Applying Reinforcement and Mastery Learning: How It Works Based on Personalized E-learning Curriculum?

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ABSTRACT

Many researchers in the field of personalized learning or topic sequencing have proposed and implemented various mechanisms to improve the learning process with the main objectives of maximizing learning and dynamically selecting the closest teaching operation in order to achieve the learning goals. However, upon recommending the personalized learning sequence, based on literature review, the e-learning instructional strategists failed to perform or address the corrective measures to immediately remediate the learning difficulty. This paper presents the combination of the reinforcement learning concepts in the area of artificial intelligence and the mastery learning in educational psychology to remediate learning difficulties of the learners. The results show that based on the presented corrective measures, which are based on students' background performance matrixes that are collected during the learning process and summative examination, the students are able to correct their learning difficulties and improved their learning performances. The end semesters' results show the guarantee that almost all of the students who undergo the reinforcement and mastery learning procedures can successfully pass the e-learning course.

KEYWORDS

Personalized learning sequence, reinforcement learning, mastery learning, rewards, punishments, fitness value

1 INTRODUCTION

The growth of e-learning system has stimulated the research on personalized learning paths and adaptive learning opportunities which are suitable to the students' needs, their preferences and learning styles [1], [2]. Although there is a variety in students' interests, which in a way or another take them in different directions, there is still a common denominator amongst them and that is the desire to learn. Consequently, personalized learning is very appropriate to describe this phenomenon because it means, "finding the best ways to engage in people with different interests, passions and ways of thinking" [3]. When the learners are able to own and take responsibility of their learning, they become more motivated and engaged in the learning process. Thus, personalized learning path is needed to support such noble endeavour.

Various approaches to personalized learning path or topic sequencing have been explored with the use of students' feedbacks, knowledge levels and material difficulties [4] genetic algorithms and learning styles [5], [6] item response theory [7], [8] ant colony optimization [9] and teaching operation sequencing [10]. Although these revolutionary techniques have personalized the learning sequence, there is no guarantee that they reinforce or remediate the learning difficulty. To guarantee and to demonstrate that learning process can be improved using reinforcement and mastery learning, this paper put and set the works of Ballera, Lukandu and Radwan published at ICETC2014, Poland [11] into a working example by adapting its personalized learning sequence with the use of the reverse roulette wheel selection algorithm. Further, the process has been augmented through adding reinforcement learning in the area of rule based system in artificial intelligence and the classical mastery learning in educational psychology.

2 RELATED LITERATURE

2.1 The Need of Reinforcement Learning

The idea of reinforcement learning (RL) is motivating the learners to positively continue their actions on what is desired and expected from them by giving rewards or points, which are tantamount to the learners' effort but they can also receive punishments if they cannot pass the learning assessments. The e-learning is characterized by giving corrective activities to remediate difficulties found during the computer summative examination. It is a principal aid in planning the corrective measures to remedy learning errors. For instance, the activities to correct may involve alternative materials or resources such as videos, simulations, interactive tutorials, scenario-based learning, or any type of learning activity that allows motivational preferences. The reinforcement activities may also include problem-solving exercises, or any learning activity that is both stimulating and rewarding to the different types of learners. If reinforcement is successful in helping the students by remediating their learning difficulties, then almost all the students will demonstrate readiness to take the remedial examination. In this sense, it becomes a motivational device by directly showing to the students their improvements in their learning and their highest possibility of becoming successful learners.

In the area of machine learning, reinforcement learning is usually implemented in robotics, information theory and games simulations that teach behaviors and eventually trigger an agent to perform the actions that generate the shortest path or trajectory to a goal state. Because the agent wishes to maximize the reinforcement, it learns to choose action that minimizes the time it takes to reach the goal state, and in so doing, learns the optimal strategy as shown in Figure 2.1. Strategies are usually governed by some sets of rules that execute the reinforcement.
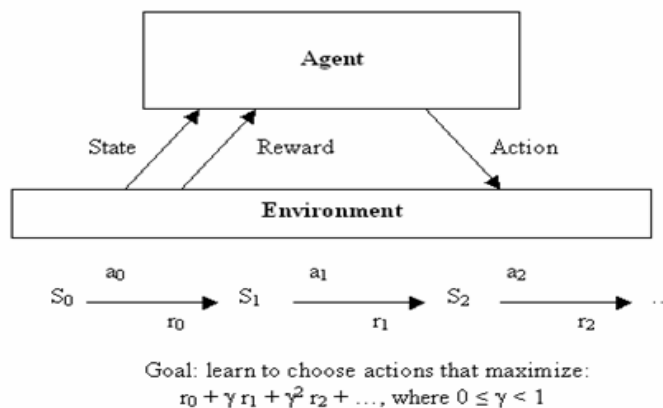

Figure 1: Standard Model of Reinforcement Learning [8]

Figure 1 models the agent in the environment wherein it chooses an action a_i, obtains reward r_i, and switch from state s_i to state s_{i+1}. The goal is to maximize the long term reward, where γ is called the discounting factor. The reinforcement learning (RL) has become a methodology of choice for learning in a variety of domains. RL is being played well in games and simulation [12], [13], [14]. Educators apply reinforcement learning in multi-agent and game-playing environment to achieve a superior level of performance in learning complex tasks. RL accelerates the learning process by giving the rewards functions [15]. If these benefits are being transformed in e-learning implementations, a guaranteed learning process will occur. The reinforcement should not be similar from the previous lesson to avoid boredom and to avoid the discontinuation of the learning process. This issue should be considered in designing the e-learning modules where the students do their self-learning.

2.2 The Need of Mastery Learning

Mastery learning (ML) is one of the notable areas of educational technology that has attracted much attention in the past. The article of Bloom [16] on mastery learning is regarded as the classic theoretical perspective where it compares two models of education: the traditional model and mastery mode, respectively. The traditional model uses the same instruction for an entire class, regardless of aptitude. The human instructor presents the required information to the students

who are then tested to measure the information they have retained. The students are typically given a chance to learn the material. The course then moves on to the next material. Once tested, the students may learn the mistakes that they have committed, but never re-tested in order to identify if they have learned from those mistakes. Consequently, the amount of learning in a classroom varies amongst the students. The students who have the aptitude to learn the requisite materials will quickly move forward, while slower students who fall behind and received lower grades. On the other hand, mastery model varies instructions according to aptitude, which results to a higher level of learning for all students. If the students have not learned the material by the first test, they can repeat it until they can achieve the required level of competence. Then they move on to the next module as demonstrated by Figure 2. As a result, human instructor employing mastery learning model of education hypothetically achieved high level of learning benefits.
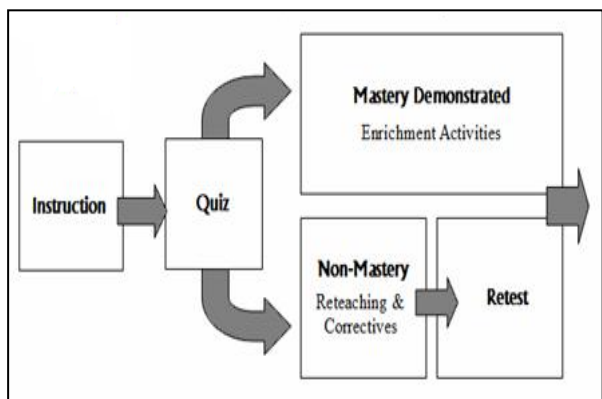

Figure 2. Learning Mastery Architecture [17]

Mastery learning has been widely applied in tertiary and primary levels in a variety of subject matters such as music [18], economics [19], mathematics [20], skill development and critical thinking [21]. Many meta-analytic studies have demonstrated consistent positive effects of reinforcement and mastery learning [22], [23]. The students are helped to master each learning unit before proceeding to a more advanced learning task in contrast to conventional instruction[24]. If

such benefits will be achieved in e-learning, a tremendous positive impact on learning process is possible.

3 METHODOLOGY

3.1 Participants and the Curriculum

The participants were enrolled in Design and Analysis of Algorithms, which is one of the core computer science courses that composed of 12 major chapters or lessons. The study has been conducted for three months, which has an equivalent of one semester among 41 students. Students are oriented and instructed how to use the e-learning course materials including discussions on the things to expect at the end of the experimental study. The e-learning curriculum contains 300 questions stored in the Item Bank and distributed among twelve different question types. A number of files with various media formats are included like videos, audios, gif and animations, pdf and powerpoint as alternative learning materials.

3.2 Reversed Roulette Wheel Selection Algorithms

The overall implementation of the reversed roulette wheel selection algorithm has been adapted based on the work of Ballera, Lukandu and Radwan [11]. The formulas and conditions in their paper have been thoroughly implemented in the study. Likewise, the same performance matrices such as *examination*, *review* and *study* have been used to extract fitness value and recommend a personalized learning sequence. Their works have successfully produced a personalized learning sequence. Based on the recommended recombination process, a third level generation is adapted.

3.3 Reinforcement and Mastery Learning Architecture

The personalized learning sequence, which is recommended by reversed-RWSA will proceed to reinforcement process by reading additional

learning materials (punishment) and mastery learning. Figure 3 shows the combined architecture of reinforcement and mastery learning to help the students in their learning process. During reinforcement process, the number of punishment is governed by the reinforcement rules. The rules determine how much number of additional learning materials should be prompted to the students by randomly selecting files in the learning materials table that are stored in the database. In this model, the system chooses an action a_i, which obtains reward r_i, and switch from state s_i to state s_{i+1}. The cumulative reward r_i, is added to the average results of the summative examination.

Reinforcement theory is "consequences influence behaviors". There are different types of consequences. There are consequences that give rewards to increase the overall performance or give punishment to increase competency level. The reinforcement theory has processes that support such mechanism using positive and negative reinforcement. Positive reinforcement is a pleasurable outcome resulting from behavior,

while negative reinforcement is the removal of the unpleasant outcome or behavior.

During mastery learning, student will be loaded with random questions for the individual formative examination. The student will not have the same set of questions due to random selection of items in the item bank. At the end of the formative examination, the scores are prompted. The students can review their answers and directly link to the lesson where the questions are related to. If needed, the students can view the explanation facilities and answers and reload another set of examination. These help the students to identify what they have learned well and what they need to learn more. The specific corrective activities for the students to use in correcting their learning difficulties or misconceptions are paired with each formative assessment. Most educational strategists match these correctives to every item or set of prompts within the assessment. Through this, the students will be helped in identifying those concepts or skills, which are not yet mastered. The concepts or skills which are not learned will be the focus of the students to work on.
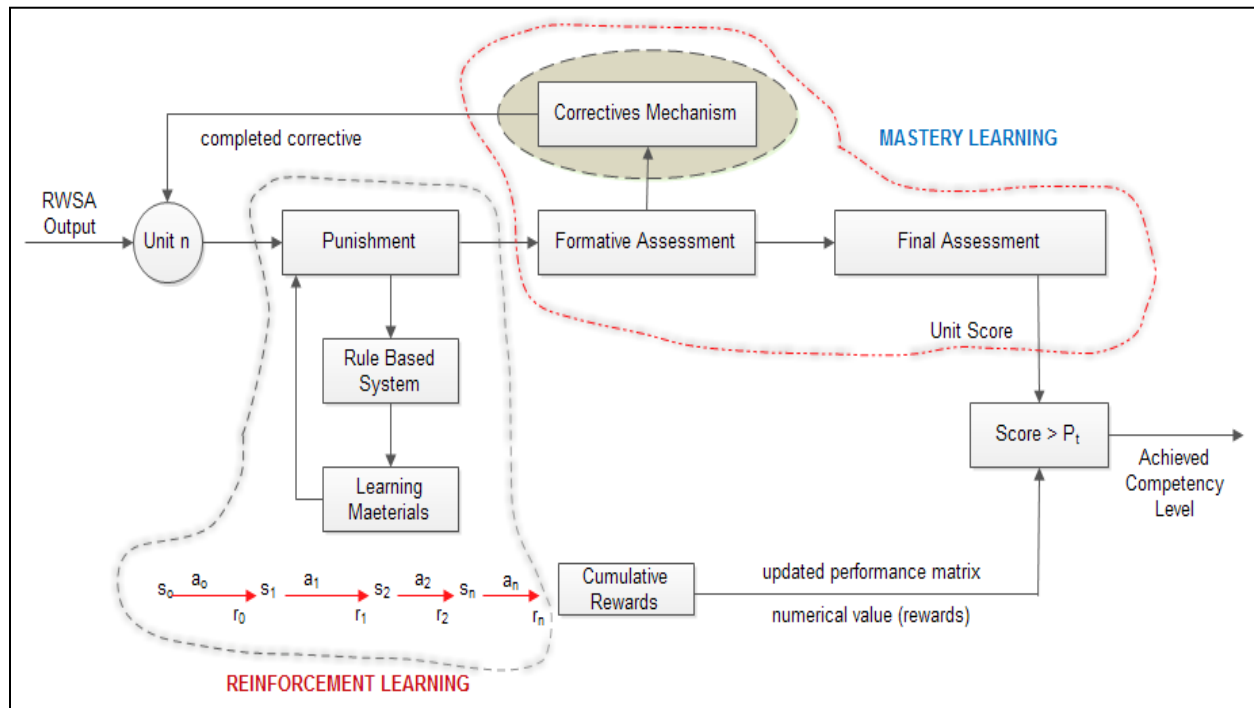

Figure 3: Architecture of Reinforcement and Mastery Learning

4 RESULTS and ANALYSIS

4.1 Personalized Learning Sequence

Initially, all learners take a summative examination after reading the learning materials to personalize their learning paths and determine which topics or lessons will be selected for further reading. The system eliminates lessons that have achieved the competency level and the retained lessons with perceived learning difficulty. The acceptable competency level is 75. The system has dynamically collected the data on the learners' various performance matrices and populated various tables in the database for profiling the students. Various performance matrices include *examination performance (Percentage Column), review performance (Review_Perf Column),* and *study performance (Study_Points Column)* of individual L_i, is extracted from various tables in the database to generate the personalized learning sequence as shown in Table 1.

The students who have passed the first summative examination with an overall average of 75 are acceptable. On the other hand, those students who fail will undergo some reinforcements and mastery learning. In Table 1, student 802197 does not successfully pass the first summative examination. With this, the new learning sequence is recommended by the system with the following sequence: $L_2 \rightarrow L_4 \rightarrow L_5 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{12}$ (formula and bases for recommending such learning sequence is based on the work of the same authors listed in the references section number 11) The e-learning system will replace the default lesson outline and activated the sequence. The students will undergo reinforcement level 1 and mastery learning. If a student successfully passes the Level 1, his or her records will be updated in the database. The database will also indicate that the student will no longer need reinforcements. However, in the event that the student fails again, the reinforcement level 2 is activated. This will replace the previous lesson outline as shown in Table 2 with a new sequence of $L_2 \rightarrow L_4 \rightarrow L_9 \rightarrow L_{12}$. Notice that the proposed learning path can simultaneously considers the curriculum difficulty level and the curriculum continuity of successive curriculum while implementing personalized learning sequence in the learning process. In fact, the new learning sequence listed in Table 2 is extracted from the previous personalized learning sequence of Table 1. In this way, the system guarantees that students will pass the e-learning course as it gradually eliminates lesson with the competency level.

The reverse roulette wheel selection algorithms systematically recommends the lessons (personalized sequence) based on random numbers generated by the computer versus fitness value. The results are heuristic. There is no guarantee that the generated personalized learning is the correct sequence or correct lesson to be re-learned, nevertheless it has the capability to reduce and recommend a personalized learning mechanism. This is valid, since even a sophisticated optimization technique is not an exact solution. This is also the common limitations of genetic algorithms. The random number, which is generated by the system is dynamic, though the bias has been eliminated by the linear ranking, it generally affect the overall performance of the algorithm. The initial results which involve 41 students show that the lesson recommended by the system is accurate, since it almost recommends lesson with failed values. Instead of recommending all the lessons with failed numerical value, the system relies on the random numbers as filtering mechanism. Once a personalized learning sequence is recommended by the system, the students will be directed to undergo reinforcement process.

4.2 Reinforcement Learning

The personalized learning sequence will undergo reinforcement mechanism as shown in Figure 4. Clicking the reinforcement link at the end of each lesson will activate the Reinforcement Window. There are a number of files that are used to reinforce the learners in different file formats such as PowerPoint, document, gif, video, pdf, solved problem files; which are readily available and can be randomly selected based on the reinforcement rules. The students are required to open each blue

colored links until all turns to red, which will indicate that the students read the reinforcement files. In case the students open another link, the system will automatically block it to avoid the opening of several windows at the same time. This mechanism is used to avoid cascading window overloading and navigational problem.

During the reinforcement learning, a numerical reward is given to a student and is added to his or her summative examination results. In the event that students fail the succeeding summative examination, a punishment in the form of additional learning materials will be loaded. These materials correspond to the level of his or her learning difficulty. These additional learning materials are designed for the reinforcement mechanism to avoid boredom. Further, these learning materials have the same concepts but presented in different formats and presentations. After the reinforcements, the students are directed to the formative assessment for mastery learning.

Table 1: Personalized Matrix (Level 1)

Reinforcement Details

Select student:

802197 - Mabrouka Bin Sharaf ▼

Lesson No	Percentage	Review Perf	Study Points	Weights	fv	Linear R	Linear Sequence	Cumulative Value	Random	Remarks	New Sequence
1	73.68	0.04	0.00	73.73	0.08	0.05	L7	0.05	0.75	Failed	L7
2	73.68	0.08	0.00	73.77	0.08	0.06	L9	0.10	0.30	Failed	L9
3	88.89	0.33	0.00	89.22	0.10	0.06	L4	0.16	0.25	Failed	L4
4	50.00	0.29	0.40	50.69	0.06	0.08	L12	0.23	0.38	Failed	L12
5	87.50	0.00	0.00	87.50	0.10	0.08	L1	0.32	0.11	Passed	
6	90.00	0.38	0.00	90.38	0.10	0.08	L2	0.40	0.44	Failed	L2
7	40.00	0.21	0.60	40.81	0.05	0.09	L8	0.49	0.85	Failed	L8
8	77.78	0.25	0.00	78.03	0.09	0.10	L5	0.59	0.92	Failed	L5
9	50.00	0.25	0.40	50.65	0.06	0.10	L3	0.69	0.07	Passed	
10	88.89	0.17	0.40	89.46	0.10	0.10	L10	0.79	0.60	Passed	
11	100.00	0.00	0.50	100.50	0.11	0.10	L6	0.89	0.78	Passed	
12	66.67	0.33	0.25	67.25	0.08	0.11	L11	1.00	0.08	Passed	
				891.97	1.00						

Table 2: Personalized Matrix (Level 2)

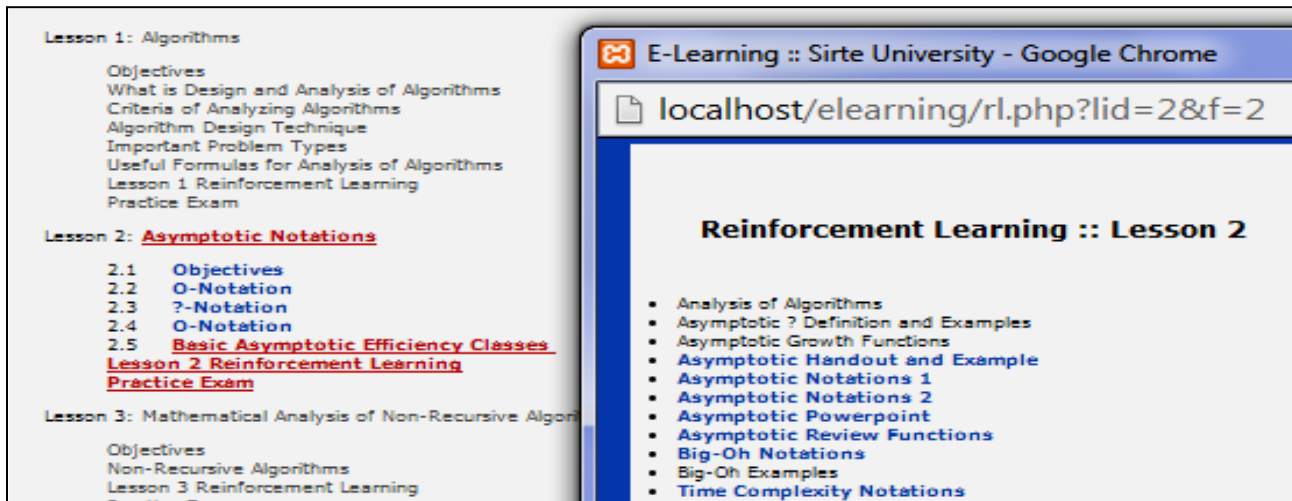| Lesson No	Percentage	Review Perf	Study Points	Weights	fv	Linear R	Linear Sequence	Cumulative Value	Random	Remarks	New Sequence
2	85.71	0.08	0.00	85.80	0.17	0.03	L12	0.03	0.43	Failed	L12
4	87.50	0.29	0.40	88.19	0.17	0.12	L9	0.15	0.95	Failed	L9
5	86.96	0.00	0.00	86.96	0.17	0.17	L2	0.31	0.46	Failed	L2
7	90.00	0.21	0.60	90.81	0.17	0.17	L5	0.48	0.44	Passed	
8	90.00	0.25	0.00	90.25	0.17	0.17	L4	0.65	0.82	Failed	L4
9	62.50	0.25	0.40	63.15	0.12	0.17	L8	0.83	0.80	Passed	
12	13.33	0.33	0.25	13.92	0.03	0.17	L7	1.00	0.53	Passed	
				519.07	1.00						

Figure 4. Reinforcement Learning

4.3 Mastery Learning

To perform the mastery learning, the students will undergo the formative examination at the end of each lesson. The students are not allowed to proceed to other learning materials without passing the formative examination or sometimes called the practice exam. The questions are randomly selected. For example, for Lesson 2 as demonstrated in Figure 5, a student has submitted her practice examination and is prompted to her score. If she fails, the system will not allow her to upload the new set of examination. All errors from her previous practice examination will be loaded for reviewing. The system will not load a new set of examination unless all "Explain" statements in red turn to blue.

Mastery learning (ML) is an education method in which a student stays with a particular learning unit until the objectives of that unit are successfully met before moving on to the next unit. Moreover, it helps the students to identify what they have learned well and what they need to learn. The specific corrective activities for the students to use in correcting their learning difficulties or misconceptions are paired with each formative assessment. Most educational strategists match these correctives with each item or set of prompts within the assessment, so the students will focus more on the concepts or skills, which are not yet mastered. With the gained feedback and corrective information from the formative assessment, each student will have a detailed prescription of the concepts or skills that need to master. This "just in time" correction prevents minor learning difficulties from accumulating and becoming major problems. It also gives the educational strategists a practical means to vary and differentiate their instruction to better meet the students' individual learning needs. In describing mastery learning, reducing variations in students' achievement does not imply making all students the same. Even in those favorable learning conditions, some students undoubtedly learn more than others, especially those who are involved in enrichment activities. But by recognizing the relevant individual differences among students and then altering instruction to better meet their diverse learning needs a guaranteed learning outcome will occur.
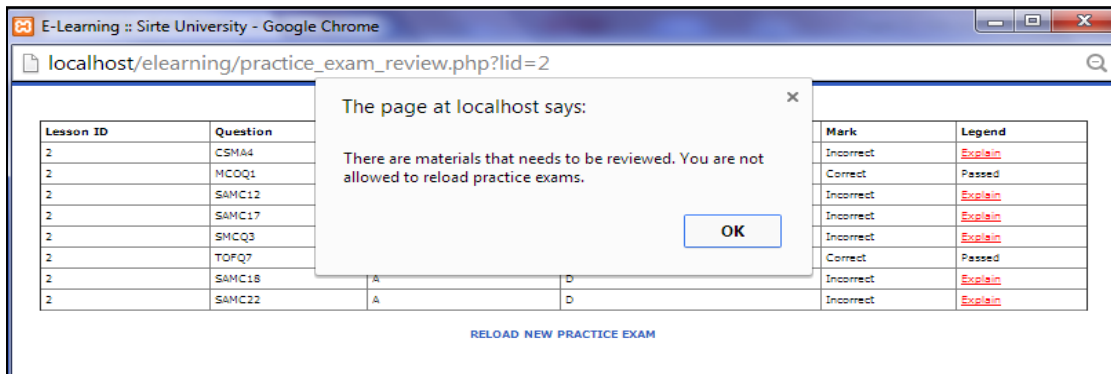
Figure 5: Mastery Learning

4.4 Summative Examination

A summative examination is the primary test that determines the overall understanding and comprehension level of all the students who are taking the course. Based on the chunk of the Final Exam (summative examination) of Figure 6, the overall passing mark is 88% with 36 out of 41 students. Among the 36 students who have passed, 22 of them take the reinforcements, while 14 students are first-takers and have satisfactory passed the course. Among the 22 students who take reinforcement, 10 of them have successfully passed the second summative examination after completing reinforcement and mastery learning level 1. On the contrary, 12 students only passed after taking the third summative examination. Among 41 students, 5 or 12% failed the course due to non-compliance and poor exam results.

The results show that student who experienced reinforcement and mastery learning lead to a better performance than a classroom-based teaching. Classroom-based teaching normally fails with the overall average, ranging from 20% to 50%. In some cases, other computing courses where Design and Analysis of Algorithm course belong even reach 60% of the total student failed the course. There is a significant increased in the overall passing average. Based on the last 3 years of teaching Design and Analysis of Algorithm course, the student average of failing is 25%. Although, the case study was taken in one semester only, a significant increase of the passing mark is an achievement in increasing the academic performance of the students.

Final Exam

Stud_ID	Name	Ave_P	Study	Review	Rewards	T_Eval	F1	F2	F3	Final Mark	Remarks	View	Action
502315	Mabrouka Suleiman	7.00	4.60	0.83	5.43	0	75.01	0.00	0.00	75.01	Passed	ANALYZE	EDIT
702452	Najah Suleiman	7.00	4.40	2.04	6.44	0	78.44	0.00	0.00	78.44	Passed	ANALYZE	EDIT
802092	Rada Rabia	6.75	3.15	1.63	4.78	0	65.81	75.20	0.00	75.20	Passed	ANALYZE	EDIT
802098	Zainab Hazar	7.25	3.15	0.88	4.03	0	67.11	78.25	0.00	78.25	Passed	ANALYZE	EDIT
802137	Sherifa Abubaker	7.33	3.90	1.08	4.98	0	74.73	63.46	59.86	59.86	Failed	ANALYZE	EDIT
802144	Salhin Muftah	7.58	4.60	2.46	7.06	0	79.65	0.00	0.00	79.65	Passed	ANALYZE	EDIT
802151	Alia Sesu	6.92	5.00	1.42	6.42	7	74.93	72.60	70.63	77.63	Passed	ANALYZE	EDIT
802178	Fatma Omar	6.75	4.25	1.13	5.38	0	69.46	67.15	82.35	82.35	Passed	ANALYZE	EDIT
802197	Mabrouka Bin Sharaf	6.42	2.55	2.33	4.88	1	73.92	73.71	74.88	75.88	Passed	ANALYZE	EDIT
802236	Nora Mohamed	6.67	2.55	1.08	3.63	6	63.86	70.00	69.19	75.19	Passed	ANALYZE	EDIT
802237	Nora Nufel	7.17	4.25	0.92	5.17	0	77.14	0.00	0.00	77.14	Passed	ANALYZE	EDIT
802491	Mona Ali	6.92	3.60	1.42	5.02	6	73.68	73.47	69.67	75.67	Passed	ANALYZE	EDIT
802513	Saif Mohammed	6.58	4.00	1.38	5.38	0	66.06	72.56	80.36	80.36	Passed	ANALYZE	EDIT
902139	Najah Muftah	7.33	3.45	0.71	4.16	0	78.13	0.00	0.00	78.13	Passed	ANALYZE	EDIT

Figure 6. Chunks of the Summative Exams
(3rd Level Reinforcement and Mastery Learning)

The strong evidence, which timely remediating the learning difficulty is an effective way in increasing the overall performance of the students. The system based on the work of Ballera et al. [11] recommends a personalized learning sequence and improve by incorporating reinforcement and mastery learning. Various mechanisms of reinforcement and mastery learning is successfully implemented in the system that lead to students' learning gain.

5 CONCLUSION and FUTURE WORKS

In this paper, the system is able to perform reinforcement learning and mastery learning based on the recommended personalized learning sequence. The personalized learning sequence has been recommended based on collected data during the learning process and the results of the summative examination; thereby individually profiling the students becomes possible. The proposed learning path can simultaneously consider the curriculum difficulty level and the curriculum continuity of successive curriculum while implementing personalized learning sequence in the learning process. During reinforcement, a numerical reward is given if the students satisfactorily perform corrective activities otherwise a punishment will be given in a formed of reading additional learning materials based on the punishment-rules system. The students will undergo mastery learning in the form of randomly selected formative examination to practice their comprehension or understanding on the previously learned lesson before taking the summative examination to identify their competency level. The results show that student who undergoes reinforcement and mastery learning guarantee to pass the e-learning course. As the generation increases, the students' competency levels also increase due to gradual elimination of learning difficulty.

In the implementation of the e-learning course, it is apparent and identifiable that there still much to be done. Although the paper has successfully implemented personalization, reinforcement and mastery learning, a focus on the assessment design

and measuring the cognitive development of the students are desirable to ultimately measure the learning process. The researchers will venture into this area; formative and summative assessments and their impact to the learning process using the classical Bloom Cognitive Taxonomy.

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