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Life Science Journal

MARSLAND PRESS
Multidisciplinary Academic Journal Publisher

# Optimization of the pedagogical path of a student in a semi e-learning environment by using Ant Colony

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**Abstract:** This paper describes the research on the optimization of the pedagogical path of a student in a semi e-learning environment. This optimization is performed following the ideas given by a recently proposed meta heuristic approach for solving hard combinatorial optimization problems in Artificial Intelligence: Ant Colony Optimization (ACO). The structure of the pedagogical environment is simulated by a graph with valued arcs whose weights represent their pedagogic importance, and by virtual ants which release virtual pheromones along their paths. By considering the released amount of pheromone on each arc at the end of the simulation, it would be possible to recognize the best collaborative-found path and suggest it in a fashion based on IMS-Simple Sequencing.
[Alireza Rezaee. **Optimization of the pedagogical path of a student in a semi e-learning environment by using Ant Colony**. *Life Sci J* 2023;20(7):29-32]. ISSN 1097-8135 (print); ISSN 2372-613X (online). http://www.lifesciencesite.com.04.doi:10.7537/marslsj200723.04.

**Key words:** Ant Colony Optimization, pedagogical path, semi e-learning.

## 1. Introduction

The introduction of artificial intelligence and neural networking has made e-Leaning soft wares smarter and more responsive. New online learning programs will be both adaptive and prescriptive [9]. These programs will sense the strengths and weaknesses of the learners and adjust the curriculum accordingly; also the program may learn from experience. All this will be driven by new breakthroughs in artificial intelligence applied to instructional methods in e-learning environments. Some of these applications of AI which will have an impact on e-Learning in near future are:

- Ant Colony Optimization: used for demonstrating “swarm intelligence” and improving group learning
- Artificial Life Algorithms: used in the study of biological and social systems
- Simulated Annealing : used in task assignment and scheduling
- etc.

Soon after the emergence of e-learning phenomena, it has been discussed to have a system which is not just “one size fits all” [13]. For instance it would enhance the user navigation by making it adaptive and user-specific, so that both individual profiles and collective characteristics could be taken into account in an automatic and dynamic fashion., e.g., some successions of lessons may prove particularly successful in helping students understand a particular notion and those successions, leading to high success rates in subsequent exercises, should be automatically detected and highlighted. Therefore, in order to address this complicated problem, different solutions, in different fields of science have been introduced: from psychological theories to evolutionary computing methods (a set of AI engineering tools of bio-mimetic inspiration). One subfield of this later subject is Ant Colony Optimization (ACO) [1,3,4,5], which seems particularly well-suited.

This work was initiated and implemented as the final project for “Bio-Computing” course, instructed by Dr. Lucas in ECE Department of Tehran University. Although the structure is designed and implemented in a course-based scale, but it can be developed to a real-world application as well.

## 2. Evolutionary Computing and Ant Colony Optimization

Ant Colony Optimization (ACO) is a paradigm for designing meta heuristic algorithms for combinatorial optimization problems. The first algorithm which can be classified within this framework was presented in 1991 and, since then, many diverse variants of the basic principle have been reported in the literature [3,5]. This approach comes from the observation of actual ant colonies and social insects in general such as bees or termites, and of their extraordinary abilities to cooperate at the individual level to make complex and intelligent behavior at the global level, an emerging phenomenon also known as “Swarm Intelligence” [6]. The ants' ability to come up with optimal paths to fetch food, for example, through the release of chemicals along their way is very remarkable and modeling this simple idea yielded exciting results in the field of combinatorial optimization [4,8] (efficient heuristic solving of the Traveling Salesman Problem (TSP), routing problems, etc.)

The main underlying idea of ACO, loosely inspired by the behavior of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result. Usually the transition function which is used by the ants for selecting the next best path is a function of both the amount of available pheromone on that path and also distance of the path from the current position. Adjusting the intensity of each factor, would depend on the problem's criteria and domain. Besides their efficiency to quickly reach near-optimal solutions, ACO algorithms are also especially appreciated for their robustness and adaptability: just as natural ant colonies quickly find a new source of food when one disappears, ACO algorithms quickly find new optimal paths when the underlying graph suddenly changes. The collective behavior emerging from the interaction of the different search threads has proved effective in solving combinatorial optimization (CO) problems.

## 3. IMS Simple Sequencing and SCORM

### 3.1. IMS Simple Sequencing Specification

Defines a method for representing the intended behavior of an authored learning experience such that any learning technology system (LTS) can sequence discrete learning activities in a consistent way. A learning designer or content developer declares the relative order in which elements of content are to be presented to the learner and the conditions under which a piece of content is selected, delivered, or skipped during presentation. It incorporates rules that describe the branching or flow of learning activities through content according to the outcomes of a learner's interactions with content. This representation of intended instructional flow may be created manually or with authoring systems that produce output that conforms to this specification. The representation of sequencing may be interchanged between systems designed to deliver instructional activities to learners.

Simple Sequencing is labeled as *simple* because it includes a limited number of widely used sequencing behaviors, not because the specification itself is simple. Simple Sequencing is not all-inclusive. It recognizes only the role of the learner and does not define sequencing capabilities that utilize or are dependent on other actors, such as instructors, mentors, or peers.

### 3.2. SCORM

The SCORM (Sharable Content Object Reference Model) is informally a "standard" that allows learning content from any vendor to play in any SCORM compliant Learning Management System (LMS). Formally it is an "application profile", (i.e. collection of standards and extension, recommended practice of how to use these standards within "one" community) .It was created in cooperation between government, academia and industry and it consolidates the work of AICC, IMS, ARIADNE and IEEEs LTSC into one unified standard. Basically there are 2 parts of the SCORM: The Run-Time Environment and The Content Aggregation Model.

- The Run-Time Environment specifies how your content should behave once it has been launched by the LMS.
- The Content Aggregation Model specifies how you should package your content so that it can be imported into an LMS. This involves creating XML files that an LMS can read and learn everything they need to know about your content.

Description of how Content Shareable Objects are combined and behave under external control is missing from SCORM 1.2, however SCORM 1.3 uses IMS Simple Sequencing for its sequencing goals and maps part of Simple Sequencing data model to CMI data model (i.e., the data items available to a SCO), it also specifies a limited set of navigation controls and maps them to sequencing events.

## 4. Design Issues and Implementation

Applying ACO techniques in learning context would seem relatively straightforward when one considers the E-learning software as a graph with valued arcs through which students navigate. Following points were considered in structural design:

- Each node represents a pedagogical item (exercise, lesson, quiz, etc.).
- Arcs represent logical/pedagogical links between those items.
- Weights on the arcs reflect the importance of the subsequent nodes to students with respect to other arcs coming out of the same node.
- Original weights are determined by the pedagogic team/tutor/instructor/professor.

### 4.1. Pheromone release and evaporation

Following the validation of a node, an ant (i.e. a student) would release pheromones along the way that led it to that node There are two kinds of pheromones that can be released on arcs to reflect students' activity

- Ph_S: Success pheromone: This value is incremented by ants/students on the adequate incoming arcs when they are successful in completing the corresponding item (node).
- Ph_F: Failure pheromone. : This value is just like the above one, but for the case of failure.

Note that release of the pheromones happen not only on the arc that led the ant to the last validated node, but also on previous ones in the ant's history with decreasing amplitude. This is considered so to reflect the fact that all the nodes (lessons, exercises) the ant has navigated before, have an influence on its ability to succeed in validating its current node, but of course with a diminishing influence. This "backward propagation" of pheromone release is limited in scope for algorithmic and 3 pedagogic reasons and a typical value of 4 nodes has been selected [7]. Also, to allow for dynamic adaptability and to prevent the system from being trapped in a particular state, evaporation is performed on both of these pheromone amounts, by a constant factor, namely 0.999.

**4.2. Fitness calculation**

Using all the information described above, each arc $a_i$ is given a *fitness value*, to allow an appropriate balance between the factors (i.e. teachers' opinion and collective experience), that should dictate an ideal pedagogic navigation: For each arc $a_i$, this balance is represented by a "fitness" value:

$$F(a) = w_1 W + w_2 Ph\_s - w_3 Ph\_F$$

The higher this value, the more "desirable" the corresponding arc will be and consequently the more likely will it be for it to be selected by the student (ant). Obviously an arc is desirable when:

- The arc is encouraged by professors (high W)
- There's an atmosphere of success around that arc (high Ph_S)
- Students have failed a little around that node (low Ph_F)

The relative influences of the different factors can be adjusted by tuning the $w_i$ values.

One arc is picked among the whole list of possible outgoing arcs; by the Roulette-Wheel selection procedure .With this very traditional procedure [7], the probability for arc $a_i$ to be picked is proportional to the fitness of the whole list:

$$P(a_i) = F(ai) / \Sigma_{j \neq i} F(a_j)$$

This method has the advantage to be entirely automatic and very sensitive to fitness variation. However if an arc becomes really preponderant, the others have really few chances to be selected.

**4.3. Implementation**

A model of user population has been derived to conduct simulation tests: each ant, representing a virtual student, is given a certain *level*, represented by a floating point number situated between 0.0 and 1.0. This value is randomly distributed over the population of students at the beginning of each simulation round. Also, each exercise is assigned a random *difficulty* value, again between 0.0 and 1.0. When an ant arrives at a given node, if its level allows it to validate the node (level > difficulty), it succeeds, otherwise, it would fail. Pheromones are released accordingly (by incrementing floating point values carried by the arc). Amount of the available pheromones ( in addition to the teachers' opinion : w )on each arc ,would behave like a rich source of information for the next-coming students (ants). Out of this information, stored in the "environment" and called "stigmergic" information [5], emerges a representation of the interaction between the students and the pedagogic environment. This representation is used to derive the best collaborative-found path and to suggest it in an XML file, based on IMS-Simple Sequencing format.

**5. Conclusion and Future work**

The task of the ACO in this system was to find the optimized path to the destination node (lesson/exercise), in order to maximize the overall students' success .As can bee seen by the simulation results, although the students may navigate through the same path for several times, continually this path would redirect to the best found one according to the amount of success and failure pheromones released by the previous students (ants). Thereby coming up with emergent information that can be used as a refined auditing tool to help the pedagogical team identify the strengths and weaknesses of the software and pedagogic material(and of the students either). Also the generated IMS-Simple Sequencing XML file could be easily integrated to a LMS package which is responsible for the e-learning environment. The key advantage of this system is that, it is both reactive and robust. And this is so, firstly because pheromones evaporate with time –which prevents the system from freezing or converging towards a particular state- and secondly because students, by browsing the graph, continually update the environment, thereby reflecting the dynamics of their weakness and strengths

As this technique is nearly original in the field of E-Learning, the present study should be seen as pointing out a potentially interesting research direction and suggesting the use of emerging properties of social insect-based models in e-learning environments, for instance the ACO heuristic would provide seemingly intelligent systems which improve the behavior of the learning environment from the student's viewpoint, , thereby the cognitive behavior of a social system (students and teachers) could be described. From a more theoretical standpoint, this study can be seen as a new take on Interactive Evolutionary Computation where the solution to a problem is gradually constructed and modified by multiple interacting entities with different and possibly opposite goals. This suggest a great deal of new and exciting applications in the field of Collective Cognition Modeling and Collective Evolutionary Design .

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7/5/2023