Optimal Substation Location and Network Routing using an Improved GA Based Solution Approach

A. Josephine Amala¹ and M. Ponnaikkko²

Abstract: The paper deals with a problem of optimizing substation locations and network routing to serve a given load demand. An objective function of fixed costs of substations and lines and the present worth cost of energy loss of the line segments is optimized, subject to a set of constraints. The problem is combinatorial and thus they have a discrete objective function. Considering the limitations of the conventional methods available to solve such problems, researchers have used various intelligent computational methods, derived from nature. Genetic Algorithm is one such technique now used popularly for solving power system problems. This paper presents yet another GA based solution procedure that uses a simple codification scheme, genetic operators and control parameters to model the Distribution System Problem within the framework of GA. The model has been intensively tested in real distribution networks, which proves their practical application to large power distribution systems with relatively smaller solution times. The paper presents an improved GA based solution approach and the results obtained when applied on to an existing large sub-transmission network.

Index Terms: combinatorial optimization, distribution system planning, Genetic algorithm and minimal spanning tree.

1. INTRODUCTION

The distribution system and the sub transmission system are the important sub-systems of a Power System both in terms of system economy and supply efficiency. These systems are characterized by uncertainties in terms of load development and network growth. The distribution system is classified as secondary distribution and primary distribution systems. In all these sub-systems, the planning objective is to place the substations in the load centers and to keep the feeders within their optimal level of loading and load distribution so that the overall investment and operational costs in the systems are minimum with the given constraints. The transformer location and feeder routing in a secondary distribution system is relatively flexible compared to primary distribution or sub transmission systems. The primary distribution systems, particularly in urban areas, and the sub transmission systems both in rural and urban areas have limitations in locating sites for substations and feasible routes for feeders to feed the substations. Thus, the problem of planning optimal systems in these cases is to determine the optimal number and location of substations and optimal number of feeders and their routings from among the feasible ones, subject to a set of physical and technical constraints.

The problem of optimal location of substations and network routing in primary distribution and sub transmission systems has been engaging the attention of researchers for quite sometime. Several solution techniques to solve this problem had been proposed in the past with varied assumptions and constraints. Earlier research concentrated in developing methods using conventional optimization techniques such as transshipment methods [1], Branch and Bound techniques [2], Quadratic Mixed Integer programming technique [3], and Bender’s decomposition approach [4]. These methods require strict continuity of search

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techniques and most of them do not allow non-linearity to appear in the solution space. Recently other methods based on more efficient heuristic techniques such as branch exchange method [6], Genetic Algorithms [5,7,8], Ant colony algorithms [12] and Simulated Annealing algorithms [13] have been applied.

In [5], a solution methodology based on Genetic Algorithm (GA) approach has been applied for the design of primary distribution circuits considering multiple system expansion stages, to determine the timing of investments to be made at intermediate stages of planning period. In this approach a special coding procedure is proposed to reduce the number of infeasible solutions evaluated by the algorithm. In [7], the potential of the GAs is shown in comparison with classical optimization techniques, reporting significant improvements in the solution times. Different conductor sizes and substation sizes are considered for which an integer variable coding scheme was used. In [8], W.M.Lin. et al. has applied GA using a set of algebraic equations to test the radiality of the network and the reliability of supply to the load. An evolutionary decision convergence approach is presented in [9] to solve network expansion planning problem under uncertainty. E.Diaz – Dorado, et al have applied evolutionary algorithms for the planning of urban distribution networks of medium voltage [11].

In [12], Ant Colony System (ACS) algorithm is adopted, to optimize primary distribution circuits for a given maximum load condition. In [13], simulated annealing algorithm is applied to obtain sub optimal solution for the static problem of connecting N consumers to M substations that are not necessarily themselves connected. In [14], an evolutionary algorithm is applied to the design of secondary distributions circuits. The codification scheme takes into consideration, the conductors dimensioning, load balancing among phases and the allocation of the transformers at the center of the secondary distribution system loads.

GA is widely applied for solving DSP problems, mainly because of its flexibility to handle the distribution system problems of different levels of complexity. Many constraints assumed in the earlier approaches can be relaxed with the application of GA techniques. In large combinatorial problems, the feasible domain where the optimal solution lies is extremely large and the computational effort to find it may entail visiting every possible solution, a process requiring a large computational effort and time that may be prohibitive. The number of constraints increases rapidly with the size and complexity of the network, increasing the computational efforts further. For such problems, the GA approach provides an effective solution procedure to locate the optimal solution with less effort. However, sometimes it may lead to a sub-optimal solution. But through careful choice of GA operators and solution procedures it is always possible to obtain the global optimal solution.

The researchers in optimal Distribution and Sub-transmission system planning, using Genetic Algorithms, continue to contribute improved solution procedures. This paper presents a yet another solution procedure using an efficient GA algorithm for solving the distribution system problem of fixing the optimal location and sizing of substations and routing of the feeders. The proposed solution procedure is applied on an existing Distribution Network of a district in Orissa state in India. Generation of a set of spanning trees concept is employed to solve the problem of connecting consumers radially to a set of substations. The solution procedure developed also determines the conductor size of feeders for each configuration.

The efficiency of the Genetic Algorithmic approach depends upon the choice of an efficient coding scheme and data structure to represent the nodes and their active and inactive neighbors. This work employs the concept an effective representation of forests (graphs composed of a set of trees) while modeling the network and makes the solution procedure more general in approach than those found in the literature.

In this research, diversification strategy is employed to accelerate the convergence and to reduce the possibility of ending at a local optimal solution.

2. MATHEMATICAL FORMULATION

The topology of the network, considered, is specified by the node-branch connection information. A set of undirected graphs (forest) with distances between each pair of nodes is specified. In the process of distributing
energy to new consumers, some branches and substations may already exist and are part of the network. While designing the network required to feed the future demand satisfying the constraints, the existing branches and substations may get rerouted, augmented and new branches may be introduced. The algorithmic procedure takes care of these issues. Among all the feasible configurations to feed the network demands, subject to the constraints, the configuration that results in a minimum total moment (km-MVA) of the feeder branches, is selected as the optimum solution.

The objective function for the problem under consideration has the following cost components:

(a) cost of the future substations as a function of substation capacity.
(b) costs associated with future feeder bays of the existing and future substations.
(c) cost of the future feeders.
(d) costs associated with capacity augmentation of existing feeders.
(e) Present worth of the energy loss costs associated with the existing and future feeders.

The objective function is minimized subject to the usual technical constraints that represent the Kirchoff’s laws, the voltage regulation constraints at the load points, radial constraints of the feeders and pre-specified possible sites for substations and routes for feeders. The objective function is minimized ensuring that:

• Every demand center \( j \) is served.
• The network has a radial configuration.
• The voltages are within the permitted limits at every node \( j \).
• Power flows are less than the feeder capacities.

3. STATEMENT OF THE PROBLEM

The mathematical formulation of the above cost function is given by

Minimize,

\[
C(\delta, w) = \sum_{i \in S} C_F \delta_i + C_B \sum_{(i, j) \in F_P \cap F_F} \delta_{ij} + \sum_{(i, j) \in F_P} (C_F)_{\Delta} L_{ij} \delta_{ij}
\]

\[
+ \sum_{(i, j) \in F_E} (C_E) L_{ij} (A_y)_{\Delta} + \sum_{(i, j) \in F} (C_E)_{\Delta} W_{ij}^2 L_{ij}
\]

\[
\Delta \in N_{\Delta}
\]

Subject to,

1. Kirchhoff’s current law

\[
\sum_{(i, j) \in F_j} W_{ij} - \sum_{(j, k) \in F_j} W_{jk} = P_j
\]

\( \forall \ j \in \text{Load centers} \)

2. for a connected graph to be radial:

\[
\sum_{j=1}^{n} \sum_{(i, j) \in F_j} \delta_{ij} = n - 1
\]

\( \forall \ j \in \text{Load centers} \)

3. \( V_{\min} \leq V_j \leq V_{\max} \)
∀ j ∈ Load centers

4. \[
\sum_{(i,j)\in F_j} \delta_{ij} + \sum_{(j,k)\in F_j} \delta_{jk} \geq 1
\] (5)

∀ j ∈ Load centers

5. for the network to be reliable:

\[
\sum_{(i,j)\in F} \delta_{ij} = 1
\] (6)

∀ j ∈ Load centers

6. power flows less than the feeder capacities:

\[
W_{ij} \leq U_{ij} (i,j) \in F
\] (7)

Where,

n - number of nodes (including source node) connected to a graph (tree).

V_{\text{Min}}, V_{\text{Max}} - lower and upper thresholds of acceptable voltages.

V_j - voltage at node j.

S_E - set of nodes, associated with the existing substations in the initial network whose sizes are retained.

S_P - set of nodes, associated with the proposed locations to build substations

F_E - set of routes between demand locations, associated with the existing feeders in the initial network.

F_P - set of proposed routes between demand locations, to be built.

F = F_E \cup F_P

S = S_E \cup S_P

P_j - diversified peak demand at node j in MVA.

(i,j) - routes between nodes i and j.

W_{ij} - Power flow, in MVA, carried through the route (i,j).

\delta_{ij} - 1, if a feeder associated with the route \((i,j) \in F_P\) is built. 0 otherwise.

\delta_{i} - 1, if \(t \in S_E\) or if a substation associated with the node \(t \in S_P\) is built. 0 otherwise.

F_{N_i} - set of neighbor routes of node i.

F_{j} - set of branches leaving node j.

F_{j} - set of branches entering node j.

N_{\Delta} - set of proposed feeder sizes to be built between nodes. These are also the sizes of existing ones.

C_{F_t} - fixed cost, in Million Rs, of a substation to be built at node \(t \in S_P\), given the different sizes of the substation for adoption in the solution.
(C_p)_Δ - cost coefficient in Million Rs/km of a feeder of size Δ to be built.

C_C - cost coefficient in Million Rs/km/mm², of an existing feeder in the initial network.

C_B - Cost of feeder bay in Million Rs, of a substation.

(C_p)_Δ - Loss cost coefficient (LCC) in Million Rs/MVA²/km of feeder of size Δ to be built.

L_{ij} - Length of a feeder on the route (i, j) in km.

(A')_Δ - Additional area of cross section in mm² of an existing feeder in the initial network augmented to the size Δ ∈ ΩΔ.

NLF - Feeder life in years.

LLF_k - Loss Load Factor in kth year.

u - annual discount rate in p.u.

Kv - circuit voltage in kilo volts.

Ce_k - cost of energy in kth year in Rs./kwh.

r_Δ - per phase resistance per km of feeder of size Δ.

H - moment for a voltage drop of one percentage.

v - percentage voltage drop.

U_{ij} - Thermal capacity of feeder to be built between nodes i and j.

### 3.1 Cost Models

Average costs per kilometer length of conductor sizes considered are specified. The possible feeder connections to a substation define the feasible number of new feeder bays at the substation. The cost of the new feeder bay includes the cost of a circuit breaker, measuring equipment, the materials and construction. Fixed cost of existing elements is taken as zero. However, the existing feeders will have an associated loss cost.

### 3.2 Feeder Loss Cost

Power loss cost is specified in Million Rupees per kilometer length of selected conductor size per MVA² of power flow. It is known from the fundamentals that the peak power loss in a feeder segment between nodes i and j can be obtained [3] as a function of the power flow in the segment as

\[
PL_{ij} = (C_v)_\Delta W_j^2 (L_j)
\]  

Where,

\[
(C_v)_\Delta = \frac{0.001(r_\Delta)}{(kv)^2}
\]  

Using (2), the present worth of the annual energy loss costs of the feeder segment during its life can be obtained as

\[
E_p = (C_v)_\Delta W_j^2 (L_j)
\]  

Where,

\[
(C_v)_\Delta = \frac{8.76}{(kv)^2} (r_\Delta) \sum_{k=1}^{n} Ce_k (LLF_k) \frac{NLF_k}{(1+u)^k}
\]
3.3 Voltage Drop Computation

Percentage voltage drop of a feeder is given by

\[
\text{sum of moments of individual routes of the feeder associated with size 1 conductor} + \frac{H \text{ of feeder size 1}}{H \text{ of feeder size 1}} = \text{sum of moments of individual routes of the feeder associated with size 2 conductor} + \frac{H \text{ of feeder size 2}}{H \text{ of feeder size 2}} + \ldots + \frac{\text{sum of moments of individual routes of the feeder associated with size n conductor}}{H \text{ of feeder size n}}
\]

(11)

Where,

\[
H = \frac{1}{r} \sum_{j=1}^{n} W_{ij} L_{ij} \quad ij \in F_i
\]

\[
= \frac{10 \times kv^2}{r(cos \theta) + x(sin \theta)}
\]

(12)

4. NETWORK DESCRIPTION

The existing sub-transmission system in the district of Puri of Eastern National Grid in the Indian subcontinent is considered for testing the proposed method. The existing network is shown in Fig. 8. The Puri district power system receives power from 2 Nos. of 132/33 kv substations at present. There are 10 Nos. of 33/11 kv substations which are the demand locations. A highly strained subtransmission network supplies them. Most of the substations and 33kv lines are overloaded. As per the load forecast study, the power demand and energy requirement at the 11kv level in the district are expected to go up from the respective present levels of 21.2MW and 59MU to 140MW and 383MU in the next 5 year period. The feasible locations for the substations and the routes for the feeders identified are as follows:

<table>
<thead>
<tr>
<th>Table 1</th>
<th>General System Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Feeder cost (Million Rs/ mm²/km)</td>
<td>0.00051</td>
</tr>
<tr>
<td>2. Load factor</td>
<td>0.4</td>
</tr>
<tr>
<td>3. Loss load factor</td>
<td>0.21</td>
</tr>
<tr>
<td>4. Cost of energy (Million Rs/ kwh)</td>
<td>0.3</td>
</tr>
<tr>
<td>5. Annual discount rate in p.u</td>
<td>0.1</td>
</tr>
<tr>
<td>6. System life in years</td>
<td>25</td>
</tr>
<tr>
<td>7. Power factor</td>
<td>0.8</td>
</tr>
<tr>
<td>8. Nominal voltage</td>
<td>33 kv</td>
</tr>
<tr>
<td>9. Voltage deviations from the declared voltage</td>
<td>−9%, 6%</td>
</tr>
<tr>
<td>10. No of Nodes</td>
<td>55</td>
</tr>
<tr>
<td>11. No of routes</td>
<td>69</td>
</tr>
<tr>
<td>12. No of potential routes</td>
<td>59</td>
</tr>
</tbody>
</table>
Optimal Substation Location and Network Routing using an Improved GA based Solution Approach

1. Sites for Grid substations are the nodes 3, 4, 5, 6, 7 and 8, shown in Fig. 8.

2. The feasible routes for the feeders are shown as dotted segments in Fig. 8.

General system data, feeder sizes data, the demands at the load nodes and the feeder routing data are given in tables 1 to 2.

5. PROPOSED GENETIC ALGORITHM

Genetic algorithms are search and optimization methods based on natural evolution. They consist of a population of bit strings in the form of chromosomes, transformed by three genetic operators: selection, crossover and mutation. Each node is represented in the chromosome by a substring. The length of each substring is equal to the number of bits needed to encode the number of possible connections to it. For example consider a node, which has four neighbors, needs two bits. Each chromosome represents a solution for the problem.

The algorithm is designed to generate initial configurations, which are a set of alternative configurations, generated by a heuristic constructive algorithm. The bit pattern of each chromosome in the initial population is generated by random selection of a neighbor from the set of neighbors of each node starting from each substation node using depth first tree search technique in a recursive routine. The search proceeds until it meets nodes connected by single neighbor. A few other heuristics are included to avoid open and closed loops, so that the generation of infeasible configurations is largely reduced.

1. repeated visit to a node is ignored.

2. visit to another source node in its path is ignored.

Unconnected nodes, if any, of each generated configuration are connected to one of their active neighbors. By virtue of its random selection, this procedure generates a versatile population compared to other algorithms such as Prim’s algorithms [10].

The selection operator creates new population by selecting individuals from the old population. Tournament selection operator is used. This selection consists of choosing the fittest individuals among a set of randomly chosen subpopulation. The tournament selection mechanism is used based on the advantage of low computational effort. With a population size equal to 10, a subpopulation of size 3 is used. The selected individuals form a new population called the mating pool. A smaller size for subpopulation helps to maintain a reasonable diversity in the mating pool.

Multiple site crossovers are adopted. The bit patterns of two randomly selected chromosomes at randomly selected sites are exchanged. The parent chromosomes for crossover are obtained by Stochastic Remainder Rowlett Wheel selection mechanism. This crossover needs the following steps: 1) determine randomly the number of genes (a number dependent on the number of nodes; about 10%-30%) and the genes to be

<table>
<thead>
<tr>
<th>Sizes</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross Al area of conductor cross section (mm²)</td>
<td>77.83</td>
<td>94.21</td>
<td>103.6</td>
</tr>
<tr>
<td>Per phase resistance (Ohms/ km)</td>
<td>0.409</td>
<td>0.338</td>
<td>0.307</td>
</tr>
<tr>
<td>Per phase reactance at 33kv (Ohms/ km)</td>
<td>0.378</td>
<td>0.374</td>
<td>0.371</td>
</tr>
<tr>
<td>Cost of feeder /km (Million Rs)</td>
<td>0.0400</td>
<td>0.0484</td>
<td>0.0532</td>
</tr>
<tr>
<td>Loss cost coefficient (Million Rs/ MVA 2/km)</td>
<td>0.00171</td>
<td>0.00141</td>
<td>0.00128</td>
</tr>
<tr>
<td>Capacity (MVA)</td>
<td>14</td>
<td>16.29</td>
<td>17.78</td>
</tr>
</tbody>
</table>
crossed 2) since each gene is represented by different number of bits, the bits to be crossed are to be determined. 3) make a mask that represents the genes to be crossed. 4) interchange the bit patterns at these sites. Genes 2 and 5 are selected randomly for crossover. With respect to the network shown in Fig. 1, the parent configurations selected for crossover are shown in Fig. 2.

The chromosome in which the bit patterns of the genes (2, 5) selected for crossover are masked and shown in Fig. 3. The bits of the parent chromosomes at the enabled sites are interchanged. The children configurations are shown in Fig. 4. Crossover probability is fixed as 0.6 in this work.
The chromosomes transformed by crossover are verified for the presence of meshes and disconnections in the network. Whenever the decoding procedure encounters a loop, it identifies routes that form loop and one of them is removed at random. Unconnected nodes of each transformed configuration are connected to one of their active neighbors.

Mutation rate assumed is 0.001 in this work. A randomly selected node (gene) is mutated. Mutation switches the infeed line of a node among its neighbors.

5.1 Tree Encoding and Decoding Procedure

The tree encoding for GAs is a critical factor in large-scale networks. Each node is represented in the chromosome by a substring. The length of each substring is equal to the number of bits needed to encode the number of possible connections to it.

For example, a node that has four neighbors needs two bits. A substring corresponding to a node is a gene representing the infeed line of the node. Thus, each substring represents a decision variable. The chromosome encoding for the configuration shown in Fig. 5 is illustrated in Fig. 6.
Assuming node 1 as the root node of the tree, node 3 needs three bits (substring /gene) to code its six neighbors. Let the neighbors of node 3 be numbered as follows:

First (000) neighbor be the line between nodes 3 and 1.
Second (001) neighbor be the line between nodes 3 and 2.
Third (010) neighbor be the line between nodes 3 and 4.
Fourth (011) neighbor be the line between nodes 3 and 5.
Fifth (100) neighbor be the line between nodes 3 and 6.
Sixth (101) neighbor be the line between nodes 3 and 7.

The 6th neighbor of node 3 chosen as its infeed line is coded as a binary number (101) in the chromosome and it represents a gene.

Nodes 1, 2, 6 and 7 need two bits as they are connected to three neighbors. Nodes 4 and 5 need one bit only to code their connections less than or equal to two.

Lists of neighbor routes and their active/inactive statuses adequately represent each node. Each chromosome is decoded to realize the set of trees in it by depth-first tree search strategy starting from each substation node in a recursive routine. The same routine simultaneously determines the power flows, farthest feeder node (the path that has the maximum cumulative km-MVA flow) and hence the main feeder. For the computed power flows of the configuration, adequate feeder sizes are built for the routes and the feeder losses are determined. The routine also serves as ‘mesh check’. A traversal list is updated on visit to every node. Repetition of a node in the list indicates a closed loop in the configuration, and existence of an open loop is indicated when the list encounters another source node thus serving as ‘mesh check’. A feasible solution is one in which all demand nodes are connected to sources and has no meshes in the network.

5.2 Diversification Strategy

In general GA exhibits a convergence towards local optimums. When a given individual generation achieves a local optimum, this solution may be maintained as the best one for a certain number of next generations. Lower quality solutions are progressively eliminated through the selection process. When the diversity on the population drops to quite a low value, premature convergence may occur. Hence, the control of the population diversity according to a population diversification rate is proposed.

\[
\text{Diversification rate} = 100 - \frac{\#C_{\text{mEqual}} \times 100}{\text{popsize}}
\]

\(\#C_{\text{mEqual}}\) is the maximum number of equal configurations in the population. If this rate drops below a given value, the mutation rate is increased to introduce diversity and to explore new searching spaces. The minimum diversification rate (20%) is fixed at a lower value.

However, great care must be taken in exercising the strategy. Else it may result in oscillatory convergence and show a tendency towards local optima. The increased mutation rate is applied over a randomly selected segment of chromosomes. The introduction of diversification strategy has shown early convergence to global optimum.
Chromosome decoding

Load flow by Km_MVA (moment) method

Radial Configuration?

N	Fitness = 0

All loads are supplied?

N	Fitness = 0

Y

Determine the feeder sizes based on power flow and thermal capacity limits

Voltage drop violations?

Y	Fitness = 0

N

Fitness = F (investments, loss cost, capacity expansion costs)

Fig. 7: Flow Chart of Fitness Function Evaluation
5.3 Heuristic Strategy
Transformations by mutation operators may result in meshes and disconnections in the network. Hence, some heuristics are adopted to avoid them as well as to expedite the search. A mutation operation switches the infeed line of a randomly selected node. The infeed line of the selected node \((j)\) is changed to one of its feasible neighbors. A case when random selection picks up node 3 for mutation in the configuration shown in Fig. 5, is performed as follows:

A line among its neighbors \(F_{31}, F_{32}, F_{34}, F_{35}\) and \(F_{36}\) need to be activated as infeed. An inactive and not a downstream neighbor \((F_{31}, F_{32}, F_{34})\), that connects a node having minimum cumulative km-MVA \((F_{31})\) is switched as infeed. The power flows of the old and the new feeder routes are updated.

5.4 Fitness Function
Fitness function is a possibility index of the final solution. The general trend is to maximize the fitness function. \(C\) is a minimization function (1). Hence, a maximization function \(F\) is defined as a fitness function.

\[
F = K - C
\]

where,

\(K\) – A large enough constant value.

1. if the voltage drop at any node exceeds the threshold (–9% to +6%), the solution is considered infeasible and the fitness function receives a 0 value.

2. Else, if voltage drops at all nodes lie within the thresholds the configuration is feasible.

Convergence is achieved when the number of generations reaches the maximum number of generations specified or the mean fitness function values do not change noticeably throughout 5 consecutive generations and after the diversification is invoked over and above a pre-specified number of times. The process stops when one of these conditions is met. Due to the randomness of GA method the solution tends to differ for each run even with the same initial population. For this reason it is suggested to perform multiple runs and select the most acceptable solution. Elitist strategy retains the best solution in any population. The population size depends on the problem. A smaller population size leads to quick convergence but a local optimum. A large population size is generally required for an acceptable optimum.

6. COMPUTATIONAL RESULTS
The proposed algorithm was tested on the system considered. The result was obtained in 300 generations over which a consistent solution was observed. The average run times was of about 10 sec, in an Intel® Pentium®M (1.60GHz) PC. The solution network is shown in Fig. 9. Voltages at the leaf node of the longest feeders of each grid substation of the solution network are given in Table 3.

<table>
<thead>
<tr>
<th>SS No.</th>
<th>Demand on SS (MVA)</th>
<th>Voltage at leaf node of the main feeder of the SS</th>
<th>Leaf node of the main feeder of the SS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.708</td>
<td>0.934935</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>28.417</td>
<td>0.956046</td>
<td>44</td>
</tr>
<tr>
<td>3</td>
<td>6.483</td>
<td>0.969956</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>18.650</td>
<td>0.956903</td>
<td>15</td>
</tr>
<tr>
<td>5</td>
<td>22.117</td>
<td>0.937537</td>
<td>37</td>
</tr>
<tr>
<td>6</td>
<td>10.892</td>
<td>0.979142</td>
<td>43</td>
</tr>
<tr>
<td>7</td>
<td>18.642</td>
<td>0.938439</td>
<td>48</td>
</tr>
<tr>
<td>8</td>
<td>0.000</td>
<td>0.000000</td>
<td>00</td>
</tr>
</tbody>
</table>
7. CONCLUSION

The proposed GA method implemented with the node encoding and the specifically manipulated crossover and mutation operators ensures optimal solution and is more effective in solving the problem. The introduction of diversification strategy helps convergence of the process to a desired optimum solution in the case of large-scale networks in a reasonably small number of generations. In the author’s opinion, the method is faster without loss of global optimality.

REFERENCES


