these results we can once again confirm the observation that using structured learning objects rather than raw media, increases the probability of generating flawless learning paths. More analysis on the results, presented in Figure 6.29, shows that when the desired number of learning objects (n) is relatively small (less or equal to 10), the efficiency of selection is almost the same for raw media and structured learning objects. However, when the desired number of learning objects is relatively large (more than 10) the success in selecting learning objects is strongly affected by the aggregation level of the learning objects.

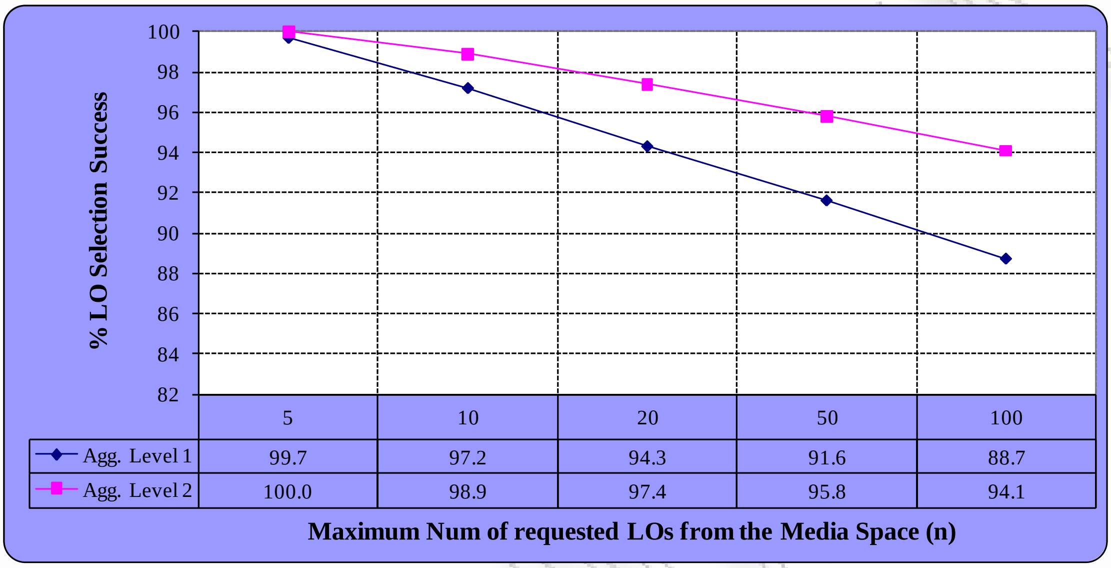

Figure 6.29: Influence of LO Aggregation Level in Adaptive LO Selection

Furthermore, if we consider that for just a single learner profile instance, the total different possible combinations of learning objects are more than one million [41], it seems almost unrealistic to assume that an instructional designer can manually define the full set of selection rules which correspond to the dependencies extracted by the proposed method and at the same time to avoid the problems of insufficiency, and/or inconsistency in the produced rule sets.

The simulation results demonstrate that the proposed approach is capable of extracting dependencies between learning object and learner characteristics producing almost accurate sequences of learning objects (that is, almost similar to the model ones). It was exhibited that the granularity of learning object sequences, as well as, the aggregation level of the learning objects are the main parameters affecting the sequencing success. A learning path that covers a whole concept area is more likely to produce mismatches when comparing with a sequence that covers only a specific unit or even a specific topic, and a sequence that uses raw media is more likely to produce mismatches when comparing with a sequence that uses structured learning objects.

This is due to the fact that structured learning objects partly contain information about the underlying pedagogical scenario. When only raw media are used for sequencing, then the pedagogical scenario is totally implied in the decisions made by the AEHS.

6.4. Conclusions

In order to define the runtime behaviour of an AEHS, the definition of how learner's characteristics influence the selection of concepts to be presented from the domain model (*Concept Selection Rules*), as well as the selection of appropriate resources (*Content Selection Rules*), is required.

In the literature, there exist several approaches aiming to support the design of the these rules by providing either direct guidance to AEHS designers, or semi-automatic mechanisms for making the rule design process less demanding.

However, still the design of adaptive educational hypermedia systems requires significant effort since dependencies between educational characteristics of learning resources and learners' characteristics are too complex to exhaust all possible combinations. This complexity introduces several problems on the definition of the rules required. The problems of inconsistency and insufficiency of the defined rule sets are responsible for generating conceptual "holes" to the produced learning resource sequence (learning path).

This is due to the fact that, even if appropriate resources exist in the Media Space, the conflict between two or more rules (inconsistency problem) or the absence of a required rule (insufficiency problem), prevents the AEHS to select them and use them in the learning resource sequence. As a result, either less appropriate resources are used from the Media Space, or required concepts are not covered at all by the resulting path.

The research question posed in this thesis was whether it is feasible to construct a semi-automated, decision-based approach, which generates a continuous decision function that estimates the desired AEHS response, aiming to overcome the above mentioned problem.

To achieve this, we proposed a semi-automated approach which uses data from the implicit definition of sample adaptation rules and attempts to fit the response function on these data. Moreover, in this thesis, we presented a set of performance evaluation metrics which we claim that they are suitable for validating the use of decision-based approaches in adaptive learning objects selection and sequencing in AEHS, and we assessed their use in the case of our proposed method for estimating the desired AEHS response.

More precisely, we presented an evaluation metric for measuring the performance of adaptive content selection, which although seems similar to the precision metric in information retrieval systems, its difference is critical. It evaluates the precision of selecting learning objects not on the entire space of the Media Space, but only on the desired sub-space, and also it takes into consideration the ranking of the selection process. This means that the proposed metric is harder, since it measures the precision over a smaller value space. Experimental results, verify the hypothesis that the presented Selection Success (SS) metric is harder than the typical Precision Metric (PM) or its' application only on the desired sub-space of the Media Space (Partial Precision Metric, PPM). This means that in the case of AEHS, where the ranking of the selected learning objects is critical, the SS metric should be used.

Additionally, we discussed the limitations of the performance metrics used by the literature for the problem of adaptive content sequencing, we introduced the need for an alternative evaluation metric which measures the sequencing performance over the instructional designer's preference space, and we presented a performance metric derived from Kendall's Tau.

Furthermore, we demonstrated how these metrics could be used in practice for providing useful feedback for the design of AEHS. More precisely, we used these metrics for the investigation of the influence of the design effort required, measuring the selection success gain per number of requested combinations. The use of this metric provides evidences about the trade-off that an instructional designer should make between the required effort and the improvement of the selection success rate.

Moreover, we applied this metric for discovering the optimal input data volume for the machine learning algorithm, so as to avoid the problem of overfitting. Moreover, we used the performance evaluation metrics in the process of refining the decision model, so as to improve the selection success without increasing the required design effort, and we evaluated the application of the Cognitive Trait Model (CTM) in our decision based approach. Finally, we evaluated the performance of adaptive learning object sequencing, focusing on the design principles that should be followed by an AEHS in order to successfully generate learning objects sequences.

The simulation results demonstrate that the proposed approach is capable of extracting dependencies between learning object and learner characteristics producing almost accurate sequences of learning objects (that is, almost similar to the model ones).

Furthermore, it was exhibited that the granularity of learning object sequences, as well as, the aggregation level of the learning objects are the main parameters affecting the sequencing success. A learning path that covers a whole concept area is more likely to produce mismatches when comparing with a sequence that covers only a specific unit or even a specific topic, and a sequence that uses raw media is more likely to produce mismatches when comparing with a sequence that uses structured learning objects.

This is due to the fact that structured learning objects partly contain information about the underlying pedagogical scenario. When only raw media are used for sequencing, then the pedagogical scenario is totally implied in the decisions made by the AEHS.

Chapter 7. Concluding Remarks

7.1. Contribution to the State of the Art

The main contributions of this thesis are the following:

1. *Adaptive Content Selection*

   The main objective of the research effort in this direction was to create a decision model that mimics the way an instructional designer selects the suitable teaching material from a Learning Object Repository, for a specific learner whose characteristics (User Profile) are known. The implementation of such a model replaces the content selection rules of the Adaptation Model of typical AEHS.

   To achieve this, we proposed a decision model which estimates the suitability of a learning object for a learner assuming that we know the characteristics of the learner. The result is a function, called suitability function, which relates the characteristics of a learning object (which are reflected in the Educational Resource Description Model) with the characteristics of a learner (which are reflected in the Learner Model) and vice versa.

   The conducted experiments have shown that the use of the proposed model leads to accurate adaptive content selection decisions, with a success rate above 80% when it is requested from an instructional designer to determine the preference order of at least 10 learning objects for 50 randomly selected learner profiles.

   The next step of the research effort was to reduce the requirements of the proposed model for adaptive content selection in respect to the required design effort, by studying the dynamic evolution capacity of the model.

   To this end, we investigated how the use of predictive models for learner characteristics could be used to improve the content selection success without increasing the required design effort. More precisely, we used the Cognitive Trait Model (CTM), which estimates learner's cognitive characteristics and proposes specific values for the elements "of the Educational Resource Description Model.

   The use of the CTM was aimed at both reducing the dimensions of the optimisation problem in hand and at providing feedback to the content selection model in order to evolutionary improve its effectiveness. The conducted experiments verify this hypothesis.

2. *Adaptive Content Sequencing*

   The main objective of the research effort in this direction was the development of a decision model for adaptive content sequencing, avoiding the use of adaptation rules. More precisely, we extended the decision model for adaptive content selection, so as to produce sequencing adaptation decision using information stored in the Educational Resource Description Model, the Learner Model and the Concept Domain Model.

   In the proposed sequencing method, we replace the content selection rules defined in the Adaptation Model with a decision-making function that estimates the suitability of a learning resource for a specific learner by relating the educational characteristics of learning resources defined in the educational resource description model with the learner's cognitive characteristics and preferences stored in the Learner Model. This suitability function is used for weighting each connection of the Learning Paths Graph, a graph containing all possible learning paths based on the relation between the Learning Goals Hierarchy, the concepts of the Domain Concept Ontology and the learning resources contained in the Media Space.

   From the weighted graph, we then select the most appropriate learning path for a specific learner (personalized learning path) by using a shortest path algorithm.

   The conducted experiments have shown that the use of the proposed model leads to accurate adaptive content sequencing decisions, with a success rate above 70% when it is requested from an instructional designer to determine the preference order of at least 10 learning objects for 50 randomly selected learner profiles.

3. *Evaluation Framework for Decision-based Approaches*

   The main objective of the research effort in this direction was to design a framework for assessing the performance of decision-based adaptive content selection and sequencing approaches.

This evaluation framework was applied in the case of our proposed approach for adaptive content selection and sequencing. The goal the evaluation in our case was twofold: first, to examine whether the proposed semi-automated decision based approach is capable of extracting decision models which replicate the Adaptation Model (AM) of existing AEHS; and second, to verify that our proposed approach is robust and can be applied in cases where large-scale adaptation rule sets are needed to describe the desired AEHS response.

The conducted experiments have shown that the use of these metrics could be used in practice for providing useful feedback for the design of AEHS.

7.2. Future Research

Our future research will focus on separating the learning scenario from the adaptation decision model. By this way, we anticipate, on one hand, to support better the sequencing of unstructured raw media, and on the other hand, to facilitate the support of different pedagogical strategies without redesigning the adaptation decision model.

Moreover, our future research will include the study of variations of the presented performance evaluation metrics, as well as, the investigation of a comparison metric between rule-based and decision based AEHS.

Finally, our future research will include the investigation of learning object decomposition from existing courses, allowing reuse of the disaggregated learning objects in different educational contexts. The intelligent selection of the disaggregation level and the automatic structuring of the atoms (raw media) inside the disaggregated components in order to preserve the educational characteristics they were initially designed for, is a key issue in the research agenda for learning objects [128].

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Appendix A. Non linear Optimisation Algorithms

A.1. General Form of an Optimisation Algorithm

Starting from a given point $x^{(1)}$ in the optimisation space, the general form of an optimisation algorithm is the following:

- Step A: Calculation of a search direction $s^{(k)}$.
- Step B: Calculation of the optimum step $\alpha^{(k)}$.
- Step C: Calculation of the new point $x^{(k+1)}=x^{(k)}+\alpha^{(k)}s^{(k)}$
- Step D: If convergence criteria are met, stop with $x^{(k)} \approx x^{*}$, where x* is the desired optimum, else repeat from Step A.

The search direction $s^{(k)}$ is calculated using search direction methods, which we will analyse in Section A.3, whereas the optimum step $\alpha^{(k)}$ is calculated using line search algorithms, presented in next section.

A.2. Line Search Algorithms

Let a function F(x) and a given direction $s^{(k)}$, over which we want to minimise the given function:

Minimise: $F\left(x^{(k)} + \alpha s^{(k)}\right), \alpha \in R$

For this function, over the line $x^{(k)} + \alpha s^{(k)}$, we have:

$$\frac{d}{d\alpha} = \sum_{i=1}^{n}\left(\frac{dx_i}{d\alpha}\frac{\partial}{\partial x_i}\right) = \sum_{i=1}^{n}\left(s_i \frac{\partial}{\partial x_i}\right) = s^{T}\nabla \text{, thus, } \frac{df}{d\alpha} = s^{T}\nabla F = s^{T} g = g^{T} s \text{, and,}$$

$$\frac{d^2 F}{d\alpha^2} = \frac{d}{d\alpha}\frac{dF}{d\alpha} = s^{T}\nabla\left(\nabla F^{T} s\right) = s^{T}\left(\nabla^2 F\right)s = s^{T} G s$$

A line search algorithm is an iterative procedure that minimises the function F(x) over the line $x^{k} + a^{k} s^{k}$. There are two phases to any line search algorithm [110]:

- *Bracketing Phase*, which searches for a bracket, that is, a feasible region that is known to contain a minimum. The existence of a minimum can be estimated by comparing the first derivative $\frac{dF}{d\alpha}$ of the function at the points a and b of a bracket [a, b]. We have a minimum, when one of the following conditions are met, as depicted in Figure A.1:

a) $(F'(\mathrm{a})<0)$ *and* $(F'(b)>0)$

b) $(F'(\mathrm{a})<0)$ *and* $(F'(b)<0)$ *and* $(F(\mathrm{a})<F(b))$

c) $(F'(\mathrm{a})>0)$ *and* $(F'(b)>0)$ *and* $(F(\mathrm{a})>F(b))$

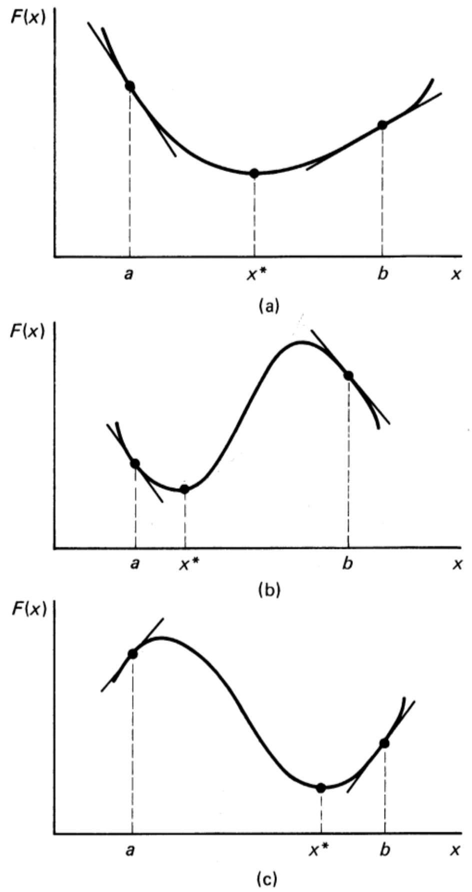

Figure A.1: Conditions for existence of a minimum in a bracket [a, b]

– *Sectioning Phase,* in which the bracket is sectioned (i.e., divided), thereby generating a sequence of brackets whose length is progressively reduced. In each sectioning phase, the new smaller bracket also contains the minimum, which is verified by the previously mentioned conditions.

The termination of a Line Search algorithm can happen in both of the two phases, as long as the following stopping criteria have been met:

a) $F\left(\alpha^{(k)}\right) \leq F(0)+\alpha^{(k)}\rho F'(0), \mathit{with}\ \rho \in \left(0,\frac{1}{2}\right]$

b) $\left|F'\left(\alpha^{(k)}\right)\right| \leq -\sigma F'(0), with\, \sigma \in (\rho,1)$

A.3. Search Direction Methods

A.3.1. First Order Methods

As first order methods we call the methods which use only the values of the function F(x) under minimisation, as well as, the values of its first derivative. These methods are quite efficient, due to the simplicity of their implementation and the small computational effort which is required in each iteration. This, makes them ideal for solving optimisation problems with big number of variables.

A.3.1.1. Steepest Descent

From the main equation for the calculation of the each step $x^{(k+1)}=x^{(k)}+\alpha^{(k)}s^{(k)}$, and the Taylor series, we have:

$$F^{(k+1)} = F_{(x^{(k)}+a^{(k)}s^{(k)})} \approx F^{(k)} + a^{(k)}g^{(k)^T}s^{(k)} \Rightarrow$$
$$F^{(k+1)} - F^{(k)} = a^{(k)}\left|g^{(k)}\right| \cdot \left|s^{(k)}\right| \cos\theta$$

If we consider the values $a^{(k)}, g^{(k)}\, and\, s^{(k)}$ as constants, then, the right part of the above equation becomes more negative when the angle θ between the derivative $g^{(k)}$ and the direction $s^{(k)}$ is equal to π. In this case, we have the bigger reduction of the function F(x). Thus, the direction $s^{(k)}= - g^{(k)}$ is called the steepest descent direction.

If we use accurate line search, the directions selected in consecutive iterations are always orthogonal: $s^{(k+1)^T}s^{(k)} = 0$. Figure A.2 presents an example of the execution of the Steepest Descent Method.

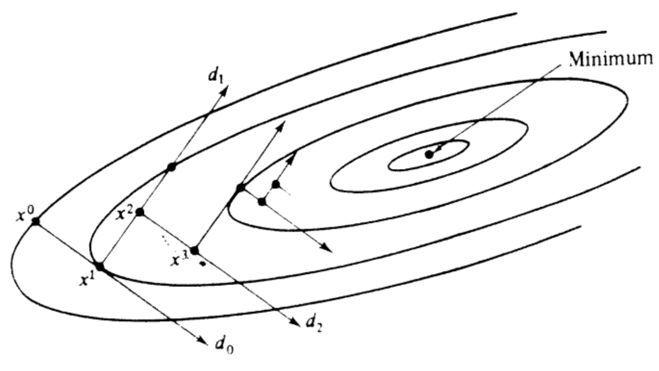

Figure A.2: The Steepest Descent Method

A.3.1.2. Conjugate Gradient Methods

Let a quadratic function $F_{(x)} = px^2 + qx + r$ or equivalently $F_{(x)} = \frac{1}{2}x^T Ax - b^T x + c$ where x is a W-by-1 parameter vector, A is a W-by-W symmetric, positive definite matrix, b is a W-by-1 vector and c is a scalar. Minimization of the quadratic function F(x) is achieved by assigning to x the unique value $x^* = A^{-1}b$. Thus, minimizing F(x) and solving the linear system of equations $Ax^* = b$ are equivalent problems.

Given the matrix A, we say that a set of nonzero vectors $s^{(0)}$, $s^{(1)}$,…, $s^{(W-1)}$ is A-conjugate (i.e., non interfering with each other in the context of matrix A) if the following condition is satisfied: $s^{(k)^T} As^{(j)} = 0, \textit{ for all } k \textit{ and } j \textit{ such that } k \neq j$. If A is equal to the identity matrix, conjugacy is equivalent to orthogonality.

An important property of A-conjugate vectors is that they are linearly independent. For a given set of A-conjugate vectors $s^{(0)}$,$s^{(1)}$,…, $s^{(W-1)}$, the corresponding conjugate direction method for unconstrained minimization of the quadratic function F(x) is defined by [110], [129], [130]:

$x^{(k+1)}=x^{(k)}+\alpha^{(k)}s^{(k)}$, k=0, 1, …, W-1 where $x^{(0)}$ is an arbitrary starting vector, and $a^{(k)}$ is a scalar defined by $F(x^{(k)} + \alpha^{(k)}s^{(k)}) = \min_{a} F(x^{(k)} + \alpha^{(k)}s^{(k)})$. The procedure of choosing α so as to minimise the function $F(x^{(k)} + \alpha^{(k)}s^{(k)})$ is referred to as a line search (that is, one-dimensional minimisation problem) over the direction s(k). In particular, for each iteration k, the iterate $x^{(k+1)}$ minimises the function F(x) over a linear vector space Δ_k that passes through some arbitrary point $x^{(0)}$ and is spanned by the A-conjugate vectors $s^{(0)}$, $s^{(1)}$, …, $s^{(k)}$, as shown by: $x^{(k+1)} = \arg\min_{x \in \Delta_k} F(x)$ where the space Δ_k is defined by: $\Delta_k = \left\{ x^{(k)} \mid x^{(k)} = x^{(0)} + \sum_{j=0}^{k} \alpha^{(j)} s^{(j)} \right\}$

For the conjugate direction method to work, we require the availability of a set of A-conjugate vectors $s^{(0)}$, $s^{(1)}$, …, $s^{(W-1)}$. In a special form of this method known as the Conjugate-Gradient Method, the successive direction vectors are generated as A-conjugate versions of the successive gradient vectors of the quadratic function F(x) as the method progresses, hence the name of the method. Thus, except for k=0, the set of direction vectors $\{s^{(k)}\}$ is not specified beforehand, but rather it is determined in a sequential manner at successive steps of the method.

Define the residual as the steepest descent direction: $r^{(k)} = b\text{-}Ax^{(k)} = -g^{(k)}$. Then to proceed, we use a liner combination of $r^{(k)}$ and $s^{(k-1)}$, as shown by: $s^{(k)}=r^{(k)}+\beta^{(k-1)}s^{(k-1)}$, k=1, 2, …, W-1 where $\beta^{(k)}$ is a scaling factor to be determined.

Multiplying this equation by A, taking the inner product of the resulting expression with $s^{(k-1)}$, invoking the A-conjugate property of the direction vectors, and then solving the resulting expression for $\beta^{(k)}$, we get: $\beta^{(k)} = -\frac{s^{(k-1)^T} A r^{(k)}}{s^{(k-1)^T} A s^{(k-1)}},\ k \geq 1$

This formula for evaluating $\beta^{(k)}$ requires knowledge of matrix A. For computational reasons, it would be desirable to evaluate $\beta^{(k)}$ without explicit knowledge of A. This evaluation can be achieved by using one of the two formulas [110]:

- *Polak-Ribiere Formula*, for which $\beta^{(k)}$ is defined by:

$$
\begin{aligned}
&s^{(k)} = -g^{(k)} + \beta^{(k-1)} s^{(k-1)} \\
&\textit{where} \\
&\beta^{(0)} = 0 \\
&\beta^{(k)} = \frac{\left(g^{(k+1)} - g^{(k)}\right)^T g^{(k+1)}}{g^{(k)^T} g^{(k)}},\ k \geq 1
\end{aligned}
$$

- *Fletcher-Reeves Formula*, for which $\beta^{(k)}$ is defined by:

$$
\begin{aligned}
&s^{(k)} = -g^{(k)} + \beta^{(k-1)} s^{(k-1)} \\
&\textit{where} \\
&\beta^{(0)} = 0 \\
&\beta^{(k)} = \frac{g^{(k+1)^T} g^{(k+1)}}{g^{(k)^T} g^{(k)}},\ k \geq 1
\end{aligned}
$$

<u>Reset in Conjugate Gradient Methods</u>

The formula $s^{(k)} = -g^{(k)} + \beta^{(k-1)} s^{(k-1)}$ produces descent directions when F(x) is a quadratic function with positive definite hessian matrix, only if $\beta^{(k)}$ is positive and the first derivative $g^{(k)}$ is non zero. These conditions should be met for both Fletcher-Reeves and Polak-Ribiere methods.

However, these directions $s^{(k)}$ may be close to orthogonal to the first derivative $g^{(k)}$, which results in very small minimisation of the cost function F(x). In this case, we have $g^{(k+1)} \approx g^{(k)}$ and thus:

$$s_{FR}^{(k+1)} \approx -g^{(k+1)} + s_{FR}^{(k)}$$
$$\textit{whereas}$$
$$s_{PR}^{(k+1)} \approx -g^{(k+1)}$$

In order to avoid this, we can reset every N iterations the direction used in conjugate gradient methods to the steepest descent direction, where N is the number of variables of the cost function F(x).

A.3.2. Second Order Methods

A.3.2.1. Newton Method

From the formula of each iterate $x^{(k+1)} = x^{(k)} + a^{(k)}s^{(k)}$, and the Taylor series for the first derivative of the cost function F(x), we have:

$$g^{(k+1)} = g_{(x^{(k)}+a^{(k)}s^{(k)})} \approx g^{(k)} + a^{(k)}G^{(k)}s^{(k)}$$

If the iterate $x^{(k+1)}$ is the minimum of the cost function, the first derivative at that point would be equal to zero, thus: $g^{(k+1)} = 0 \Rightarrow a^{(k)}s^{(k)} = -G^{(k)^{-1}}g^{(k)}$. From this equation, we can redefine the formula for each iterate $x^{(k+1)} = x^{(k)} - G^{(k)^{-1}}g^{(k)}$.

This method is called Newton method, and requires the calculation of the inverse Hessian matrix. This method converges faster than the first order methods examined in previous section, however, it requires significantly more computational power for calculating both the Hessian matrix $G^{(k)}$ and its inverse matrix. Moreover, this method cannot be used in cases where the Hessian matrix cannot be inversed.

A.3.2.2. Quasi-Newton Methods

The Quasi-Newton methods are gradient methods described by the update equation: $x^{(k+1)} = x^{(k)} + a^{(k)}s^{(k)}$ where the direction vector $s^{(k)}$ is defined in terms of the gradient vector $g^{(k)}$ by $s^{(k)} = -S^{(k)}g^{(k)}$. The matrix $S^{(k)}$ is a positive definite matrix that is adjusted from one iteration to the next. This is done in order to make the direction vector $s^{(k)}$ approximate the Newton direction.

Quasi-Newton methods use second-order (curvature) information about the error surface without actually requiring knowledge of the Hessian matrix H. They do so by using two successive iterates $x^{(k)}$ and $x^{(k+1)}$, together with the respective gradient vectors $g^{(k)}$ and $g^{(k+1)}$. Let $q^{(k)} = g^{(k+1)} - g^{(k)}$ and $\Delta x^{(k)} = x^{(k+1)} - x^{(k)}$. We may then derive curvature information by using the formula: $q^{(k)} \approx \left(\frac{\partial}{\partial x} g^{(k)} \right) \Delta x^{(k)}$

In particular, given W linearly independent increments $\Delta x^{(0)}$, $\Delta x^{(0)}$, …, $\Delta x^{(W-1)}$ and the respective gradient increments $q^{(0)}$, $q^{(1)}$, …, $q^{(W-1)}$, we may approximate the Hessian matrix H as: $H \approx \left[q^{(0)}, q^{(1)}, ..., q^{(W-1)} \right] \left[\Delta x^{(0)}, \Delta x^{(1)}, ..., \Delta x^{(W-1)} \right]^{-1}$

We may also approximate the inverse Hessian matrix as:

$$H^{-1} \approx \left[\Delta x^{(0)}, \Delta x^{(1)}, ..., \Delta x^{(W-1)} \right] \left[q^{(0)}, q^{(1)}, ..., q^{(W-1)} \right]^{-1}$$

In the most popular class of Quasi-Newton methods, the matrix $S^{(k+1)}$ is obtained from its previous value $S^{(k)}$, the vectors $\Delta x^{(k)}$ and $q^{(k)}$, by using the recursion [110], [130]:

$$S^{(k+1)} = S^{(k)} + \frac{\Delta x^{(k)} \, \Delta x^{(k)^T}}{q^{(k)^T} \, q^{(k)}} - \frac{S^{(k)} q^{(k)} q^{(k)^T} S^{(k)}}{q^{(k)^T} S^{(k)} q^{(k)}} + \xi^{(k)} \left[q^{(k)^T} S^{(k)} q^{(k)} \right] \left[v^{(k)} v^{(k)^T} \right]$$

where $v^{(k)} = \frac{\Delta x^{(k)}}{\Delta x^{(k)^T} \Delta x^{(k)}} - \frac{S^{(k)} q^{(k)}}{q^{(k)^T} S^{(k)} q^{(k)}}$ and $0 \le \xi \le 1, \forall k$

The algorithm is initiated with some arbitrary positive definite matrix $S^{(0)}$. The particular form of the Quasi-Newton method is parameterized by how the scalar $\xi^{(k)}$ is defined :

- For $\xi^{(k)}=0$ for all k, we obtain the *Davidon-Fletcher-Powell (DFP) algorithm*, which is historically the first Quasi-Newton method.
- For $\xi^{(k)}=1$ for all k, we obtain the *Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm*, which is considered to be the best form of Quasi-Newton methods currently known.

Appendix B. Multivariable Functions used as Simulated Instructional Designers' Preference Models

In our experiments, we simulate the instructional designers' preference models, using the functions presented below. These functions are suggested by the CUTE library (CUTE - Constrained and Unconstrained Testing Environment, http://hsl.rl.ac.uk/cuter-www/index.html), as ideal for testing optimisation problems with many variables. From this library we have selected those functions that could model 18 variables. These variables model the eleven (11) elements of the Educational Resource Description Model in use (that is, the elements used from the "General" and the "Educational" IEEE LOM categories) and the seven (7) elements of the Learner Model in use. These functions are the following:

[1] Rosenbrock function

$$f(x)=\sum_{i=1}^{n-1}\left[100\cdot\left(x_{i+1}-x_i^2\right)^2+\left(1-x_i\right)^2\right]$$

[2] Rastrigin function

$$f(x)=10\cdot n+\sum_{i=1}^{n}\left[x_i^2-10\cdot\cos\left(2\cdot\pi\cdot x_i\right)\right]$$

[3] Schwefel function

$$f(x)=\sum_{i=1}^{n}\left[-x_i\cdot\sin\left(\sqrt{|x_i|}\right)\right]$$

[4] Griewangk function

$$f(x)=\sum_{i=1}^{n}\frac{x_i^2}{4000}-\prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$$

[5] Sum of different powers function

$$f(x)=\sum_{i=1}^{n}|x_i|^{(i+1)}$$

[6] Penalty function (n variables, $m = n+1$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = a^{\frac{1}{2}}(x_i - 1),\ 1 \le i \le n$$

$$f_{n+1}(x) = \left(\sum_{j=1}^{n} x_j^{\ 2}\right) - \frac{1}{4}$$

$$where\ \ a = 10^{-5}$$

[7] Variably dimensioned function (n variables, $m = n+2$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = x_i - 1,\ \ i = 1,\ldots,n$$

$$f_{n+1}(x) = \sum_{j=1}^{n} j(x_j - 1)$$

$$f_{n+2}(x) = \left(\sum_{j=1}^{n} j(x_j - 1)\right)^2$$

[8] Trigonometric function (n variables, $m = n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = n - \sum_{j=1}^{n} \cos(x_j) + i(1 - \cos x_i) - \sin x_i$$

[9] Discrete boundary value function (n variables, $m = n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = 2x_i - x_{i-1} - x_{i+1} + \frac{h^2 (x_i + t_i + 1)^3}{2}$$

$$where \quad h = \frac{1}{n+1}, \; t_i = ih, \; and \quad x_0 = x_{n+1} = 0$$

[10] Discrete integral equation function (n variables, $m = n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = x + h \frac{\left[(1-t_i) \sum_{j=1}^{i} t_j (x_j + t_j + 1)^3 + t_i \sum_{j=i+1}^{n} (1-t_j)(x_j + t_j + 1)^3 \right]}{2}$$

$$where \quad h = \frac{1}{n+1}, \; t_i = ih, \; and \quad x_0 = x_{n+1} = 0$$

[11] Broyden tridiagonal function (n variables, $m = n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = (3 - 2x_i) x_i - x_{i-1} - 2x_{i+1} + 1$$

$$x_0 = x_{n+1} = 0$$

[12] Broyden banded function (n variables, $m = n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = x_i (2 + 5x_i^{\,2}) + 1 - \sum_{j \in J_1} x_j (1 + x_j)$$

$$where \quad J_1 = \{ j : j \neq i, \; \max(1, i - m_i) \leq j \leq \min(n, i + m_u) \}$$

$$and \quad m_i = 5, \; m_u = 1$$

[13] Linear function-full rank (n variables, $m \geq n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = x_i - \frac{2}{m}\left(\sum_{j=1}^{n} x_j\right) - 1, \; 1 \le i \le n$$

$$f_i(x) = -\frac{2}{m}\left(\sum_{j=1}^{n} x_j\right) - 1, \; n < i \le m$$

[14] Linear function-rank 1 (n variables, $m \ge n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = i\left(\sum_{j=1}^{n} jx_j\right) - 1$$

[15] Chebyquad function (n variables, $m \ge n$)

$$f_{(x)} = \sum_{i=1}^{m} f_{i_{(x)}}^2$$

$$f_i(x) = \frac{1}{n}\sum_{j=1}^{n} T_i(x_j) - \int_0^1 T_i(x)dx$$

where T_i is the ith chebyshev polynomial shifted to the interval $[0,1]$ *and hence,*

$$\int_0^1 T_i(x)dx = 0 \quad \text{for } i \text{ odd}$$

$$\int_0^1 T_i(x)dx = \frac{-1}{i^2 - 1} \quad \text{for } i \text{ even}$$

Short Bio

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