Student Modeling in Distributed Adaptive Knowledge based E-Learning Environment

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ABSTRACT

The previously developed and researches of e-learning system are based on "one size fits all" approaches. Where differences among the learners and student were disregarded and supplied the same learning materials to the learner or students. The newly research and development style changes the needs and preferences for the researcher and learners. The result of this required most adaptive and distribute knowledge-based e-learning system. In the present paper distributed adaptive knowledge based model for e –learning system is described which primarily focuses on student modelling module. The student modelling is responsible to fulfil the individual requirement in teaching –learning environment.

General Terms

E-learning, Intelligent learning, Knowledge Based System, Web based System

Keywords

Adaptive Learning, Student Modelling, Distributed e-learning, Tutor Modelling, Learning Objectives.

1. INTRODUCTION

Expert learning environments are teacher-student models that compute in the intelligent manner. The mechanism from fuzzy logic (artificial intelligent community) is used to accept or adapt the teaching-learning processes for the requirements of the individual learner. The Distributed Adaptive Knowledge Based E-learning System (DAKBES) is an expert intelligent learning system that can access or used through the Web server. A DAKBES make originally adaptive distribute e-learning system available to thousands of student in the world via web connected computer systems. A Distributed adaptive knowledge based student model helps most of the students to achieve their learning goals and requirements. The efficient and effective delivering of knowledge for an individual in an adaptive manner is the key of DAKBES.

Most of the attempts in this area are based on adaptation to user's level of knowledge (Stash and De Bra, 2004; Popescu et al., 2007). Other learner features taken into account are background, hyperspace experience, preferences and interests (Brusilovsky, 2001; Popescu et al., 2007). However, less attention was paid to learning styles and their effects on learning achievement. This is despite the fact that learning styles constitute a valuable tool for improving individual learning among the user features (Paredes and Rodriguez, 2002). Statistics revealed that considering students' learning style is a significant factor that improves learning performance in web-based learning or e-learning (Manochehr, 2006). In addition, there is also the equally important issue of evaluating the effect of adaptation to learning styles on students' achievement. In the development of an adaptive e-learning system based on fuzzy clustering approach(K. M. Fouad, M. A. Hogo, S. Ganalel-Din, N. M. Nagdy 9, 2010), the student model is constructed by analyzing the web-log to extract the interested terms in the visited pages by the learners. Then, the fuzzy clustering approach and statistical k-means clustering method is used to predict student's interest for delivering learning contents from semantic web. In their recent research(Brown et al. 2009) investigated adaptive e-learning hypermedia that specially utilize learning style as their adaptation mechanism, they found that out of 10 systems, 6 systems did not seem to have published any quantitative evaluations.

The advantage of the distributed adaptive student model is that it inherits both fuzzy logic and web-base modern techniques, following are some other advantages:

- Distributed adaptive knowledge based e-learning system is not classroom dependent. The DAKBES uses the same learning system not only in the classroom but also use around the world again and again.
- Distributed adaptive knowledge based e-learning system are cross-platform deliverable. Most of the platform that can utilise other web resources also share the learning materials used in the learning systems.
- Distributed adaptive knowledge based e-learning systems provide adaptation of individual. The flexible teaching and individual adaptive learning environment have been established according the knowledge, information and requirement of individual student and the knowledge of the subject domain and teaching methodology.
- Distributed adaptive knowledge based e-learning systems provide adaptive hypermedia. Using the web-based hypermedia and multimedia techniques learning materials and course contents are produced and organized dynamically.
- Distributed adaptive knowledge based e-learning systems have centralised maintenance. The server maintained overall system and the learning material uploaded or posted to the clients (learner/student) through browser, all over the world.
- Distributed adaptive knowledge based e-learning systems are cost effective. Once the learning material or course contents have been produces, they have reused by many number of learners/students.

Adaptation is most important for the web base learning systems than the other 'standalone' and 'one-size-fit' learning systems:

- The adaptive e-learning system shall be used much larger variety of learners. Since the learner have very different knowledge levels, goals, backgrounds, learning style, behaviour, individual preferences, and education qualification, a system particularly any student design is not always suitable for others students.
- The knowledge level of the individual learner is growing very fast and quickly. So the learning material and content pages which are quite difficult and complex for a particular learner at the beginning, as soon as become quite trivial and boring to the same learner. The knowledge and standard of the presentation require to changed with the student learning process.
- The system can be used by the learner in different area of places. In whole the world no teacher and classroom is available for face-to-face learning assistance in most cases. The system should provide learning material and help individual learner just as a classroom counsellor.
- The system is more appropriate for the individual and adaptive student centric learning model instead of tutor/teacher centric model. The learning materials and contents are accessible and presented according to the preferences, goals and knowledge level that make the study and reading processes more effective, efficient and interesting.

Rest of the paper is organized as follows: section-2 describes recent work and relevant issues in this field and definition of the distributed adaptive knowledge based e-learning system and state of art. Section-3 described the proposed model followed by different e-learning modules of the learners and presents the details of implementation. Finally section-4 gives conclusion and scope of future work in this regards.

2. DISTRIBUTED ADAPTIVE KNOWLEDGE BASED E-LEARNING

Student Module is the most important component of DAKBES. It helps for an individualised learning/teaching environment. The adaptive process is described in three phases: Get the information of the learner, process and test the information to initialise and update and modify the student model, using the student model to give the adaptation.

The student model is most important and very essential tool in the distributed adaptive knowledge based e-learning system. The adaptation of a system mainly involves choosing and presenting each successive learning activity as a procedure of whole scope of the student/learner's knowledge of the subject being learn and other relevant features of the learner that are maintained in the student model. Since the student model is used to update and modify the interaction between the student and the system to suit the requirement of the individual learner.

2.1 State of art

The key idea to keep in mind is that the true power of educational technology comes not from replicating things that can be done in other ways, but when it is used to do things that couldn't be done without it. (Thornburg, as cited in National Association of State Boards of Education Study Group [NASBE], 2001). Today`s the examples of the e-learning on Internet, mostly little more than some web links associated upload in HTML format and Lecture notes. However, the previous quote, the power of e-learning comes from the exploitation of the wide variety of capabilities that technologies afford. Most of them provide instructional contents and assessment that adapted to students or learner's requirement or desires. That should comprise an online real-time application. Another effective technology providing the multimedia presentation, opportunities for extra emergent skills, dynamic events of simulations and hypermedia representation.

The requirement for content to build the same specification with current industry research and development associate with learning objectives e.g. see IEEE LTSC, 2003, IMS Global Learning Consortium 2001. Learning objectives (LOs) are small reusable components- power-point presentations, tutorials, examples, questions, exercises, assessments, simulations and case studies. However, rather than use them to build castles, they are used to build larger collections of learning materials.
The arrangement of these LOs to achieve instructional goals is done during this assembly. These collections will be specified using the Sharable Content Object Reference Model (SCORM; Advanced Distributed Learning, 2001) specification for defining courses. Although the current practice is to assemble the LOs before the collection is delivered, there is no reason why the LOs could not be assemble into a structure that would allow an expert and intelligent distributed adaptive system to reassemble them on the fly to meet the needs of the particular learner.

3. PROPOSED DESIGN MODEL

The main goal of the distribute adaptive e-learning to delivered the correct and right content to the requirements of the learners at the proper time in the appropriate way-any time, any place, any path, any pace (NASBE 2001). In the paper, the requirement to achieve this fuzzy goal in an e-learning context is focused and synthesized. The necessary modules of e-learning system are shown in Figure-1 and further these modules are briefly explained.

The *content module* is the domain of knowledge and skill an also their related structure or interdependent. It is a knowledge map of what is to be instructed and assessed and this intended to capture and prescribed course content, examples, exercises, including instructions for authors on how to design course contents, examples and exercises for the model. This module provides the basis for assessment, diagnosis, instructions and remediation. The content module can be linked to the hierarchical array of knowledge and skills.

The *learner/student module* includes the individual's knowledge profile and individual test and it can include other characteristics of the learner. So that, it capture and analyse the important aspects of the learner, for individual instruction purpose. This is includes assessment measures for determining of where the learner stands on those aspects.

The *instructional module* check and manages the quality and presentation of the contents and course material and ascertains or if not ensures learner mastery by monitoring the student model in relation to the content module, addressing discrepancies in a principled manner and prescribed optimal learning path for individual learner. The information in this module provides the basis for deciding how to present content to a given learner and when and how to intervene.

The *adaptive system* integrates and uses information obtained from the preceding modules to drive presentation of an adaptive learning module.

of this system, such as grain size will vary, depending on the use or purpose of the content and course material.

3.1.1 Learning objectives:

LOs can be selectively applied, either alone or in combination, by computer S/W, learning facilitators, or learners themselves, to meet individual requirements for learning or performance supports. In modern industry practice, LOs are assembled into course before the time that they are delivered. The basic fundamental idea involves dividing the LO collection such that it contain sub-collections, each of which contains all the instructional components necessary to teach that skill. Using this hierarchy, the adaptive system can first decide that what needs to be taught and then decide how to teach.

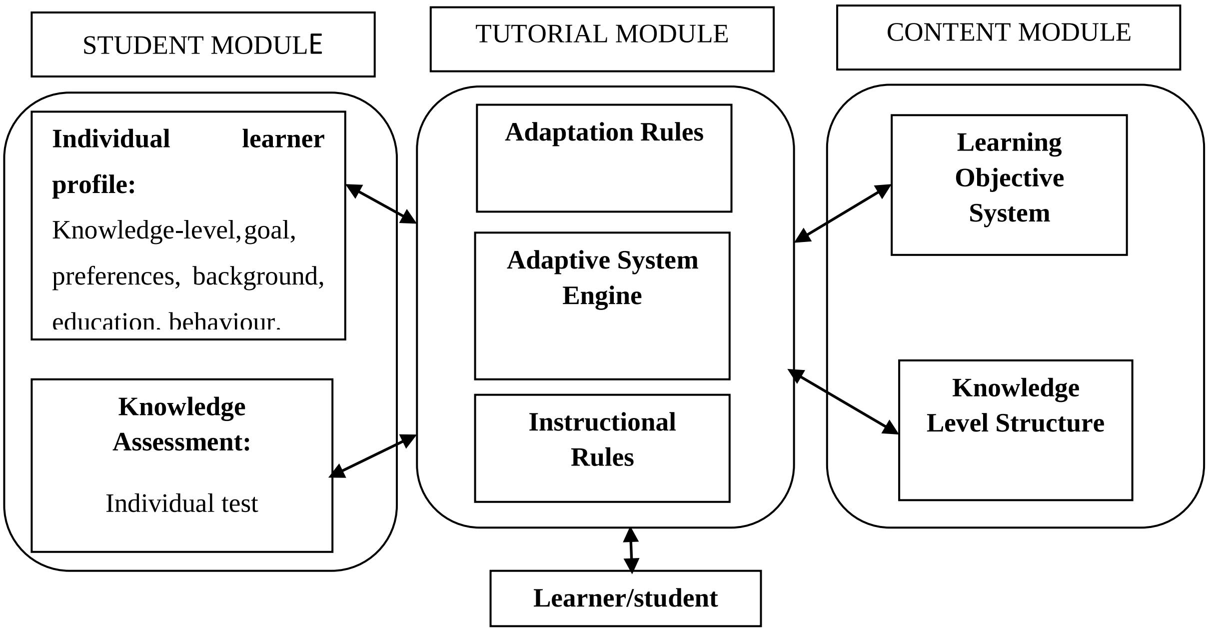

Figure1: Learning management system framework including two types of assessments.

3.1 Content module

There are two types of needs of the content module: needs of the delivery system and needs of the leaning contents and course material that is to be delivered. On the delivery side of the equation which require a system that are content independent, robust, flexible and scalable.

The content independent means the system will serve any content that designed within the content requirements. Robust means that lives on the net and that should be capable of delivering instruction to multiple users concurrently. Flexible means an adaptivity, needs different types and sequence of content. Scalable means the system will adjust to increase demands, such as accommodate greater components, maximum users and so on.

On the learning content and course material side of the equation, the content must be composed in such a way that the delivery system can adopt it to the requirements of particular student or learner.
Each content and course material aggregation will have need to composed of predictable pieces, therefore the delivery system can know what to expect. Which means all of the course content and course material served by this delivery system will have to build to the same specification. The issues

3.1.2 Knowledge level structures:

The importance of establishing a knowledge level structure in the content model in any e-learning system is that it allows dependency relationship to be established. It provides the basis for the following: assessment (what is the current status of a particular topic or LOs?), cognitive diagnosis (What's the source of the problem, if any?), and instruction or remediation (Which LOs need to be taught next to fix a problem area or present a new topic?). Each element or node in the knowledge level structure can be classified of different levels of knowledge, skills, or ability. Some knowledge level examples considered are:

- Basic Knowledge Level (BKL) of topic: this includes definitions, examples, diagrams, formulas, symbols act. and addresses what part of the content.
- Procedural Knowledge Level (PKL): this define the step-by-step information, relations among steps, methods, functions, sub-functions and so on and addresses the how part of content.
- Conceptual Knowledge Level (CKL): this includes the relational information among concepts and the explicit connections with BKL and PKL elements, draws all into a "big picture" and addresses the why part of content.

To the restricting the knowledge level structure (each node associated collection of LOs) to a single knowledge level helps ensure the course broken down to an appropriate grain size, by limiting the scope of what can be in any single node. This restriction also suggests different strategies for the authoring of instruction and assessment: Many different types of knowledge level require different strategies. Some suggested guidelines are: BKL instruction would be involves the introduction of new definitions and formulas in a straight forward, didactic manner, whereas BKL assessment relates to measuring the learner's ability to recognize or produce some formula, basic definition, rule, and so on. PKL instruction will occur within the context of experiential environments where the learner can practice doing the skill or procedure (problem solving),

Whereas, PKL assessment relates to the learner's ability to actually accomplish some procedure or apply a rule, not simply recognize those things. Finally, CKL instruction typically occurs after the learner has been presented with relevant base information (BKL–PKL), and then the big picture may be presented, either literally or via well-designed analogies, case studies, and so on, whereas, CKL assessment contains to a learner being able to transfer BKL and PKL to novel areas, explain a system or phenomenon, predict some outcome, or strategize. The outcome tests described earlier in relation to the electricity tutor study exemplify each of these outcome types. The simplified network of elements (nodes) and associated knowledge level types is shown in Figure 2. Each node has associated collection of LOs that teach or assess a any component of a concept or skill.

In summary, different knowledge level types associated with their own special way of being instructed and assessed. So now the questions are: How do we optimally assess and diagnose different outcome types and what happens after diagnosis? Before answering these questions, the learner model is presented which is the repository of information concerning the learner's current status in relation to the various LOs (i.e., domain-related proficiencies).

3.2 Learner module

The student/learner model refers information which comes from assessments and ensures the inferences of proficiencies. This information is used by the system to decide what to do next. In the context of distributed adaptive e-learning, that decision related to customizing and then optimizing the learning experience. However, the critical component is the validity and reliability of the assessment.

One idea is to employ that is called the evidence-centre design approach to assessment. This allows an instructional designer to (a) define the claims to be made about the students (i.e., the knowledge, skills, abilities, and other traits to be measured), (b) delineate what constitutes valid evidence of the claim (i.e., student performance data demonstrating varying levels of proficiency), and (c) create assessment tasks that will elicit that evidence. Evidence is what ties the assessment tasks back to the proficiencies, and the entire process is theory driven, as opposed to a more common data- or item-driven manner.

3.2.1 Assessing the learner:

It concern first issue that what is to be assessed. Learners have two aspects that have adaptive implications. (i) *domain-independent information*— this relates to learner profile data (e.g., cognitive abilities or personality traits) and allows the system to pick and serve optimal LO sequences and formats and *(ii) domain-dependent information*— it contains the knowledge level assessment via pre-test and performance data to allow the system to initialize a learner model in

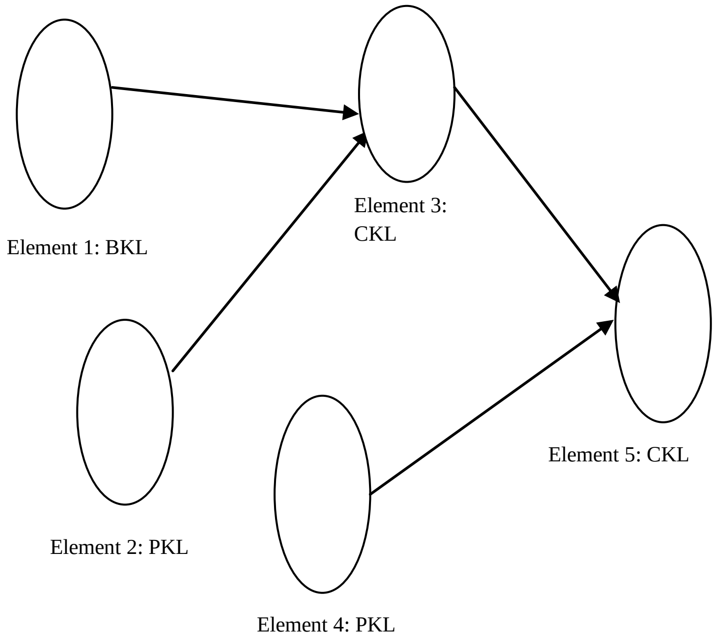

Figure2: Simple Knowledge level structure hierarchy

relation to content, course material and LOs, eliminate those already "known," and focus instruction or assessment (or both) on weak areas.
Assessing a particular learner traits indicate specific content and course material delivery in relation to either different sequence of topics or providing appropriate, alternative formats and media. In the different sequence of topics, valid instructional system design sequence consists of these steps: (i) present the introductory material (ii) follow the rule or concept of the presentation (iii) provide the illustrative examples and questions (iv) give liberal practice opportunities and case studies and (v) summarize and call for reflection. Thus, across these topics, one general sequencing rule can be serve easier topics before more difficult ones and within a topic, a general rule can be default delivery of certain learning objectives: introduction, body (rule or concept, with examples), interactivity (explorations, practice, and explicit assessments of knowledge or skill), and reflection (summary)
In Figure 1, shows which part comes together, the bottom row of the figure shows the typical way of serving content based on inferred gaps in a learner's knowledge level structure. That is reflecting differences between the learner's knowledge level profile and the expert knowledge level structure embodied in the content model. "Instructional rules" then determine which knowledge or skill element should be selected next (i.e., selecting from the pool of non-mastered objects). The top row shows an additional assessment, representing another way to adapt instruction based on learners' cognitive abilities, learning styles, personality, or whatever relevant. It provides information about how to present the selected knowledge or skills.

3.3 Instructional module

There are many general and specific guidelines to instructional design for systematic approaches, such as those described by Robert Gagne. But how do we progress from guidelines to determining which LOs should be selected, and why? To answer this question, after delineating the guidelines presented in Gagne's (1965) book entitled *The Conditions of Learning,* describe a student modelling approach that implements some of these instructional ideas within the context of an ITS. The following represents an abridged version of Gagne`s "events of instruction", along with the corresponding cognitive processes. These events provide the necessary conditions for learning and serve as the basis for designing instruction and selecting appropriate media (Gagne, Briggs, & Wager, 1992). For designing good e-learning environments the guidelines are:

1. Gain the learner's attention (reception).
2. Inform the learner of the objectives(expectancy) 3. Stimulate recall of prior learning (retrieval).
4. Present the learning stimulus (selective Perception)
5. Provide learning guidance (semantic encoding).
6. Elicit appropriate performance (responding).
7. Provide feedback (reinforcement).
8. Assess the learner's performance (retrieval).
9. Enhance retention and transfer (generalization).

Applying Gagne`s (Gagne, Briggs, & Wager, 1992) nine-step model to an e-learning program is a good way to facilitate learners successful acquisition of the knowledge and skills presented there. In contrast, an e-learning program which is replete with bells and whistles, or provides unlimited access to Web-based documents, is no substitute for sound instructional design. Although those types of programs might be valuable as references or entertainment, they will not maximize the effectiveness of information processing or learning. In addition to the specific prescriptions mentioned previously, there are a few key presumptions and principles for instructional design that should be considered when designing an e-learning system. In general, these include the: knowledge is constructed actively, multiple representations for a concept or rule are better than a single one, problem solving tasks should be realistic and complex and learners opportunity of promoting abstraction and reflection should be provided to demonstrate performance.

In terms of relevant features of the adaptive system that have many things:

(i) The student should involve the creation and manipulation of representations activities. If the student is expected a mental model that corresponds to representation, he/she needs to involved actively in the creation or manipulation of the representations.

(ii)The content and course material should be design with multiple representations for a concept or a rule. That have two purposes, it allows the adaptive engine (discuss later), which provide the single representation for the student that have best matches the student aptitude profile, while the engine simultaneously giving additional representations to present in the event that the student fails to master or acquire the topic first time. These multiple representations should include different visual representation (textual & graphical or different graphical representations of the same concept) as well as different styles of conceptual explanation.

(iii) The student should be provided with a final learning activity that encourages reflection and integration of the knowledge learned into the body of knowledge as a whole.

Finally the system should incorporate enough support and help so that the student can spend time learning the material and not the system. That is simply to ensure that as much of the student's cognitive effort as possible goes into learning the material being presented, and not into learning the system that is doing the presenting. How do we move from these general and specific guidelines to determining which learning object or objects should be selected, and why? One solution is to employ something like student modelling approach to Responsive Tutoring (SMART; Shute, 1995), a principle approach to student modelling. It works within an instructional system design where low-level knowledge and skill elements are identified and separated into the three main outcome types previously mentioned (i.e., BKL, PKL, CKL). As the student moves through an instructional session, LOs i.e. the online manifestations of the knowledge and skill elements) are served to instruct and assess. Those knowledge elements showing values below a preset mastery criterion become candidates for additional instruction, evaluation, and remediation, if necessary. Remediation is invoked when a learner fails to achieve mastery during assessment, which follows or is directly embedded within the instructional sequence.

This involves assessing students prior to as well as during their use of the system, mainly focusing on general, long-term aptitudes (e.g., working memory capacity, inductive reasoning skill, exploratory behaviour, impulsivity) and their relations to different learning needs. An alternative approach to student modelling includes using Bayesian inference networks (BINs) to generate estimates of learner proficiencies in relation to the content (e.g. Mislevy, Almond, Yan & Steinberg, 1999). Both the SMART and BIN approaches are intended to answer the following questions: (a) What is the learner's current mastery status of a topic, and (b) what is the nature and source of the learner's problem, if any? Typical ways of evaluating success (e.g., pass or fail, or correct solution of two consecutive problems) do not offer the degree of precision needed to go beyond assessment into cognitive diagnosis. Both SMART and BINs provide probabilistic mastery values associated with nodes or topics (regardless of grain size). With regard to the instructional decision about what should subsequently be presented, the knowledge structure, along with an indication of how well a learning objective is attained, informs the adaptive engine of the next recommended bit or bits of content to present.

3.4 Adaptive system engine

To given the content module, learner module and instructional module, the fundamentals of the adaptive system engine are very simple. First step involves selecting the node (element or topic) to present, based on diagnosis of the student's knowledge needs. Next step involves deciding which LOs within that node to present, sequenced of flavoured according to the characteristics and particular learner needs. The presentation of LOs is continued until the student has mastered the topic or node and the topic selection process is repeated until all topics have been mastered. However that is simple overview, the actual process is more complicated. We should examine each part of the process (selecting a node, and hen presenting the content within the node or topic) separately.

In our solution, selecting a topic, it is very simple exercise, the adaptive system engine simply chooses from the pool of nodes or topics that have been not completed and whose prerequisites have been mastered. However one additional feature of our structure is to pre-test can be generated on the fly and assessment can incorporate a sequencing algorithm. Recall that the LOs in each node have been categorized by their role in the educational process, and the authoring guidelines have restricted each learning object to a single role only. Because of this, for any collection of nodes, the system can create another collection of nodes that contains only the assessment tasks from the original collection. This is presenting new collection of functions as a pre-test. If the student passes the assessment without any presentation, he or she is presumed to have already mastered the associated content.

When the engine is presenting objects relating to a particular node, it uses a set of rules to drive the selection of individual LOs for presentation to the student. These rules examine the information contained in the student model, the student's interaction within the node so far, and the content model of each individual LO contained within the node. Using this information, the rules assign a priority to each LO within the node. Once the priority of every LO has been calculated (which occurs almost instantly), the LO with the highest priority is delivered to the student. An example of how it works for instructional objects. We have considered an initial arbitrary weighting is assigned to every Loin the node. One rule states that if the student's interaction with the node is empty (i.e., the student is just beginning the node), then decrease the priority of every LO *except* those which full-fill the role of "introduction." This rule ensures that the default sequence provides for an introduction-type LO to be presented at the beginning of an instructional sequence. On the other hand, to considered learner who prefers a more flexible contextualized learning experience, such as a learner characterized as very concrete and experimental? To handle that, there is a rule that stets if the learner is "highly concrete" and "highly experiential" and if the learner`s interaction with the topic is empty, then increase the priority of associated assessment-task LOs. If a learner is not concrete and experiential, then no effect second rule. However, if she/he is, then the second rule overrides the first and the learner sees an assessment task at the beginning of the instructional sequences.

The rest of rules working an analogous fashion that is each one examine a set of conditions that is associated instructional prescription and adjusts priorities on the appropriate LOs. All of these rules serve to provide the instructionally correct learning object for the student at every point of the student's interaction with the node.

One of the issue is that it should be addressed concerned the accuracy of the rule set; it designing such that it provides a natural and effective learning experience regardless of learner characteristics. One way to accomplish it by using the Genetic Programming techniques (GP; Koza, 1992) to improve the performance of the rule set. Research has shows that this technique is applicable to the design of rules for rule-based systems (e.g. Andre, 1994; Edmonds, Burkhardt, & Adjei, 1995; Tunstel & Jamshidi, 1996). The general idea is to treat each individual rule set as a single individual in the population of algorithms; the rule sets can then be evolved according to standard GP methods.

The interesting feature of GP is that it turns a design task (create a rule set that treats learners effectively) into a recognition task (determine how well a given rule set performs at treating learners). One of the possible ways to handle large sample of learner data can be used to evaluate a learner's potential experience with a given rule set, and this can be used as the basis of the evaluation function that drives the GP approach. Further, this is the combination of human-designed rules with computer-driven evolution may be give high likelihood of success and avoids many of the risks inherent in rule-based systems.

4. CONCLUSION

There are many reasons to pursue distribute adaptive e-learning. The main potential of designing, developing and employing best e-learning solutions and they include improved efficiency, effectiveness and enjoyment of the learning experience. These student centered instructional purposes, there are other potential uses, such as online assessments. Mostly an assessment comprises important events in the learning process, reflection and understanding of progress. Mainly, assessments are used to determine placement, promotion, graduation or retention. We pursue the ideal via online diagnostic assessments. As Snow and Jones (2001) pointed out, however, tests alone cannot enhance educational outcomes. Rather, tests can guide improvement—presuming they are valid and reliable—if they motivate adjustments to the educational system. There are clear and important roles for good e-learning programs here.

However, the current state of e-learning is little more than online lectures, where educators create electronic versions of traditional printed student manuals, articles, tip sheets, and reference guides. Although these materials may be valuable and provide good resources, their conversion to the Web cannot be considered true teaching and learning. Instead of the page-turners of yesterday, we now have scrolling pages, which is really no improvement at all. Distributed Adaptive e-learning provides the opportunity to dynamically order the "pages" so that the learner sees the right material at the right time. There are currently a handful of companies attempting to provide adaptive e-learning solutions.

However, many of these are not concerned with adaptive instruction at all; rather, they are concerned with adapting the format of the content to meet the constraints of the delivery device, or adapting the interface to the content to meet the needs of disabled learners. Of those that are concerned with adaptive instruction, most tend to base their "adaptivity" on assessments of emergent content knowledge or skill or adjustments of material based on "learner styles"—less suitable criteria than cognitive abilities for making adaptive instructional decisions. We believe that the time is ripe to develop e-learning systems that can reliably deliver uniquely effective, efficient, and engaging learning experiences, created to meet the needs of the particular learner. The required ingredients in such a personalized learning milieu include rich descriptions of content elements and learner information, along with robust, valid mappings between learner characteristics and appropriate content. The result is adaptive e-learning, a natural extension of Snow's considerable contributions to the field of educational psychology.

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