A Fuzzy Approach of Sensitivity for Multiple Colonies on Ant Colony Optimization

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Abstract. In order to solve combinatorial optimization problem are used mainly hybrid heuristics. Inspired from nature, both genetic and ant colony algorithms could be used in a hybrid model by using their benefits. The paper introduces a new model of Ant Colony Optimization using multiple colonies with different level of sensitivity to the ant's pheromone. The colonies react different to the changing environment, based on their level of sensitivity and thus the exploration of the solution space is extended. Several discussion follows about the fuzziness degree of sensitivity and its influence on the solution of a complex problem.

1 Introduction

Complex problems from different real-life domains use heuristics to efficiently find high-quality near optimal solutions in a reasonable running time [1]. Ant Colony Optimization (ACO) it is a class of metaheuristic optimization methods using the concepts of distributed optimization for solving Combinatorial Optimization Problems [7, 8]. In ACO metaheuristic [8], the ants simulates real ant behavior. The ants produce pheromone trails used as indirect communication between ants. The stigmergic behavior of ants [3, 10] it is used to obtain a problem solution.

In real-life incompleteness and uncertainty are usual for nowadays information. This is a very challenging task when it is the time to take decisions. A fuzzy set is a class of objects with a continuum of grades of membership [26]. Fuzzy logic handles the concept of partial truth, where the value of truth it is in a range from completely true to completely false. In the scientific literature there are several directions to handle uncertain events. For example processing uncertain databases [1] or using resilient algorithms to tolerate degrees of errors in data without losing performance, storage capability and correctness [21, 9].

The current paper investigates the Ant Colony Optimization when the artificial ants have to take decisions influenced by fuzzy degrees of sensitivity. The identification of solutions for complex problems it is based on the ants colonies self-organization and by the indirect interactions between ants. The indirect communication occur when the environment is modified, this process is *stigmergy* and influences the artificial ants decisions.

The paper is organized as follows: Section 2 is about the Ant Colony Optimization; Section 3 introduces the fuzzy approach of Sensitive Multiple Colonies followed in Section 4 by the fuzzy approach for ACO with Multiple Sensitive Colonies. The last part of the paper includes several discussions on the proposed technique and concludes with future work and final remarks.

2 Prerequisites

The concept of stigmergy it is behind the collective behaviour of social individuals as for example the ants or why not, the humans. Grassé [10] studied the stigmergic behaviour of ants and in [12] it is described the indirect communication between bees within a colony. "Stigmergy occurs when an insect's actions are determined or influenced by the consequences of another insect's previous action." [2]

Nowadays are made artificial environments [25] called smart-dust network with tiny micro-electromechanical systems as sensors, robots or other devices installed with wireless communication able to detect vibrations, light, smells or others.

The environment mediates the indirect communication between individuals, and ants in particular in *Ant Colony Optimization (ACO)* [8]. The *ACO* metaheuristic includes several ant algorithms. In ant algorithms are used artificial ants; the artificial ants mimic the behaviour of real ants, mainly the using the indirect communication based on the amount of pheromone deposited on a path of a network (graph), the probabilistic preference for a network paths with a larger amount of pheromone and in time, the shorter paths will have larger amount of pheromone.

The natural behaviour of ants includes cooperation and adaptation. There are several variants of ant mechanisms [23, 19].

A combinatorial optimization problem represented as a network /graph could be solved with an ant algorithm. In general, all ant algorithms are based on the following items, regarding the problems' candidate solution.

- In the problem related network, each path followed by an ant has a solution associated.
- The amount of the pheromone deposited by an ant on a network's path it is proportional to the quality of the corresponding solution.
- When an ant has the possibility to chose between several paths, it will chose, more probably, the path with the larger amount of pheromone.

So, finally the majority / all the ants will follow the paths with the larger pheromone trail, that will be, hopefully, the shortest tour and also the better solution for the optimization problem.

ACO it is successfully used to solve complex real world problems in different domains [8]: transport, routing, communication, scheduling, semantic web, bio-informatics etc.

3 A new fuzzy approach of Multiple Sensitivity Colonies for ACO

An ant colony it is a system endowed with stigmergy where not all the individuals have the same reaction to the pheromone trails. An ant has a certain pheromone sensitivity level (psl) expressed as a real number in the $[0,1]$ range. When *psl* it is null the ants ignores the indirect stigmergic information, so it is considered pheromone blind.

The ants are environment explorers when their sensitivity is rather small, so they are more independent then the others considered environment exploiters. The independent ants have the goal to sustain search diversification. The ants with high pheromone sensitivity will exploit further intensively the potential search areas [4, 14, 15, 17–19].

In the newly Multiple Sensitive Colonies, each colony it is endowed with a new parameter called *sensitivity level range* (rsl). An ant from a given colony has its pheromone level included in the specific range sensitivity level, *psl* it is included in slr. As for example an ant j with $psl_j = 0.15$ it is included into a colony with $slr = [0.10, 0.25]$.

In theory could be considered two variants for the *psl* of an ant:

- The *psl* could be considered fixed, a static value during the search ant's activity.
- The *psl* could be considered variable, a dynamic value, but with the constraint to be limited by slr.

In the current approach it will be used the second variant with a particular fuzzy approach on the slr range. Other related fuzzy approaches are in [5, 6]. A sensitivity degree is based on the uncertain environment influence, so it is called the *fuzziness degree of sensitivity,* fds; in particular are used the *dimension regularity* and *scale regularity*. Each *psl* is relocated randomly in an interval I, with the bounds: *psl* and the nearest *psl* bound of slr.

For example, a particular case for the new sensitive *psl* value could be considered the average between the initial sensitivity level, *psl*, and the nearest bound range, $Average(Min(l, psl), Min(psl, r))$, where l and r are the extremes left (l) and right (r) of the slr range.

So, for example, the ant j with the initial $psl_j = 0.15$, included into the colony with $slr = [0.10, 0.25]$ will have the potential to change its *psl* value into another *psl* value, based on a fuzzy approach.

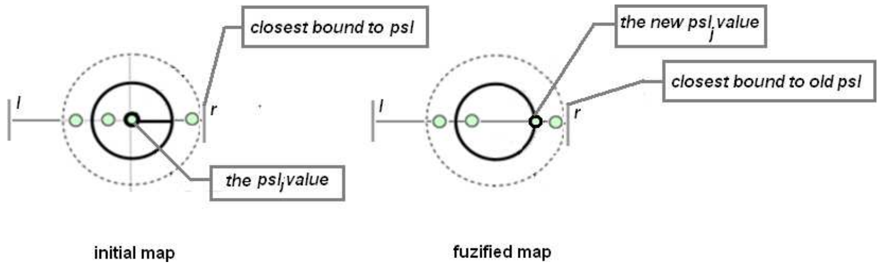

Fig. 1. A symbolic representation of the initial map (left side) and the fuzzified map (right side).

For the considered example, the newly pheromone sensitivity level of the ant j could be: $psl_j = 0.125$, but when using the fuzziness degree of sensibility could be any real value between $[0.10, 0.15]$.

The global parameters, considered as integers values: a and b on the $(0, 100)$ are expressing the uncertainty, as in [20]. The parameter a, the *dimension regularity*, specifies here how many ant's sensitivity values are modified, with the same impact irrespective of the number of ants. The parameter b, the *scale regularity*, specifies how far the *psl* value moves, but keeping the same impact irrespective of the distance [20]. Each *psl* value it is relocated randomly within a range. In Figure 1 are shown the modified values of ant j sensitivity psl_j, randomly chosen in the interval I, with the bounds: *psl* and the nearest *psl* bound of slr.

The introduced *Ant Colony Optimization with Multiple Colonies endowed with Fuzzy Degrees of Sensitivity* for solving combinatorial optimization problems can be described as follows.
ACO with Multiple Colonies endowed with Fuzzy Degrees of Sensitivity

```
Begin
  Set parameters
  Initialize "pheromone" trails
  Loop
    Activate a colony of ants with a sensitivity range, rsl
    Each ant is positioned in the search space
    Loop
      Fuzzy approach to modify the ant's sensitivity
      Each ant applies a state transition rule
       to incrementally build a solution
      A local "pheromone" updating rule is applied (Optional)
    Until all ants have built a complete solution
    A global "pheromone" updating rule is applied
  Until end_condition
End.
```

In time the ant colonies, with different levels of sensitivity obtain beneficent result for complex problems. Engaging multiple ant colonies the proposed model aims to achieve robust solutions in an evolutionary manner as further is illustrated by the numerical experiments.

4 Numerical experiments and Discussions

The main software used is the public software of T. Stützle *ACOTSPV1.0* [22] considering also the *3-opt* optional heuristic [11] for all algorithms.

Based on [14] with *Sensitive Ant Model (SAM)*, there are used colonies with different pheromone sensitivities non-overlapping interval distribution. The newest tests are made on the fuzzyified data-sets.

The fuzzy data are obtain similar with [20]: several nodes i are modified, randomly chosen using $C(i, radius)$, the circle with the center in the current node i; the radius is $y = x \cdot b/100$, where x is the distance from node i to the nearest node.

For four of the initial instances included in [14] were obtain eight new fuzzified instances. From each original instance were obtain new instances using the parameters a and b: (10,25) and (10,50).

The following cases and notations are considered as in [14].

- *SAM*: the Sensitive Ant Model use a random pheromone sensitivity PSL in [0,1] for the colonies of ants;
- *h-SAM*: *SAM* with *half* of the colonies of ants use a random PSL in [0,1] and the other colonies of ants, PSL in [0,0.25];
- *q-SAM*: *SAM* with a *quarter* of ants use a random PSL in [0,1] and the others with PSL in [0,0.25].

There are considered different parameters sets: $\alpha = 1$, $\beta = 2$, τ_0=0.01; the number of ants considered is 10; the termination criteria is 60sec./trial for ten trials and maximum 500 tours. For the current work are used also the parameters $\rho = 0.5$ and $q_0 = 0.7$.

As in [20], for each case is included a statistical anayis based on the Percentage Change of the solution related to the optimal solution $PC = \frac{solution - optimum}{optimum} \cdot$ 100%, where, in our case, the *solution* is the best solution found and *optimum* is the optimum found in the TSPLib [24] for each considered instance.

Tables 1-4 and Figures 2-4 illustrate that the multiple-colonies with different levels of pheromone sensitivity have good results when solving *TSP*.

Practically, the paper shows that implementation of ACO is fairly stable when some uncertain data are involved. So, this could shown the ability of multiple colonies, with different pheromone sensitivity, to be adaptable to many difficult situation.

Future work will be on testing data with other parameters and other data, including more complex data as for example from generalized routing problems [13, 15, 16, 19].

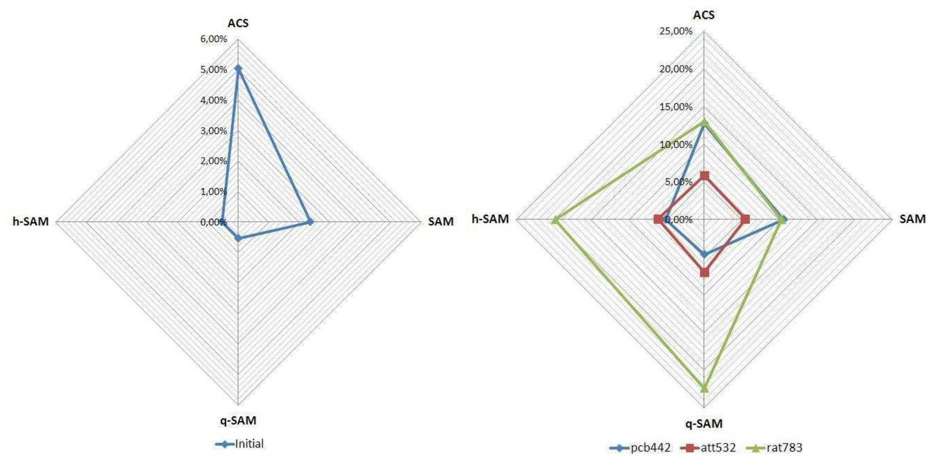

Fig. 2. Comparision of Pecentage Change (PC) for the initial data-sets: $lin318$ in the left side and the other three instances considered in the right side.

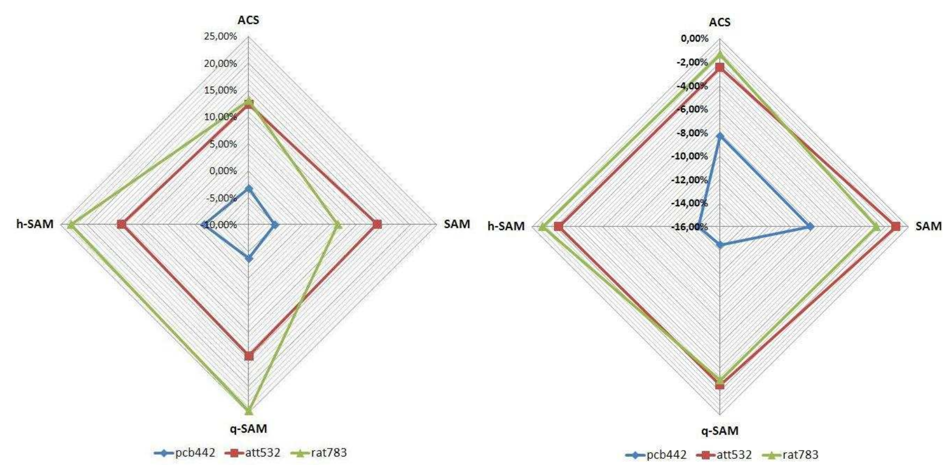

Fig. 3. Comparision of Pecentage Change (PC) for three fuzzy data-sets: (10,25) (left) (10,50) (right).

Instance	Optim	ACS	PC	(10,50) ACS	PC	(10,25) ACS	PC
lin318	42029.00	42050.16	5.03%	42314.6	67.95%	42086.6	13.70%
pcb442	50778.00	50842.86	12.77%	50735.9	-8.29%	50761.4	-3.27%
att532	27686.00	27702.08	5.81%	27679.1	-2.49%	27720.2	12.35%
rat783	8806.00	8817.44	12.99%	8804.8	-1.36%	8817.5	13.06%

Table 1. Average of best results: ACS on TSP instances; fuzzy instances: $(a, b) \in (10, 50, (10, 25)$; initial value of ACS [14]; pecentage change (PC) is computed.

Instance	Optim	SAM	PC	(10,50) SAM	PC	(10,25) SAM	PC
lin318	42029.00	42038.92	2.36%	42298.4	64.10%	42054.6	6.09%
pcb442	50778.00	50831.42	10.52%	50735.5	-8.37%	50751.8	-5.16%
att532	27686.00	27701.12	5.46%	27683.1	-1.05%	27724.4	13.87%
rat783	8806.00	8815.02		8803.610.24%	-2.73%	8811.8	6.59%

Table 2. Average of best results: Sensitive Ant Model (SAM) on TSP instances; fuzzy instances: $(a, b) \in (10, 50, (10, 25)$; initial value of SAM [14]; pecentage change (PC) is computed.

Instance	Optim	q-SAM	PC	(10,50) q-SAM)	PC	(10,25) q-SAM	PC
lin318	42029.00	42031.28	0.54%	42304.5	65.55%	42040	2.62%
pcb442	50778.00	50801.58	4.64%	50704.7	-14.44%	50759.2	-3.70%
att532	27686.00	27705.50	7.04%	27679	-2.53%	27726	14.45%
rat783	8806.00	8825.74	22.42%	8803.4	-2.95%	8827.7	24.64%

Table 3. Average of best results: q-SAM (quarter of ants use random $PSL \in [0, 1]$, others: $PSL \in [0, 0.25]$) on TSP instances; fuzzy instances: $(a, b) \in (10, 50, (10, 25)$; initial value of q-SAM [14]; pecentage change (PC) is computed.

Instance	Optim	h-SAM	PC	(10,50) h-SAM	PC	(10,25) h-SAM	PC
lin318	42029.00	42031.28	0.54%	42302.4	65.05%	42073	10.47%
pcb442	50778.00	50804.14	5.15%	50706.2	-14.14%	50769.5	-1.67%
att532	27686.00	27702.94	6.12%	27679.7	-2.28%	27723.7	13.62%
rat783	8806.00	8823.42	19.78%	8805.2	-0.91%	8826.3	23.05%

Table 4. Average of best results: h-SAM (half of ants use random $PSL \in [0, 1]$, others: $PSL \in [0, 0.25]$) on TSP instances; fuzzy instances: $(a, b) \in (10, 50, (10, 25)$; initial value of h-SAM [14]; pecentage change (PC) is computed.

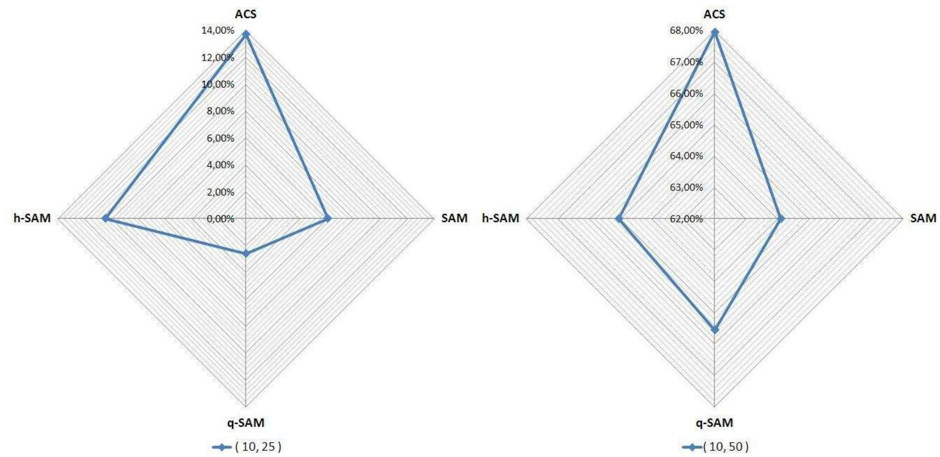

Fig. 4. Comparision of Pecentage Change (PC) for the $lin318$ data set: (10,25) (left) and with (10,50) (right) fuzzy data.

5 Conclusion

Ant Colony Optimization is today a powerful bio-inspired tool for solving difficult optimization problems. Inter-operation among ants is based on indirect communication mediated by "pheromone" trails. The article introduces fuzzy degrees of sensitivity when using multiple colonies of ants with different levels of pheromone sensitivity on ACO. The exploration and exploitation are enhanced and lead to potentially better ACO solution of optimization problems. Ongoing research focuses on several numerical experiments on several optimization problems, as Traveling Salesman Problem and its generalized version, to test the effects of the proposed fuzzy approach.

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