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Adaptive and Personalizing Learning Sequence Using Modified Roulette Wheel Selection Algorithm

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Abstract**—**Prior literature in the field of adaptive and personalized learning sequence in e-learning have proposed and implemented various mechanisms to improve the learning process such as individualization and personalization, but complex to implement due to expensive algorithmic programming and need of extensive and prior data. The main objective of personalizing learning sequence is to maximize learning by dynamically selecting the closest teaching operation in order to achieve the learning competency of learner. In this paper, a revolutionary technique has been proposed and tested to perform individualization and personalization using modified reversed roulette wheel selection algorithm that runs at O(n). The technique is simpler to implement and is algorithmically less expensive compared to other revolutionary algorithms since it collects the dynamic real time performance matrix such as examinations, reviews, and study to form the RWSA single numerical fitness value. Results show that the implemented system is capable of recommending new learning sequences that lessens time of study based on student's prior knowledge and real performance matrix.

Keywords**—**E-learning, fitness value, personalized learning sequence, reversed roulette wheel selection algorithms.

I. Introduction

THE proliferation and unprecedented increased of e-learning system stimulated research output on personalized learning sequence and adaptive learning. This new educational pedagogy becomes a trend in educational system, suitable to the students' needs, their individual preferences, and learning styles [1]. Personalizing learning sequence enables customization and personalizing topic sequence by autosuggestion of learning sequence and dynamic insertion of content in an appropriate format that is relevant or important to the individual learner, based on the learner's behavior, prior details, and personal preferences [2]. Personalizing learning sequence is easy, practical and a flexible way to achieve learning goal at students' own time and own paces. According to National Educational Technology Plan (N.E.T.P.) developed by the U.S. Department of Education, Personalized Learning Sequence or P.L.S. is defined as assessing the pace, assessing the approach, and combining the learners' attributes such as interests, learning style, and personal experiences [3]. Moreover, personalized learning sequence is the process of conforming or contouring learning to the learners that emphasize and recognize learners' different weaknesses and strengths, and diversified ways of learning [4].

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Although there are different ways in students' interests and personal objectives in learning and take them in different directions in learning process; they want all to learn. Personalized Learning Sequence or P.L.S. is suitable and appropriate to describe this concept because it means, "finding the best and easy ways to learn". Students should understand how to learn best and become active in designing their individual learning objectives [5]. Student should express what they know and how they prefer to engage in the learning process. When students' take responsibility and manage their own learning process, they are more active, more motivated and more engaged in the learning process. Thus, personalized learning sequence is timely needed to support dispersed and heterogeneous students.

II. Related Literatures

Personalized topic or learning sequencing is used to generate an individualized course sequence or structure for each learner by selecting optimal pedagogical and teaching operation [6]. Optimal pedagogy means a process that is in the presence of other available teaching techniques or strategies; it will bring the students to their educational goals. The most common goal is to learn a required concepts till to a specific level in a minimal time and minimal learning errors. Due to diversity of students, there are no specific or fixed learning paths for all learners due to individual learning attributes. The success depends on the learning environment system capability to automatically adapt the learning material to the student's educational needs to promote learning performance [7]. Experiments and case studies showed that the benefits and academic achievements in PLS system were higher compared to non-personalized learning system [8], [9].

Many and different approaches to PLS or topic sequencing has been explored in the area of e-learning and online learning implementations. Research shows that PLS is recommended by using student's feedback, knowledge level, and the perceived materials difficulty [10] while, others have used learning styles and personal prior data [11], genetic algorithms [12] and item response theory mechanism or I.R.T. [13]. These researches are algorithmically expensive and complex due to various components such as learning style and data or numerical value extraction. Other literature manipulated the sequence of problems amongst learners simultaneously using predetermine measurement [14] while others were able to sequence several kinds of teaching mechanism such as presentations, examples and most importantly, the assessments [15], [16]. Personalized Learning Sequence or PLS is a popular and an excellent technology for online-based education. Although, these researches inevitably contribute in PLS area, an alternative mechanism is under study and explored to produce personalized learning sequence. The algorithm in Fig. 1 produced an optimal solution that guarantees a new learning sequence based on tertiary curriculum.

III. Methodologies

A. Improving Roulette Wheel Selection Algorithm

Roulette wheel selection algorithm (RWSA) is the simplest and most common selection algorithm for optimization because of its adaptability and its heuristic searching. The algorithm is used as selection stage of genetic algorithms (GA) in which individual or chromosomes are chosen from the population for future breeding, which test hundreds or thousands of set of samples [17]. The process is done by filtering the entire populations using the probabilistic single fitness function. Moreover, genetic algorithm or GA runs through various stages that requires a large set of data for filtering, validating and reliability testing – the more the populations is available, the more chances it yield to better results. In the absence of large or big data, GA becomes unreliable and biased. However, relaxing the implementation of RWSA algorithms can optimize and minimize the learning sequence without any doubt on the results. Fig. 1 shows the reversed implementation of RWSA algorithm, capable of eliminating bias, and capable of recommending a heuristic personalized learning sequence.

Based on Fig. 1, the first part of the algorithm collects and computes the fitness function of all lessons, $L_{1....}L_x$, then summing up for normalization using (1). Normalization is the quotient of dividing the fitness values of each individual by the sum of all fitness so that the sum of all resulting fitness values is equal to 1. The accumulated fitness is the sum of its own fitness value plus the fitness values of all the previous individuals. The accumulated fitness of the last individual should be one; otherwise something went wrong in the normalization step.

$$Normalized\ FV\ (Li) = FV\ (L_i)/\sum_{i=1}^{L} FV(Li) \qquad (1)$$

The second part of the algorithm has sorted the available population into increasing order of the fitness value and ranked according to its interval range. Interval range is the beginning and ending of the fitness value in accordance to the normalization process. The fitness value is assigned to each member of the population and depends only on its current position in the individual rank. The ranking is extended along a straight line so that it ~~eliminates~~ or overcomes the scaling bias of roulette wheel selection algorithm. The bias is the immobilization of member in the population, wherein selective pressure is too small causing the selection to narrow down too quickly [18], [19]. Rank N is assigned to the best individual while rank 1 is for the worst individual. Sorting and ranking introduces a proportional scaling across the population and provides an effective way of controlling the selective pressure. The third part of the algorithm is computing the accumulated fitness value of an individual in the population or Lesson. The fourth part of the algorithm is the generation of random number between 0 and 1, R (0,1) that filters the selection process while the fifth part selects individual whose accumulated normalized value is less than the random number, R. Lesson with a lower probability will be selected for recombination process indicating presence of misconceptions or deficient learning competency level. At the end, a list of new populations (lessons) is recommended as new personalized learning sequence or PLS. The running time of the algorithm is O (n).

```
ALGORITHM    Reversed Roulette Wheel Selection Algorithm (L[1...12])
    //Combining RWSA and Linear Ranking
     Algorithm
    //Input: Collected Performance
     Matrix
    //Output: New Personalized Learning
     Sequence
  1. S ← 0;// Computing the fitness function
      for i ← 1 to N do compute (FVi)
           S = S + FVi
  2. for  i ← 1 to N do //sort and rank FV followed by Lesson ID accordingly perform linear
     ranking ((FVi + Li)
  3. for  i ← 1 to N do//compute the cumulative FV according  to its rank compute cumulative FV
     (cFVi)
  4. generate random number r from interval (0,S)
  5. for  i ← 1 to N do//identifying lesson with misconceptions
            if ri ≥ cFVi, select Li
            return{Li, Li+1, ..., Ln}
```

Fig. 1 Improved Version of the RWSA Algorithm

B. Computing the Fitness Value

A fitness function to compute the fitness value *FV*, is a particular type of learning function that is used to summarize a single numerical figure of merit for each lesson. This value shows how close a given design solution in achieving the set learning goals. The idea is to delete the 'n' best performing in the population and retain new 'n' for learning remediation. The fitness function of the RWSA depends dynamically on three performance parameters such as; examination performance, study performance and review performance of the learner.

1. Examination Performance–this performance is the direct indicator about the student's knowledge obtained during learning process which is dynamically constructed based

on the student's background performance in reading the learning materials. Questions are provided to cover the topic and each question has a certain level of difficulty. An answer on a harder question demonstrates higher ability than correctly answering an easier question. Equation (2) is used to compute the examination performance of a student.

$$Exper(L_i) = (\sum_{i=1}^{N} \frac{Qdf(Li)}{Tdf(Li)} * 100) \quad (2)$$

2. Study performance- this performance is measured by interaction of students with the system. The interaction refers to viewing or listening to the course materials in multimedia form and measures, how much comprehension the student has gained through these learning activities. Usually, a topic is presented in multiple pages and each topic is assigned a weight, which corresponds to its importance. Equation (3) computes the study performance.

$$SP(Li) = 5*NW_i \quad (3)$$

3. Reviewed Topics Performance – This review topics performance is the score on a topic that shows records on how much the student review the topic by clicking arrow back and forth. It is based on how many times the topic is reviewed and how much of the materials are viewed each time. The review score is in the range from 0 to1 for each topic. Each time a student reviews the topic, a discriminating value of 0.1 is deducted to ideal_ review_score that initially set to 1. The students are allowed to navigate the learning materials up to 10 times. The value is dynamic for each student since each learner has his or her own pace of reading the e-learning materials. Equation 4 is the review performance formula.

$$Review\_Perf(Li) = \sum_{i=1}^{L} 5 * Review\_Points(Li) \quad (4)$$

Results of (2)-(4) were then combined into a single numerical value called fitness value, which indicates how well the topic was learned. The examination performance score is the most important among the three. When a student got a reasonably high examination score, usually greater than or equal to 75, then the other score does not matter much and the final mark is computed, denoted by (5).

$$FScore = \sum_{i=1}^{L}((\sum_{i=1}^{N} Qdf(Li)/Tdf(Li)) * (100) \quad (5)$$

However, if the examination performance score is less than 75, the other equations become relevant and will produce a single numerical value called fitness value for each Lesson, $FV(L_i)$, in the e-learning module as indicated by using (6).

$$FV(Li) = Exper(Li) + Review\_Perf(Li) + SP(Li) \quad (6)$$

In the case study, e-learning implementations, a chromosome or individual is denoted by lesson L_i, where L stand for lesson and i refers to lesson number on the curriculum. Each lesson has fitness value that dynamically changes according to learner's various performance matrixes. A high fitness value indicates high competency level achieve by the learners, while low fitness value indicates the presence of misconceptions. Misconception is defined as difficulty in learning, learning errors, low competency level, or a state that needs reinforcement and mastery. Thus, in e-learning, the lower the fitness values the more chances it will be included in the newly recommended personalized learning sequence.

C. Correctness of the Equations

The equations posted in previous section were simulated in excel and were tested separately before implemented in the prototype. Specifically (2)-(4) were normalized to be sure that each lesson score is directly proportional and distributed within the maximum score. Table I is a live data taken from different excel tables, and then dynamically populated the other table attributes. The simulations successfully recommend a personalized learning sequence; in the example, originally from 12 and then into four lessons. For the purpose of discussion, Table I was structured and presented to validate the implementation of the prototype. It can be seen that out of 12 lessons, the system recommends a new sequence, L_3, L_{10}, L_{12} and L_7, a decrease of 66%. Instead, the students will read and study the 12 chapter; the system recommends just four lessons. It is highly noted that only those lesson with "Failed" remarks in the Remarks column is recommended for further reading. The simulation was tested among 41 learners as subject for the case study.

Based on the simulation, the performance of the reverse roulette wheel selection algorithms is heuristic after comparing the cumulative value column in Table I to the random numbers generated by the computer. This is valid in optimization and minimization technique since no exact learning path can be established in students' learning process due to heterogenic nature of learners, nevertheless it has the capability to reduce and recommend a personalized learning sequence. Based on Table I, the personalized learning path is almost accurate. Instead of recommending the entire lesson results, lesson L_3, L_7, L_{10} and L_{12}, have been selected as the new list of personalized sequence for re-study. In reading the learning materials, the system dynamically collected data of the learners' and populate various performance matrixes in the database, for profiling learners.

IV. Results and Analysis

Personalized learning sequence or PLS is a list of lessons which is generated from the e-learning prototype for re-study and possible learning reinforcement. The e-learning prototype was posted for 8 weeks online, where students can freely navigate the course materials and perform teaching tasks as discussed during the orientation. With 41 students, 10 students were selected as shown in Table II, structured for the purpose of discussion. Students were allowed to take summative examination three times. This number of summative examination is enough or perceived that at Level 2, all students were able to achieved competency level as the PLS is gradually decreasing. For example Student 1, started at Level 0 with nine 9 lessons; $L_2 \rightarrow L_4 \rightarrow L_3 \rightarrow L_7 \rightarrow L_8 \rightarrow L_9 \rightarrow L_{10} \rightarrow L_{12} \rightarrow L_5$ and failed the first summative examination, then lessons $L_2 \rightarrow L_4 \rightarrow L_3 \rightarrow L_7 \rightarrow L_8 \rightarrow L_{12} \rightarrow L_5$ is recommended for further reading at Level 1. However, the student failed the second summative examination at Level 1, forcing the system to recommend a new list of personalized learning sequence taken from previous list which *are* $L_2 \rightarrow L_4 \rightarrow L_3 \rightarrow L_5$ at Level 2. The student passed the summative examinations at Level 2. Based on Table II, the personalized learning sequence varies for each student due to his or her personal learning attributes during learning process. It can be observed that, the 10 students have different learning sequence at Level 0 and successively considered the learning sequence in the curriculum vector as the reinforcement level reaches Level 2. The learning path or sequence simultaneously considers both the curriculum difficulty level and the curriculum continuity of the successive curriculum while implementing the personalized learning sequence of the learning process. The system guarantees that students will pass the e-learning course as it gradually eliminated the lesson in the curriculum vector while increasing the gap of passing the competency level. For example, Student 6, has 8 lessons at Level 0 then 5 lessons for Level 1, having a decreased of 37.5% based on his original sequence. It means that Student 6, instead of reading the original 8 lessons, 3 lessons were eliminated from his or her previous personalized learning list and focus on the new lists $L_4 \rightarrow L_3 \rightarrow L_2 \rightarrow L_{10}$ and L_7. At Level 2, a new sequence is recommended based on Level 1, lessons $L_4 \rightarrow L_{10}$ and L_7 with 40% decreased. It can therefore generalize that as the level of reinforcement or level is increasing, the number of personalized learning sequence is also decreasing. Once a personalized learning sequence is recommended by the system, the students will be directed to undergo re-reading or mastery to achieve learning goal.

Fig. 1 shows the improved performance of 10 students as they involved in the case study. For discussion, only these 10 students were captured in the graph showing their average performance in each PLS. Student 1, have score of 50 in his summative examination one and increased his score by 27 marks in the second summative examination, summing into 67 and passed in third summative examination with a score of 89 percent. The overall average of these ten students is 89%. An interesting thing to note is; as the number of lesson is decreasing based on PLS of Table II, students' score in their summative examination also increases, indicating that their competency level is achieved.

The results are heuristic yet they guarantee that the new learning sequence becomes smaller as the process approaches the stop criterion. Being heuristic in nature, there is a minimal chance that a lesson with a very high fitness value will be selected. This mechanism is leveraged by the rule-based punishment system in the form of giving minimal reinforcement. Instead of recommending all the lessons that have failed, the system relies on the random numbers as filtering mechanism.

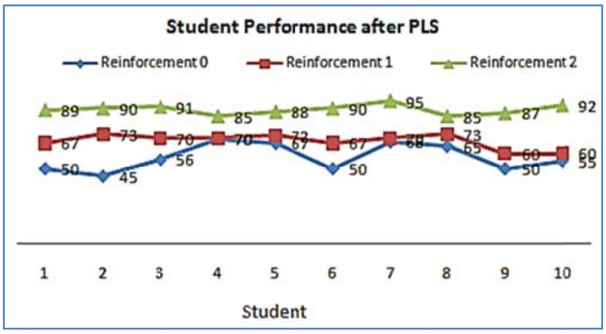

Fig. 2 Summative Examination Results after Undergoing PLS

TABLE I
SIMULATED EXCEL RESULTS IN RECOMMENDING NEW LEARNING SEQUENCE

Li	Exam_ Perf	Review _Perf	Study_ Points	I_FV	N-Fv	Rank	Sequence	C-Value	R	Remark	New Sequence
L1	66.67	0.21	0.00	66.88	0.09	0.05	**L3**	0.05	0.89	Failed	L3
L2	80.00	0.25	0.00	80.25	0.11	0.05	**L4**	0.11	0.03	Passed	
L3	40.00	0.29	0.00	40.29	0.05	0.07	**L10**	0.18	0.63	Failed	**L10**
L4	40.00	0.33	0.00	40.33	0.05	0.07	**L12**	0.25	0.49	Failed	**L12**
L5	83.33	0.38	0.50	84.21	0.11	0.07	**L7**	0.32	0.61	Failed	***L7***
L6	54.55	0.38	0.35	55.27	0.08	0.08	**L6**	0.39	0.11	Passed	
L7	50.00	0.38	0.60	50.98	0.07	0.08	**L8**	0.47	0.07	Passed	
L8	60.00	0.29	0.35	60.64	0.08	0.09	**L1**	0.56	0.33	Passed	
L9	80.00	0.00	0.40	80.40	0.11	0.10	**L11**	0.67	0.29	Passed	
L10	50.00	0.00	0.40	50.40	0.07	0.11	**L2**	0.78	0.24	Passed	
L11	75.00	0.08	0.00	75.08	0.10	0.11	**L9**	0.89	0.36	Passed	
L12	50.00	0.33	0.25	50.58	0.07	0.11	**L5**	1.00	0.29	Passed	
				735.31	1.00						

TABLE II
SUMMARY OF PERSONALIZE LEARNING SEQUENCE

	Personalizes Learning Sequence		
Students	**Level 0**	**Level 1**	**Level 2**
1	L2, L4, L3, L7, L8, L9, L10, L12, L5	L2, L4, L3, L7, L8,L12, L5	L2, L4, L3, L5
2	L1, L5, L3, L7, L8, L10, L12, L4	L1, L5, L4, L8, L10, L12, L7	L5, L8, L10, L12
3	L2, L6, L3, L8, L7, L9, L1, L12, L5	L6, L3, L8, L7, L1, L12	L6, L3,L7, L1, L12
4	L6, L4, L3, L7, L8, L9, L10, L12, L1	L7, L8, L9, L10, L12, L1	L9, L10, L12, L1
5	L12, L6, L3, L7, L8, L9, L10, L1, L2	L6, L3, L2, L8, L9, L10, L1, L7	L6, L3, L2,L7
6	L4, L3, L2, L7, L10, L9, L8, L12, L7	L4, L3, L2, L10, L7	L4,L10, L7
7	L2, L4, L3, L7, L8, L9, L10, L12	L2, L4, L7, L8, L9, L10, L12	L2,L7, , L9, L10, L12
8	L2, L4, L6, L7, L8, L9, L10, L12, L5	L8, L9, L10, L12, L5, L2	L9, L12, L5, L2
9	L6, L1, L3, L7, L9, L10, L12, L4,L8	L6, L10, L3, L7, L1, L12, L4 ,L8	L6, L3, L1, L4 ,L8
10	L2, L4, L3, L7, L5, L9, L10, L12, L11	L12, L4, L3, , L9,L11	L12, L4, L3,

V. CONCLUSION AND FUTURE WORKS

In this paper, the validity of the proposed reversed roulette wheel selection algorithm with sorting and linear ranking has been successfully implemented to produce a heuristic personalized learning sequence. Though heuristic, this concept is generally acceptable in the area of optimization since there is no exact learning path solution for a particular student due to varying background and prior knowledge of learner. The data used for computing the fitness value of each lesson is based on real and dynamic performance matrix of the student during the learning process. Likewise, the correctness of the fitness function were tested several time both in excel spreadsheet simulation and the prototype. Based on the algorithm, the complexity and the running time of the algorithm is O(n). Result shows that the achievement of the student during online assessment is increasing based on three summative examination results while their personalized leaning sequence is decreasing. Future works will take advantage of the results and will employ a corrective and reinforcement process to guarantee learning process. Also, testing will be done in a large scale implementation to benchmark with other PLS system that uses different revolutionary technique.

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