ACO Based Method for Service Restoration in Distribution System using Fuzzy M.O.M.C Approach

Rajneesh Karn, Yogendra Kumar, Gayatri Agnihotri

***Abstract*—Service restoration in power distribution system is to restore power in healthy portion of out of service area as much as possible followed by a fault and isolating the faulted zone by operating the line switches connected in the network. In service restoration, not only the final network configuration but also the number of switching operations held for service restoration is important with a number of constraints like node voltage deviation, load balancing and priority customers. Thus the Service restoration problem is a multi objective multi constraint (M.O.M.C) combinatorial optimization problem. This paper proposes an Ant Colony optimization based methodology for minimizing the area where energy is not supplied and no of manually controlled and remotely controlled switching operations during the restoration process. A fuzzy membership function is defined for each term in objective according to relevant conditions and the final solutions are ranked according to the importance of objective under consideration.**

***Index Terms*—Ant colony optimization, Fuzzy logic, Service restoration.**

I. INTRODUCTION

Faulted events are unavoidable in any complex electrical power distribution systems. These faults affect the system's reliability and customer's satisfaction. When a fault occurs, in order to ensure minimal reduction in system reliability, the healthy areas isolated by the fault should be supplied with power. This procedure is called service restoration.

The main objective of service restoration is to restore as many loads as possible by transferring loads in the out of service areas to other distribution feeders via changing the status of normally closed and normally open switches which is known as network reconfiguration.

After occurrence of the fault, the operator finds the location of fault, isolate the fault and then restore the service to the healthy components of the out of service area. To meet the service restoration, the alteration of topological structure of distribution system is done by changing the status of switches in distribution system satisfying electrical and structural constraints. For the modern day distribution system, it is hard to implement service restoration solely depending on experimental rules by human operators. To reduce the out of service area as efficiently as possible and the burden of operators, a computer aided decision supports assist the operators. The researchers have developed many methods to solve the service restoration problem in distribution systems [1]-[12]. Heuristic techniques [1]-[4] and Expert systems [5]-[8] have been developed to quickly determine restoration plans and build look-up tables for distribution personals, but both of the above approaches require knowledge base of switching sequence used by the operators for service restoration. This knowledge base is stored in form of rules which are used by the above two approaches to get appropriate solution. However, the required knowledge base of switching sequence of the operators is a complex task to collect. In Fuzzy set approaches [9]-[10], out of service load, number of switching operation, line current, load voltage etc are taken as fuzzy variables and the solution is found on the basis of maximum membership function. But it also does not guarantee optimal solution. Conventional GA based techniques [11]-[16] have also been proposed for service restoration in which multi objective optimization problem is converted into a single objective optimization by using weighting factors and subsequently ,GA is used to solve this single objective function. Now the values of weighting factors depend upon the importance of objective functions as well as on the scaling of the objective functions and constraints. As the values of the objective functions and constraints vary from network to network, scaling factors also vary from network to network which in turn causes the variation of weighting factors for different networks. Hence for every network, weighting factors should be tuned accordingly. The improved technique using GA is NSGA-II [17] proposed by Y. Kumar, where for solving the service restoration problem, the multi objective nature of the problem is retained without the need for any tunable weights or parameters. As, a result, the proposed algorithm is generalized enough to be applicable to any power distribution network. But due to radial operation of distribution network, GA based on binary code generates a lot of infeasible solution in the evolutionary process and memory space required is very high. Among all above techniques a new metaheuristic approach 'Ant Colony Optimization' [25]-[28] influenced by the behavior of real ants was proposed by Dorigo, Maniezzo and Colorni in 1992. In early stage this approach was implemented for Travelling Salesman Problem [25].

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After the successful implementation of ACO, this new kind of Metahuristic technique based on swarm intelligence was proposed for various combinatorial optimization problems. Jen-Hao Teng [18] - [19] proposed ant colony system for optimum switch adjustment to improve the service reliability and compared the results from Genetic Algorithm and concluded ACS based optimization finds good results within reasonable computational time and found better one in comparison to GA-based method, since the ACS has the characteristics of positive feedback, distributed computation and the use of a constructive greedy heuristic. Sanjoy Das [20] proposed Ant algorithm for the optimal restoration of distribution feeders during cold load pick up and found better result in comparison to the method based on simulated annealing. Isamu Watanabe [21] proposed Hyper cube ACO for Service restoration in distribution System as the Hyper cube framework for ACO does not depend upon the scale of the problem. A standard ACO algorithm can give different results and more generally may have different behavior, when applied to two isomorphic problems differing only in that one is obtained from the other by multiplying the objective function by a constant value which is an undesirable property and can be removed by implementing ACO algorithm in Hypercube Framework.Lu, Wen and Yang [22] proposed improved ACO for service restoration where to improve the searching efficiency, the behavior of ants are controlled in the feasible set by the spanning tree algorithm and introduced two improved aspects for pheromone update in ACO algorithm. But in all the ACS based techniques mentioned in [18]-[22], the multiobjective nature of the problem is converted to a single objective by the use of weighting factors. In, this paper, an improved ant colony algorithm is presented for the network reconfiguration for service restoration of two practical distribution systems where multiobjective nature of the problem has been retained by ranking the objective by using fuzzy logic to get a quality function. Results by the proposed algorithm are compared on the basis of changing the weighting factors to demonstrate the prominent efficiency.

Some times service restoration for whole out of service area is not possible because power flow in the feeders goes beyond their power transfer capacity. Including the capacitor service controlled action can increase the power transfer capacity of the feeder and, therefore, enhances the chances of full service restoration. If full service restoration is not possible with capacitor control action also, including capacitor control action is definitely helpful to reduce out of service area.

The distribution systems are required to operate in radial fashion for proper relay coordination and ease of fault location etc. So the structure of distribution system should remain radial after service restoration also.

In this paper the authors solved the service restoration problem using Ant colony Optimization algorithm. During the optimization process of ACO, there is high probability of generation of better solution at every iteration. The string solution is represented by status of switches. In this work the original configuration and the nearest switch from fault point is considered as starting city of movement for ants. In this method, the following points are considered. 1. Area where Energy not supplied (ENS) and number of switching operations are minimized. 2. Voltage, current, radiality of the network and line losses are taken as the constraints. 3. To restore the service to the out of service area, capacitor switches are also considered along with tie switches and sectionalizing switches.

II. PROBLEM FORMULATION

In this paper, the service restoration problem has been formulated as a multi-objective, multi-constrained combinatorial optimization problem. The various formulations for objective functions and constraints developed in this work are described as follows:

Objective Functions:

1) Minimization of Energy not Supplied (ENS):

$$\text{Min } f_1(\overline{X}) = \sum_{i=1}^{b1} L_i - \sum_{i \in B} L_i \quad \ldots\ldots\ldots\ldots. \quad (1)$$

$\overline{X}$ is switch state vector of network under consideration for service restoration, i.e. $\overline{X} = [SW_1, SW_2, \ldots\ldots\ldots\ldots SW_{N_S}]$

$SW_j =$ Status of j^{th} switch. A closed switch is represented by 1 and an open switch is represented by 0.

$N_S =$ Total number of switches in the network.

$b1$ = No. of energized buses in the network before fault.

L_i = load on i^{th} bus.

B: Set of energized buses in the restored network.

In eqn. (1), it is assumed that in a ‘n’ bus power system, the buses are numbered from 1 to n and in the pre-fault case, all the buses in the network are energized. Therefore ‘b1’ is equal to ‘n’. However, in the post fault scenario, all the buses would not be necessarily energized. Hence, ‘B’ would contain only the energized buses. For example, in a 5 bus system, b1 = 5 and if, in the post-fault case, bus 3 can not be energized, then B = (1, 2, 4, 5).

2) Minimization of number of manually controlled switch operation:

$$\min F_2(\overline{X}) = \sum_{j=1}^{N_m} \left| SWM_j - SWMR_j \right| \quad (2)$$

Where, N_m is number of manually controlled switches.

SWM_j = Status of j^{th} manually controlled switch in network just after fault.

$SWMR_j$ = Status of j^{th} manually controlled switch in the restored network.

3) Minimization of number of remotely controlled switch

operation: $$\min F_3(\bar{X}) = \sum_{j=1}^{N_a} \left| SWA_j - SWAR_j \right| \quad (3)$$

Where, N_a is number of remotely controlled switches.

SWA_j = Status of j^{th} remotely controlled switch in network just after fault.

$SWAR_j$ = Status of j^{th} remotely controlled switch in the restored network.

4) Minimize the losses:

$\min F_4(\bar{X}) =$ Power loss in the restored network which can be calculated with help of load flow. (4)

Constraints:

1) Radial network structure should be maintained.

2) Bus voltage limits should not be violated.

$$V_{min} < V_j < V_{max} \quad .....(5)$$

$V_{min} =$ Minimum acceptable bus voltage.

$V_j =$ Voltage at j^{th} bus.

$V_{max} =$ Maximum acceptable bus voltage.

3) Feeder line current limits should not be violated.

$$I_{min} < I_j < I_{max} \quad ......(6)$$

$I_{min} =$ minimum acceptable line current.

$I_j =$ Current in j^{th} line.

$I_{max} =$ Maximum acceptable line current.

4) Higher priority customers should always be supplied.

In this paper, a fuzzy optimization procedure is used for handling the multiple conflicting objectives . It transforms all the objectives into fuzzy domain with a membership function. Membership function represents degree of satisfaction of the objectives. A higher membership value of an objective represents higher degree of satisfaction. Then all the objectives give a single output value lying between 0 to 1 representing the quality function. These four objectives in fuzzy domain are transformed into a single fuzzy satisfaction objective function which is formulated as follows

F=Max J = w1µENS + w2µMCS + w3µRCS + w4µLOSS-(7)

Where J is the overall satisfaction and Max J represents Quality function (F) of the restoration plan. µENS represents the value of membership function of Energy not supplied.µMCS is the membership value assigned to the no of manually controlled switching operations, µRCS is the no of remotely controlled switching operation. w1, w2, w3 and w4 are non negative weighting factors that satisfy the condition w1 + w2 + w3 + w4 = 1. Here the interesting feature is that optimization procedure can be readily adapted for different purposes by simply changing the values of weighting factors. These weighting factors help in the ranking of multiple solutions. If w1 = w2 =w3 =w4= 0.25 then all the objectives have equal importance and equally ranked. If w1 > w2 > w3 >w4 say w1 =0.4,w2 =0.3, w3=0.2 and w4 =0.1 then solution will be ranked giving priority to first objective to fourth one in order. If w2 =0 then the solution will be based on the first third and fourth objective.

In the crisp domain, either the objective is satisfied or it is violated, implying membership values of unity and zero respectively. On the contrary, Fuzzy membership values vary from zero to unity. The proposed membership functions used to describe the objectives and constraints are detailed in the following sections.

Membership functions for objectives

(i) Membership function for Energy not Supplied (ENS)

The basic purpose of this membership function is to improve service reliability or to obtain mimimum ENS. Therefore a minimum ENS is given a higher membership value. According to [23], the exponential function meets this condition , it is selected for reliability improvement as shown in fig 1 and is expressed as follows:

$$\mu ENS = \begin{cases} 1, & \text{if } \text{ENS} \le ENS\min \\ \exp\left(\dfrac{ENS\min - ENS}{ENS\min}\right) & \text{otherwise} \end{cases}$$

Where

µENS=Membership function for the magnitude of power supply in interrupted areas

ENSmin=Minimum power supplied which is equal to the total interrupted area

ENS = Power not supplied even after reconfiguration

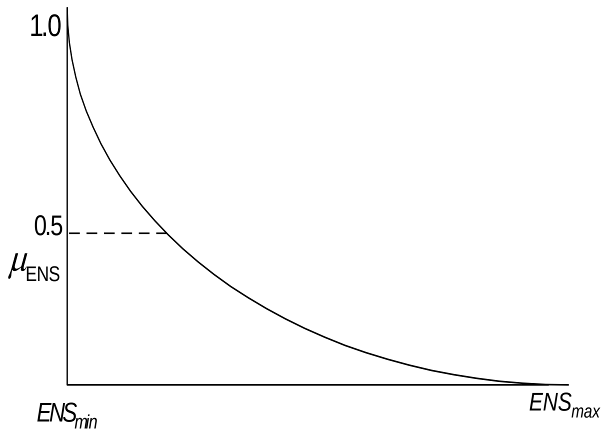

Fig.1 Membership function for energy not supplied

(ii) Membership function for number of manually controlled switching operations

Since our goal is to have smaller number of manually controlled switching operation as compared to no of remotely controlled switch operations so this objective is kept at 2nd preference as the operating time of manually controlled switch is higher than remotely controlled switches. Here, we use a decreasing membership function µMCS as shown in fig 2.

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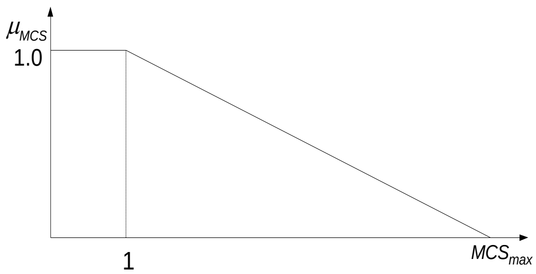

Fig. 2 Membership function for number of manually controlled switches

It is noted that, in fuzzy set notation, a high membership value indicates a desirable situation. For Example, the membership value for a number of manually controlled switching operation equal to one , which is a very desirable situation , is assigned value 1 in fig 2. A higher number of switching operations is given a lower membership val *ue and MCSmax is the max number of permissible manually controlled switching operation in the given system.

(iii) Membership functions for remotely controlled switching operation.

The operating time of remotely controlled switches is negligible (45-50 seconds) in comparison to manually controlled switches (1200 -1500 seconds), so higher no of remotely controlled switch operation will not effect the time needed to reach optimum restoration plan. Keeping this in mind number of remotely controlled switch operation equal to 5 is assigned a membership value equal to 1 and decreasing membership values as the no of switch operations increases from 5.

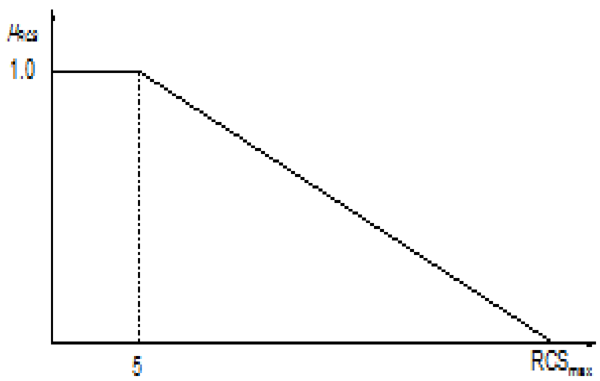

Fig.3 Membership function for number of remotely controlled switches

(iv) Membership function for Loss Reduction

Reconfiguration of distribution system for service restoration may also affect the line losses. If the prefault configuration is well behaved then the reconfigured network is expected near to the original configuration. That's why losses equal to or less than the previous value at prefault condition is assigned membership value equal to 1 and the decreasing membership value as the loss increases from the previous value. The maximum permissible loss is 1.5 times of prefault value.

The shape of the membership function is as follows

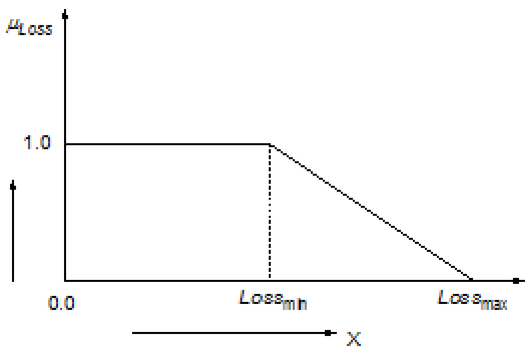

Fig.4 Membership function for Line losses

III. ANT COLONY OPTIMIZATION (ACO)

An Ant Colony Optimization [25]-[28] is a random stochastic population based heuristic algorithm on agents that simulate the natural behavior of ants developing mechanisms of cooperation and learning which enables the exploration of the positive feedback between agents as a search mechanism. An important and interesting behavior of ant colonies is their foraging behavior and, in particular, how ants can find shortest paths between food sources and their nest. While walking from food sources to the nest and vice versa, ants deposit on the ground a chemical substance called pheromone, forming in this way a pheromone trail. The sketch shown in the Fig.5.gives a general idea how real ants find a shortest path. Ants can smell pheromone and, when choosing their path, they tend to choose, in probability, paths marked by strong pheromone concentrations. The pheromone trail allows the ants to find their way back to the food by their nest-mates.

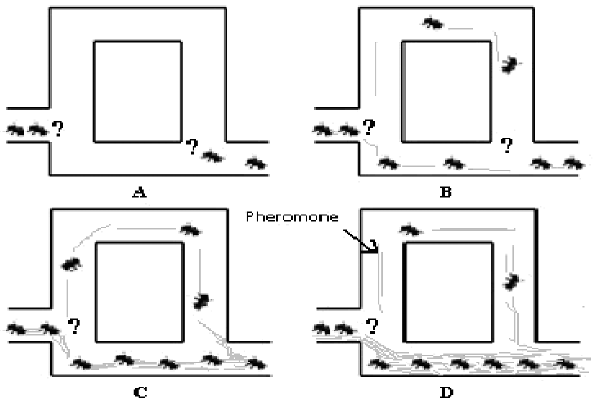

Fig5. Natural Behavior of Ants

The above sketch shows how real ants find a shortest path. A) Ants arrive at a decision point. B) Some ants choose the upper path and some the lower path. The choice is random. C) Since ants move at approximately constant speed, the ants which choose the lower, shorter, path reach the opposite destination point faster than those which choose the upper, longer, path. D) Pheromone accumulates at a higher rate on the shorter path.

The number of dashed lines is approximately proportional to the amount of pheromone deposited by ants.

ACO-implementation for optimization problem

Step1. Initialization
-Initialize pheromone trail
Step2. Solution Construction
-For each ant Repeat
Solution Construction using the pheromone trail
Step3.Update the pheromone trail
- Until stopping criteria

Fig.6 Steps for ACO

The above fig.(6) illustrates the general ACO algorithm derived from the behavior of real ants. The ACO algorithm manages the scheduling of three activities [25]-[28]. The first step consists the initialization of pheromone trail. In the second iteration step, each ant constructs the complete solution to the problem according to probabilistic state transition rule. The state transition rule depends mainly on the state of the pheromone. The third step updates quantity of the pheromone; a pheromone updating rule is applied in two phases. The first is an evaporation phase where a fraction of pheromone evaporates, and then there is a reinforcement phase increasing the amount of pheromone on path with high quality solutions. This process is iterated until a stopping criterion is reached.

Several different ways have been proposed to implement the above principles into a computational procedure to solve the optimization problem. The optimization approach proposed for service restoration in this paper is based on the ACO algorithm presented in [23] and has been mentioned in the next section.

IV. APPLICATION OF ACO WITH FUZZY M.O.M.C. APPROACH

The ACO has been applied to various distribution network optimization problem, such as network reconfiguration [18]-[22], capacitor placement [24] and SSP [23]. In this paper, the ACO algorithm is applied to the service restoration problem. The main steps of the proposed ACO algorithm are as follows.

1. Graph representation of search space- In this step, a representation structure of search space for ants is developed which is suitable for ants to search for solution of the problem. Solutions can be represented as a string of binary bits which indicates installation status of switches in the corresponding candidate locations. Thus the search space of the problem is modeled as directed graph as shown below. The no of stages in the graph is equal to the no of candidate sites for switch installation. In each stage there are two states that signify situations of switch installation in candidate site related to that stage. The artificial ants search the values of the bits. A solution to the problem is produced after an ant completes its decision process for the sub paths forming a tour between the home and food. The search space for the ants is restricted to meet the following requirements.

(i) Root switches are always connected i.e. kept always equal to “1” in all the possible binary strings of the expected newly reconfigured network as the opening the root switch will isolate the entire bus system. Root switch is one nearest to the substation connecting the entire bus system.

(ii) The faulted zone is always isolated by making the element in all strings, corresponding to switches around the faulted zone, “0”.

(iii)By running load flow calculation all the constraints are checked and only those possible strings are allowed for search space which satisfy the constraints. At first all the constraints are checked by load flow calculation considering total loads to be supplied for service restoration. If not, some load must be curtailed. The curtailment policy used here is such to possibly include the priority customer like industries, hospitals etc in all the strings. This procedure continues until the all constraints are satisfied.

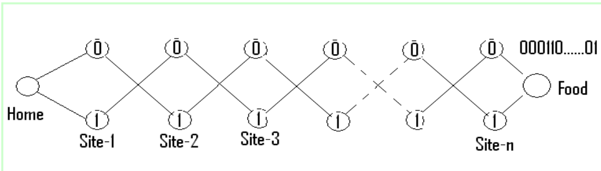

Fig. 7 Search space for Ants in terms of Binary Strings

2. ACO initialization – in the beginning of ACO algorithm, the pheromone values of edges in search space are all initialized to a constant value $\tau 0 > 0$. This initialization causes ants to choose their paths randomly and therefore, search the solution space more effectively.Initialize the other parameters, heuristic parameter (β), pheromone parameter (α), evaporation parameter (ρ) for local updating rule and evaporation factor (μ) for global updating rule.

3. Ant Dispatch – In this step, the ants are dispatched and solutions are constructed based on the level of pheromone on edges. Each ant will start its tour from its home colony and choose one of the states in the next stage to move according to the following transition probability

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[T_{ij}(t)]^{\alpha} . [n_{ij}]^{\beta}}{\sum k \in allowed_k \quad [T_{ik}(t)]^{\alpha} . [n_{ik}]^{\beta}} & if\ j \in allowed_k \\ 0 & otherwise \end{cases}$$

Where Tij (t) is the total pheromone deposited on edge i,j at iteration ‘t’ and α , β are control parameters that control the relative importance of trail versus visibility.

4. Quality function assessment- In this step the quality of tours generated by ants is assessed based on the corresponding quality function given by equation (7) in this paper. The Quality Function “F” for the service restoration problem is defined as follows

$F = Max\ J = w_1\ \mu_{ENS} + w_2\ \mu_{MCS} + w_3\ \mu_{RCS} + W_4\ \mu_{LOSS}$

5. Pheromone Update-The aim of the pheromone value update rule is to increase the pheromone values on solution components that have been found in high quality solutions.

Also from the practical point of view, pheromone evaporation is needed to avoid too rapid convergence of the algorithm towards a sub optimal region. It implements a useful form of forgetting favoring the exploration of new areas in the search space

When all ants complete their tour (an iteration) , this rule is applied to the states (switches) belonging to the best solution. The rule provides a great amount of pheromone to best solution and is given by

$$\tau_{ij}(t+1) = (1-\mu)\tau_{ij}(t) + \mu\sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$$

$$\Delta T_{ij}^{k} = \begin{cases} \dfrac{1}{F_k} & \textit{if the kth ant uses edge}(i,j) \textit{ in its tour} \\ & (\textit{between time } t \textit{ and } t+n) \\ 0 & \textit{otherwise} \end{cases}$$

Where
ΔT_{ij}^{k} is the change in the pheromone
μ is the evaporation factor
F_k is the quality function assessed in equation
m is the number of ants i.e. solution

The coefficient μ must be set to a value < 1 to avoid unlimited accumulation of trail. In order to satisfy the constraint that an ant visits all the n different towns, we associate with each ant a data structure called the tabu list that saves the possible string already visited up to time t and forbids the ant to visit them again before n iterations (a tour) have been completed. When a tour is completed, the tabu list is used to compute the ant's current solution (i.e., the distance of the path followed by the ant). The tabu list is then emptied and the ant is free again to choose. We define tabuk the dynamically growing vector which contains the tabu list, of the kth ant, tabuk the set obtained from the elements of tabuk, and tabuk(s) the sth element of the list (i.e., the sth town visited by the kth ant in the current tour).

6. Convergence determination-Steps 3 to 5 continue until the iteration counter reaches the predefined maximum number. The best tour selected among all iterations implies the optimum solution.

V. APPLICATION STUDIES

In order to demonstrate its effectiveness, the proposed approach is applied to two practical distribution networks named System-1 & System-2. Due to constraint of space results of only system-2 shown in fig.8 has been shown in this paper. Several cases have been tested and the results are analyzed and reported.

TABLE-I Detail Of Different Test Systems

S.No	Description	No of buses	No of switches	Systems nominal voltage (KV)	Load in KVA
1	System-1	13	10	11	2652
2	System-2	10	14	13.8	220

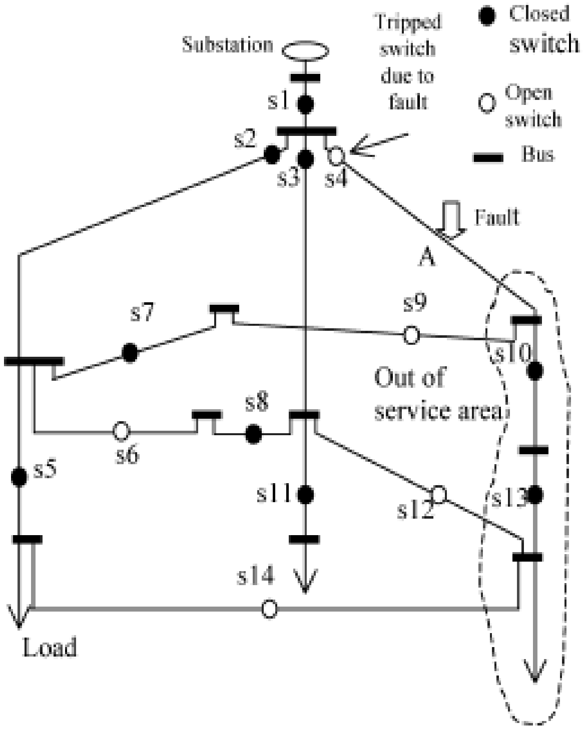

Fig. 8 network before service restoration for system-2

Table- II .Various Single Fault Location Considered And Priority Customers In Two Systems

System	System-1	System-2
Fault location	Z_4 (between bus 4 and 8)	Z_3 (between bus 1 and 4)
Priority customer	Z_6	Z_9

Prefault configuration is included in one of the strings of search space in the proposed method to achieve the possible restoration plan in short time and near to the original configuration. The network graph of the system is drawn showing zones and branches. Network area not including any switch is considered as zones. Normally closed switch is shown by dark lines while normally open switches by hashed lines in the following network graph.

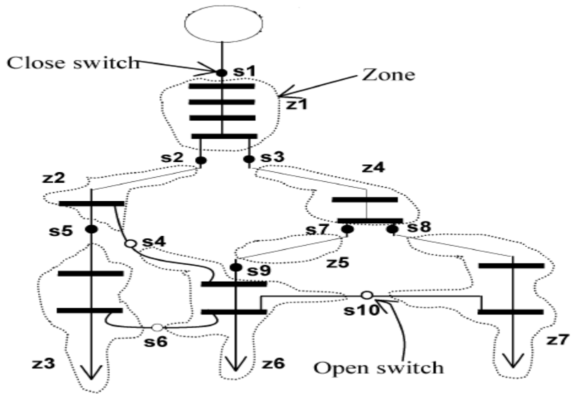

Fig. 9 Zone representation of System-2

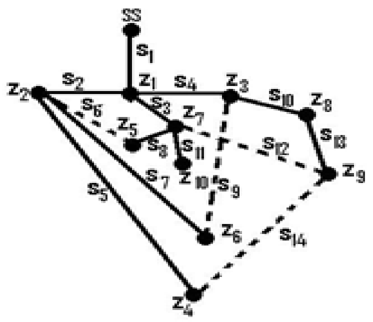

Fig.10 Network Graph of System-2 at pre fault

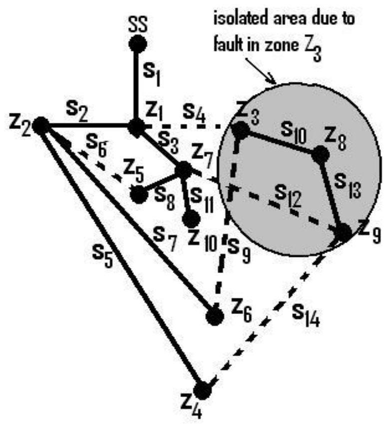

Fig.11 Network Graph of System-2 at post fault

A fault is considered at line between bus 1 and 4 of zone Z3. To isolate the fault the switch S4 will be tripped immediately and the other zones Z8 and Z9 will also isolate in present situation due to tripping of switch S4. The network graph of the post fault distribution system is shown in fig.11. To restore service in Zone Z8 and Z9, a number of restoration plan is possible which will be searched by ants from the candidate sites in terms of binary strings. In all possible binary strings satisfying constraints all the following points are considered mentioned earlier.

- Root switch S1 is always kept “1”

- To isolate the zone Z3, switch S4 and S10 are always open i.e. kept “0” in binary string.

- Priority customers say Z9 having industries, hospitals etc. is always considered in all possible restoration plan.

Table III. ACO parameters in test cases

Parameters	Value
Number of Ants	10
Pheromone evaporation rate	0.9
Maximum no of iterations	50
Initial value of pheromone on edges	0.1

All the parameters considered above are on the trial basis. The other parameters considered are as follows

$\alpha=1$, $\beta=2$

Case-I: When all the objectives have equal importance i.e. weighting factors for quality functions are tuned as w1=w2=w3=w4=2.5 then the results are shown in table IV

Table- IV. Single fault service restoration

Systems	1	2
Out of service area	6.67	10.82
Number of Manually controlled switch operation	2	1
Number of Remotely controlled switch operation	2	1
Losses	10.32	34.35
Status of priority customers	Yes	Yes

Case-II- When the objectives are ranked from 1st to 4th by tuning the weighting factors in the quality functions as $w_1=0.4$, $w_2=0.3$, $w_3=0.2$, $w_4=0.1$, then the results are as follows shown in Table V

Table-V. Single fault service restoration

Systems	1	2
Out of service area	4.77	8.67
Number of Manually controlled switch operation	1	1
Number of Remotely controlled switch operation	3	1
Losses	11.82	39.97
Status of priority customers	Yes	Yes

By comparing the results from TABLE-IV and TABLE-V it is clear that if all the objectives are treated equally important then the out of service area is more but the line losses are less while when the objectives are ranked from 1st to 4th then the results are on the basis of preference and out of service area is less but the line losses increases slightly. For system 2 there is no effect on the numbers of manually and remotely controlled switch operation while for system 1, the number of manually controlled switch operation is decreases and no of remotely controlled switch operation is increased due to ranking of objectives. The operating time of remotely controlled switches is negligible in order of 50 seconds but the operating time of manually controlled switches are in order of 1200-1500 seconds depending on the location of switch and distance from the operator to come and operate the switch so restoration plan from table V will be reached in shorter time than table IV. The results show that the algorithm adapts itself to the variation of weighting factor.

The planners/ decision maker can choose proper weighting factors for objectives according to his/her needs and preferences and obtain an appropriate restoration plan using the proposed approach.

VI. CONCLUSION

This paper has presented a fuzzy multiobjective model and ACO-based approach to provide decision support in the service restoration problem in distribution network. This formulation incorporates four objectives: minimization of energy not supplied, minimization of number of manually controlled switch operation, minimization of number of remotely controlled switch operation and minimization of losses. Based on real planning considerations, fuzzy membership functions related to the objectives are proposed. For decision making, the information provided by the multiobjective model has been shown to be more valuable than the traditional mono objective optimal solutions. The proposed approach has been applied to two practical distribution systems and the effectiveness of the ACO-based method to solve this service restoration problem has been demonstrated through the results obtained.

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