Incorporating Psychology Model of Emotion into Ant Colony Optimization Algorithm

Jiann-Horng Lin
Department of Information Management
I-Shou university,Taiwan

Meei-Ru Lin
Department of Biomedical Laboratory Science,
Kaohsiung Medical University, Taiwan

Chain-Hao Lee
Department of Information Management
I-Shou University,Taiwan

Abstract: - This paper presents a modification of the ant colony optimization algorithm (ACO) intended to introduce psychology factor of emotion into the algorithm. We define only two emotions ants could have, positive and negative, and correspond to two reaction to perception respectively. For avoiding premature convergence allows Emotional Ant Colony Optimization (EACO) to continue search for better even best optimization in difficult optimization problems, reaching better solutions than ACO with a faster convergence speed.

Key-Words: - Ant Colony Optimization, Emotional Ant Colony Optimization, Psychology Model

1 Introduction

Swarm intelligence research originates from work into the simulation of the emergence of collective intelligent behaviors of real ants [1,2,3]. Ant colony optimization (ACO) is an optimization computation inspired by the behavior of natural ants that succeed in finding the shortest paths from their nest to food. Ants deposit a chemical substance while traveling.
This substance carries information and is called pheromone. Biologist found that the movement of individuals was heuristic during a long term observation of ants. When ants run into a new branch, they will choose a path randomly. It is a simple stochastic model that adequately describes the dynamics of the ant colony [4,10].

2 The Ant Colony Optimization

Ant colony algorithms are becoming popular approaches for solving combinatorial optimization problems. Biologist found that the movement of individuals was heuristic during a long term observation of ants. When ants run into a new branch, they will choose a path randomly. It is a simple stochastic model that adequately describes the dynamics of the ant colony.

The fundamental idea of ant heuristics is based on the behavior of natural ants that succeed in finding the shortest paths from their nest to food sources by communicating via a collective memory that consists of pheromone trails. As a result of ant's weak global perception of its environment, each ant moves essentially at random when no pheromone is available [6].
Ants deposit the pheromone about the information which contain the length of the path (Fig 1.). The path length is longer, the intensity of pheromone is lesser.
In AS, m (artificial) ants concurrently build a tour of the TSP. Initially, ants are put on randomly chosen cities. At each construction step, ant k applies a probabilistic action choice rule, called random proportional rule, to decide which city to visit next. In particular, the probability with which ant k, currently at city i, chooses to go to city j is

$$p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, \quad if\ j \in N_i^k \qquad (1)$$

where $\eta_{ij} = 1/d_{ij}$ is a heuristic value that is available a priori, α and β are two parameters which determine the relative influence of the pheromone trail and the heuristic information, and N_i^k is the feasible neighborhood of ant k when being at city i, that is, the set of cities that ant k has not visited yet (the probability of choosing a city outside N_i^k is 0). By this probabilistic rule, the probability of choosing a particular arc (i,j) increases with the value of the associated pheromone trail τ_{ij} and of the heuristic information value η_{ij} The role of the parameters α and β is the following. If α= 0, the closest cities are more likely to be selected: this

corresponds to a classic stochastic greedy algorithm (with multiple starting points since ants are initially randomly distributed over the cities). If β=0, only pheromone amplification is at work, that is, only pheromone is used, without any heuristic bias. This generally leads to rather poor results and, in particular, for values of $\alpha > 1$ it leads to the rapid emergence of a stagnation situation, that is, a situation in which all the ants follow the same path and construct the same tour, which, in general, is strongly suboptimal [4].
After all the ants have constructed their tours, the pheromone trails are updated. This is done by first lowering the pheromone value on all arcs by a constant factor, and then adding pheromone on the arcs the ants have crossed in their tours. Pheromone evaporation is implemented by:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \quad \forall (i,j) \in L, \tag{2}$$

where $0 < \rho \leqq 1$ is the pheromone evaporation rate. The parameter ρ is used to avoid unlimited accumulation of the pheromone trails and it enables the algorithm to "forget" bad decisions previously taken. In fact, if an arc is not chosen by the ants, its associated pheromone value decreases exponentially in the number of iterations. After evaporation, all ants deposit pheromone on the arcs they have crossed in their tour:

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \quad \forall (i,j) \in L, \tag{3}$$

where $\Delta\tau_{ij}^{k}$ is the amount of pheromone ant k deposits on the arcs it has visited. It is defined as follows:

$$\Delta\tau_{ij}^{k} = \begin{cases} 1/C^{k}, & \textit{if arc}(i,j)\,\textit{belongs to}\,T^{k} \cdot \\ 0, & \textit{otherwise}; \end{cases} \tag{4}$$

where C^k, the length of the tour T^k built by the k-th ant, is computed as the sum of the lengths of the arcs belonging to T^k. By means of equation (2), the better an ant's tour is, the more pheromone the arcs belonging to this tour receive. In general,arcs that are used by many ants and *which* are part of short tours, receive more pheromone and are therefore more likely to be chosen by ants in future iterations of the algorithm [4].
Ants can smell the pheromone and they tend to choose, probabilistically, paths marked by strong pheromone concentrations.

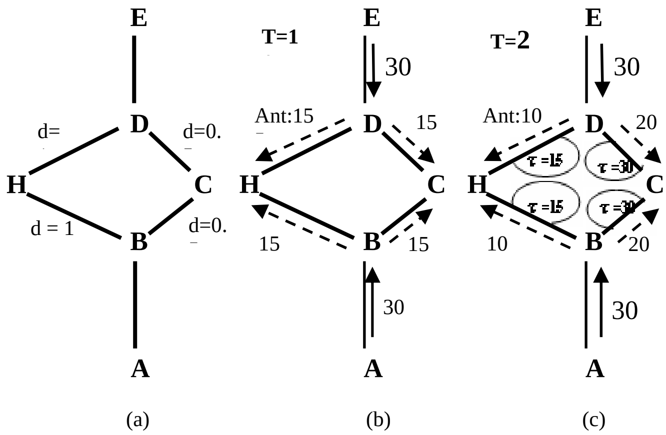

Fig 1. The pheromone deposite of ants

3 Emotion ACO

A. Psychology Method

In psychology, emotion is considered a response to stimulus that involves characteristic physiological changes—such as increase in pulse rate, rise in body temperature, etc. Weber, the first psychologist who quantitatively studies the human response to a physical stimulus, found that the response was proportional to a relative increase in the weight.
By Weber-Fechner Law, the relationship between stimulus and perception is logarithmic. This logarithmic relationship means that if the perception is altered in an arithmetic progression the corresponding stimulus varies as a geometric progression. That is to say, if the weight is 1 kg, an increase of a few grams will not be noticed. Rather, when the mass in increased by a certain factor, an increase in weight is perceived. If the mass is doubled, the threshold is also doubled. This kind of relationship can be described by a differential equation as:

$$dp = k\frac{dS}{S} \tag{5}$$

where dp is the differential change in perception, dS is the differential increase in the stimulus and S is the stimulus at the instant. A constant factor k is to be determined experimentally.
Integrating the above equation

$$p = k \ln S + C \tag{6}$$

with C is the constant of integration, ln is the natural logarithm. To determine C, put p = 0, i.e. no perception; then

$$C = -k \ln S_0 \qquad (7)$$

where S_0 is that threshold of stimulus below which it is not perceived at all, and can be called Absolute Stimulus Threshold (AST).
Therefore, the equation becomes[7]:

$$p = -k \ln \frac{S}{S_0} \qquad (8)$$

The pheromone is stimulus to ants, so we decide to use p to improve the path selection of ant.
We define only two emotions ants could have, positive and negative, and correspond to two reaction to perception respectively as follow:

$$\text{IF}\,(\text{random}() < e_s)\ \text{THEN}\ \textit{positive}$$
$$\text{ELSE}\ \textit{negative}$$

The emotion of ants can determine by es. We determine ant's emotion at random in order to make the emotional system more unpredictable. If the ant is in positive situation, it will exploit the path of high pheromone intensity in higher probability. On the contrary, if the ant is in negative situation, it will exploit other path with lower pheromone intensity in higher probability.

B. Propose Method

In ACO, pheromone is the stimulus to ants. We want using the psychology parameter r to influence the probability of path selection according to emotion of ant.
Assume the ants have psychology; thus we can introduce the models mentioned before to improve ACO's performance. The ant can sense the stimulus from the best trail whole ant colony ever arrived, and it can also feel the difference from other ants. When the stimulus can cause noticeable perception, which is much bigger than threshold, the particle will respond to the stimulus strongly. On the other hand, the stimuli will be compared with the history it ever experienced. As we have discussed in psychology model, if the history value is also very high, the respondence will not be very notable. Along with pheromone and time, the emotion state of ant will change.
Here are two only two emotions ants could have, positive and negative, and correspond to two reactions to perception respectively. The perception of ants can be described by following:

$$r = k \ln \frac{\tau_{ij}}{\tau_{MAX}} \qquad (9)$$

where r is the perception from pheromone, the pheromone τ of path (i,j) means the stimulus, τ MAX means stimulus threshold. And the emotional effect can be described by following:

$$\text{Positive: } p_{ij}^k = \frac{[\tau_{ij} * r]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, \quad \textit{if } j \in N_i^k, \qquad (10)$$

$$\text{Negative: } p_{ij}^k = \frac{[\tau_{ij}]^\alpha [\eta_{ij} * r]^\beta}{\sum_{l \in N_i^k} [\tau_{il}]^\alpha [\eta_{il}]^\beta}, \quad \textit{if } j \in N_i^k \qquad (11)$$

Emotion process:
Step 1. Decide the emotion of ant.
Step 2. Calculate the perception from stimulus
Step 3. Using parameter r to influence the path selection of ant

4 Simulation Results

In this section, we try to highlight differences in performance among ACO algorithms by running computational experiments on instances available from TSPLIB benchmark library. Most of the TSPLIB instances are geometrict TSP instances, they are defined by the coordinates of a set of points and distance between these point is computed according to metric.
The simulation results show that the proposed method can provide greater efficiency and satisfactory accuracy.
According to Fig 2,4,6 we can see that AS has premature convergence, and our EAS with various parameter k and emotion factor es has better performance. In fig 3,5, these figures in average tour length experiments show that the path search of AS is easy to sink in suboptimal. And the EAS has more adventureful exploration, for this reason, we can avoid the suboptimal and continue to find better even best solution.Furthermore, in Fig 6, we examine the suitable combination parameter with k=-0.5 and e_s=0.5 on,eil51, TSP instance, to compare with AS, the quality of solution is more accuracy than AS.

5 Conclusion

In this paper, we introduced a modified ant colony optimization by combining psychology model with ACO. Each ant calculates its emotion before path selection. The introduce of the model makes ant colony have the ability of self-adapting during the progress of exploring.

From experiment results, the modified ACO could avoid premature convergence successfully. The psychology model allows EACO to continue search for better even best solution in difficult optimization problems, reaching better solutions than ACO.

References:

[1] S. Zheng, G. Zhang and Z. Zhou, Ant Colony Optimization based on Pheromone Trail Centralization, *Proceedings of the 6th World Congress on Intelligent Control and Automation, June 21 - 23*, 2006.

[2] M. Dorigo, and L-M Gambardella, Ant Colony System: A Cooperative Learning Approach to the Traveling Salesman Problem, *IEEE Transactions on Evolutionary Computation, VOL. 1, NO. 1,* APRIL 1997.

[3] M. Mouhoub and Z. Wang, Ant Colony with Stochastic Local Search for the Quadratic Assignment Problem, *Proceedings of the 18th IEEE International Conference on Tools with Artificial Intelligence,* 2006.

[4] M. Dorigo and T. Stutzle, *Ant Colony Optimization*, 2004.

[5] V-S Hernaindez and A. Weitzenfeld, Ant Colony Algorithm for Swarm Systems, *Robotics Symposium, 2006. LARS* '06.

[6] J. Pan and D. Wang, An Ant Colony Optimization Algorithm for Multiple Traveling Salesman Problem, *Proceedings of the First International Conference on Innovative Computing, Information and Control (ICICIC'06)*, 2006.

[7] G. Yang and R. Zhang, An Emotional Particle Swarm Optimization Algorithm, *ICNC 2005, LNCS 3612, pp. 553 – 561,* 2005.

[8] F. Cannavo, L. Fortuna, M. Frasca, L. Patan, Chaotic Sequences in ACO Algorithms, *IEEE International Symposium on Circuits and Systems (ISCAS)*, 2004.

[9] H-H Huang and J-H Lin, Optimization Theory and Algorithms Based on Computational Intelligence for Complex Systems, *Thesis of Department of Information Management I-Shou University Taiwan,*2006.

[10] X. Song, B. Li, H. Yang, Improved Ant Colony Algorithm and Its Applications in TSP, *Proceedings of the Sixth International Conference on Intelligent Systems Design and Applications*,2006.

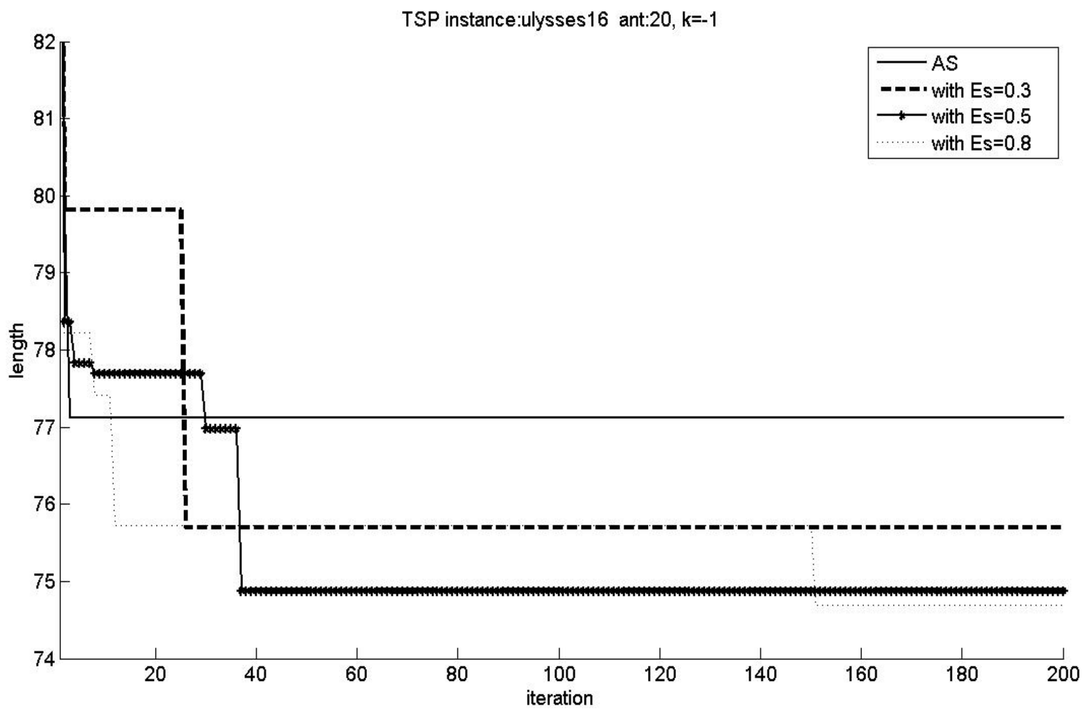

Fig 2. Shortest length search about AS versus EAS with various emotion factor e_s on TSP instance:ulysses16

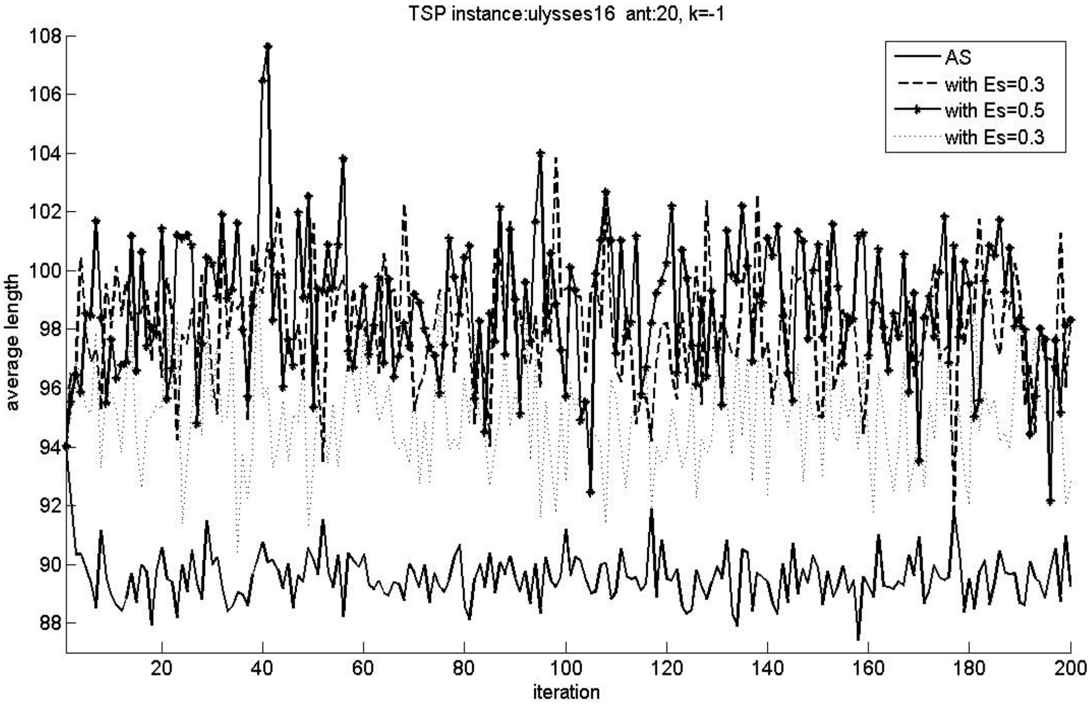

Fig 3. Average length search about AS versus EAS with various emotion factor *Es* on TSP instance:ulysses16

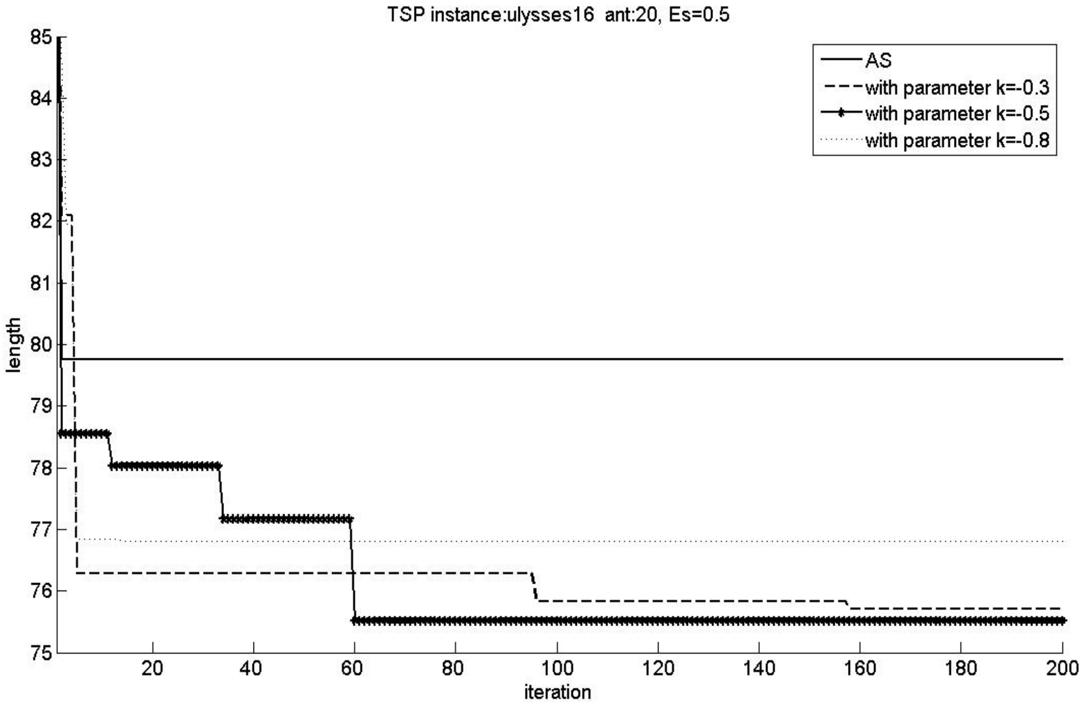

Fig 4. Shortest length search about AS versus EAS with various parameter *k* on TSP instance:ulysses16

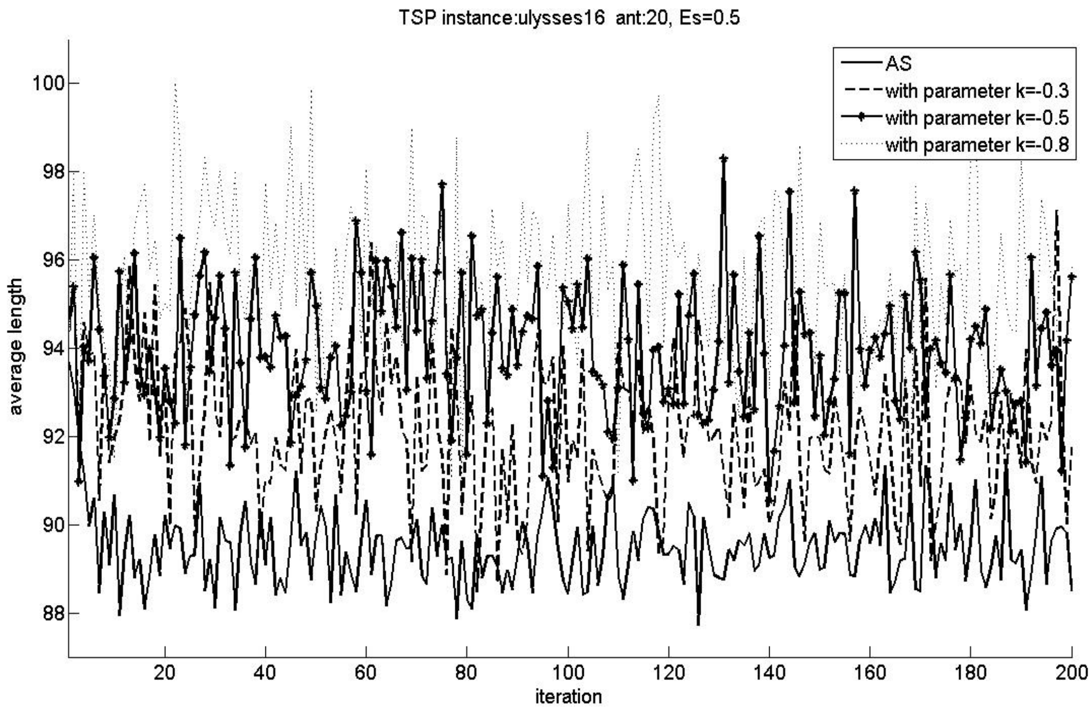

Fig 5. Average length search about AS versus EAS with various emotion factor *k* on TSP instance:ulysses16

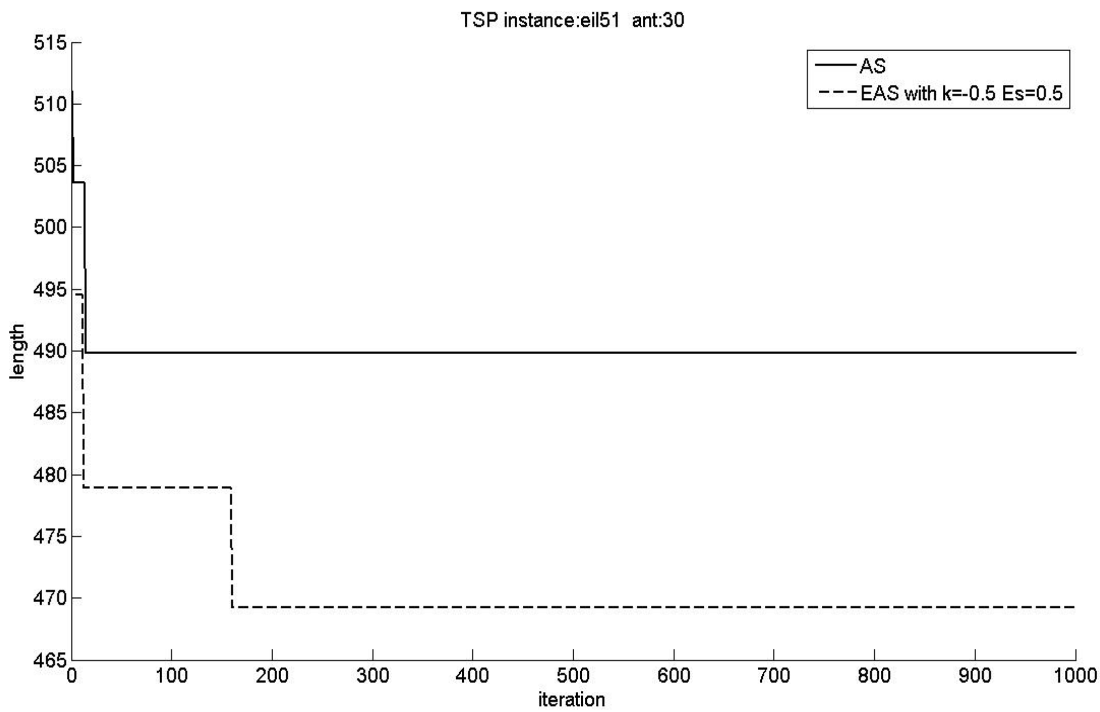

Fig 6. Shortest length search about AS versus EAS with suit combination of parameter settings: k=-0.5 and Es=0.5 on TSP instance:eil51 in 1000 iterations