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# A Novel Genetic Approach Applied for Power Loss Reduction and Improved Bus Voltage Profile in Distribution Network System

**Youssef Barradi[1]*** **Naoufel Khaldi[2]** **Khalida Zazi[1]** **Malika Zazi[1]**

[1]*Electrical Engineering Department in The Higher School of Technical Education (ENSET), Mohammed V University, BP 6207 Rabat, Morocco*
[2]*Department of Electrical Engineering, Mohammadia School of Engineering, Mohamed V University, Rabat, Morocco*
* Corresponding author's Email: youssef.barradi@um5s.net.ma

**Abstract:** This paper presents a network reconfiguration which is a vital analysis process for optimizing and controlling distribution systems. The method is based on genetic algorithm by changing the status of the switches to improve the operational performance. The main objective is to minimize the system power losses and to keep bus voltage profile into limits with radial distribution to provide the consumers with quality electrical energy while minimizing the cost. For this optimization problem, an objective function is developed from an electrical branch to sort the fittest solution. Selection, Crossover and mutation are the necessary three operators in which some improvements are made for the effectiveness of the genetic approach. The method can be successfully applied for loss minimum problem. Numerical example simulated with MATLAB/GUI is demonstrated by 33-bus distribution network and tested using a default mode network. As results, premature convergence is avoided, it shows the validity of the proposed methodology while respecting all the constraints.

**Keywords:** Distribution system, Genetic algorithm, Power losses reduction, System re-configuration, default network.

## 1. Introduction

The energy diagnosis is the process of consulting the state of transit of energy in all infrastructures [1]. It is the heart of any electrical network management program. Actually, energy losses in power grids and in distribution grids in particular, represent a major challenge for grid managers [2] and [3]. The losses represent on the distribution network not less than 5% of the energy consumed which reduce the financial gain [5]. These losses origin can be technical and non-technical due to the circulation of an electric current in the equipment or from an energy consumption no recorded. According to criteria and constraints which depend to the current operating regime, an optimum exploitation for distribution network (urban, rural or mixed) is developed. The two main reasons for a reconfiguration are eliminating overloads on the system components and reducing the active power losses of the system network. In order to find a radial operating structure, the reconfiguration of a physical system consists in changing the functional links between the component elements, changing also the topological state using sectionalizing and tie switches of certain branches in the network. Many methods in the past have tried to provide a solution for this load flow problem such as the branch exchange approach which is a gradient method, with one normally-open switch closed. In every step, when closed switch in the loop opens, a new topology is produced which violates the topological constraints [4] and [6]. Otherwise, in the literature, the most used algorithms are heuristic search techniques [4] and [5]. Based on analytical methods, the above-mentioned algorithm starts with empty network, disconnected load and open switches, then they get

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just an approximate local optimum. In this paper, a new genetic algorithm (GA) is successfully applied to minimize the system power losses and keep the voltage drop out of penalty values while satisfying the operating constraints and to guarantee also a global optima. GA are different from classical search procedures, they work with coding of parameters, final solution is searched from a population of points rather than a single point, and they use only an objective function. All these properties make it more accurate, efficient and powerful. A String in GA is referred to a chromosome or set of genes. GA provides a solution by working with a population of strings [6] and [7]. Thereafter, through the following operations called selection, crossover, and mutation, a successive population is generated to produce a fitter offsprings, which guarantees a smooth convergence towards a global optimum. Results show that the GA is more robust and powerful from any other classical techniques, especially in terms of speed, precision and accuracy. It shows also how that technique can transform a failure branch system into a radial functional reconfiguration. In this step, an outage is simulated, the algorithm performs the search, identify and isolate the branch containing the fault and communicate the best solution found at the end. The proposed methodology firstly is tested on 33 buses distribution system and secondly with a default mode network. In section 2, the optimization mathematical problem is formulated using an objective function. In section 3, the essential parts of genetic algorithm are developed and explained. Numerical case study with and without default mode network, is studied in section 4. Finally, a precise conclusion is described.

## 2. Mathematical problem formulation

The minimum power loss reconfiguration problem is formulated as a complex combinatorial optimization problem [8]. We define an objective function which should be minimized to guarantee a solution satisfying also the operating constraints [10].

$$F_{obj}(X) = min( 3\sum_{b=1}^{Nr} R_b {I_b}^2 ) \quad (1)$$

Where $R_b$ and $I_b$ are respectively the resistance end the current in the branch b.

Nr represents the number of the total nodes.

To find an open loop radial distribution, this power flow is analyzed from a single electrical branch in the system. The representation is given by Fig. 1 :

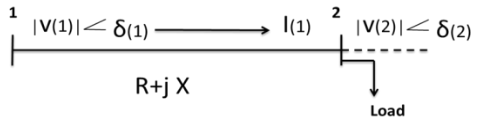


Figure.1 Electrical branch

According to Fig. 1:

$$I(1) = \frac{|V(1)| < (\delta 1) - |V(2)| < (\delta 2)}{R(1) + jX(1)} \quad (2)$$

$$P(2) - jQ(2) = 3.V(2).I(1) \quad (3)$$

Using Eqs. (2) and (3), the node voltage at (i+1) is given by :

$$V(i+1) = \sqrt{\left(\sqrt{(a^2 - b)}\right) - a} \quad (4)$$

with :

$$a = P(i+1)R(i) + Q(i+1)x(i) - 0.5|V(i)|^2$$
$$b = \left(P^2(i+1) + Q^2(i+1)\right)((R^2(i) + X^2(i)) \quad (5)$$

The node voltage limits $V_{imin} < V_i < V_{imax}$ where ‘min’ and ‘max’ are the bounds of the constraint.

The generalized power flow equations at the $i^{th}$ node are given by :

$$LP(i) = \frac{R(i).\left(P^2(i+1) + Q^2(i+1)\right)}{3.|V(i+1)|^2} \quad (6)$$

$$LQ(i) = \frac{X(i).\left(P^2(i+1) + Q^2(i+1)\right)}{3.|V(i+1)|^2} \quad (7)$$

The iteration calculation will be ceased if the value of the difference between the real and reactive power losses in the successive iterations is less than the given permissive error.

From Eqs. (1) and (6), the objective function is given by:

$$F_{obj}(X) = min( \sum_{i=1}^{Nr} \frac{R(i).\left(P^2(i+1) + Q^2(i+1)\right)}{3.|V(i+1)|^2} ) \quad (8)$$

## 3. Genetic algorithm

Genetic algorithm is a technique for solving an optimization problem [11]. Inspired by biological evolution [12], the method repeatedly modifies a population of individual solutions throughout three main types of rules (selection, crossover and mutation) to create the next generation. Over successive created generations, the population evolves toward an optimal solution.

The genetic algorithm is applied to the solution procedure for the loss minimum problem by taking the following five steps:

- Step 1: Create initial population
- Step 2: Copy individual strings
- Step 3: Bring population to the selection, crossover and mutation pattern.
- Step 4: Reach the maximum generation
- Step 5: Report the global optimum solution

The above-mentioned operations of GA are shown in Fig. 2:

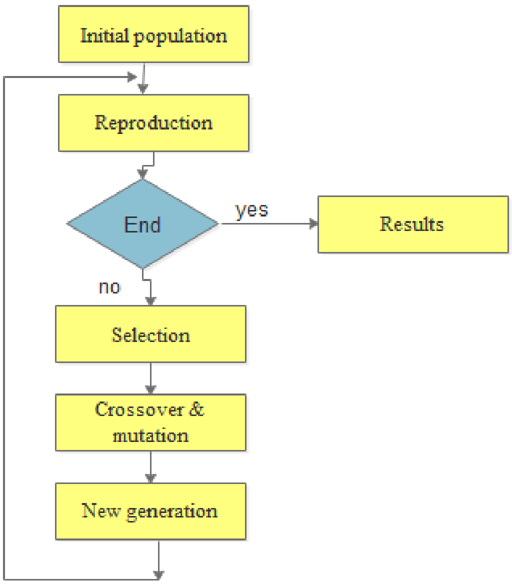


Figure.2 Flowchart of GA

### 3.1 Genetic String

To generate initial population, each individual in the population must be coded as a string. A binary code can be generated by considering a '1'for a closed switch, and a '0' for an open sectionalized switch. In Fig. 3, position of five initially open switches B13, B33, B35, B36 and B37 specify a radial configuration topology. Therefore, the position of open switch is the only parameter which determines the loss minimum configuration. Also, an open switch can be remembered by memorizing its string structure.

A matrix based in the coupled R/X (Resistance/Reactance) for every transmission line is generated. For each configuration, no load point interruption must be ensured by considering the direction of the current in the branches using this matrix. Once the transmission lines are oriented, the presence of a loop must be verified to ensure a radial distribution system.

A flowchart for this process is given by Fig. 4:

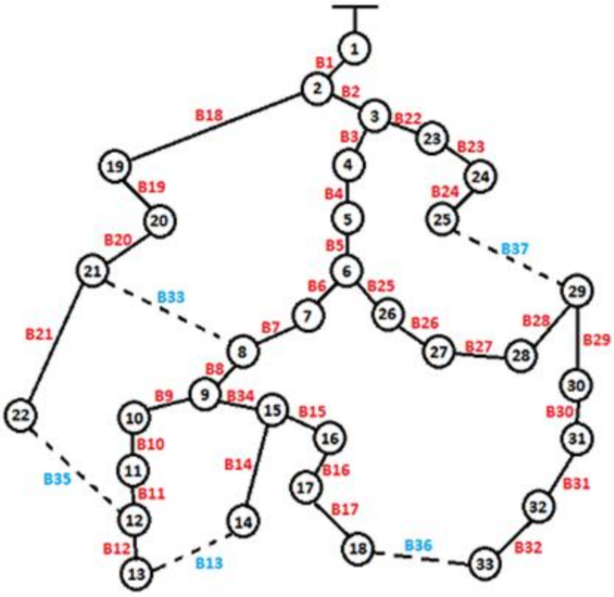

Figure.3 33-nodes network distribution

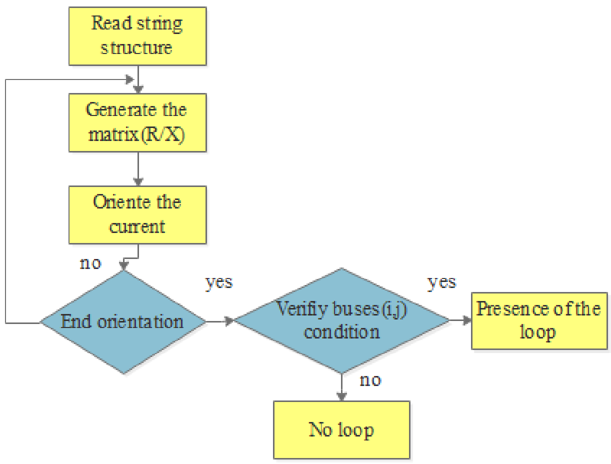


Figure.4 Flowchart of oriented algorithm

### 3.2 Fitness function

To sort the most promising individuals for our population, it's very important to form an accurate fitness function by using the object function [7]. Its value is crucial parameter to guide the search.

$$Fit\ (x)\ = {}^{1}/_{F_{obj}(x)} \tag{9}$$

### 3.3 Selection

After reproduction, to keep and maintain good performance, it is important to select from the population the best individuals to survive and to create a new offspring for the next generation. In this paper, fitness proportionate selection is used to parent selection. Consider the roulette wheel in Fig. 5, each individual gets a portion of the circle

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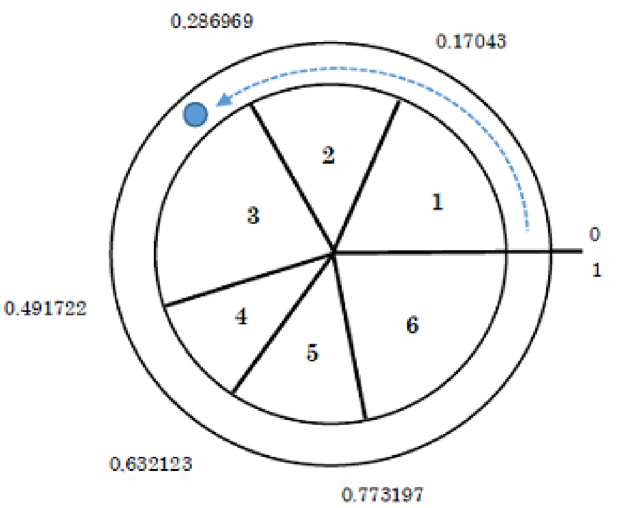


Figure.5 Roulette wheel selection

according to its fitness value. Then, fitter individuals will be selected more times, and have a higher chance of mating and propagating their features for the next generation.

$$Fit_{norm}(i) = \frac{Fit(i)}{\sum_{i=1}^{N} Fit(i)} \quad (10)$$

$$\begin{cases} Fit_{cum}(i) = Fit_{cum}(i-1) + Fit_{norm}(i) \\ Fit_{cum}(0) = 0 \end{cases}$$
$$i = 1,2 \ldots,N$$

Where $\mathrm{Fit}_{\mathrm{norm}}(\mathrm{i})$ and $\mathrm{Fit}_{\mathrm{cum}}(\mathrm{i})$ are respectively the normalized and cumulative fitness function of individual ‘i’ in the population, and N is the number of individuals in the population.

### 3.4 Crossover and mutation

Individuals are selected from the population to be parents [7]. Crossover and mutation perform two different roles. Crossover is used to combine the string structure of two parents. To produce two new offspring, a high probability crossover ( $\mathrm{P_c}$ ) is applied. Mutation provides a way to apply a small random tweak in the individuals to diversify the population for the next generation. With a low probability ($\mathrm{P_m}$), this operator is used to add new genetic information in order to perform a global search over the solution space [9, 10].

A flowchart for distribution system reconfiguration using genetic algorithm is shown in Fig. 6.

## 4. Numerical case study

The proposed method is tested by a radial network distribution 20KV with 33 nodes [8]. 5 sectionalizing switches are open to reconfigure the system, as shown in Fig 3. The minimum and maximum voltage is respectively between 0.9 and 1.1 pu. The active and reactive power nodes data are given in Table 1. Table 2 present resistance and reactance data necessary for our algorithm.

For the simulation, 10 individuals are taken for initializing the first population. The probability of crossover is $\mathrm{P_c} = 0.8$, the probability of mutation is $\mathrm{P_c} = 0.2$, and the genetic algorithm will stop after 100 iterations.

To control and visualize the performance and the evolution of our network distribution system, a graphical user interface is developed sous Matlab which present all characteristics.

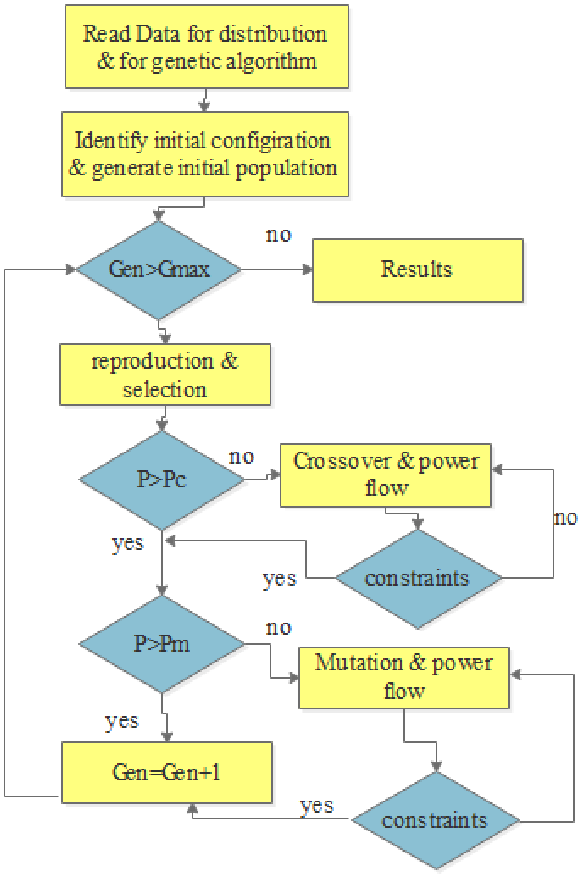


Figure.6 Flowchart for reconfiguration distribution system

### 4.1 Initial and optimal configuration

From the graphical interface, an initial distribution system model is generated. For this configuration, the value of power losses is computed to be 223.414 KW, and the bus voltage is found violated Fig. 9.

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Table 1. Active ad reactive power for 33 consumers.

| **N° of Node** | P (KW) | Q (KVar) | **N° of Node** | P (KW) | Q (KVar) |
|---|---|---|---|---|---|
| **1** | 0 | 0 | **18** | 90 | 50 |
| **2** | 400 | 20 | **19** | 80 | 30 |
| **3** | 100 | 50 | **20** | 90 | 40 |
| **4** | 90 | 30 | **21** | 80 | 20 |
| **5** | 60 | 10 | **22** | 100 | 40 |
| **6** | 70 | 20 | **23** | 90 | 50 |
| **7** | 320 | 200 | **24** | 450 | 350 |
| **8** | 200 | 90 | **25** | 420 | 200 |
| **9** | 110 | 20 | **26** | 60 | 30 |
| **10** | 60 | 30 | **27** | 70 | 25 |
| **11** | 120 | 60 | **28** | 50 | 10 |
| **12** | 80 | 35 | **29** | 120 | 90 |
| **13** | 60 | 35 | **30** | 300 | 150 |
| **14** | 120 | 80 | **31** | 150 | 70 |
| **15** | 70 | 20 | **32** | 210 | 100 |
| **16** | 80 | 50 | **33** | 60 | 40 |
| **17** | 70 | 20 | | | |

Table 2. Electrical branch data

| N° of branch | Node i | Node j | R(Ω) | X(Ω) |
|---|---|---|---|---|
| 1 | 1 | 2 | 0.0831 | 0.0931 |
| 2 | 2 | 3 | 0.6212 | 0.9122 |
| 3 | 3 | 4 | 0.4755 | 0.7511 |
| 4 | 4 | 5 | 0.2956 | 0.5233 |
| 5 | 5 | 6 | 0.7128 | 0.8907 |
| 6 | 6 | 7 | 0.1927 | 0.5287 |
| 7 | 7 | 8 | 0.2144 | 0.5500 |
| 8 | 8 | 9 | 0.6433 | 1.0311 |
| 9 | 9 | 10 | 0.8400 | 1.0440 |
| 10 | 10 | 11 | 0.0200 | 0.0650 |
| 11 | 11 | 12 | 0.3155 | 0.5158 |
| 12 | 12 | 13 | 1.4680 | 1.8120 |
| 13 | 13 | 14 | 0.5416 | 0.7129 |
| 14 | 14 | 15 | 0.2010 | 0.5260 |
| 15 | 15 | 16 | 0.1463 | 0.4450 |
| 16 | 16 | 17 | 1.2890 | 1.7210 |
| 17 | 17 | 18 | 0.1320 | 0.5740 |
| 18 | 18 | 19 | 0.1040 | 0.1565 |
| 19 | 19 | 20 | 1.5042 | 1.8854 |
| 20 | 20 | 21 | 0.4095 | 0.4784 |
| 21 | 21 | 22 | 0.7089 | 0.9373 |
| 22 | 22 | 23 | 0.0212 | 0.3583 |
| 23 | 23 | 24 | 0.3980 | 0.7091 |
| 24 | 24 | 25 | 0.2260 | 0.7011 |
| 25 | 25 | 26 | 0.2030 | 0.7700 |
| 26 | 26 | 27 | 0.2842 | 0.3999 |
| 27 | 27 | 28 | 1.0590 | 1.9337 |
| 28 | 28 | 29 | 0.5042 | 0.7106 |
| 29 | 29 | 30 | 0.5075 | 0.8585 |
| 30 | 30 | 31 | 0.9044 | 0.9630 |
| 31 | 31 | 32 | 0.3105 | 0.3619 |
| 32 | 32 | 33 | 0.3410 | 0.5302 |
| 33 | 33 | 34 | 1.8 | 1.8 |
| 34 | 34 | 35 | 1.5 | 1.5 |
| 35 | 35 | 36 | 1.3 | 1.3 |
| 36 | 36 | 37 | 1 | 1 |
| 37 | 37 | 38 | 0.5 | 0.5 |

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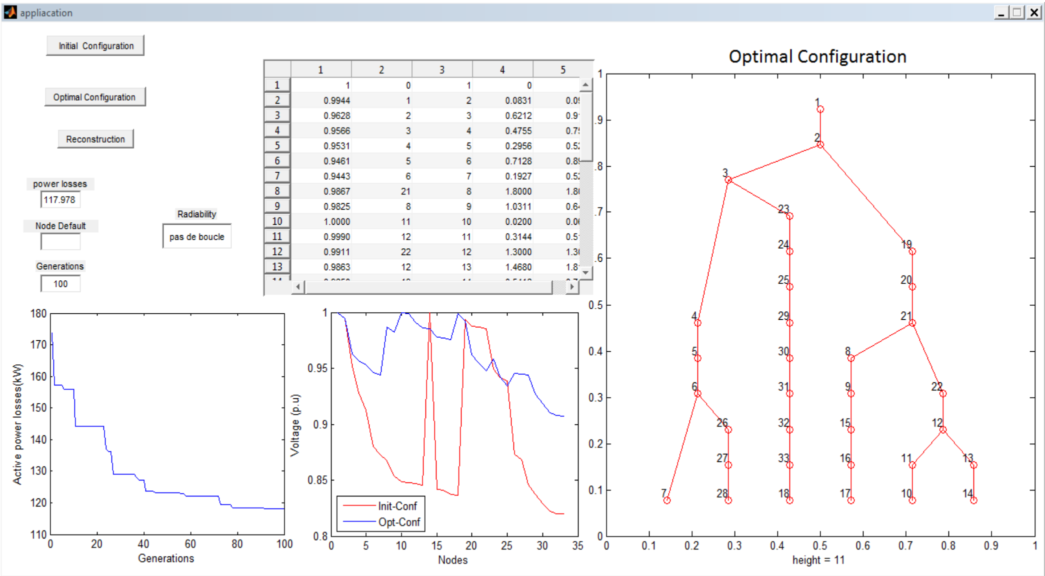


Figure.7 Graphical user interface

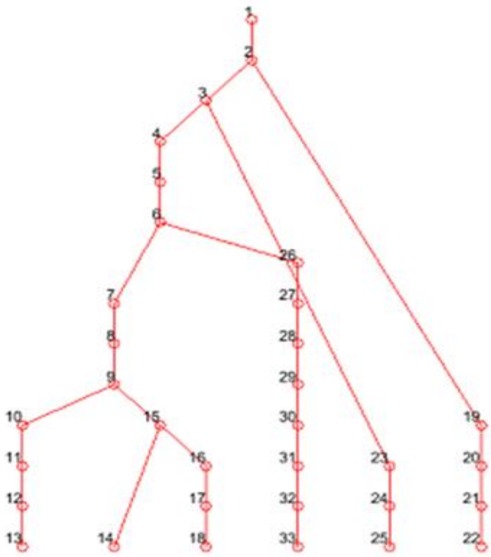

Figure.8 Initial configuration

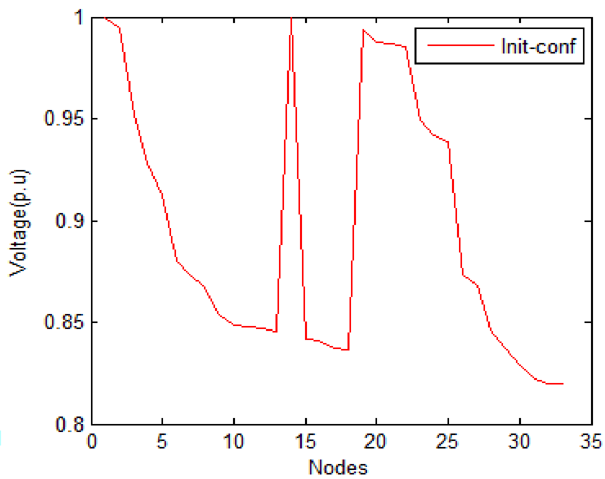


Figure.9 Bus voltage profile of initial configuration

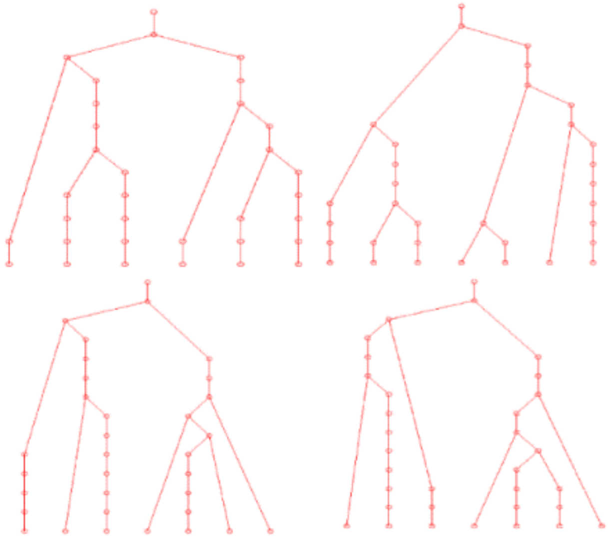

Figure.10 Some generated reconfigurations

From the simulation of the genetic algorithm, many distribution network configurations are created Fig. 10.

The fittest one is shown in Fig. 10. This solution helps to reduce the system loss from 223.414 Kw to 117.978 Kw, or 47.2%. Fig. 12 shows that the optimal on/off status of the switches keep also the bus voltage profile between [0.9, 1.1].

Fig. 13 shows that the power losses decrease with the successive created generations, which depend to the iterations number.

The numerical results for the initial and optimal configuration are summarized in Tab. 3. It can be noticed that the results are even better compared with those in ref [10], which means that the global optima were found based in GA method. The computational time for the simulation is very low between 11 and 15 seconds.

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Table 3. Calculation results

| Radial network | Initial configuration | Method in ref. [10] | GA Optimal configuration |
|---|---|---|---|
| Open switches | B13, B33, B35, B36 and B37 | B7, B9, B14, B32 and B33 | B7, B9, B14, B28 and B36 |
| Power loss (Kw) | 223.414 | 139.532 | 117.978 |
| Loss reduction (%) | - | 37.54% | 47.2% |
| Minimum voltage (p.u) | 0.82 | 0.9131 | 0.925 |

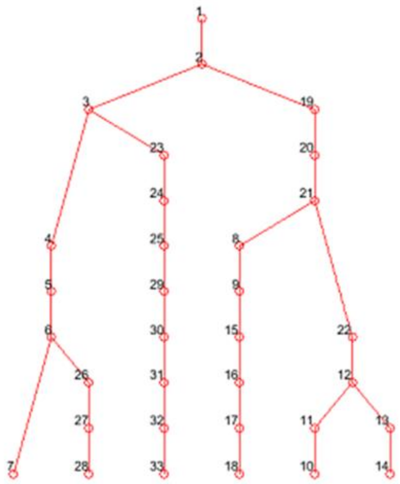


Figure.11 Optimal configuration

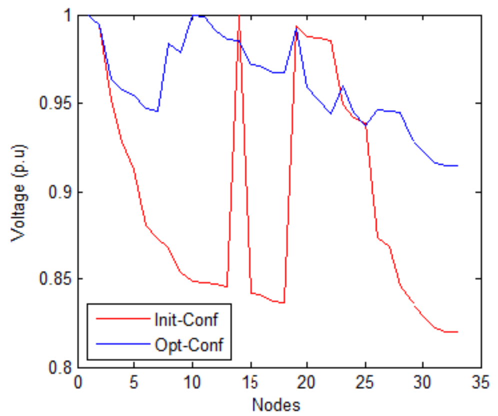


Figure.12 Bus voltage profile of initial and optimal configuration

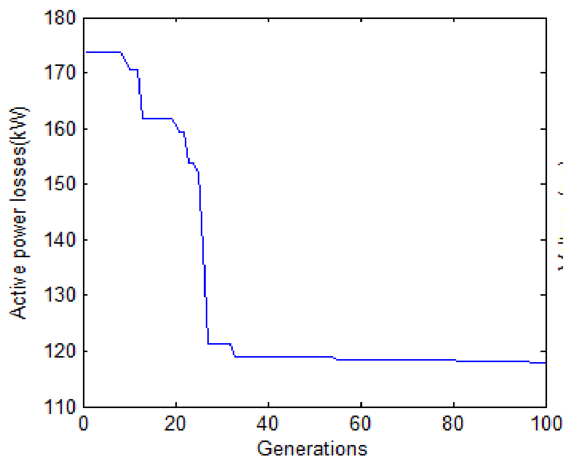


Figure.13 Power losses after reconfiguration

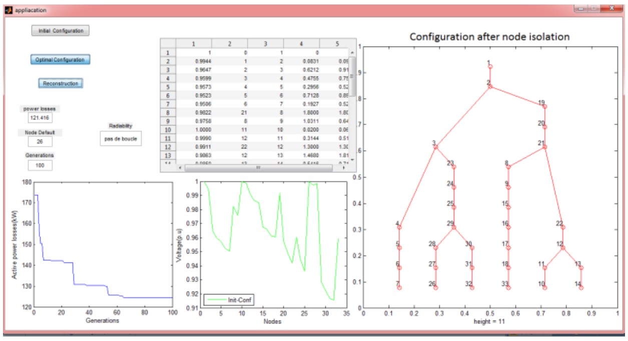


Figure.14 Graphical user interface after default mode network

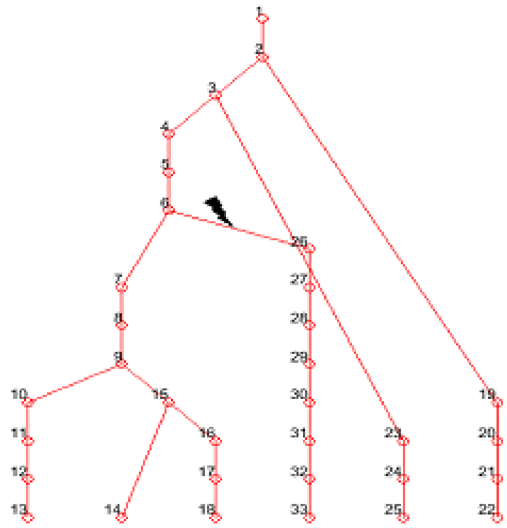


Figure.15 System distribution with failure

## 4.2 Example with default mode network

Default mode network is suggested with a critical node (branch 6-26) using the created user interface in Fig. 14. Fig. 15 shows how the network system will be reconfigured after this failure.

Therefore, all loads after the node 26 are de-energized. In order to restore power supply as soon as possible for all loads with the respect of initially constraints, a reconstruction technique is applied. This process is a way to disable the branch 6-26, which means the opening of the branch B25, and to find an optimal reconfiguration with minimum power losses Fig. 16. With this failure, the reconstruction technique reduces the power losses to 121.416Kw in Fig. 17. The bus voltage is also ameliorated to be between the bounds values Fig. 18.

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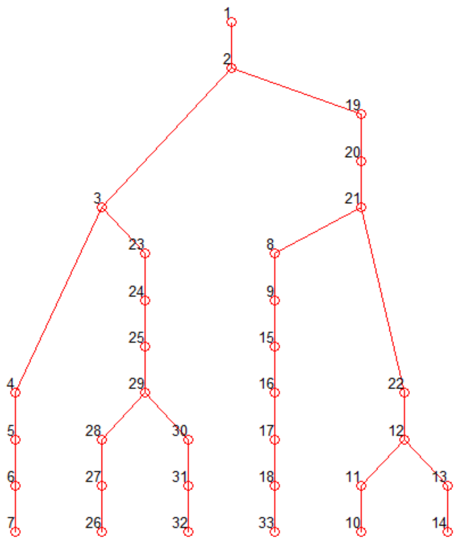

Figure.16 System distribution after reconstruction

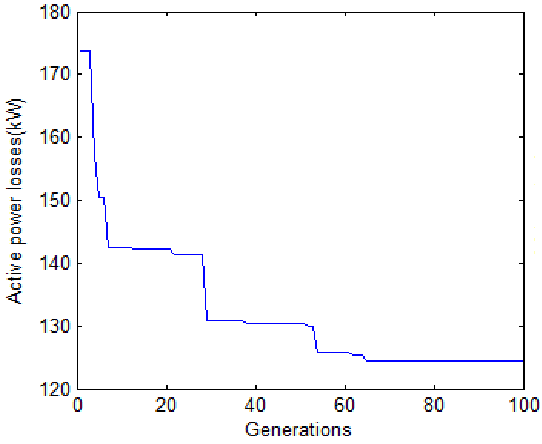


Figure.17 Power losses after reconstruction

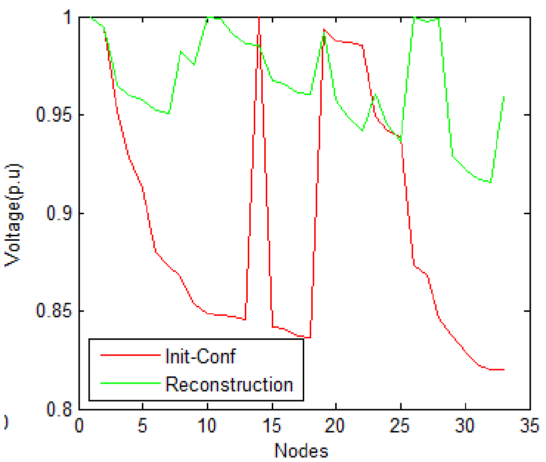


Figure.18 Bus voltage profile of failure and reconstruction configuration

Figs. 13 and 17 show that the value of the power losses of the optimal configuration and the reconstruction process is very close even with the presence of the default mode network.

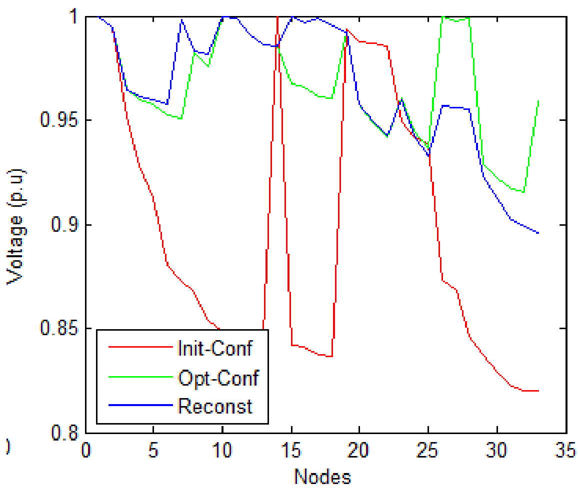


Figure.19 Bus voltage profile comparison

As shown in Fig. 19, both cases (reconstruction and the optimal configuration) allow to improve the bus voltage profile with good quality to consumers.

## 5. Conclusion

In this paper, genetic approach is applied to resolve an optimization power losses problem. To guide the search, objective function has been developed. Two case studies of a 33-bus distribution system is applied, in which some improvements of genetic algorithm are insured throughout selection, crossover and mutation pattern. From numerical example and comparison with other methods, it can be noticed that the global optima have been found with more than 45 per cent power loss reduction, and the bus voltage profile is kept into acceptable limits. Results show the validity and effectiveness of the proposed methodology.

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