ACO Algorithm with Additional Reinforcement

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The aim of the paper is to develop the functionality of the ant colony optimization (ACO) algorithms by adding some diversification such as additional reinforcement of the pheromone. This diversification guides the search to areas in the search space which have not been yet explored and forces the ants to search for better solutions. In the ACO algorithms $[1, 2]$ after the initialization, a main loop is repeated until a termination condition is met. In the beginning ants construct feasible solutions, then the pheromone trails are updated. Partial solutions are seen as states: each ant moves from a state i to another state j corresponding to a more complete partial solution. For ant k, the probability p_{ij}^k of movement from state i to a state j as a next state is given as:

$$p_{ij}^k = \begin{cases} \frac{\tau_{ij}\eta_{ij}^{\beta}}{\sum_{l \in allowed_k} \tau_{il}\eta_{il}^{\beta}} \text{ if } j \in allowed_k \\ \\ 0 \qquad\qquad\qquad otherwise \end{cases}, \tag{1}$$

where τ_{ij} is a pheromone level corresponding to this movement, η_{ij} is the heuristic information and $allowed_k$ is the set of remaining feasible states.

In the beginning initial pheromone level is set to be τ_0. After all ants have completed their tours, the pheromone level is updated as follows:

$$\tau_{ij} \leftarrow \rho\tau_{ij} + \Delta\tau_{ij} \tag{2}$$

where $0 < \rho < 1$ is a pheromone decay parameter and $\Delta\tau_{ij}$ is different for different ACO algorithms.

When we perform the ACO algorithm search stagnation may occur. This can be happen, if the pheromone trail is significantly higher for one choice than for all others. The main purpose of this research is to avoid the stagnation situations by using additional reinforcement for unused movements and to search for better solutions. If some movement is not used in current tour we use additional pheromone reinforcement as follows:

$$\tau_{ij} \leftarrow \tau_{ij} + q\tau_{max}, \tag{3}$$

where $q \geq 0$ is a parameter and τ_{max} is a maximal amount of the pheromone. After additional reinforcement unused movements have great amount of pheromone than used one which, belong to the poor solutions and less to used movements that belong to best solution. Thus, we force ants to choose new direction of search space without repeating the bad experience. Preliminary results for the traveling salesman problem (TSP) suggest the usefulness of above diversification. Table 1 shows a comparison between our ACO algorithm with additional reinforcement and MMAS. We use a particular implementation of ACO algorithm, known as ant system with an elitist ant. Set of TSP from TSPLIB benchmark library (*http://www.iwr.uniheidelberg.de/iw/compt/software/TSLIB95*) is used as a test problems. The selected parameters for the test are , m=25 ants, $\rho = 0.8$, $\beta = 2$ and $q = 0.2$. The maximum number of cycles was set to 20000 for all experiments and the average are taken over 25 trials. For comparison, the same program is used for both algorithms, with same parameters and same number of iterations and the difference is only in the pheromone updating. Bold numbers indicate the better results. From the achieved result of table 1, it is clear that our ACO algorithm with additional reinforcement performs better than MMAS. For future research is to develop this new ACO algorithm and test on different optimization problems.

Table 1. The results of ACO algorithm with additional reinforcement and MMAS algorithm

	Add. Reinforcement		MMAS	
Instance	Best	Average	Best	Average
d198	15780	**15780.3**	15780	15780.9
lin318	42029	42051.8	42029	42051.8
pcb442	**50785**	**507891**	50795	509421
att532	**27686**	**27706.8**	27693	27707.4
rat783	8808	**8820**	8808	8841
dsj1000	**18688548**	**18704977.1**	18708266	18736562.2
pr1002	**259167**	**259692.5**	259290	260025
vm1084	239321	**239434**	239321	239490.17
pcb1173	**56897**	56970.5	56909	**56969.4**
d1291	50801	**50820**	50801	50847.7
rl1304	252948	**253159**	252948	253528.17
rl1323	**270226**	**270580.17**	270281	270725.5
fl1400	**20161**	**20229.67**	20254	20299.17
fl1577	**22337**	**22412.83**	22349	22423.67
vm1748	**336873**	**337107.17**	337506	337772.83
u1817	**57294**	**57346.5**	57314	57458.67
rl1889	**317430**	**317743.33**	318284	319295

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