Hybridization of Fuzzy PSO and Fuzzy ACO Applied to TSP

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***Abstract*—Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) algorithms have attracted the interest of researchers due to their simplicity, effectiveness and efficiency in solving real world optimization problems. Swarm-inspired optimization has recently become very popular. Both ACO and PSO are successfully applied in the Traveling Salesman Problem (TSP). Our approach consists in combining Fuzzy Logic with ACO (FACO - Fuzzy Ant Colony Optimization) and PSO (FPSO - Fuzzy Particle Swarm Optimization) for solving the TSP. Experimental results and comparative studies illustrate the importance of Fuzzy logic in reducing the time and the best length for the TSP problems considered.**

***Keywords*-Fuzzy Ant Colony Optimization; Fuzzy Particle Swarm Optimization; Traveling Salesman Problem; Swarm intelligence.**

I. Introduction

The roots of swarm intelligence are set so deeply in the study of self-organized behavior in social insects. It was born from the incredible abilities of social insects to solve their problems [1]. Their colonies incorporating either few animals or millions of individuals show fascinating behaviors, which combine the efficiency of the flexibility and robustness [2]. The optimization using swarm intelligence can be applied in different fields, covering swarm optimization, distributed control of collective robotics or network traffic management [3]–[5]. The reader may consult [6] for some examples of complex and sophisticated behaviors of social insects' optimization paradigms.

Swarm intelligent methods are part of the meta-heuristic family [7], [8] of algorithms, which is an iterative technique. The latter reproduces a natural process of physical, chemical or biological system with a self organization and evolving capacities. Like in nature, it can search local optimal solutions or global optimal solution using simple rules. In fact, the results will depend partially on the problem that we are solving and execution time limit (number of iteration or stop condition). Usually heuristics are reserved for solving difficult optimization problems. Many heuristic search methods have been used in a cooperative search environment including Tabu Search (TS) [9], Genetic Algorithms (GA) [10], [11], Ant Colony Optimization [12], [13] and Particle Swarm Optimization [14], [15]. For all these methods, the challenging issue is the choice of their parameters. For example, in PSO, the number of iterations, the number of particles and the choice of the fitness function are the key elements that control how PSO will assess and explore the search space.

Two popular swarm inspired methods are ant colony optimization (ACO) and particle swarm optimization (PSO). The PSO is simple and promising, and it requires less computation time, though it faces difficulties for solving discrete optimization problems [16], [17]. Whereas for ant systems, inspired by the food-seeking behavior of real ants, attributable to [18], they have demonstrated itself to be an efficient and effective tool for optimization problems. But the main problems of classical PSO and ACO algorithms consist in the weak ability to find optimal solution as they are missing a mechanism for parameter adaptation [19], [20].

In the literature, it has been demonstrated that combing those algorithms with intelligent techniques provide better results. Few researchers [21]–[23] used fuzzy logic to adapt the inertia weight in PSO algorithms. Authors [24]–[26] also proposed improved ACO algorithms using a fuzzy pheromone updating mechanism. In this paper, we propose a new fuzzy PSO (FPSO), and a new Fuzzy ACO (FACO) algorithm. The main idea consists essentially in the use of fuzzy logic in combination with the PSO and ACO algorithms. For the PSO algorithm, we proposed a Fuzzy System (FS) for the inertia weight update, whereas for the ACO algorithm we propose a new fuzzy system for the the weighting coefficient of the pheromone trails update. Both FPSO and FACO are applied successfully to the Traveling Salesman Problem (TSP).

This paper is organized as follows. Section 2 gives an overview on PSO, ACO and FLS accomplishments. Section 3 presents the new methods namely Fuzzy PSO and Fuzzy ACO. In Section 4, we illustrate experimental results and comparative studies for the TSP problem. The paper is concluded in Section 5.

II. Fundamentals of PSO, ACO and FLS

A. Particle Swarm Optimization

According to Kennedy [16] and Eberhart, a particle moves according to its own position with respect to its best neighborhood and to the best global position of the swarm [27]. The best number is selected on the basis of a limited search space and a fitness function. The best global is selected from the best locals as the one how fits better the fitness, maximizing or minimizing the cost depending on the problem that the swarm is attempting to solve. The system iterates but with a fixed number of iteration known before launching the search process, that ensures the PSO to converge to a solution, even if this one is not the best one. Kennedy and Eberhart, in 1995 made the first attempt to describe how this kind of social intelligence rose from simple and implicit rules.

$$\begin{aligned} &v_{ij}(t+1) = wv_{ij}(t) + c_1r_1(p_{il}(t) - x_{ij}(t)) + \\ &c_2r_2(p_{ig}(t) - x_{ij}(t)) \\ &x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \qquad 1 \leq i, j \leq N \end{aligned} \tag{1}$$

where w is a parameter called the inertial weight; $i = 1, 2, ..., N$ indicates the number of particles of population (swarm); $t = 1, 2, ...t_{max}$, indicates the generations (iterations), v_{ij} stands for the velocity of the ij^{th} particle, stands for the position of the ij^{th} particle of population, and represents the best previous position of the ij^{th} particle. Positive constants c1 and c2 are the cognitive and social factors, respectively, which are the acceleration constants responsible for varying the particle velocity towards p_{il} and p_{ig} respectively. Index p_{ig} represents the index of the best particle among all the particles in the swarm. PSO have been used successfully in several applications [28]–[30].

B. Ant Colony Optimization

The ant colony optimization was firstly proposed by Dorigo et al. [31], [18]. The inspiration of the ACO algorithms consists in the observation of real ant's ability to find the shortest path from a source of food to their nest. Colorni [32] showed how a very simple pheromone following behavior could be used to optimize the traveling salesman problem [31]. The ant colony optimization was based on the observation that ants would find the shortest path around an obstacle separating their nest from a target such as a piece of candy simmering on a summer sidewalk. In fact, as ants move around they leave pheromone trails, which dissipate over time and distance. The pheromone intensity at a spot, that is the number of pheromone molecules, which a wandering ant might encounter, is higher either when ants have passed over the spot more recently or when a greater number of ants have passed over the spot. Thus, ants following pheromone trails will tend to congregate simply from the fact that the pheromone density increases with each additional ant that follows the trail. Dorigo [18] focused on the fact that ants meandering from the nest to the candy and back will return more quickly, and thus will pass the same points more frequently, when following a shorter path. Passing more frequently, they will lay down a denser pheromone trail. If τ_{ij} represents the quantity of pheromone of ant_{ij}, the ant path depends on the following probability:

$$P_{ij}^k(t) = \begin{cases} \dfrac{(\tau_{ij}(t)^{\alpha})(\eta_{ij})^{\beta})}{\sum_{i \in J_i^k}(\tau_{ij}(t)^{\alpha})(\eta_{ij})^{\beta}} & \text{Si } (i,j) \in J_i^k \\ 0 & \text{Si } (i,j) \notin J_i^k \end{cases} \tag{2}$$

Where the values η_{ij} are called heuristic information values, that we get through some problem-specific heuristic. The quantities $\eta_{ij}(u)$ may depend on the entire partial path u traversed.

C. Fuzzy Logic System (FLS)

Fuzzy logic was proposed by Zadeh [33]. Since then it was successfully used in several applications [34]–[38]. FLS can handle uncertainties, imprecision and incomplete data. Indeed it can model non-linerar systems and complex functions. A Fuzzy Logic System (FLS) or a fuzzy expert system is generally composed of three parts: fuzzification, inference engine and defuzzification. The block diagram of an FLC is shown in figure 1.

- The fuzzification part corresponds to the definition of linguistic variables of inputs and outputs.
- The inference part corresponds to the definition of rules describing the system working.
- The defuzzification part computes outputs command.

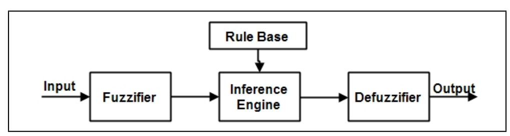


Figure 1. Architecture of a fuzzy controller

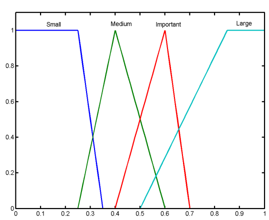
III. Fuzzy PSO and Fuzzy ACO

A. Fuzzy PSO

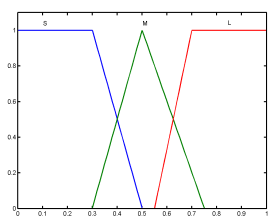
In most general applications of the conventional PSO algorithm, the inertia weight is used as a constant value. The drawback of these works consisted in that they can not provide any feedback about how far the fitness of the particles are far from the optimal real values [39]. Hence the need to use an intelligent method seems very logical to overcome this point. Fuzzy logic was incorporated in few works in the PSO algorithm for searching the inertia parameter. Authors in [22] designed a nine rules' fuzzy system for evaluating the inertia parameter. We designed a twelve rule fuzzy logic system for every particle letting to have an accurate system to achieve better results. The first input of the FLS is the normalized fitness of the current best position, which is calculated as:

$$NFCB_i^k = \frac{fitness(pbest_i^k) - fitness_{op}}{fitness(pbest_i^1) - fitness_{op}} \tag{3}$$

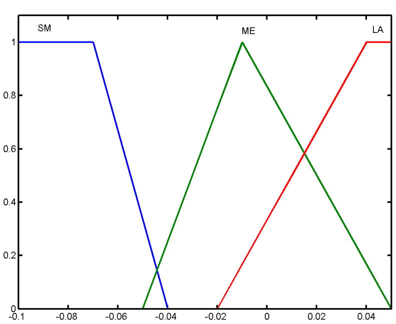
Where $fitness(pbest_i^k)$ represents the best previous position's fitness in the k^{th} iteration, of the i^{th} particle. $fitness(pbest_i^1)$ represents the fitness of the i^{th} particle in the first iteration. It is generally the worst value for the considered particle. Membership functions of this variable are shown in Figure 2(a) and $fitness_{op}$ is the real optimal value.



(a) MF of the $NFCB_i^k$ input



(b) MF of the ω_i input



(c) MF of the $\Delta\omega_i$ output

Figure 2. Membership functions of Inputs and Output

The second input of our FS is the current value of the inertia weight ω_i for the i^{th} particle. It is represented by three membership functions,'Small', 'Medium' and 'Large' as illustrated in Figure 2(b).

Whereas the fuzzy ouput of our system is the variation of the inertia weight $\Delta\omega_i$ which is illustrated in figure 2(c) In the inference part of the FLS, we designed twelve rules, which are illustrated in Table I and we used the min-max Mamdani method. Whereas for the defuzzification part, we used the centroid of sets method, which is the most used method in literature that is computed using the following equation:

$$\Delta\omega_i = \frac{\sum_{i=1}^{12} w^i \Delta\omega i}{\sum_{i=1}^{12} w^i} \tag{4}$$

B. Fuzzy ACO

Several works combined the use of fuzzy logic with ACO as in [40], where authors proposed the fuzzified Ant K-means Algorithm. They used fuzzy logic to classify data,

Table I
FUZZY RULES OF FPSO

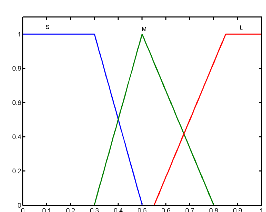
ω_i	$NFCB_i^k$			
	Small	Medium	Important	Large
S	LA	LA	LA	LA
M	SM	ME	ME	ME
L	SM	SM	SM	SM

and then used the ACO idea. Fuzzy ant based clustering algorithms were proposed in [41], [42]. Lefever and al. [42] presented a fuzzy ant approach for clustering web people search results. Others [41] used fuzzy ants in clustering web search results.

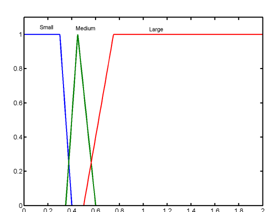
Authors in [24] presented an adaptive α parameter, which is the weighting coefficient of the pheromone trails τ_{ij}. In our work we presented a new adaptation of this parameter, by using fuzzy logic. Hence we defined the α parameter as a fuzzy value α_j^i depending on the quantity of the present pheromone trails τ_{ij}. In fact the convergence of the ACO algorithm depends strongly on the pheromone trails by this it depends strongly on the α_j^i parameter. We proposed a Mamdani type fuzzy system in which we defined the first input the Normalized Weight of the current best position expressed as follows:

$$NW_i^k = \frac{\alpha_j^i - \alpha_{min}}{\alpha_{max} - \alpha_{min}} \tag{5}$$

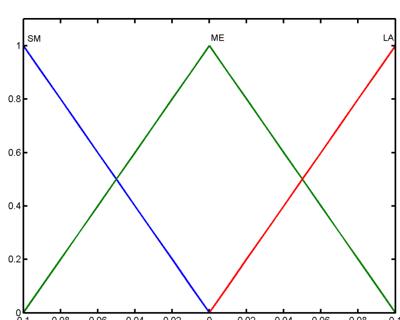
Membership functions of this variable are shown in figure 3 (a).



(a) MF of the NW input



(b) MF of the α_j^i input



(c) MF of the $\Delta\alpha_j^i$ output

Figure 3. Membership functions of Inputs and Output

The second input of the proposed FS is the α_j^i parameter, which is presented using three membership functions 'Small','Medium' and 'Large' as illustrated in Figure 3(b). The output of the fuzzy system is the variation in the α parameter which is denoted by $\Delta\alpha_j^i$. This variable which represents the correction variable for the α_j^i is represented by three membership functions upon a universe of discourse $[-0.1\ 0.1]$. The output variable is shown in Figure 3(c). We elaborated nine rules as shown in Table II. The fuzzy system is based upon the idea : best values of α will be near to the maximum value as the purpose in the ACO algorithm is to have the shortest path.

Table II
FUZZY RULES OF FACO

α_i	NW_i^k		
	S	M	L
Small	LA	LA	LA
Medium	SM	ME	ME
Large	SM	SM	SM

IV. EXPERIMENTAL RESULTS

A. TSP statement presentation

The traveling salesman problem is a classical example of a combinatorial optimization problem, which has proved to be NP-hard. In the TSP, the objective is to find the salesman's tour to visit all the N cities on his list once and only once, returning to the starting point after traveling the shortest possible distance. If we assume that the distance from city i to city j is the same as from city j to city i (symmetrical TSP), and a tour is represented as an ordered list of N cities. In this case, for $N > 2$ there is $N!/2N$ different tours (the same tour may be started from any city from among N cities and traversed either clockwise or anti-clockwise). Many methods are used for solving the TSP, e.g.: the Lin-Kernighan algorithm, neural network [43] , Hopfield network [44] and few others. Using PSO and ACO, many solutions are also presented in the literature [45].

B. Experimental results

Experimental results illustrate the importance of fuzzy logic in reducing the time and the best length for the TSP. Comparisons with classical PSO and ACO and the results achieved by the proposed FACO and FPSO are summarized in Table III. In this Table, N denotes the number of nodes, S.p: Size of population, T.FACO: the best Time of Fuzzy PSO (per seconds), L.FACO: the best Length Fuzzy ACO, T.ACO: the best Time for ACO (per seconds), L.ACO: the best Length for ACO, T.FPSO: the best Time for Fuzzy PSO (per seconds), L.FPSO: the best Length for Fuzzy PSO, T.PSO: the best Time for PSO (per seconds) and L.PSO: the best Length for PSO. We used 1000 iterations because when tested 2000 and 3000 iterations we concluded that the cycle numbers and time are proportionate to that of 1000 iterations. Our approach is coded in Matlab and run on an Pentium (R) Dual core CPU 2 GHz PC with 2.92GB memory. There are many parameters used for our approach: The Size of population, which we increased three times, is the number of nodes of the social and cognitive probabilities, having c_1 and c_2, set as $c_1 = c_2 = 2$. while the maximum of velocity v is taken as 100 and dimension of space as 10. Both α and β control the relative significance of pheromone trail and distance between cities in TSP where $\beta = 2$. ρ refers to the rate of pheromone evaporation $\rho = 0.7$. Each TSP run is conducted for 5 times for 1000 iterations. Table III sums up the new results and illustrates improved results published in our previous work [30]. We notice that, more the size of population the best length of FACO and FPSO decreases and the execution time increases too. Indeed, from the same Table, we can see that the execution time of PSO is better compared to the ACO, which is normal since the PSO is faster than ACO. For the length of the shortest path, PSO is poor compared to that of the ACO. This illustrates the importance of FACO and FPSO to find the best solution and the best execution time.

V. CONCLUSIONS

Fuzzy Swarm intelligence was presented in this article as an effective solution to solve TSP. We have proposed a new Fuzzy PSO and a Fuzzy ACO algorithm. Comparative studies using the Traveling Salesman Problem (TSP), illustrate the importance of Fuzzy logic in reducing the time and the best length.

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Table III
COMPARISON BETWEEN RESULTS

N	S.p	T.FACO	L.FACO	T.ACO	L.ACO	T.FPSO	L.FPSO	T.PSO	L.PSO
22	22	0.8130	**76.1195**	0.2438	77.8000	0,7810	**80.2718**	0.1406	90.6884
	70	1.0780	**76.0570**	0.4969	77.1834	1,0620	**78.0252**	0.4556	90.4220
	100	1.9340	**76.0097**	0.6866	77.0269	1,2340	**77.9584**	0.5707	89.4898
29	29	1.5310	**9.6056e+003**	0.4190	1.1621e+004	1.3713	**1.1632e+004**	0.4181	1.1761e+004
	70	2.0310	**9.3413e+003**	1.0881	1.0677e+004	1,9540	**1.0861e+004**	0.9632	1.0900e+004
	100	2.4060	**9.2053e+003**	1.3713	1.0432e+004	2,2860	**1.0463e+004**	1.2177	1.0472e+004
30	30	1,6410	**488.7036**	0.3724	539.0477	1.4225	**560.4898**	0.3577	584.0341
	70	2,2350	**486.9804**	0.7652	495.5985	2.0530	**539.0477**	0.7334	562.0160
	100	2,6560	**485.8849**	1.4225	491.7651	2.3657	**535.8849**	1.1059	545.7844
48	48	4.1843	**4.2035e+004**	4.0005	4.2086e+004	4.1009	**4.4235e+004**	3.0961	4.5973e+004
	70	4.7161	**4.1403e+004**	4.5047	4.1420e+004	4.6358	**4.3679e+004**	4.3249	4.4654e+004
	100	7.0152	**4.0070e+004**	6.8139	4.0801e+004	6.9047	**4.1001 e+004**	4.8480	4.1158e+004

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