Adaptive and Personalized e/m-Learning : Approaches and Techniques

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***Abstract*— Adaptive and personalized approaches within e/m learning systems enable adapting learning Objects (LOs) and process to the different needs and contexts, to help the learners in improving their knowledge or skills. In this paper, we review the recent research on learning adaptation to pursue two goals: First is to unify the classification of adaptation types; the second is to study the different approaches and techniques used to implement the learning adaptation in its two main types : adaptation of the LOs selection and adaptation of the LOs sequencing.**

Keywords—Adaptive e/m Learning, Learning path adaptation, Adaptation by selection

I. Introduction

With the rapid development of information technology in education and learning field, researchers have created myriad learning resources. It has been a difficult task for learners to find suitable learning resources from the Internet. Without effective adaptation, irrelevant resources will lead to learners' cognitive overload and affect learning outcomes. Therefore, learning systems need to be adapted to the learners' context and needs.

An adaptive learning environment provides personalized learning resources and processes to the learner through self-directed study. An adaptive learning model can be subdivided basically into a learner model, domain model, and adaptive engine. In such environment, the adaptive e/m learning system should adapt its services to a learner's needs and context. The purpose of adaptation is to optimize the relationship between the learner context and learning content; hence, the learning outcome could be obtained with minimum time and interaction and could also increase the learner satisfaction [1].

Even though academic research on adaptive learning environments has increased, the field lacks a comprehensive literature analysis of the classification of the adaptation types, and the most used approaches and algorithms used to implement every type of adaptation.

This paper presents a study of learning adaptation in e/m learning systems from 2008 up to 2019. It aims to specify:

Rq1- What should be adapted?

Rq2- How it should be adapted?

The rest of this paper is structured as follows: Section 2 describes the main types of learning adaptation. Section 3 collects the most used approaches and algorithms used to implement the adaptation of the learning content and the learning path. Finally, Section 4 presents the conclusion of the work.

II. Overview of the Learning Adaptation Classification

The first research question can be answered by presenting a general classification of adaptation types used in the field of e/m-learning. Several researchers have addressed the adaptation type classification applied in the field of adaptive learning, but these classifications are slightly different. In this section we will study them and propose a new classification.

Sampson [2] identifies three main categories of adaptation related to educational resources within adaptive and personalized learning systems: -Selection Adaptation: This type of adaptation deals with selecting appropriate learning objects LO based on different selection criteria derived from learners' contextual elements. -Presentation Adaptation : considers that LOs is adaptively structured for access via mobile devices by taking into account parameters related to the learners' type of mobile device, the learner's profile (including learner's preferences and learning style), Parameters related with learner's location, physical conditions and learner's temporal information. -Sequencing Adaptation : This type of adaptation rearranges or reorders the navigation and sequencing possibilities of different LOs that are linked to each other towards creating personalized learning paths by taking into account different criteria derived from learners' contextual elements (previous knowledge, availability and current location, Time,…).

Premlatha defines two adaptation types: adaptive presentation at the content level and adaptive navigation support at the link level [1].

El jenati [3] adopts in his work three types of adaptation : -Adaptive content: The adaptation of the content is based on the selection of the adequate pedagogical content which take into account the learner's context. Some learners may wish to get a simple version of the content and others may wish to get a detailed version. - Adaptive navigation: The Adaptive navigation allows to learners to find their paths by adapting the presentation of links to the objectives, knowledge and the preferences of the learner. -Adaptive presentation: The adaptive presentation is to adapt the visual presentation to the preferences and needs of the learner. Some learner can easily read the presented music score and will know how it sounds, but others will want an audio version.

The work presented in [4] focused on various e-learning problems, from these problems, we can extract a set of adaptation types: -Learning path generation (LPG): focused on providing a sequence of learning object materials to the learners -Object recommendation (OR): Allows an adaptive selection of LOs and -Personalization of content (POC): specifies what learning objects are needed for the course established for a specific learner requiring a specific subject.

Based on the works presented above, we can define two main classes of adaptation:

- Adaptation related to the content: It can be divided into two sub categories:

- Adaptation of the content selection: Proposes a set of LOs adapted to the learner's needs and contexts.

-Adaptation of the content presentation: Different presentation forms of educational resources include [2]: Changing the format for the same type of educational resource (e.g. wav files to mp3 files), Changing the type of the educational resource (e.g. -Changing the dimensions of the educational resource (e.g. scaling down or scaling the dimensions of the educational resource).

- Adaptation related to the learning path: It aims to find the learners' paths while learning in e-learning system by adapting the learner preferences, learning styles, and other characteristics of an individual user.

In this work, we have excluded the adaptation of the Content presentation, that's because we are convinced that the adaptation of the format and the scale can be avoided and replaced by a selection adaptation which will include the Content selection with the most appropriate format and scale according to the learner's learning style and / or characteristics of his mobile while being based on the density and high availability of resources pedagogical models in the LO Repositories, which store several format of the same content. So in our study, we will focus only on two major types of adaptation that are: adaptation by selection and adaptation of the learning path.

In the following sections, we will move to the second research question which is "How pedagogical content should be adapted? And this, by studying the different approaches, techniques or algorithms used to achieve each type of adaptation.

III. Overview of the Learning Adaptation Approches and Algorithms

A. *Adaptation of LOs Selection:*

Table 1 presents a collection of works that propose an adaptation by selection, these works can be divided into two categories: the first implements only the adaptation by selection, which consists of selecting LOs adapted to the needs and/or context of the user. The second category aims at performing adaptation by selection as the first phase followed by a second phase which is the adaptation of the LO s sequencing. In this second case, we are limited to study the technique or the algorithm used in the first phase of the adaptation.

Among 16 works collected in Table 1, 9 works perform the adaptation by selection based on the learner model [6-3-9-13-14-16-17-18-19]. This model includes information such as learner profile, learning needs or objective, learning style, knowledge level, ..., this means that these works have not integrated the notion of the context which constitutes what is called a context model, this model must integrate information such as the location of the learner, time, the environmental characteristics (noise level, lighting level), device characteristics…etc [5-7-8-10-11-12-15].

Arriving to the second research question:"How the learning content should be adapted'. The answer to this question consists to find the most applied approaches and algorithms in the learning adaptation field.

As can be seen from Table 1, the majority of the works depends on Ontologies enriched with Semantic Web Rule Language (SWRL). Ontologies as a key and important component of semantic web technologies are used to represent knowledge about e-learning domain. SWRL is a strong mechanism for inferring new relations and knowledge which cannot be reached using ontologies [5-6-3-7-8-9-10-11].

Another category of works is based on ontology modeling of the context and the Leaning domain but it is not based on rules but rather on Algorithms [12-13-14-15]:

Erazo-Garzón in [12] used semantic search (keywords) and route algorithms applied to ontological models due to their expressiveness and extensible architecture, to determine with precision the concepts and semantic relations that exist among academic and contextual information. In [13] and [14], Semantic learning objects search is proposed, it is based on the query expansion of the user query and uses the semantic similarity to retrieve semantic matched learning objects. In [15], a novel context-aware mobile learning application is proposed to encourage and promote Hadith learning, three dimensions (location, time and profile) of user context are implemented, context-filtering based regular expression and ontology matching-recommending techniques are used to match appropriate hadith on learner's context.

The third category of works applied Evolutionary computing algorithms (EC) to implement the adaptation by selection:

Latha in [16] presents an evolutionary approach for tuning the parameters required for personalizing the learning content delivery. The compatibility level of the LO are tuned with respect to the learning style of the learner; the complexity levels of the learner are tuned based on the feedbacks from similar learners and the knowledge levels of the learners are tuned with respect to the complexity level of the learning objects. The interactivity levels of the learners are tuned based on the behavior of the learners during the learning process. For that purpose Compatible Genetic Algorithm (CGA) is applied.

Yang [17] in his work, proposed an Attributes-based Ant Colony Optimisation System (AACS) to help learners find an adaptive learning object more effectively by considering the relationship between learner attributes (e.g. learning style, domain knowledge) and LO's attributes. For that AACS algorithm is proposed, it is derived from an extension of the Ant colony system that updates the trails' pheromones from different knowledge levels and different styles of a group's learners to create a powerful and dynamic learning object search mechanism.

In Dwivedi [18], the author develops learning path recommendation framework by employing course generator's advice and evolutionary approach namely a variable length genetic algorithm (VLGA) after generating learner profiles through registration process.

Discrete Particle Swarm Optimization (PSO) was employed by Wang and Tsai [19] to choose the material suitable for a review course based on the material relevance degree, difficulty level and the number of available learning resources.

Based on the related works analysis presented above, we notice that the adaptation algorithms used to select a set of LOs adapted to the profile/Context of the learner can be classified into two main categories (see Fig. 1):

- Rule-based techniques:

Ontology combined with SWRL adaptation rules is the most used Rule-based technique. Ontology helps in improving adaptive learning by providing a suitable vocabulary for learners to describe the course materials and represent the learner's belief, expectation and context being used for the recommendation of LOs which are dependent on the domain ontology [4].

- Algorithms-based techniques :

- Semantic Algorithms**:** based on Ontology modeling and reasoning based on different types of algorithms

- Evolutionary computing Algorithms that includes genetic algorithm (GA), Swarm optimization techniques (PSO and ACO techniques).

TABLE I. ALGORITHMS USED TO IMPLEMENT THE ADAPTATION BY LOS SELECTION

Work	Approach	Technique	Learner's context dimensions
[05]	Rule-based	Ontology + SWRL Rules	Network and Battery level, learner profile (Age,Knowledge level)
[06]	Rule-based	Ontology + SWRL Rules	Learning Style – Knowledge level-
[03]	Rule-based	Ontology + SWRL Rules	Learner profile Learning Style – Knowledge level- Language preferences)
[07]	Rule-based	Ontology + SWRL Rules	Location, time
[08]	Rule-based	Ontology + SWRL Rules	Location time kewords knowledge level device
[09]	Rule-based	Ontology + SWRL + LO weighting Algo)	Pre-requisite- Knowledge level- LO history- Social relation
[10]	Rule-based	Ontology + SWRL Rules	Learning Style- Location- TimeTechnology- objective- mobility
[11]	Rule-based	Ontology + SWRL rules + Greedy algo	Location, time, device, profile
[12]	Semantic Algorithm	Ontology – Route algo+Semantic search (Keywords)	Context model (Location, time)
[13]	Semantic Algorithm	Ontology - Semantic LO search (Query expansion and Semantic similarity Algo)	Learner profile
[14]	Semantic Algorithm	Ontology - Semantic search (Query expension	Learning style, teaching methods, learning activities
[15]	Semantic Algorithm	Ontology -context- filtering based regular expression + Ontology matching	Location-Time- Profile
[16]	Evolutionar y Algorithm	GA - Compatible Genetic Algorithm (CGA)	Learning style Knowledge level Feedback
[17]	Evolutionar y Algorithm	ACO - attribute-based ant colony system (AACS)	Learning style- Knowledge level
[18]	Evolutionar y Algorithm	GA - Variable lentgh genetic algo	Learning Style – Knowledge level – Goal
[19]	Evolutionar y Algorithm	PSO for selecting LO	Difficultly level, relevance of material

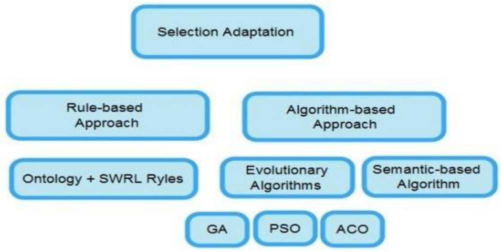

Fig. 1. Approaches and techniques to implement Adaptation by Selection

B. *Adaptation of LOs sequencing (Learning path adaptation):*

Curriculum sequencing, learning path adaptation, adaptive learning path generation and adaptive learning schema generation, designate all the same purpose, which is the personalization and the adaptation of the learning material sequence called learning path. Providing an optimal learning path tailoring to the context of the learners is a crucial issue in online learning adaptation. An optimal learning path could reduce the student's cognitive overload and disorientation; consequently, this process would improve the learner's learning outcome and efficiency of the adaptation in the online learning systems [5].

This section presents a survey on learning path adaptation efforts in the m/e learning environment from 2008 up to 2019. The survey highlights two points:

- The different approaches to formulate the learning path problem.
- The algorithms applied to solve the learning path adaptation problem.

1) *Approaches (Problem formulation):*

The main objective in learning path adaptation is to minimize the path or route of individual learning. According to [18], to formulate the issue of learning path adaptation, various approaches have emerged. Among these approaches:

- Constraints Satisfaction Problem (CSP): It's a single objective with several constraints. The problem in CSP is defined as the state of the variable definition. The solution space of the problem comprises all possible sequences and the objective function is to minimize or maximized the penalty function designed to evaluate the sequencing [5-20]. Many works in the literature proposed evolutionary algorithm, such as Genetic Algorithm (GA) [28-29], Particle Swarm Optimization (PSO) [34] or Ant Colony Optimization (ACO) [32] and scheduling and planning Problem [38].

- Multi-Objective Optimization Problem (MOOP): The concern in multi-objective optimization problem is to satisfy multiple objectives simultaneously [5]. In MOOP approach several algorithms are used, among them GA[25-27], PSO[35], Heuristic algorithms [25-26] and Planning and Scheduling Technique [39].
- Domain modeling: This approach is implanted Through: directed graph, concept map and ontology [3-9-21-22-11], however, there has been no formal model for discussing learning path problems based on Domain modeling [].

2) Techniques:

Once the learning path model has been formulated, the methods to build the approach are chosen according to the problem [5]. Table 2 presents the most used Algorithms in the field of learning path adaptation.

Reasoning based On ontology is present in several works [3-9-21-22-11]. In such approach, reasoning techniques are usually applied on metadata derived from an ontology model [8]. The reasoning is performed in terms of SWRL (Semantic Web Rule Language) rules that are applied on knowledge represented in the OWL-DL (Description Logics) ontology. Problem of concern with this approach is their inappropriateness to reasoning with uncertainty. It should be noted that some of the context elements are quantized with uncertainty leading to certain ambiguity while defining and reasoning with context, [8]. This problem can be dealt with by integrating various reasoning models that may combine probabilistic, Fuzzy reasoning techniques [8]. For that, we highlight in this survey other works, which propose a hybrid solution by combining Ontology-based reasoning with: Fuzzy logic [9] and with a Greedy algo [11].

Case based reasoning technique CBR as another reasoning technique [23-24] is also used to implement the learning path adaptation problem. CBR is the process of solving new problems based on the solutions of similar past problems. CBR has both the capacity to represent knowledge and to reason about it. However, CBR suffers from the inexistence of genericity in knowledge representation; specific requirements for CBR are usually processed as they come. There are also some limitations like as knowledge acquisition problems for unavailable or limited cases, Inference efficiency is not always good as desired, straight forward provision of explanation is missing [5].

Since Learning path problem is NP-Hard problem, heuristic and meta-heuristics are usually used to approximate its solutions. Heuristic search optimization algorithms are used to implement a solution for the learning path adaptation; among these algorithms we have Greedy algorithm and Hill Clumbing algorithm. Greedy algorithm [25, 20, 11] is an algorithmic paradigm that builds up a solution piece by piece, always choosing the next piece that offers the most obvious and immediate benefit. So the problem where choosing locally optimal also leads to global solution are best fit for Greedy. Hill Climbing algo [26], which is another evolutionary Optimizer for optimal search, is used for mathematical optimization problems in the field of Artificial Intelligence. Given a large set of inputs and a good heuristic function, it tries to find a sufficiently good solution to the problem. This solution may not be the global optimal maximum.

According to [4], Meta-heuristic algorithms like Evolutionary computation approaches (EC), have great impact in the solution of the learning path adaptation problem by providing appropriate learning paths to learners. Genetic algorithms [25-27-28-29], Ant colony algorithms [30-31-32-33] and Particle swarm optimization [34-35] are widely used techniques in the construction of learning path sequence.

Machine learning techniques are widely present in the learning path adaptation field; Through the use of Reinforcement learning (RL) and Bayesian Network (BN). RL is an area of Machine Learning. It is about taking suitable action to maximize reward in a particular situation. It is employed to find the best possible behavior or path it should take in a specific situation. In the field of adaptive learning, RL is used in [36]. The proposed approach consists of the following steps. Firstly, the learner's state is determined. Secondly, a learning material or path is suggested through a set of actions. Thirdly, based on RL, the learner state is updated, in addition, the rewards received by recommended learning paths or materials are updated.

Bayesian Network BN (also known as Bayesian probability theory) is also used for finding the adaptive learning path [37]. BN is a directed graph whose nodes represent the uncertain variables of interest and edges are influential links between the variables. Node probability table contains conditional probability (CP) values which are assigned on the basis of the level of expertise, learning style and learning pace of the learner. In the second step, BN is constructed to calculate CP value for each knowledge unit in the learning path. Finally, the shortest path is selected to provide appropriate learning path for the learner [4].

Planning& scheduling techniques [38-39-40], as an Artificial intelligence (AI) techniques, are also proposed to generate sequences of e-learning routes which are tailored to the students' profiles.

Employing Data mining (DM) in intelligent learning systems has become a trend in developing learning systems, which makes educational data mining the focus of a new and growing research community. Such a technique has the following strengths: (1) it reduces the constraints on the scale of the database quality and the variable types; (2) it can analyze both a continuous variable and discontinuous variables efficiently; and (3) its results with graphical or rule expressions can be understood easily and can be explained. Lin in [41] suggested that learning materials based on the tree mechanism can meet individual requirements and can enhance learning efficiency in a learning environment.

Other algorithms derived from the graph theory approach are used for the same purpose, among these algorithms we can mention: the first-search depth (DFS) [42], binary integer programming and Adaptive Shortest path algorithm [44] (See Fig. 2).

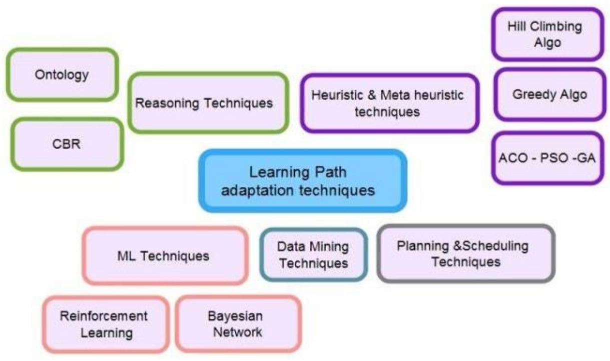

Fig. 2. Approaches and techniques to implement Learning Path Adaptation

TABLE II. ALGORITHMS USED TO IMPLEMENT THE LEARNING PATH ADAPTATION

Work	Approach	Technique	Learner's context dimensions
[3]	Ontology	Ontology + SWRL Rules	Learner context
[9]	Ontology	Ontology + SWRL Rules+ Fuzzy Logic	Location time kewords knowledge level device
[21]	Ontology	Ontology + SWRL Rules	Knowledge level- Prerequisites -satisfaction
[22]	Ontology	Ontology + SWRL Rules	Objective, personality type, Academic state
[11]	Ontology	Ontology + Rules + Greedy algorithm	Context model (Location, Time, device, environment)
[24]	CBR	CBR + Ontology for indexing cases	Not Mentioned
[23]	CBR	CBR + Distance heuclédienne	Context model (Location, time, technology)
[25]	Heuristic based approach	Greedy Algorithm for shortest path	Prequisites and competencies
[20]	Heuristic based approach	Greedy Algorithm	Learner preferences, previous knowledge, availibility of time
[26]	Heuristic based approach	hill-climbing heuristic learning path)	Learner model
[30]	Evolutionary Computing	Shortest path Ant Colony Optimization (ACO) algorithms	Context (Mobility, Luminosity level, noise level Leraning style, knowlege level)
[31]	Evolutionary Computing	ACO	Learner profile(Knowledge level)
[32]	Evolutionary Computing	ACO	Learner model (Cognitive level s, LO complexity level metadata)
[33]	Evolutionary Computing	ACO from data mining based frequent pattern graph model	Knowledge level – prerequisites
[34]	Evolutionary Computing	PSO	Learning objective, previous knowledge
[35]	Evolutionary Computing	PSO	Learning objective, learner knowledge level, time for learning, weights of concepts
[27]	Evolutionary Computing	GA	Context model (Learner motivation)
[25]	Evolutionary Computing	GA	Knolwledge level,
[29]	Evolutionary Computing	GA	Knowledge level, Concept, learning objective, Time
[36]	Machine learning	RL	Context model (environmental context, social, cognitive, Feedback)
[37]	Machine learning	BN	preferences
[38]	Planning & Scheduling	Case based planning	Learner model
[39]	Planning & Scheduling	Planning technique + ontology + Intelligent agents (Hybrid technique)	Learner model
[40]	Planning & Scheduling	AI Planning and scheduling technique	Knowledge level, Metadata LO, learning style, learning objective Time
[44]	Graph based	Adaptive Shortest path algo	Learning objective, Learning background, Preferences Prior knowledge, learning style
[42]	Graph based	the depth First-search (DFS)	Previous knowledge, time restriction

IV. SUMMARY AND CONCLUSION

Learning adaptation and personalization is an important research field in e/m-learning environment. It is quite necessary to discover the most efficient approach to realize it. This paper presents a literature review of personalized and adaptive learning algorithms from the two sides of adaptation: the adaptation of the LOs selection and the adaptation of the learning path or the LOs sequencing.

Through the statistical analysis of the current individualized learning algorithms, the different approaches that are applied to construct them vary between semantic algorithms based on the ontology modeling of the domain model and the learner's context model and evolutionary computing techniques that includes genetic algorithms and swarm optimization techniques. An additional set of algorithms are used for the purpose of the learning path adaptation, in this category we can find machine learning-based algorithms like BN and RL, graph-based algorithms and planning and scheduling techniques.

In future work we will focus on the adaptation within m-Learning environment, which offer adapted learning services in mobility, according to the nature of this kind of learning systems, we need to integrate on the one hand more learners contextual data like, location, time, mobility state, device characteristics, environment characteristics…and in the other hand information that characterizes the learning task like learner's Learning style, knowledge level, preferences,… As adaptation type, we are interested in the well-known learning path adaptation problem which plays a central role in intelligent learning systems and it is considered as one of the most challenging problems. Since this problem is seen as a combinatorial optimization problem, we are going to study the effects of the application of computational evolutionary algorithms, which is still a hot research field.

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