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Ant Colony Optimization Method Applied to Distribution Network Reconfiguration

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Abstract: Ant Colony Optimization (ACO) is a meta-heuristic iterative algorithm used to solve different combinatorial optimization problems. In this method, a number of artificial ants build solutions for an optimization problem and exchange information on their quality through a communication scheme that is similar to the one adopted by real ants. In this paper, Ant Colony Optimization is used to solve reconfiguration of a benchmark distribution system consisting of 14 buses for loss minimization. Solving this problem is a formidable task even for a simple distribution network as the number of possible switching options that are to be considered is numerous. The results obtained using any meta-heuristic method strongly depends on the control parameter values chosen. Here an attempt is made to study this aspect in detail with respect to Ant Colony Optimization algorithm applied for distribution network reconfiguration.

Keywords: Ant Colony Optimization, Network Reconfiguration, Loss reduction, Control parameters.

I. INTRODUCTION

Power industry worldwide has undergone significant changes leading to the creation of a power market. This introduced competition in wholesale and retail trading of power. Power engineers require computational intelligence tools for proper planning, operation and control of the power system due to deregulation in the power sector. The computational intelligence techniques are formulated to solve types of optimization and decision making problems. They provide the power utilities with innovative solutions for efficient analysis, optimal operation and control and intelligent decision making.

Neural Network, Fuzzy Logic, Genetic Algorithm, Simulated Annealing and the Swarm Intelligence techniques like Particle Swarm Optimization, Ant Colony Optimization play an important role in power industry for decision-making, modelling, and control problems. Due to the nonlinear nature of power system networks and industrial electric systems like FACTS and HVDC, fuzzy logic and neural networks are promising candidates for planning, fault detection, automatic control, system identification, load and load/weather forecasting, etc. Distribution system routing and loss minimization are dealt effectively using Evolutionary algorithms and Swarm intelligence techniques.

In this paper a distribution network reconfiguration problem is solved using Ant Colony Optimization algorithm for minimizing active power losses of the system. Section II of the paper presents Ant Colony Optimization and Section III briefs about distribution network reconfiguration. In Section IV, the computational results obtained for reconfiguration of a 3-feeder, 14-bus benchmark system using Ant Colony Optimization is presented. Various aspects of tuning of different control parameters for the algorithm used are discussed in Section V. Finally, the conclusions are given in Section VI.

II. ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) is one of the population based meta-heuristic optimization methods for finding approximate solutions to discrete optimization problems. The method was first applied to the Travelling Salesman Problem (TSP) by M. Dorigo and L. M. Gambardella [1]. The method was later successfully extended to other optimization problems like vehicle routing problems [2,3] and quadratic assignment problems [4].

Ant colony optimization method was inspired from natural behaviour of the ant colonies on how they find the food source and bring them back to the nest by building the unique trail formation. In 2004, E. Carpaneto and G. Chicco [5] introduced ant colony search method to solve the network reconfiguration problem. In the same year, Ching-Tzong Su et al. [6] introduced the global updating rule to the ant colony search algorithm. They concluded from the research, that compared to simulated annealing and genetic algorithm methods ant colony search algorithm offers a better average solution. The method also was computationally less intensive compared to the other two methods.

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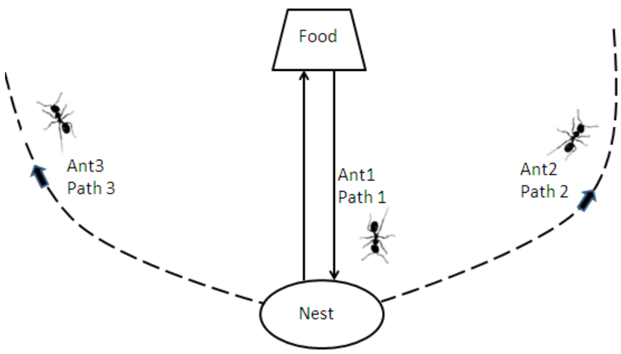

Fig. 1 Illustration of ants foraging for food

An illustrative description of the foraging behaviour of ants is shown in Fig. 1. Initially, three ants leave their nest in random directions to search for food. They deposit certain amount of pheromone trails in the paths they visit. The deposited pheromone will evaporate slowly but are detectable by other ants. In the first case assume that Ant 1 finds a food source. It returns to the nest after collecting its food by following its own pheromone trail. While doing so it will deposit additional pheromone on the same path. If the next group of ants start their search for food before Ant 2 and Ant 3 returns to the nest, they detect twice as much pheromone on Path 1 than on Path 2 and Path 3, assuming the evaporation of pheromone is negligible. The probability for a path to be followed is proportional to its pheromone value. The shortest path will have the maximum pheromone. Thus more ants will follow that path in the consecutive rounds of search for food. The concentration of pheromone on the best path will increase at a faster rate, since the path is shorter and the ants move with the same speed. Thus with each iteration, the concentration of pheromone of the shortest path will rise at a faster rate.

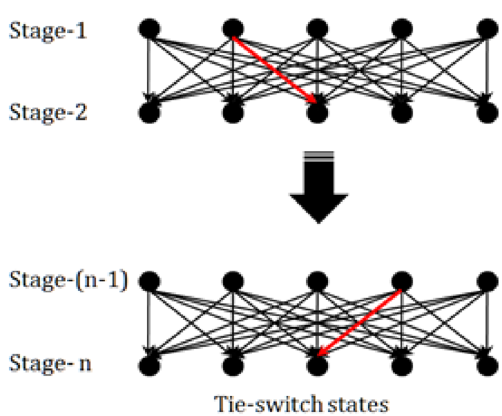

Fig. 2 ACO search space. (Red line indicates the solution)

Fig. 2 shows the search space for ACO algorithm. For a feeder reconfiguration problem, all possible tie-switches for a given stage are represented by the states in the search space. The number of stages will be equal to the number of loops. All ants are distributed randomly at all the tie-switches at the starting. In each stage, an ant chooses only one state based on the probability which is calculated using the equation (1).

$$p_k(i,j)=\begin{cases}\dfrac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum\limits_{m\in J_k(i)}[\tau(i,m)]^{\alpha}[\eta(i,m)]^{\beta}}, & if\ j\in J_k(i)\\ 0\ , & otherwise\end{cases}\quad ..(1)$$

In the above equation, $\tau(i, j)$ is the pheromone content of the path from the tie-switch i of previous stage to tie-switch j of the present stage $\eta(i, j)$ is the inverse of power loss of the corresponding path and $J_k(i)$ is the set of tie switches that remain to be visited in the present stage by ant k positioned at tie-switch i. The denominator of the expression is the sum of probabilities of all the tie-switch options that are available for the k^{th} ant for the present stage. The above equation is called the state-transition rule. This process is continued until the ant reaches the last stage. Once an ant completes its tour, the pheromone content of the complete path travelled by it is updated using equations (2) and (3).

$$\Delta\tau(i,j)=\Delta\tau(i,j)+q\sum_{Stage-1}^{Stage-n}p_{Loss}(k)\ldots\ldots\ldots\ldots(2)$$

$$\tau(i,j)=(1-\rho)\,\tau(i,j)+\Delta\tau(i,j)\ldots\ldots\ldots\ldots(3)$$

In the above equations, $\Delta\tau(i, j)$ is the incremental change in pheromone for a path from tie-switch i to tie-switch j of the next stage, q is a heuristic parameter, $\sum p_{Loss}(k)$ is the power loss of the completed path from stage-1 to stage-n. ρ is the pheromone trail decay co-efficient, which is defined to diversify the search by shuffling the search process.

III. DISTRIBUTION NETWORK RECONFIGURATION

Distribution systems are normally operated as radial networks. Under normal operating conditions, the distribution feeders can be reconfigured by switching operations for increased network reliability and reduced line losses. The new configuration should be radial and should also meet the load requirements. Feeder reconfiguration is the process by which the topology of a distribution system is changed by altering the open/closed status of the sectionalizing switches and tie switches [7, 8]. Sectionalizing switches are normally closed and tie switches are kept normally open. The crux of the reconfiguration problem lies in identifying the tie and sectionalizing switches that are to be opened and closed, respectively so as to achieve the maximum possible reduction in losses.

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Mathematically, distribution system reconfiguration problem is a complex, combinatorial, constrained optimization problem. The objective function of the problem is given by equations (4) and (5).

$$Min\,F = \min\left(P_{T,Loss} + \lambda_V \times S_{CV}\right) \qquad (4)$$

Subject to the constraint:

$$V_{\min} \le |V_i| \le V_{\max} \qquad (5)$$

Here, $P_{T,Loss}$ is the total real power loss of the system, λ_V is the penalty constant, S_{CV} is the squared sum of the violated voltage constraints, $|V_i|$ is voltage magnitude of bus i and $V_{\min}, V_{\max}$ are the minimum and maximum bus voltage limits respectively. In addition to the above inequality constraint specified by equation (5), following constraints also need to be satisfied:

1) The operating structure of the network should be radial in nature.

2) There should be no nodes without a power supply path present in the network.

The complexity of the problem is due to the fact that, distribution network topology has to be radial and power flow constraints are non-linear in nature. The radiality constraint and the discrete nature of the switch status prevent the use of classical optimization techniques to solve the reconfiguration problem. Therefore, most of the algorithms in literature are based on heuristic search techniques. A. Merlin and H. Back [9] proposed a branch-and-bound type heuristic method to determine the network configuration for minimum line losses. S. Civanlar et al. [7] suggested a branch-exchange type algorithm, where a simple formula has been derived to determine how a branch exchange affects the losses. In [10, 11] the authors used genetic algorithm to find the minimum loss configuration. Y. J. Jeon and J. C. Kim [12] proposed a loss minimum reconfiguration methodology using simulated annealing. In [13, 14] the authors proposed solution procedure using particle swarm methods.

IV. COMPUTATIONAL RESULTS

Fig. 3 shows the flow chart for the code developed for feeder reconfiguration.

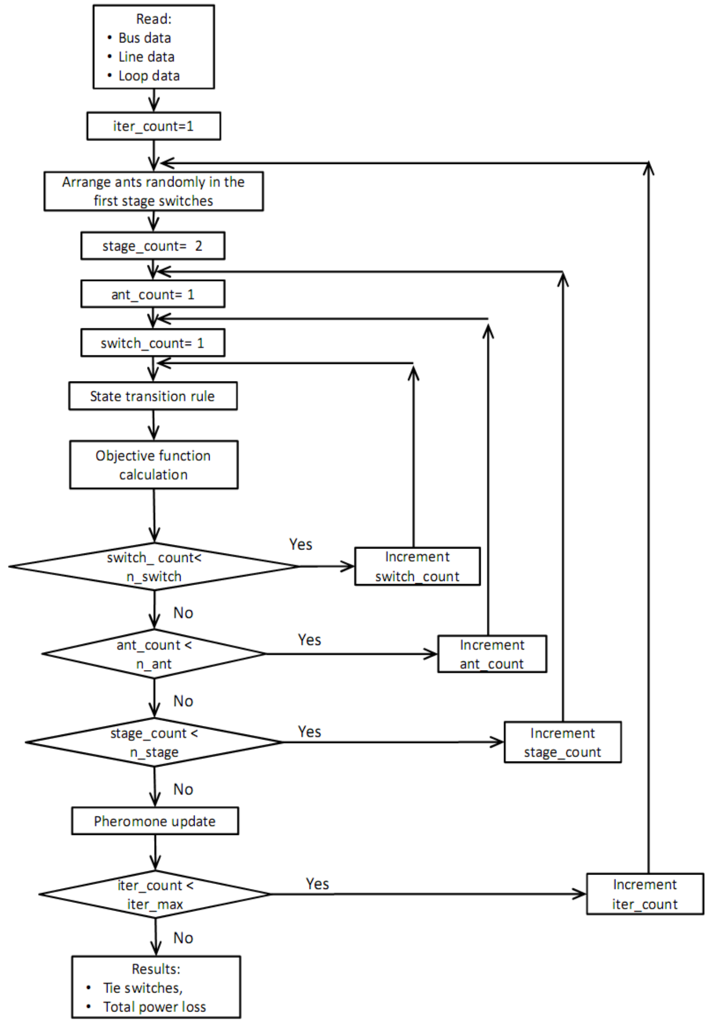

Fig. 3 Flow chart for feeder reconfiguration

To study application of Ant Colony Optimization in network reconfiguration in distribution systems a 14 bus, 3 feeder system from the literature was used. Details of the data of the system can be found in [7]. The system is shown in Fig. 4. The system consists of three radial feeders, connected at the root node, thirteen sectionalizing switches and three tie switches. The system load is assumed to be constant and the base values are $100\,MVA$ and $23\,kV$. The original system has 15, 21 and 26 as the tie switches.

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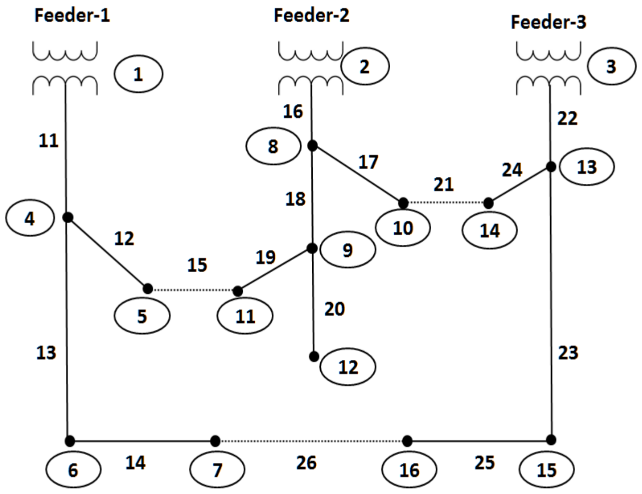

Fig. 4 Civanlar 3-feeder system

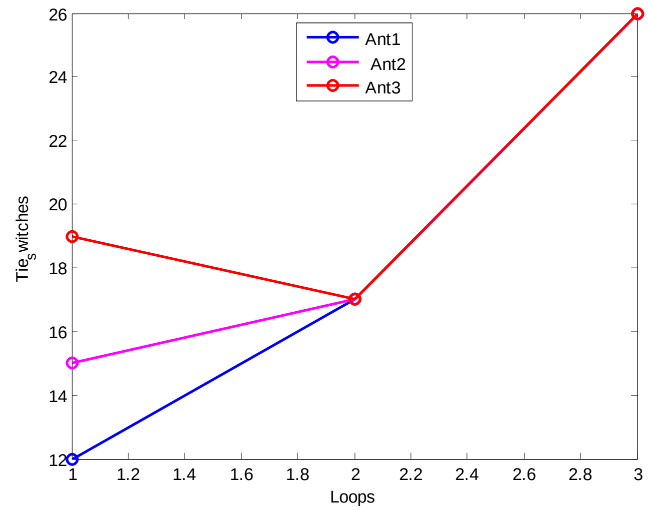

Fig. 5 Ant paths for reconfiguration of Civanlar system

Table I gives the values of control parameters and the number of iterations used for the run.

TABLE I
PARAMETERS USED FOR RECONFIGURATION OF CIVANLAR SYSTEM

Parameter	**Value**
Trail intensity factor, α	2
Visibility factor, β	8
Pheromone trail decay co-efficient, ρ	0.5
Heuristic parameter, q	10
Number of ants, n	3
Number of iterations, N	25

Fig. 5 shows the positions of ants-1, 2 and 3 at all loops corresponding to the last iteration. There are three loops formed when all tie and sectionalizing switches of the system are closed. It should be noted that for loop-1, switches 12, 15 and 19 are the tie-switch options available for reconfiguration. Similarly, 17, 21 and 24 are the tie-switch options for loop-2 and 14, 25 and 26 are the tie-switch options for loop-3. In figure 4.1, ant-1 is positioned at switch-12, ant-2 at switch-15 and ant-3 at switch-19 for stage-1. In the second stage, ants 1, 2 and 3 have chosen switch-17 as tie-switch. For stage-3, all the ants have chosen switch-26 as the tie-switch. Ant-3 has chosen the optimal tie-switch path in this iteration.

Fig. 6 shows the active power loss of the ant corresponding to minimum active power loss path for each iteration of the run. Since ants are placed randomly at the first stage of all iterations the minimum active power loss path need not corresponds to the same ant for all iterations. It can be seen from the figure that the solution has converged by 4th iteration.

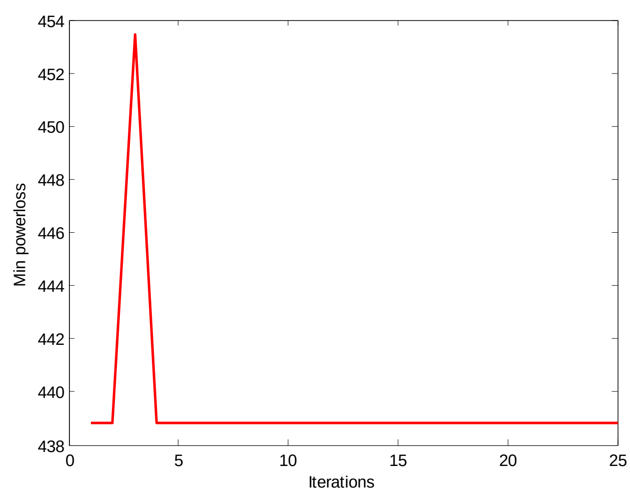

Fig. 6 Minimum active power loss per iteration for reconfiguration of Civanlar system

Fig. 7 gives the voltages at all buses before and after reconfiguration. The tie switches of the original configuration were switches 15, 21 and 26. Tie-switches of the reconfigured system are switches 17, 19 and 26. From the figure, it can be seen that the maximum and minimum voltages of the original system were $1.00\,p.u$ (feeder nodes 1, 2 and 3) and $0.9053\,p.u$ (node 11) respectively and for the reconfigured system they are $1.00\,p.u$ (feeder

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nodes 1, 2 and 3) and $0.9143\,p.u$ (node 12) respectively. It may be noted that the voltage deviations are within $\pm 0.1\,pu$.

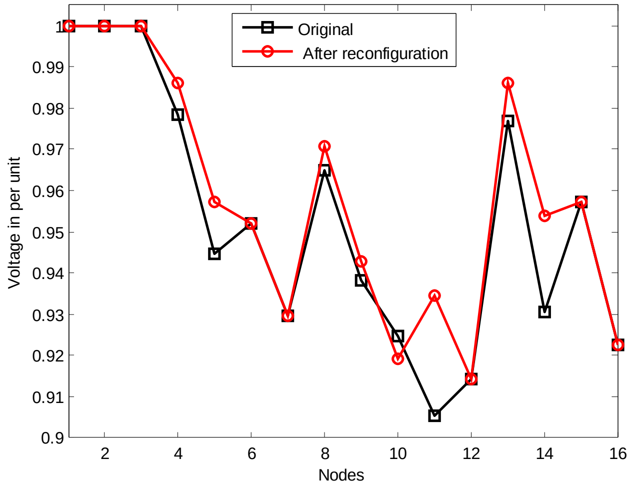

Fig. 7 Voltage profile at all nodes of the system before and after reconfiguration of Civanlar system

Summary of the results obtained for the reconfiguration carried out for Civanlar system is given in Table II. It can be seen from the table that two switches have been changed from 'normally close' to 'open' status (switches 19 and 17). This leads to changing the status of switches 15 and 21 to closed position. Total loss reduction achieved by the reconfiguration procedure is 28.33%.

TABLE II
SUMMARY OF RESULTS

Parameters	Original configuration	After reconfiguration
Tie switches	15,21,26	19,17,26
Power loss (kW)	612.31	438.82
Loss reduction (%)		28.33
Maximum voltage (p.u)	1	0.9053
Minimum voltage (p.u)	1	0.9143
CPU time/ iteration (s)		0.2964

V. TUNING OF CONTROL PARAMETERS

The ACO algorithm has a set of control parameters that has to be tuned in order to provide the best possible solutions in least possible time. The parameters include the following:

- Pheromone trail intensity factor, α
- Visibility factor , β
- Pheromone trail decay co-efficient, ρ
- Heuristic parameter, q
- Number of ants, n
- Number of iterations, N

The optimal values of these parameters were determined after numerous trial simulations, until it provided the best possible result for a given system. In the following sections the effects of the parameters are analyzed for the reconfiguration problem of Civanlar system.

A. *Effect of α and β*

During the simulations carried out to assess the effect of parameters α and β, the pheromone trail decay co-efficient (ρ) is set to 0.5. The heuristic parameter q is set as 10. For the Civanlar system which is under consideration, the number of ants (n) is taken as 3. The number of iterations (N) is taken as 25. As α appears as the exponent to the pheromone value during the probability calculation, it directly affects the amount of pheromone information used.

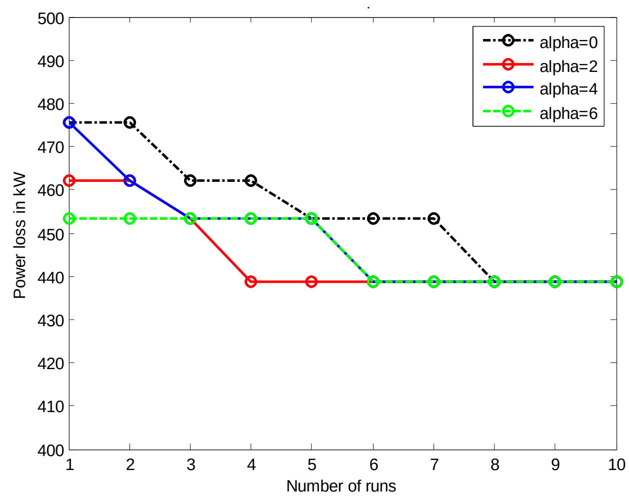

Fig. 8 The variation of power loss with different values of α

Fig. 8 shows the variation of losses calculated for different values of α. Here β is kept constant at 5. A situation where $\alpha = 0$ implies that the probability calculation is independent of the pheromone intensities. This will cause the algorithm to keep searching for better and better alternatives leading to higher number of iterations required for convergence. On the other hand, if the value of α is increased relative to β, then the algorithm tends to converge to local optimal solutions. This is evident from the fact that α signifies the importance of experience whereas, β signifies the importance of knowledge. It can be seen from the figure that the optimum value of α for the fixed values of $\beta = 8, \rho = 0.5,\ q = 10$ and $n = 3$ for the reconfiguration of Civanlar system is 2.

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Fig. 9 shows the variation of losses calculated for different values of β keeping α constant at 2. Lower values of β implies that the probability calculation is dependent on the pheromone content. This will cause the algorithm to keep converge fast at a local optima. On the other hand, if the value of β is increased by a large extend relative to α, then the algorithm keep searching for better and better alternatives leading to higher number of iterations required for convergence. It can be seen from the figure that the optimum value of β for the fixed values of $\alpha = 2,\ \rho = 0.5,\ q = 10$ and $n = 3$ for the reconfiguration of Civanlar system is 8.

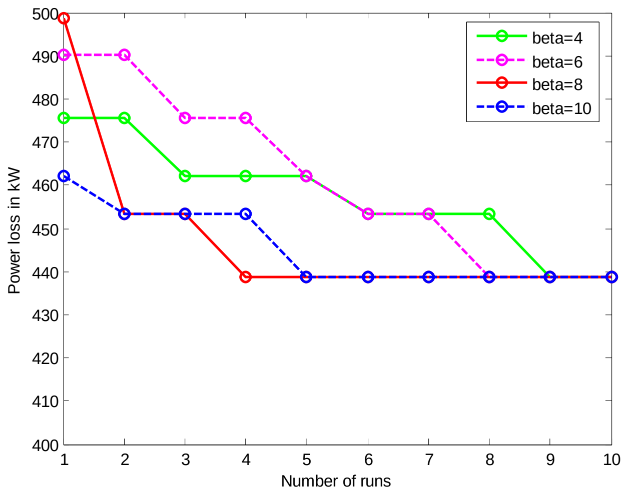

Fig. 9 The variation of power loss with different values of β

From several trial simulations carried out, the optimal values of the control parameters, for the reconfiguration of Civanlar system using the developed code, were found to be $\alpha = 1, \beta = 8, \rho = 0.5$ and $q = 10$.

B. Effect of evaporation parameter (ρ)

This parameter is strongly related to the parameter α. It accounts for the transfer of experience from one generation to the next. If the value of ρ is too small, then the algorithm may tend to converge to local optima (refer Fig. 10) as it places high importance on the previously constructed solutions. On the other hand, if the value of ρ is very high, the algorithm will place very high importance to the pheromone increments received in the current step leading to a greedy search. It can be seen from the figure that the optimum value of ρ for the fixed values of $\alpha = 1, \beta = 8,\ q = 10$ and $n = 3$ for the reconfiguration of Civanlar system is 0.5.

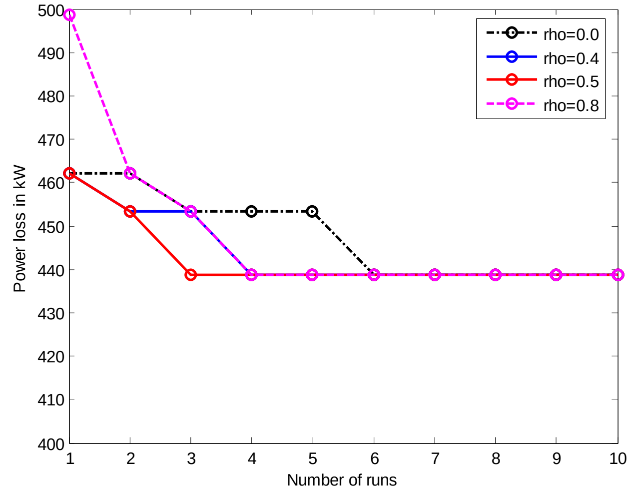

Fig. 10 The variation of power loss with different values of ρ

C. Effect of heuristic parameter (q)

From equation (2), it is evident that a higher value of q will imply higher importance to the knowledge acquired. Therefore, the effect is similar to that of ρ. Increase in value of ρ will lead to reduction in importance of the experience. The effect of increase in q also has the same effect (refer Fig. 11). If the value of q is too small, then the algorithm may tend to converge to local optima since it places high importance on the previously constructed solutions. $q = 10$ was selected for reconfiguration problem of Civanlar system.

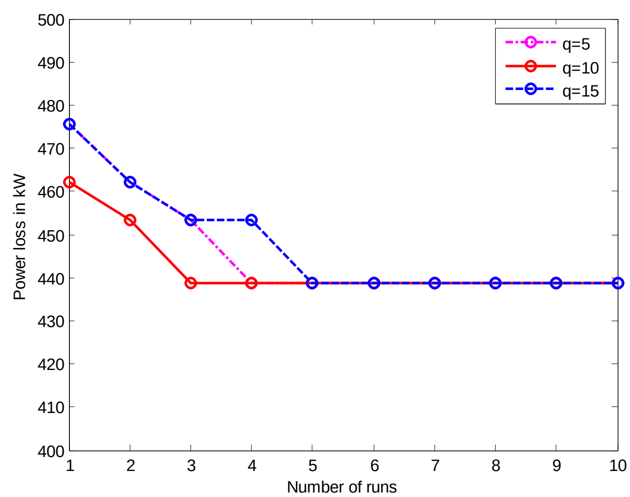

Fig. 11 The variation of power loss with different values of q

D. Effect of number of ants (n)

In the formulation used for the present study, it was found that it is highly advisable to have the same number of ants as

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the number of tie-switch options available in the first stage or its multiples. A different number of ants sometimes leads to long converging time (refer Fig. 12).

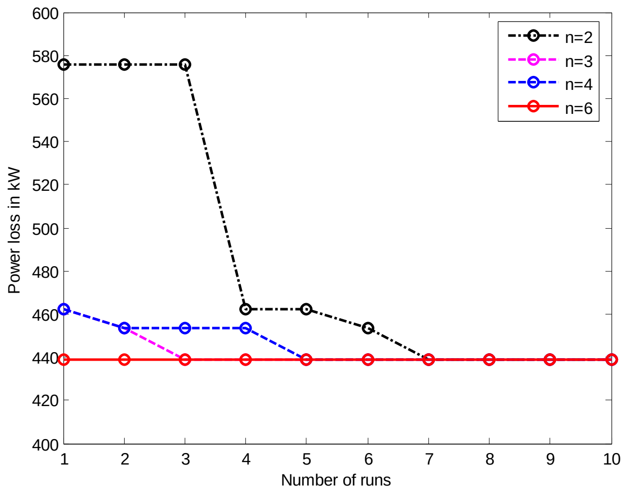

Fig. 12 The variation of power loss with different values of n

If proportionally higher numbers of ants are placed initially on switches that are not optimal, the pheromone intensity in these trails increase and the algorithm tends to converge to these non-optimal solutions. Therefore, it is better to place same number of ants on all the tie-switch options of stage-1 so as to prevent the algorithm getting biased to any solution. In a similar fashion, if the number of ants is less than the number of tie-switch options in stage-1, the optimal tie-switch may not have any ants placed on it to begin with. For reconfiguration of Civanlar system 3 ants were used.

E. Effect of number of iterations (N)

Other parameters remaining the same, there will be a minimum number of iterations required for a given problem to converge, which has to be arrived at by conducting several trials. Increasing the number of iterations beyond this will not lead to any improvement in the solution. The minimum number of iterations required for a particular is a function of all the other parameters like α , β , ρ and n . For the reconfiguration problem of Civanlar system using the developed code, for the chosen values of control parameters, it has been identified that the optimal solution converged within 25 iterations.

VI. CONCLUSION

In this paper Ant Colony Optimization, a meta-heuristic optimization algorithm, is used to solve a distribution network reconfiguration problem. A 3-feeder, 14-bus benchmark system was used as application example. The results show that the performance of the algorithm on reconfiguration problem is satisfactory with respect to optimal solution, speed of convergence and constraint realizations. An attempt was made to analyze different aspects of tuning of the control parameters of the algorithm. It has been seen that the success of the algorithm for an application depends on the proper setting of these parameters.

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