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Integration of evolutionary algorithm in an agent-oriented approach for an adaptive e-learning

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ABSTRACT

This paper describes an agent-oriented approach that aims to create learning situations by solving problems. The proposed system is designed as a multi-agent that organizes interfaces, coordinators, sources of information, and mobiles. The objective of this approach is to get learners to solve a problem that leads them to get engaged in several learning activities, chosen according to their level of knowledge and preferences in order to ensure adaptive learning and reduce the rate of learner abundance in an e-learning system. The search for learning activities procedure is based on evolutionary algorithms typically a genetic algorithm, to offer learners the optimal solution adapted to their profiles and ensure a resolution of the proposed learning problem. In terms of results, we have adopted “immigration strategies” to improve the performance of the genetic algorithm. To show the effectiveness of the proposed approach we have made a comparative study with other artificial intelligence optimization methods. We conducted a real experiment with primary school learners in order to test the effectiveness of the proposed approach and to set up its functioning. The experiment results showed a high rate of success and engagement among the learners who followed the proposed adaptive learning scenario.

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1. INTRODUCTION

The development of information technologies has led to the emergence of new technologies of artificial intelligence that will be adopted gradually in the teaching/learning process. E-learning is the most appropriate field to benefit from these technologies [1], [2]. It aims to free learners from the constraints of time and place in order to achieve interactive and personalized learning. Adaptive learning takes into account the learner’s profile specifications: knowledge level, goals, preferences, and intentions. This type of learning has been applied on many levels: presentation of courses, evaluation, and remediation. In this work, we have focused on solving problems as a strategy to help learners learn. This learning technique allows learners to solve problems they have not been familiar with before.

The problem of adaptation has been and is still a subject for many research studies; trying to ensure personalized learning according to the needs of each learner in terms of presentation and content [3]–[5]. The majority of this research focuses on the process of knowledge assimilation as being a primordial phase of the teaching/learning process. One of the most active and effective learning methods is learning by solving problems, it focuses on the mobilization of learners' resources to lead them to solve any given situation. But when this method is applied through an e-learning system it becomes difficult to succeed because the engagement of learners won’t be guaranteed in every situation, especially during a complex learning situation for the level and skills of the target public. They will have the impression that they won't be able to solve the problem and follow the process to the end, which provokes an increase in the rates of abundance. Therefore, we need a method to improve learner engagement through e-learning systems. We have taken problem-solving learning to illustrate the importance of adaptive learning through another field of application.

Several studies have been conducted in order to properly implement the learning process via e-learning systems [6], [7]. Learner engagement is considered an index of learning effectiveness in e-learning systems. For this reason, several efforts have done to highlight the importance of this factor. Take the example of Aziz *et al.* [8] who carried out a study to identify the technology that could effectively support learner engagement through a technology assessment process. Also, researchers in the field of e-learning have thought of improving the efficiency of these systems by integrating the concept of adaptive learning. The technology of artificial intelligence has shown its productivity for this type of problem through several works based on optimization algorithms such as genetic algorithm (GA), ant colony optimization (ACO), and particle swarm optimization (PSO).

In literature, we find several works using artificial methods, typically, genetic algorithms, to ensure adaptive learning in order to offer the learner content that is appropriate to his or her profile. Azough *et al.* [9] conceived an adaptive educational system based on the modeling of the pedagogical resources' description to produce the most suitable path for every learner's profile. The idea is to transform the problem of searching for the adapted path into an optimization problem. The starting point is the learner's profile, the arrival point is the teaching goal of the formation, and the intermediate states are the evolutions of the profile after taking the available courses. Madani *et al.* [10] focuses on the integration of the genetic algorithm by combining the concepts of information retrieval systems, social networks, sentiment analysis, and big data with the Hadoop framework. This combination aims to ensure adaptive learning to the learner's profile via two levels: the first is based on the use of genetic algorithms to find the most appropriate goal for the learner's profile while the second aims to determine the period of activity of each learner using his social network (Facebook). Bhaskar *et al.* [11] described a learning pattern that adapts to learner characteristics based on the genetic algorithm. The proposed structure is composed of three levels: content, presentation, and media to generate a learning path that adapts to the whole context of the learner. Chang and Ke proposed a personalized online course composition based on the genetic algorithm that has shown its effectiveness and relevance through an experimental comparative study with other algorithms such as PSO, and Lakkah *et al.* [13] proposed an adaptive and personalized system based on the Felder-Silverman learning style model combined with ACO, in order to provide learners with a suitable educational object to increase their performance. The proposed solution is organized through the concept of ontologies to provide learners with an adaptive and optimal learning path. Allach *et al.* [14] described an approach to modeling and adaptation of the e-learning context. The proposed modeling is based on the ACO algorithm. Pushpa [15] presented an overview of the existing ACO approach toward providing a personalized learning path, to make the e-learning system more adaptable to the learners' needs. Sivakumar and Praveena [16] analyzed the learning process in an e-learning environment by using the ACO algorithm. Priya *et al.* [17] formulated a new approach to obtain a learning path for different learner groups as a constraint satisfaction problem (CSP), where the course materials are used to define the relationships between the learning objects. The proposed model is tested in a simulated environment; the results reveal that the artificial ants give a solution to the proposed problem in an optimized way.

We propose a new approach to learning by solving the problems based on the integration of an effective method of artificial intelligence: that's the genetic algorithm. The usefulness of the integration of this algorithm is to propose adaptive learning scenarios leading to the resolution of the learning situation. The problem-solving learning method is chosen to mobilize the learners' prerequisites in order to lead them to solve the proposed learning situation. The adoption of artificial intelligence (AI) technologies especially the GA represents a new field of implementation for adaptive e-learning in order to increase learners' motivation and engagement and to ensure better results. Problem-based learning is considered an active and efficient learning method, but its implementation in e-learning systems is still limited. For this reason, we thought of accompanying the learner in the process of research, resolution, and acquisition. The traditional strategy of problem-based learning is based on a series of problems that the learner sometimes feels unable to solve, which leads to a decrease in the rate of learner engagement. The choice of genetic algorithm can be easily adapted to the structure of an e-learning course to propose the optimal solutions through adaptive activities to the learner's profile in order to lead him/her to solve the proposed learning situation. Through the use of GA, we aim to offer learners optimal and adaptive solutions to the needs of the learners, as well as to ensure diversification in the proposed learning scenarios. To show the effectiveness of the approach we have done a comparative study of the results obtained with other optimization methods such as PSO and ACO. Nevertheless, we have noticed that during a certain number of iterations the optimal solution remains constant during some generations and then, iteratively, a number of individuals are ignored. To overcome this problem, we propose the integration of a new genetic operator "genetic immigration operator" to improve the quality of the solution obtained. We conducted a real experiment with primary school learners as an example of the target audience. The aim of this experiment is to illustrate the functioning of the proposed approach and to test its effectiveness with the learners. This paper is organized into 6 sections. Section 2 provides a general overview of the work, section 3 describes the proposed agent architecture, section 4 is dedicated to the presentation of optimization methods in the search for resources, section 5 describes the adopted strategy of the proposed optimization approach, section 6 focuses on the numerical results of a comparative study between three optimization algorithms (PSO, ACO, and GA), the application of the immigration strategy in GA to improve the quality of the solution obtained and the experiments' results, then we will end with a conclusion and perspectives.

2. PROPOSED METHOD

2.1. Agent approach for adaptive learning

2.1.1. Using agent architecture to improve the adaptive learning process

Adaptive learning represents a promising approach to improving the quality and effectiveness of learning via digital environments. The aim of this concept is to implement a learning strategy with personalized learning paths according to the learner's profile, interests, and progress in the online course. The learning process is a varied process based on the use of several learning techniques and methods. For this reason, the application of adaptive learning cannot be limited to the course presentation phase. Adaptive learning finds its main limitation in the personalization of learning activities. In fact, receiving only resources of the same type is not always sufficient to achieve better results. Moreover, adaptive learning does not necessarily cover all topics or learning situations. Also, it should be mentioned that the application of adaptive learning is still limited. Through the present work, we aim to implement an adaptive learning strategy that can be adapted to any learning situation through the use of different types of resources. The idea is to structure the learning process through an agent architecture that will allow the learning situations to be organized and varied according to the different learner profiles.

2.1.2. Architectures agents

Agent architecture is a description of the organization of its components; it can define the data and the knowledge of each agent, and also the interaction between them. They are deployed as part of the development of distributed applications. These architectures are based on the integration of several agents ensuring coordination and cooperation between them. Among the agent architectures, Seghir and Kazar [18] proposed a mobile agent approach designed to search for information in heterogeneous and distributed sources. The architecture of this system is constructed of four layers: interfaces, mediation, mobile search agents, and information sources. Also, Yuan and Fan [19] propose a mechanism for the management of failures. Kamoun [20] proposes a multi-agent organization of the type of interface-mediator-adapter to implement a traveler information system. Other studies have adopted the agent approach in education as a solution for improving the quality of learning. Ehimwenma *et al.* [21] presented a learning pre-assessment system based on the use of interactive agents. The objective of this system is to evaluate the learners' prerequisites in order to classify their skills and propose some recommendations. Matazi *et al.* [22] implemented an intelligent multi-agent system for collaborative e-learning support.

All these agents' architectures are dedicated to distributed systems that are characterized by the sharing of resources and information in real-time through multiple machines, such as an e-learning system. For that, we have based this work on [20] to determine the agent architecture of the proposed system. The use of agent architectures represents an efficient and intelligent solution for the operation of distributed systems such as e-learning systems, but the problem lies in the specificity of these environments. Effective e-learning systems must be based primarily on the pedagogical framework of the learning process including better integration of technological tools. This combination promotes the improvement and effectiveness of the learning process. The respect for the pedagogical approach presents a limit when implementing agent architecture. To this end, we have opted for the problem-based learning method as a strategy to ensure an active learning process that focuses on the needs of the learner.

The architecture adopted for this type of learning is an agent architecture that respects the functioning of the problem-based learning method. We have taken into consideration the phases of this method during the implementation of the agent architecture that will be detailed in section 3. On the other hand, the proposed architecture adopts the concept of adaptive learning. The search for resources or learning activities helps learners to solve the proposed problem according to their profile. We have used the genetic algorithm as a solution to the problem of searching for resources. This is discussed in more detail in section 4.

2.2. Proposed agent architecture

In this work, we propose agent architecture to improve the adaptive learning process. Among the agent architectures, we find client-servers and mobile agents.

a. Client server: This represents an organization of type interface-mediator-source of information. At the level of each layer, each agent has a specific function. Interface agent deals with the personalization of learner requests. Mediating agent manages the breakdown of the learning problem into sub-problems. Information source agent: searches for appropriate resources.
b. Mobile agent: This type of organization is widely used in environments that have a rich source of information such as e-learning systems. It allows for improving traffic on the network and reduces the number of transactions.

2.2.1. Client server

Scenario (1-n) mediating agent: Learners define their situation problem by sending requests directly to the data protection advisor (DPA) agents, which are responsible for breaking down the problem into sub-problems (mediating agent) and sending it to the source of information agent (SIA). The DPA agent manages all requests from different learners. This can cause an overload in their treatments, which involves the integration of other DPA agents into the system where each mediating agent manages a predefined set of SIA agents. However, it will be difficult for the user to distinguish the DPA agent who has a global knowledge of the field of the SIA agents that the user needs.

Scenario (0-n) interface agent: The integration of the interface agents within an agent-oriented approach into an e-learning system helps to define the learner's needs and ensures a personalization of the information, through the agentification of the human interaction with the machine. Each learner is associated with an assistant; an interface agent (IA) that helps them to formulate their requests and to define their needs in order to transmit them to the DPA agent. To avoid the problem of overload query's treatment by the DPA agent, each user is associated with not only an IA but also a DPA agent which will be responsible for processing only his requests.

Scenario (0-1) directory agent: Many educational resources are available in an e-learning environment to ensure quality learning (courses, additional documentation, collaborative tools, web pages, articles, completed projects, and digital media). The search for information can be done through two methods of mediation; the first is static when the DPA agent has advanced knowledge of the domains and network addresses of all the SIA agents present in the system. The second is dynamic when the system has a large number of information sources and the DPA agents are unable to distinguish the appropriate source for solving the learning problem, which causes a limitation in the information search domain. In this case, Figure 1 shows a directory agent (DA) can guide the DPA agents to improve the relevance of information search.

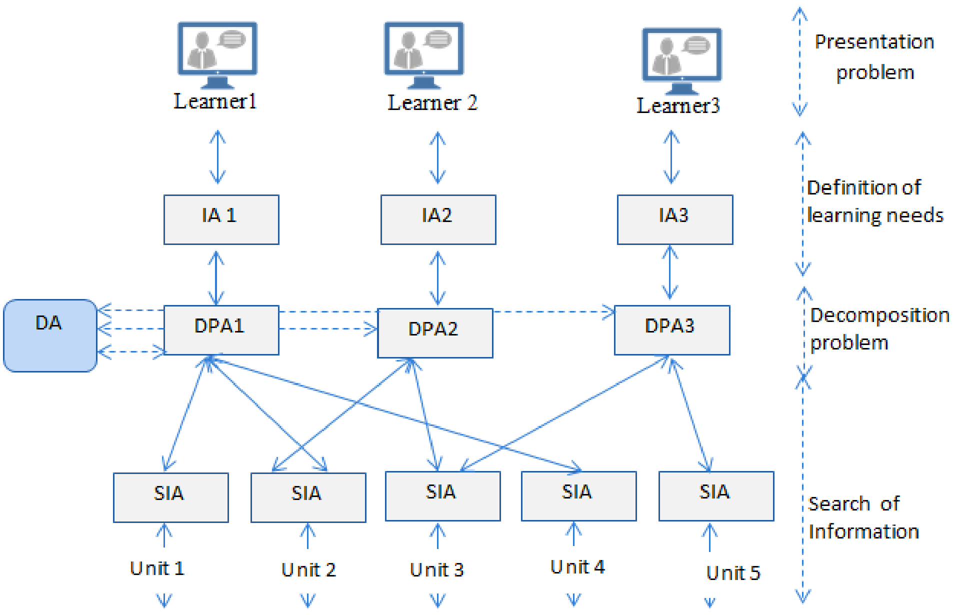


Figure 1. Client server agent architecture

Multi-agent systems are widely used in education, mainly in distance learning platforms. Their application represents a structural and organizational framework for the implementation of an adaptive learning strategy. In this work, we have considered the problem of adaptive learning as an optimization problem in order to provide learners with the most appropriate content for their profile. For this, the agent architecture was carefully chosen to meet the pedagogical and technical requirements of the approach. The client-server architecture has limitations, especially at the level of the resource search layer.

In this layer, we can find a problem with the relevance of the resources found as well as there is a problem with the traffic on the network. Through the use of mobile agents, the process of searching for learning activities has become more operational. The mobile agent architecture has allowed us to a better implementation of the adaptive learning environment by the integration of the genetic algorithm.

2.2.2. Mobile agent

In an environment rich with sources of information such as an e-learning system, several transactions are done through a client-server model. This causes a network overload during the process of search and collecting information on several data sources of the e-learning system. However, mobile agents can reduce the number of sending messages over the network in order to improve the traffic; they are also useful for mastery of network latency. The mobile agent approach is based on the use of IA and SIA agents to ensure the communication between learners and the sources of information in an e-learning system. In fact, the DPA agent will be replaced by a coordinating agent that will coordinate the tasks of the IA and SIA agents and plan the best path to be covered in the data source network. The architectural structure shown in Figure 2 is reduced to three layers for better traffic management. The first is the presentation of the problem. Learners will send requests to interface agents. They are responsible for defining the learning needs, that is, the objectives of the proposed problem. Then, the coordinating agent takes on the role of coordinating between the interface agents and the information source agents. That has a direct relationship with the learning units formed by a series of activities presented to the learners to guide them in solving the proposed situation. At the search information layer, it is difficult to identify the most appropriate resources for the profile of each learner, so we will have an optimization problem which is why we propose an approach based on evolutionary algorithms.

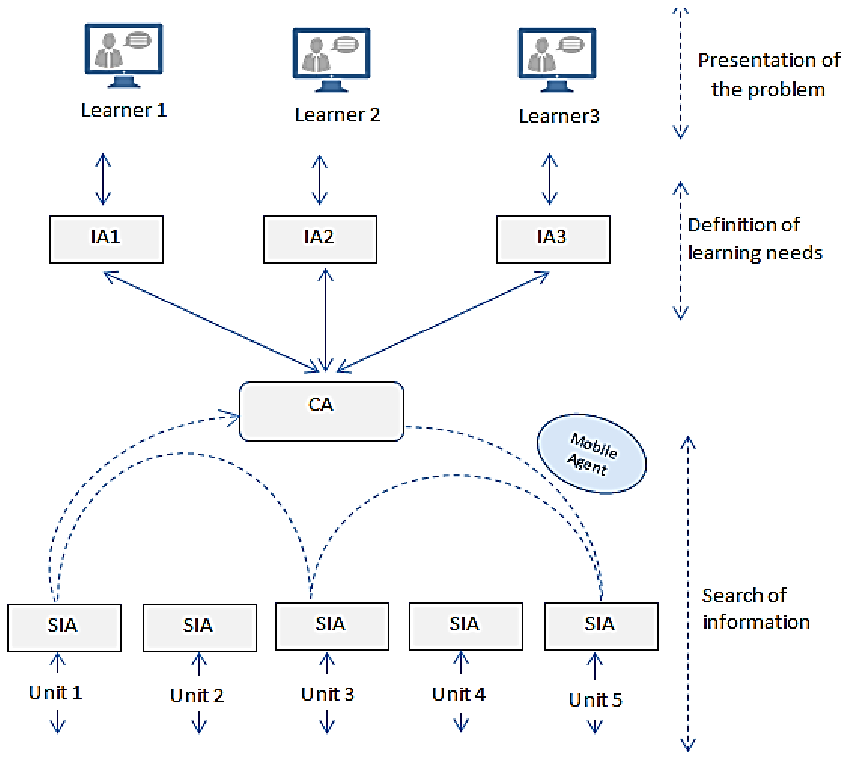


Figure 2. Mobile agent architecture

We have chosen problem-based learning as an active method to ensure effective learning. The application of this method requires motivation and guidance for the learners. To this end, for each problem situation, we have planned learning activities that help learners to solve the proposed problem. These activities are diversified either in terms of the level of difficulty or type of media. The aim of this diversification is to cover the needs and profiles of all learners. At the level of the search information layer, we have used the genetic algorithm to identify which activities are adaptive to each learner. The use of this algorithm ensures an intelligent and relevant search that promotes adaptive learning.

3. RESEARCH METHOD

3.1. Optimizing the search for resources

An e-learning platform has several educational resources for the purpose of providing quality learning. Some of these resources are developed by the internal actors of the platform (teacher, tutor, trainer, and administrator) and others are available on the web in order to enrich the learning process and provide a personalization of the proposed training. In front of this enormous number of educational resources, the task of research and assignment of knowledge is more complicated. The act of learning via an e-learning system or face-to-face training must be focused on the learner in order to get him/her to understand, apply, analyze, evaluate, and create. On the other hand, each learner has a way in which he is programmed to learn efficiently according to his profile. The question here is, how can we take advantage of these pedagogical resources while respecting the profile of each learner? So, we are faced with an optimization problem to find the indispensable resources that will be used to cover the learners' needs. Recent works have used artificial intelligence technologies and more precisely of optimization methods for the implementation of intelligent and optimized search strategies to ensure finer management of resources available in an e-learning platform. The objective of this intelligent and optimized search is the elaboration of an approximate solution to the profile of each learner in a reasonable amount of time to get them to solve the proposed situation through the available resources while ensuring preferment learning.

3.1.1. Optimization methods

It is rather complex to find an exact solution to any kind of problem, for that resolution methods attempt to approximate the global optimum while using a recursive process to minimize or maximize the optimization. The evolutionary algorithm such as GA, PSO, and ACO provide a good sufficient solution to an optimization problem. The PSO algorithm was first introduced by Eberhart and Kennedy. Instead of using evolutionary operators to manipulate the individuals, like in other evolutionary computational algorithms. In the search space, each individual has a velocity that varies dynamically according to their own flight experience and that of their companions [23]. In PSO, a solution is represented as a particle, and the population of solutions is called a swarm of particles. Each particle moves to a new position using the velocity. Once a new position is reached, the best position of each particle and the best position of the swarm are updated as needed. The velocity of each particle is then adjusted based on the experiences of the particle. The process is repeated until a stopping criterion is met [24].

ACO is a swarm intelligence technique that is inspired by the foraging behavior of the biological ant species. It is a population-based generally on a search technique used to find out optimal solutions for complex combinatorial problems. This technique is guided by the real behavior of ants during pheromone lying. 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 the food source and back to the nest. This action is used to direct and locate other ants in the colony following the path where pheromone concentration is higher, thereby finally following an optimized path. Moreover, the laid pheromones will eventually evaporate over time, which will avoid the convergence to a locally optimal solution [15].

The principle of GA, developed by Holland in 1975 [25], is an optimization algorithm based on the theory of the evolution of the species of Charles Darwin [26]. Genetic algorithm is the process that uses a stochastic approach to randomly search for better solutions to a specified problem [27], several researchers have exploited this principle to solve optimization problems [28], [29]. The execution steps are represented as:

a. Initialization of the population: the gene values are created randomly while respecting the specified interval.
b. Evaluation*:* to evaluate the performance of each individual, we must define a fitness function that varies according to the specificity of each problem. It is calculated using the values of the individual parameters.
c. Selection*:* the selection operator is used to choose two parents with better performance depending on the value of the fitness function to participate in the construction of the new generation.
d. Crossover*:* the chosen pairs will be crossed in order to ensure some diversity in the population.
e. Mutation*:* modify the value of a gene according to a certain probability.

Several works have shown the effectiveness of the genetic algorithm in various fields such as health, energy, robotics, education, and logistics. The performance of the GA is related to the fast convergence towards the optimum as well as at the level of the pertinent solutions obtained. For that, the proposed approach is based on this algorithm.

3.1. Proposed optimization approach
3.2.1. Representation method

The general structure of the educational content in an e-learning system is composed of modules, units, and learning activities. We have tried to keep this hierarchy to facilitate the process of research. A module is represented by a population that brings all the individuals described in the form of a chromosomal string, also each chromosomal string consists of a set of genes that represent learning activities. The learning scenario that represents a solution proposed by the genetic algorithm is made up of a set of activities that form the size of a chromosome as shown in Figure 3. These activities can be simulations, exercises, presentations, demonstrations, and case studies. The choice of the type of activities depends on the profile and preferences of each learner to ensure adaptive learning that suits their needs.

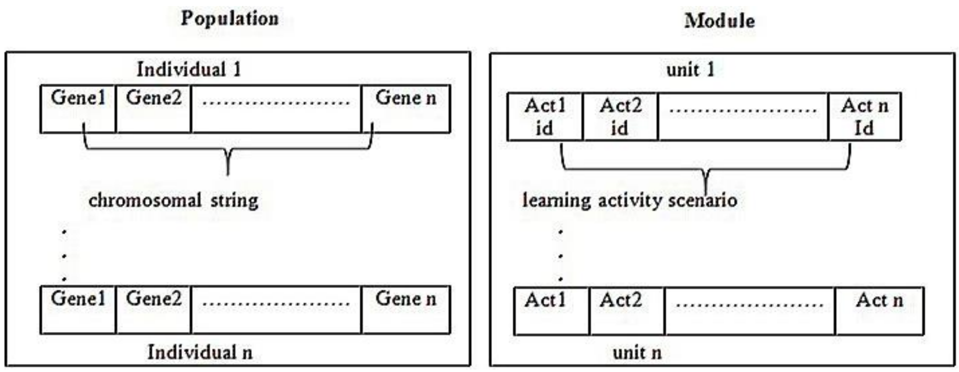


Figure 3. Representation method

3.2.2. Evaluation (fitness function)

To choose the best solution adapted to solving the learning problem, we must focus primarily on the definition of the fitness function, which evaluates the performance of the proposed solutions to judge the quality of the learning scenarios generated. The method of calculating the fitness function that we have chosen is based mainly on [11], this method is based on three levels: content, presentation, and media each level is evaluated separately. After, they will be combined to calculate the overall fitness.

$$F = F(s) + F(p) + F(m) \tag{1}$$

where F(s) is content’s fitness, F (p) is presentation’s fitness, and F (m) is media’s fitness

For each type of function, we have defined a set of parameters with a fixed weight that allows evaluation of the content, presentation, and the type of media used for the creation of the learning activities. The weight of each criterion is assigned according to an order of priority.

– Content fitness *F(s)* (2): represents the content of the proposed activity; its value is based on the level of difficulty and the duration of the activity as shown in Table 1. It is calculated by using (2).

$$F(s) = (Duration) * (level\ of\ difficulty) \tag{2}$$

Table 1. The criteria of content function

Function	Criterion	Value
Content f(s)	Duration	60 min (max)
	Difficulty level	
	Low	1
	Medium	2
	High	3

– Presentation fitness: The *F(p)* (3) function deals with the evaluation at the level of preferences and intentions of the learning objects as shown in Table 2.

$$F(p) = \sum \text{Weight}[preferences] * [intentions] \tag{3}$$

Table 2. The criteria of presentation function

Function	Criteria	Weight
Presentation F(p)	Preferences	
	Conceptual	1
	Example	2
	Case Study	3
	Simulation	4
	Demonstration	5
	Intentions	
	Search	1
	Investigation	2
	References	3
	Project	4
	Seminar	5
	Assessment	6

– Media fitness: The *F(m)* in (4) is equal to the summation of the weights media coefficients as shown in Table 3.

$$F\ (m) = \sum Weight\ of\ media \tag{4}$$

Table 3. The criteria of media function

Function	Types of media	Weight
Media f(m)	Text	1
	Audio	2
	Image	3
	Video	4

3.2.3. Selection

The selection strategy determines the choice of the chromosomes that will participate in the next-generation training. The selection operator is carefully formulated to ensure that better members of the population (with higher fitness) have a greater probability of being selected for mating or mutating, but that worse members of the population still have a small probability of being selected. There are several selection methods that offer solutions based on the principle of survival of the fittest [27]. In this work, we have used the tournament selection method. This type of selection is probably the most popular method due to its efficiency and simplicity of implementation In the selection of tournaments, n individuals are selected randomly from the large population; the individual with the best fitness function will be included in the next generation population [27].

3.2.4. Crossover

The crossover operator aims to combine two parents' chromosomes to generate better child chromosomes for the formation of the new generation. The individuals selected via the selection operation do not necessarily undergo the crossing operation which is carried out through a certain probability determined according to the problem concerned. The crossover allows innovation (children are different from their parents) and is based on the idea that two successful parents will produce better-performing children [28]. The most popular crossover methods are: 1) Single-point crossover, which represents the simplest and most classic operator of the crossing process in the genetic algorithm. It involves selecting randomly a cut of point for each pair of chromosomes and performing an exchange to create the children's genotypes, 2) two-point and k-point crossover, where several cut points are randomly selected to do an exchange between the different fragments of the chromosome. In this work, we used the Single-point crossover, but with three points of cuts (beginning, middle, and end) to ensure the diversity of the population over generations.

3.2.5. Mutation

The mutation is a random modification of the value of a gene that occurs with a fixed probability in order to introduce diversity into the population. Some most used mutations are changes in the value of a gene, transposition of two consecutive genes, transposition of genes on a chromosome, and inversion of the order of the genes between two sections. To solve the optimization problem in the proposed approach, the genetic algorithm represents an adaptive solution to the learning process through an e-learning system, due to its hierarchical structure (population, chromosome, and gene) which facilitates its implementation, also by the manipulation of the selection, crossover, and mutation operators.

4. RESULTS AND DISCUSSION

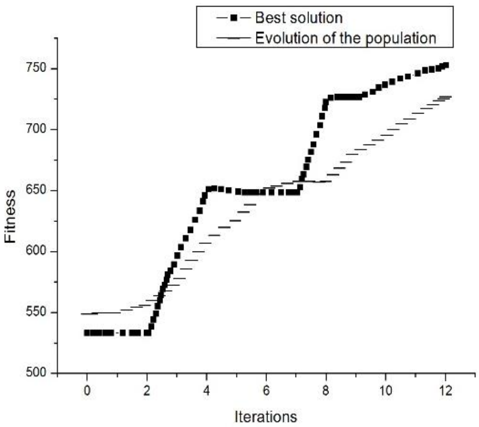
4.1. Numerical results

Before starting the learning process, it is essential to identify the learner's profile to ensure adaptive and dynamic learning. For each learner, we have proposed a diagnostic (pretest) to test the degree of competencies and also to have a global perception of the preferences and attitudes of the learners through the e-learning system. Depending on the answers to this pre-test, a personalized learning path will be proposed for each learner. As the first test, it is dedicated to the study of the performance of the results obtained by the GA. The various parameters used for the GA are presented in Table 4.

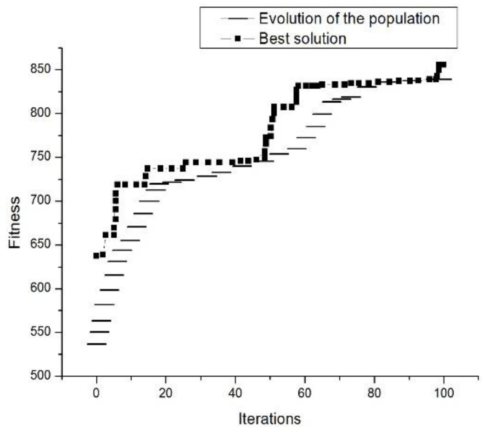
To validate the effectiveness of the proposed approach, we tested the program using two stop criteria: the value of the fitness function and number of iterations. The presentation of an adaptive learning scenario requires an analysis of the learner's profile. According to this analysis, the scenario covering a learner's needs has a fitness value equal to 756. For this reason, we have set this value as a stop condition for the program. Figure 4(a) shows the evolution of the population and the best solution according to the iterations. We can clearly realize the rapid convergence of the program towards the optimum by the increasing value of the fitness function because after only 12 generations we were able to obtain the solution that represents the optimal scenario.

Table 4. GA parameters

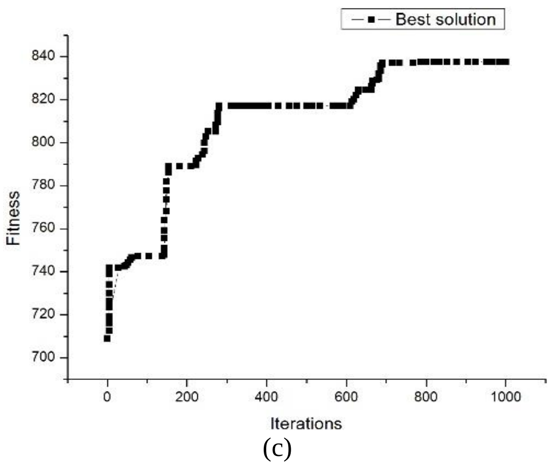
Programming language	Java
Number of iterations	100, 200, 300, 1000, 2000, 3000
Population size	10, 20, 100, 200,300
Crossover type	Single point (beginning, middle, end)
selection type	tournament selection
Mutation type	Randomly



(a)



(b)



(c)

Figure 4. Evolution of the optimal solution (a) fitness value as a stop criteria, (b) 100 iterations as a stop criteria, and (c) 1000 iterations as a stop criteria

To better illustrate the efficiency of the proposed approach we conducted a test with a population of 10 learning scenarios during 100 iterations as shown in Figure 4(b) and also with a population of 100 scenarios during 1,000 iterations as shown in Figure 4(c) at the end of the execution, we can notice the relevance of the solutions obtained through the fitness value. According to Figures 4(a) and 4(c), we can clearly identify the improvement of the quality of the proposed scenarios through the evolution of the fitness function value during the iterations.

This evolution has allowed us to have several possible scenarios proposed to the learners in order to enrich and diversify the learning process while respecting the profile of each learner. The optimal solution identified at the end of the iterations represents the best scenario to offer, thanks to its maximum value of the fitness function. The quality and performance of the solutions are measured by the evolution and diversity of the scenarios because in an adaptive learning system, it is essential to vary and improve the pedagogical content to satisfy all the needs of learners.

4.1.1. Comparative study

In e-learning, GA, PSO, and ACO are the most used optimization algorithms to find out an adaptive learning path; a comparative study has been done between these algorithms to show their effectiveness in terms of adaptability, diversity, evolution, and convergence to the optimal solution. We have applied the principle of the proposed approach to all three algorithms in order to identify the best choice for an adaptive learning system. For that, we made a test on a population of 100 (individuals, particles, and ants) during 1,000 iterations.

Based on the results obtained as shown in Figure 5, the numerical values do not encourage the use of PSO as an algorithm for this approach, because after only 100 iterations we do not detect a great improvement in the quality of the proposed solutions. On the other hand, we have noticed the stability of the solutions during several iterations (for example from 100 to 500 iterations) which show a lack of diversity in the learning scenarios. This problem decreases the choice of learning paths and does not favor adaptive learning that satisfies the diverse profiles of learners. So, the GA is more efficient at the level of the evolution of the best solution compared to PSO. Also, at the level of the convergence towards the optimal solution, we have noticed that at the end of the execution of the program, the value of the fitness function of the GA is more optimal than the PSO for a minimum duration (GA 847, PSO 836). These two values reflect the quality of the optimal solution.

ACO is considered to be one of the strongest optimization algorithms. We chose it in order to test its effectiveness in an e-learning system through adaptive learning. The results shown in Figure 6 are proposing an activity iteratively to build a complete learning scenario. For this purpose, we can clearly see the sequence of activities, starting with an activity with a low weight (activity 15) and ending with the most adaptive and effective one (activity 7) founded by ant number 34. The ACO has shown its performance in the convergence towards the optimal solution through the construction of a learning path with a minimal number of iterations which can cause better management of the execution time. The major advantage of this algorithm lies in its convergence towards the optimal solution; on the other hand, the desired diversity of the proposed scenarios is very limited, which again favors the genetic algorithm. We can conclude these results by Table 5, which compares the effectiveness of those algorithms at the level of adaptability, diversity, the evolution of population, and convergence toward the optimal solution in the context of adaptive learning.

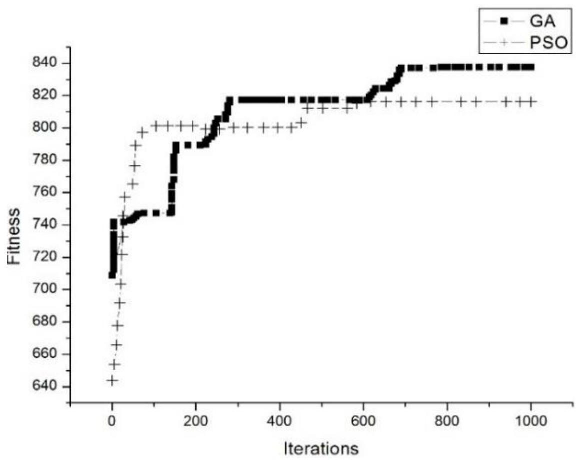


Figure 5. Comparative study between PSO and GA

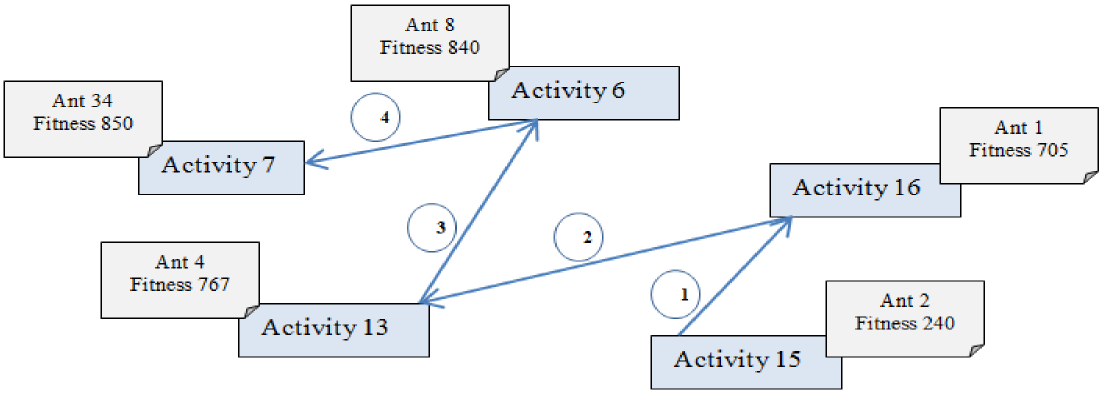


Figure 6. ACO results

Table 5. Comparative study

	AG	PSO	ACO
Adaptability	✓	✓	✓
Diversity	✓	×	×
Evolution	✓	×	✓
Optimal Solution	✓	×	✓

4.1.2. Improvement of the proposed approach

According to the results obtained from the GA, we have noticed that during a certain number of iterations the optimal solution remains constant during some generations and then a number of individuals are ignored after each iteration, which can decrease the performance of the program at the level of its evolution and the diversity of the obtained solution. The impact of this problem on the process of our approach, particularly on the quality of the proposed solutions, influences the diversity of the learning scenarios, because during a certain number of iterations these scenarios remain the same, as what is called a stagnation problem, therefore the choice of the various learning paths leading to the solution of the learning situation remains limited for a certain time before reaching the stop condition.

To remedy this problem, we propose the integration of a new genetic operator “genetic immigration operator” to improve the quality of the solution obtained in order to ensure the diversity of the proposed solutions, we are interested in improving the performance of the program by using a new GA adopting immigration strategy proposed by Tajani *et al*. [31] to solve the asymmetric traveling salesman problem (ATSP). The approach is based on a strategy of immigration solutions. After the crossover phase in the genetic algorithm process, we obtain two solutions: the best one is directly integrated with the next population but the second one is normally ignored. The immigration strategy offers an opportunity for these solutions to improve the quality of the results obtained. The immigration operator can work through two strategies as shown in Table 6 in order to benefit of the previous generations and some individuals that are not able to be introduced into the population. The first strategy is an improved genetic immigration algorithm (AIG) to choose the best individuals stored to replace the worst. The second strategy is the standard genetic immigration algorithm (SIG), based on a random choice of the individuals stored to replace the bad.

According to the graph in Figure 7, we can notice the effect of the integration of the immigration operator. Concerning the SIG which is based on a random choice of the stored solutions, we can evidently perceive the rapid convergence towards the optimal solution compared with UGA which remains constant during several iterations and decrease the diversity of the solutions, on the other hand, the AIG offers more relevant results than SIG and UGA at the end of the iterations thanks to the quality of the scenarios chosen and integrated into the new generation.

Table 6. Statistical results

	Nb of activities		Nb of learners		Complete the process		Abandoning the process	
	Grp 1 (GA)	Grp 2	Grp 1 (GA)	Grp 2	Grp 1 (GA)	Grp 2	Grp 1 (GA)	Grp 2
Situation 1	4	4	8	8	8	5	0	3
Situation 2	4	4	11	11	11	10	0	1

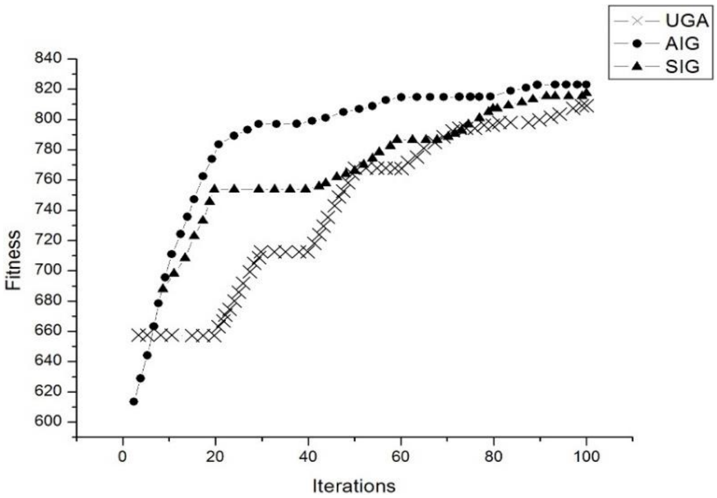


Figure 7. Comparative study between SIG, UGA, AIG

4.1.3. Experiments results

To test the proposed optimization method with the feature of adaptation, we conducted a real experiment with the learners. The idea is to develop a comparison with the method adopted for adaptive learning through the application of the genetic algorithm and the classical research method. We have chosen a sample of 30 primary school students to participate in this research for 1 month. After doing the registration process, learners were asked to follow the proposed learning scenario. We grouped the learners into two groups who received the same problem situation. The difference is that the first group received adaptive learning activities according to their needs, while the choice of activities for the second group was random. The objective of this comparison is to identify the number of learners who will be able to solve the problem situation using both methods. For each problem situation, we have designed activities that help learners to mobilize their resources to find a solution to the proposed problem. The genetic algorithm represented a solution for this type of learning. It allowed us to design adaptive scenarios for the learners. According to the results obtained during the last iteration. The optimal solution has formed the object of the mediatization of the activities following the criteria mentioned by the program such as level of difficulty, preference, intention, and type of media used. We evaluated the quality of our work by measuring and comparing the number of learners who were able to succeed in finding a solution to the proposed problem situation. Besides their success rate in resolving the situation, the number of learners who complete the scenario with all its activities is an index to measure learner engagement and motivation.

a. Design of the experiment

The experimental group of our study is composed of 30 learners from the primary cycle of the academic year 2020/2021. The problem situations proposed in mathematics aims to mobilize the learners' resources in the field of geometry, especially the characteristics of geometric forms and the exploitation of addition and multiplication operations. While the problem situation proposed in science aims to lead learners to build a balanced food system. A brief view of implemented optimization approach in the e-learning systems is shown in Figure 8.

Figure 8. Brief view of implemented approach

b. Results and interpretation

To test the effectiveness of the proposed approach an independent test was executed. The results of these analyses are shown in Table 6. As can be seen in Table 6, the rate of learner engagement for the first group who received adaptive activities is 100%. This shows the positive impact of the process adopted. In other words, the pedagogical and technological strategy that we have experienced has made the learning process through the problem-solving learning method more attractive and motivating. During the experimentation phase, two problem situations were presented to learners. According to the results obtained, the majority of the learners in the first group were able to solve the proposed situations following the scenarios presented as shown in Figure 9.

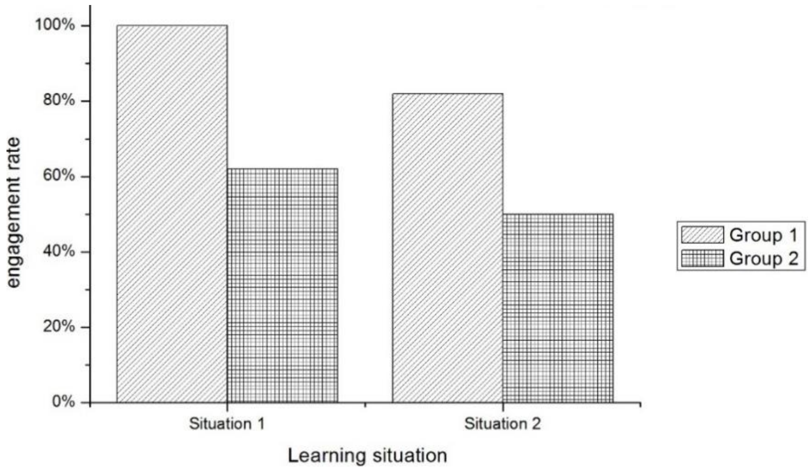


Figure 9. Comparing success rate

Based on the results of this experience, we can deduce that the strategy adopted for the resolution of the situation represented a favorable element for learning. First of all, by offering orientation activities, learners commit themselves to complete their learning process. This is shown by the number of learners who have completed the process of solving the situation. Otherwise, the pedagogical strategy adopted has helped to facilitate the situation and increase the rate of engagement among learners. Furthermore, the solutions proposed by the genetic algorithm, as an adaptive activity, made a difference in terms of resource acquisition and mobilization, as the majority of learners were able to solve the problem.

4.2. General discussion

The objective of this study is to ensure adaptive learning that encourages learner engagement via e-learning systems by using the problem-solving method as a field of application. The genetic algorithm favors the implementation of this approach thanks to its structure and its performance. The results obtained show the efficiency of the proposed approach through the evolution of the quality of the proposed scenarios. Each learning scenario consists of four activities with four parameters (content, preferences, intention, media) used to calculate the fitness function value that indicates the quality of the preferred scenarios. From the results, we have noticed that either with a minimum or a maximum number of iterations Figure 5 shows the quality of the evolving learning scenarios is improved, this improvement promotes the desired diversity in adaptive learning in order to cover the different needs of the learners. On the other hand, when we tested the same approach using the PSO algorithm, we did not achieve the same positive results at the level of the optimal solution and the evolution of the generated scenarios. This problem was clearly identified graph in Figure 6 which showed us similar solutions during several iterations that do not favor the desirable diversity. Regarding the ACO, it has shown its effectiveness in terms of convergence toward the optimal solution, but it does not offer us several learning paths such as the GA. We have thought of further improvement of the scenarios proposed by the GA in order to avoid the problem of stagnation noticed during some iterations, for that, we have used an immigration operator that takes advantage of the second scenario obtained after the crossing phase, this method is based on a random selection (SIG) or by order of merit according to the fitness function value (AIG).

The AIG method has approved a better result compared to the UGA and SIG because after a certain number of iterations the best stored scenarios will be integrated automatically to avoid the problem of stagnation and to ensure diversification and enrichment in the learning path. The principle of adaptive learning as an effective and efficient method to improve the quality of this process is based on the diversification and adaptation of the content to meet all the desires and preferences of the learners. These constraints have been identified in the results obtained by the GA. At the experimentation level, the results obtained showed the functioning and the effectiveness of the proposed approach through the rate of learner engagement and the number of learners who succeeded in solving the proposed problem.

The phase of the experimentation highlighted the new aspects of the obtained results. It showed the effectiveness of the proposed approach at the technical and pedagogical levels. The aim of the approach was to get learners to mobilize their resources and prerequisites in order to solve the proposed problem. This method is an active and effective learning process. The major pedagogical advantage of this approach is to ensure the motivation and engagement of learners through the scalarization of learning activities, the adoption of the problem-solving learning method, and the individualization of knowledge using the concept of adaptive learning. On the other hand, the integration of artificial intelligence technologies especially the GA was a solution to achieve the intended objective thanks to its functioning mechanism which can be easily adapted to the proposed problem. The results obtained in the form of learning scenarios provide a source for freeing the teaching staff from heavy planning tasks. In addition, the GA presented a diversity of results with a large choice of learning scenarios.

5. CONCLUSION

This paper describes a new approach to learning by solving problems based on the GA. The objective of this approach is to provide learners with a series of activities that are appropriate to their profiles in terms of their level of knowledge and preferences in order to help them to solve the proposed learning situation. We based our work on a multi-agent architecture. The results of the comparative study between the PSO, ACO, and GA show the effectiveness of the genetic algorithm, especially during the integration of the immigration operator. In order to evaluate the proposed optimization approach, we conducted a real test with learners in the primary cycle, through two problem situations. The experimental results confirmed the validity of the proposed method and the effectiveness of the GA through the rate of learner engagement and the number of learners who succeeded in solving the proposed problem. Regarding our perspective, in order to identify the learners' profiles, we propose to make the learning process more dynamic and adapt to the evolution of the learners by using machine learning.

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