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Fuzzy Based Parameter Adaptation in ACO for Solving VRP

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ABSTRACT

Ant Colony Optimization, a popular class of metaheuristics, have been widely applied for solving optimization problems like Vehicle Routing Problem. The performance of ACO is affected by the values of parameters used. However, in literature, few methods are proposed for parameter adaptation of ACO. In this article, a fuzzy-based parameter control mechanism for ACO has been developed. Three adaptive strategies FACO-1, FACO-2, FACO-3 are proposed for determining values of parameters alpha and beta, and evaporation factor separately as well as for all three parameters simultaneously. The performance of proposed strategies is compared with standard ACS on TSP and VRP benchmarks. Computational results on standard benchmark problems shows the effectiveness of the strategies.

KEYWORDS

Ant Colony Optimization, Fuzzy System, Parameter Adaptation, Vehicle Routing Problem

1. INTRODUCTION

Vehicle Routing Problem (VRP) is one of the typical examples of combinatorial optimization problems. The problem was first formulated by Dantizg and Ramesher in 1959. VRP is one of the extensively studied problems in operation research because of its wide applications in the area of transportation and logistics. It can also be applied to other applications such as waste collection (Kim et al., 2006), tour planning (Zing & Zhang, 2010) etc. A typical VRP can be described as: a depot that wants to offer services to geographically scattered customers at the lowest tour planning cost. VRP has been proved to be NP Hard problem. Many methods have been proposed to solve VRP. During recent years soft computing techniques like meta heuristics and fuzzy logic have been also used for solving these complex problems in place of traditional methods. Some of the meta heuristics can solve this problem in reasonable time. Ant Colony Optimization (ACO) is one of the meta heuristic which is being used to solve VRP problem. ACO was proposed by Marco Dorigo in 1990 (Dorigo & Di Caro, 1990). ACO is a nature inspired metaheuristic that mimics the behavior of real ant in finding the shortest path to food source from the nest. Till now many variations of ACO have been proposed (Dorigo, 2007). A lot of literature (Dorigo & Birattari, 2011; Afshar, 2015; Sakthipriya & Kalaipriyan,

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2015) exists where efforts have been made to improve performance of ACO. One of the important issues in ACO is the parameters value selection. The algorithm starts with the initialization of some parameters that effect the performance of the algorithm used for solving a particular problem. Moreover, the adopted values of parameters also control the balance between exploration and exploitation. In literature, most of the ACO studies, either use static parameters value or use hand tuned parameters value. However, choice of parameters values used at run time significantly affect the performance of the algorithm. Finding the appropriate values of the parameters and their adjustment of those values requires a considerable effort and lot of computation. In fact, parameter tuning and parameter adaptation are the two important research topics in the field of meta heuristics (Stützle et al., 2011; Eiben et al., 1999). Parameter tuning is a process of finding appropriate settings of parameters before the algorithm is actually employed and then running the algorithm with these values. However, this process is error prone, time consuming and human intensive. An alternative to this is parameter adaptation, in which the algorithm adapts the values of the parameter dynamically according to the problem characteristics. In this paper, a fuzzy based parameter adaptation scheme is proposed in ACO for solving VRP problem. The parameters in ACS include alpha $\left(\alpha\right)$, beta $\left(\beta\right)$ and pheromone evaporation rate $\left(\rho\right)$. These parameters have relatively more importance than other parameters like number of ants etc.

In this paper fuzzy logic based three adaptive strategies FACO-1, FACO-2, FACO-3 is proposed for parameter adaptation of ACO. FACO-1 determines appropriate values of α and β while keeping other parameters static. FACO-2 decides the value of evaporation factor (ρ) while keeping others as constant. FACO-3 determines the values of all three parameters simultaneously. Performance of the proposed three strategies are compared with static ACS for VRP.

The main contribution of this paper is the proposal of systematic approach for dynamic parameter adaptation of ACO using fuzzy logic system. The ACO can now be easily applied to VRP without choosing values of parameters ACO. The proposed approach can select the values of these automatically and can control these values throughout the run of the algorithm, which can lead to improved solution quality and faster convergence rate. Three adaptive strategies are proposed to regulate the values of α and β, evaporation factor (ρ) and all three simultaneously respectively. All three strategies are applied to VRP. Results demonstrates that FACO-3 is better than other two strategies.

Rest of the paper is organized as follows: Section 2 gives the introduction to ACO and Fuzzy logic. Section 3 presents the literature review and the research gaps that motivates us to consider this problem. In section 4 working methodology has been presented. Experimental results are presented in section 5. Finally, section 6 presents the conclusion and future work.

2. INTRODUCTION TO RELATED METHODOLOGIES

2.1. Ant Colony System (ACS)

ACS is one of the most efficient variation of ACO. It works in three steps:

1. Parameter and Pheromone Initialization
2. Solution Construction
3. Pheromone Updation

While searching solution for VRP ACS algorithm, firstly initializes all the parameter and pheromone. After this each ant *k* iteratively builds its solution from customer *i* to customer *j* using a pseudo random proportional rule (*j*):

$$j = \begin{cases} \arg max_{j \in \varnothing_i^k} \left\{ \tau\left(i,j\right)^{\alpha} \eta\left(i,j\right)^{\beta} \right. & if\, q \leq q_0 \\ J & otherwise \end{cases} \tag{1}$$

where:

- $\tau\left(i,j\right)$ is the pheromone level between customer *i* and *j*;
- $\eta\left(i,j\right)$ is the heuristic value between customer *i* and *j*;
- α is the parameter which determines the importance of pheromone value;
- β is the parameter which determines the importance of heuristic value;
- *q* is the random variable uniformly distributed over [0,1];
- q_0 is the variable that controls exploitation and exploration;
- ϕ_i^k is the allowed feasible customers by ant *k* positioned on customer *i*.

In this rule the best edge is selected with a probability q_0, otherwise with probability (1- q_0) an edge is selected by rule *J* obtained by AS rule called biased exploration as follows:

$$p_{ij}^k = \begin{cases} \dfrac{\tau\left(i,j\right)^{\alpha} \eta\left(i,j\right)^{\beta}}{\sum_{j \in \varnothing_i^k} \tau\left(i,j\right)^{\alpha} \eta\left(i,j\right)^{\beta}} & if\, j \in \varnothing_i^k \\ 0 & otherwise \end{cases} \tag{2}$$

During the construction of solution, each ant modifies the value of pheromone on the visited arcs by following local pheromone update rule:

$$\tau\left(i_k, j_k\right) = \left(1 - \xi\right) \tau\left(i_k, j_k\right) + \xi \tau_0 \tag{3}$$

where:

- ξ is the local evaporation factor;
- τ_0 is initial pheromone value.

After the completion of one cycle, pheromone value on the arcs belonging to global best tour is updated according to global pheromone updating rule:

$$\tau\left(i_k, j_k\right) = \left(1 - \rho\right) \tau\left(i_k, j_k\right) + \frac{\rho_0}{L_{Best}} \tag{4}$$

where:

- L_{Best} is the length of globally best tour;
- ρ_0 is the global evaporation factor.

2.1.1. Importance of Parameters

An important issue in ACO is the balance between exploration and exploitation (Pellonperä, 2014; Bansal et al., 2014). As they directly affect the solution quality and computation time. Too much exploration of search space improves the solution quality but at the cost of CPU time and hence slow convergence rate. On the other hand, too much exploitation of search space cuts the CPU time but at the cost of worsened solution quality and hence faster convergence rate. ACO algorithm maintains this balance with the help of $\alpha, \beta\, and\, \rho_0$.

2.2. Fuzzy Logic System (FLS)

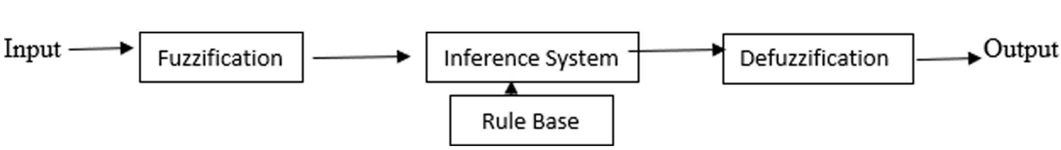
Fuzzy logic was introduced by Lofti Zadeh (Zahed, 1983) in 1965. FLS can handle imprecise, uncertain and incomplete data efficiently. Moreover, it can model nonlinear systems very easily. So, it finds applications in various fields ranging from control system to artificial intelligence (Baklouti et al., 2012; Bousnina et al.,2012; Collotta et al., 2014; Pasieka et al., 2017). FLS consists of three parts: fuzzification, inference system and defuzzification. Block diagram of FLS is shown in Figure 1.

Fuzzification: This is the first phase of FLS which deals with the definition of linguistic variables of inputs and outputs and defining their descriptors.
Inference System: It describes the system working and hence simulates the human thinking in terms of fuzzy IF-THEN rules.
Defuzzification: It calculates the crisp output from the fuzzy input obtained from inference system.

3. LITERATURE REVIEW

(Elloumi et al., 2013) presents two swarm-based algorithms namely FPSO and FACO for solving TSP. These two algorithms are enhanced by using fuzzy logic. Fuzzy logic has been used for updating of inertia weight and pheromone trails of PSO and ACO respectively. Experimental results reveal that fuzzy logic helps in reduction of time and tour length. (Olivas et al., 2014) proposes a fuzzy system for the adaptation of ACO parameters. The objective of the paper is to control the diversity of the solution. Three fuzzy systems are created on the basis of different inputs and a comparison among them is made. TSP has been used for demonstration of results. In addition to this (Olivas et. al., 2017) has extended this work on the basis of type 2 fuzzy logic system. Again type 2 fuzzy logic system has been used for the dynamic parameter adaptation of ACO so that it can be applied to wide variety of problems without tuning the parameters. The proposed algorithm has been applied to two problems namely: TSP and trajectory optimization of an autonomous mobile robot. (Wang et al., 2015) uses fuzzy logic for the control of parameters of ACO. Among various flavor of ACO, AS and ACS has been used for the control of parameters. Three adaptive control strategies SI, SII and SIII are proposed to control the pheromone evaporation rate, exploration probability factor and number of ants respectively. Feature selection problem has been chosen for evaluation of these strategies. In addition to this the proposed approaches are enhanced to make them suitable for feature selection problem. A comparison is made between the proposed strategies, PSO and genetic algorithm. (Stutzel et al., 2011) presents a review of approaches that have been used for the settings of parameters while at run time of ACO algorithm. The review has been given in two parts. The first part of the study

Figure 1. Block diagram of FLS



provides an understanding of effects of parameters on ACO. The second part of the study uses the first part to propose simple, pre-scheduled parameter variations. Experimental results show that run time parameter settings can dramatically improve the performance of algorithm. (Eiben et al., 1999) presents a discussion on parameter control for evolutionary algorithms and also provides a survey control technique. (Belmechari et al., 2011) proposes a PSO approach to solve complex VRP. Fuzzy logic controller is used to control the parameters of PSO. The fuzzy logic allows the PSO to maintain an equilibrium between intensification and diversification. (Stodola et al., 2015) presents a parameter tuning scheme for ACO used in ISR systems. ACO algorithm designed for multi depot VRP has been integrated into TDSS. Various parameters of ACO like number of ants, evaporation factor etc. are tuned. (Salehinejad &Talebi, 2010) proposes a fuzzy enabled ACO for dynamic route selection in urban areas. Pheromone are updated on the basis of fuzzy parameters distance, risk, and traffic flow. (EI Afia et al., 2017) presents a fuzzy logic controller for parameter adaptation of meta heuristics. The local evaporation factor of ACS has been adapted by FLS. Computational results are produced on TSP problem. The simulation results show that dynamic parameter adaptation of ACS has faster convergence and better-quality results.

(Zhang et al., 2016) develops a framework of constructing invariant ACO algorithm for TSP and experimental analysis has been used to study the effect of parameters on algorithm performance.

(Erol et al., 2012) uses neural network for the adaptation of $\alpha\, and\, \beta$ parameters of ACO. NN is used for choosing best parameters and ACO serves as evaluation algorithm. Effectiveness of the results are shown on TSP problem. In (Yu et al., 2009) an adaptive ACS (AASC) has been proposed for the optimization of TSP problem. The proposed algorithm uses normalized values of ACS for the adaptation of pheromone decay and α. Finally, (Bajer et al., 2016) develops a parameter control for differential evolution algorithm by ACO. Crossover rate and mutation factor are controlled by pheromone model of ACO. From the above mined literature, it is clear that values of parameters have significant effect on the performance of the algorithm.

3.1. Research Gaps

Most of the proposed work (Elloumi et al., 2013; Olivas et al., 2014; Olivas et al., 2017; El Afia et al., 2017; Zhang et al., 2016; Erol et al., 2012) solves TSP problem which cannot be directly applied to VRP due to constraints like capacity and demand. Work proposed in (Olivas et al., 2014) is a parameter tuning approach which consumes lot of resources. Moreover, the work which focuses on parameter adaptation using fuzzy logic (El Afia et al., 2017) considers one parameter for adaptation at a time keeping others as static. In (Yu et al., 2009) parameters are adjusted using formula which results in biasing. The main disadvantage of (Bansal et al., 2014) is the use of fixed parameters throughout the iterations and premature convergence.

4. PROPOSED METHODOLOGY

To dynamically adapt the $\alpha\, and\, \rho$, Fuzzy logic system has been used. Three Fuzzy adaptive strategies FACO-1, FACO-2 and FACO-3 has been implemented on Mamdani fuzzy system. FACO-1 decides the values for $\alpha\, and\, \beta$ parameter. FACO-2 determines the value for ρ. FACO-3 combines both FACO-1 and FACO-2. FACO-3 predicts the values for all α , $\beta\, and\, \rho$ parameter. Two input parameters namely iteration, variance has been used where:

$$Iteration = \frac{Current\, Iteration}{Total\, No.of\, Iterations} \tag{5}$$

$$Variance = current\, best\, solution - global\, best\, solution \tag{6}$$

where in Equation 5 current iteration is the number of past iterations and total no. of iteration is the maximum iterations allowed. Variance is the difference between the current best and global best solution. Current best solution represents the best solution in the current iteration and global best solution represent the global best solution till the current iteration. Algorithms 1-3 show the main FACO algorithm that calls FACO-1, FACO-2 and FACO-3 fuzzy controlled algorithm respectively.

4.1. Fuzzification

This is the first process in FLS. Iteration and variance are fuzzified in the range of [0 1000] and [0 to 100] respectively using triangular membership function as shown in Figure 2 and 3. For each input variable three membership {Small, Medium, High} are defined. The membership function for iteration can be defined as follows:

$$\mu_{small}\left(x\right)=\begin{cases}\dfrac{500-x}{500} & if\,0<x<500\\ 0 & if\,x>500\end{cases} \tag{7}$$

Algorithm 1. Adaptive FACO

Input: VRP instances, number of ants, α, β, ξ, ρ , total no. of iterations. **Output:** best tour
BEGIN Step 1: Initialize all the parameters Step 2: Repeat step 3-10 until stopping condition is met Step 3: Construct Ant Solution using Equation (1) and (2) Step 4: Update local pheromone using Equation (3). Step 5: Calculate the length of tour formed by each ant and assign the best to current best solution. Step 5: Update global pheromone using Equation (4). Step 6: Calculate global best solution. Step 7: Calculate Variance using Eq (6) Step 8: $\left[\alpha,\beta\right]=FACO-1\left(Iteration, Variance\right)$ Step 9: $\left[\rho\right]=FACO-2\left(Iteration, Variance\right)$ Step 10: $\left[\alpha,\beta,\rho\right]=FACO-3\left(Iteration, Variance\right)$ END

Algorithm 2. FACO-2

Input: Iteration, Variance **Output:** ρ
BEGIN Step1: Fuzzify Iteration and Variance using Figure 2 and 3 respectively. Step 2: Evaluate the fuzzy rules for ρ. Step 3: Defuzzify the result and output the crisp values for ρ parameters END

Algorithm 3. FACO-3

Input: Iteration, Variance **Output:** α, β, ρ
BEGIN Step1: Fuzzify Iteration and Variance using Figure 2 and 3 respectively. Step 2: Evaluate the fuzzy rules for α, β, ρ. Step 3: Defuzzify the result and output the crisp values for α, β, ρ parameters END

Figure 2. Iteration as input variable

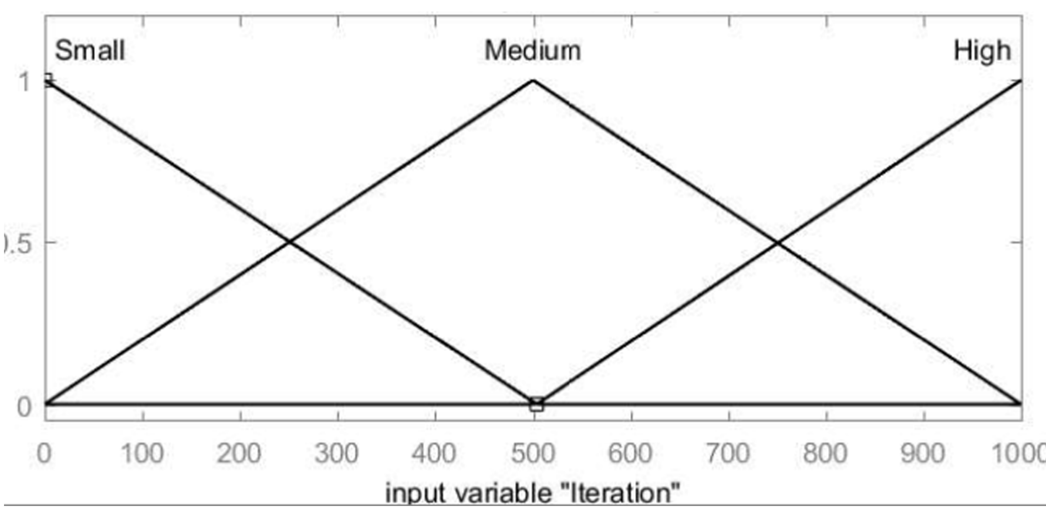
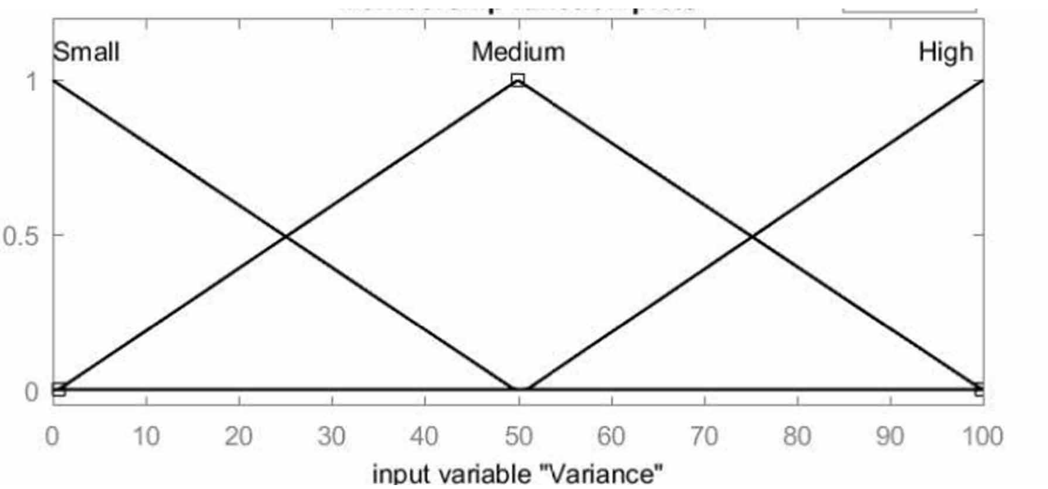


Figure 3. Variance as input variable



$$\mu_{medium}\left(x\right) = \begin{cases} \dfrac{x}{500-x} & if\, 0 < x < 500 \\ \dfrac{x-1000}{500} & if\, 500 < x < 1000 \\ 0 & if\ \ x > 1000 \end{cases} \tag{8}$$

$$\mu_{High}\left(x\right) = \begin{cases} \dfrac{x-500}{500} & if\, 500 < x < 1000 \\ 1 & if\, x > 1000 \end{cases} \tag{9}$$

Similarly, we can define membership function for input variable variance in the range of [0,100].

4.2. Rule Evaluation

After fuzzification of input parameters rule base were prepared. The fuzzy rules for the FACO-1, FACO-2 and FACO-3 are developed according to prior knowledge of ACS and the chosen parameters. This work uses Mamdani fuzzy conjunction (AND) fuzzy rules to combine inputs (outputs). The rule base for FACO-1, FACO-2 and FACO-3 are shown in Tables 1-3.

To give an illustration of how these rules are constructed let us consider an example: if the percentage of iteration is small (at early stage of an algorithm) and when the variance is low (colony of ants are closer to the best ant) then we want the exploration of search space. So we set alpha as low and beta as high and evaporation rate to low. This reasoning is realized for rule 1 in Table 3. On the other hand, in Rule 9 of Table 3 *"If iteration is high and variance is high then alpha is high and beta is low and evaporation factor is high"* means at the last iteration and ants having high diversity the value of parameter should be set to obtain low exploration and high exploitation. The surface view of all three parameters are show in Figures 4-6.

4.3. Defuzzification

After rule evaluation, we get the fuzzy output as shown in Figures 7-9 for required parameters to obtain crisp value for these parameters various defuzzification methods are available like: Mean of

Table 1. Rules for FACO-1

Rule No.	INPUT		OUTPUT	
	Iteration	Variance	Alpha	Beta
1	Small	Small	Low	High
2	Small	Medium	Medium	Medium High
3	Small	High	Medium Low	Medium High
4	Medium	Small	Medium Low	Medium High
5	Medium	Medium	Medium	Medium
6	Medium	High	Medium High	Medium Low
7	High	Small	High	Medium
8	High	Medium	Medium High	Medium Low
9	High	High	High	Medium

Table 2. Rules for FACO-2

Rule No.	INPUT		OUTPUT
	Iteration	Variance	Global Evaporation
1	Small	Small	Low
2	Small	Medium	Medium Low
3	Small	High	Medium
4	Medium	Small	Medium Low
5	Medium	Medium	Medium
6	Medium	High	Medium High
7	High	Small	Medium
8	High	Medium	Medium High
9	High	High	High

Table 3. Rules for FACO-3

Rule No.	INPUT		OUTPUT		
	Iteration	Variance	Alpha	Beta	Global Evaporation
1	Small	Small	Low	High	Low
2	Small	Medium	Medium	Medium High	Medium Low
3	Small	High	Medium Low	Medium High	Medium
4	Medium	Small	Medium Low	Medium High	Medium Low
5	Medium	Medium	Medium	Medium	Medium
6	Medium	High	Medium High	Medium Low	Medium High
7	High	Small	High	Medium	Medium
8	High	Medium	Medium High	Medium Low	Medium High
9	High	High	High	Medium	High

Figure 4. Surface view of Alpha Variable

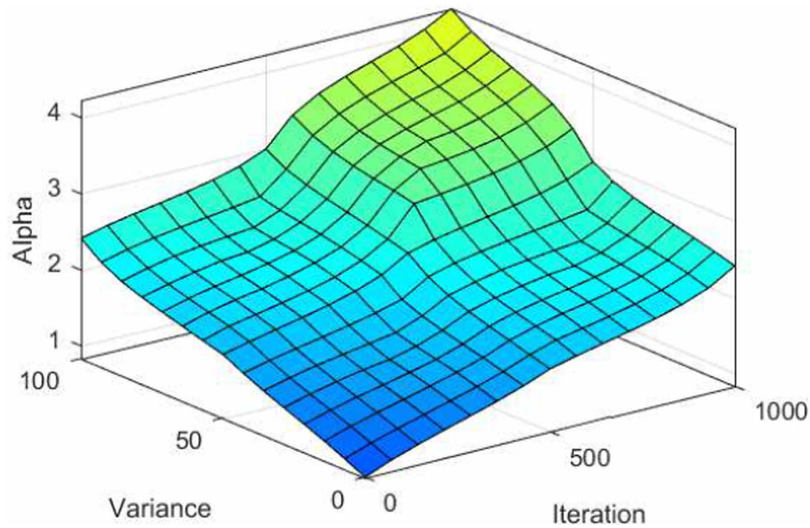
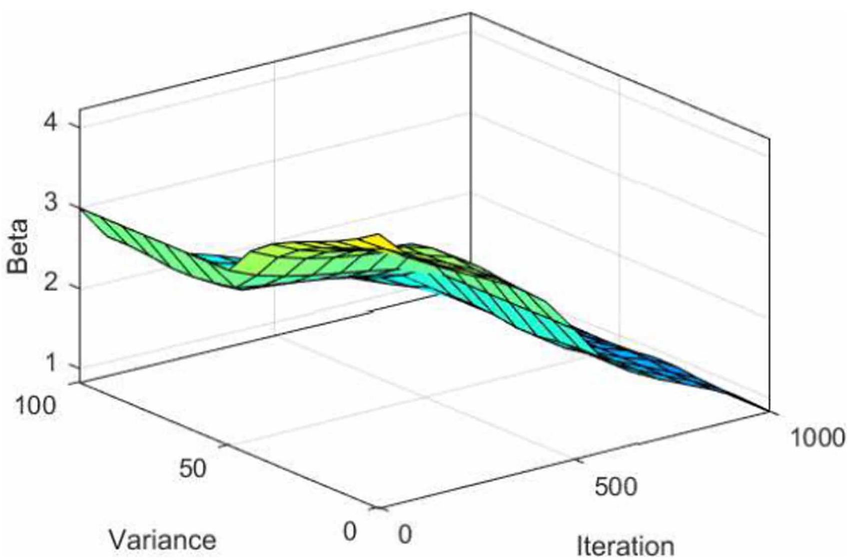


Figure 5. Surface view of Beta Variable



Max, Centroid, Centre of gravity etc. In this paper, Centroid method has been used for defuzzificaion. Following values and MFS are used for the three output variables:

```
[Output1]
Name='Alpha'
Range=[0 5]
NumMFs=5
MF1='Low':'trimf',[0 0.75 1.75]
MF2='MediumLow':'trimf',[0.75 1.75 2.5]
```

Figure 6. Surface view of Rho Variable

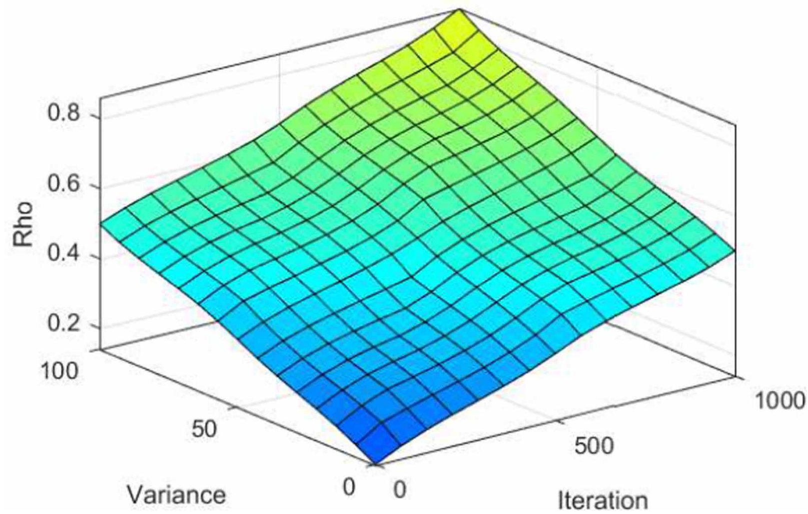


Figure 7. Alpha as output variable

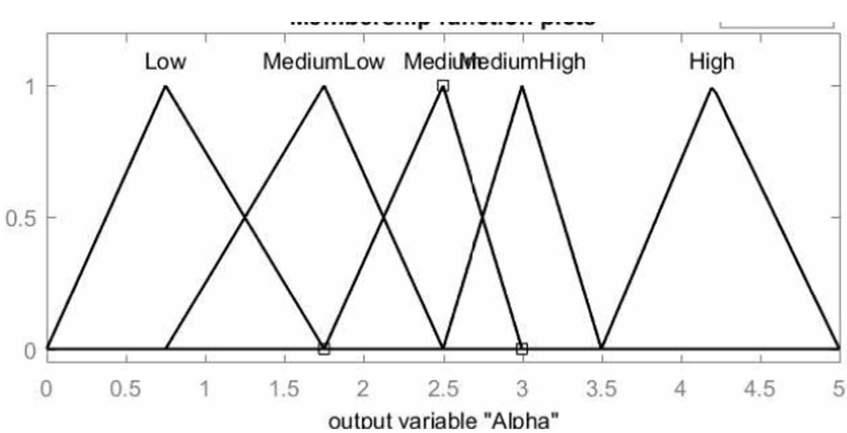


Figure 8. Beta as output variable

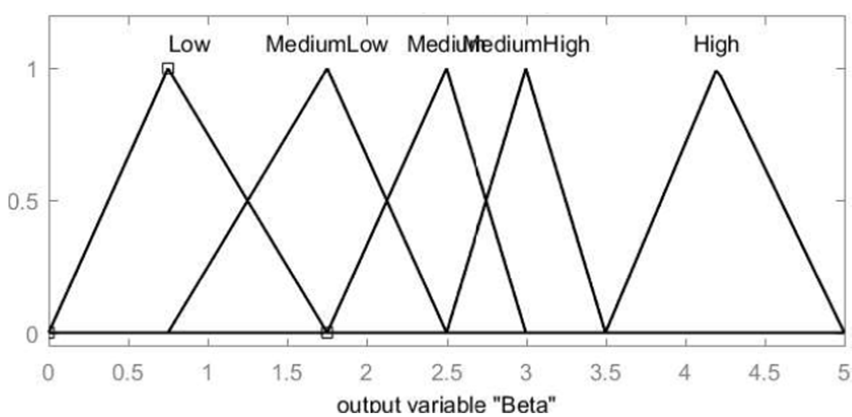
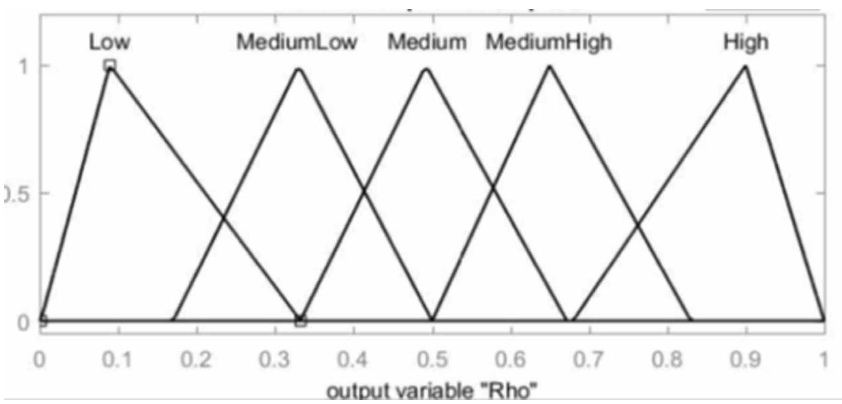


Figure 9. Rho as output variable




```
MF3='Medium':'trimf',[1.75 2.5 3]
MF4='MediumHigh':'trimf',[2.5 3 3.5]
MF5='High':'trimf',[3.5 4.2 5]
[Output2]
Name='Alpha'
Range=[0 5]
NumMFs=5
MF1='Low':'trimf',[0 0.75 1.75]
MF2='MediumLow':'trimf',[0.75 1.75 2.5]
MF3='Medium':'trimf',[1.75 2.5 3]
MF4='MediumHigh':'trimf',[2.5 3 3.5]
MF5='High':'trimf',[3.5 4.2 5]
[Output3]
Name='Rho'
Range=[0 1]
NumMFs=5
MF1='Low':'trimf',[0.00131750793650791 0.0894165079365079
0.332436507936508]
MF2='MediumLow':'trimf',[0.17 0.33 0.5]
MF3='Medium':'trimf',[0.332063492063492 0.492063492063492
0.672063492063492]
MF4='MediumHigh':'trimf',[0.5 0.65 0.83]
MF5='High':'trimf',[0.68 0.9 1]
```

5. EXPERIMENTAL RESULTS

To evaluate the effectiveness of adaptive FACO we had compared it firstly with the TSP instances and then with standard ACS with a set of VRP benchmarks from *neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances/*. Out of these benchmarks 10 instances from Augerat et al. were taken. The proposed algorithm has been implemented in MATLAB 2016a and were run on Intel Core i-3 with 2.3 GHZ. All instances are run 10 times with 10 ants and with 1000 maximum iterations. $\alpha = 1, \beta = 2, \rho = 0.1$ were chosen for standard ACS.

5.1. Comparison on Solution Quality for TSP Instances

To compare the results of three proposed strategies 5 instances of TSP problem has been selected and their comparison has been made with strategies of AS_{Rank}+FS-3 (Olivas et al., 2014) and ACFSL (El Afia et al., 2017). The AS_{Rank}+FS-3 decides the value of alpha parameter on the basis of iteration and diversity parameter. ACFLS approach determines the value of local pheromone evaluation factor. The average results are shown in Table 4. From the table, it is clear that all three proposed strategies obtain the same tour length and the results obtained are comparable with optimal solutions and better than ACFSL approach.

5.2. Comparison on Solution Quality for VRP Instances

Table 5 shows the average results for solution accuracy for all three strategies. From the Table 5 it can be observed the FACO-3 with fuzzy system resulting dynamic values for $\alpha, \beta \text{ and } \rho$ with iteration and variance as input have on average better solution quality than other two fuzzy strategies. It can also be observed that Fuzzy controlled ACS outperforms the standard ACS in terms of solution quality. Table 6 shows the standard deviation of results of all three strategies and ACS from optimum results. It is clear that FACO-3 has less deviation from the optimum solution. Even FACO-1 that controls the alpha and beta parameter is better than FACO-2 that controls global evaporation factor.

Table 4. Average results (solution quality TSP instances)

TSP Instances	Optimum Solution	AS_{Rank}+FS-3 (Olivas et al., 2014)	ACFSL (El Afia et al., 2017)	FACO-1	FACO-2	FACO-3
Burma14	3323	3323	-	3323	3323	3323
Ulysses22	7013	7013	-	7013	7013	7013
Berlin52	7542	7549.3	7546.53	7544.36	7544.36	7544.36
Eil76	538	541.93	556.31	552.92	552.92	552.92
Kr0A100	21282	21470	21611.54	21355.28	21355.28	21355.28

Table 5. Average results (solution quality for VRP instances)

VRP Instances	Optimum Solution	ACS	FACO-1	FACO-2	FACO-3
A-n32-K5	784	883.2	792.8	793	792.4
A-n33-K5	661	742	667.48	706.57	667.97
A-n34-K5	778	878	783.43	781.96	778.8
A-n48-K7	1074	1199.03	1188.86	1199.08	1074.51
A-n53-K7	1010	1093.51	1023.15	1025.87	1020
A-n54-K7	1167	1258.5	1175.6	1175.6	1175.6
A-n60-K9	1408	1570.43	1412.8	1412.8	1411.7
A-n61-K9	1035	1246.41	1181.58	1162.11	1038
A-n69-K9	1167	1281.7	1207.8	1202.4	1192.4
A-n80-K10	1760	1886.13	1779.14	1772.8	1767.8

Table 6. Standard deviation from the optimum solutions

VRP Instances	ACS	FACO-1	FACO-2	FACO-3
A-n32-K5	99.2	8.8	9	8.4
A-n33-K5	81	6.48	45.57	6.97
A-n34-K5	100	5.43	3.96	0.8
A-n48-K7	125.034	114.856	125.08	0.507
A-n53-K7	83.51	13.15	15.87	10
A-n54-K7	91.5	8.6	8.6	8.6
A-n60-K9	162.43	4.8	4.8	3.7
A-n61-K9	211.41	146.58	127.11	3
A-n69-K9	114.7	40.8	35.4	25.4
A-n80-K10	126.13	19.14	12.8	7.8

5.3. Comparison on Convergence Rate for VRP

Figure 10 shows the convergence rate of FACO-3 is better than standard ACS as in FACO-3 after 500 iterations the best cost is 792.4 for A-n32-K5 instances whereas the standard ACS achieves the same result after 850 iterations. For A-n60-K9 the FACO-3 converges after 800 iterations whereas ACS achieves its results after 1000 iterations.

5.4. Statistical Test for VRP

To compare the fuzzy controlled ACS with the standard ACS, we have used the nonparametric Kruskal-Wallis, Friedman test as a statistical test that is to find differences in differences across multiple treatments. Tables 7, 8 and 9 show the result obtained after applying the test.

The null hypothesis H_o says that the proposed method has no significant differences between the proposed approaches while the alternative hypothesis H_1 has a significant difference between the proposed approaches, the level of significance is 5%, and the critical value=1.483. As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis Ho, and accept the alternative hypothesis H1. From the above tables it is clear that all the fuzzy controlled

Figure 10. Convergence of ACS and FACO-3 for A-n32-K5 and for A-n60-K9

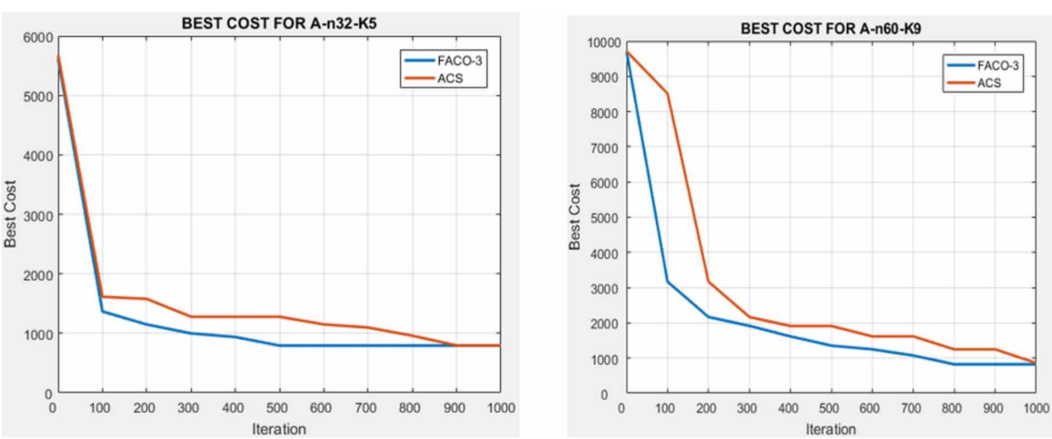


Table 7. Pair wise differences

	FACO-3	ACS	FACO-1	FACO-2
FACO-3	0	-2.7000	-1.1500	-1.3500
ACS	2.7000	0	1.5500	1.3500
FACO-1	1.1500	-1.5500	0	-0.2000
FACO-2	1.3500	-1.3500	0.2000	0

Table 8. P-values

Critical difference: 1.4833				
	FACO-3	ACS	FACO-1	FACO-2
FACO-3	1	**< 0.0001**	0.1910	0.0895
ACS	**< 0.0001**	1	**0.0365**	0.0895
FACO-1	0.1910	**0.0365**	1	0.9857
FACO-2	0.0895	0.0895	0.9857	1

Table 9. Significant differences

	FACO-3	ACS	FACO-1	FACO-2
FACO-3	No	**Yes**	No	No
ACS	**Yes**	No	**Yes**	No
FACO-1	No	**Yes**	No	No
FACO-2	No	No	No	No

strategies are better than standard ACS. In addition to this FACO-3 and FACO-1 have more significant differences from standard ACS as compared to FACO-2.

6. CONCLUSION

This paper proposes a fuzzy based parameter adaptation of ACO for solving VRP. Three different strategies FACO-1, FACO-2 and FACO-3 that controls the dynamic adaptation of α, β, ρ and all three simultaneously are proposed. Iteration and variance are chosen as the input parameter. The proposed strategies are evaluated on both TSP and VRP instances. The experimental results on TSP shows that all three strategies obtain equivalent results whereas on VRP showed that the FACO-3 and FACO-1 method that dynamically adapt the parameters has better quality of results and higher convergence speed. Also, from the Table 5 it can be observed that FACO-3 gives better results than other two strategies. In other words, the dynamic adaptation of significant parameters of ACO can control the balance between exploration and exploitation of ACO. For future work we will try to implement the same strategies on different variants of VRP, on other evolutionary techniques and will implement type-2 fuzzy logic to add robustness to the proposed algorithm. Moreover, the efficiency of the algorithm will be checked for uncertain environment with imprecision and vague data inputs.

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