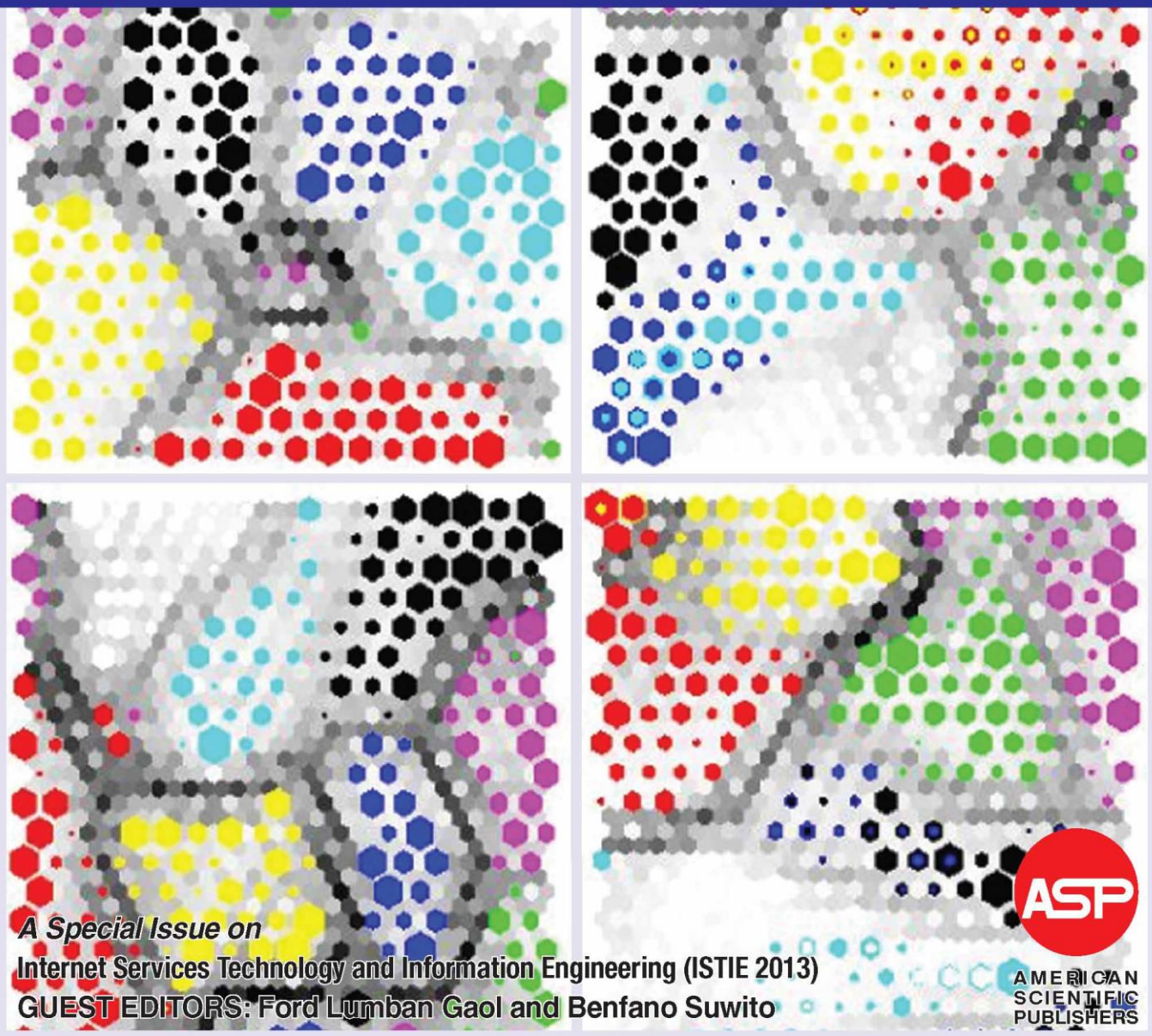
VOLUME 20 • NUMBER 1 JANUARY 2014

www.aspbs.com/science

Advanced SCIENCE LETTERS

A Journal Dedicated to All Aspects of Scientific Research



A Special Issue on

Internet Services Technology and Information Engineering (ISTIE 2013)

GUEST EDITORS: Ford Lumban Gaol and Benfano Suwito

ASP

AMERICAN SCIENTIFIC PUBLISHERS

Advanced Science Letters

ISSN: 1936-6612 (Print): EISSN: 1936-7317 (Online)

EDITORIAL BOARD

EDITOR-IN-CHIEF

EUROPEAN EDITOR

HONORARY EDITORS

ASSOCIATE EDITORS

Jim Al-Khalili (Foundations of Physics, Nuclear Reaction Theory)
University of Surrey, UK.

Jake Blanchard (Engineering Physics, Nuclear Engineering)
University of Wisconsin–Madison, USA.

Simon Baron-Cohen (Cognitive Neuroscience)
University of Cambridge, UK.

Franz X. Bogner (Cognitive Achievement)
University of Bayreuth, Germany.

John Borneman (Anthropology)
Princeton University, USA.

John Casti (Complexity Science)
Internationales Institut für Angewandte Systemanalyse, Austria.

Masud Chaichian (High Energy Physics, String Theory)
University of Helsink, Finland.

Sergey V. Chervon(Gravitation, Cosmology, Astrophysics)
Ulyanovsk State Pedagogical University, Russia

Kevin Davey (Philosophy of Science)
University of Chicago, Chicago, USA.

Tania Dey (Colloids/Polymers/Nanohybrids)
Canada.

Roland Eils (Bioinformatics)
Deutsches Krebsforschungszentrum Heidelberg, Germany.

Thomas Görnitz (Quantum theory, Cosmology)
University of Frankfurt, Germany.

Bert Gordijn (Nanoethics, Neuroethics, Bioethics)
Radboud University Nijmegen, The Netherlands.

Ji-Huan He (Textile Engineering, Functional Materials)
Soochow University, Suzhou, China.

Nongyue He (Biosensors/Biomaterials)
China.

Irving P. Herman (Materials and Solid State Physics)
Columbia University, USA.

Dipankar Home (Foundations of Quantum Mechanics)
Bose Institute, Kolkata, India.

Jucundus Jacobeit (Climate, Global Change Ecology)
University of Augsburg, Germany.

Yuriy A. Knirel (Bioorganic Chemistry)
N. D. Zelinsky Institute of Organic Chemistry, Russia.

Arthur Konnerth (Neurophysiology, Molecular Mechanisms)
University of Munich, Germany.

G. A. Kourouklis (Physics Solid State Physics)
Aristotle University Thessaloniki, Greece.

Peter Krammer (Genetics)
Deutsches Krebsforschungszentrum Heidelberg, Germany.

Andrew F. Laine (Biomedical Engineering)
Columbia University, USA.

Minbo Lan (Organic Functional Materials)
China.

Martha Lux-Steiner (Physics, Materials Science)
Hahn-Meitner-Institut Berlin, Germany.

Klaus Mainzer (Complex Systems, Computational Mind, Philosophy of Science)
University of Augsburg, Germany.

JoAnn E. Manson (Medicine, Cardiovascular Disease)
Harvard University, USA.

Mark P. Mattson (Neuroscience)
National Institute on Aging, Baltimore, USA.

Lucio Mayer (Astrophysics, Cosmology)
ETH Zürich, Switzerland.

Efstathios Meletis (Physics, Thin films, Nanomaterials, Corrosion, Tribology)
University of Texas at Arlington, USA.

Karl Menten (Radioastromy)
Max-Planck-Institut für Radioastromie, Germany.

Yoshiko Miura (Biomaterials/Biosensors)
Japan.

Fred M. Mueller (Solid State Physics)
Los Alamos National Laboratory, USA.

Garth Nicolson (Illness Research, Cancer Cell Biology)

EDITORIAL BOARD

TABLE OF CONTENTS

A SPECIAL ISSUE

RESEARCH ARTICLES

Advanced Science Letters
Vol. 20 (1), 213-217, 2014

Design of Intelligent Tutoring System For Mastery Learning

Dwijoko Purbohadi[1,*], Lukito Nugroho[2], Insap Santosa[3], Amitya Kumara[4]

[1]Department of Information Technology, Universitas Muhammadiyah Yogyakarta, Yogyakarta 55183, Indonesia
[2,3]Department of Electrical Engineering and Information Technology, Univeritas Gadjah Mada, Yogyakarta Indonesia
[4]Department of Education Psychology, Universitas Gadjah Mada, Indonesia

Intelligent Tutoring System (ITS) is an interactive e-learning tool to help students learn independently. Currently, the implementation ITS is still in laboratory scale, means ITS has not been used in large scale using internet technology. One of the difficulties is ITS has not fulfill yet the learning needs. The main requirement of current learning based-competency is the high number of students in mastery learning, on the other hand current learning activities could not overcome the problems of student characteristics and different learning speed in each student as well. The concept of mastery learning is an approach used in competency-based learning, which consists of repetition of learning for slow students, mastering for good progress students, and enrichment for fast students. In this paper, the model of ITS is designed to accommodate the competency-based mastery learning needs and be able to follow learning speed of each student. The design of ITS has learning sequences and gradually test student`s cognitive level. It could measure the position of student`s cognitive knowledge, be able to guide to reach mastery level, and give challenges for smart students.

Keywords: ITS, mastery learning, cognitive level, learning sequence

1. INTRODUCTION

Intelligent Tutoring System (ITS) is interactive application program that is used as an information, a learning and an evaluation medium. One of the ways to make students could be learnt independently is by using ITS[1]. ITS is developed based on Computer Aided Instructional (CAI). CAI is appropriate for both fast and slow students, because the speed and material learning sequences is chosen by the student itself. Then, Learning Management System (LMS) is an e-learning web-based tool that successfully to manage the activities and learning administration[2]. ITS and LMS is supporting each other so possible combine both of them become iLMS (Intelligent Learning Management System)[3].

In conventional systems, the lecturer has a role as instructor and manager of learning activities. If an LMS is applied, the role as the instructor could be changed as a facilitator to the student to do learning activities independently. LMS was designed as tools to manage the activities in order to the interactive tutorial facility need to be added. If an LMS is combined with ITS, the learning activities could be conducted by student anywhere and anytime. Then, the student has a higher opportunity to learn independently. If a student learns independently using ITS, means the teacher has a chance to monitor, to supervise student, and implement a variety of teaching strategies[4] so that the number of students to mastery learning is higher.

2. PROBLEM STATEMENT

One of the problems in the implementation of mastery learning, is that each student has a different learning speed making it difficult for teachers to give students individual treatment, especially in the number of students learning a lot. ITS can be used to solve this problem because it can be integrated with the LMS to handle many of the students but is able to provide individual treatment.

*Email Address: purbohadi@yahoo.com

 doi: 10.1166/asl.2014.5313

ITS can be used to help students achieve a certain learning objectives using the principles of mastery learning. In this paper the core of ITS is to provide a set of learning and assessment in order. ITS will adjust the learning sequences according to the level of understanding a student's pace. ITS shall be provided with a program to determine the next step of learning the most appropriate use of a specific algorithm, the paper uses Markov algorithm. The new problem that arises is how to use Markov algorithms for ITS sequence of learning so as to provide the most appropriate for a student to achieve learning objectives as quickly as possible according to the principles of mastery learning**.**

3. OBJECTIVE AND MASTERY LEARNING

The learning objective is competency for students that involved in an instructional set in form of learning activities. The result of this instructional activity is known by measuring the indicator by using diagnostic test. One of the learning objectives is achieved cognitive competency. The basic assumption of measuring indicator through diagnostic test is the amount of right answer shows the level of instructional objective achievement[5]. The students are considered the mastery learning if right answer at least 70% of total questions[6]. The learning based competency uses the mastery learning approach, in order to there are 95% student achieve mastery learning through an instructional set. The mastery learning is attained if the student has enough learning time and appropriate learning[7].

The approach of mastery learning was conducted when giving the learning properly and all students able to learn well[8]. Principally, the mastery learning happens students give appropriate learning, timing of study, and additional learning for students who has not understood yet. These ways are hard to be implemented using conventional one, moreover in group learning. The lecturer is hard to control and handle one-by-one of the student that have difficulties example of the faculty associated with emotional expression[9,10], body language and communication[11,12], and the provision of educational messages[9,10], as well as of the students there is a need for alternative learning experiences, such as the use of interactive software mentioned in several previous studies[9,10,13,14]. Not only time limitation, but also many reasons are faced. Therefore, this is why the design of ITS is required to help the concept of mastery learning.

The advanced cognitive taxonomy that is already made and becomes to be an operational taxonomy15. Table 1 shows the example of the learning objective to understand a concept which has four activities (activity 1,2,3,4). Based on that taxonomy, the instructional design is easier to be made. The sentences arrange an instructional objective consists of processing statement (cognitive) using verb followed by an object that is processed (knowledge). The cognitive process consist of: (1) remember, (2) understand, (3) apply, (4) analyze, (5) evaluate, and (6) create. On the other hand, the knowledge process consists of knowledge about: (1) factual, (2) conceptual, (3) procedural, and (4) metacognitive.

Table 1. Revised taxonomy table[9]

Knowledge	Cognitive					
	Remember	Understand	Apply	Analyze	Evaluate	Create
Factual	Activity 1	Activity 2	-	-	-	-
Conceptual	-	Objective	-	Activity 4	-	-
Procedural	Activity 3	-	-	-	-	-
Metacognitive	-	-	-	-	-	-

4. MODEL FORMULATION

Every subject of learnings has objective to reach certain competency, or called as objective of general instructional. This competency is reached through sub competency or objective of particular instructional. Each sub competency is a sub topic and each sub topic is arranged to be finished in a certain time. In each sub topic is arranged an intelligent learning system module (ITS) to help students to reach sub competency. Next, the approach of mastery learning is used to divide the sub topic into three levels, such as repetition, completion, and enrichment (Table 2).

Completion is the main part of learning to achieve sub competency, the repetition is the learning activities to help reach the sub competencies, and the enrichment is to develop knowledge of good students. Factual and conceptual material at a low cognitive level placed on the repetition of the students have studied their own assumptions or follow classroom learning activities, failing at the completion need to learn in the repetition. Mostly, the purpose of studying is on conceptual and procedural so that medium level is the subject of sub completions or a minimum standard of competency to be mastered by the students. Part enrichment material selected from procedural and metacognitive.

Table 2. The design of ITS

No	Level	Sub Part	Cognitive Level
1	Repetition	Factual	1, 2
		Conceptual	2, 3
2	Completion	Conceptual	2, 3, 4
		Procedural	2, 3, 4, 5
3	Enrichment	Procedural	4, 5, 6
		Metacognitive	2, 3

Intelligent of learning formulation is to determine the next best learning material for students, after completing a set of learning competencies to achieve a sub as soon as possible and as deep as possible.

Every intelligent learning has a pre-test and post-test, which function as a placement test. Pre-test is to determine the initial state of the material or learn the topic for students. The state of student learning indicates the level of understanding for students learn at mastery learning. Student learning state measured by the test with a value between 0

and 100%, there are three conditions that are prescribed, namely:

1. Learning outcome "excellent", if it achieves scores of ≥ 85%
2. Learning outcome "good", if it achieves 65% ≤ score < 85%
3. Learning outcome "less", if it is achieved scores of < 65%

Intelligent learning module state diagram shown in Figure 1 below.

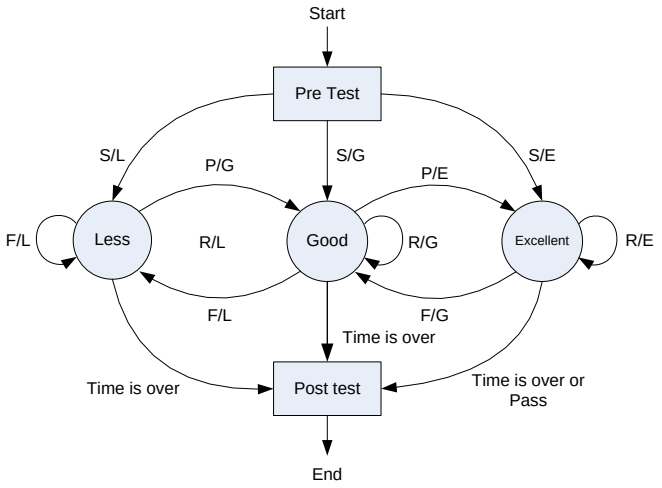


Fig.1. Intelligent learning module state diagram

If students are categorized as "Excellent" means it can be said to achieve basic competence (achieve mastery learning). Students in this condition will be given a series of learning that leads to the enrichment of learning, although it is likely to fail. There are four possible outcomes of learning:

1. Finish (because of time limitation), ready to follow the post - test.
2. Pass with learning outcome "excellent" (P/E) ready to follow the post - test.
3. Repeat with learning outcome "excellent" (R/E) to give re-learning through enrichment materials
4. Failed with learning outcomes "good" (F/G) to give learning for achievement level learning "medium" (mastering)

Students who have a category of "good" means nearly reach the principal competence (mastering) but still needs reinforcement learning in order to achieve excellent category. There are three possible outcomes of "good":

1. Finish (because of time limitation), ready to follow the post - test.
2. Pass with learning outcome "excellent" (P/E) so that able to get student achievement "excellent" or enrichment.
3. Repeat with category "good" (R/G) ready to have re-learning
4. Failed with category "less" (F/L) must follow remedial

Students who have a category of "less" does not mean to say achieve basic competence though, they require to take a series of lessons to reach the category of "good". There are three possible outcomes of learning in the category of "less":

1. Finish (because of time limitation), out or try to follow the post – test
2. Pass with learning outcomes "good" (P/G), ready to get learning with learning achievement "medium" or mastering
3. Repeat with category "less" (R/L), ready to get next learning with remedial learning
4. Failed with category "less" (F/L), that will be got link to out.

Decision making in ITS is used to determine next learning if a learning and test already be completed. There are two ways of decision-making that can be used: Markov algorithm (computational intelligence) or condition-action rules (unconventional intelligence). The intelligent learning module is built using three basic assumptions:

1. A study subject (topic) consists of some basic concepts (sub-topic)
2. Mastery learning of a topic could be achieved through learning accustomed to the learning progress
3. One way to determine a student's learning progress is to measure the ability to answer random questions from a subject of study

Intelligent learning module (ITS) is implemented on a course that consists of theory learning in some subjects (topics) with many supporting concepts (sub-topics). The working principle is to choose the order of ITS Training (tutorials) and quizzes which are most appropriate for a student to achieve mastery learning a topic with reasonable time and steps.

The algorithm to determine the next state computationally using Markov decision theory has been used by Witheley[4], the algorithm is as follows:

a. Choosing initial policy $R = \{R_i, i \in I\}$

b. Solving the equation:

$$v_i + g = q_i(R_i) + \sum_{j \in I}^{N} P_{ij}(R_i) v_j$$

c. Determining decision k to each condition $i \in I$ so that giving maximum value:

$$\underset{k \in A(i)}{Maximum}, \left\{ q_i^k + \sum_{j \in I}^{N} P_{ij}(a).v_j(R) - g \right\}$$

d. Value k maximum to each condition i resulting new decision $R=\{R_i, i \in I\}$

e. If the new decision resulting q_i^k is not equal to previous decision then repeated the step b and c, otherwise stop

f. The next learning is conducted as alternative k in convergent condition.

Above algorithm will be adapted as the basis for the design of ITS for mastery learning which will be described further in the next chapter.

5. DISCUSSION

Intelligent learning module (ITS module) is applied with respect to the learning outcomes of the lecturing set. The working principle is choosing sequence ITS module by

 doi: 10.1166/asl.2014.5313

providing lecturing (tutorials) and quizzes that are most appropriate for students to achieve mastery learning a topic with reasonable time and steps. The state of learning is known by looking at the answers and score positions that have been obtained. Students, with the same score and answering questions with the same answer, have a different tutorial subject for next learning. It is depending on the calculation of the next position. More, the Witheley's adaptation of the algorithm is described as follows:

a. Learning state

State S_o is a condition arising from an action taken by the previous decision. State written by i = 0, 1, 2 .... , N and displacement state written by j = 0, 1, 2, ..., N. The set of all states is denoted by I. If (S_0) is the student's current state then there are 3 possible subsequent actions and 2 states which is made (Figure 2), namely:

a. Learning state L
b. Correct answer state C
c. Incorrect answer state IC

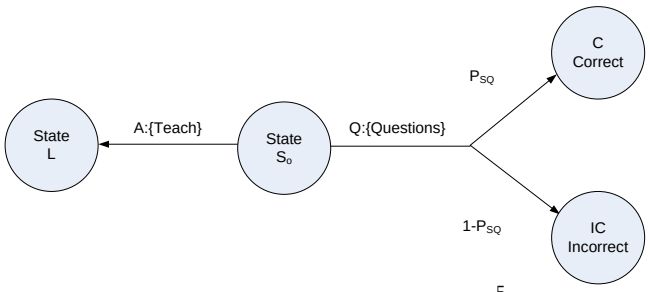


Fig.2. States based on Witheley[5]

b. Next learning activities

Next activities or alternative decisions in ITS are all possible actions taken to a state, denoted by the notation k ∈(I) = {1, 2, ...}. Next activity may be selected are:

a. Continuing to the lower level
b. Repeating in the same topic
c. Repeating a new topic on the same level
d. Continuing to the higher level

c. Learning transition opportunities

Opportunity of a process to move from one state to another on an alternative decision to k. Opportunity or probability of transition was written by notation $P_{IJ}^{(k)}$, i, j = 1, 2, ... N.

d. Learning reward transition

The reward is earned income as interstate implications of the transition to the alternative decision-k. Reward denoted by $R_{IJ}^{(k)}$, i, j = 1, 2, ... N. The reward has a value between -1 and 1 (excellent category), between -1 and 2 (good category), or between -1 to 3 (less category), the value of negative reward called the piece.

e. Next learning decision

The decision is a step in taking an action as a procedural policy to achieve a strategic steps to get the optimal next state for the next learning activity. Mathematically expressed as a set of all the decisions taken in each state after a learning activity done.

f. Optimal Decision

Decision or optimal policy is one of the best decisions among alternative decisions taken. Optimal decision established through a Markov decision process. Mathematically expressed as a set of all decisions in any state that gives maximum reward or minimal pieces.

g. Expectation Immediate Reward *q*

Expectation Immediate Reward (EIR) is an award granted before moving from one state to the next. EIR denoted using q, written by:

$$q_I^K = \sum_{j=i}^{N} P_{ij}^k R_{ij}^k$$

h. Reward Expectation Value *v*

Reward expectation value g(R) is if the system has been running up to infinite time, and use R to policy decisions, if v_i = the value of the variable reward, can be structured equation:

$$g + v_i = q_i R + \sum_{j=i}^{N} P_{ij}^k R_{ij}^k$$

Where i = 1, 2, …. N.

Referring to the state diagram (Figure 1) and the formulation developed a state table can be set up as shown in table 2 below. The table consists of a state variable (i), alternative state (k), the next state probability $P_{IJ}^{(k)}$, reward obtained $R_{IJ}^{(k)}$, and the rewards are obtained according to the answer the EIR (Immediate Reward Expectation).

Table 3 shows the shape of the data matrix to be processed using Whiteley's algorithm. Here is the procedure that will be done by the ITS's program to determine the position of the best of next activity.

a. Giving the pretest.
b. Choosing initial value $R = \{R_i, i\ (I\}$ by using the pretest score, where R = pretest scores.
c. Giving a learning and a problem for a theme according to the value R.
d. Solving the equation after a question answered:

$$v_i + g = q_i(R_i) + \sum_{j \in I}^{N} P_{ij}(R_i) v_j$$

e. Determining decision k to each condition $i \in I$ so that giving maximum value:

$$\underset{k \in A(i)}{Maximum}, \left\{ q_i^k + \sum_{j \in I}^{N} P_{ij}(a).v_j(R) - g \right\}$$

f. Value k maximum to each condition I resulting new decision R= {RI, I (I}
g. If the new decision resulting q_i^k is equal to previous decision not then repeated the step 2 and 3, otherwise (convergent) stop.
h. The next learning is conducted as alternative k in convergent condition.
i. Setting: new score = score + new R.
j. Check the results of learning for a new position and move within their corresponding scores.
k. Setting: R = new score.
l. Repeat steps 3 to step 10 until completion or timeout
m. Giving the posttest.

Table 3. Matrix of *ITS* states

State (1:Excellent, 2:Good, 3:Less)	Alternative K	Probability P_{ij}^k	Reward R_{ij}^k	EIR (q_i)
		State j=1, 2, 3	State j=1, 2,3	$q_i^k = \sum_{j=1}^{N} P_{i,j}^k R_{i,j}^k$
State i=1, 2, 3	Pass (k=1)	$P_{i,j}^1$	$R_{i,j}^1$	$q_1^1 = \sum_{j=1}^{3} P_{i,j}^1 R_{i,j}^1$
	Repeat (k=2)	$P_{i,j}^2$	$R_{i,j}^2$	$q_1^2 = \sum_{j=1}^{3} P_{i,j}^2 R_{i,j}^2$
	Fail (k=3)	$P_{i,j}^3$	$R_{i,j}^3$	$q_1^3 = \sum_{j=1}^{3} P_{i,j}^2 R_{i,j}^2$

6. CONCLUSION

From the above, the working principle is to choose the sequence of ITS module providing training (tutorials) and quizzes that are most appropriate for a learner to achieve mastery learning a topic with time and moves as possible. The next step is determined by looking at the current position and the results of calculations using the Whiteley's algorithm. An adaptation of the algorithm is done by entering the algorithm into the learning cycle. Learning material adapted to a new position determined based on the score and the calculation of the best R value. Tutorial model of an intelligent learning module is built using three basic assumptions:

a. A study subject (topic) consists of some basic concepts (sub-topic)
b. Mastery learning a topic could be achieved through learning tailored to the learning progress.
c. One way to determine a student`s learning progress is to measure the ability to answer random questions from a subject of study.

7. SUGGESTION

The design of ITS with a complete learning approach using adapted Whiteley's algorithm needs to be tested on the side of computing. Furthermore, require further study if applied to the higher number of users, this is necessary because the today mastery learning approach is designed to help a lecture to teach students in large numbers. ITS should be made using the SCORM standard so it can be included in an LMS. Adapted Whiteley's algorithm involves matrix and repetition to solve an equation for each step and for each student. The greater the weight of students means a server so that the distributed model is more suitable.

REFERENCES

[1] Nugroho, W., Pengembangan ITS (Intelligent Tutoring System) Sebagai Media Pembelajaran pada Mata Kuliah Pengantar Teori Graf. (2008). http://www.teknologipendidikan.net/?p=17, Accessed on: 02/02/2012

[2] Šimić, G., Gašević, D., Devedžić, V., Semantic Web and Intelligent Learning Management Systems, FON – School of Business Administration, University of Belgrade, POB 52, Jove Ilića 154, 11000 Belgrade, Serbia and Montenegro, (2004).

[3] Lin, F., Holt, P., Leung, S., Hogeboom, H., Cao, Y., A Multi-Agent and Service-Oriented Architecture for Developing Integrated and Intelligent Web-based Educational Systems, Center for Computing and Information Systems, 1 University Drive, Athabasca, Alberta, Canada, T9S 3A3, (2004).

[4] Rodrigo, Ma. Mercedes T., Ryan S.J.d. Baker, Jenilyn Agapito, Julieta Nabos, Ma. Concepcion Repalam, Salvador S. Reyes Jr., Student Member, IEEE, and Maria Ofelia C.Z. San Pedro. The Effects of an Interactive Software Agent on Student Affective Dynamics while Using an Intelligent Tutoring System. IEEE Transactions on Affective Computing, Vol. 3, No. 2, April-June, (2012).

[5] Whiteley, W., Artificially Intelligent Adaptive Tutoring System, Stanford School of Engineering, Stanford, CA 94305, (2008).

[6] Leonard, William J., C.V. Hollot, and William J. Gerace. Mastering Circuit Analysis: An innovative approach to a foundational sequence. 38th ASEE/IEEE Frontiers in Education Conference. Saratoga Springs, NY (October, 2008) 22-25.

[7] Bloom, B.S., Learning for Mastery, Instruction and Curriculum: RELCV Topical Papers and Reprints No. 1, University of California, Los Angeles, (1968) 3.

[8] Yamin, M. Desain Pembelajaran Berbasis Tingkat Satuan Pendidikan, Gaung Persada Press, Jakarta, (2007) Bab V: 130-144.

[9] R.S.J.d. Baker, A.T. Corbett, K.R. Koedinger, S.E. Evenson, I. Roll, A.Z. Wagner, M. Naim, J. Raspat, D.J. Baker, and J. Beck. Adapting to When Students Game an Intelligent Tutoring System. Proceedings, Eighth International Conference. Intelligent Tutoring Systems, (2006) 92-401.

[10] B. Woolf, W. Burleson, I. Arroyo, T. Dragon, D. Cooper, and R.Picard. Affect-Aware Tutors: Recognizing and Responding to Student Affect. International Journal Learning Technology, 4 (4), (2009) 129-163.

[11] V.J. Shute. Focus on Formative Feedback. Rev. Educational Research, 78 (1), (2008) 153-189.

[12] J. Rickel and W.L. Johnson. Integrating Pedagogical Capabilities in a Virtual Environment Agent. Proceedings First International Conference: Autonomous Agents, (1997) 30-38.

[13] C. Conati and X. Zhao. Building and Evaluating an Intelligent Pedagogical Agent to Improve the Effectiveness of an Educational Game. Proceeding. Ninth International Conference, Intelligent User Interface, (2004) 6-13,2004.

[14] W. Burleson. Affective Learning Companions: Strategies for Empathetic Agents with Real-Time Multimodal Affective Sensing to Foster Metacognitive and Meta-Affective Approaches to Learning, Motivation, and Perseverance. PhD dissertation, Massachusetts Institute of Technology, (2006).

[15] Anderson, LW., and Krathwohl DR., A Taxonomy for Learning, Teaching, and Assessing, Revision of Bloom's Taxonomy of Educational Objectives, Addison Wesley Longman, Inc., ISBN, 0-8013-1903-X, USA. (2001) 95-109.

 doi: 10.1166/asl.2014.5313