Swarm Intelligence Method Ant Colony Optimization forReconfiguration of Distribution System

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***Abstract*—Network reconfiguration in distribution systems is a process of changing the topology of distribution network by altering the open or closed status of switches. The reconfiguration problem can be formulated as a nonlinear optimization problem with both integer and real variables. The objective of this study is to present a new algorithm to solve the optimal feeder reconfiguration problem, for loss reduction in distribution systems. This employs a heuristic method called Ant Colony Optimization (ACO). The Ant Colony Optimization algorithm is a relatively new and powerful swarm intelligence method for solving optimization problems. It is also called an Ant Colony Search Algorithm (ACSA). It is a population based approach that uses exploration ofpositive feedback as well as greedy search. The Ant Colony Optimization (ACO) Algorithm was inspired from the natural behavior of ants and tries to emulate them in locating food sources and bring them back to their colony by the formation of unique trials. Therefore, through collection of cooperative agents called "ants", the near optimal solution to the feeder reconfiguration can be effectively achieved.In addition, the ACSA applies the state transition and Global pheromone updating rules to facilitate the computation.In this project work the presented algorithm involves selecting, among all the possible configurations, the one that incurs the smallest power loss and that satisfies constraints like voltage magnitude, current limit of the branches and Radial topology.The proposed approach is demonstrated using IEEE 16 BUS test system. The simulation code is written in MATLAB software for the analysis.**

***IndexTerms*— Topology, Ant Colony Optimization, Reconfiguration, Radial.**

I. INTRODUCTION

India is world's 6th largest energy consumer, accounting for 3.4% of global energy consumption. Due to India's economic rise, the demand for energy has grown at an average of 3.6% per annum over the past 30 years. In March 2014, the installed power generation capacity of India stood at 147,000MW while the per capita power consumption stood at 612 kWh. The country's annual power production increased from about 190 billion kWh in 1986 to more than 680 billion kWh in 2006. The Indian government has set an ambitious target to add approximately 78,000MW of installed generation capacity by 2012. The total demand for electricity in India is expected to cross 950,000 MW by 2030. [1]Electricity losses in India during transmission and distribution are extremely high and vary between 30 to 45%. In 2004-05, electricity demand outstripped supply by 7-11%. Due to shortage of electricity, power cuts are common throughout India and this has adversely effected the country's economic growth.The reduction of these losses was essential to bring economic viability to the State Utilities .High technical losses in the system are primarily due to inadequate investments over the years for system improvement works, which has resulted in unplanned extensions of the distribution lines, overloading of the system elements like transformers and conductors, and lack of adequate reactive power support. Hence, a good lot of programs have been organized to minimize these huge technical losses in the transmission and distribution sector. So, there is a considerable exposure for power systems engineers to look into the problem and wide ways to minimize the losses in these sectors and aid the government organized programs in minimizing these losses.

II. DISTRIBUTION SYSTEM RECONFIGURATION

Electrical power is transmitted by high voltage transmission lines from sending end substation to receiving end substation. The secondary transmission system transfer power from this receiving end substation to secondary substation. A secondary substation consists of two or more step down power transformers together with voltage regulating equipment's, buses and switchgear. At the secondary substation voltage is stepped down to 11kV. The portion of the power network between a secondary substation and consumers is known as distribution system. The distribution system can be classified into primary and secondary system. Some large consumers are given high voltage supply from the receiving end substations or secondary substation.The area served by a secondary substation can be subdivided into a number of sub- areas. Each sub area has its primary and secondary distribution system. The primary distribution system consists of main feeders and laterals. The main feeder runs from the low voltage bus of the secondary substation and acts as the main source of supply to sub feeders, laterals or direct connected distribution transformers. The lateral is supplied by the main feeder and extends through the load area with connection to distribution transformers. The distribution transformers are located at convenient places in the load area. They may be located in specially constructed enclosures or pole mounted. The secondary distribution system consists of distributors which are laid along across road sides. The service connections to consumers are tapped off from the distributors. The main feeders, laterals and distributors consist of overhead lines or cables or both. The distributors are 3 phase, 4 wire circuits, the neutral wire being necessary to supply the single phase loads. Most of the residential and commercial consumers are given single phase supply. Some large residential and commercial consumers get 3 phase supply. The service connections of consumers are known as service mains.The consumer receives power from the distribution system.Fig2.1 Single line diagram of power system network.

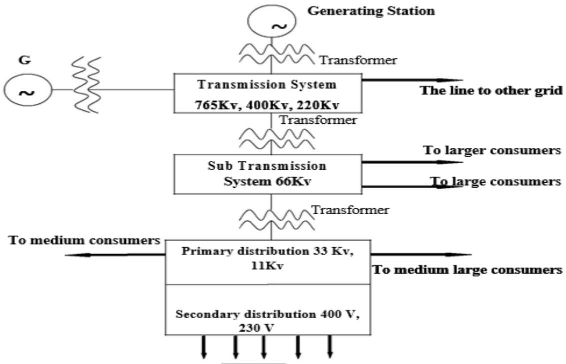

Fig. 2.1 Single Line Diagram of Power System Network

III. NETWORK RECONFIGURATION

The electric power distribution system delivers power to the customers from a set of distribution substations. While the transmission and sub-transmission lines are configured in a meshed network, the distribution feeders are configured radially in almost all cases. This radial configuration simplifies over current protection of the feeder. Distribution System is configured using two kinds of switches namely Tie Switch and Sectionalizing Switch. Tie Switches are normally open whereas the Sectionalizing Switches are normally closed. The presence of switches distributed over the network supports different configurations to supply power to the loads. Tie switches between circuits provides alternate feeds. Both types of switches are designed for protection configuration management. The process of altering the topology of the distribution systems by changing the status of both Tie switches and Sectionalizing Switches is entailed as Feeder Reconfiguration. For each configuration, there is an associated loss of power in the feeders. The losses would be minimized if all switches were closed, but this is not done because it complicates the system's protection against over currents. Whenever a component fails, some of the switches must be operated to restore power to as many customers as possible.

3.1 Methods for Distribution Network Reconfiguration

There are various methods exist for the reconfiguration of distribution system. Some of them are explained below:

1. Branch and Bound Method

A significant number of studies have been devoted to optimize the distribution system using different computational methods, and the Branch and Bound algorithm of the linear programming methods has been employed to find an optimal solution to design problem. Consider a close loop network consisting of number of nodes. The branch and bound method is an effective math device, as it is based on implicit systematic enumeration of feasible solution set and it provides us with the

The efficiency of this methodology depends on two important factors: the branching rule or the principle of branching, and the bound calculation bases. However, the exact efficiency improvement is very hard to pin down. It cannot be mathematically represented, as it's differs for each different problem. And the designers (design engineers) sometimes have different opinions for different reasons for the same problem and so they carry out different configurations. This makes the task more sophisticated.

2. Branch-Exchange Algorithm

The branch exchange technique, applied for the reconfiguration of distribution network, basically converts a radial network into a meshed network by connecting the tie lines. The radial structure is restored again by opening some other lines of the network so as to minimize an objective function. The exact form of objective function being dependent upon the purpose of reconfiguration. In the proposed algorithm branch exchange technique is implemented by forming one loop only at a time.

Two types of branch exchanges are performed

1. Branch exchange within each distribution zone – called intrazone branch exchange.
2. Branch exchange between the adjacent distribution zones called interzone exchange.

Intrazone exchange and interzone exchanges are performed repeatedly. A set of interzone and intrazone branch exchanges constitute an iteration of the algorithm. The branch exchange continues till the system cost or limit violation can be minimized. When the optimum solution is obtained for the selected substations, we check the optimality of the substation capacity. If the optimum is not reached a new solution is obtained byreducing the number of substation by one. The substation having the maximum cost per KVA is closed and a new optimum network configuration is obtained with the selected substations. This process is repeated till a cost reduction is achieved by reducing the number of substation. A complete load flow is performed after each successful branch exchange. Since the number of successful branch exchanges is generally much less than the number of exchanges attempted, number of full load flows are not many. It may be noted here that the solution obtained from radial load flow has to be changed every time when a branch exchange is attempted.

3. Evolutionary Algorithms

Evolutionary algorithms work with a population of individuals (codified solutions), which is able to evolve in a given environment by application of the selection, crossover, and mutation operators. The “elite” or best individuals (solutions) survive during the optimization process. Each individual or “chromosome,” represents a complete solution of the network. The chromosomes are integer strings that codify the connection between the nodes of the distribution network.The first step of an evolutionary algorithm is to generate the initial population. The initial population consists of μ different chromosomes generated randomly, that represent μ different solutions for the configurations.A random sampling of this initial population is selected to create an intermediate population, and the crossover and mutation operators are applied to them in order to obtain a new population with λ chromosomes. This process is called a generation and it is repeated until a stop function is decided. The population of the next generation must haveμ chromosomes. These μ chromosomes will be the best (minimal cost function) of the set composed by the μ and λ chromosomes of the previous generation.

IV. SWARM INTELLIGENCE

A long time ago, people discovered the variety of interesting insect or animal behaviors in the nature. A flock of birds sweeps across the sky. A group of ants forages for food. A school of fish swims, turns, bees together, etc. Hence swarm is a large number of homogeneous, simple agents interacting locally among themselves, and their environment, with no central control to allow global interesting behaviors to emerge. Swarm based algorithms have recently emerged as a family of nature-inspired, population based algorithms that are capable of producing low cost, fast, and robust salutations to several complex problems." This apparent collective intelligence seems to emerge from what are often large groups of relatively simple agents. The agents use simple local rules to govern their actions and via the interactions of the entire group, the swarm achieves its objectives. Swarm intelligence (SI) can therefore be defined as a relatively new branch of Artificial Intelligence that is used to model or describe the collective behavior of decentralized, self-organized swarms natural or artificial.SI systems are typically made up of a population of simple agents or boids interacting locally with one another and with their environment.Computational modeling of swarms has been further applied to a wide-range of diverse domains, including machine learning, bioinformatics and medical informatics, dynamical systems and operations research they have been even applied in finance and business. Natural examples of SI include ant colonies, bird flocking, animal herding, bacterial growth, and fish schooling. In this project work, Ant colony optimization (ACO) technique is used as an optimization tool to reduce the power loss by optimizing few problems in distribution systems. ACO is based on ‘Ant Colonies’ which belongs to swarm intelligence groups which aims to solve single optimization problem using many number of co-operative agents.

V. Ant Colony Optimization (ACO) Model.

The first example of a successful swarm intelligence model is Ant Colony Optimization (ACO). It is a probabilistic technique derived basically from Swarm Intelligence methods for solving computational problems which can be reduced to finding good paths through graphs. This algorithm is a member of ant colony algorithms family, in swarm intelligence methods, and it constitutes some met heuristic optimizations. Initially proposed by Marco Dorigo in 1992 in his Ph. D thesis, the first algorithm was aiming to search for an optimal path in a graph based on the behavior of ants seeking a path between their colony and a source of food..It is a recent method for solving hard combinatorial optimization problems. It mimics the behavior of real ants. It uses the heuristic information of the problem and the pheromone trails to build the solution and guides the search. In this project, the ant colony optimization method is used for the application of optimal reconfiguration of distribution system.

5.1 Ants in Nature.

Since tens of millions of years ago, ants have survived different environments, climates and ages that dinosaurs, did not. The secret of the remarkable ecological success of ants can be explained by a single word: sociality. Ants have demonstrated exceptional social organization in several ways: They are inclined to live in organized societies made up of individuals that cooperate, communicate, and divide daily tasks. Ants have impressive abilities in finding their way, building their nests, and locating food supplies. They are not only efficient, but hard-working and thrifty creatures that can adapt to different ecosystems and survive harsh weather conditions.

5.2 Ant Colony Behavior.

An analogy with the way ant colonies function has suggested the definition of a new computational paradigm, which we call *Ant System*. We propose it as a viable new approach to stochastic combinatorial optimization.In the real world, ants (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but to instead follow the trail; returning and reinforcing it if they eventually find food.
Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over faster, and thus the pheromone density remains high as it is laid on the path as fast as it can evaporate. Pheromone evaporation has also the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.

Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads all the ants following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve. By means of an indirect communication mechanism known as stigmergy (pheromone laying), ants can share local and global information that can lead to the construction of shorter paths in that space. Ant system is based on positive feedback (the deposit of pheromone attracts other ants that will strengthen it themselves) and negative (dissipation of the route by evaporation prevents the system from thrashing). Theoretically, if the quantity of pheromone remained the same over time on all edges, no route would be chosen. However, because of feedback, a slight variation on an edge will be amplified and thus allow the choice of an edge. The algorithm will move from an unstable state in which no edge is stronger than another, to a stable state where the route is composed of the strongest edges. The ant colony behavior is depicted in the following figure 5.1 and figure 5.2.

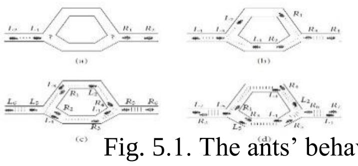

Fig. 5.1. The ants' behavior:
(a) The ants reach to the point of making a decision. (b) The ants choose one of the two paths randomly. (c) If the ants move with the same speed, the ants which have chosen the shorter path reach sooner to the point of making next decision. (d) The amount of pheromone in the shorter branch increases at a higher rate. (Adapted from Dorigo and Gambardella)

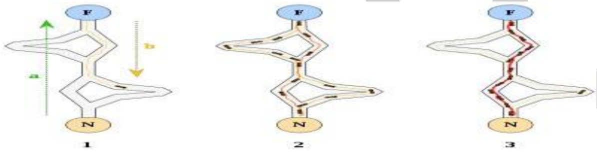

Fig. 5.2. The ants' behavior

1. The first ant finds the food source (F), via any way (a), then returns to the nest (N), leaving behind a trail pheromone (b);
2. Ants indiscriminately follow four possible ways, but the strengthening of the runway makes it more attractive as the shortest route;
3. Ants take the shortest route, long portions of other ways lose their trail pheromones.

5.3 Characteristics of the proposed method

- Positive Feedback: It reinforces good solution directly by pheromone accumulation.
- Negative Feedback: It avoids premature convergence (stagnation) by pheromone evaporation.
- Cooperation: It explores different solutions, where multiple ants exploring solution space and pheromone trial reflecting multiple perspective on solution space.
- Distributed Computation: It avoids premature convergence.
- Greedy heuristic: It helps to find acceptable solutions in the early stages of the optimization process.
- Versatile: It can be applied to similar versions of the same problem.
- Robust: It can be applied with only minimal changes to other combinatorial optimization problems.

5.4 Differences between Real and Artificial Ants

Understanding a natural phenomenon and designing a nature-inspired algorithm are two related, yet different tasks. Understanding a natural phenomenon is constrained by observations and experiments, while designing a nature-inspired algorithm is only limited by one's imagination and available technology.Modeling serves as an interface between understanding nature and designing artificial systems. In other words, one starts from the observed natural phenomenon, tries to make a nature-inspired model of it, and then design an artificial system after exploring the model without constraints. Figure 5.4 illustrates the framework that is generally used to move from a natural phenomenon to a nature-inspired algorithm. It is worth emphasizing that, memory is the key difference between real and artificial ants; real ants have no memory, while artificial ants are offered a limited form of memory. The use of memory helps artificial ants to implement a number of useful behaviors that allow them to efficiently build solutions for more complex optimization problems than the simple double bridge experiment. One of such useful behaviors is that artificial ants evaluate the quality of the solutions generated, and use the solution quality in determining the quantity of pheromone to deposit. That is why pheromone is deposited only on the return way after a full path is constructed and evaluated in terms of the path length.

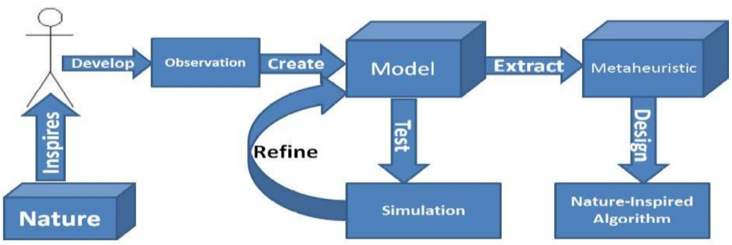

Figure 5.4: An illustration to the general framework used to move from a naturalphenomenon to a nature-inspired algorithm.

5.5COMPUTATIONAL RULES IN ACO.

1). **State Transition Rule**: The state transition rule used by the ant system, called a random-proportional rule, is given by the following, which gives the probability with which ant in node i chooses to move to node j:

$$\mathbf{P_k\ (i,\ j)} = \begin{cases} \dfrac{[\tau(i,j)][\eta(i,j)]^{\beta}}{\sum[\tau(i,m)]\,[\eta(i,m)]^{\beta}} & \text{if } j \in J_k(i) \\ 0 & \text{otherwise} \end{cases} \text{---------}\ (3.1)$$

Where, τ is the pheromone which is deposited on the edge between nodei and node j, η is the inverse of the edge distance, J_k (i) is the set of edges to be visited by ant k and β is the parameter which determines the relative importance between pheromone and distance. Equation (3.1) indicates that the state transition rule favours transitions toward nodes connected by shorter edges and with large amount of pheromone.

2) **Local Updating Rule**: While constructing its tour, each ant modifies the pheromone by the local updating rule. This can be written as follows:

$$\tau(i,j)=(1-\rho)*\tau(i,j)+\rho*\tau_0 \text{----------------------------} \qquad (3.2)$$

where, τ_0 is the initial pheromone value, and is a heuristically defined parameter. The local updating rule is intended to shuffle the search process. Hence the desirability of paths can be dynamically changed. The nodes visited earlier by a certain ant can be also explored later by other ants. The search space can be therefore extended. Furthermore, in so doing, ants will make a better use of pheromone information. Without local updating all ants would search in a narrow neighborhood of the best previous tour.

3) **Global Updating Rule**: When tours are completed, the global updating rule is applied to edges belonging to the best ant tour. This rule is intended to provide a greater amount of pheromone to shorter tours, which can be expressed as follows:

$$\tau(i,j)=(1-\sigma)*\tau(i,j)+\sigma*\delta^{1} \text{------------------------------------} \qquad (3.3)$$

Where, δ is the distance of the globally best tour from the beginning of the trail, and $\sigma \in$

[0,1] is the pheromone decay parameter. This rule is intended to make the search more directed; therefore the capability of finding the optimal solution can be enhanced through this rule in the problem solving process.

VI. SOLUTION METHODOLGY

The computational procedures of the proposed method are mainly composed of power-loss calculation, bus voltage determination, determination of radial topology and ant colony application. The computational procedures find a series of configurations with different status of switches such that the objective function is successively reduced.This chapter determines the main features of the ACO method, which is the basis of the proposed algorithm. Finally, an algorithm and flowchart for distribution system reconfiguration based on ACO is presented.

6.1 Search Space for Ant

Initially, we need to define search space for the formulated problem. The search space for feeder reconfiguration (ant reconfiguration) is shown in the following figure 6.1.

6.2 Search Space for Feeder Reconfiguration

To solve only feeder reconfiguration problem, the solution process begins with encoding parameters. A tie switches (TS) and some sectionalizing switches with the feeders form a loop. A particular switch of each loop is selected to open to make a loop radial such that the selected switch naturally becomes a tie switch. The network reconfiguration problem is identical to the problem of selecting an appropriate tie switch for each loop to minimize the power loss. A coding scheme that recognizes the positions of the tie switches is proposed. The total number of tie switches is kept constant, regardless of any change in the system's topology or the tie switches' positions. Different switches from a loop are, respectively, selected for cutting the loop circuit and trying to become a tie switch. After each loop is made radial, a configuration is proposed.

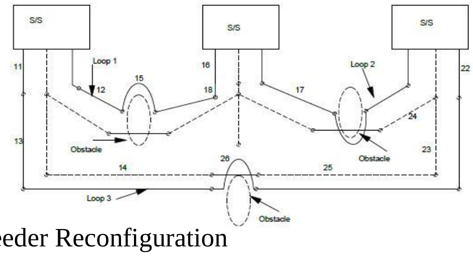

Fig. 6.1Search Space for Feeder Reconfiguration

6.3. Optimization Based on the Collective Behavior of Ants.

In the ACO method, a set of artificial ants (called agents) cooperate in finding"optimal" solutions to difficult discrete optimization problems. These problems are represented as a set of points (called states) and the agents move through adjacent states. Exact definitions of state and adjacency are problem-specific. The agents use a mechanism of indirect communication, called stigmergy [13], and have access only to local information about the environment. Most of the ideas of the ACO method come from the foraging behavior observed in real ant colonies [14]. When an ant moves through the environment and discovers a food source, it deposits on the ground a chemical substance, called pheromone [12]. This substance attracts other ants from the nest to collect the discovered food. Ants follow the pheromone trail built by the first ant and reinforce it. If there are several pheromone trails leading to a food source, ants will choose probabilistically the path to follow, based on the pheromone concentrations on the existing paths.

6.4 ACO for Distribution System Reconfiguration

An algorithm for distribution system reconfiguration based on the ACO method was proposed [8], in which the distribution system is represented as an undirected graph *G = (B, L)*, composed of a set *B* of nodes and a set *L* of arcs indicating the buses and their connecting lines. Agents move through adjacent nodes, selecting switches that remain closed, to minimize the system power loss.At the start, each network line has an initial pheromone concentration. Then, a certain number of ants are generated and positioned randomly at different nodes. When an agent is on node *i*, it chooses to move to the neighboring node *j* (where neighbors are directly connected nodes), according to the pheromone concentration on line (*i, j*) and the inverse of the distance between nodes *i* and *j*, relative to these values for the other neighbors of *i*. The selection of node *j* is probabilistic. After selecting node *j*, the agent updates the pheromone concentration on line (*i*, *j*). After (*n* - 1) steps, where *n* is the number of nodes in the system, each agent has traversed a complete path, meaning that all nodes have been visited. The period of (*n* - 1) steps can also be called an iteration. Next, the pheromone concentration on the best path (with the lowest power losses) is increased, representing to a global updating. After a given number of cycles the algorithm terminates, giving the best path found by the colony.

6.5 Computational Procedure

Step 1: Initiation

At the start problem variables are defined and the initial ant population is generated. In addition, these ants are positioned randomly at different nodes. During which the initial pheromone value τ_0 at each network line is also given at this step. And also the change in pheromone intensity is set to zero. i.e., $\tau_{ij}(0)=C$ and $\tau_{ij}=0$. Set time, t=0; Cycles NC=0;Place all the ants on nodes randomly and store the starting nodes of all ants in the Tabu list.

Step 2: State Transition Rule

Each ant placed on a starting stare will build a full path from the beginning to the end state through the repetitive application of state transition rule which is given by,

$$\mathbf{P_k\,(i,j)} = \begin{cases} \dfrac{[\tau(i,j)][\eta(i,j)]^{\beta}}{\sum[\tau(i,m)]\,[\eta(i,m)]^{\beta}} & \text{if } j \in J_k(i) \\ 0 & \text{otherwise} \end{cases} \quad \text{-------} \ (4.1)$$

Where, P_k (i, j) is the probability of agent k choosing to visit node j from node i

Step 3: Calculation of Objective function

$$\text{PT, Loss} = \min \sum_{k=1}^{m} \Big(\sum_{i=0}^{n-1} P_{Loss}(i,i+1) \Big) \quad \text{-----------------------}(4.2)$$

Where, m is the total number of feeder and n is the number of nodes in any feeder After (*n* - 1) steps, where *n* is the number of nodes in the system, each agent has traversed a complete path, meaning that all nodes have been visited. The period of (*n* - 1) steps can also be called an iteration. At this moment, the value of the objective function (4.2) is estimated for each path traversed by agents. This value corresponds to the sum of the power losses in every line visited by an ant.

Step 4: Global updating rule

If, in a given iteration, an agent *k* is on node *i* and all the neighbors of *i* have already been visited by *k*, it dies and with it, all memory of nodes it has visited. It is for this reason that the pheromone trail is not updated locally. If it were, a no feasible path (i.e. giving a non-radial topology) could become "attractive" in some future iteration,

$$\tau\,(i,j) = \tau\,(i,j) + \rho \quad \text{--} \quad (4.3)$$

Where ρ is the pheromone increment (0< ρ <1).

Before starting a new iteration, the pheromone concentration evaporates on each line of the system at the rate σ

$$\tau(i, j) = \tau\, \sigma\, (i, j) \text{ ---} \qquad (4.4)$$

Where σ is the pheromone decay-rate (0< σ <1).The evaporation of pheromone was performed to prevent some lines acquiring much more pheromone than others, inducing the stagnation of agents on these lines and consequently, leading the algorithm to a premature convergence at a local minimum.

Step 5: Termination of the algorithm

End the process if “the maximum iteration number is reached” or “all ants have selected the same tour” is satisfied; otherwise repeat the outer loop. In addition, the number of ants and the number of iterations were experimentally determined. All the tour visited by ants in each iteration should be evaluated. The algorithm obtains the route found by the agents that produces the lowest power losses. Thus, the lines of this route will normally have closed switches, while the other lines of the system will normally have open switches. The above procedure can be thoroughly explained by the following flowchart shown in figure 6.2

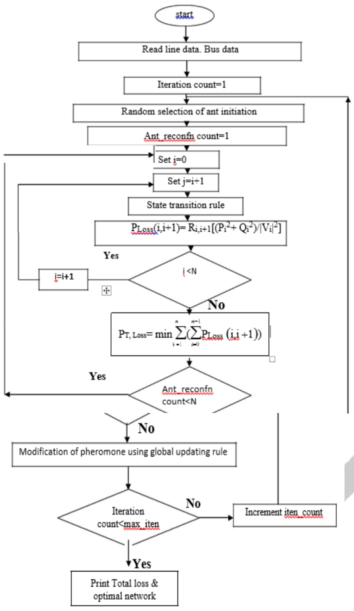

Fig.6.2 Flow chart for the proposed method.

6.6 IEEE 16 bus Radial Distribution Network Description

The developed algorithm has been applied on a standard 16 bus test system taken from literature [15]. It is a three feeder distribution system having three closed loops, thirteen sectionalizing switches and three tie switches. 16 bus system is shown in figure 6.3.The base chosen for this system is 23kV and 100 MVA and loads are assumed to be constant. It is having 13 sectionalizing switches and 3 tie switches.

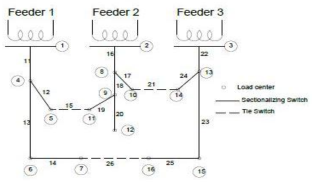

Fig. 6.3 Three feeder distribution system before reconfiguration.

6.7 **Results**

16 bus	Original configuration	After Feeder Reconfiguration
Items	15,21,26	17,19,26
Maximum Voltage(pu)	1	1
Minimum Voltage(pu)	0.9693 at bus 12	0.972 at bus 12
Power Loss (kW)	511.4	420.0
Loss reduction (%)	-	8.9

Table 6.1 Power Loss Minimization at a given Operational Situation

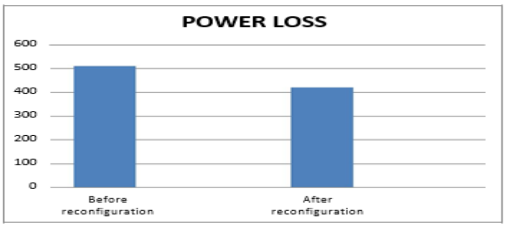

Fig.6.4 Power loss of 16 Bus system before and after reconfiguration.

The total real power loss in the existing configuration for the above system is 511.4 kW with tie switches as 15, 21 and 26. Then, the proposed methodology was implemented and following results are obtained and tabulated as shown in Table 4.2. The Table 6.1 shows the obtained results (Power Loss in kW) at a given operational situation. The Voltages at all the buses at a given operational situation is also shown in Table 6.1.

The proposed solution methodology of section 6.2 has been applied to the system under study and results are tabulated. The parameter selection was chosen based on the table 4.1. It can be witnessed that the power loss got reduced by 17.87% when network reconfiguration is used as a loss minimization tool. The system in Fig 6.4 Represents IEEE 16 Bus system before reconfiguration and Fig.4.6 represents after reconfiguration.

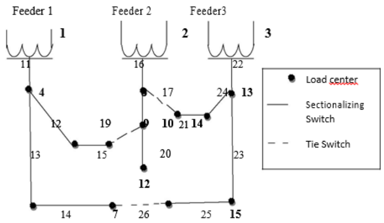

Fig. 6.4 Three feeder distribution system after reconfiguration

7 CONCLUSION AND SCOPE FOR FUTURE WORK

This project work proposed an algorithm, based on an ant colony behavior (Ant Colony Optimization-ACO), to solve the problem of network reconfiguration for power loss reduction.The proposed algorithm efficiently found the topology with the lowest power loss for the system presented in Fig 6.4. As per the results obtained and discussions made, the proposed algorithm is able to minimize the given objective function to an optimal or near optimal value while meeting all given constraints. Initially in the original configuration, the total real power loss was 511.4kW, but after the implementation of proposed methodology losses get reduced to 420.1kW. Hence, it is possible to achieve 17.87% of overall loss reduction. While minimizing the losses, it is also possible to improve the voltage profile of all the buses. This is substantiated in the improvement of voltage at bus 12 at the end of the algorithm. Initially the bus voltage at bus 12 was 0.9693 p.u. after the implementation of the proposed methodology, voltage at bus 12 get improved to 0.974 p.u.

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