A Genetic Algorithm for Supply Restoration and Optimal Load Shedding in Power System Distribution Networks

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Abstract: In this paper, a Genetic Algorithm (GA) is employed to search for the optimal supply restoration strategy in distribution networks. An 'integer permutation' encoding scheme is adopted in which each chromosome is a list of indices of switches. The status of each of these switches is decided according to graph theory subject to the radiality constraint of distribution networks. Each chromosome then maps to a feasible network topology. A special gene '0' is also introduced into the chromosome. Instead of representing a switch, this is a flag that keeps some parts of the network disconnected enabling the GA to find the optimal load shedding strategy where necessary. The proposed algorithm has been tested on a practical system and shown to find an optimal post-fault supply restoration strategy, but also the optimal load shedding point when total demand cannot be supplied.

Keywords: Supply Restoration; Network Reconfiguration; Genetic Algorithm

1. Introduction

Supply restoration aims to restore as many loads as possible from the out-of-service areas via network reconfiguration at minimal operational costs and at the same time to minimise the network loss. It is a multi-objective, combinatorial, nonlinear constrained optimisation problem.

Since an effective post-fault supply restoration strategy for distribution networks plays a key part in improving service reliability and enhancing customer satisfaction, there has been considerable research effort focused on this problem. The main challenge has been in reducing the search space so as to achieve an optimal solution within an acceptable computing time.

Approaches proposed for this problem can be roughly divided into three categories:

1). Domain specific knowledge based methods [1, 2, 4, 5]. These expert-system based methods attempt to capture the knowledge and heuristic rules used by power system operators to determine switching sequences for supply restoration under a range of fault conditions. This information is typically stored in a knowledge base in the form of rules. The knowledge base is normally interpreted by an expert system shell in a way that seeks to mimic the decision-making process of human operators. However, the heuristic knowledge base is difficult and costly to gather and interpret. Since the resulting knowledge base is likely to be specific to a given system and its normal running configuration, a specific knowledge base would have to be built for each network to which the method was applied. In addition, there is no guarantee that, in a given case, the solution found will be close to the optimal solution under the prevailing conditions.

2). Optimisation methods [3]. These methods formulate the supply restoration problem as an optimisation problem suitable for solution by one of the standard mathematical programming techniques, e.g. linear programming. Such methods can be applied to any network configuration, and can find the optimal solution provided the problem is adequately formulated. However, they have been proved to be computationally very costly for large systems.

3). Heuristic search methods [7, 8, 9]. These compare a number of candidate restoration solutions with specified performance criteria. Heuristic rules are employed during the search for solutions to reduce the search space; as a result, solutions can be reached within an acceptable time period. The approach is efficient and does not rely on specific knowledge about a system. However, the number of possible solutions will be prohibitively large unless effective heuristic rules can be developed. In addition, when load is transferred from feeder to feeder in multi-part switching, there is no guarantee of a strictly optimal solution.

A GA is a method for search and optimisation that imitates the processes of natural selection and evolution [15]. Due to their ability to find global optimal solutions for solving large-scale combinatorial optimisation problems, GAs have been found to be efficient methods for power system problems, including the supply restoration problem. A GA application to network reconfiguration for distribution system loss minimisation was first reported in reference [12]. By incorporating heuristic techniques, a parallel genetic algorithm for service restoration was also proposed in reference [13]. However, the string encoding method used makes the approach difficult to apply in practice.

A systematic supply restoration algorithm based on a genetic algorithm is proposed in this paper. Instead of the standard ‘binary’ encoding method, an ‘integer permutation’ encoding scheme is adopted in which each gene in the chromosome is an integer representing one controllable switch. Graph theory is employed to decide the final status of each switch according to the radiality constraint of distribution networks. The GA objective function includes all the objectives and constraints required for a practical supply restoration scheme. A special gene ‘0’ is incorporated in the chromosome, indicating the optimal load shedding point for the system, for cases where a network cannot supply all the demands. Software implementing the proposed algorithm has been developed, and has been tested on a practical system.

2. Problem Formulation

Network reconfiguration after a line removal for supply restoration aims to transfer de-energised loads in the out-of-service areas to other supporting distribution feeders without violating operating or engineering constraints. When the system is not able to supply all of its loads, load with low priority should be shed. The solution to this multi-objective constrained optimisation problem should meet the following requirements:

- As much load as possible should be supplied in the resulted network within an allowable time frame; optimal load shedding (in term of load priority and magnitude) should take place when the demand is greater than supply capability;

- The switch operation costs occurring during reconfiguration should be minimised. This would take into account factors of switch operation time and cost, such as whether the switch is manually operated or remote controllable, and (for manually operated switches) the time needed to access the switch.
- The energy loss in the resulting network should be minimised.

To achieve these objectives, the following constraints should be observed in the resulting network:

- The radial structure of the distribution network should be retained;
- No violation of busbar voltage limits;
- No current overloading in any line.

3. Genetic Algorithms

Inspired by the theory of evolution, genetic algorithms are adaptive search techniques that derive their models from the genetic processes of biological organisms. A GA starts with a number of solutions to a problem, encoded as strings of symbols. The string that encodes each solution is a 'chromosome' and the set of solutions is called 'population'. The position of a symbol in the string is called 'allele'. The symbol or value that an allele can contain is called 'gene'. The initial population can be generated randomly, or may consist of a number of known solutions, or a combination of both. The GA goes through a number of steps in which the population at the beginning of each step is replaced with another population, which it is hoped will include better solutions to the problem. A process called reproduction, in which the chromosomes of the old population are combined to create new ones, is applied to define each new generation. Reproduction works by repeatedly applying three operations to the current generation: selection, crossover and mutation, until the required number of chromosomes are available in the new population.

A GA requires an evaluation function that assigns a 'fitness' value to each potential solution (chromosome). A GA works with only the symbol strings and has no inherent knowledge about the problem. Problem specific information is provided by the objective or evaluation function. It is the evaluation function that guides the GA to evolve towards better solutions. The fitter the chromosome, the higher the probability that it will be retained and selected to generate a new candidate solution.

The GA evolution process is a powerful global search mechanism, whose computational code is very simple.

4. Genetic Algorithm for Supply Restoration and Optimal Load Shedding

A GA is suitable for the supply restoration algorithm because it is very easy to change constraints or objectives, or apply new ones.

4.1 String Encoding

4.1.1. Integer Permutation Encoding Scheme

Before a GA can be applied to an optimisation problem, an encoding scheme that maps all possible solutions of the problem into symbol strings (chromosomes) must be introduced. It is also helpful if the encoding maps as many chromosomes as possible to feasible solutions. The ideal encoding would give only feasible solutions, so that the GA would not need to test for feasibility.

Since the topology of a distribution network can be uniquely defined by the status of all available switches, a solution to the supply restoration problem can be encoded as a function of the controllable switch states of the network. The most natural coding method is to have a binary string with length equal to the number of switches in the network. Each switch state is represented by one bit with a value ‘1’ or ‘0’ corresponding to ‘closed’ or ‘open’. However, this encoding is a poor choice because it does not ensure that the chromosome will generate a feasible solution.

Instead, an ‘integer permutation’ encoding scheme is proposed here. A similar approach has been widely applied to the well-known ‘travelling salesman problem’. The problem is to find the minimum cost path through a graph or network visiting all the nodes exactly once. If every node is assigned a unique integer, then the ordering of the integers in the chromosome defines the order in which the nodes are visited.

In an integer permutation encoding, the genes are the integers from one up to the number of positions, and the solution that the chromosome represents depends on the relative ordering of the integers.

For the supply restoration problem, each integer in the permutation will be an index into a list of switches that can be used for restoring the supply. The integers therefore take values from one to the number of switches which need to be investigated, i.e. if there are k switches in the study, each chromosome will be composed of k unique integers with values from 1 to k.

The sequence of these integers represents an ordered operation sequence of switches to be followed to generate a valid network topology. For instance, for a system with 6 switches (initially all open) considered for supply restoration, the string of length six:

(3 2 6 5 1 4)

defines an ordered switch sequence: Switch 3, Switch 2, Switch 6, Switch 5, Switch 1 and finally Switch 4.

4.1.2 String Interpretation for Supply Restoration Problem

The string shown above is only a permutation of switches, in order for the string to be meaningful and map a valid network topology, these switches must be assigned status values either as ‘closed’ or ‘open’. Here, a scheme based on graph theory is proposed which decides the status of these switches by ensuring the radiality constraint of the distribution network is met.

Before the GA begins, the actual distribution network is mapped to a graph. The branches of the graph correspond to switches that can be operated for supply restoration, while the nodes of the graph represent all the connected elements of the network that do not include any of these switches. Each node therefore will represent an island of the network that does not need to be further subdivided during supply restoration analysis.

Initially all switches are assumed to be open, and starting with the first gene (integer) in the chromosome, its corresponding switch is closed. The process is repeated for each gene until the end of the chromosome is reached. If closing a switch would violate the radiality constraint for the distribution network by creating loops or connecting sources together, then that switch operation is abandoned and the next gene in the chromosome is considered.

To test for loop or source connection violations, each node of the graph is initially assigned a unique 'colour' value (represented as a positive integer), excepting those nodes that contain generators or infeeds (considered as source nodes) which are assigned a particular 'colour' value of '0'. All the branches are removed to represent a network in which all switches are open. Each branch is visited in the order determined by the chromosome. If a visited branch connects two nodes of different colours, then it is inserted into the graph and all nodes having the higher colour of the two will be changed to have the lower colour.

Loops are avoided by preventing two nodes of the same colour being connected, and assigning the same colour value '0' to all source nodes ensures that two sources will never be connected together. At the end of this procedure the switches in the network that have their corresponding branches inserted in the graph will be closed and the other switches will remain open, thus generating the complete set of switch states corresponding to this chromosome.

If there are k switches in the network under study, then the chromosome takes the form:

$$(I_1 \ \ I_2 \ \ I_3 \ \ \ldots \ \ I_k), \qquad (1)$$

where $1 \leq I_i \leq K$ and $I_i \neq I_j$ for $i \neq j$ (I denotes Integer). Suppose there are N nodes in the graph of which N_s are source nodes. The problem is to connect each of the $(N-N_s)$ non-source nodes (with uniquely assigned colour value from '1' to '$N-N_s$') to any of the N_s source nodes (each having colour value '0') according to the sequence order defined by the chromosome.

The switch operation status decided by the above mentioned branch insertion scheme guarantees that each chromosome will be mapped to a valid network configuration which is normally a radial network consisting of N_s spanning trees rooted at the N_s source nodes of the network.

If a prefix symbol '+' denotes the switch state is 'open', while '-' denotes the switch state to be 'closed', the initial string can be denoted by:

$$(+I_1 \ \ +I_2 \ \ +I_3 \ \ \ldots \ \ +I_k), \qquad (2)$$

Where all switches are in 'open' states. The permutation finally obtained will be of the form:

$$(-I_1 \ \ (+-)I_2 \ \ (+-)I_3 \ \ \ldots \ \ (+-)I_k), \qquad (3)$$

Where (+-) denotes either the 'open' or 'closed' state according to the graph constraints.

It can be seen that the original string expressed in (1) can uniquely lead to a unique sequence of switch states expressed as in (3) which defines a radial network configuration for supply restoration.

An AC loadflow is calculated for each trial network configuration to allow the fitness of the corresponding chromosome to be evaluated. This requires a measured value (or an estimated value) for each load in the distribution network. In practice, individual loads in a distribution network may be unmeasured. In this case an appropriate load estimation process should be applied [14].

4.1.3 '0' Gene for Optimal Load Shedding

According to the proposed algorithm, the switch operations are determined by the integer permutation contained in the GA chromosome. The switch setting algorithm proposed guarantees that a valid network configuration is generated, which is a spanning tree or spanning forest with each load connected to a source (if any possible connection exists). The number of spanning trees should be equal to the number of supply sources available in the network. If in any spanning tree, the source cannot supply all of its loads (e.g. the AC load flow is divergent), these loads will remain unsupplied and be treated as lost load.

In practice, however it is expected that as much of the demand as possible will be supplied. Where demand exceeds supply, some loads with lower priority should be discarded and each source would supply the remaining loads to its maximum capability.

Based on this consideration, a special gene '0' is introduced into the chromosome. The string length now becomes 'k+1' if there are k switches in the study. The '0' gene is different from the other (strictly positive) genes, in that instead of denoting one switch it is simply a flag. In the process of switch status setting all remaining switches are kept 'open' beyond the '0' gene in the chromosome, so as to keep some parts of the system unconnected (or some loads unsupplied). In the initial population, the '0' gene's position is randomly generated, but it is expected that the '0' gene will evolve to somewhere near the end of the chromosome, after a few generations. This is because such chromosomes are likely to be fitter than those in which the '0' gene occurs at an earlier position. Eventually, the GA should converge to the optimal network configuration for supply restoration. Where the network has the capability to supply all of the loads, the optimal chromosome should have the '0' gene in the last position, or a position near the end of the chromosome so that the switches denoted by the subsequent genes do not require to be closed. However, when the network cannot supply all of the loads, the '0' gene will occur at an earlier position preventing one or more selected loads from being supplied. The switches through which these loads would have been supplied would have their genes located after the '0' gene in the chromosome. Since GA is a global search technique, the loads to be shed identified by the genes occurring after the '0' gene, in the final chromosome, should indicate the global optimum solution in terms of the defined objective function.

For instance, chromosome (3 2 6 5 0 1 4) will only allow the status of switches represented by (3 2 6 5) to be evaluated by graph theory, '0' is a stop sign and switches 1 and 4 are kept open. Loads connected to sources by switches 1 and 4 will be shed according to this chromosome. Since the position of the '0' gene in the initial population is randomly generated, the introduction of the '0' gene allows the GA effectively to search for an optimum solution from a series of strings: (0), (3), (3 2), (3

2 6), (3 2 6 5), (3 2 6 5 1), (3 2 6 5 1 4). The optimal position for ‘0’ gene will be determined via the evolutionary process.

4.2 GA Operations

The **Order Crossover (OX)** operator is adopted, which builds offspring by choosing a sub-sequence from one parent and preserving the relative sequence order from the other parent [16].

Mutation is achieved through exchanging two integer positions in a chromosome.

Since a GA chromosome will uniquely generate a valid feasible network configuration for supply restoration, its fitness can be evaluated using a standard AC load flow on the candidate network to provide the quantities required in the objective function.

4.3 GA Objective Function

Most optimisation problems impose constraints on the acceptable solutions, so it is possible that the solution that a chromosome describes would not be feasible. The option of simply rejecting every infeasible solution may lead to the rejection of some good partial solutions, and is likely to be computationally inefficient.

An objective function can be modified to account for these constraints by penalising any solution that violates a constraint. In this approach a penalty term, which depends on the constraint and the extent of its violation, is subtracted from the calculated fitness value. This ‘penalty function method’ permits new constraint formulations to be added readily to a GA based optimisation method.

The GA objective function for the supply restoration problem consists of five terms:

- The demand that cannot be supplied because the corresponding parts of the network are not connected to a source, or the load that has been shed to avoid constraint violations;
- The network power losses;
- Branch current overloads;
- Busbar voltage deviations;
- Switch operation costs.

Each factor contributes a penalty term and the objective function for the chromosome is the weighted sum of all these penalties. Since the smaller the value of the objective function the greater its fitness, searching for maximum fitness corresponds to minimising the total penalty.

The objective function is defined as:

$$f = W_{LL} P_{LL} + W_L P_L + W_{IO} I_O + W_{VD} V_D + W_{SW} \sum_{i=1}^{n_{sw}} C_i$$

Where:

P_{LL} is the ratio of total weighted lost load to total weighted demand ($\sum_i W_{L_i} P_{LL_i} / \sum_j W_{L_i} P_{L_j}$)

W_{LL} is the weight for P_{LL}

P_L is the ratio of total losses to total power supplied ($P_{Loss} / \sum P_{G_i}$)

W_L is the weight for P_L

I_O is the sum of the ratios of current overload to maximum permitted current for each line ($\sum_{i=1}^{l} \frac{I_i^+ - I_{\max_i}}{I_{\max_i}}$)

W_{IO} is the weight for I_O

V_D is the sum of the ratios of voltage deviations from limits for each node ($\sum_{i=1}^{N} \frac{|\Delta V_i|}{\Delta V_{\max_i}}$)

W_{VD} is the weight for V_D

n_{SW} is the number of switches that can be used for restoring supply

C_i is the cost of operating switch i from the existing state to the state required by the evaluated configuration

W_{SW} is the weight for the switch operation cost term

The first term in the objective function is defined as lost load: $W_{LL} * P_{LL}$ where P_{LL} = $\sum_i W_{L_i} P_{LL_i} / \sum_j W_{L_i} P_{L_j}$. The priority of each load is reflected by the weighting factor W_{L_i}. The lost load term is meaningful when some load cannot be connected to any source, or load has to be shed in order for the system to meet other constraints. Heavy penalties are applied for lost load, but where necessary, the GA can decide the optimal load shedding points to reach the best solution for the supply restoration problem.

The second term accounts for the network losses. It has the minimum weight since compared to other items it is the least crucial in the supply restoration scheme.

The third and fourth term incorporate the traditional steady state security constraints into the objective function. Since breaking these constraints may bring about serious damage to the system, heavy penalties are applied to these two items.

The fifth term accounts for the cost of switch operations required during network reconfiguration. The parameter C_i denotes the cost of changing switch i from the existing state to the state required by the desired configuration, taking into account factors such as whether the switch is remote controlled or manual operated, the access time for the switch, etc.

In the current objective function, most terms are defined as ratios. It is expected that users will adjust the weighting coefficients to reflect the relative importance of the various objective terms and according to experience with the solutions obtained.

Typical weight values, used in the experiments reported here, are 10.0 for lost load, 10.0 for power losses, 500.0 for current overloads, 50.0 for voltage deviations and 1.0 for switch operation. Varying the weights can lead to alternative solutions being produced, but does not seem to have much influence on the speed of convergence.

5. Test Results

The GA based supply restoration and optimal load shedding algorithm has been tested on an example system that is part of a practical system in the UK. The system is shown in Figure 1.

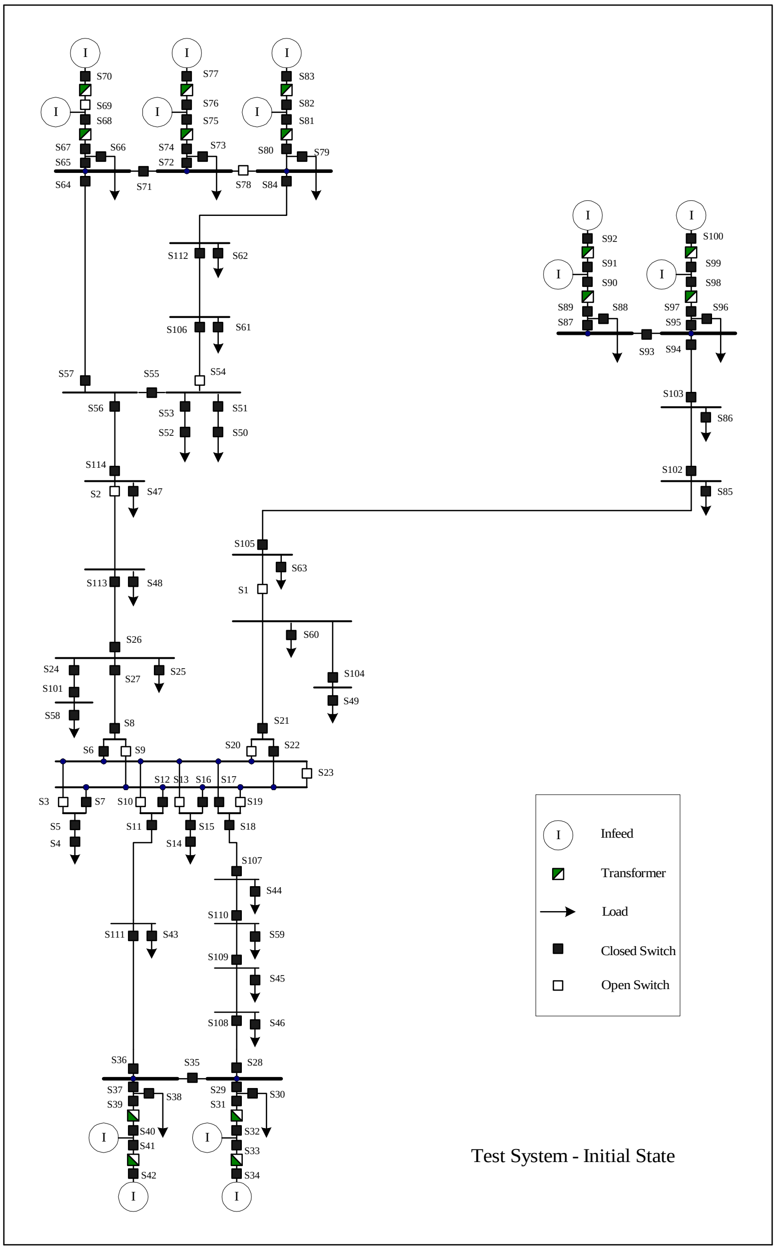

Figure 1. Test System

For this system, suppose the fault occurs on the line where switch S102 is located. Switch S102 is tripped off to isolate the fault. Since normally those switches located at the power sources will not be operated during the reconfiguration, restoring the supply to the loads connected to the network via S63 and S85, requires only the states of 63 switches (from a total of 114) to be considered in the study. The chromosome is of length 64, composed of 63 genes denoting switches plus the '0' gene. The test system shown is a typical sized problem for post-fault restoration in an urban distribution network. For on-line implementation a pre-processing stage is required to limit the dimensionality of the network model. The model should include sufficient lines and substations adjacent to the fault, so that all reasonable switching options are possible. On the other hand, it is desirable to limit the dimensionality so that the computer time required for solution is not excessive.

5.1 GA for Full Supply Restoration

Suppose the fault occurs at the base load level. The GA has a pool size of 50. By tuning the GA parameters, the optimal performance was reached for a crossover rate of 0.6, and mutation rate of 0.08125. After 337 iterations of evolution, the GA reaches its minimum objective function value 2.0429, of which 1.0429 is contributed by network loss while the remaining 1.0 is contributed by the single switch operation: switch S1 is changed from 'open' to 'closed'. This is obviously the global optimal solution under this condition. The resulting network topology is shown in Figure 2.

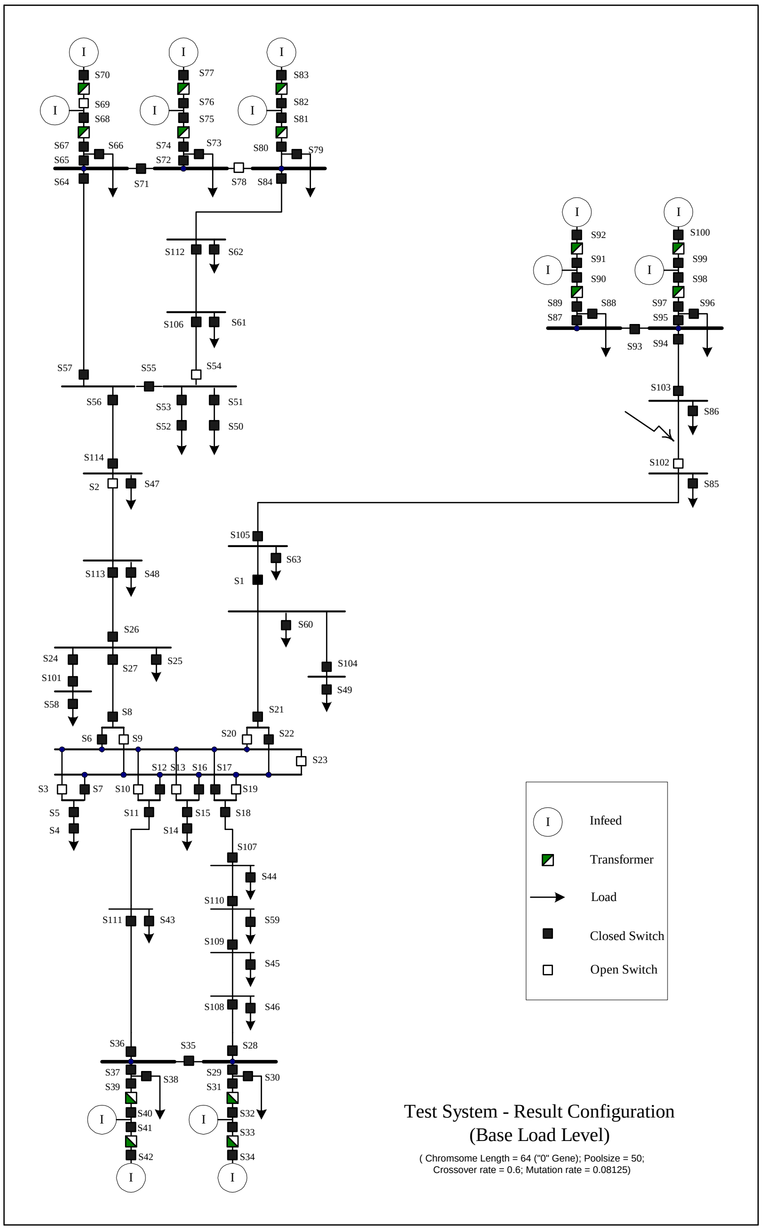

Figure 2. Network Configuration after Supply Restoration at Base Load Level

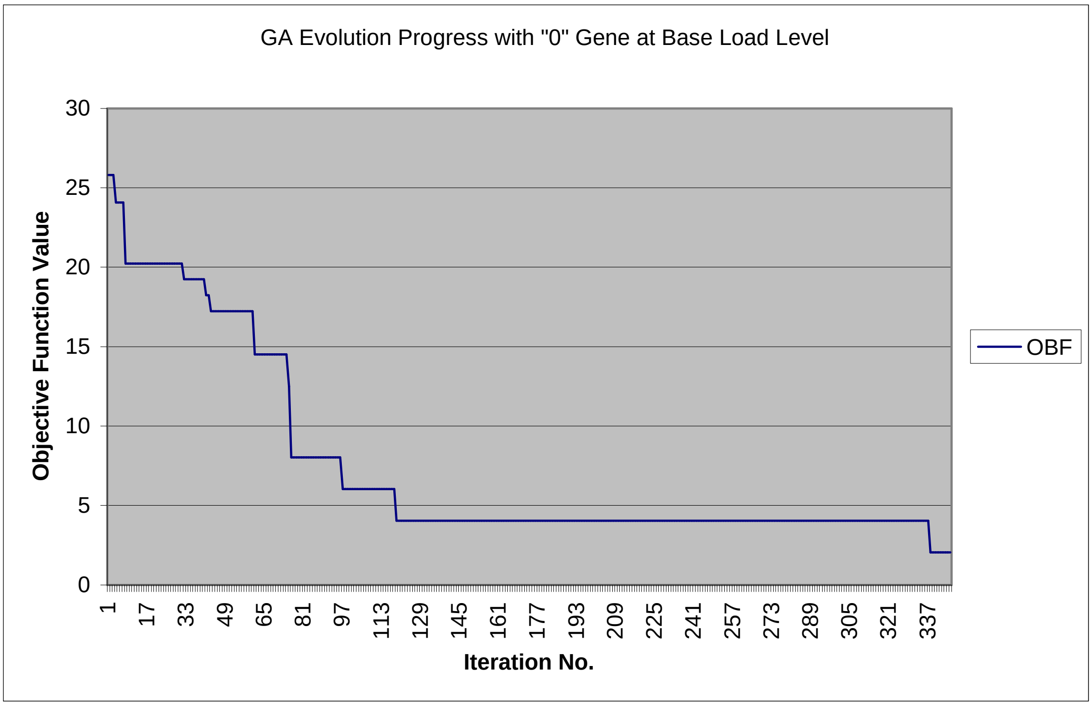

Figure 3. GA Evolution Process for Supply Restoration at Base Load Level

The GA evolution process is shown in Figure 3, where OBF shows the minimum objective function value achieved by chromosomes in the pool. From Figure 3, it can been seen that at the beginning of evolution, the objective function values are high indicating the existence of constraint violations or load shedding. However, in the 76th iteration, the objective function value drops sharply from 14.5095 to 8.04167. After that, the GA objective function values consist of only two parts: switch operation costs and network losses. The optimal solution is finally achieved after 3 further step improvements occurring at the 97th, 120th and 337th iterations, each reducing the switch operation cost by 2.0. It is obvious that the '0' gene has moved far enough back in the chromosome in the 76th iteration not to prevent any load from being connected to the network.

Although the optimal solution for this example is quite obvious, a general disadvantage of using a GA is that there is no simple algorithmic indication of when an optimal solution has been reached. The usual approach is to continue the evolutionary process until a threshold number of generations have been passed with no further improvement in objective function value. This inherent difficulty is illustrated in the present example, where a long period of stagnation occurs between generation 121 and generation 337. For more difficult examples, such as that considered in the following section, a further disadvantage is that there is no indication of whether the final solution is indeed optimal. In applying the GA approach to complex problems, it is generally expected that a near-optimal solution will be obtained. However, proving optimality for any complex problem is inherently intractable.

Using a DEC Alpha 433au Personal Workstation, it takes about 3.5 minutes of computer time for the GA to reach the optimal supply restoration solution.

5.2. GA for Optimal Load Shedding

Suppose now that the system is operated in a stressed condition at 120% base load level. With the same GA parameters as in 5.1, the minimum objective function value achieved is 13.166, of which 3.26 is due to load shedding and 0.905 is for network loss, and 9.0 is for switch operations. The resulting network is shown in Figure 4. The GA evolution process is shown in Figure 5.

It can be seen from Figure 5 that, in the beginning of GA evolution, the objective function is high due to the unreasonable network topologies generated by the (initially randomly positioned) ‘0’ gene. However, through evolution, the ‘0’ gene moves towards the end of the chromosome. Since the system is in a very stressed condition and cannot supply all loads without violating security constraints, one or more selected loads have to be shed. The optimal load shedding point is indicated by the position of the ‘0’ gene in the final chromosome. Its position is ‘tuned’ by the GA evolution to minimise the GA objective function value. The load is shed if it can only be connected to the network via switches located behind the ‘0’ gene in the final chromosome. In this case, as can be seen in Figure 4, switch S49 is tripped off to shed the appropriate load.

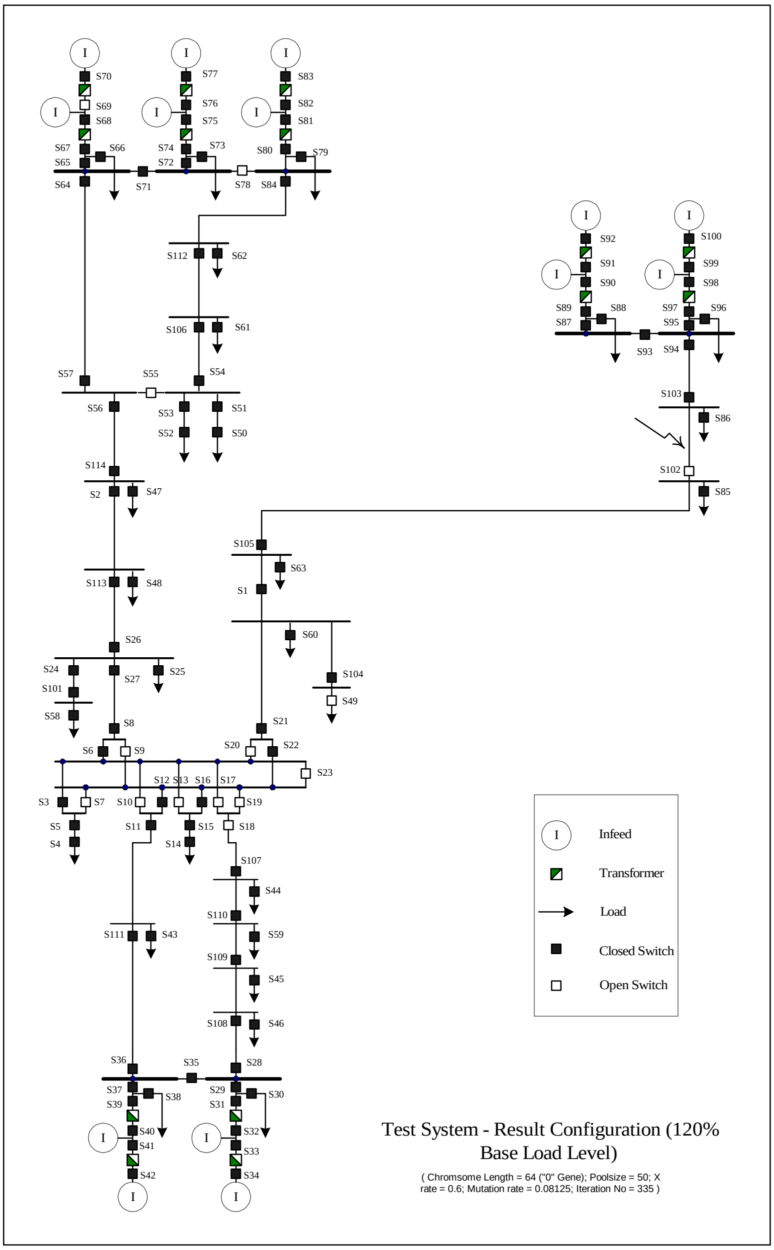

Figure 4. Network Configuration after Optimal Load Shedding in Stressed Condition (at 120% Base Load Level)

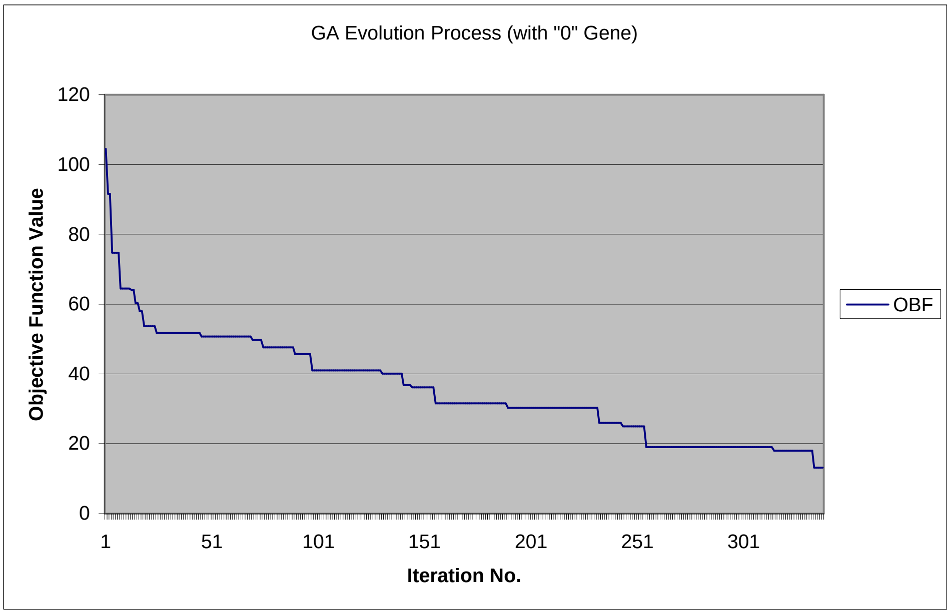

Figure 5. GA Evolution Process for Optimal Load Shedding

5.3 Results Analysis

From the test results, it can be seen that at the base load level where full supply restoration can be achieved, the proposed algorithm gives an optimal re-configured network and supply restoration strategy.

When the system is in a stressed condition, and the network can not supply all of its loads, the position of the '0' gene and the genes following it in the GA chromosome determine the optimal load shedding points, so that the network can supply all other loads.

The radiality constraint is respected by the graph-theory-based switch setting algorithm. The security limit constraints are unlikely to be violated due to the heavy penalty weightings selected for them in the objective function of the GA. It can be seen from the resulting objective function values that in both examples, no overload exists in any line, and no voltage excursion occurs at any bus. In the case of violations of these security limit constraints, the GA would prefer to shed some loads to correct the problem, since the penalty weighting value for the unsupplied load term is smaller.

In both cases, the optimum network configurations are achieved after about 340 generations of evolution. It takes approximately 3.5 minutes of computer time for the system to read the data from database, run the GA for 340 generations and display the suggested supply restoration result and optimal load shedding point (if applicable) to the user. This level of performance would allow online application in the distribution control centre.

It can be clearly seen that by omitting the switch operation cost term and lost load term in the objective function formulae, the proposed algorithm could also function as a network loss minimiser for distribution network operation and planning. The '0' gene will not be required in this application.

6. Conclusions

A GA based method is proposed to decide the supply restoration and optimal load shedding strategy for distribution networks. The 'integer permutation' encoding scheme is adopted in which each chromosome represents the set of controllable switches the final states of which the algorithm is to determine. Graph theory guarantees that the chromosome will be mapped to a unique and valid radial distribution network. A '0' gene can be introduced in the chromosome to indicate the optimal load shedding points when demand is beyond the ability of supply. The algorithm has been tested successfully on a practical system.

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