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The Development of an Adaptive Group Composition System on Facebook for Collaborative Learning using an Artificial Bee Colony Algorithm

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Abstract: Facebook, the most popular social networking site, has recently been applied in a wide variety of fields for educational purposes. The social network site provides some social features such as communication methods, individual profiles, and personal posts that are shared with friends. Although learners can obtain lots of knowledge and improve their learning performance through discussions with friends in a social networking site, a learning group may not enhance learning performance in learning activities for specific courses. This study proposes an adaptive group composition system on Facebook to support adaptive group learning based on the background knowledge of individuals in a computer science project for college students. The system collects learner profile data automatically using Facebook and analyzes main course topics and professional abilities. This system utilizes an artificial bee colony algorithm to optimize group composing of students. Experimental results indicate that the proposed method improves the grouping process and enables students to achieve better performance.

Keywords: Facebook, Artificial Bee Colony, E-learning, Collaborative Learning, Group Composition

1 Introduction

Collaborative learning has attracted considerable attention in education research, and a large number of studies have applied related approach in a wide variety of educational contexts [1,2,3]. Collaborative learning facilitates the construction of knowledge via social interaction among individuals based on the constructivist theory of learning [4]. Learners can easily share their thoughts and opinions in a collaborative learning environment, which thus promotes a sense of participation and leads to a greater understanding of the learning content [5]. In the process of collaborative learning, learners who utilize social interactions to stimulate creative ideas between group members become contributors of collaborative knowledge construction [6].

Based on the rapid development of computer and network technology, an increasing number of studies have investigated the beneficial effects of computer-supported collaborative learning (CSCL) [7,8]. Dori and Herscovitz [9] stated that in web-based CSCL systems, students can ask their collaborators questions related to the learning contents; these questions can then be collected to design an appropriate post-test for learners. Liaw et al. [10] indicated that applying web-based collaborative learning systems for knowledge management can enable more learners to participate in the processes of discussing and sharing ideas, allowing them to work together to solve each others problems. Su et al. [2] proposed a Web 2.0 collaborative annotation system that allows learners to share individual annotations with collaborators, which facilitates the understanding of the learning content.

Social networking sites, such as Facebook, MySpace, and Plurk, are becoming increasingly integrated into the daily lives of many users, and are also being applied in educational contexts. Such sites allow individuals to create a profile that describes their backgrounds and interests, and connect with friends [11,12]. The integration of social networking services (SNS) and e-learning provides a platform for knowledge delivery

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and collaborative learning. Facebook, the largest such site, has already been applied in a wide variety of fields for education; it provides a well-prepared platform for instructors and students to communicate with each other.

Facebook has been widely accepted and applied in the educational field. Many studies have been conducted on the educational uses of Facebook, and research has shown that learners can construct knowledge, obtain meaningful educational experiences, and improve their thinking skills via online communities [13]. Blattner and Fiori [14] examined using Facebook to construct an environment for learning foreign languages. They allowed learners to interact with peers, instructors, and foreign speakers, with the results showing that it promoted authentic language interaction and socio-pragmatic competence via group discussions. In addition, Kabilan et al. [15] found that Facebook has some potential benefits with regard to improving students language skills and their motivation, confidence and attitudes towards English language learning. Learning in an online community facilitates the exchange of opinions, mutual engagement, the understanding of content, and consensus building [16]. Bosch [17] concluded that establishing educational micro-communities on Facebook has a number of potential benefits for both teaching and learning, as learners can share interests and ideas and take part in collaborative discussions in this context. For these reasons, Facebook is able to enhance the effects of collaborative learning and enable learners to construct knowledge more efficiently in a social community.

One of the key factors for enhancing the effect of collaborative learning is the composition of groups [18]. In conventional teaching, instructors utilize random grouping to construct a group, which may not meet the needs of the specific course since it does not consider whether all members of a group have related and necessary abilities; random grouping is thus likely to produce sub-optimal learning performance [19,20]. An effective group composition method should consider the needs of the course, learner interests, and individual abilities to increase students performance in collaborative learning.

In this study, an adaptive group composition system on Facebook is proposed to provide an adaptive collaborative learning group for a computer science project for college students. An effective group composition method should group learners who are interested in a specific project topic and have related abilities. The proposed system records learners interests and abilities automatically based on their behavior on Facebook, and then it utilizes an artificial bee colony algorithm to construct an optimal collaborative learning group based on the needs of a specific project.

2 Artificial Bee Colony (ABC) Algorithm

Karaboga [21] proposed the ABC algorithm, which employs swarm intelligence and a population that mimics the foraging behavior and interaction of real bees to solve optimization problems. The ABC algorithm has been shown to optimize a wide range of functions, and has been successfully applied to various fields, such as engineering science[22,23,24], and e-learning [25,26,27,28,29,30].

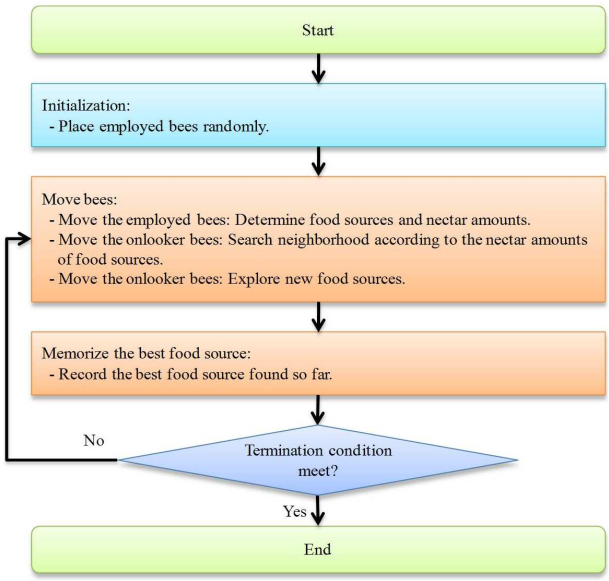

Fig. 1: Flow chart of the ABC algorithm.

In the natural world, a honey bee colony includes three types of bee, namely a queen, a few drones, and thousands of workers. The workers are in charge of foraging for the sources of nectar and share information about food sources with other bees in the hive. In the ABC algorithm, there are three types of artificial bee, namely scout bees, employed bees, and onlooker bees. Each kind of bee is responsible for executing its own mission. The process of gathering nectar is as follows. The main mission for the scout is looking for new sources of nectar. When a scout has found a new food source, it becomes an employed bee and stays there memorizing the position of the food source and searching its neighborhood. The employed bee then goes back to the hive and shares the position of the food source with the onlooker bees. Finally, when the onlooker bees have acquired the location of the nectar, they leave the hive to gather nectar. The procedure of the ABC algorithm is shown in Fig. 1.

First, N employed bees explore food sources randomly in the search space; the amount of nectar of the

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chosen food sources represents the calculated fitness value. Second, each employed bee goes to the chosen food sources in their memory, and then selects a new food source near the original one. Third, an onlooker bee moves to a food source area according to the probability P_i of food source selection:

$$P_i = \frac{F(\lambda_i)}{\sum_{k=1}^{E} F(\lambda_k)}, \quad (1)$$

where E is the number of employed bees, λ_i represents the position of the i^{th} employed bee, $F(\lambda_i)$ is the fitness value of the position of the i^{th} employed bee, $1 \le i \le E$, and P_i is the probability of the position of the i^{th} employed bee. The onlooker bee then chooses a new food source following Eq. (2) to determine the amount of nectar.

$$X_{id}(t+1) = \lambda_{id} + \phi(\lambda_{id}(t) - \lambda_{kd}(t)), \quad (2)$$

where t is the number of iterations, d is the dimension of the position, k is the randomly chosen employed bee, λ_{id} denotes the position of dimension d of the i^{th} onlooker bee, λ_{kd} is the position of dimension d of the randomly chosen employed bee, $\phi()$ is a random value in the range $[-1,1]$, $1 \le i \le E$, $1 \le k \le E$, and $1 \le d \le D$. Fourth, the food source is abandoned by the employed bee, when a solution representing a food source cannot be improved in a predetermined number of cycles, called limit. Then, the employed bee becomes a scout bee, and explores randomly to find a replacement for the abandoned food source. The scout moves according to:

$$\lambda_{id} = \lambda_{id_{min}} + \zeta(\lambda_{id_{max}} - \lambda_{id_{min}}), \quad (3)$$

where ζ is a random value and ζ is in the range [0, 1]. Finally, the system records the best fitness value found and the position of the food source. If the number of cycles reaches the termination condition, the process stops and the best results are recorded; otherwise, it goes back to the second step.

By mimicking the behaviors of foraging for food sources and interactions of real bees, the bees effectively derive the near-optimal food source for a large number of problems. In this study, ABC algorithm is used to search the suitable group according to an instructors needs. The considered criteria for the learning group are described in the next section.

3 Adaptive Group Composition Scheme

This study proposes a model that utilizes estimated criteria to represent variables in the learner profiles. The model includes two variables: (1) learners interests, and (2) learners professional abilities. The important variables used in the fitness function are defined in Table 1. Assume that the system database includes M learners, $L_1, L_2, \ldots, L_M$. The system selects N learners from database for a learning group. The N learners are a subset of M , $N \in M$, and s_i is a selected learner from a learning group based on the group composition system. There are some considered conditions for the learners interests. The system records a selected learner's browsing behavior, replies to comments, and clicks on the like button for specific newsfeed posts automatically to analyze his or her interests, using keywords to determine which of the newsfeed posts a learner views are relevant to a particular project. The relevance t_{ij} , $1 \le j \le P$, between the interest topic j in the viewed newsfeed posts for learner i and the project, is set to 1 if the interest topic j of learner i is related to the interest topic of the project, and 0 otherwise. The weight of the relevance t_{ij} is called w_{ij} , which is used to indicate the importance of the interest topic j of learner i to the interest topic of the project and is expressed by a percentage viewing posts with interest topic j . The degree of relevance μ between the interests of the learners and the specific project for the selected learners is:

Table 1: Variables used in the fitness function.

Variables	Meaning
s_i	The selection of a learner, $1 \le i \le M$.
w_{ij}	The weight of course topic of interest, $1 \le i \le M$, $1 \le j \le P$.
t_{ij}	The relationship between a interest topic of a learner and a project, $1 \le i \le M$, $1 \le j \le P$.
μ	The relational degree between the learners interests and the project.
l_i	The selected learner in a learning group, $1 \le i \le N$.
a_{ik}	The professional ability k of learner i, $1 \le i \le M$, $1 \le k \le Q$.
$T(a_{ik})$	The transformed function of professional ability k of learner i.
u_{ik}	The transformed professional ability value, $1 \le i \le M$, $1 \le k \le Q$.
φ	The relational degree between the professional ability of the selected learners and the needs of the project.
$F(s_i)$	A fitness function of the adaptive group composition scheme.

$$\mu = \frac{\sum_{i=1}^{M}(s_i \times (\delta - \sum_{j=1}^{P}(w_{ij}t_{ij}))}{N}, 1 \le i \le M, 1 \le j \le P, \quad (4)$$

where parameter δ is a constant which ensures that μ is reasonable.

In addition, the system analyzes the learners professional abilities automatically according to their posted information to select learners who have the abilities needed to complete a specific project. Assume that a learner has k abilities out of Q items of all professional abilities, $1 \le k \le Q$, and that each

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professional ability has a different ability value, a_{ik} . In addition, the total ability value of learners for a variety of professional abilities is represented by matrix A:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1Q} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2Q} \\ \dots & \dots & \dots & \dots & \dots \\ a_{N1} & a_{N2} & a_{N3} & \dots & a_{NQ} \end{bmatrix} \quad (5)$$

To select learners that are able to meet the needs of the project, the instructor defines the threshold of professional abilities for the various projects. If the ability value k of the learner is over the threshold, the professional ability k of the learner meets the requirements of this project. Then the transformed professional ability value u_{ik} is set to 1 using the transformation function $T(a_{ik})$; otherwise, it is 0. The transformation function is defined as:

$$T(a_{ik}) = u_{ik} = \begin{cases} 0, & a_{ik} < a_{threshold}, 0 \le a_{threshold} \le 1 \\ 1, & a_{ik} \ge a_{threshold}, 0 \le a_{threshold} \le 1 \end{cases}. \quad (6)$$

The total results of all the learners for a variety of professional abilities are represented by matrix U:

$$U = T(A) = \begin{bmatrix} u_{11} & u_{12} & u_{13} & \dots & u_{1Q} \\ u_{21} & u_{22} & u_{23} & \dots & u_{2Q} \\ \dots & \dots & \dots & \dots & \dots \\ u_{N1} & u_{N2} & u_{N3} & \dots & u_{NQ} \end{bmatrix}. \quad (7)$$

To determine the relevance of the professional abilities and learners, the degree of relevance φ for the selected learners and their abilities is obtained as:

$$\varphi = \frac{\sum_{i=1}^{M} (s_i \times (\theta - \frac{\sum_{k=1}^{Q} (T(a_{ik}))}{Q}))}{N}, 1 \le i \le M, 1 \le k \le Q, \quad (8)$$

where parameter θ is a constant which ensures that φ is reasonable.

The above formula is the fitness function of the adaptive group composition system model; it has two constraints. $F(s_i)$ is a fitness function for the adaptive group composition scheme. The fitness value for each learner is computed using the fitness function. Learner l_i with the lowest fitness value is selected by the adaptive group composition system. The formal definition of the adaptive group composition system model is:

$$F(s_i) = \frac{\sum_{i=1}^{M} (s_i \times (\delta - \sum_{j=1}^{P} (w_{ij} t_{ij})))}{N} + \frac{\sum_{i=1}^{M} (s_i \times (\theta - \frac{\sum_{k=1}^{Q} (T(a_{ik}))}{Q}))}{N}. \quad (9)$$

4 Framework of Proposed Adaptive Group Composition System

The adaptive group composition system is integrated into a web-based learning management system. The adaptive group composition system is developed on Facebook, as shown in Fig. 2. The system architecture consists of three main parts; the instructor side, the learner side, and the server system. With regarding to the instructor side, a teacher can create, edit, and design a course via the instructor management interface. In addition, the teacher can assign some learning subjects and set related parameters. A student group is automatically created by the adaptive group composition system. In the learner side, students can log into the course website to take part in the assigned learning task, and then discuss topics with their learning partners in the web-based collaborative learning environment.

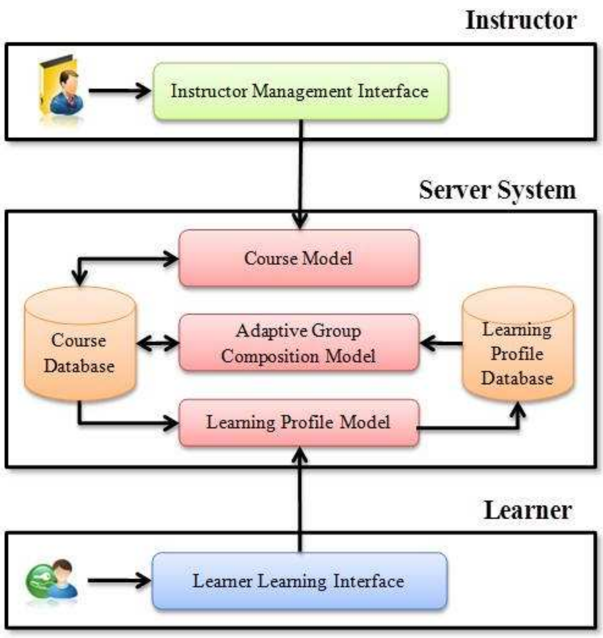

Fig. 2: Framework of the proposed adaptive group composition system.

The server system is in charge of accessing course resource, monitoring all learning activities, and helping teachers create a well-structured group via the instructor management interface. Keywords are used to determine which interests and professional abilities are associated with particular topics. The interests and professional abilities can be obtained from individual profiles. The interests of learners can also be acquired from their history of browsing specific topics or discussions with peers related to topics of interest. The professional

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abilities of learners can be determined from the number of published articles that are accepted or liked by peers. The server system monitors the completed learning activities and automatically records information related to interests and professional abilities.

The adaptive group composition system provides a user-friendly interface for the instructor, as shown in Fig. 3. The teacher can designate items of interests and professional abilities. After the settings have been adjusted, pressing “Result” creates a list of group members. The teacher can save the results.

Fig. 3: Instructor management interface for the proposed adaptive group composition system.

5 Experiment Results

A series of experiments was conducted under various scenarios to evaluate the performance of the proposed adaptive group composition system. The system was implemented on a personal computer with an Intel Core 2 Quad Q6600 2.4-GHz CPU, 2GB of RAM, and a 320 GB hard disk.

To investigate the performance of the adaptive group composition system under various scenarios, the database of learner profiles included ten data sets, with 400 to 4000 learners in each. Two control parameters of the ABC algorithm are the number of bees and the number of iterations. The number of bees was set to 20, 40, 60, 80 and 100, respectively. The maximum number of iterations was set to 500. In addition, *limit* for releasing a food source was fixed at 100.

A random search method was also used for comparison. The two search methods were executed 10 times for each data set. Fig. 4 and Fig. 5 show the fitness values and execution time values for the ABC algorithm and the random search method. The results in Fig. 4 demonstrate that the average best fitness values obtained by the random search method are around 0.9, and those obtained by the ABC algorithm are below 0.4. The execution time of the random search method was close to zero, whereas that of the ABC algorithm increased with the number of learners, bees, and iterations, but remained below 10 seconds for the conditions tested. The results indicate that the ABC algorithm outperforms the random search algorithm in terms of fitness value at the cost of execution time.

To determine the effect of population on the performance of the ABC algorithm, the number of bees was varied from 20 to 100. Fig. 6 and Fig. 7 show the fitness values and execution time values for various numbers of bees. The average best fitness values obtained using 100 bees were smaller than those obtained using 20 bees, but the difference did not exceed 0.05. The execution time of the ABC algorithm, it increased with the number of bees. The results demonstrate that the number of bees has only slight effect on the performance of the ABC algorithm.

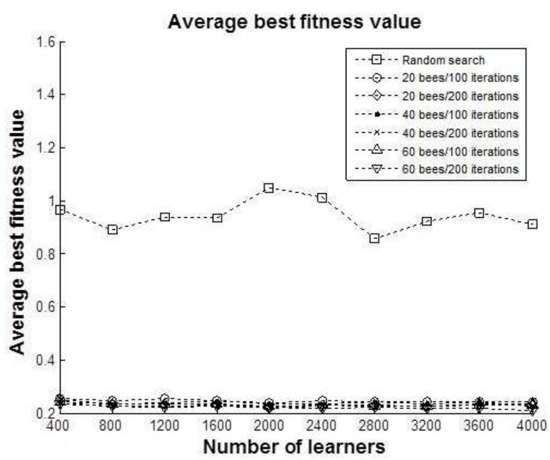

Fig. 4: Comparison of average best fitness values for the two search methods.

Finally, the effect of the number of iterations on the performance of the ABC algorithm was evaluated. The number of bees was fixed at 40, and number of iterations was varied from 100 to 500. Fig. 8 and Fig. 9 show the fitness values and execution time values for various numbers of iterations. When the number of iterations was at 100, the fitness value went down quickly to around 0.24. When the number of iterations was increased from

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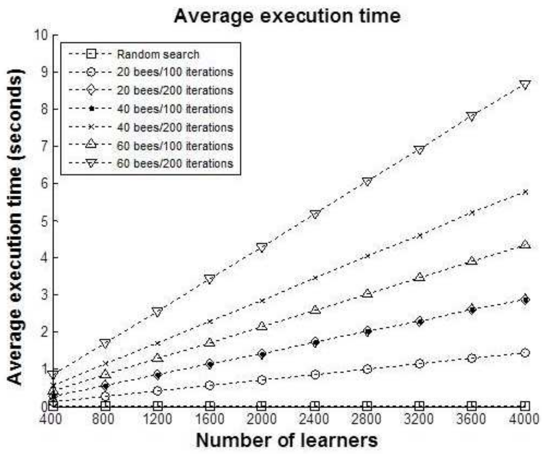

Fig. 5: Comparison of average execution time for the two search methods.

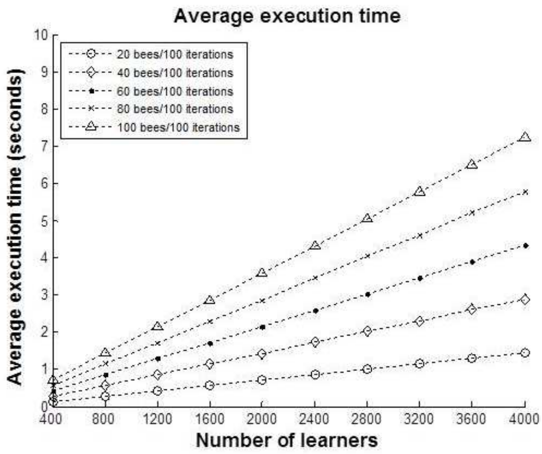

Fig. 7: Average execution time of 100 iterations and various numbers of bees.

100 to 500, the fitness value decreased slightly. The execution time increased linearly with the number of iterations. The results show that the ABC algorithm can reach the near-optimal solution in a small number of iterations.

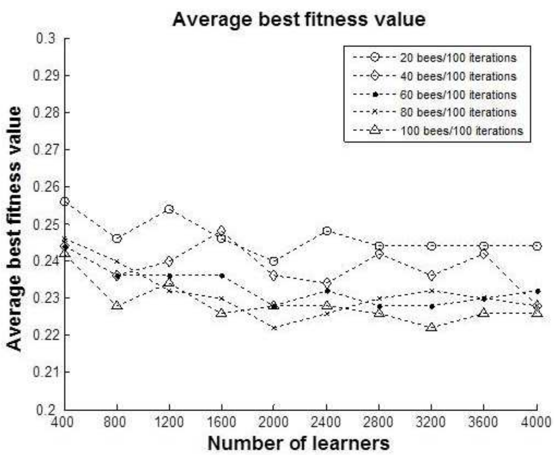

Fig. 6: Average best fitness values for 100 iterations and various numbers of bees.

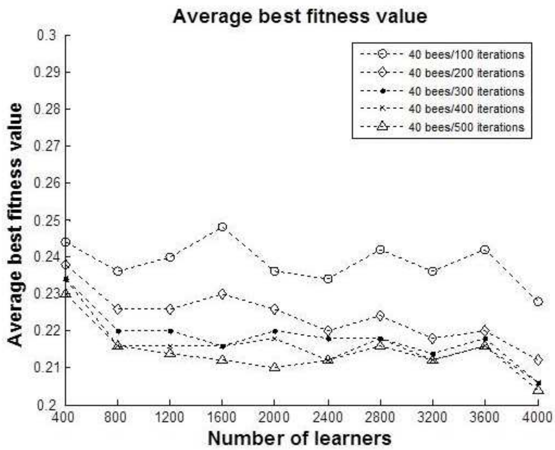

Fig. 8: Average best fitness values for 40 bees and various numbers of iterations.

6 Conclusions

This study utilized an artificial bee colony (ABC) approach to implement an adaptive group composition system built on Facebook for a collaborative learning environment. The adaptive group composition system can assist instructors in creating an adaptive learning group based on the knowledge of individual learners via social interaction on Facebook. To evaluate the performance of the proposed system, several experiments were conducted. The proposed method was compared to a random search method. The results reveal that the ABC approach can obtain a near-optimal solution more accurate than can a random search method. The ABC method produces results within a reasonable period of time. The results clearly indicate that the proposed system has a positive effect on learning activities and reduces the load of teachers. The future, the system will be integrated

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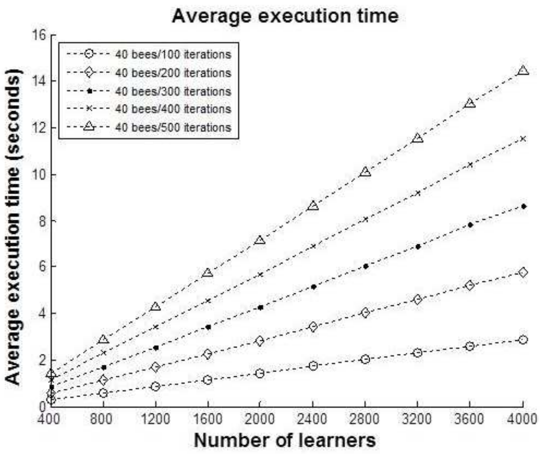

Fig. 9: Average execution time for 40 bees and various numbers of iterations.

into the learning activities to improve the performance of students in an online collaborative learning environment.

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