APPLICATION OF ANT COLONY ALGORITHM FOR NETWORK RECONFIGURATION IN DISTRIBUTION SYSTEMS

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Abstract: This paper presents an efficient algorithm for the loss minimization by automatic sectionalizing switch operation in distribution systems. Ant colony algorithm is a multi-agent system in which the behaviour of each single agent, called artificial ant, is inspired by the behaviour of real ants. Ant colony algorithm is suitable for combinatorial optimization. The proposed methodology with some modification to the ant colony algorithm improves the computation time and convergence property. Numerical examples demonstrate the validity and effectiveness of the proposed methodology on a 32 bus system and a KEPCO 148 bus system. Copyright © 2002 IFAC

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1. INTRODUCTION

Network reconfiguration is performed by opening/closing of switches to reduce power loss. There are many switches and operating constraints, which make it difficult to find the optimal solution in distribution systems.

Network reconfiguration problem is to find a minimum spanning tree in a distribution system because of its radial structure. There have been many algorithms developed for the network reconfiguration problem (Baran, 1989; Civanlar, 1988; Shirmohammadi, 1989; Gosowami, 1992; Chiang, (1990); Augugliaro, 1992; Nara, 1992). Although the branch and bound, branch exchange, and expert system techniques can solve the problem with rather less computational burden, solutions are only approximates and local minima. Recently, genetic algorithm, simulated annealing, and tabu search are used in combinatorial optimization problems (Song, 1999; Mantawy, 1999, Kim, 1997, Gallego, 1997). Genetic algorithm generates new solution candidates through the crossover and mutation of strings, but many infeasible solutions are generated because the distribution systems are sparse spanning trees. Simulated annealing can generally find an optimal solution, but it requires much computation time. Tabu search generally finds a good solution, but it does not have a good convergence property. Because of its flexible nature, tabu search would be better in hybrid with other algorithm rather than in an independent application.

Simulated annealing, tabu search, and branch exchange techniques are based on local search, which require diversification strategies based on the long-term memory in order to search unvisited regions. But diversification strategies cannot be easily applied to a distribution system. Therefore, ant colony algorithm is applied to the network reconfiguration problem since it has superior solution properties by using pheromone as the long-term memory.

The ant colony algorithm is based on the natural metaphor of ant colonies. Real ants are capable of finding the shortest path from a food source to their nest without using visual cues, but by exploiting pheromone information. Although ant colony algorithm is the latest optimization algorithm, it has been successfully applied in many optimization problems.

In this paper perturbation mechanism and pheromone updating rule are proposed for network reconfiguration problem and integrated with local search capability of the ant colony algorithm to improve the efficiency of search. The proposed search algorithm is demonstrated in a 32-bus and a 148-bus system to verify its the validity and effectiveness.

2. ANT COLONY ALGORITHM

Ant colony algorithm is a multi-agent system in which the behavior of each single agent, called artificial ant, is inspired by the behavior of real ants. Ant colony algorithm is one of the most successful examples of swarm intelligent systems, and has been applied to many combinatorial optimization problems (Colorni, 1991; Corne, 1999).

Real ants are capable of finding the shortest path from a food source to their nest without using visual cues, but by exploiting pheromone information. A way ants exploit pheromone to find a shortest path between two points is shown in Fig. 1.

![Fig. 1. Behavior of real ants](image-url)
In Fig. 1(a), ants are moving in a straight line, which connects a food source to the nest. Once an obstacle appears as shown in Fig. 1(b), the path is cut off. Those ants, which are just in front of the obstacle, cannot continue to follow the pheromone. When they arrive at a decision point, they make a probabilistic choice, which is biased by the amount of pheromone they smell on the two paths. This behavior has an autocatalytic effect because the very fact of choosing a path will increase the probability that it will be chosen again by future ants. At the beginning of the experiment there is no pheromone on the two paths and therefore ants going from the nest to the food source will choose any one of the two paths with equal probability. Due to differential path length, in Fig. 1(c), the ants choosing the right path will be the first ones to reach the food source. When these ants, on their way back to the nest, reach the decision point, they will see some pheromone trail on the shorter path (this is the trail they released during their forward journey) and will therefore choose the shorter path with higher probability than the longer one. New pheromone will then be released on the chosen path, making it even more attractive for the subsequent ants. While the process iterates, pheromone on the shorter path is deposited at a higher rate than on the longer one. Therefore, the shorter path is more frequently selected by ants until, eventually, all ants end up using this path.

The above behavior of real ants has inspired the ant colony algorithm, an algorithm in which a set of artificial ants cooperate toward the solution of a problem by exchanging information via pheromone deposited on graph edges. Ant colony algorithm has been applied to combinatorial optimization problems such as the traveling salesman problem and the quadratic assignment problem (Corne, 1999).

3. APPLICATION OF ANT COLONY ALGORITHM

Ant colony algorithm is performed by the heuristic information and pheromone update rule. In this paper the heuristic information is updated by a perturbation mechanism and ants choose new solutions by using the proposed local and global update rules.

3.1 The perturbation mechanism in ant colony algorithm

In combinatorial optimization problem the objective function, perturbation mechanism, and parameter tuning are necessary to find global optimum. Since a distribution system is operating in a radial structure, switch pairs are used in the branch exchange, simulated annealing, and tabu search. However, the selection method, which determines the property and direction for search, is slightly different for each algorithm

The branch exchange algorithm determines the sectionalizing switch, which yields the minimum change in loss among all sectionalizing switches in a loop created by closing a tie switch. In all loops the same procedure is performed and then the sectionalizing and tie switches having the least power loss are selected. Simulated annealing creates a new solution by selecting any sectionalizing switch in the loop after creating a loop by selecting a tie switch randomly. Tabu search chooses the optimal solution among neighboring solutions, which are created by using the perturbation mechanism in simulated annealing.

Simulated annealing requires a long computation time for search, but the convergence property is guaranteed. Branch exchange algorithm converges with rather less computation time, but the results are only local minima. Tabu search may be a trade-off between simulated annealing and branch exchange because the minimum solution in the neighborhood is determined while a tie and sectionalizing switches are randomly selected. In tabu search intensification and diversification mechanisms are necessary because the convergence property cannot be guaranteed, which makes it difficult to apply in the network reconfiguration problem. Therefore, power loss changes obtained by branch exchange method are used as heuristic information for the search strategy used in the ant colony algorithm.

Power loss changes by branch exchange can be obtained by selecting a sectionalizing switch in the loop that is created by closing a tie switch; details are explained by using Fig. 2.

![Fig. 2. A loop with a sectionalizing and tie switches](image)

For notational convenience, tie switches will be identified by the corresponding tie numbers. Without loss of generality, let us assume that there are sectionalizing switches on every branch of the system. All switches will also be identified by the corresponding branch numbers. In Fig. 2 it is assumed that the voltage of bus \( k \) is lower than that of bus \( n \); let the lower voltage side be \( L\)-side and the higher voltage side be \( R\)-side. Power loss change obtained due to the status exchange between tie switch \( b \) and sectionalizing switch \( m \) or \( s \) is determined by equations (1) or (2), respectively:

\[
\Delta L_{P_{bm}} = 2P_m \left( \sum_{l \in L} r_l P_l - \sum_{l \in R} r_l P_l \right) + 2Q_m \left( \sum_{l \in L} r_l Q_l \right) \\
- \sum_{l \in R} r_l Q_l - (P_m^2 + Q_m^2) \sum_{l \in RLYL} r_l 
\]

\[
\Delta L_{P_{bs}} = 2P_s \left( \sum_{l \in R} r_l P_l - \sum_{l \in L} r_l P_l \right) + 2Q_s \left( \sum_{l \in L} r_l Q_l \right) \\
- \sum_{l \in L} r_l Q_l - (P_s^2 + Q_s^2) \sum_{l \in LYL} r_l 
\]
Voltage of L-side is lower than that of R-side means L-side has more power loss. If loads in L-side are transferred to R-side, the power loss is expected to be reduced. On the other hand, if loads in R-side are transferred to L-side, the power loss is expected to be increased. For this reason, branch exchange generally expects sectionalizing switches in L-side. However, loss reduction occasionally can be achieved by exchanging sectionalizing switches in R-side. Therefore, equation (1) for only L-side in Baran (1989) is modified to equation (2) to calculate power loss change for R-side.

Loss change by selecting a sectionalizing switch in a loop can be calculated by equations (1) or (2), which is used as a heuristic information in the ant colony algorithm. This information together with pheromone can make it possible to search for the solution in probability; the probability of opening sectionalizing switch $i$ is determined by

$$p_{k}(i) = \begin{cases} \frac{[\eta(t)]^\beta / [\tau(t)]}{\sum_{s \in J_k(l)} [\eta(s)]^\beta / [\tau(s)]} & \text{if } s \in J_k(l), \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where $\tau(s)$ is pheromone and $\eta(s)$ is the inverse of the changed loss for selecting a sectionalizing switch $s$, with all changed loss normalized for negative change, $k$ is the number of ants and, $J_k(l)$ is the set of sectionalizing switches in loop $l$. The parameter $\beta$ is for determining the effect of changed loss on pheromone. Equation (3) indicates that a sectionalizing switch which was less visited has higher probability to be selected.

Sectionalizing switches are basically selected by using the roulette wheel selection scheme in genetic algorithm, where proportionate weights are based on equation (3). Proportionate selection generally introduces a good solution, but all ants need not participate in the proportionate search because ant colony algorithm generally uses many ants. Therefore, in this paper two methods are used in the selection scheme:

$$\text{selection} = \begin{cases} \max \left\{ \left[ \frac{\eta(t)}{\tau(t)} \right]^\beta \right\} & \text{if } \gamma \leq \gamma_0, \\ \text{equation (3)} & \text{otherwise} \end{cases} \quad (4)$$

where $\gamma$ is the random number uniformly distributed between 0 and 1, $\gamma_0$ is a parameter($0 \leq \gamma_0 \leq 1$).

In equation (4), some ants select sectionalizing switches by using equation (3) and others select the best solution. The parameter $\gamma_0$ determines the relative importance of exploitation versus exploration.

3.2 Updating rule of pheromone

In Section 3.1, the selection method for sectionalizing switches is described by using a heuristic information and pheromone without an explanation for the property of pheromone. The successful application of ant colony algorithm depends on the control of pheromone according to the property and size of the optimization problem.

Global updating rule of pheromone

Pheromone corresponds to the long-term memory of tabu search. It accumulates search history, which makes it possible to converge to an optimal solution by memorizing the information obtained in the search procedure.

After all ants create network configurations by equation (4), only the best ant is allowed to update pheromone. It is called global updating rule and is performed by

$$\tau(s) = (1 - \alpha) \cdot \tau(s) + \alpha \cdot \Delta \tau(s) \quad (5)$$

where $\Delta \tau(s) = \begin{cases} 1/f_k(s) & \text{if } s \in S, \\ 0 & \text{otherwise} \end{cases}$ 0<\alpha<1 is the decrement parameter of pheromone, $f_k(s)$ is the $k$-th ant’s total loss, and $S$ is the set of sectionalizing switches included in the configuration with minimum loss.

Since the pheromone of sectionalizing switches included in the best solution is increased, the updated sectionalizing switches have higher probability to be included in the next best solution. The pheromone remembers and accumulates a part of good solutions through the global updating rule, which makes the solution to approach the global minimum.

Local updating rule of pheromone

Combinatorial optimization algorithm is generally designed to drive the search into attractive regions and into new promising regions. In ant colony algorithm intensification strategy is performed by using the global updating rule, while diversification strategy is performed by using the local updating rule as follows:

$$\tau(s) = (1 - \rho) \cdot \tau(s) + \rho \cdot \tau_0(s) \quad (6)$$

where $\rho$ is a parameter(0<\rho<1), $\tau_0(s)$ is obtained by multiplying 0.1 to ‘1/(total power loss)’ of the initial configuration.

The local updating rule for diversification strategy decreases the pheromone of sectionalizing switches that are included in a solution created by an ant. Since the pheromone of sectionalizing switches that are included in solutions is slightly decreased, the switches frequently selected by prior ants may not be selected in the next. This procedure is performed until all ants create solutions, which drives the search into new promising region.
Pheromone is significantly increased by the global updating rule and slightly decreased by the local updating rule. Therefore, in the search process the pheromone of sectionalizing switches included in the global minimum is gradually increased.

3.3 Search procedure of the proposed algorithm

In this paper the main procedure for search is based on the branch exchange and the pheromone updating rule, and the proposed methodology is described in detail as follows:

**Step 1:** Input data and initialize parameters. Input the system and network data; initialize the current solution $x_0$, the optimal solution $x_{opt}=x_0$, and the parameters of the ant colony algorithm.

**Step 2:** Select a tie switch and define a loop. Randomly select a tie switch in a system, and then a loop is created by the tie switch. Sectionalizing switches in the loop are defined.

**Step 3:** Calculation of the change in loss for the branch exchange. Calculate the change in loss for all switch pairs by equations (1) and (2).

**Step 4:** Select a sectionalizing switch and reconfiguration. Select the sectionalizing switch by using the heuristic information in Step 3 and equation (4).

**Step 5:** Local update. Perform local update with equation (6).

**Step 6:** Check all ants. If all ants perform search procedures, go to Step 7; otherwise, go to Step 2.

**Step 7:** Global update. Perform global update with equation (5).

**Step 8:** Check the stop criterion. If the defined iteration is performed, stop; otherwise, continue the process by returning to Step 2.

4. NUMERICAL RESULTS

Two methodologies were implemented in C language on an Intel Pentium III 750MHz PC. The proposed methodology is tested by using the same calculation in the 32-bus and the KEPCO 148-bus system. In an initial configuration, total power loss is calculated by Simplified DistFlow equations and the power loss change for new configuration is calculated with equations (1) and (2). In this paper pheromone on the set of sectionalizing switches is updated as a solution, but this set is difficult to present and compare with other algorithms. For this reason, the set of tie switches, i.e., the complement set for sectionalizing switches, is used in numerical results.

Parameters mentioned in Section 3 are tuned for an optimal solution as shown in Table 1.

<table>
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<tr>
<th>Table 1. Parameters for Ant Colony Algorithm</th>
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<td></td>
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<tr>
<td>Number of ants</td>
</tr>
<tr>
<td>Iteration number</td>
</tr>
<tr>
<td>$\alpha$</td>
</tr>
<tr>
<td>$\beta$</td>
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<td>$\rho$</td>
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<td>$\gamma_0$</td>
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The first test system has 32 bus and 5 tie switches as shown in Fig. 3 (Baran, 1989). The rated voltage is 12.66 kV and total load is 3715 kW with 2300 kVAR.
Branch exchange is the fastest, but converged to a local minimum. Simulated annealing and ant colony algorithm both have the same solution. Ant colony algorithm finds an optimal solution by using the branch exchange and pheromone updating rule in the search procedure. To verify pheromone update in search, the final pheromone is illustrated in Fig. 5.
simulated annealing and ant colony algorithm both have the same solution. The ant colony algorithm obtains a good result in terms of the convergence property and computation time. It has been demonstrated that the proposed methodology is effective for the network reconfiguration problem.

5. CONCLUSION

This paper presents an efficient algorithm for loss minimization in an automatic sectionalizing switch operation in distribution systems. The branch exchange and the ant colony algorithm are successfully integrated to find the global optimum in distribution systems. The proposed methodology is shown to improve the computation time and convergence property. Numerical examples demonstrate the validity and effectiveness of the proposed methodology on the 32-bus system and 148-bus system.

REFERENCES


