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# Collaborative optimization algorithm for learning path construction in E-learning ☆

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ABSTRACT

In e-learning, learning object sequencing is a challenging task. It is difficult to sequence learning objects manually due to their abundant availability and the numerous combinations possible. An adaptive e-learning system that offers a personalized learning path would enhance the academic performance of learners. The main challenge in providing a personalized learning path is finding the right match between individual characteristics and learning content sequences. This paper presents a collaborative optimization algorithm, combining ant colony optimization and a genetic algorithm to provide learners with a personalized learning path. The proposed algorithm utilizes the stochastic nature of ant colony optimization and exploration characteristics of the genetic algorithm to build an optimal solution. Performance of the proposed algorithm has been assessed by conducting qualitative and quantitative experiments. This study establishes that the hybrid approach provides a better solution than the traditional approach.



## 1. Introduction

E-learning is "learning via computing devices and the internet" [1]. It enables learners to study in their own time, at their own pace and in their preferred space. However, e-learning environments have a significant drawback – that of limited personal support from instructors, meaning that students have to rely on self-support and self-guided learning. Personalization is, therefore, one of the desired requirements of e-learning. New learning materials are regularly made available, which can be overwhelming and lead to information overload and disorientation [2]. An efficient e-learning system should be capable of guiding learners in a tutor-less environment, directing the relevant information to them. This can be achieved by offering personalized learning, which satisfies individual needs, preferences and capabilities, such as knowledge or learning styles.

In an e-learning context, personalized systems support two types of adaptation: adaptive presentation and adaptive navigation support [3]. In adaptive presentation, different content is presented to different learners. This content is customized according to learners' interests or preferences, rather than presenting the same information to everyone. For example, additional supporting information will be presented to beginners, whereas detailed and more in-depth information will be

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presented to advanced learners. Difficulty, media and content levels can also be varied for every learner. Adaptive navigation support provides adaptive links, guiding different users to different information that is relevant to them.

Adaptive presentation and navigation support may increase the motivation, sustain the interest and may show better comprehension. But, it is not sufficient to support learners to attain the learning outcomes or goals. More to it, every time a learner revisits a certain page, the presentation and navigation support may be different which may confuse him. Secondly, the prerequisite relationships cannot be taken into account in these adaptive techniques. It is crucial to provide adaptation in learning path composed of appropriate learning objects (LO).

A learning path is the organization and structure of learning objects in a particular way ensuring the association between learning objectives and contents. It determines how learning happens, guiding learners about what content they should learn at a specific time and how they should learn. It defines the way a course progresses. Thus, it has a major part to improve learner's efficiency. As e-learning systems are characterized by limited support from tutors, a personalized learning path would help learners to improve their performance. Also, it provides guiding steps for learners to construct the knowledge, and skills, and to achieve their goal.

The selection of appropriate learning objects and sequence them in the right order is a complex and challenging task. A learning path construction problem can be defined as selecting appropriate learning contents and sequencing them in a way in order to help learners to acquire knowledge and skill [4]. As there are several hundreds of resources (say, 'n' number of resources), there is a possibility of 'n' sequences. It can be deemed as NP-hard problem. The complexity increases when learner characteristics and prerequisites are considered. To provide a personalized learning path, a collaborative approach is proposed through hybridizing ant colony optimization (ACO) with genetic algorithm (GA).

The combination of ACO and GA has been applied to solve a few sequential problems, but has not been utilized either for learning path problem or in e-learning domain. This study makes three critical contributions:

- It presents a hybrid ACO-GA approach to generate a personalized learning path.
- The way ACO is integrated with GA. In literature, researchers have used ACO and GA as two independent modules. In our study, ACO and GA are combined in a collaborative manner.
- This approach takes into account the dynamic nature of the learner for constructing learning path.

The rest of the paper is organized as follows. Section 2 reviews the related work in learning path construction using evolutionary approaches. Section 3 describes the problem formulation and scheme of representation. Section 4 details the construction of optimal learning path using proposed collaborative algorithm. Section 5 discusses the experimental results and conclusions are presented in Section 6

## 2. Related work

In the last few years, several approaches including rule based, soft computing, have been proposed to provide customized learning path. According to [5], evolutionary computing (EC) approaches are best suited to provide solution to learning path problem. EC approaches have also been applied for many real time tasks including signal processing [6], adaptive cognitive radio [7].

### *2.1. Learning path based on ACO*

Ant colony optimization method was developed to find the shortest route between source and destination. Sement et al. [8] applied a modified ACO to find the optimal learning path. The course units were divided into sub-units and each sub-unit represented a node. Arcs signified the connection between two nodes and associated weights reflected the goodness of the path. The value of the weight depended on three parameters: pedagogical weight, visits made to that arc and success/failure. The drawback of this approach is that the arc joining nodes with difficulty level were never visited. To overcome this issue, Valigiani et al. [9] and Gutieŕrez et al. [10] modified the objective and fitness function which did not produce promising results. Style-based Ant Colony System (SACS) [11] was proposed to find the optimal path based on learning. Attribute-based Ant Colony System (AACS) [12] aids in finding the best match between learning content attributes (content level and content type) and learner's attributes (learning style and prior knowledge level). The Dynamic Learning Path Advisor [13] combined ACO technique and perspective rules to recommend learning path, thus preventing the cold-start problem. Kurilovas et al. [14] delivered dynamic learning path using ACO based on learning style. Kardan et al. [15] proposed a two-stage process called ACO-MAP to generate adaptive learning sequence using Ausubel Meaningful Learning Theory.

### *2.2. Learning path based on GA*

Seki et al. [16] constructed a learning scenario by sequencing the learning objects based on their attributes, considering it as a multi-objective function. Hovakimyan et al. [17] used GA to construct teaching scenarios from teaching materials having different qualitative and quantitative characteristics. Samia and Mostafa [18] proposed a genetic algorithm based e-learning system to generate learning path matching student profile and educational goal. Huang et al. [19] combined GA and case based reasoning (CBR) approach to construct an optimal learning path for each individual. A learning path recommendation system (LPRS) was proposed to recommend suitable paths based on learning styles and knowledge levels using variable length genetic algorithm [20].

Apart from the evolutionary based approaches, various other approaches like Collaborative Filtering, Decision Tree, Bayesian Network, Neural Network, Petri-nets, Case Based Reasoning, Ontology, Immune Algorithm, Knowledge Map have also been employed. They failed to generate the customized and more precise learning path to maximize the learning performance. The other drawbacks include the following.

- Learning paths are generated according to domain dependent traits of the learner and are based on the preference, interest, learning style or background knowledge of the learners.
- The relationship among the learning objects is not considered in many approaches.
- The cognitive aspect of learner and its implications on learning are not adequately factored.
- The adaptive nature of learner is not considered. The learning path is generated at the initial stage of the course, failing to address the dynamic nature of the learner.
- Emotional illiteracy is evident in these studies.

## 3. Problem definition

Learning path construction is deemed as NP-hard due to availability of abundant LO and possibility of several ways of combining them. The problem of learning path is to construct a sequence of LO suitable to the individual learner, depending on his/her emotional state and cognitive ability. For each learner, emotional state and cognitive ability were obtained from electroencephalogram [21]. Each learner studied the LO and took the assessment as given in the sequence. The marks obtained in assessments were the indicator of the performance. The objective was to find a suitable learning path that maximizes the performance of the learner and effectiveness of learning.

### *3.1. Parameters of learner model*

In the personalized approach, learner attributes determine the LO and thus the learning path. The emotion and cognitive capability were considered as parameters for personalization. The frequently occurring e-learning emotions that considered in this study were fear, frustration, confusion, anxiety, anger, boredom, curious, and eureka. Working memory capacity (WMC) and cognitive load underpin cognitive ability.

Learners were represented as L; $L$= {$L_1$, $L_2$, $L_3$ … $L_n$} and the following attributes were considered for each learner. The learner model constituted of 4 tuples. $L$={LOB, E, C, P}, where LOB represents Learning Objectives, E represents Emotion that a learner undergoes while learning, C represents the Cognitive ability of the learner and P represents Performance of the learner. Each tuple is explained below.

- Learning Objectives (LOB) = {LOB1, LOB2, LOB3,… LOBN}.
- Emotional State (E) = {E1, E2, E3 …. EN}. E takes the value {Anger, Anxiety, Boredom, Confusion, Curious, Eureka, Fear, and Frustration}.
- Cognitive Ability (C) = {C1, C2, C3….CN}.
- Performance (P) = {P1, P2, P3….PN} and would take values between 0 and 100.

### *3.2. Parameters of domain model*

Learning objects were considered as reusable learning content and their attributes were given by the author of LO. The learning object is represented as LO. LO= {$LO_1$, $LO_2$, $LO_3$…$LO_N$}. Generally, LOs and their relationship are represented as a precedence graph in Fig. 1.

Domain Model has 3 tuples; LO= {$D_i$, $T_i$, $PR_i$} and are defined as follows.

- Difficulty level of content (D) = {D 1, D 2, D 3…. D N}. It takes the value as {0, 1, 2, 3, 4}, 0 being easy level and 4 being the most difficult level.
- Time (T) = {Ti} where Ti is the time needed to complete the LO.
- Prerequisite (PR) = {PR 1, PR 2, PR 3…. PR N}. It indicates the prior learning materials needed to complete before taking up the current LO.

### *3.3. Problem formulation*

This problem is formulated as weight directed graph, the basic components of which are (i) Weighted graph - Comprising nodes and edges; (ii) Edges between nodes; (iii) Weights on edges and (iv) Ants, the search automata.

Learning path construction is represented as graph $G$ = (C, E), where C represents nodes, which is a set of LO and E represents edge, a link connecting the LOs. Each edge is associated with a value $S_{ij}$ between node i and node j. It is computed based on the performance in terms of the score of learners who visited the edge. The path selection from the graph method shows promising result, when applied to network analysis problem [22].

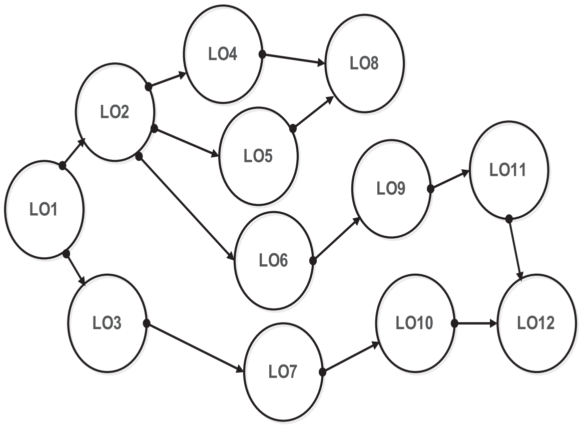


**Fig. 1.** Precedence graph.

## 4. Methodology for learning path construction

A learning path is the art of arranging learning content, exercises, and activities to achieve the learning objectives. As each learner have different characteristics, different paths are required according to his/her profile. The framework for learning path construction is given in Fig. 2. Learners who have similar characteristics (emotion and cognitive ability) were grouped using genetic K-means algorithm (GA K-means).

### *4.1. Genetic K-means clustering algorithm*

The genetic K-means algorithm is a technique designed to overcome the disadvantages of popular k-means algorithm. Firstly, the selection of initial points or centers should not affect the quality of formed cluster. Secondly, as clustering is done in real time when learners are learning, the algorithm should not be computationally expensive. To satisfy these conditions, GA K-means was chosen for clustering similar learners (alumnus) and is discussed below.

**Representation of chromosome:** Individual representation or encoding transforms possible solution from solution space to search space, which can be handled by GA. One individual or chromosome represents one possible solution to the problem. Chromosomes are represented in binary format. Each chromosome contains eight genes representing the learner characteristics as shown in Fig. 3.

**Initialization of population:** An important step is to decide the number of chromosomes in a population, known as population size, which depends on the nature, type and complexity of the problem to be solved. If the size is small, it leads to fast convergence but may not essentially result in a good solution. On the other hand, fixing a large size leads to slow

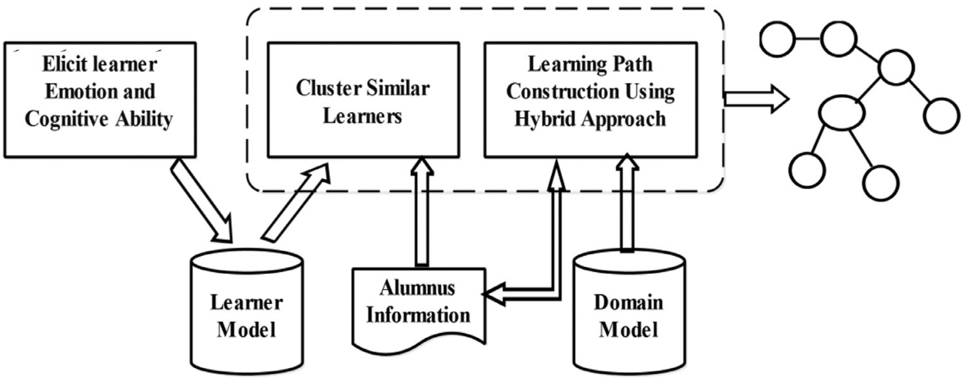


**Fig. 2.** Block diagram for learning path construction.

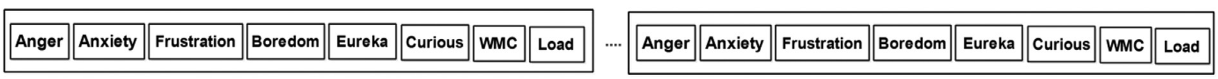


**Fig. 3.** Representation of chromosome.

convergence but would have a greater likelihood of yielding an optimal solution. To strike a balance between computational complexity and quality solution, a population size of 200 chromosomes was chosen.

**Fitness function calculation**: The fitness function evaluates how good each chromosome expresses the goal. The fitness of the chromosome was calculated using Eq. (1).

$$F = \sum_{i=1}^{k} \sum_{p \in c_i}^{k} |p - m_i|^2 \tag{1}$$

**Crossover:** Crossover operation is to produce the best off-springs. It combines two parental chromosomes to produce either one or two off-springs. The selection of the parental chromosomes, the parts of the parental chromosomes for reproduction and the way they are combined were determined randomly. The idea behind this operator is that if two parents having different desirable traits are combined, it would produce off-springs containing desirable characters of both parents. Two-point crossover was chosen, in the current study.

**Mutation:** It is another significant unary operator of genetic algorithm. This operator ensures genetic diversity in the population and is performed with the probability of $P_c$ in order to prevent trapping into local maxima. It inserts a new LO in the learning path.

### *4.2. Hybrid approach*

In this study, ACO algorithm and genetic algorithm were combined to solve the learning object sequencing problem. ACO is an iterative algorithm where the optimal solution is reached through pheromone update and evaporation process. The process may get trapped into local optimum and may not reach the global optimum. GA is a computational and iterative algorithm, where a new population of chromosomes is produced by genetic operators and evaluated for fitness. The quality of the solution depends on the parameters and initial population.

The hybrid of GA and ACO will not only bring the advantages of both approaches, but also complement each other in sequencing the learning objects. The ant colony optimization algorithm provides the optimal learning path followed by similar alumni. The genetic algorithm selects the best-suited path according to individual traits from the paths generated by ACO. The key idea behind combining ACO and GA together is to utilize the synergy of GA and ACO to seek the best path among the paths followed by alumni. GA and ACO were combined to enhance the local search ability and to decrease the computational effort. Thus, ACO was utilized for constructive process and GA for improvement process.

The role of GA is to produce quality chromosomes and to improve the quality of population. The good quality population in turn updates the pheromone of the ACO. Here, GA support ACO by strengthening search possibilities for ants and ACO supports GAs by improving potential solutions into its mating pool. This collaborative way of combining the operations of ACO and GA will increase the probability of unearthing the best possible solution. The proposed collaborative ACO-GA algorithm for sequencing learning object is shown in Fig. 4.

The hybrid ACO-GA algorithm utilizes solution construction, pheromone update, population generation, fitness evaluation, genetic operations in a collaborative manner. The hybrid algorithm invokes both ACO and GA to construct solution and population respectively. ACO algorithm generates ant-like agents corresponding to individually selected alumni to traverse the course graph network. Each alumnus (ant) constructs a solution and terminates on satisfying the stopping criterion. The K% of the best solutions generated by alumni is fed to the mating pool along with the selected population generated by GA. The genetic operators are applied to generate a new population. After the termination criterion is met, M% of the best population is used to update global pheromone value and L% of the worst population is used for pheromone evaporation. The entire collaborative process is repeated until it reaches the specified number of iterations. Each procedure and the flow of the algorithm are discussed below.

#### *4.2.1. Step 1: ACO and GA – initialization*

The value for pheromone trail ($\alpha$), heuristic information($\beta$), pheromone evaporation constant ($\gamma$), number of ants (alumni) (n) for ACO was predetermined before running the algorithm. The number of iterations, population size, crossover probability, mutation probability was initialized. The value for K, M, L were also initialized. L represents a certain percentage of the best solution from ACO. M and K represent the certain percentage of best and worst population of GA respectively.

#### *4.2.2. Step 2: ACO – Generate solution*

ACO generates ant-like agents corresponding to individually selected alumni to traverse the course graph network and constructs a solution. Then each alumnus will share the solution by updating the value of pheromone. The strength of the pheromone indicates the suitability of LO.

**Pheromone computation:** When a learner completed a concept by studying an associated set of learning objects, he undertakes an assessment. There may be an overall assessment at the end of the course (at end node), which is also utilized to calculate the pheromone value along the edges. Thus, the pheromone value is computed based on the performance of the alumni. Results of the formative assessments such as quiz, MCQ (Multiple Choice Questions) were taken at certain individual nodes that have been visited by alumni, while the results of the summative assessment were taken at the end of the course.

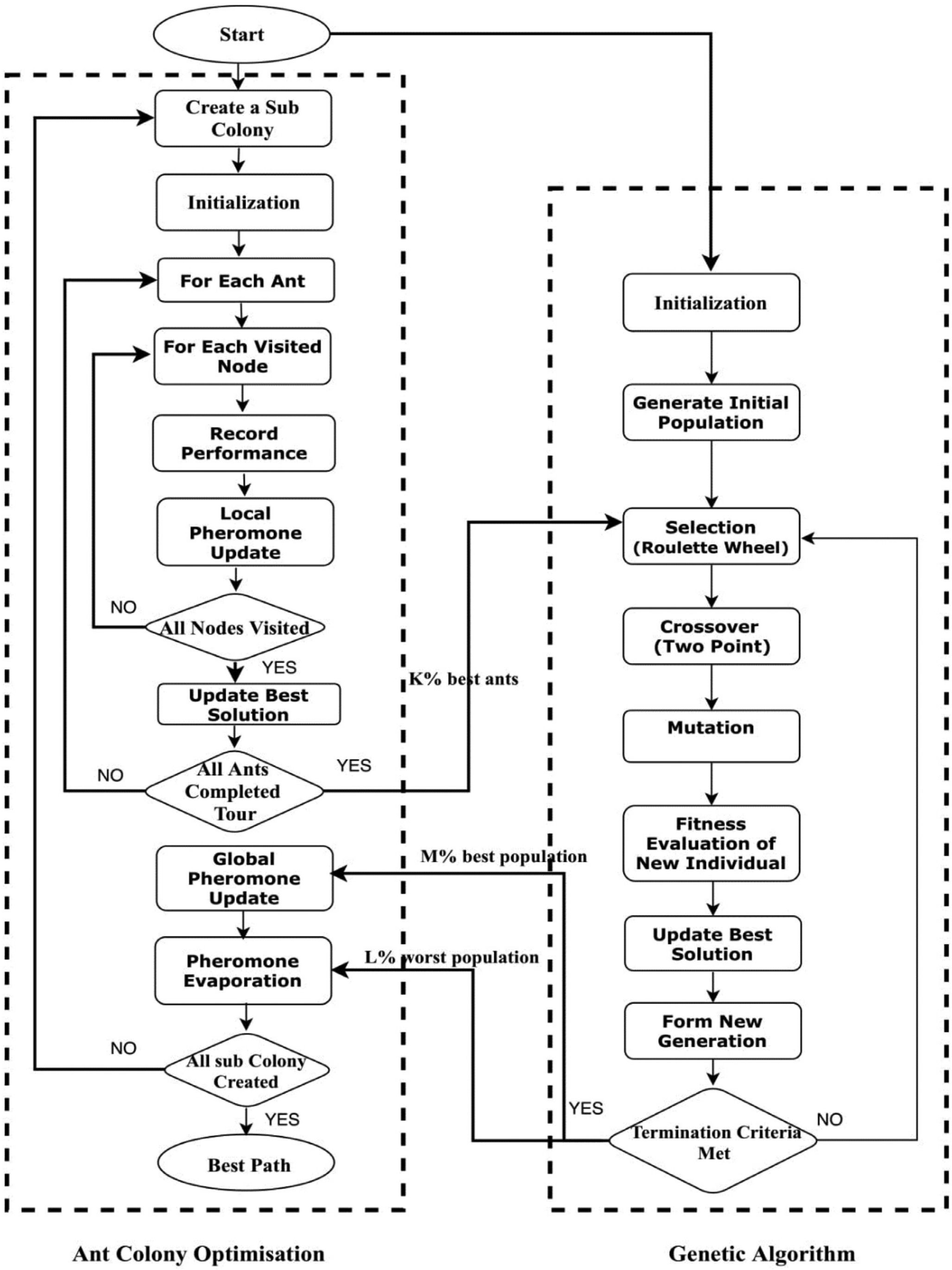


**Fig. 4.** Hybrid ACO-GA architecture.

**Selection of next suitable material:** When a learner completes a specific node (LO), the next node to visit will be chosen from all possible nodes based on pheromone values. If the value of pheromone is high on the edge associated between the nodes, there is a higher chance that the node will be chosen as the next node.

The parameters considered for the selection of the next node are (i) Pheromone value; (ii) Heuristic information and (iii) Information about visited nodes to avoid loop from memory.

*Pheromone value:* It is a dynamic attribute and varies with time. All the outgoing edges from the node were sorted based on the pheromone value. One edge was chosen among all possible arcs based on Roulette Wheel selection method, which employs probability selection to choose the best possible next node. Each candidate was given a slice in the wheel based on the fitness value. Next node was selected by spinning the wheel ‘n’ times. Higher the fitness of the individual, higher was the selection, as it occupies a large proportion in the wheel. In roulette wheel, the probability of selecting a subsequent node is proportional to its fitness value and is given by Eq. (2).

$$\tau_{ij(t)} = \frac{f(a_i)}{\sum_{j\neq i} f(a_j)} \tag{2}$$

*Heuristic information*: The heuristic information, which is determined locally and varies with the nature of the problem, is crucial to improve the performance of ACO. It guides artificial ants towards the most promising solutions. It is a static parameter and is represented as a conscious constant indicating the heuristic preference while moving from one node to the next one. Heuristic information $\eta_{\mathrm{ij}}$ is inversely proportional to the time taken to study, as given in Eq. (3).

$$\eta_{\mathrm{ij}} = \frac{1}{1 + \frac{1}{\lambda s}\ln\left(1 + \lambda t_{ij}\right)} \tag{3}$$

where $t_{\mathrm{ij}}$ represents the time taken to study $i$th material, $\lambda$ is a constant and S is the relative power of memory. $\eta_{\mathrm{ij}}$ represents the ability of the learner to recall the concept i when moving to concept j.

*Information to avoid loop*: The artificial ant’s memory stores the list of visited nodes so far. This information is used to avoid loop and build a good feasible solution. The probability of choosing the next node was determined using Eq. (4).

$$P_{ij}^{m} = \begin{cases} \dfrac{\left[(\tau_{ij})^{\alpha}\right]\left[(\eta_{ij}{}^{\beta})\right]}{\sum_{l\in c_i^k}\left[(\tau_{il})^{\alpha}\right]\left[(\eta_{il}{}^{\beta})\right]} & if\ j \in C_m \\ 0 \quad otherwise \end{cases} \tag{4}$$

Where $\alpha$, $\beta$ are parameters. If $\alpha$ is set to zero, it works as a stochastic greedy algorithm. If $\beta = 0$, it causes stagnation; all ants follow the same path.

*4.2.3. Step 3: ACO- local pheromone update*

The value of pheromone is updated based on two main parameters namely score obtained by the learner and time taken to complete the concept. The trail is updated as given in Eq. (5)

$$\tau_{ij}(t) = \tau_{ij}(t-1) + \sum_{k=1}^{m} \nabla\tau_{ij}^{k}(t)\ \forall (i,j) \in C \tag{5}$$

and $\nabla\tau_{ij}^{k}(t)$ is computed as

$$\nabla\tau_{ij}^{k}(t) = \left(\eta\mathrm{ij} + \left(\frac{Score_{ij}^{k}}{Max_{Score}} . \frac{1}{time_{ij}^{k}}\right)\right)$$

### *4.3. Step 4: Genetic algorithm operations*

The K% of solution generated by ACO is inserted into mating pool along with population generated by GA. The genetic algorithm is outlined below:

Step 1: Initialisation of parameters.
Step 2: Generate population randomly.
Step 3: Evaluate the fitness of each population.
Step 4: Include a certain percentage of the solution obtained from ACO.
Repeat till termination condition is satisfied.
Step 5: Select a pair of chromosome based on their fitness to undergo a genetic operation.
Step 6: Perform two-point cross over.
Step 7: Perform mutation.
Step 8: Evaluate the fitness of the newly generated off-spring.
Step 9: Form a new generation.
End repeat
Step 10: Extract M% of best chromosome and L% of worst chromosome for pheromone update.

*4.3.1. Fitness function*

The quality of the learning path is determined by the fitness function and hence it is crucial to design one that accurately symbolizes the goodness of the solution. For learning object sequence, it is important to consider the difficulty level and the time spent on each LO. The fitness function is given as

$$F = \sum_{i=1}^{n}\left(\frac{TimeSpent}{TimeRequired}\right) * (difficulty\ level\ of\ LO) \tag{6}$$

where n is the number of LO. The difficulty level and time required for a LO is obtained from the metadata of LO.

#### 4.3.2. Selection

Selection is an important driving force in genetic algorithm to narrow down the searching space. A Roulette wheel is the simplest and commonly used selection mechanism. The goal of the roulette wheel was to stochastically select an individual with the largest fitness to form the next generation. The roulette wheel method replicates a roulette formed by chromosomes, in which slice for each chromosome is apportioned to its fitness value. Then, the roulette is spun randomly. Considering a number of chromosomes C, the probability for chromosome $C_i$ ($i = 1 \ldots N$) of being chosen ($P_i$) is given by,

$$\mathrm{P(choice = i)} = \frac{fitness(i)}{\sum_{j=0}^{n} fitness(j)} \tag{7}$$

The process was repeated until the desired number of individuals, called mating population, was obtained.

#### 4.3.3. Cross over

Crossover is one of the primary operators to determine the performance of the algorithm. Selection process picks up the good parents. The crossover operation combines parents to produce the best possible off-spring. Off-spring generated through this process will not be similar to any of the parents. Two-point crossover was chosen based on the success of implementing it in the task precedence problem [23–25]. The crossover between parents was carried out with probability Pc. If Pc is 0, off-spring is as same as the parent. Normally Pc is set at a value ranging between 0.5 and 1.0 and in this case, Pc was set at 0.9.

#### 4.3.4. Mutation

In the crossover, if both parents have good allele, offspring is guaranteed to be the best. But if the parents are not good, offspring inherits the same traits from the parents. They will be similar to one of the parents. To overcome this, the mutation process induces diversity in the population with a probability $P_m$. It is set between 0.005−0.05 and in this study, $P_m$ was set as 0.005.

#### 4.3.5. New generation

The elitism mechanism is used to determine the population in the new generation by evaluating the fitness values of the parents, offspring who underwent crossover and mutation and the individuals from ACO.

### 4.4. Step 5: Global pheromone update

Once the GA algorithm is completed, the pheromone trail is updated. It is performed in two steps viz., (i) pheromone evaporation and (ii) Global pheromone update.

*Pheromone Evaporation:* The values of pheromone on the visited nodes were decreased by a constant factor. After each alumnus moved to next node, pheromone trail $\tau$ was decreased by an evaporation factor $\rho$ in the interval [0,1]. It was decreased as given in Eq. (8).

$$\tau_{\mathrm{ij}} \leftarrow (1 - \mathrm{p})\tau_{\mathrm{ij}} \tag{8}$$

The reason for incorporating this factor was to delay faster convergence of all ants towards a suboptimal path; avoid an unlimited accumulation of trails over some component and forget the bad decision taken previously.

*Global pheromone update:* The overall pheromone update effect of all ants in each path (i, j) is given in Eqs. (9) and (10):

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + \nabla\tau_{ij}^{k}(t) \tag{9}$$

$$\tau_{ij}(t) = \sum_{k=1}^{m} \nabla\tau_{ij}^{k}(t) \quad \forall (i, j) \in C \tag{10}$$

where $\tau_{ij}(t)$ and $\tau_{ij}(t+1)$ are the pheromone value on the edge (ij) at time t and $(t+1)$ respectively. $\nabla\tau_{ij}^{k}(t)$ represents the increment in pheromone value.

## 5. Experimental design – performance comparison

The effectiveness of the proposed algorithm was assessed and evaluated in two stages. Firstly, the importance of system constructed learning path against the traditional one was evaluated. Secondly, the performance of the students using the proposed approach was compared against the performance of the students using the traditional approach of learning.

**Table 1**
Parameter setting in ACO and GA.

| ACO parameters | Value | GA parameters | Value |
|---|---|---|---|
| Number of ants (Alumni) | 200 | Population | 200 |
| Pheromone trail evaporation ($\rho$) | 0.3 | Number of generations | 50 |
| Pheromone parameter ($\alpha$) | 1 | Crossover probability(Pc) | 0.9 |
| Heuristics parameter ($\beta$) | 3 | Mutation probability (Pm) | 0.05 |
| Iterations | 1000 | Elite | 30% |

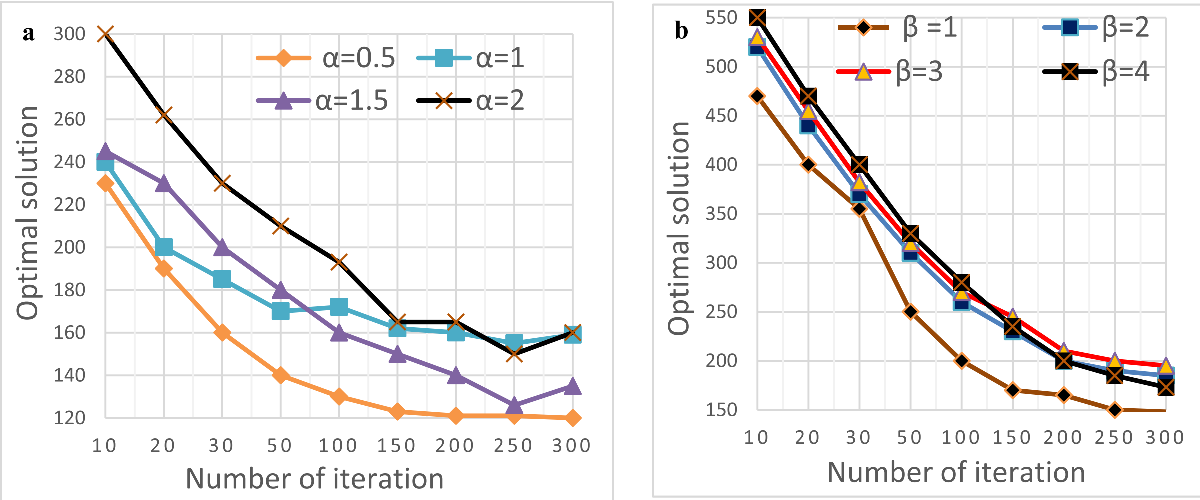


**Fig. 5.** (a). Optimal solution VS number of iterations values of $\alpha$. (b). Optimal solution VS number of iterations values of $\beta$.

### 5.1. Parameter setting

Experiments were conducted to determine the value of pheromone trail ($\alpha$), heuristic information ($\beta$), pheromone evaporation constant ($\rho$) number of ants (alumni) (n), population size, number of generations crossover probability ($P_c$), mutation probability ($P_m$) and to examine their impact on the behavior of proposed algorithm. In order to pick optimal values, proposed algorithm was implemented in MATLAB. The behavior of alumni (ants) was simulated. The data needed to conduct the experiment such as emotion, WMC level, load, time spent on learning materials, score obtained on assessment were manually generated for each alumnus. An experiment was conducted to obtain the optimal value for the parameters in ACO-GA and is shown in Table 1.

#### 5.1.1. Determination of $\alpha$ and $\beta$ parameters

In order to determine the value of $\alpha$, $\beta$ and $\rho$ parameters were maintained constant at 1 and 0.5, respectively. The value of $\alpha$ was varied from 0.5 to 2, and up to 300 iterations were performed. The plot of optimal solution versus time (in sec) for different values of $\alpha$ ($\alpha$ =0.5,1.0,1.5,2.0) is shown in Fig. 5a. The quality of an optimal solution was used as a measure to determine alpha value. The experiment was repeated to determine $\beta$ parameter, but keeping the parameters $\alpha$ and $\rho$ at a constant value of 1 and 0.5 respectively. The value of $\beta$ was varied from 1 to 4 and up to 300 iterations were performed. The quality of an optimal solution used as a measure to determine $\beta$ value is shown in Fig. 5b. If higher value is set to parameters $\alpha$ and $\beta$, it leads to faster convergence and aid in finding the solution quickly. It is ascertained from the experiments that suitable range of values of $\alpha$ and $\beta$ are

$$\alpha \in \langle 1;\ 2 \rangle \text{ and } \beta \in \langle 2;\ 3 \rangle.$$

#### 5.1.3. Determination of evaporation parameter

The optimal number of ants was determined through trials. The number of ants was set at 1, 25, 100, 200, 500 and iteration was set at 300. It is understood that quality of solution increases with number of ants and also the execution time increases with increase in ant counts. With smaller number of ants, it is not possible to find the optimal solution. When the ant size is increased, the convergence towards the solution is better. Based on this, an ant size of 200 was chosen.

The experiment was conducted to measure the convergence time of the algorithm for different evaporation factor ($\rho$). The parameter $\rho$ was set to different values of 0.1, 0.3, 0.6, 0.75, 1.0. When it was set at 0.1, it converges quickly. When decay constant was set at 1.0, it takes a long time to converge towards a solution. When this constant is set at a lower

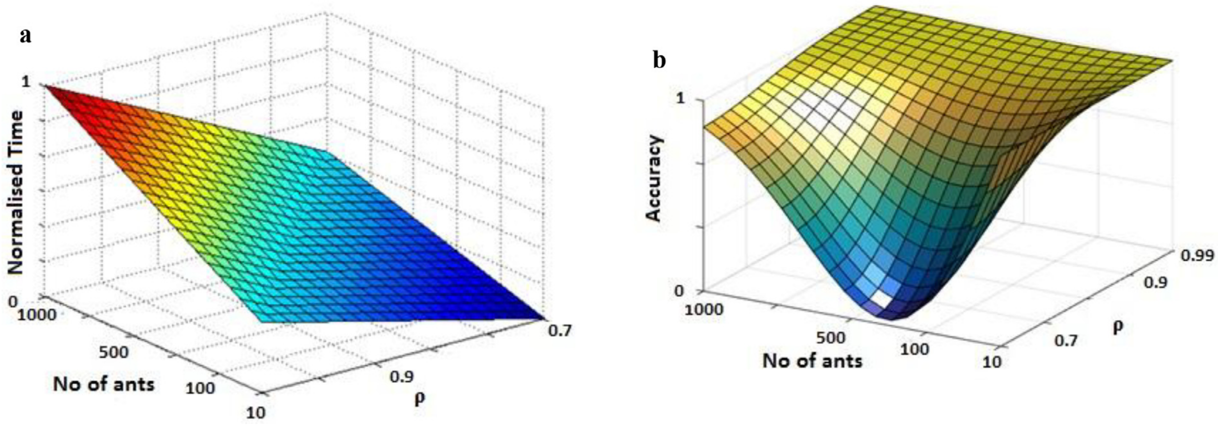


**Fig. 6.** (a). Influence of ant size and evaporation parameter on time. (b). Influence of ant size and evaporation parameter on accuracy.

value, it means less evaporation and hence the intensity of the pheromone degrades slowly. Naturally, high value for this factor implies that the impact of the previous followed path will be diminished quickly. The new path will have a huge impact on the solution. From the result, it is observed that the higher value of evaporation gives a better solution at the cost of the convergence rate and best range of values for $\rho \in \langle 0.2;\ 0.6 \rangle$. Setting the right value guarantees the balance between exploration and exploitation and the optimal value for the parameter $\rho$ was chosen as 0.3. The computation time is determined by the number of ants and the evaporation parameter. The two-dimensional plots in Fig. 6a and b show the influence of these two parameters on time and accuracy, respectively.

### *5.2. Experimental setting and participants*

A course on Database Management Systems (DBMS) taught for undergraduate students has been taken for this study and five concepts from DBMS were chosen viz., (i) Relational database – Fundamentals, (ii) Data models, (iii) Database query language, (iv) Data organization architecture and (v) RAID. Each concept was made up of several topics and two topics for each concept were chosen. Each topic comprised of learning objects, which varied in difficulty level and presentation format. Each of the topics could be explained through different combination of LOs to make it personalized for the learners. It was vital to deliver the right LO to the right learner according to his/her adaptation parameters. There were assessments at the end of concept which were the same for all learners irrespective of the LOs they studied to master the concept.

The experiment was conducted in two stages.

Stage 1: The proposed approach recommends a learning path to a learner based on the previous learners' (Alumni) experience. In the first stage, data required from the alumni were collected. A course on Database Management Systems was developed and around 220 students took the course over a period of time. It took 12 weeks to complete the entire course and took assessment at the end of each concept. At the end of each concept, they undertook a formative assessment to assess their understanding. At end of the course, they took a summative assessment containing 15 questions covering all concepts to evaluate the knowledge gained. The scores obtained in both the assessments were utilized for pheromone computation. All the other information needed from alumni to construct the personalized learning path was recorded.

Stage 2: In the second stage, same course was introduced to new set of students. 80 students were enrolled into the study for 4 weeks. They were divided into two groups randomly and the effectiveness of the proposed system was evaluated. Both groups of learners started with a pre-test to assess their initial knowledge. The control group followed the traditional learning and the treatment group followed the proposed approach. At the end, both groups took the same post-test questionnaire.

### *5.3. Comparing manually selected learning path with that recommended by proposed approach*

Two experts from the field assigned a significance value to each LO according to its importance to master the concept and the mean value was calculated as the final significance value for the respective LO. The importance of the constructed path was determined by the importance of the LOs that constitute the path. The basic premise was that the LOs recommended by the proposed approach should be of significance for the knowledge construction as irrelevant LOs would increase the load of the learner, leading to impairment of learning.

Five experienced teachers from the subject domain constructed the learning path using their expertise, who in turn were unaware of the significance value associated with each LO. The manually constructed path was compared against the system

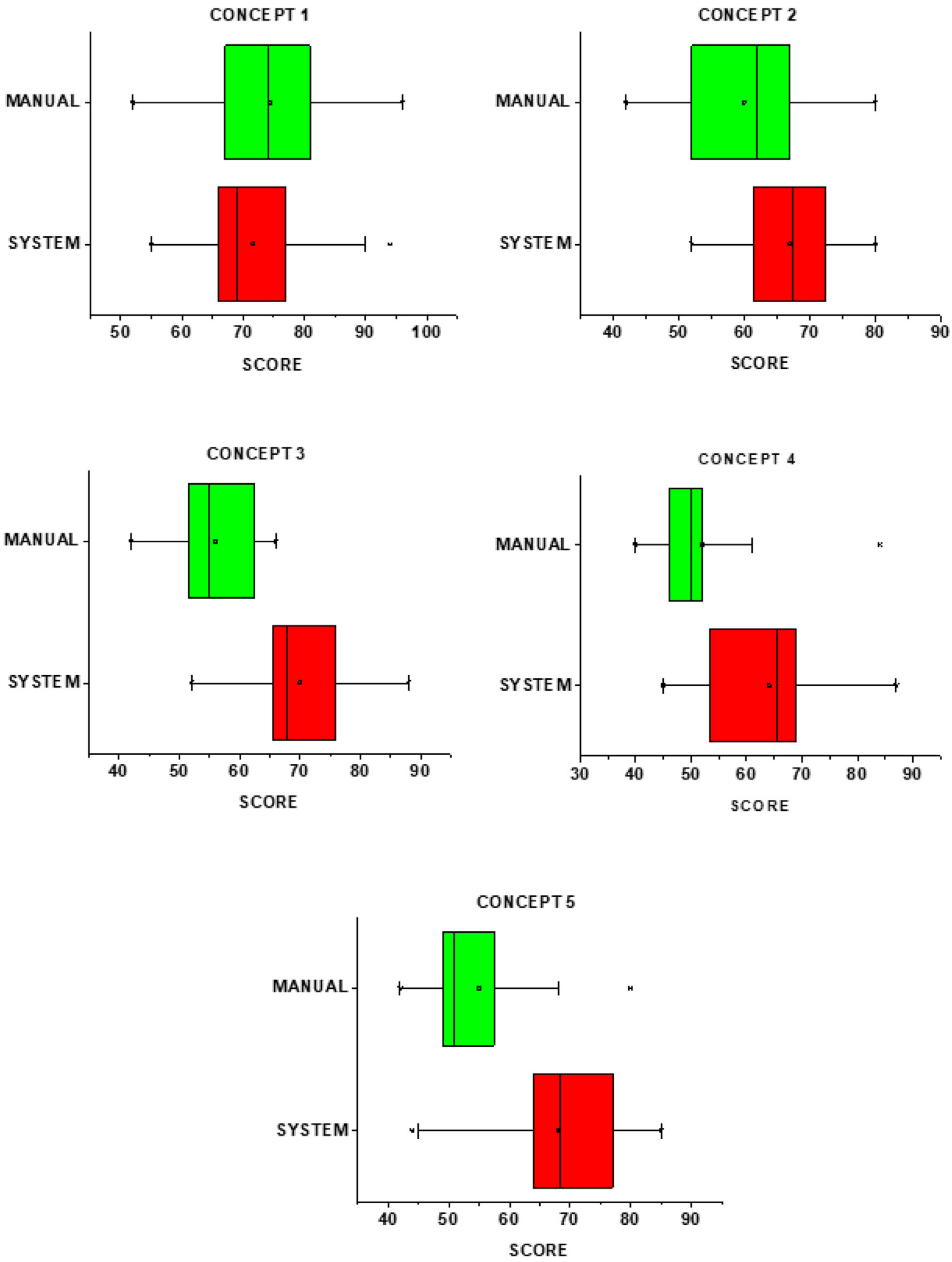


**Fig. 7.** Comparison of performance between control and treatment groups.

recommended path. Table 2 shows the manually selected path and system recommended path along with significance value. It is evident that the system recommended learning path has more significance value indicating the quality of the path.

The performance of two groups of students in five concepts was compared (Fig. 7). The control group performed better in Concept 1, which covers basic information and does not need pre-requisite knowledge to understand it. Whereas, in the remaining four higher order concepts, where the learners need to possess prior knowledge and create a schema to

**Table 2**
Significance value of manually selected and system recommended learning paths.

| | Concept 1 | Concept 2 | Concept 3 | Concept 4 | Concept 5 | Degree of significance |
|---|---|---|---|---|---|---|
| Teacher 1 | $LO_{c1\_11}$ | $LO_{c2\_02}$ | $LO_{c3\_05}$ | $LO_{c4\_03}$ | $LO_{c5\_02}$ | 9 |
| Teacher 2 | $LO_{c1\_03}$ | $LO_{c2\_01}$ | $LO_{c3\_12}$ | $LO_{c4\_03}$ | $LO_{c5\_01}$ | 7 |
| Teacher 3 | $LO_{c1\_05}$ | $LO_{c2\_03}$ | $LO_{c3\_03}$ | $LO_{c4\_05}$ | $LO_{c5\_11}$ | 12 |
| Teacher 4 | $LO_{c1\_03}$ | $LO_{c2\_02}$ | $LO_{c3\_02}$ | $LO_{c4\_06}$ | $LO_{c5\_09}$ | 11 |
| Teacher 5 | $LO_{c1\_07}$ | $LO_{c2\_05}$ | $LO_{c3\_04}$ | $LO_{c4\_11}$ | $LO_{c5\_04}$ | 16 |
| System | $LO_{c1\_03}$ | $LO_{c2\_08}$ | $LO_{c3\_04}$ | $LO_{c4\_01}$ | $LO_{c5\_04}$ | 22 |

*(In LOx _yy, 'x' represents the concept number and 'yy' is the identifier of LO for the concept X).*

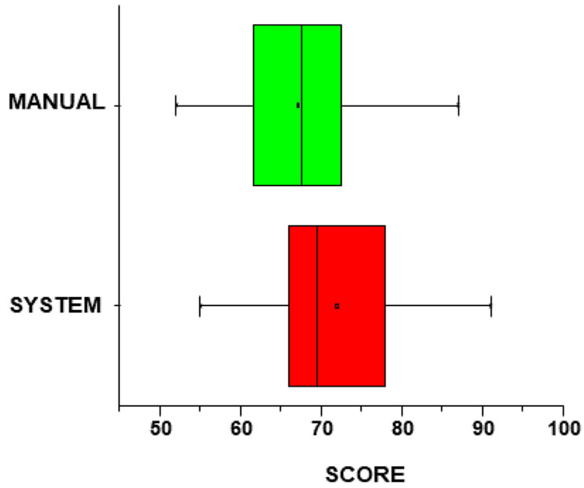


**Fig. 8.** Overall performance of two groups of students.

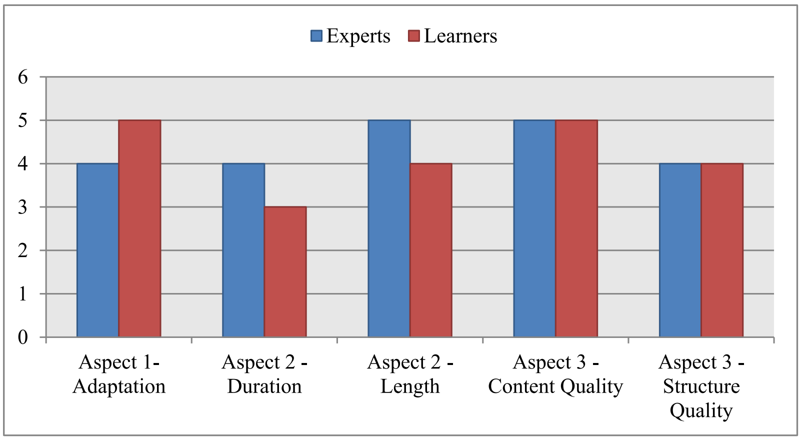


**Fig. 9.** Results of survey.

understand them, the treatment group performed better than the control group. Further, the proposed system helps the learners to acquire relevant knowledge without overloading their WMC. These two factors mainly contributed to the better performance of the treatment group.

The overall performance exhibited by the experimental and control group of students is depicted in Fig. 8. As observed from the results, it is evident that the proposed approach is more effective than the traditional learning approach in improving the overall performance of the students without burdening their working memory capacity.

### *5.4. Qualitative evaluation*

The personalized learning paths recommended for students in the treatment group were qualitatively evaluated by 80 students enrolled for the courses and five experts of this course based on three aspects viz., (i) match between learners' traits and learning path, (ii) duration and length (number of LOs) of the path in regard with learner's traits and (iii) content (LO) quality and structure (LO sequence) of the path.

The metadata associated with LO such as learning time, interactivity type, difficulty, aggregation level, and typical age range along with the emotional state and cognitive load of the learners were presented for evaluation. The experts evaluated 40 personalized paths, whereas the students evaluated only the path presented to them using a Likert scale of 1–5, with level 5 being the best. The response obtained from the subjects is shown in the Fig. 9.

The result showed that both experts and learners have obtained high satisfaction degree for the recommended path. Both experts and students found the adaptation and quality of the content to be good. The main problem for the students was the duration and they were not convinced with the length of the path recommended.

## 6. Conclusion

Each learner is a unique individual with different learning needs and abilities. Personalized learning is particularly essential in e-learning as it gives learners a degree of flexibility in terms of how and what they learn. Personalized learning paths are crucial for helping learners to understand concepts and gain knowledge, enabling them to build upon their strengths, needs and goals. It is also equally important to reduce cognitive load when students are faced with a wide array of resources. Given these factors, this paper proposes a collaborative algorithm, which hybridizes ACO and GA to improve the accuracy of learning path personalization, thereby improving the performance of learners. The efficiency of the learning path generated by this algorithm has been compared to a learning path prepared by subject experts. Our findings lead us to conclude that the learning path generated by the proposed algorithm is more effective in enhancing the overall performance of students and its application could be extended to include other constrained optimization problems.

## Declaration of Competing Interest

None.

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