

Personalized Recommendation for Web-based Learning Based on Ant Colony Optimization with Segmented-goal and Meta-Control Strategies

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Abstract—Personalized web-based learning has become an important learning form in the 21st century. An earlier research result showed that a fuzzy knowledge extraction model can be established to extract personalized recommendation knowledge by discovering effective learning paths from an access database through an ant colony model. However, critical limitations arose when considering its applications in real world situations. In this paper, the aim is to improve the model by devising more efficient algorithms that requires a reasonable number of learners and training cycles to find satisfying good results. The key approaches to resolving the practical issues include revising the global update policy, an adaptive search policy and a segmented-goal training strategy. Based on simulation results, it is shown that these new ingredients added to the original knowledge extraction algorithm result in more efficient ones that can be applied in practical situations.

Keywords- *Web-based learning ;personalized recommendation; learning style; fuzzy set theory; ant colony optimization*

I. INTRODUCTION

As the explosion of information due to the Internet in modern age, it becomes more important and more difficult to retrieve information adapted to user preferences. Therefore, personalized recommendation systems are in need to provide proper recommendations based on users' requirements and preferences [10]. Recommendation systems also find their applications in the eLearning area, especially as personalized web-based learning has become an important learning paradigm in the 21st century. Since learning resources grow so abundant on the Internet that the problem of how to help learners get appropriate learning materials to fit their learning needs has become a popular research subject in the area of adaptive content delivery.

A challenging work of this research lies in how to discover recommendation knowledge efficiently from a huge access database of a web-based learning platform [1][2]. An earlier research of ours [6] showed that a fuzzy knowledge extraction model can be established to extract personalized recommendation knowledge by discovering effective learning paths from the access database through a novel approach that is inspired by the experience sharing mechanism of natural ants.

This approach imitates the experience sharing mechanism of natural ants, which share the paths they have found leading to food by scattering pheromone along the paths. In this approach, learners play the role of ants, scattering trail marks in a proper way according to their learning performances along the learning paths characterized by appropriate learning contexts. These trail marks can then be used to discover effective learning paths for learners with specific learning styles and competency.

However, though the research results [6] revealed the theoretical potential of the proposed method in discovering effective learning paths for learners, critical limitations arose when considering its application in real world situations, such as the requirement of a large amount of learners and a long period of training cycles in order to discover good learning paths for learners. That requirement is impractical for large classes in life and the reasonable time for a course to accumulate good learning experiences should be as short as possible. Therefore, the aim of this research is to resolve the aforementioned issues by devising more efficient algorithms that basically run on the same ant colony model yet requiring only a reasonable number of learners and training cycles to find satisfactory good results.

II. LITERATURE REVIEW

In the context of personalized recommendation on the Internet, web usage mining has been used as a potential approach to fulfill the requirement of web personalization [4][11][12][13][14][15]. In some commercial applications, the problem is approached by building an anticipation model through analyzing the content of items that a user has purchased in the past or were in his personal preference list. Sometimes, the items can be those in the user's navigation history. However, this content-based approach has several shortcomings and critical issues, including that only a very shallow analysis of specific kinds of content (text documents, etc.) are available; users can receive only recommendations similar to their earlier experiences; and the sparseness problem of item rating information [16][17].

On the other hand, in the approach of collaborative filtering [10], items are recommended to a particular user when other similar users also prefer them. The definition of ‘similarity’ between users depends on applications. For example, it may be defined as users having similar ratings of items or users having similar navigation behavior. However, a pure collaborative filtering system also has several shortcomings and critical issues, including that the coverage of item ratings could be very sparse, hence yielding poor recommendation efficiency; it is difficult to provide services for users who have unusual tastes; and the user clustering and classification problems for users with changing and/or evolving preferences [18].

As far as learning on the web is concerned, the experiences that learners have left need to be further distinguished into good and bad ones in terms of learning effectiveness. Therefore, the aforementioned approaches to personalized recommendation have to be extended in some way so that they can distinguish good experiences from bad ones in terms of some performance measurement. Another fact that distinguishes recommendation systems for eLearning from other fields is that intrinsic characteristics of a learner, such as learning style and competency, need to be considered to deliver appropriate contents to his/her needs. From this view point, our approach can deal with the recommendation problem for personalized learning by considering all the special demands in a seamless way.

Finally, a research area that relates to this research is the development of a new paradigm for computational optimization algorithms, called ACO (Ant Colony Optimization) in computer science. The ant algorithm proposed by Dorigo (1996) [9] generated an artificial wisdom (heuristic) which was developed based on the behavior of nature ants to control the direction of finding good solutions to optimization problems. Computational threads, called artificial ants, are executed separately to find solutions based on their individual states. At each move of an artificial ant, the choice is made in a certain probabilistic distribution, which is determined by a proper combination of a priori information of the structure of good solutions and a posteriori information of the structure of previously found solutions. A posteriori information of the structure of previously found solutions is accumulated by the amount of “pheromone” spread over the moves of the solutions previously found. The better quality of a found solution is of, the more pheromone it will spread over its moves. In order to avoid the phenomena of “local optimization”, evaporation of pheromone in a proper rate is allowed. It was also found that a global update of the pheromone amount along the moves of the best solution only is useful to speed the convergence of solutions.

Compared with the problem to be dealt with in this research, the problems to be solved by ACO algorithms are simpler in the sense that there is only one goal to be solved for all artificial ants, and the goal to be solved is independent of the internal states of the artificial ants during the search of solutions. In contrast, the problem addressed in this research considers different goals pursued by individuals with different and changing internal states. For example, a learner who is a beginner pursues a more achievable learning goal that is easier than the one pursued when s/he becomes an advanced learner.

III. THE ANT-COLONY MODEL

In the following, to facilitate a better understanding of the problem dealt with in this research, we first give a brief explanation about the term “learning experience”. Learning experience is defined as the sequence of resource accesses, where resources refer to those in a web-based learning platform that are helpful for student learning, such as contents, assessments, learning activities and so on. Another term for learning experience we use interchangeably here is “learning path”. Furthermore, “good” learning experiences refer to those that can help certain types of students (with specific learning styles and competency) to achieve significant improvement in learning performance. In other words, good learning experiences mean different for different types of learners. Finally, learning performance is assumed to be measurable by assessment tools such as those developed in [7]. Therefore, the “value” of a learning experience can be measured by the degree to which it can help students to improve their learning performance. Next, we present the main idea of our approach in the following sections.

In the context of web-based learning, learners learn through accessing online materials and doing self-assessments to evaluate their performance. Learners with different characteristics such as competency and learning styles may need different kinds of materials to meet their current learning needs. The problem here is how to provide appropriate recommendations for learners matching their individual characteristics so that they can learn to achieve optimal performance.

In this research, individual characteristics are described in terms of competency and learning styles. As for learning styles, categories developed by researchers can be represented as a discrete symbolic set like $\{L_1, L_2, L_3, L_4\}$ for the Kolb styles [3]. Competency is represented as a numerical value, coding the level of a learner’s proficiency in a certain concept of a specific domain. Furthermore, the competency level is divided into a fixed set of linguistic categories using fuzzy classifications. Without loss of generality, three linguistic categories of competency are used, that is, the “Novice”, “Experienced” and “Master”. For the limitation of the size of the paper, readers could refer to [19] for more details about fuzzy sets.

The problem is modeled as finding solution paths for different types of learners in a multiple-dimensional knowledge space consisting of nodes and edges, dictating the learning paths of learners with particular learning contexts, forming knowledge subspaces indexed by competency levels and learning styles. Specifically, each node in a knowledge subspace represents an online resource. An edge, labeled as e , linking from one node to another node represents the transition of the corresponding nodes caused by accessing a resource e . The knowledge space plays the role of recording, accumulating and sharing learning experiences with learner characteristics, including learner competency and learning styles, encoded appropriately.

For example, consider the knowledge subspaces illustrated in Figure 1, where a learner with learning style L_x and competency level c has the fuzzy competency levels

represented as $\mu_{\text{Novice}}(c) = 0.4$, $\mu_{\text{Experienced}}(c) = 0.8$, and $\mu_{\text{Master}}(c) = 0.2$. Suppose the learner is now in the knowledge node of $\{e\}$. When the learner accesses a resource f , it will lead him to the knowledge node of $\{f\}$. In this situation, the system will mark the learner's trail by adding an edge linking from $\{e\}$ to $\{f\}$ with a strength proportional to the learner's membership in the corresponding knowledge subspaces. After updating the trail marks in the knowledge subspaces, the learner's current state is relocated at the knowledge node of $\{f\}$. This event is called a "local" update of the trails in the knowledge subspaces.

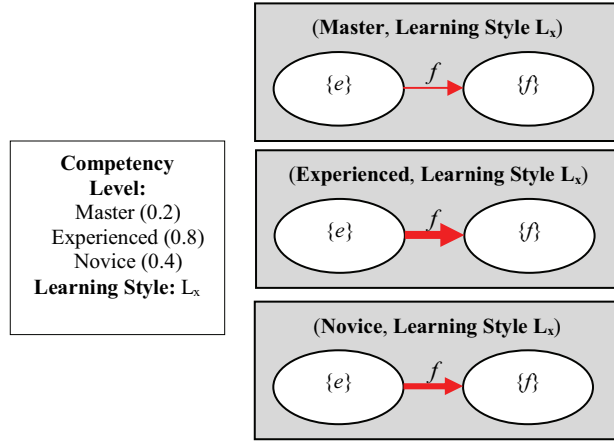


Figure 1. State transitions and local update in fuzzy knowledge subspaces.

Specifically, for a given learner x , the local update formula on the pheromone of an edge in a subspace S is given by (1):

Local update:

$$\begin{aligned} \tau &= (1 - \lambda)\tau + \lambda\Delta\tau \\ \Delta\tau &= \mu_s(x) * \tau_0 \end{aligned} \quad (1)$$

where τ is the current pheromone of an edge, λ is the evaporation parameter, $\Delta\tau$ is the change amount of pheromone, which is specified by $\mu_s(x)$ the user membership degree of the learner in the subspace S , and τ_0 is a fixed amount of pheromone.

On the other hand, Figure 2 shows how the trails in the knowledge subspaces are reinforced in the situation when changes of a learner's competency are affirmed through feedbacks obtained from either a self-assessment test or by a self-evaluation questionnaire. (It is assumed that learning styles are not changed during the learning course. Otherwise, the trail reinforcement also happens for changes of learning styles). Specifically, the edges of the path passed through in-between the change of learner states are updated in each knowledge subspace with an appropriate amount of trail marks dependent on the learner's membership in the corresponding knowledge subspaces. This is called a "global" update of the trails in the knowledge subspaces. The global update formula on the pheromone of a path in a subspace S is given by (2):

Global update:

$$\tau_{\text{path}} = (1 - \rho)\tau_{\text{path}} + \Delta\tau_{\text{path}} \quad (2)$$

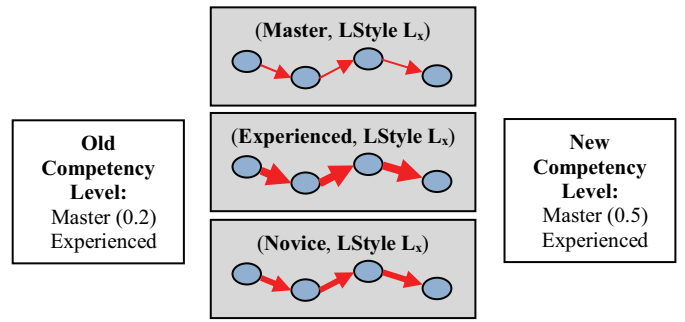


Figure 2. Learner state change and global update in fuzzy knowledge subspaces.

where τ_{path} is a set of pheromone values of the edges in a path, and ρ is the evaporation parameter, and $\Delta\tau_{\text{path}}$ is the change of pheromone values on the edges of the path, which is given by (3):

$$\begin{aligned} \Delta\tau_{\text{path}} &= \mu_S(x) * \Delta D \\ \Delta D &= \text{effectiveness} * \Delta Q \end{aligned} \quad (3)$$

where ΔQ is a constant value, and ΔD increases when the learner's performance (effectiveness) in that session is better. The effectiveness of a learner's performance can be defined in a certain form dependent on applications. For example, the competency estimated by the assessment tool developed in [7] can be used to measure the learner's performance.

Now, as far as personalized recommendation is concerned, a knowledge subspace provides recommendations for a learner of certain characteristics by considering the membership degree to which s/he belong to it and the knowledge node that s/he is currently in. The transitions (resource) that leads out from the current node in each subspace are candidates for recommendation, and they are associated with a strength (amount of pheromone) that is computed as the product of the transition strength and the membership degree of the learner in the subspace. Different recommendation policies can be used in this phase. For example, recommendations can be given by selecting the top R-ranked transitions under the transition strength, where R is a number chosen by the system designer.

IV. THE REVISED METHOD

As shown in [6], the method has the theoretical potential in discovering effective learning paths for learners. Table I shows one of the results.

TABLE I. NUMBER OF CYCLES REQUIRED FOR DIFFERENT EFFECTIVENESS AND NUMBERS OF LEARNERS [6]

Effectiveness	0.5	0.6	0.7	0.8	0.9
100 人	48	55	95	172	251
200 人	23	28	47	86	115
500 人	9	11	18	33	45
1000 人	5	6	10	17	33

However, critical limitations arose when considering its applications in real world situations. For example, for a large class of 100-200 students, it would take almost 300 training cycles to discover good learning paths for learners. Though increasing the number of students to 1000 might help, it is still impractical for real large classes in life, where the number of students is often limited by 200 to 300.

Three observations are worth mentioning from the research of [6]:

1. The more number of virtual ants involved, the sooner the network gets staged (the situation of being unable to improve paths easily).

2. Another fact is that during the searching of good paths, the memory of those good paths are apt to lost if more number of virtual ants are passing through them due to the local-update effect. This means that in certain situations, adding more virtual ants might cause the system to lose memory of its good paths due to the fading pheromone on the edges.

3. One last fact is that in situations of low global evaporation rates, newly found good paths are apt to hold the pheromones it had during global updates. That is, they tended to be dominated by their old states. In contrast, in situations of high global evaporation rates, newly found good paths are apt to be dominated by their current states.

The key approaches to resolving the practical issues will include (1) revising the ant exploration and global update policy, (2) adopting segmented-goal training strategy, and (3) adopting an adaptive randomness control policy. In the following, we describe the rationale behind each new approach to solving the practical issues of the problem.

A. Revise the ant exploration and global update policy

The original global update policy is to activate the global update mechanism once a virtual ant has produced its evaluation feedback. That is, the system updates the pheromone trail using all the solutions produced by the ant colony. As indicated in [8][9], it would be more effective if only the best solution found since the beginning of the computation is used to globally update the pheromone, since it avoids long convergence time by directly concentrate the search in a neighborhood of the best path found up to the current iteration of the algorithm.

B. Adopt segmented-goal training strategy

It was also observed in [6] that the length of the goal path also affect the convergence time of the algorithm. As the length increased, the convergence time also increased in an exponential way. To handle this problem, one possible way is to divide a learning session into more but a reasonable number of stages, with a sub goal specified in each stage.

C. Adopt an adaptive randomness control policy

In our previous work [6], the exploration policy is a two-fold decision. First, a random number in-between 0 and 1 is generated, and if it is larger than a threshold (say 0.1) the virtual ant would explore a visited neighboring node according

to the accumulated probability distribution formed from the out-going edge weights of its current knowledge node. Otherwise, it will randomly choose an unvisited neighboring node. In other words, the decision about whether to explore a new edge or follow existing good (more weighted) edges is determined by a randomness control parameter, which was set to 0.1.

The original exploration policy in [6] may incur another problem when quality of the good paths is in good situations. In that circumstance, it should be better to deterministically follow the edges of the paths. On the other hand, when the quality of the good paths is poor, exploration of unvisited edges should be encouraged. Therefore, the new ant exploration policy is updated so that it will prefer choosing best nodes if the quality of the current best paths is good enough. To achieve this goal we adopt the “value” of the best-found solutions computed by (5) as an indicator of the system’s solution quality.

V. DESIGN OF SIMULATION

To investigate whether the proposed method is useful for extracting effective recommendation knowledge, a simulation program was developed that simulates learners of different competency levels and learning styles exploring a web-based knowledge space consisted of material documents based on the aforementioned path finding model. In one simulation run, simulated learners explore the knowledge space by receiving system recommendations of documents or choose a document as they wish to explore. The decision about whether to explore a new edge (document) or follow existing edges (documents) is determined by a randomness control parameter, which can be fixed (say 0.1) or adaptive.

In the program, we predefined a set of “good” learning paths to be found for simulated learners of different competency levels and learning styles. The competency of a simulated learner gets an increment to a degree proportional to the similarity between its current learning path and the “hidden” good learning paths. The increment of competency will be fed back to the ant colony model according to the global update mechanism. In particular, the similarity between a learner’s learning path and a “hidden” good learning path is calculated as follows [5]:

$$\text{Similarity} : S = S_1 + S_2 + \dots + S_i + \dots + S_n$$

$$\text{hidden good path} : X = X_1 X_2 \dots X_j \dots X_n$$

$$\text{user's path} : Y = Y_1 Y_2 \dots Y_i \dots Y_m$$

$$\text{for } i = 1, \dots, n,$$

$$(1) \exists j, j = 1, \dots, m, \text{ such that } X_i = Y_j \text{ and } i = j \Rightarrow S_i = \frac{1}{n}$$

$$(2) \exists j, j = 1, \dots, m, X_i = Y_j \text{ but } i \neq j \Rightarrow S_i = \frac{1}{n} * \frac{1}{|i - j|}$$

$$(3) \forall j, j = 1, \dots, m, X_i \neq Y_j \Rightarrow S_i = 0$$

As a result, for a learner with a learning path of $Y = Y_1 Y_2 \dots Y_i \dots Y_m$, its effectiveness regarding to the hidden good path of $X = X_1 X_2 \dots X_j \dots X_n$, is defined as (5):

$$effectiveness(s, A) = \mu_A(s) \times Sim, \quad (5)$$

where $\mu_A(s)$ is the degree that the learner belongs to the subspace of competency level of A .

The simulation program runs iteratively for a number of training cycles, and in each cycle a virtual learner can give a number of self-evaluation feedbacks as is given by (5) to the system. The effectiveness of one simulation run is defined as the best similarity between user learning paths and the “hidden” good paths.

VI. RESULTS AND DISCUSSION

The simulations are run under different combinations of strategies and parameter settings. Specifically, the ant number can be 50, 100, and 200; and the GE (Global Evaporation) rate can be 0.01, 0.1 and 0.9; and the goal structure can be single-goal or segmented-goal; and the meta-control for search can be fixed or adaptive. The local evaporation rate is set to 0.01 for all simulations. All the simulations are run within 100 cycles and three times of intermediate feedbacks for each cycle. The size of the search space is determined by 30 resource items with the maximum length of the goal sequence set to 10.

Figure 3 shows the effectiveness of the algorithm under “fixed” randomness control and single-goal strategies with different number of ants (50, 100, 200) and GE settings (0.01, 0.1, 0.9); while Figure 4 shows the effectiveness of the algorithm under “adaptive” randomness control and segmented-goal strategies with the counter-parameter settings. From the figures, it can be seen that the algorithms get convergent quite fast, and as is common in ACO algorithms, the phenomena of “stagnation” appears in the algorithms. It also seems that different combinations of the ant number and GE settings have higher impacts on the effectiveness for algorithms under “adaptive” randomness control and segmented-goal strategies than those under “fixed” randomness control and single-goal strategies.

To further investigate the effect of the proposed strategies on the effectiveness of the algorithms, look at Figures 5-7. From Figure 5, it can be seen that under the fixed randomness control strategy, the algorithm equipped with segmented-goal strategy works comparable with the one equipped with the single-goal strategy.

From Figure 6, it can be seen that under the adaptive randomness control strategy, the new algorithm equipped with segmented-goal strategy outperforms the one equipped with the single-goal strategy in effectiveness.

From Figure 7, it can be seen that the new algorithm under the segmented-goal and adaptive randomness strategies has higher effectiveness than the one with the single-goal and fixed randomness strategies.

Furthermore, as shown in Table II and III, the new algorithm under the segmented-goal and adaptive randomness strategies requires few cycles than the one with the single-goal and fixed randomness strategies. And they are both much better than the original one reported in [6], as shown in Table I. As a result, the combinations of the new ingredients added to the

original knowledge extraction algorithm can result in more efficient algorithms in the long run.

VII. CONCLUSION

In this paper, an improved ACO algorithm is devised to handle the problem of personalized recommendation for Web-based learning. It was verified through simulation that the segmented-goal training and meta-search control strategies proposed in this paper are useful for extracting personalized recommendation knowledge with a smaller amount of learners and training cycles. This makes our algorithm more suitable for practical situations. In the future, we will conduct experiments on real students to investigate its effectiveness in sharing good learning experiences among learners.

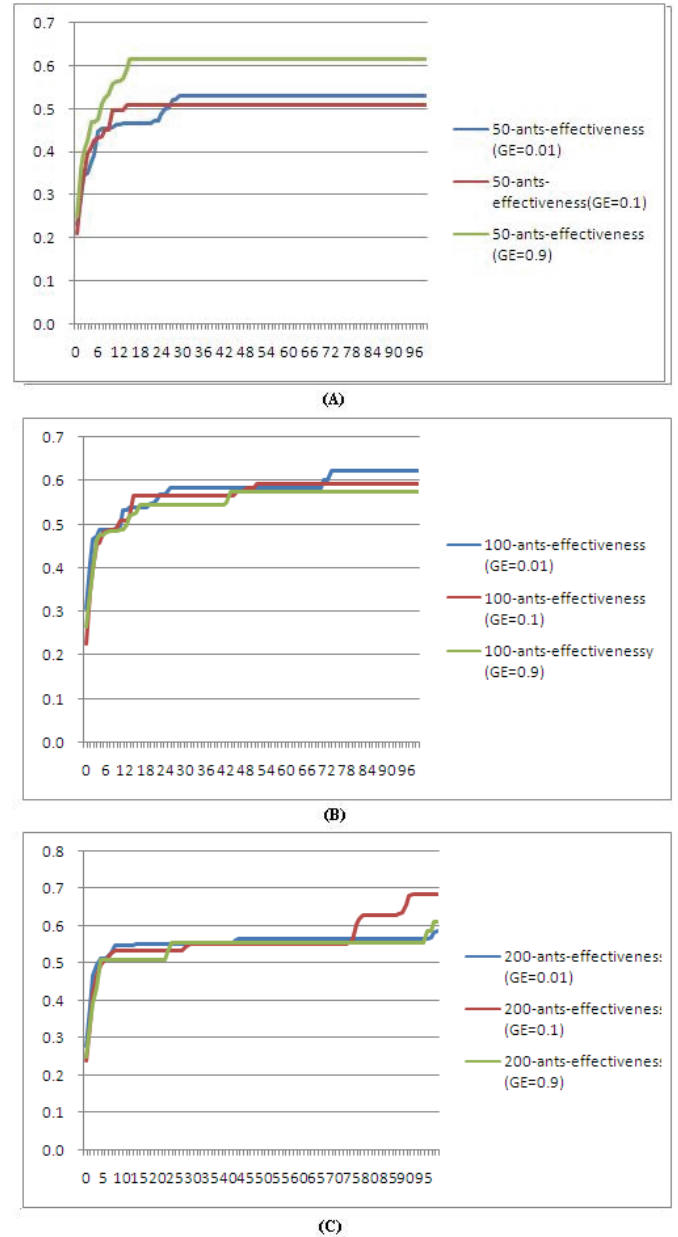
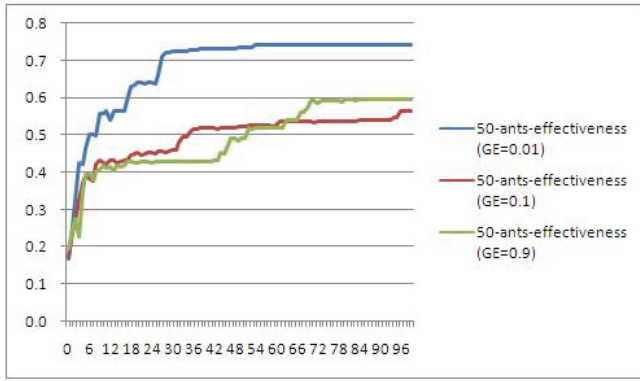
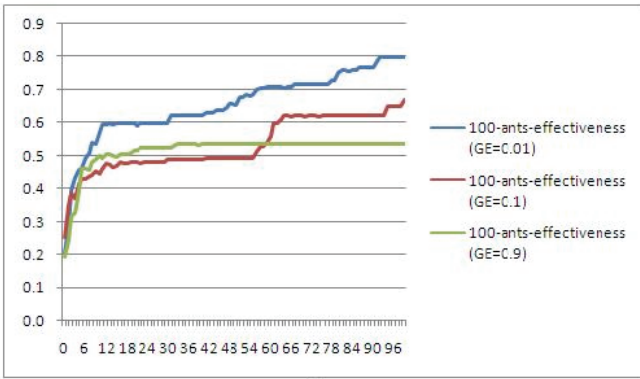


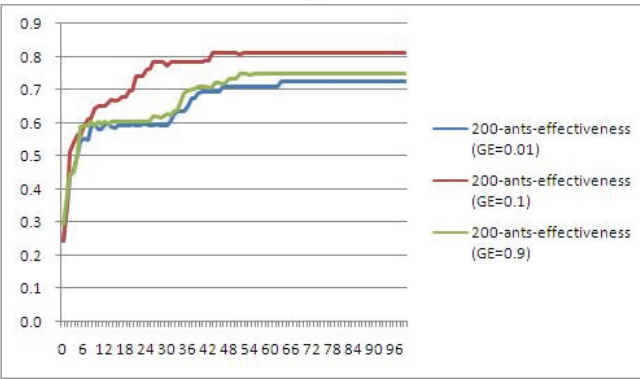
Figure 3. The performance under “fixed” randomness control and single-goal strategies with different number of ants and GE settings.



(A)



(B)



(C)

Figure 4. The performance under “adaptive” randomness control and segmented-goal strategies with different number of ants and GE settings..

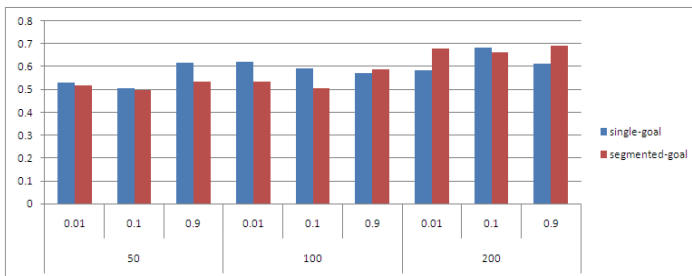


Figure 5. The performance under “fixed” randomness with single-goal and segmented-goal strategies.

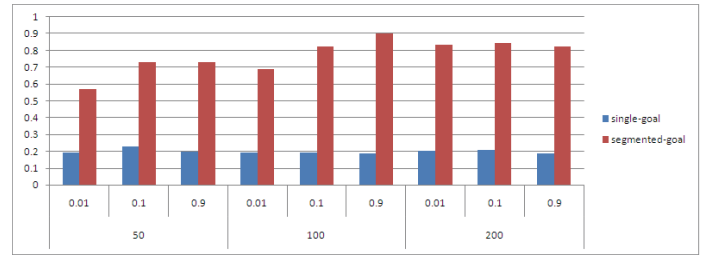


Figure 6. The performance under “adaptive” randomness with single-goal and segmented-goal strategies.

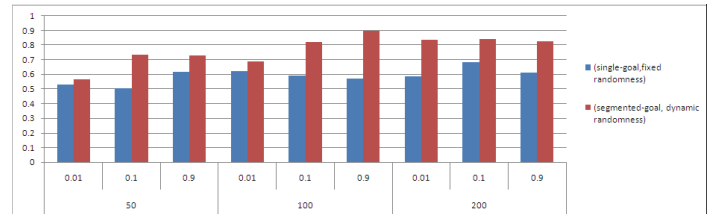


Figure 7. The performance under (single-goal, fixed randomness) and (segmented-goal, adaptive randomness) strategies with different number of ants (50, 100, 200) and global evaporation rates (0.01, 0.1, 0.9).

TABLE II. NUMBER OF CYCLES REQUIRED FOR DIFFERENT EFFECTIVENESS AND NUMBERS OF LEARNERS FOR THE ALGORITHM UNDER (SINGLE-GOAL, FIXED RANDOMNESS) CONFIGURATIONS WITHIN 100 CYCLES

Effectiveness	0.5	0.6	0.7	0.8	0.9
50 人	8	15	-	-	-
100 人	3	15	-	-	-
200 人	3	15	91	-	-

TABLE III. NUMBER OF CYCLES REQUIRED FOR DIFFERENT EFFECTIVENESS AND NUMBERS OF LEARNERS FOR THE ALGORITHM UNDER (SEGMENTED-GOAL, ADAPTIVE RANDOMNESS) CONFIGURATIONS WITHIN 100 CYCLES

Effectiveness	0.5	0.6	0.7	0.8	0.9
50 人	6	10	27	-	-
100 人	5	12	49	81	-
200 人	4	5	11	25	-

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