On the General Paradigms for Implementing Adaptive e-Learning Systems

Emilija Kamceva[1] and Pece Mitrevski[2]

[1]FON University, Bul. Vojvodina bb, 1000 Skopje, Republic of Macedonia
emilija.kamceva@fon.edu.mk
[2]St. Clement Ohridski University, Faculty of Technical Sciences, Ivo Lola Ribar bb
7000 Bitola, Republic of Macedonia
pece.mitrevski@uklo.edu.mk

Abstract. Adaptive e-Learning systems are the newest paradigm in modern learning approaches. Nowadays, adaptive e-Learning systems are accountable for selecting learning materials or contents according to the learners' style, profile, interest, previous knowledge level, goal, pedagogical method, etc., all in order to provide highly personalized learning sessions. A number of researches have been conducted in the area of adaptive learning and different adaptive learning methods have been proposed. Due to similarity between learning objects graph and the formalism of Petri Nets, an approach based on Petri Nets for controlling the learning path among learning activities has brought many improvements to the paradigm of adaptive e-Learning systems. A model based on High-Level Petri Nets (HLPN) for modeling and generating behavioral pattern of students has been presented recently, bringing numerous advantages, but also a lot of open issues that need to be resolved. This paper exposes the fundamental characteristics of adaptive e-Learning systems, as well as the students' behavior, such as learning styles and levels of knowledge, thus providing a basis for a novel modeling framework for performance analysis of such systems, as our main goal in future research.

Keywords: e-Learning systems, Petri Nets, learning style, adaptive learning

1 Introduction

e-Learning for decades is one of the most attractive areas of scientific research that involves both pedagogical aspects and application of ICT in various domains (software engineering, semantic technology, communications, computer networks, etc.). The problem of development of personalized adaptive systems has been recognized from the outset as one of the permanent objectives, and current research efforts on the global level have resulted in the development of platforms that support and provide access to the general use.

Tang and Mccalla [1] proposed an evolving web-based learning system, which finds a relevant learning content according to the accumulated ratings given by students. Liu and Yang [2] introduced the Adaptive and Personalized e-Learning System

(APeLS), which provides dynamic learning content and adaptive learning processes for students to enhance the quality of learning. Papanikolaou *et al.* [3] suggested integrated theories of instructional design with learning styles to develop a framework that adapts different students to provide the presentation sequence of the learning content in a lesson. Chen [4] proposed genetic-based personalized e-Learning system to (i) generate appropriate learning paths according to the incorrect testing responses of an individual student in a pre-test, and (ii) provide benefits in terms of learning performance promotion.

2 The Concept of Adaptivity in e-Learning

During the past years, a lot of companies, faculties, universities and other institutions developed systems for common or personal use. There are many systems developed for e-Learning, such as: LRN; Blackboard; BSCW[1]; CLIX; InterWise; Moodle; OLAT[2], etc. Some of them have extensive support for adaptivity and provide both adaptive presentation support and adaptive navigation support [5]: AHA[3]; ALFANET[4] [6]; ELM-ART; EPIAIM; SQL-Tutor.

This section deals with adaptivity in e-Learning systems and explains *why* and *how* adaptivity is able to improve the quality of e-Learning environments.

The goal of adaptive e-Learning is aligned with exemplary instruction: delivering the right content, to the right person, at the proper time, in the most appropriate way - any time, any place, any path, any pace (NASBE)[5]. According to [7] adaptivity is of particular importance in the field of e-Learning for two main reasons:

- learners differ in their goals, learning styles, preferences, knowledge and background and the profile of a single learner changes (e.g. the knowledge increases as an effect of learning);
- the system can help the learner to navigate through a course by providing user-specific (not necessarily linear) paths.

Providing personalized access to the content (fitting the individual user's needs) and taking care of a single user (decisions on what is presented are based on the user's goals, knowledge, etc.) compensate for one significant problem of common e-Learning systems that provide the same view of the information for all learners. There are several different ways to categorize adaptivity features: Adaptive presentation support, Adaptive navigation support, Criteria for adaptation [7].

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[1] Basic Support for Cooperative Work
[2] Online Learning And Training
[3] Adaptive Hypermedia Architecture
[4] Active Learning For Adaptive Internet
[5] National Association of State Boards of Education Study Group

2.1 Studies on Adaptive e-Learning

The adaptation of the teaching and learning process can be divided in four elements, based on a hypothetical e-Learning system, as described below: Adaptive content aggregation, Adaptive presentation, Adaptive navigation, and Adaptive collaboration support.

There were some studies related to adaptive e-Learning but they had different focuses and approaches. Semet *et al.* [8] used an artificial intelligence approach, called *"ant colony optimization"*. In this system ants are presumed as learners, and adaptive learning path is made by considering pheromone (a secreted or excreted chemical factor that triggers a social response in members of the same species) which is released by other learners. Zhu [9] used a *learning activity graph* and allocated Boolean expression to every edge of the graph. This expression includes required precondition and post condition for traveling through the edge. If this expression is evaluated correctly, corresponding edge is traversed by learner. Chen *et al.* [10] used *"Item response theory"* for providing individual learning path for each learner. Chang *et al.* [11] used a *Behavioral Browsing model* (B^2 model) based on High Level Petri Nets (HLPNs), which was introduced for modeling and generating behavioral pattern of students. Su *et al.* [12] proposed *object-oriented course modeling* based on HLPNs, whereas Liu *et al.* [13] proposed an approach based on Petri Nets for controlling learning path among learning activities.

2.2 Style and Models for e-Learning

Learning styles are various approaches or ways of learning. They involve educating methods, particular to an individual, which are presumed to allow that individual to learn best. Most people prefer an identifiable method of interacting with, taking in, and processing stimuli or information [14].

A learning style is a student's consistent way of responding to and using stimuli in the context of learning. There are several definitions of learning styles.

Keefe [15] defines learning styles as the "composite of characteristic cognitive, affective, and physiological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment." Stewart and Felicetti [16] define learning styles as those "educational conditions under which a student is most likely to learn". Thus, learning styles are not really concerned with what learners learn, but rather *how* they prefer to learn. Honey and Mumford [17] defined the learning style as the attitudes and behaviors that determine student's preferred ways of learning. Learning style influences the effectiveness of training, whether that training is provided on-line or in more traditional ways.

This section describes the models developed for styles in e-Learning.

(Kolb's model). The ELT model outlines two related approaches toward grasping experience: Concrete Experience and Abstract Conceptualization, as well as two related approaches toward transforming experience: Reflective Observation and Active Experimentation. According to Kolb's model, the ideal learning process engages all four of these modes in response to situational demands. In order for learning to be

effective, all four of these approaches must be incorporated. As individuals attempt to use all four approaches, however, they tend to develop strengths in one experience-grasping approach and one experience-transforming approach. The resulting learning styles are combinations of the individual's preferred approaches. These learning styles are as follows: Converger; Diverger; Assimilator; Accommodator [18]. Kolb's model gave rise to the Learning Style Inventory, an assessment method used to determine an individual's learning style. An individual may exhibit a preference for one of the four styles – accommodating, converging, diverging and assimilating – depending on their approach to learning via the experiential learning theory model [19].

(Honey and Mumford's model.) Two adaptations were made to Kolb's experiential model. Firstly, the stages in the cycle were renamed to accord with managerial experiences of decision making/problem solving. The Honey & Mumford stages are: Having an experience, Reviewing the experience, Concluding from the experience and Planning the next steps. Secondly, the styles were directly aligned to the stages in the cycle and named Activist, Reflector, Theorist and Pragmatist. These are assumed to be acquired preferences that are adaptable, either at will or through changed circumstances, rather than being fixed personality characteristics [17].

(Neil Fleming's VAK/VARK model). One of the most common and widely-used [20] categorizations of the various types of learning styles is Fleming's VARK model (sometimes VAK), which expanded upon earlier neuro-linguistic programming (VARK) models [21] visual learners; auditory learners; kinesthetic learners or tactile learners [22]. Fleming claimed that visual learners have a preference for seeing (think in pictures; visual aids such as overhead slides, diagrams, handouts, etc.). Auditory learners best learn through listening (lectures, discussions, tapes, etc.). Tactile/kinesthetic learners prefer to learn via experience – moving, touching and doing (active exploration of the world; science projects; experiments, etc.). Students can also use the model to identify their preferred learning style and maximize their educational experience by focusing on what benefits them the most [14].

2.3 Components of e-Learning

The *content model* houses domain-related bits of knowledge and skill, as well as their associated structure or interdependencies. This may be thought of as a knowledge map of what is to be instructed and assessed, and it is intended to capture and prescribe important aspects of course content, including instructions for authors on how to design content for the model. A content model provides the basis for assessment, diagnosis, instruction, and remediation.

A *learning object* is "a collection of content items, practice items, and assessment items that are combined based on a single learning objective". The requirements for any content model fall into two categories: requirements of the delivery system and requirements of the learning content that is to be delivered [23].

Knowledge structures. The purpose of establishing a knowledge structure as part of the content model in any e-Learning system is that it allows for dependency relations to be established. Each element (or node) in the knowledge structure may be classified in terms of different types of knowledge, skill, or ability. Some example knowledge types include:

- *Basic knowledge (BK):* This includes definitions, examples, supplemental links (jpgs, avis, wavs), formulas, and so on, and addresses the *What* part of content.
- *Procedural knowledge (PK):* This defines step-by-step information, relations among steps, subprocedures, and so on, and addresses the *How* part of content.
- *Conceptual knowledge (CK):* This refers to relational information among concepts and the explicit connections with BK and PK elements, draws all into a "big picture" and addresses the *Why* part of content [23].

The *learner model* [23] represents the individual's knowledge and progress in relation to the knowledge map, and it may include other characteristics of the learner as a learner. As such, it captures important aspects of a learner for purposes of individualizing instruction. This includes assessment measures that determine where a learner stands on those aspects. Different student models have been explored: Han B. et al [24], AHAM [25] and NetCoach [26].

The *instructional model* manages the presentation of material and establishes (if not ensures) learner mastery by monitoring the student model in relation to the content model, addressing discrepancies in a principled manner, and prescribing an optimal learning path for that particular learner. Information in this model provides the basis for deciding how to present content to a given learner and when and how to intervene.

3 Petri Nets as a Modeling Tool

Many researchers have conducted research in the field of adaptive learning and have used different methods. At first, Liu *et al.* [13] proposed an approach based on Petri Nets for controlling the learning path among learning activities. This model has brought many improvements in adaptive systems but also many disadvantages, such as learning styles of students. Recently, the "B^2 model" [11] has been constructed, based on High-Level Petri Nets (HLPN), which was proposed for modeling and generating behavioral pattern of students. This new paradigm brings numerous advantages, but also a lot of open issues that need to be resolved.

3.1 Comparison of Models

To evaluate the practicability and accuracy of the B^2 model, behavioral patterns generated by the B^2 modeling tool have been compared with the actual behavioral patterns collected from elementary school students [27]. Actual behavioral patterns have been acquired by Chiu, Chuang, Hsiao, and Yang [28]. By two-stage cluster analysis, they classify three kinds of learning styles:

1. *Dilatorily type:* The student belonging to this type takes more time to browse a learning unit than other students. She/he often reviews the same learning unit and skips learning units.
2. *Transitory type:* The student spends the least amount of time in browsing and has the least browsing depth. Browsing order is irregular.
3. *Persistent type:* The browsing depth is the highest and browsing order is regular.

The B^2 model can capture students' learning behavior and then generate behavioral patterns for facilitating the verification of the researches regarding e-Learning.

For the generated behavioral patterns, whether or not a student quits an e-Learning course is determined by:

$$Prob_{quit} = C\frac{e^{-\lambda\theta}(\lambda\theta)^{x}}{x!}$$

where $\theta = \theta_{total} / \theta_{unit}$ refers to the time that a student has already stayed in an e-Learning course; θ_{unit} is the unit of time; λ refers to the rate of leave; and C is a constant for regulating the distribution curve. Since $Prob_{quit}$ is used to determine that a student quits, x=1. After the result derived using this equation determines that a student remains in an e-Learning course, the roulette wheel selection is used to select the next browsing action from: depth-first, breadth-first, skip, and review.

A conclusion has been drawn that the generated behavioral patterns based on the B^2 model are fairly similar to the actual behavioral patterns acquired from Chiu *et al.* [27] and confirms that the number of students who remain in an e-Learning system exponentially decreases in time. Furthermore, the experimental e-Learning system must also possess the additional function of collecting learners' behavior. It needs to take redundant time and effort in the development of the additional function for collecting learners' behavior. Obviously, the B^2 model, indeed, reduces cost and time of collecting learners' behavior. In terms of practicability, the generated behavioral patterns based on the B^2 model can serve as test data to validate the accuracy of an intelligent tutoring system. Therefore, the B^2 model can facilitate the verification process of an intelligent tutoring system.

In contrast the previous two models, Omrani *et al.* [29] have also developed a model based on High Level Petri Nets (i.e. Colored Petri Nets (CPNs), where a value (color) is allocated to each token, and Timed Petri Nets, where a real value corresponds to each token, representing the token age). This model is quite similar to the B^2 model and uses the same formulas (Poisson and normal distribution) to calculate the time of searching, the time required for assessment and the time the student spends in the queue. Three factors to adaptation are used: 1) Learning Style; 2) Knowledge Level; 3) Score. It should be noted that this adaptive model uses Petri Nets for the determination of adaptive learning style. Four learning styles are considered: Visual, Audio, Read/Write and Kinesthetic. A learning object in the learning object graph, which can be a chapter, is mapped to a place in the Petri Net. Colored tokens are learners, and they travel through learning object via transitions.

Although the method constructed on the basis of High Level Petri Nets uses the same mathematical formulas as well as the B^2 method, it differs in that the calculated response time is computed in two viewpoints of black and white box. In viewpoint of black box, authors calculate only response time for each learner, whereas, in viewpoint of white box, in addition to response time, they show traveled path, time spent for each middle learning unit, earned score in each test, learning style and knowledge level for each learner.

Characteristic of this model is that the learning style of a new learner is checked before entering into introduction node and based on its type he/she is guided to two individual paths. These two paths represent the same course, but their content, due to its style, is presented with different media. However, authors use CPN tools (a fast simulator that efficiently handles untimed and timed nets) for editing, simulating, and analyzing the proposed model.

4 Discussion and Conclusion

In this paper we presented an overview of e-Learning systems and thoroughly described the concept of adaptivity. Various researchers, in different ways, have constructed models to improve adaptive e-Learning systems. We made a comparison of models that are created by means of Petri Nets and described their advantages and disadvantages.

Original Petri nets did not contain a concept of time, and an enabled transition would fire instantaneously. The introduction of deterministic time delays (that is, firing takes place if a transition is enabled for a specified amount of time, or tokens have memory, i.e. “aging tokens”) has led to Timed Petri nets that were later extended to Stochastic Petri Nets (SPNs), where such delays are random variables based on given distributions. The firing of a transition corresponds to any discrete event of the modeled system, and represents a fundamental feature of Petri nets: the ability to graphically depict the *dynamic behavior* of a system. The analysis of an SPN model is usually aimed at the computation of more aggregate performance indices than the probabilities of individual markings. Several kinds of aggregate results are easily obtained from the steady-state distribution over reachable markings. Some of the most commonly and easily computed aggregate steady-state performance parameters include: the probability of an event, the probability mass function (*pmf*) of the number of tokens in a place, the average number of tokens in a place, the frequency of firing of a transition, the average delay of a token, etc. Moreover, efficient numerical algorithms for transient analysis of deterministic and stochastic Petri nets (DSPNs) and other discrete-event stochastic systems with exponential and deterministic events have been widely introduced [30].

Herewith, motivated by the aforementioned research papers, we propose our promising idea of using *analytical modeling approach* and Stochastic Petri Nets as a tool for adaptive model development and performance analysis. In this manner, lots of questions about the characteristics of adaptive e-Learning systems could be answered. Inspired by these ideas, our future work will be focused on developing (D)SPN model for performance analysis of adaptive e-Learning systems, by first investigating the dynamic behavior of learners.

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