

ARTIFICIAL INTELLIGENCE APPROACHES FOR IMPROVED ADAPTABILITY IN AN ADAPTIVE E-LEARNING ENVIRONMENT: A REVIEW

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Abstract- The concept of e-Learning, which has emerged with the rapid advancement in technology, is a crucial aspect in the field of education. The major issue with the traditional concept of e-learning is that it delivers information to all students in the same manner, irrespective of their individual learning requirements. Adaptive e-Learning Systems, which emphasise the significance of the differences in individual learning styles in modelling the ideal learning environment, attempts to bridge the gap between the student and the instructor that can be observed in a traditional e-learning environment by identifying and catering to individual learner requirements and capabilities. Artificial Intelligence techniques which have the ability to replicate the decisionmaking process of humans, are significant in the domain of adaptive e- Learning as they can be used to improve the adaptivity of the system. This paper assesses the Artificial techniques; Fuzzy Logic, Neural Networks, Bayesian Networks and Genetic Algorithms, emphasising their contribution towards the concept of adaptivity in the context of Adaptive e-learning. The study indicated an increase in the adaptation of Fuzzy Logic techniques, specifically Type 2 Fuzzy Logic Systems, and Bayesian Networks in the development of the Student Model in order to deal with the uncertainty of learning and student diagnosing processes. The application of Artificial Neural Networks to overcome issues in the existing Adaptive E-learning Systems, has also been identified through this review where the application of feature extraction via the Neural Network approach is an effective methodology to be used in the development of the Adaptation Model of an Adaptive E-Learning System to extract the most

appropriate characteristics that can be used to identify learning styles of learners.

Keywords- adaptive e-Learning, Artificial Intelligence techniques, fuzzy logic, Bayesian networks, Neural Networks, Genetic Algorithms

I. INTRODUCTION

The role of information technology in education has changed rapidly and significantly with the introduction of the concept of e-Learning, which provides distance learning opportunities to students all over the world. The focus has been shifted from teacher-centric education to learner centric education where guidance is provided to the learners based on their interests, desires, ability and skills (Lee et al., 2009). In a traditional classroom environment, the instructor can change or adapt his method of delivery according to the learners' behaviour, level of interaction and knowledge level whereas traditional e-Learning provides the same delivery to all students irrespective of their individual learning requirements or preferences (Surjono,2007). Adaptive learning is a new approach to e-Learning, which attempts to bridge this gap which is observed in traditional e-Learning systems by changing the presentation of learning materials to suit the learning style of each individual (Mahajan, Ret. Al, 2012). It is based on the assumption that each learner has different learner-characteristics and that they require different educational settings in order to have an effective learning experience (Cronbach and Snow, 1977). An adaptive learning system

provides a personalized learning environment taking in to consideration the specific learning requirements and knowledge levels of each individual student.

An Adaptive e-Learning System (AES) consists of three models; Student model, Domain model and an Adaptation model (Cannataro et al., 2002). The student model, also referred to as the learning model or the user model, is the contains all student information such as their domain knowledge, behaviour, knowledge level and other information and is used to adapt the interaction mode of the e-Learning system according to the user's needs (Brusilovsky and Peylo, 2003). The Domain model contains the course content to support adaptive course delivery. It acts as a data repository that consists of topics, contents, pages or nodes and navigation links related to the design structure of the represented data. The adaptive model incorporates the adaptive theory of an AES by combining the domain model with the student model. It defines what can be adapted and how and when it is to be adapted. The levels of abstraction at which adaptation may be defined range from specific programmatic rules to general specifications of logical relationships between Adaptive Learning Environments (Paramythis and Loidl-Reisinger,2004).

The efficiency of the AES relies heavily on the methodology used to collect information regarding the learning requirements and characteristics of students as well as how this information is processed to develop an adaptive and intelligent learning context (Shute and Zapata-Rivera, 2012). AES emphasises the importance of individual differences between learners when attempting to model an ideal e-Learning environment, focusing on identifying and catering their individual learning requirements. Artificial Intelligence concepts have a significant value in the development of an adaptive e-Learning environment as they have the ability to replicate the decision-making process adopted by humans (Frias-Martinez et al., 2004).

This paper assesses the Artificial Intelligence approach to effective learning in an adaptive e-Learning environment. An overview of the artificial intelligence techniques; Fuzzy Logic, Neural Networks, Bayesian Networks and Genetic Algorithms, how they are used in an adaptive learning environment and the manner in which they contribute towards enhancing the adaptability of the system to cater to individual learning styles of the learners is discussed.

II. RELATED WORK

The concept of adaptation in the context of learning has become a major topic of research in the past few years. Research has shown that the application of adaptation can provide a better learning experience since learners perceive and process information in very different ways. With the advancements in educational technology, specifically the concept of e-Learning, it is important to understand the learning style and preference of learners in order to make learning more effective (Radwan N, 2014). Adaptive e-Learning is a new approach which is based on AI, that can make a traditional e-Learning system more effective by adapting the presentation of information and overall linkage structure to individual users in accordance with their knowledge and behaviour (Esichaikul et al., 2011).

According to Modritscher et al (2004), the adaptation of the teaching and learning process can be divided into four aspects based on a hypothetical e-Learning System as Adaptive Content Aggregation systems, Adaptive Presentation, Adaptive Navigation and Adaptive Collaborative Support. Adaptive Content Aggregation Systems provides students with different content types depending on the teaching and learning styles. Adaptive Presentation refers to the adaptation of the presentation of content within a page by providing prerequisite, additional, or comparative explanations whereas Adaptive Navigation helps the adaptation process by managing personalized views in the content pages. A network-based educational system is used to form a collaborating group of learners in Adaptive Collaborative Support. There are some other studies which explore certain other approaches to adaptive e-Learning. A multidimensional design model which describes specifications needed for an educational environment proposed by Dall'Acqua (2009) examined the conditions that make a learning environment 'adaptive'. Dekson and Suresh (2010) carried out a survey on the various models of adaptive content delivery system and proposed newer methods of delivering adaptive content for an adaptive e-portfolio system. A new approach to integrate learning styles into adaptive e-Learning hypermedia system was presented by Mustafa and Sharif (2011), who assessed the effect of adapting educational materials individualized to the student's learning style.

The aim of an adaptive e-Learning environment is to tailor the overall learning approach in order to fulfil the learning

requirements of students (Essalmi et al., 2010). An adaptive system adjusts itself to suit particular characteristics and requirements of the learner. Artificial Intelligence (AI) techniques are significant in the domain of adaptive e-Learning as they have the ability to develop and replicate the decision-making process of humans. The application of AI within e-learning has the potential of creating a realistic and interactive educational environment. AI approaches are used in adaptive educational concepts in a variety of ways. For instance, in some systems, the main focus is to examine and assess student characteristics in order to generate student profiles with the intention of evaluating their overall level of knowledge to be used as a basis in the Student Modelling process (Gamboa 2001, Gertner and VanLehn 2000). AI approaches are also used to facilitate the diagnostic process completion so that course content can be adjusted to cater to the learning requirements of every student, and some of them are used to learn from student behaviours to adjust the prescribed software pedagogy (Xu et al. 2002, Moreno et al. 2005).

III. ARTIFICIAL INTELLEGE TECHNIQUES FOR ADAPTIVE E-LEARNING

Adaptive educational systems emphasise the significance of individual learning requirements of students in the process of E-learning where it seeks to bridge the gap between the student and the instructor in the traditional e-learning environment. Artificial Intelligence approaches are regarded as valuable tools in many contexts as they have the ability to develop and replicate the decision-making process of humans. The AI techniques; Fuzzy Logic, Neural Networks, Bayesian Networks and Genetic Algorithms and their deployment in the adaptive learning context are discussed in this section.

A. Fuzzy Logic

Initially presented by Zadeh (1965), Fuzzy Logic is considered an efficient user modelling technique in adaptive e-Learning, specifically as it can mimic the logical reasoning process of humans (Bih, 2006). Learning-teaching behaviour is represented in a human readable and linguistically interpretable manner through the use of fuzzy rules. The Fuzzy Logic System (FLS), as represented in Figure 1, consists of four components: Fuzzifier, Rule base, Inference engine and Defuzzifier (Mendel, 1995).



Figure 1. Overview of a Fuzzy Logic System
(Almohomodi and Hagrass, 2013)

A framework geared towards user modelling, based on FLS, can be developed in the context of adaptive e-Learning, inducing simplified reasoning for users as well as developers (Jameson 1996, Kavi et al. 2003). FLSs can be adopted in order to evaluate and assess learning and knowledge-related outcomes, more precisely examine task objectives, multiple criteria assessments etc. FLS can also be deployed in the Student Modelling process in the development of AES, so that the course content can be adopted in order to cater to individual learning styles. Type 2 FLSs is a new classification of fuzzy systems, used to convey numeric and linguistic uncertainty and can be proposed to directly model and reduce the effects of uncertainties. Extended form type 1 FL, type 2 FL provides a methodology for handling various sources of numeric and linguistic uncertainty which prevail in e-Learning environments.

Xu et al. (2002) presented a profiling system which employs the multi agent approach where fuzzy models were created for content and students based on a dynamic plan formally predefined for a specific individual. This framework was developed through profile abstraction and the content framework which was devised and created through the use of fuzzy links between the subject areas and the knowledge of individuals which were established to be utilized in order to determine learning adaptation. Students are able to receive personalized learning material, quizzes and advices through the proposed system. Although results based on a questionnaire regarding the personalization function of the proposed system as opposed to the traditional learning environment indicate that the proposed system makes a great improvement on personalization of learning, the awareness of the system of the changes in the learning styles and other traits of the student has to be taken into consideration in order to maintain the personalization levels of the system.

Gupta and Dhawan (2012) formulated a unique mathematical model for academic performance synthesis and analysis of an institute. FL is applied in the model for crafting decisions where decision vectors are deployed to deliver suggestions on improving the academic performance of the institute. An FL based student model, which removes the arbitrary specification of precise numbers and facilitates modelling at a higher level of abstraction, was developed by Goel et al. (2012). The proposed student model is designed based on Knowledge tracing and Fuzzy inference where two-rule based systems; one for student knowledge diagnosis and the other for the prediction of a parameter for student performance, have also been designed. However, the results demonstrate overfitting and lack of precision initially, where the integration of machine learning techniques will help in improving the accuracy of the model at the initial stage. Research proposed by Almohomodi and Hagrass (2013) makes use of a self-learning mechanism that generates a FL-based model from the available data. The practical and theoretical environment proposed, incorporated a system which determined student engagement levels based on visual information utilization, which differed from the traditional method of using sensors. Type 2 FL models was used to improve the knowledge delivery to students based on their individual characteristics. Continuous adaptation was maintained in the proposed system in order to ensure that the generated models adapted to the individual learning styles, preferences and needs of the students. Although experiments were carried out targeting only 17 post-graduate students, the system facilitated knowledge delivery improvements to individuals, thus helping to create better performance than type 1 fuzzy systems.

B. Neural Networks

Information processing and problem solving can be performed through the use of a large number of interwoven neurons or components, known as an Artificial Neural Network (ANN). They are specifically in modelling human behaviour due to their ability to process and produce complex information (Frias-Martinez et al., 2004). ANNs which are considered as an effective mechanism to solve various problems, particularly in the field of science, also contribute to the educational field specifically in the context of adaptive e-Learning.

Research has been carried out with regard to the use of ANNs in the field of education, specifically in the context of adaptive e-Learning. Villaverde et al. (2006) described an approach based on a three-layered feed-forward ANN to recognize the learning styles of students based on the actions they have performed in the e-learning system. The proposed automatic style recognition mechanism facilitates the gathering of information about learning preferences where the proposed algorithm uses the recent system usage history to recognize changes in learning styles. This approach has the ability to improve adaptive e-learning environments by identifying individual learning styles of students and presenting them with a customized learning environment to meet their individual learning requirements. A personalized multi-agent e-learning system based on item response theory and ANN which presents adaptive tests and personalized recommendations, was proposed by Baylari and Montazer (2009). The proposed system contains four agents; activity agent, planning agent, test agent and remediation agent. The Remediation agent, designed using ANN, specifically back-propagation, acts as a human instructor with the ability to diagnose the learning problems of the learner and recommend necessary learning materials to the learner. It also has the ability to guide the learner through a remediation session in order to improve his/her learning problems. The proposed system is also capable of determining the learners' ability based on explicit responses on tests to present him/her with a personalized and adaptive test based on that ability. Although the experimental results demonstrated an 83.3% precision in providing personalized and appropriate course material recommendations, this result was obtained through the use of only 30 test cases, thus the level of compatibility between the level of personalization provided by the system and the actual learning style of the learner cannot be clearly established.

Chaplot et al (2016) presented a new adaptive learning system architecture based on ANN which has the ability to handle multi-concept items for effective prediction of student performance and select practice items of optimal difficulty personalized to the student's skill level. The proposed system overcomes the two shortcomings of existing AES; inability of the Student Model to handle multi-concept problems and the inability of the Domain Model to systematically select problems of appropriate difficulty for the student to maximize learning gain, through the use of ANN.

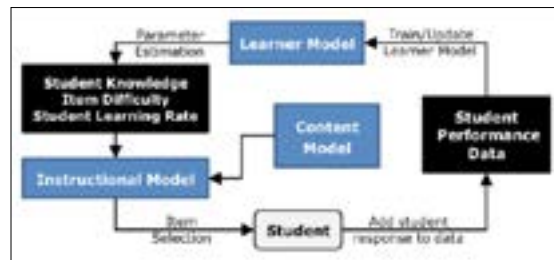


Figure 2. Proposed Adaptive Learning System Architecture (Chaplot et al., 2016)

In order to handle multi-concept problems, the Student Model or the Learner Model in the proposed system architecture (Figure 2), is designed using an ANN, which does not assume any relationship between inputs, contrary to previous methods. Hmedna et al. (2017) describes a methodology on how ANN can be used to identify the learning styles of learners based on the actions performed by them in Massive Open Online Courses (MOOC). The proposed system has a six-stage approach; Data collection, Pre-processing, Feature extraction, Classification, Learner profile and Adaptation. The feature extraction method which is applied after pre-processing extracts the most appropriate characteristics that can be used to identify learning styles of learners. A Neural Network is used in the classification phase (Supervised classification) to detect and recognize learning styles. This methodology can be adapted by AES in identifying individual learning styles thereby helping to improve the adaptability of the system. Supervised classification approach used in this project is a significant step where the learning material can be provided to learners in a more effective manner according to their individual learning style, but the full advantage of this approach cannot be achieved due to the fact that this system only has the feature of recommending content based on the learning style of the learner.

C. Bayesian Networks

A Bayesian Network(BN) is a Direct Acyclic Graph (DAG) explaining the probability distribution in a manner which allows proficient probability dissemination as well as an accurate representation (Gamboa 2001, Moreno and Moreno 2005). It is widely used for student modelling in intelligent learning systems.

An e-Learning system with an integrated learner assessment module that implements personalized content delivery through the use of case-based reasoning and BN

was developed by Mangalwede and Rao (2010). A set of questions for a particular course are considered where the set of questions are divided in to three categories as easy, moderate and difficult. The questions are structured in an acyclic graph where the probabilistic relationship between two successive questions are captured using BN. This approach attempts to test the real understanding and the capability of the learner where the motivation is to never ask a question that the learner can answer effortlessly. The learner’s performance in the given assessments will be used in order for the process of generating and delivering appropriate learning content in the next session.

Jeo and Su (2011) presents an approach which introduces a new rule specification language and provide a user interface for the domain expert to specify the condition part of an adaptation rule probabilistically. A Bayesian model is used in this approach to enable the evaluation and apply proper adaptation rules to tailor an instruction for each new learner in the presence of data anomalies. The accumulation of ‘group data’ in the proposed approach will improve the accuracy of evaluating the next new learner enabling continuous improvement of the adaptive capability of the system. However, the proposed methodology will be much beneficial if the structural learning approach, acquiring the structure of a Bayesian Model based on learners’ data, was also explored.

Bachari et al (2014) proposed a new personalized education system based on the personality of the learner. The proposed framework consists of three elements, namely the domain model, learner model which includes a preference engine and the pedagogical model which includes an adaptive engine model and a revised strategy model. The adaptive strategy engine sets a learner in one of four kinds of independent groups (Figure 3), which are derived based on the preference engine which detects and stores preferences in student model according to Myers-Briggs Type Indicators (MBTI) Tools.

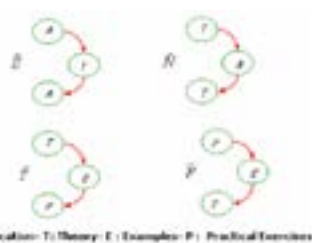


Figure 3. Adaptive Taxonomy: LS dimensions and TS relationships (Bachari et al, 2014)

The revisited strategy engine helps determine the suitability of a particular teaching style to a given learning style using Dynamic Bayesian Network Classifiers. The system offers a suitable teaching style and if the learners grade is less than 60%, the system presents another teaching style.

D. Genetic Algorithms

Genetic algorithms(GA) are optimization algorithms based on the theory of the evolution of the species by Charles Darwin, where the purpose is to seek an extreme of a function defined on a space of data (Azough et al., 2010). According to Davis (1991) the optimization process is performed by GA in four stages: initialization, Selection, crossover and mutation. GAs have become increasingly popular in the development of educational systems as they are especially helpful in understanding the preferences and requirements of the end user (Drigas et al., 2009).

A personalized approach for curriculum generation supported by a GA-based module to facilitate a personalized generation of learning paths, was proposed by Huang et al. (2007). The learning path generation proposed, has the ability to consider the curriculum difficulty level and the curriculum continuity of successive curriculums simultaneously, while implementing a personalized curriculum generation in learning processes. The GA based module of the proposed system, composed of a generation engine and an XML-based knowledge description, allows the generation of the personalized learning path for web-based instruction. This system provides a significant contribution towards the involvement of GA’s in the adaptive eLearning process where it has the ability to provide personalised material and quizzes as well as generate curriculums accordingly. A drawback of the proposed system is that it does not accept user feedback which is an important feature which enhances the adaptive nature of a learning environment.

A GA based adaptive learning scheme for context aware eLearning was proposed by Bhaskar et al (2010). Three levels of contexts of learner; Content level, Presentation level and Media level context, are considered when generating a learning scheme in the developed system, where the Content layer deals with learning path generation, the presentation level with learner preferences and intentions and the media level with the media preferences of the learner. The system also includes four

context tracking modules and a genetic based adaptive learning scheme generation algorithm module where the learning path generation algorithm is enhanced and evolved to a leaning scheme generation which generates a learning path accommodating the entire learner’s context. This learning scheme generation algorithm is designed to be genetic as the various learner’s context parameter values are viewed as constraints to be fulfilled in the learning scheme generation. When compared to the system proposed by Huang et al. (2007) this system has less features considering that the former has the capability of providing suggestions to learners.

Azough et al. (2010) developed an adaptive educational system based on the modulization of the description of learning resources which has the ability to provide the path that is most adapted to the learner profile by using optimization algorithms. The main focus of the system is to establish an optimal path from the learner profile extending to the learning objective based on intermediate courses through the utilization of GAs. It helps a learner to be more autonomous, to have a better comprehension of the course and to better apprehend and manage his learning process. This system has the groundwork to provide personalized learning content as well as quizzes and suggestions by further evaluating and enhancing the mechanism that has been used in order to generate pedagogical paths.

An AES which allows the learner to take courses adapted to his profile and to the pedagogical objectives set by the instructor was described by Madani et al. (2017). A GA, which consists of iterating the three operations; reproduction, crossing and mutation, have been used for the adaptation process to provide the learner the concepts to be learned in an optimal manner by seeking the objectives most adapted to his profile. A measure called a period of activity is introduced to calculate the period of day in which the learner was active where all the publications that are done during this period is filtered in terms of teaching and education. A classification of the collected publications is done where they are classified in to three as motivate, demotivate or neutral. A parallelization of the GA in order to find the optimal pedagogical objective for the learner as well as a parallelization of the classification of publications for finding the sentiment of the learner during the period of activity is also performed. The concept of parallelization as well as sentiment analysis which have been used in this system are new approaches that have not been used in other existing AES and are of much significance.

IV. CONCLUSION

The concept of adaptive e-learning emphasises that the learning process of one learner differs from that of another. The establishment of accurate student models and profiles by modelling the personality traits, skills and the knowledge level of students is crucial when developing an adaptive learning environment. The AI approaches; Fuzzy Logic, Neural Networks, Bayesian Networks and Genetic Algorithms, were assessed in this paper in relation to the concept of adaptive e-learning. This review shows an increase in the adaptation of Fuzzy Logic, specifically Type 2, and the application of Artificial Neural Networks to overcome the major issues in the existing AES systems. The use of Bayesian Networks in the development of a student model in order to deal with the uncertainty of learning and student diagnosing processes has also been identified through this review where the use of Genetic Algorithms in the adaptation process to provide the learner the concepts to be learned in an optimal manner has also been assessed. From the AI methodologies discussed, feature extraction via the Neural Network approach can be considered as an effective methodology to be used in the development of the Adaptation Model of an Adaptive E-Learning System where the most appropriate characteristics that can be used to identify learning styles of learners can be extracted. This methodology provides an accurate identification of a learners individual learning style which is essential in an AES in order to deliver course materials to each student in an effective manner. This study can be further carried out by way of implementation where an adaptive eLearning system can be developed with the use of ANN, as it was identified as the more effective methodology to be used, in order to determine the effectiveness of the above mentioned methodology.

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