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Learning path recommendation based on modified variable length genetic algorithm

Pragya Dwivedi[1] **· Vibhor Kant**[2] **·**
Kamal K. Bharadwaj[3]

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Abstract With the rapid advancement of information and communication technologies, e-learning has gained a considerable attention in recent years. Many researchers have attempted to develop various e-learning systems with personalized learning mechanisms for assisting learners so that they can learn more efficiently. In this context, curriculum sequencing is considered as an important concern for developing more efficient personalized e-learning systems. A more effective personalized e-learning recommender system should recommend a sequence of learning materials called learning path, in an appropriate order with a starting and ending point, rather than a sequence of unordered learning materials. Further the recommended sequence should also match the learner preferences for enhancing their learning capabilities. Moreover, the length of recommended sequence cannot be fixed for each learner because these learners differ from one another in their preferences such as knowledge levels, learning styles, emotions, etc. In this paper, we present an effective learning path recommendation system (LPRS) for e-learners through a variable length genetic algorithm (VLGA) by considering learners'

✉ Pragya Dwivedi
pragya.dwijnu@gmail.com

Vibhor Kant
vibhor.kant@gmail.com

Kamal K. Bharadwaj
kbharadwaj@gmail.com

1 Computer Science and Engineering Department, Motilal Nehru National Institute of Technology Allahabad, Allahabad, India

2 Computer Science and Engineering Department, The LNM Institute of Information Technology, Jaipur, India

3 School of Computer and Systems Sciences, Jawaharlal Nehru University New Delhi, New Delhi, India

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learning styles and knowledge levels. Experimental results are presented to demonstrate the effectiveness of the proposed LPRS in e-learning environment.

Keywords E-learning · Recommender system · Genetic algorithm · Learning styles · Knowledge levels

1 Introduction

The advancement and popularity of information and communication technologies have induced a huge impact on education as well as on commercial environment and also raised a situation of proliferation of learning materials on e-learning systems in recent years. Due to the explosion of learning materials on e-learning systems, it is very difficult for learners to find relevant learning material according to their needs. One way to address this problem is the use of e-learning recommender system that retrieves relevant learning materials based on learner preferences (Dwivedi and Bharadwaj 2011, 2013; Ghauth and Abdullah 2010; Erdt et al. 2015; Kasemsap 2016). E-learning recommender systems (ELRSs) efficiently guide learners by providing interesting, learning materials within a very large complex space of possible options. These systems also ensure that the right material is provided to the right learner at the right time at any place (Adomavicius and Tuzhilin 2005; Yeon Choi et al. 2007; Christensen and Schiaffino 2011; Khribi et al. 2015; Klašnja-Milićević et al. 2015).

Generally, collaborative and content based filtering are employed in the field of ELRSs to provide effective recommendations by considering one of the most important preferences of learners such as learning styles, knowledge levels, emotions and goals. However, only recommendations of learners' leaning materials are not adequate for the enhancement of learning capability of a learner. Every learner has different goal for learning. Consequently, learners are puzzled for constructing appropriate learning sequences from a set of recommended learning materials to reach their goals. For example, if a mechanical engineering student needs to design a machine using neural network, she does not require to study the entire machine learning. She only needs to learn about neural network concepts. Appropriate sequencing of learning material is a major concern in the area of ELRSs. Many researchers have tried to resolve this issue by constructing a learning path utilizing difficulty parameter of learning material in e-learning (Wong and Looi 2009; Chen 2008). Learning path, referred as a sequence of learning resources, is provided to learner for accomplishing their needs and achieving their goals. Recently, various techniques have been proposed to construct or recommend the learning path to learners in the area of ELRSs by employing evolutionary approaches. Further, these techniques are classified into two groups mainly, ***social sequencing*** depending on the solution that incorporates experiences of other similar learners and ***individual sequencing*** based on only the individual learner's experience (Al-Muhaideb and Menai 2011).

1.1 Motivation

Generally, e-learning is defined as "learning via computing devices and the Internet" (Chu et al. 2011; Jung 2011). It opens the opportunity for learning activities to take place at anytime and anywhere based on a learner's preferred sequence and pace (Chen 2008). To provide personalized mechanism in e-learning is considered as an important feature for efficient learning experiences in recent years. An e-learning system can help learners (1) by providing the learning materials or services; (2) by monitoring the learning experience and (3) to manage the e-learning content as well as the associated e-courses (Chu et al. 2011; Tam et al. 2014). Usually, e-learning systems follow a 'one-size-fits all' approach in which a same learning sequence or same learning materials are provided to all learners by considering only common aspects of those learners. However, these learners vary in their learning styles, knowledge levels, background and goals (Huang et al. 2007). It would be nice to provide personalized learning materials in an appropriate sequence to an individual learner based on his/ her learning preferences.

Recently, the contributions of data mining and recommendation technologies have emerged in personalized e-learning environments to facilitate learners' task of finding learning materials by providing appropriate learning resources to learners. However, these technologies assure the instant interest of learners rather than considering the recommendation of learning materials in an organized sequential manner. This approach might be problematic because the sequence of the learning materials has to match a particular learning strategy where each learning object is valid with the previous and the next one (Durand et al. 2013). In this regard, curriculum sequencing is considered as an important concern in the area of ELRSs where learning materials are arranged in appropriate manner and delivered to active learners based on their preferences and pedagogical conventions (Huang et al. 2007). Therefore, many researchers have developed various e-learning systems with personalized learning mechanisms to assist online learners by adaptively providing appropriate learning paths for enhancing the learning capability of those learners.

1.2 Curriculum sequencing problem

E-learning environment has the ability of limited instructor/trainer support and self-guided learning using various methods including curriculum sequencing. E-learning is beneficial to adult and lifelong learners who are willing to study through self guided learning process (de-Marcos et al. 2007). Curriculum sequencing (CS), an important concern in e-learning, refers to the sequence of recommended learning materials that has to match a particular learning process (Sentance and Csizmadia 2017). It replaces the rigid, general and 'one size fits all' course structure set by experts with a more flexible and personalized learning path. It includes the learner's behaviour, knowledge levels, learning styles and learning capabilities as well as curriculum related prerequisites constraints (Al-Muhaideb and Menai 2011). The CS problem, an NP-hard problem can be considered as either a multi-objective optimization problem (Chu et al. 2011; Shmelev et al. 2015) or a constraint satisfaction problem (de Marcos et al. 2009). In the literature, various techniques such as statistical, evolutionary computation are utilized to find optimal learning path sequence that satisfies the pedagogical structure as well as learner individual needs. The details of these techniques for possible solutions to CS problem are discussed in Section 2.

1.3 Contribution

For enhancing the performances of learners in e-learning environments, it is quite practical to provide learning materials for learners in a sequential form based on their requirements and preferences. In this regard, we have proposed a novel approach which generates higher quality recommendations and also tackle the problem of learning path by developing sequential form of these recommendations in e-learning environment.

The major contributions of our paper are three fold:

- Firstly, we have developed learner profile based on data extracted from the registration process.
- After that, we have developed personalized learning path recommendation framework based on variable length genetic algorithm for individuals.
- Finally, for demonstrating the effectiveness of proposed approach, we have performed various experiments on dataset collected through survey.

The rest of the paper is organized as follows: Section 2 describes the various techniques such as statistical, evolutionary computation employed for CS problem. In Section 3, we have presented our proposed model based on modified variable length algorithm. The experimental results are presented in Section 4. Finally, the last Section concludes our work with some future research directions.

2 Literature survey

To resolve the issue of curriculum sequencing, various approaches have emerged in the field of ELRS. Among these approaches, the approaches based on statistical methods, concept map, evolutionary algorithm and data mining algorithms for constructing and recommending the learning path to learners are as follows:

- ***Approaches based on Statistical methods, Neural network, Concept map***
- ***Approaches based on Evolutionary Algorithm***

2.1 Approaches based on statistical method, neural network, concept map

Anh et al. (2008) generated the shortest learning path by applying statistical method such as Bayesian probability theory. In this paper, they are divided whole approach into two phases. In the first phase, they utilize learner preferences for calculating the probability of subsequent nodes and generates candidate learning path while in second phase, shortest path is selected among candidate LPs based on Bayesian network. Kwasnicka et al. (2008), proposed a Neural network based technique through which an intelligent agent called Learning Assistant is responsible for generating learning path for individual. This paper utilizes the learner's information collected through primary test and their characteristic for generating the learning path. Hsieh and Wang (2010) presented a system that supports Apriori algorithm for finding a set of candidate resources and formal concept analysis is used for learning path construction. This support system can be employed in any information retrieval system so that learners enhance their learning through efficient servicing of Internet. Recently, Salehia et al. (2013) proposed hybrid technique for recommending the learning path based on two modules: explicit attribute based recommendation module and implicit attribute-based module. First module considers the implicit features of material as chromosome genes and generates the chromosome for genetic algorithm to optimize the weight of past rating. In the second module preference matrix based on explicit features of material is developed. Further recommendations in the both modules are generated through the nearest neighbour approach.

2.2 Approaches based on evolutionary algorithm

Evolutionary techniques have great impact in the solution of this curriculum sequencing problem by providing appropriate learning paths to learners. Genetic algorithms (Lopes and Fernandes 2009; Guo and Zhang 2009; Chen 2008; Tam et al. 2014), Ant colony algorithms (Semet et al. 2003; Yang and Wu 2009; Wong and Looi 2009; Wang et al. 2008; Kamsa et al. 2016), Memetic algorithms (Acampora et al. 2009) and Particle swarm optimization (Wang and Tsai 2009; Chu et al. 2011; de Marcos et al. 2009) are widely used techniques in the construction of learning path sequence.

- *Learning path based on genetic algorithm*

Romero et al. (2002) proposed a GA-based data mining approach to guide instructor for designing course structure and content. In this paper, GA is applied to obtain association rules from the learner evaluation data for discovering the relations between knowledge levels, learner scores and the time spent on different learning contents. Hovakimyan et al. (2004) suggest a different view of the problem by considering the cumulative cognitive complexity. They used a GA to find the optimal sequence for minimizing the cognitive complexity measured by the total time needed to reach a pedagogical goal. Seki et al. (2005) generated optimal learning paths that persuade multiple objectives based on distributed GA. Here, they used difficulty level, pre-requisite satisfaction and relation between consecutive objects for building the fitness function. GAs was also employed by Samia and Mostafa (2007) by considering both the learner's profile and the learning objectives.

Another GA algorithm based framework was also proposed by Huang et al. (2007) to construct an individualized near-optimal learning path based on a pre-test to identify student's weakness points. Chen (2008) proposed a personalized learning path scheme for individual learner based on genetic algorithm. During learning process, they considered course difficulty level and concept continuity of successive courses simultaneously for implementing personalized curriculum sequencing.

- *Learning path based on swarm intelligence*

For learning path generation or recommendation, there are basically two popular techniques are used namely Ant colony optimization (ACO) and Particle swarm optimization (PSO). A Style-based ACO system (SACS) generates the learning path by utilizing history of those learners who have similar learning styles is proposed by

Wang et al. (2008). Wong and Looi (2009) present a Dynamic Learning Path Advisor (DYLPA) that utilizes a modified ACO mechanism for the sequencing of objects. For generation of learning path, firstly they compute similarity based on several factors including prior knowledge, language proficiency and a number of learning preferences after that on the basis similar learner's historic data, learning path is recommended. Optimizing learning path using ACO for collaborative groups is also suggested by Kamsa et al. (2016). Rastegarmoghadam and Ziarati (2016) utilized ACO algorithm for developing the intelligent improved tutoring system. Discrete PSO was employed by Wang and Tsai (2009) to choose the material suitable for a review course based on the material relevance degree, difficulty level and the number of available learning resources. A greedy-like algorithm is used to sequence this material and smooth the reading order.

From above literature, we have noticed that the length of learning path cannot be same for each learner because learners are varied in their learning styles, knowledge levels and other preferences. In this context, the length should be decided by learner background and learning ability or learner knowledge in related contents. In this paper, we present a learning path recommendation framework based on social sequencing by using variable length genetic algorithm (VLGA). The application of VLGA provides a more flexible length of recommended learning path for an active learner based on his learning styles and knowledge levels.

3 Proposed learning path recommendation framework

We propose a learning path recommender system for e-learners (LPRS_EL) that suggests personalized learning path sequences for learners in e-learning environments. Learners are differentiated through their learning styles, knowledge levels and learning goals. To provide an appropriate learning path sequence to an e-learner is an open issue by taking into the consideration of these learner preferences. In this section, we describe the main characteristics of our proposed system, the information required for learning path recommendations and our proposed framework. Our LPRS_EL offers a recommendation set of learning path sequences for learners in online e-learning environments through two stage process, namely registration and learning path recommendation processes as depicted in Fig. 1.

(a) **Registration process:** We extract the preferences of an individual learner through the registration process and generate an individual learner profile. A learner profile, an important feature for our proposed system has two major components- learner preferences and learner activity information. Generally, the first component *learner preferences* consists of the information about learner's learning styles, knowledge levels, relevant background, prior knowledge and explicit ratings for experienced learning resources. Whereas the second component *learner activity information* has records about the learning path that he/she has visited and his/her overall performance in the course as well as performances in learning objects of selected learning path. In our system, learners are characterized as (1) active learners for whom the system recommends the learning paths

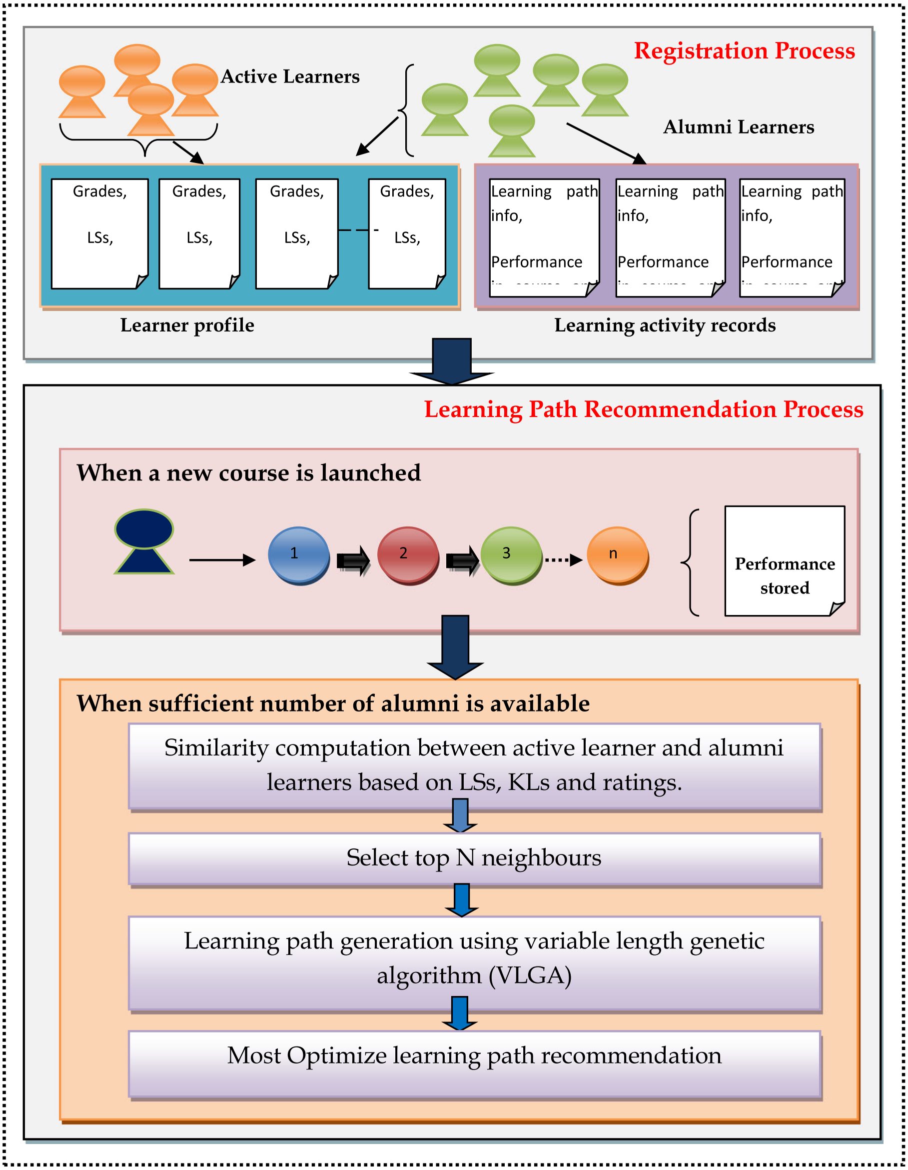

Fig. 1 The whole architecture of LPRS_EL

and (2) alumni learners who have enrolled previously in the same course. The details of registration process are described in Section 3.1.

(b) **Learning path recommendation process:** In this stage, we develop learning path recommendation framework by employing course generator's advice and evolutionary approach namely a variable length genetic algorithm (VLGA) after generating learner profiles through registration process. Our main focus is to generate as well as to recommend a suitable learning path for an active e-learner through VLGA. Our proposed system initially recommends a predefined learning path sequence to an active learner at the early stage of launching a new course with the help of course generator's advice and iteratively updates the previous recommended learning path through alumni's learning path sequences using VLGA until the termination condition is satisfied. The details about learning path recommendation process are described in Section 3.2.

In our LPRS_EL, we present a collaborative recommendation framework for generating learning path recommendations for e-learners through a variable length genetic algorithm. By taming the learner profile efficiently, our system can provide the effective learning path recommendations for learners. In the following subsections, we will describe learner profile information and recommendation framework.

3.1 Learner profile formation

Generally, a learner profile can be considered as a collection of personal information about the learner. It contains the information about learner preferences such as LSs, KLs, goals, background, learner ratings etc. and the information about the learning activity. A learner profile has two components- learner preferences (learner's learning styles, learner's knowledge levels, learner's ratings and learner's learning goals) and learning activity information. As described earlier, learners are characterized into two categories namely, active learners and alumni learners. We generate each learner profile of active learners by considering information about learner preferences only and also collect the information about each alumni by considering their learner preferences as well as their learning activities through registration process.

There are following ways of collecting such information (1) each learner (active or alumni) is asked to fill a pre enrollment questionnaire based on Index of Learning Styles (ILS) for extracting his/her learning styles and to provide his/her previous grades for analyzing his/her learning ability. (2) Each learner (active or alumni) provides his ratings on experienced learning resources and (3) For analyzing learning activity information and performance of each alumni learner after finishing the course, system conducts a post-test which is analogous to end term exam for that course and stores his overall grade as well as grades on various subjects of that course. Each learner provides his grades in the selective learning path in various subjects on a five point rating scale. Information about learning activity of each alumni comprises the learning path which is followed by each alumni and final grades on various subjects included in the selected learning path. These grades provide the information about alumni learner performance on the prescribed course. This is a key information for our proposed collaborative framework which must be stored in the form of node by node (here subject can be considered as node in the selected learning path) basis associated with grades. For example: Table 1 presents a learning path of an alumnus with his grades in various subjects.

This example illustrates the learning path associated with grades. In this example, the selected learning path of a learner is P → Q → R → S → T.

Table 1 Learner performances in various subjects of selected learning path

Subjects (Nodes)	Grades (Out of 5)
P	3
Q	2
R	5
S	1
T	4

3.2 Learning path recommendation framework

In this section, we describe how we recommend an appropriate learning path for an individual learner by using variable length genetic algorithm. The entire mechanism for recommending learning path of an individual can be summarized as follows-

(a) ***When a new course is launched***

When a new course is introduced into the system i.e. when a new course is launched (cold start problem in recommender system), our proposed system can only recommend a predefined learning path sequence to an active learner based on course generator's advice/ built in prescriptive rules. However, it is not mandatory for the learner to follow the provided recommendations. After completing the course, learner's learning paths and performances in that course are stored and analyzed. After sometime, more and more learners enter into the system for completing this course and would have graduated from this course. Our proposed framework comes into the picture based on the number of alumni who have previously completed this course.

(b) ***When sufficient number of alumni is available***

Now our proposed system selects a set of similar alumni after computing similarity between the active or active learner and alumni. These learners (active as well as alumni) are characterized by their different learning styles, knowledge levels and experienced resources. As discussed earlier, in our system, learner profile consists of learner's ratings on experienced resources, his learning styles generated through index of learning style questionnaire (ILS) (Felder and Silverman 1988) and his grade scores on various subjects of that course in a 5-point grading scale(Dwivedi and Bharadwaj 2012, 2015). Firstly, we compute the knowledge level of a learner based on the grade scores of various subjects. For the illustration, we can use Table 1 for computing the knowledge level of a learner representing the grade scores of a learner on various subjects. Knowledge level of that learner is (3 + 2 + 5 + 4 + 1)/5*5 = .6. Where first '5' in denominators represent the number of subjects and second '5' in denominator represents the highest grade score on the grading scale. In our system, similarity has three major components, learning style based similarity (*Sim_LS*), knowledge levels based similarity (*Sim_KL*) and ratings based similarity (*Sim_RAT*) which are described as follows-

$$Sim\_LS(l_1,l_2) = \left(1 - {\sum_{i=1}^{4}|l_{1,i}-l_{2,i}|}/_{4*(max-min)}\right) \tag{1}$$

where $l_{1,i}$, $l_{2,i}$ are the scores of i^{th} dimension of learners l_1 *and* l_2 respectively and max and min are referred to maximum and minimum score.

$$Sim\_KL(l_1,l_2) = (1-|KL_1-KL_2|) \tag{2}$$

where KL_1 *and* KL_2 are knowledge levels of l_1 *and* l_2 respectively.

$$Sim\_RAT(l_1,l_2) = \frac{\sum_{i\in S_{l_1,l_2}}\left(r_{l_1}-\overline{r}_{l_1}\right)\left(r_{l_2}-\overline{r}_{l_2}\right)}{\sqrt{\sum_{i\in S_{l_1,l_2}}\left(r_{l_1}-\overline{r}_{l_1}\right)^2\sum_{i\in S_{l_1,l_2}}\left(r_{l_2}-\overline{r}_{l_2}\right)^2}} \tag{3}$$

where, $r_{l_1,i}$ is the rating of active learner l_1 on resource i, $\overline{r}_{l_1}$ is the average rating of learner l_1, $\overline{r}_{l_2}$ is the average rating of a alumni l_2 and S_{l_1,l_2} is the set of common experienced resources.

Overall similarity between learners l_1 and l_2 is computed as

$$Sim(l_1,l_2) = \frac{Sim\_LS(l_1,l_2) + Sim\_KL(l_1,l_2) + \ Sim\_RAT(l_1,l_2)}{3} \tag{4}$$

After computing similarity between an active learner and all alumni, our system selects a set of N neighbor learners (similar alumni) based on either k-nearest neighbor approach or training threshold parameter.

(c) ***Learning path generation based on VLGA***

In this section, we will explain how we generate the personalized learning path for an online active learner *l* by utilizing variable length genetic algorithm (VLGA). The following main steps are used to construct an optimal learning path through VLGA.

Chromosome representation: We assign a serial number to each subject from 1 to n if there are a total number of n subjects in a curriculum course for constructing the learning path. Thus, the assigned serial number of each subject is combined directly with the serial number of appropriate successive subjects as strings to represent the possible generated learning path. Besides the definition of chromosome, we applied topological sort for the logical sequence of curriculum structure in that course because some subjects require a few number of prerequisites. For example, there are three subjects mainly, A, B and C subjects in a particular course and a relationship called, precedes. If A precedes B and B precedes C i.e. A is prerequisite for B and B is prerequisite for C then the final valid learning path for these subjects through topological sort will be ABC. Moreover if A is prerequisite for both B and C subjects then partial valid learning path will be either ABC or ACB through topological sort. Finally, the overall representation of chromosome of various subjects (whole individual) is depicted in Fig. 2.

Initial population generation: Usually, the size of initial population depends on the complexity of the solved problem. In our system, the size of the population is equal to the number of the selected similar alumni and initial population consists of various learning path sequences which were adapted by these similar alumni for a particular course.

Selecting fitness function: Designing an efficient fitness function in genetic algorithm is a major concern that is dependent on the problem. The performance of GA is based on the selected fitness function. Generally, fitness function is considered as a performance index that is applied to investigate the quality of the solution of the problem. In our system, the quality of individual solution (selected learning path sequences by alumni) and generated learning path can be dependent on the difficulty parameters of various subjects included in the learning path sequence after completing the course. The proposed fitness function is defined as follows:

$$f = \sum_{i=1}^{n} w * (1 - dp_i) \tag{5}$$

where f is the proposed fitness function for personalized learning path of length n, dp_i is the difficulty parameter of the i^{th} subject and w is the adjustable weight. The difficulty parameter dp_i of i^{th} subject can be computed as follows:

$$dp_i = \frac{\sum_{l \in L} gr_{l,i}}{N^* |L|} \tag{6}$$

where L is the set of those learners who have read the subject i, $gr_{l,i}$ is the grade score of learner l on the subject i and N is the normalizing constant. For example, if five users read a particular subject i and score 2,3,4,5 and 1 on a 5-point grading scale respectively, then difficulty parameter

$$dp_i = \frac{2+3+4+5+1}{5*5} = .6.$$

Variation operators: In the reproduction phase of GA, the chromosome with the higher fitness value will have a higher chance to generate new individuals for the next generation. For selecting individuals (chromosomes) for reproduction, we

Subject serial no 1	**Subject serial no 2**	**Subject serial no 3**	**Subject serial no 4**	**Subject serial no 5**	**….**	**Subject serial no *n***

Subject serial no 1	**Subject serial no 5**	**Subject serial no 6**	**Subject serial no n**

Subject serial no 3	**Subject serial no 4**	**Subject serial no 5**	**Subject serial no 8**	**Subject serial no *n***

Fig. 2 Variable length chromosomes representation

employed the stochastic universal sampling mechanism that is the extension of roulette wheel selection. After selecting individuals, there is a need of selection of appropriate variation operators such as crossover and mutation, for generating offspring for the next generation. In our framework, we have employed the following crossover and mutation operators where chromosome follows a permutation based representation scheme

Modified double point crossover Since sizes of parental chromosomes vary in VLGA, therefore there is a need of special attention when applying double point crossover. We employed double point crossover with providing mechanisms which are responsible to avoid illegality in children chromosomes. We consider two chromosomes of lengths len_1 and len_2 and select substring from that chromosome which is smaller by using two random crossover points. For example, we can choose a crossover point such as $c_i = (r_i \bmod len_i) > 0$, where r_i is random number. Example: Let the two parents are described as

2	**3**	**6**	**1**	**4**	**5**

1	**4**	**6**	**5**

Now we generate two random numbers for selecting the substring from second parent. Let these random numbers are 6 and 7, therefore, $c_1 = 2$, $c_2 = 3$

After applying double point crossover, we obtain the following children:

2	**4**	**6**	**1**	**4**	**5**

1	**3**	**6**	**5**

But these children are illegal because these do not follow the permutation representation. Hence we initiate a mapping mechanism procedure to avoid illegality. In this example, 2–1, 3–4, 6–6 and 1–5 are mappings between these parental chromosomes. Now the new children are

2	**4**	**6**	**1**	**3**	**5**

1	**3**	**6**	**5**

Mutation operator: There are many mutation operators available for permutation based representation, swap, inversion, insert and scramble, In our work, we suggest to employ the scramble mutation operator which is defined as

2	**3**	**6**	**1**	**4**	**5**

2	**1**	**3**	**4**	**6**	**5**

After getting children chromosomes, we use topological sort for the validity of these children. In this mechanism, we follow the topological sort procedure for curriculum sequencing suggested by Meinke and Bauer (1976); Szabo and Falkner (2014).

Termination criteria: The VLGA repeatedly runs the selection, recombination, mutation and replacement operations until it gets termination criteria. In our proposed framework, the termination criteria is set to be 100 generations because it can obtain optimal learning paths for personalized learning path generation.

4 Experiments and results

4.1 LPRS prototype development

Firstly, we have designed a web based learning portal for LPRS system using PHP for collecting the dataset and then we have developed LPRS system prototype. We have collected database of B. Tech. four years program from CSED department in MNNIT Allahabad. In this database, we have chosen currently two previous years' students as alumni learners and current students in final year as target learners for whom learning path recommendations will be generated. For extracting learning styles of these students, we have used the index of learning style (ILS) based on FSLSM model. We have implemented our proposed system for learning path recommendations in MATLAB. The whole architecture of LPRS system as shown in Fig. 3 is divided into

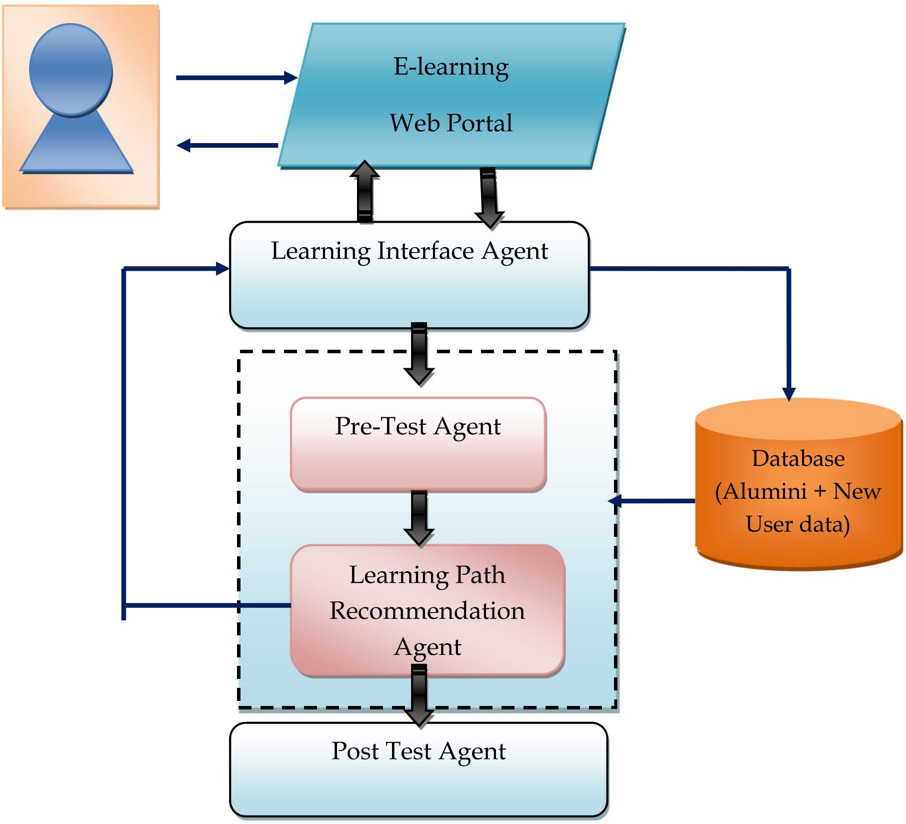

Fig. 3 Web based architecture of Learning Path recommendation agent

five parts namely, Interface agents, Database management agent, Pre-test agent, Path recommendation agents, Post test performance agent.

When learner interact and registered on the portal of the LPRS system, the system collects the registered information by using interface agent then information agent transmit this information to pre test agent, after analysing the information by pre-test agent the result is transmitted to learning path recommendation agent. This path agent is also connected to the database where alumnus data as well as new learner preferences are stored. By using similarity function, firstly path agent finds similar alumnus and then utilizing variable length genetic algorithm, it creates the learning path and display the learning path or next node to the new target learner on learning portal.

Suppose new learner entered to system and he / she wants to learn java course. Firstly, he/ she fill all information. Then, Pre-test agent organizes the test for that new learner and checks the ability. The result of Pre test is on grading scale is 3.5. The regular path for java course is 1☛2 ☛3 ☛4☛5☛ 6 ☛7☛ 8 ☛9. Using the similarity Eqs. (4), filter the similar alumini from database. After using Eqs. (5) and (6), recommended the path for new learner is 2☛4☛5☛6☛7☛9. Further using the post test agent, compute the performance of new learner in java course are 8.4 out of 9 grade scales. Post test performance validates that proposed framework is quite feasible for enhancing the learning of e-learners.

Performance evaluation The criterion for performance evaluation is based on pre test knowledge of learner to post knowledge of learners. We have compared our proposed algorithm LP-VLGA based on learning style and knowledge level with LP-VLGA and self learning.

Experiment 1 For analysing the performance of system, we have conducted experiments under configuration of collected dataset. Current year students are used as target learners and 200 alumni are used as training learners. For performance evaluation under schemes LP-VLGA based on learning styles and knowledge and LP-VLGA without learner preferences and LP-self selection, we have randomly divided the 150 number of target learners set in three target learners sets namely TL-set 1, TL-set 2 and TLset-3 where, each set consist of fifty learners. So TL-set1 is used for LP-VLGA based on learning styles and knowledge level, TL-Set2 is used for LP-VLGA without learning styles and knowledge level and TLset-3 is used for LP based on self selection. In the TL-set1 and TL-set2, alumni database is used for similarity computation and path recommendation (Table 2).

Table 2 Comparison of learner's performance based on pre test and post test under various learning path techniques

	TLset1 used by LP-VLGA based on LSs and KLs		TLset2 used by LP-VLGA		TLset −3 used by LP-Selfselection	
	Pre-test	Post test	Pre test	Post test	Pre-test	Post test
Sample	30%	85%	30%	70%	30%	55%

The performance of each learner based on pre-test and post test utilizing LP-VLGA based on learning styles and knowledge levels, LP-VLGA and LP with self selection is shown in following Fig. 4.

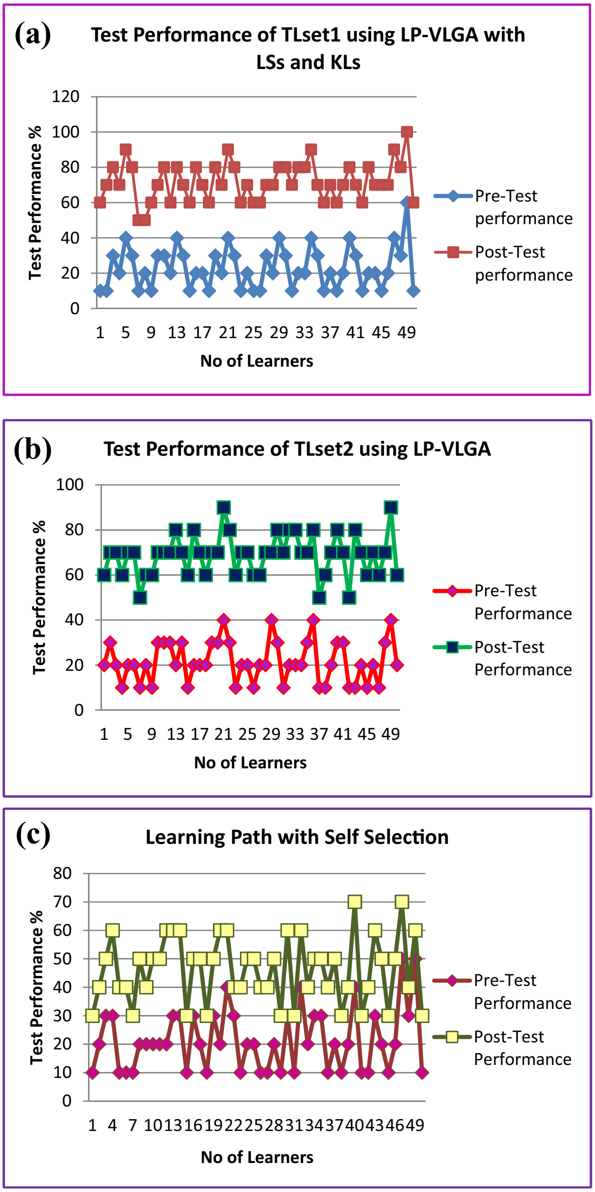

Fig. 4 Comparison of post-test performance with Pre-test performance using (**a**) LP-VLGA with LS-KL (**b**) LP-VLGA without LS-KL (**c**) LP-self selection

5 Conclusion and future work

For enhancing the performances of learners in e-learning environments, it is quite practical to provide learning materials for learners in a sequential form based on their requirements and preferences. Many researchers have shown their interests to develop various e-learning systems which are responsible for providing learning materials through the construction of optimal learning paths for handling curriculum sequencing problem. With the emergence of learning path requirement in e-learning domain, we have designed a learning path recommender system by employing variable length genetic algorithm (VLGA) which recommends optimal learning paths for learners by considering learners' requirements and preferences. In this framework, VLGA is used for searching distinct optimal learning paths varying in their sizes according to various learners. The use of VLGA in our framework is quite feasible because we cannot provide learning paths of fixed lengths to learners characterized by their learning styles and knowledge levels.

Our proposed system is based on collaborative filtering methods. Therefore, one of the promising direction for extending the capabilities of our proposed collaborative framework would be to incorporate trust\distrust (Kant and Bharadwaj 2013) and reputation values (Bharadwaj and Al-Shamri 2009) into our proposed system for the reliability of suggested learning paths for individuals.

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