7

Effective knowledge acquisition by means of teaching strategies

Marek Woda
Wroclaw University of Technology
Poland

1. Introduction

Despite of the fact that e-learning already proved its great usefulness, it still suffers from many childlike deficiencies. We can point among the other things, the lack of the coherent vision for learning process accomplishment, practical guidelines how to organize consistent learning content (Woda & Walkowiak, 2004). Due to these disadvantages e-learning is being perceived ambiguously and usually incorrectly implemented in real life e-systems that finally lead to limitation of its reliability. Usually, in real world, theory and practice are not on the par, exactly same situation can be observed in the theory of e-learning and its implementations. In the e-learning, whole stress was put on the learning theory, and there are no restrictions or even practical guidelines present in field of technology used for implementations, best implementation practices, which in many cases has negative influence on newly developed e-systems (Woda & Walkowiak, 2008). Currently most of the academics, and schoolteachers noticed the need of standardization and rationalization of this type of teaching.

Not infrequently, knowledge acquisition process in e-learning has a way worse effectiveness than traditional one that takes place in a conventional teaching – and this is especially noticeable in case of the students that are not very proficient in computers. Main cause of this phenomenon is inability to select essential information by students from so-called "informational noise" and the lack of the direct contact with a tutor and/or learning materials have been prepared in inappropriate way by the course organizers.

Focusing only on a knowledge delivery problem in e-learning systems, we can find course material selection with relation to expertise level of a particular student as a main shortcoming. The other, also major drawback is an immense burden for the course administrators, when number of course students exceeds a few dozen or so. Then a number of people who are involved in planning, control, scheduling of classes and students' progress assessment, increases in proportion to a number of students. Effectiveness of knowledge acquisition is a function of different forms, methods and variety of teaching methods (Nichols, 2008). Nowadays, in a computerization era, teaching effectiveness in e-systems may increase, only when appropriate steps are undertaken along with an application of classical forms and methods teaching, leading to a construction of suitable teaching structures, which are integrated with latest technologies combined with the formal ways of presentation (Woda, 2008).

Teaching technology is an interdisciplinary disciple about education efficiency, pursuing the answer for the question, how to educate quicker, faster, better and less expensive in a defined conditions.
Interdisciplinary nature of the disciple relies on that, it draws its subject of the interest and research methods other disciples like computer science, cybernetics, theory of systems and communication theories.

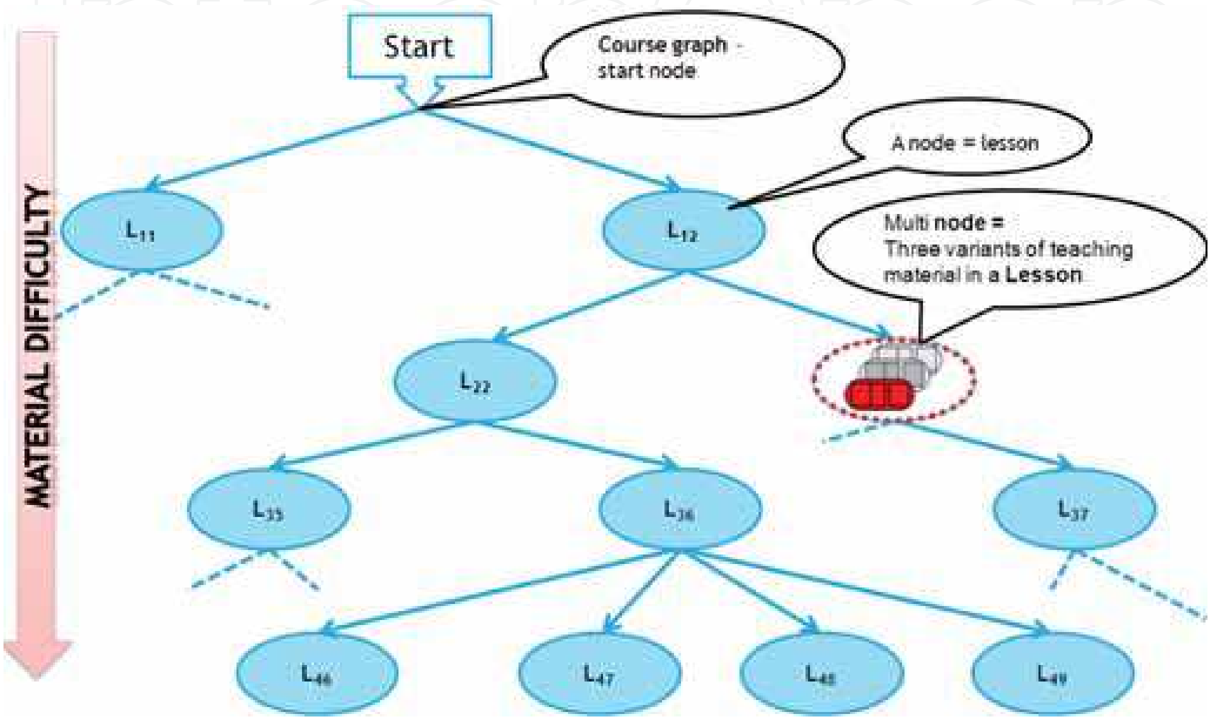


Fig. 1. Teaching material represented as a learning tree

In traditional method learning, human factor is responsible for entire teaching process (Woda & Walkowiak, 2004). This may lead to situations (and usually does), like loss of control over learning progress (due to e.g. mental fatigue of a teacher, badly adapted teaching materials to the students' skills), which finally results in loss of student's attention and willingness to learn (Mghawish & Woda & Michalec, 2006). Nonetheless, excluding completely "human factor" is not possible, and at the same time from a teaching perspective very disadvantageous factor (Al-Dahoud & Walkowiak & Woda, 2008), and it is tightly connected with students feeling of being alienated and which lead to a loss of the control.
The remedy for the presented above distant learning inconveniences and a way to improve efficiency of knowledge acquire process could be application of intelligent system that is driven by smart teaching algorithms (Baloian & Motelet & Pino, 2003, Capusano & Marsella & Salerno, 2000, Dinosereanu & Salomie, 2003, Mghawish & Woda & Michalec, 2006).

2. Teaching strategies

Teaching strategies are algorithms that support navigation within a learning path, during knowledge acquisition process by a student. These algorithms are responsible for directing students on the suitable lesson's variants in the nodes of the learning path (Woda, 2006). Appropriate assignment made by the strategies is being made in a way that teaching material is being selected to suit more adequately student's expertise level, and what is more his ability to learn, according to the criteria.
Navigation algorithms have to lead a student or a group of students thru learning path from first node (starting phase), to another, until end of learning path is reached. State after starting phase is named adaptive state (phase) and it lasts to the end of knowledge acquisition process.

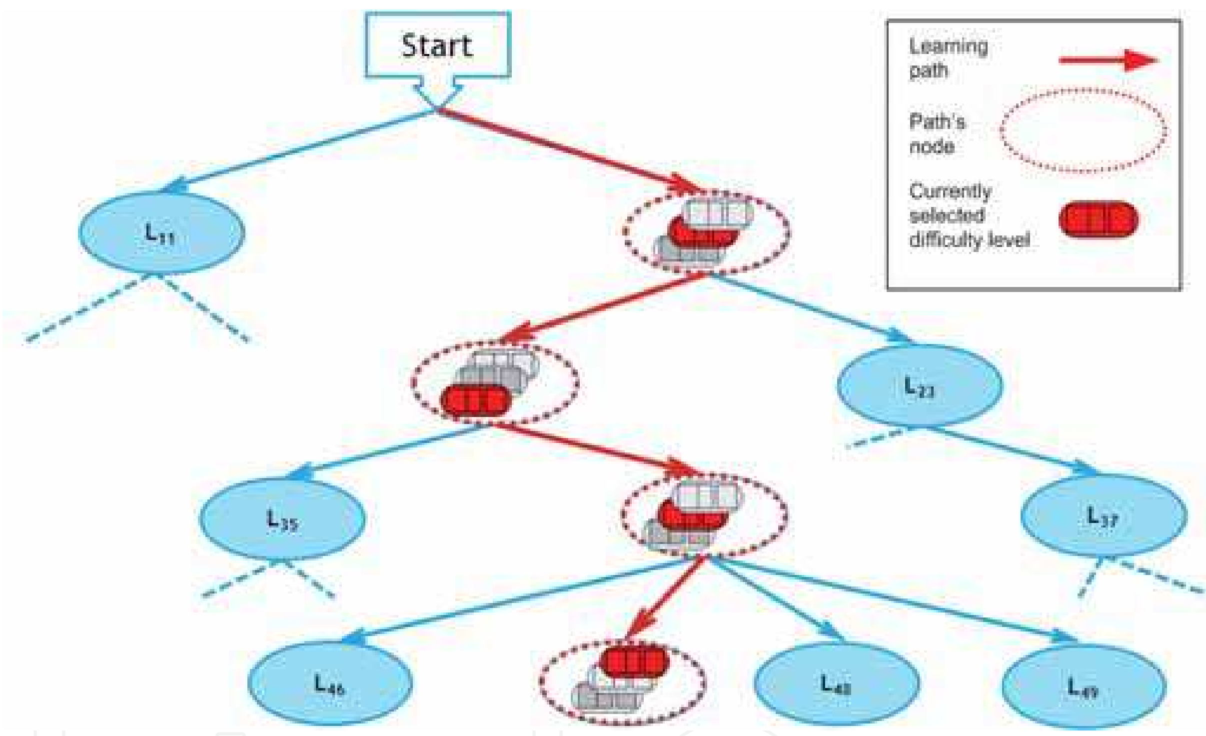


Fig. 2. A learning path with selected nodes (lesson's variants) in the learning tree

Teaching algorithm operation is based on the learning adaptation mechanisms, where knowledge absorption process is being scrutinized on the fly, and historical data, about lessons learnt and scores achieved, are being taken into account in order to assign precise and adequate learning material in a next node from the learning path to achieve best possible (optimal) knowledge acquisition. Learning adaptation means drawing conclusions out of gathered historical data, and then based on them learning "parameters" tuning to match optimal learning pace and form, for a student.
Main task for an adaptive teaching algorithm is to assign each student from a group, appropriate lesson difficult variant (in current the lesson), in order to achieve best result (a note) in a competence test after the lesson. Best result, means required /set by the teacher at the beginning of learning process, usually it is a combination of notes (after a lesson) and credit points (received upon completion of the most difficult lesson variant in a node).

Additionally, at the beginning of learning process one should pay special attention to verify student's initial expertise level, to assign base lesson variant in a start node (starting phase) to match student capability to learn. If the initial expertise is not detected well, it will affect learning efficiency later on, during learning progress (in the adaptive phase). During the adaptive phase, one of available learning strategies, is being assigned to a student, based on his initial expertise level so when an inaccurate strategy is chosen, it greatly affects learning progress and its effectives. Lesson difficulty factor is correlated with student's ability to comprehend given material.

3. Learning progress verification

The verification of the knowledge acquisition during duration of a course, takes place after each lesson, in a competence test. It is essential, in order to go to next lesson to firstly pass based current lesson variant (usually least complicated one) in a node. Each student is assessed in a competence test and note is being assigned afterwards and it defines knowledge absorption factor for a lesson. Upon a lesson completion on a specific difficulty factor (lesson variant) student receives a number of credit points, which reflects how the variant was elaborated. Note's value that qualifies student to pass to next lesson is strictly dependent on his base expertise level and lesson's variant, which defines also current competence test.

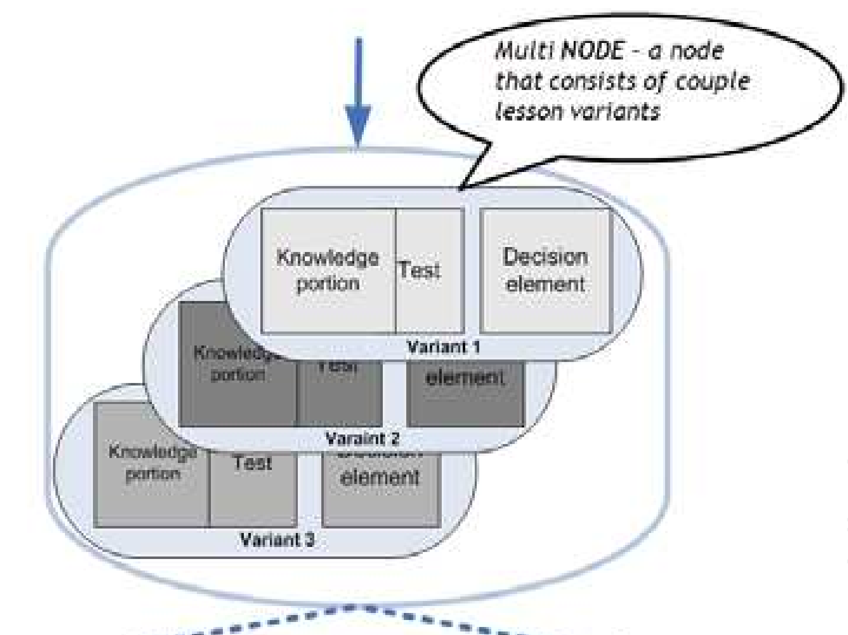


Fig. 3. A multi node of the learning path – variants of the lesson.

The validation of the knowledge acquisition is being done for both a student and for a group (all course participants), after each lesson passed in a learning path (within competence test). Validation procedure has to substantiate (according to taken assumptions), that in fact, strategies of the learning adaption influence on improved knowledge acquisition during learning phase.

The notes received in a competence test, serve as an input data for the strategies. Historical data are taken from student's records (notes, received in previously passed competence tests along with a sum of credit points), which constitute a base for the final assessment of learning progress quality.
In order to be eligible to pass to a next lesson, student must, at least, pass thru easiest material variant in a current lesson node (current competence test must be completed with an acceptable note value) and receiving, at least, one credit point.

4. Learning effectiveness

One of the most common e-learning problems is lower than expected effectiveness of the knowledge absorption. Author, in this chapter focused mainly on that issue. Author concentrated on increasing learning effectiveness by means of teaching strategies. It comes down to best teaching algorithm assignment either for a student or a group from a set of possible adaptive learning strategies. Each strategy ought to meet to given down below criteria.
These strategies ought to organize learning process in a way that best suits student's abilities to learn and finally improve the results (grades and credits) received.
Main criterion, taken into consideration during assessment of learning effectiveness improvement process, is striving after receiving best possible grades and at the same time, more credits. These are two opposing criteria. Receiving best grades could be achieved in an easy way by assignment in every node easiest lesson variant, however it would result in receiving less credits than expected afterwards. Receiving greatest number of credits is only possible once the most elaborated lesson variants are being assigned and finished in the node. Aforementioned facts allow us to clearly asses the quality of teaching strategies.
Other characteristics that prove usefulness of a particular strategy is a total number of students (from a test group) that received at least a half possible credit points during entire learning process. Grades average in a learning process is a supporting factor.
Strategies also strive after fulfilling given below assumptions:

- minimize number of students that cannot comply the optimal learning postulate (minimize drop out from learning process – do not complete competence tests on a required level)
- detect students with incorrectly detected initial expertise level (especially in a start phase)
- "exploit" best students – to assign them more difficult lesson's variants

As a criteria for starting phase strategies quality assessment following have been taken into account:

- a percentage of students that have received more than half credits possible, number of grades scored above group's average, group grade's average, lowest and highest student grade's average

As a criteria for adaptive phase strategies quality assessment following have been taken into account:

- an expertise level distribution changes in time (compare before and after learning), sum of credits after learning process is over, student/group grade's average, number of students that finished learning with more than half possible credits to earn

Each strategy, should meet at least one of aforementioned (main) criteria. Besides each strategy have its own characteristics e.g. global optimum strategy strives to find strategies should be able to find students that are more talented (once found – they are being assigned more difficult / challenging task / lessons). Each strategy acts in a different way based on a student profile detected during learning process. For example minimalistic strategy, strives after assignment students easiest possible lesson's variant in a learning path.

6. Results

All the results have been received in a simulated environment. There were three groups of students, each 100 student, tested. Each group had different base student's expertise level (refer to the Table 1.) and it was served with the same amount of the lesson nodes (50). Simulation was divided in two phases: start phase and adaptive one, where groups were governed by the learning strategies.

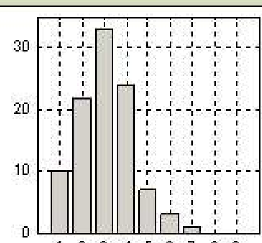
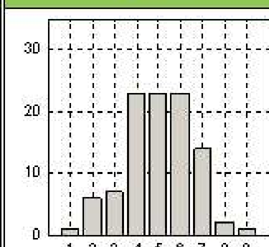
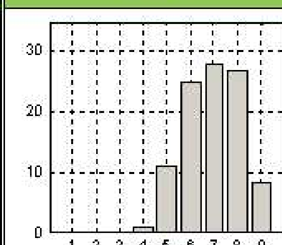
Strategy	[%] of students in tested group with better credit points average than average of credit points for a group		
Conservative	19%	22%	27%
Optimal	41%	42%	48%
Simplistic	17%	12%	21%
Reference	37%	44%	49%
Tested group			
Strategy	The average grades of tested group after the learning process is over		
Conservative	0,4064	0,5054	0,6441
Optimal	0,4528	0,5308	0,6361
Simplistic	0,3579	0,4239	0,5289
Reference	0,4092	0,4657	0,5501

Table 1. Results for different teaching strategies received after adaptive phase – learning process is over. Grades [0-1].

Starting phase. All the students from the test groups were treated by the start phase strategies, and the experiment data were evaluated against optimal teaching criteria postulate – namely striving after receiving top grades with most possible credits earned and to match difficulty factor with student's expertise level.

Primitive strategy did not prove its usefulness, failing to match second part of requirements (differentiate students base on their expertise level). This strategy was not intended to be applied ever, in any system, and the results received after primitive strategy application, constituted a base for comparison. *Random* strategy, in spite of the fact that partially (since only some of the students were assigned lesson's difficulty factors that match their expertise level) met the requirements, gave good results (mainly in the group where most of the students were good learners – no matter what lesson's difficulty they were faced to they were able to cope with).
Proportional lesson difficulty variant assignment done by a proportional third strategy turned to be most efficient (against each test group), both in terms of average grades scored and credits earned. Thanks to it, more than 60% of students received better scores than expected.
Adaptive phase. Best strategy assessed in this phase should meet criteria described in section 4. In order to quickly sum up discussion of received results, if the priority was to get most students that passed learning path with higher than a group credit points average number, one should focus on Reference strategy or Optimal one. Focusing only average of grades maximization the most suitable are reference *conservative* and *reference* ones. Most balanced strategy that matches all criteria is *optimal* strategy. It equally good strives after grades and credits scored during entire learning path.

7. Conclusion

Quick and unfortunately chaotic e-learning systems development, created an urgent demand to adjust teaching process to the individual characteristics. Along with the growth of interests around distant learning, numerous systems are being implemented, yet again without orientation on a learner. The systems do not base on any student model or what is even worse do not adjust pace of learning to the student needs. This paper was intended to provide a solution to ease teaching material delivery, in an personalized way, that match student's expertise level. Based on a defined model of learner – system has to ascribe a teaching strategy that will facilitate knowledge acquisition during entire learning process. Tested, in two phases (start and adaptive) strategies allowed to increase learning effectiveness, portrayed by the results (increased number of credit points and average of grades) gathered in the table 1.
Future work will encompass experiments with real students as a part of working production e-learning system.

8. References

Al-Dahoud A., Walkowiak T., Woda M. (2008). Dependability aspects of e-learning systems. *Proceedings of International Conference on Dependability of Computer Systems*, DepCoS - RELCOMEX 2008, pp. 73-79, Szklarska Poręba, June 2008, IEEE Computer Society [Press], Los Alamitos

Baloian N., Motelet O., Pino J. (2003) Collaborative Authoring, Use and Reuse of Learning Material in a Computer-integrated Classroom, *Proceedings of the CRIGW 2003*, 2003, France.

Bacopo A. (2004) Shaping Learning Adaptive Technologies for Teachers: a Proposal for an Adaptive Learning Management System, *Proceedings of the 4th IEEE International Conference on Advanced Learning Technologies*, 2004.

Capusano N., Marsella M., Salerno S. (2000) An agent based Intelligent Tutoring System for distance learning. *Proceedings of the International Workshop on Adaptive and Intelligent Web-Based Education Systems*, ITS, 2000

Dinosereanu M., Salomie I. (2003) Mobile Agent Solutions for Student Assessment in Virtual Learning Environments, *Proceedings of the IAWTIC*, 2003, Austria

Kavcic A. (2000) The role of user models in adaptive hypermedia systems, *Proceedings of the Electrotechnical Conference MELECON*, 2000.

Mghawish A., Woda M., Michalec P. (2006). Computer aided composing learning material into primary learning tree. *Proceedings of the WSEAS International Conferences: The 5th WSEAS International Conference on Applied Computer Science (ACOS '06)* pp. 80-85, Hangzhou, April 2006, WSEAS 2006 Hangzhou.

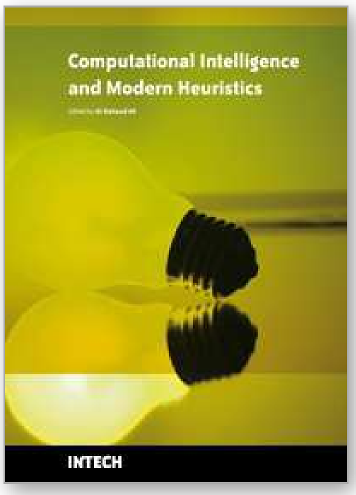
Nichols, M. (2008). E-Learning in context. http://akoaotearoa.ac.nz/sites/default/files/ng/group-661/n877-1---e-learning-in-context.pdf

Woda M. (2008). Zarządzanie procesem uczenia w komputerowych systemach wspomagających nauczanie. *Proceedings of the Nowe Media w Edukacji 2008: zastosowania technik informacyjnych i komunikacyjnych w kształceniu.* pp. 147-155, Wrocław, September 2008, Oficyna Wydawnicza Politechniki Wrocławskiej, Wrocław

Woda M., Walkowiak T. (2008). Wybór optymalnej platformy zdalnego nauczania. *Proceedings of Komputerowe wspomaganie dydaktyki : materiały krajowej konferencji naukowej.* pp. 119-122, Łódź, June 2008, Wyższa Szkoła Informatyki, Łódź

Woda M. (2006). Conception of composing learning content into learning tree to ensure reliability of learning material. *Proceedings of International Conference on Dependability of Computer Systems. DepCoS - RELCOMEX 2006*, pp. 374-381, Szklarska Poręba, May 2006, IEEE Computer Society [Press], Los Alamitos

Woda M., Walkowiak T. (2004). Internet - a modern e-learning medium. *Proceedings of the Second International Conference on Soft Computing Applied in Computer and Economic Environments ICSC 2004.* pp. 205-214. Kunovice, Czech Republic, January 2004. Evropsky Polytechnicky Institut, Kunovice.



Computational Intelligence and Modern Heuristics
Edited by Al-Dahoud Ali

ISBN 978-953-7619-28-2
Hard cover, 348 pages
Publisher InTech
Published online 01, February, 2010
Published in print edition February, 2010

The chapters of this book are collected mainly from the best selected papers that have been published in the 4th International conference on Information Technology ICIT 2009, that has been held in Al-Zaytoonah University, Jordan in the period 3-5/6/2009. The other chapters have been collected as related works to the topics of the book.