ACO in e-Learning: Towards an adaptive learning path

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Abstract— Today we are in an era where drastic advancements in networking and information technology are in action. The learning process has also taken these advancements, as a result of which e-learning came to the scene. Personalization in e-learning will improve the performance of the system. Recent researches are concentrating on providing adaptability to the learning management systems, depending upon the varying user needs and contexts. Adaptability can be provided at different levels .Providing an adaptive learning path according to the context of the learners' is an important issue. An optimal adaptive learning path will help the learners in reducing the cognitive overload and disorientation, and thereby improving the efficiency of the Learning Management System (LMS). Ant Colony Optimization (ACO) is a widely accepted technique since it provides an adaptive learning path to the learners. Meta-heuristic which is used in intelligent tutoring systems provides the learning path in an adaptive way. The most interesting feature of ACO is its adaptation and robustness in an environment where the learning materials and learners are changing frequently. In this paper we can have a look through the existing ACO approaches towards providing an adaptive learning path and an introduction towards an enhanced attribute ant for making the e-learning system more adaptive.

Keywords- Adaptive learning path; ACO; e-Learning

I. INTRODUCTION

The traditional learning systems follows "one size fits all" approach [1]. where all the learners are provided with same learning content. But the learners' requirements and goals dynamically change over time which can't be addressed by the traditional approach. The adaptive learning provides an alternative to the traditional approach, where learning objects can be provided dynamically as per learner preferences and needs. An e-learning system with the provision of adaptability, will act as a virtual teacher who is giving individual care to each learner. Providing adaptability is a notion which considers the learner characteristics such as his preferences, knowledge levels, learning style, interest, goal, learner performance etc. Thus by considering such learner contexts and providing the learning objects depending up on these contexts will significantly improve the efficiency of the e-learning. The adaptation can be done at different levels such as presentation level adaptation, Link level adaptation, content level adaptation and adaptive learning path. In a web based learning environment the immense amount of available learning objects will increase the cognitive overload for the learner [2]. and it will lead towards disorientation. These problems can be overcome using an adaptive learning path [3]. provided based on the user context. Using an optimal learning path the learning objects can be provided in an effective way for the learner. That is each learner can be provided with an individualized learning objects depending upon their needs and contexts. Finding out an optimal learning path is an NP-hard problem. Ant colony optimization plays a major role in providing adaptive learning path [4]. Besides ACO many other approaches are there in existence for this curriculum sequencing problem.

This paper is as follows : section II deals with the existing approaches for learning path adaptation problem, section III elaborates the ACO for adaptive learning path, section IV details the proposed approach and section V concludes the paper.

II. EXISTING APPROACHES FOR LEARNING PATH ADAPTATION

There exist a number of approaches, towards finding out optimal learning path in an adaptive manner, which includes techniques based on

A. Evolutionary Computation Approaches

The Evolutionary Computation (EC) methods are widely in use for finding out the adaptive learning path. The EC methods used for adaptive learning path are classified as social sequencing and individual sequencing approaches. In the social sequencing approach the choice of the optimal learning path is based on the collective path and performance of the entire learners' society. The second approach is based on the individual learner rather than a group's characteristic.

The main Techniques used for social sequencing is Genetic Algorithm [5, 6]. For individual sequencing also GA is used [7, 8, 9, 10, 11, 12].Other EC techniques such as Memetic Algorithm is mainly used for individual sequencing [13]. Particle Swarm Optimization is also used in individual sequencing [14, 15]. Among these, in the direction of social sequencing ACO provides more adaptive and robust solution. The use of ACO can be seen in section 3.

B. Other Approaches

Another approach is using a Learning path graph. A Learning Path Graph is an acyclic graph which describes the structure of domain knowledge and the associated learning goals. It matches all the possible learning paths and goal in hand [16]. Based on learner's attributes in the user model, a personalized learning path is selected from the graph that contains all the available learning paths. User model consist of learner level of expertise and characteristics like learning style and preferences.

The whole courseware structure and core knowledge about a subject domain can be clearly revealed using the graphical representation of ontology called concept map [17, 18]. Learning activity graph [19]. is used to organize learning resources in a learning task. Based on learner preferences and level of expertise Learning Activity sequencing algorithm integrates the use of learner model and learning activity graph.

By using the clustering technique, the learners are grouped into clusters according to their learning styles. A Self Organizing Map (SOM) neural network [27]. is used for grouping the learners and providing path suitable for the cluster in which the learner belongs. Bayesian probability theory [28]. is used for finding the adaptive learning path. Here firstly a node probability table based on Bayesian probability theory is created. The probability value is assigned based on the learner level of expertise, learning style and learning pace, which are called candidate learning paths. Next a Bayesian network is constructed to calculate probability value which represents for each knowledge unit in learning path. A shortest path is selected from this to provide a suitable learning path for a learner. Petri Net based approach [29, 30]. is presented in to provide adaptability to the learning system.

III. ACO FOR ADAPTIVE LEARNING PATH

Ant Colony Optimization is a swarm intelligence technique which is inspired from the foraging behavior of the biological ant species. It is a population based general search technique used to find out optimal solutions for complex combinatorial problems which is motivated by the pheromone trail laying behavior of real ant colonies. In the real world scenario the ants roam in search of food and upon finding out the sources they lay chemicals called pheromones on the ground through the way to food source and back to nest. This act as a stigmergy for other ants .This stigmergic action is used for indirect and local communication. Subsequently the other ants in the colony follow the path where pheromone concentration is higher. There by finally following an optimized path. More over the laid pheromones will eventually evaporates over time, which will avoid the convergence to a locally optimal solution. There are a variety of ant colony algorithms in existence which includes: Ant system, Elitist ant system, ANT-Q, Ant colony system, Max-Min ant system, Rank based ant system, ANTS, Hyper-cube AS etc.

In E-Learning, ACO is the most used meta-heuristic for finding out an adaptive as well as optimal learning path. The natural behavior of ants are simulated with the help of a colony of artificial ant agents .This agents will cooperatively work towards finding out the adaptive learning path using the pheromone trails and heuristic information. Depending upon the visit of other ants through the path some trails may be reinforced and others paths may be allowed to evaporate. Both the exploration and exploitation nature of ACO algorithms helps in finding out the optimal path. For example the elitist ant system is more explorative, i.e. the algorithm broadly allow to search through the solution space. Whereas the max-min ant system is more exploitative in nature i.e. the algorithm has the ability to search thoroughly in the local neighborhood where good solutions have previously been found. For finding out an adaptive learning path both these characteristics are utilized. An interesting property of the ant colony system probabilistic approach is that the individual learners can benefit from the collective behavior of their peers. Next we can have a look at the existing ant colony approaches towards adaptive learning path.

An ant based system for a paraschool [20]. is presented. This is designed to provide an automatic smart system, without manual intervention which could adapt according to varying users. This is attained by making the structure individual specific from the gradual modification of learning path suggested by teachers. The site navigation is made adaptive to user according to the history of the system (recording of failure or success for each student along with considering parameters like time spent on an exercise etc.).

Depending upon the learning style, a pedagogical path for a learner is provided [21]. This takes the Kolb's learning style model. Here the e-learning structure is represented using a graph with valued arcs. The arc weights are optimized by virtual ants (learners) which release virtual pheromones along their paths. The weights on the arcs reflect the probabilities to suggest subsequent nodes to learners.

A combination of Bayesian network and ant colony system for personalized learning path [22]. is provided where the system considers the personal needs such as language, capacity, complexity, comprehension level etc. These considerations can enable the LMS to provide varying personalized paths to the same goal (i.e) learners with same learning goal can be provided with different learning path. Here, to address the problem of learning together, collaborative filtering techniques are used, while keeping individual control over their space, time, activity, presence, identity and relationship. A Bayesian network is used to calculate the suitability factor of an arc.

The Style based Ant Colony System (SACS) [23]. used an extended ant colony system for providing adaptive learning path. As per the recent studies the learning style of a learner has a great impact on the e-learning performance. This paper considered the relationship among the learning style of each learner and the learning content. It had taken the Visual, Aural, Read/write, and Kinesthetic (VARK) learning style model. The SACS has promoted content sharing and learning collaboration while enhancing learner's participation in learning activities. The SACS approach reveals information appropriate for each learners having different learning style, which gradually leads to the suitable learning path.

A Dynamic Learning Pathway Advisor (DYLPA) [24]. combines a rule based perspective planning and Ant Colony Optimization based inductive planning. This approach provides adaptive learning pathway by considering learning profile, preferences, and ability of the student. The learner profile in DYLPA has two components like learner attributes and activity log. Learner attributes quantifies Learner's prior knowledge, learning preferences, learner's relevant background and other information such as analytical skill competency language proficiency etc. The learners' activity log records the learning path that has been visited by the learner and the performance of the learner (Assessment results).

An attribute based ant colony system (AACS) [25]. considers the relationship between the learner attributes such as domain knowledge, learning style and learning object's (LO) attributes. The "attribute ant" proposed in this paper combines the Kolb's learning style model as well as learner's domain knowledge level with learning objects attributes to provide an adaptive optimal recommendation of the learning objects for the learners.

An improved ACO algorithm [26], is formulated for addressing the problem of personalized recommendation. It utilizes the fuzzy knowledge extraction model. By discovering effective learning paths from the database through ant colony model it extracts personalized recommendation knowledge. To overcome this, a segmented-goal training and meta search control strategies are provided. Here they considered the learner characteristics such as learning style and learner competency. The Kolb's learning style model is adopted. Competency is represented as a numerical value. Coding the level of the learner's proficiency in a certain concept of a specific domain.

Table I shows learner contexts taken in to consideration in the existing Ant Colony based approaches for the provision of adaptive learning path.

TABLE I. LIST OF LEARNER CONTEXTS TAKEN , TO PROVIDE ADAPTABILITY, ALONG WITH ACO

Article reference No.	**Learner contexts considered**
[20]	Individual history (recording of success or failure for each student, time spent on each exercise)
[21]	Learning style (Kolb's model)
[22]	Personal needs : Language, Capacity, Complexity, Comprehension level
[23]	Learning style (VARK model)
[24]	Learner prior knowledge, Learning preferences, Learner's relevant background, analytical skill competency, language proficiency
[25]	Learning style (Kolb's model), Learner's domain knowledge level
[26]	Competency (learner's proficiency in a concept), Learning style (Kolb's model)

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IV. PROPOSED APPROACH

A. *Need for the proposed approach*

Most of the existing ACO based approaches considers the learning style of the learner. None of the existing systems considers all the user context parameters. When more learner contexts are included, then the efficiency of the e-learning system will be improved. Considering the learner attributes and matching it with the learning object's attribute will help in providing more suitable learning object and thereby providing the most suitable learning path for individualized learners.

B. *Proposed approach: An 'enhanced attribute Ant' for providing adaptive learning path*

The learner attributes like learning style and learner prior knowledge level and matching these attributes with corresponding learning object attributes will help in improving the provision of suitable learning objects. But both the learning style and learner knowledge level are static characteristic of a learner. There exist other characteristic for a learner which may dynamically change over time such as learner preference. Learner preference of a learner may change over varying sessions of learning process. So considering learner preference along with the above mentioned learner attributes will improve the performance of the system by providing most suitable learning object in a dynamic manner.

For this the proposed system consider the following learner parameters and match that with the corresponding LO attributes .A match ration is provided as the heuristic information for the attribute ant (i.e) the proposed system enhances the attribute ant [25]. with an extra learner attribute 'learner preference' and LO attributes' 'learning object orientation'. The detailed description of the learner attributes and learning object attributes are shown in Table II. Matching is done by comparing the corresponding attributes such as learning style with LO type, Knowledge level with LO Level and learner preference with LO orientation and the match ration is calculated which is used as the heuristic value given to the ant colony system.

V. CONCLUSION

The adaptive learning provides an alternative to the traditional approach, where learning objects can be provided dynamically as per learner preferences and needs. Providing an adaptive learning path is an approach towards making the online learning dynamically adaptive. An optimal adaptive learning path can reduce the cognitive overload as well as disorientation for the learners. Ant Colony Optimization is a probabilistic approach which is widely used to provide the adaptive learning path. The learning object attributes along with the learner characteristics, will enhance the provision of most suitable learning objects. For improving the degree of adaptability, the learner characteristics such as dynamic learner preference is added along with static learning style and learner knowledge level. For this an enhanced attribute ant is proposed, which combines the Kolb's learning style model, learner knowledge level and learner preference with learning object attributes. Thus by considering both static and dynamic characteristic of the learner along with the learning object attributes will make the learning system more adaptive to the learners in an individual manner.

TABLE II. THE LEARNER'S ATTRIBUTES AND LEARNING OBJECT'S ATTRIBUTES

SI No	Learner Attributes			Learning Object (LO) Attributes		
	Kolb's Learning Style	***Knowledge Level***	***Learner Preference***	***LO Type***	***LO Level***	***LO Orientation***
1	Diverging	Apprentice	Conceptual	Graphic(Image, Charts. Symbol)	Initial	Concept
2	Assimilating	Beginner	Example Oriented	Video (Audio, Animation)	Introductory	Example
3	Converging	Intermediate	Case Study	Text (Word, ppt, excel)	Advance	Case study
4	Accommodating	Expert	Problem Oriented	XML (Web, SCORM, LOM)	Professional	Problem
5	-	-	Demonstration	-	-	Demonstration
6	-	-	Simulation	-	-	Simulation

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