OPTIMAL SHUNT CAPACITORS ALLOCATION IN DISTRIBUTION NETWORKS USING GENETIC ALGORITHM- PRACTICAL CASE STUDY

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Abstract: The optimal shunt capacitor allocation problem is the determination of the location and sizes of the capacitor to be placed in distribution networks in an optimal manner to reduce the energy losses and peak power losses of the networks. This paper shows the capability of Genetic Algorithm (GA) technique in solving such problem. It includes a study done in a real distribution networks in Muscat, Sultanate of Oman, and shows the effectiveness of GA technique in such application. Finally, a brief financial comparison of the optimal capacitor placement is presented to compare between the obtained results using GA technique and the ordinary standard used in Oman.

Keywords
Genetic Algorithm, Electrical Distribution Network, Optimal Capacitors Placement

1. INTRODUCTION

Capacitors have been commonly used to provide reactive power compensation in distribution systems. They are provided to minimize power and energy losses, maintain best voltage regulations for load buses and improve system security. The amount of compensation provided is very much linked to the placement of capacitors in the distribution system which is essentially determination of the location, size, number and type of capacitors to be placed in the system [1]. A large variety of research work has been done on capacitor placement problem in the past [2], [3]. All the approaches differ from each other by way of their problem formulation and the problem solution method employed. Some of the early works have not considered capacitor cost in the formulation. In some approaches the objective function considered is to control the voltage. In some techniques, only fixed capacitors are considered and load changes which are very important in capacitor placement have not been considered. Other techniques have considered load changes only in three different levels. A few proposals were schemes for determining the optimal design and control of switched capacitors with non-simultaneous switching [4]. It is also very important to consider the real cost of the capacitors found in the market. Different problem solution methods have been employed to solve the capacitor placement problem. Such as; gradient search optimization, local variation method, optimization of equal area criteria method for fixed capacitors, dynamic programs [4], [5], [6]. Although these techniques have solved the problem, most of early works used analytical methods with some kind of heuristics. In doing so, the problem formulation was oversimplified with certain assumption, which lacked generality. There is also the problem of local minimal in some of these methods. Furthermore, since the capacitor banks are non continuous variables, taking them as continuous compensation, by some authors, can cause very high inaccuracy with the obtained results. Genetic Algorithms (GA) have been applied in various power system problems [7], [8]. GA is a very well known and capable method for optimization problems. It is capable of determining near global solution with lesser computational burden. In this respect, it is very suitable to solve the capacitor placement problem.

In the present work GA is applied to determine the optimal capacitors location for Zone3 in Muscat distribution network. The network model and analysis of the Zone3 have been performed using Electrical Transient Analyzer Program (ETAP) [9]. The design variables are the capacitor sizes and the capacitor locations for fixed and switched capacitors used in the network. Load model of different levels, load flow study, and the cost of capacitors for that corresponding configuration of capacitor size are also considered in the system simulation.

2. GENETIC ALGORITHM

The theoretical foundations for genetic algorithms were first described by John Holland [10] and then presented tutorially by David Goldberg [11]. Genetic algorithms are search algorithms based on the process of biological evolution. In genetic algorithms the mechanics of natural selection and genetics are emulated artificially. The search for a global optimum to an optimization problem is conducted by moving from an old population of individuals to a new population using genetics-like operators. Each individual represents a candidate solution to the optimization problem. An individual is modeled as a fixed length string of symbols, usually taken from the binary alphabet. An evaluation function, called fitness function, assigns a fitness value to each individual within the population. This fitness value is a measure for the quality of an individual. The basic optimization procedure involves nothing more than processing highly fit individuals in order to produce better individuals as the search progresses. Genetic algorithms find widespread applications as a consequence of two fundamental issues:

- The computational code to implement them is quite simple and yet provides a powerful search mechanism.
- They are very robust schemes in that they can be applied to a broad range of optimization problems.

The robust behavior, which is the distinguishing feature of genetic algorithms with respect to other optimization methods, implies that genetic algorithms must differ in some fundamental ways. These are mainly the following four:

1. Genetic algorithms work with a coding of the problem parameters and do not work with the problem parameters themselves.
2. Genetic algorithms search from a population of candidate solutions and do not process only a single solution.
3. Genetic algorithms exploit only the fitness values of these candidate solutions to guide their search towards the global optimum. They do not depend on any additional information like the existence of derivatives.
4. Genetic algorithms use probabilistic transition rules and do not use deterministic transition rules.

Genetic Algorithm Cycle

A flow chart for genetic algorithms is shown in Figure 1. At the beginning, the variable *gen*, which keeps track on the actual number of generations, is set to zero. An initial population of chromosomes is constructed by choosing the binary values of the strings at random. Then, the fitness value is evaluated for each chromosome. After that, the main iterative loop is entered. The variable *gen* is incremented by one. The three basic genetic operators are applied in the following two steps. First, the selection or reproduction procedure is executed. The crossover and mutation operators are combined in the next step. This action enables efficient computational coding. Then, the quality of the chromosomes is assessed by means of the fitness function. Subsequently, the generation is advanced. The iterative loop is executed until the termination condition is satisfied. The termination condition is met when either the process has converged or the specified maximum number of generations has been reached. The degree of change in the quality of the individuals within the population over successive generations can serve as a measure for convergence. Before the algorithm finally terminates, the best individual of the last generation is returned as the solution of the optimization.

Reproduction

Reproduction is a process in which individuals are selected and copied according to their fitness values. The relative fitness of an individual, that is, the fraction of an individual's fitness of the fitness of all individuals, determines its chance to be reproduced. Let f_k be the fitness of the kth individual within the population. Furthermore, the population size is described by the variable n_p. Then the kth individual is selected with the probability described by Eq. (1). Selection is repeated n_p times. Therefore, during the reproduction procedure, the kth individual is selected $P_k \times np$ times on average. An individual with average fitness is illustrated by Eq. (2).

$$P_k = \frac{f_k}{\sum_{m=1}^{np} f_m} \qquad (1)$$

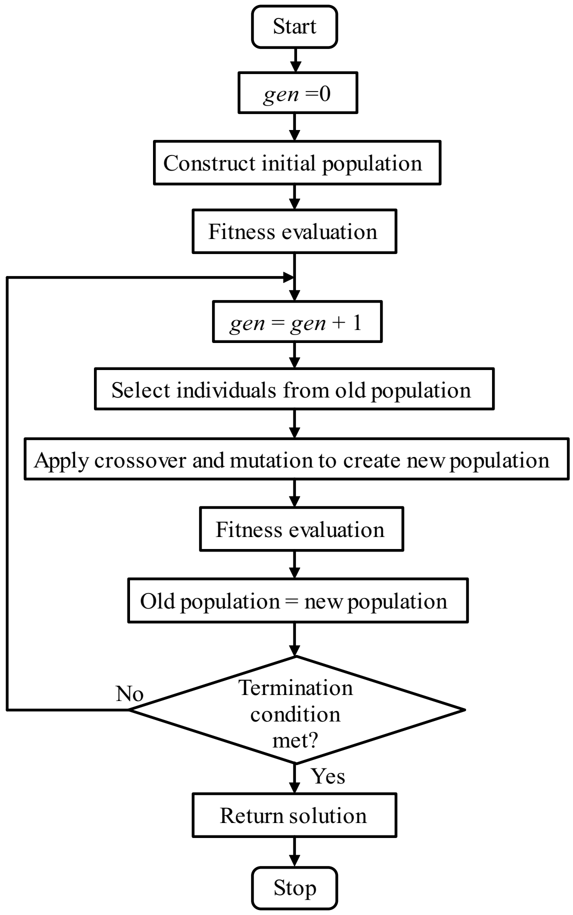

Figure 1: Genetic Algorithm Flow Chart.

$$f_{avg} = \frac{\sum_{m=1}^{np} f_m}{np} \qquad (2)$$

Then this individual is expected to be reproduced once. Each selected chromosome is then entered into a mating pool, an intermediate population, where it awaits further genetic operator action.

Crossover

Crossover follows the reproduction procedure. First, a pair of chromosomes is taken out of the mating pool. Then, a biased coin is tossed that comes up true with a specified crossover probability Pc. If the experiment yields false, then the crossover procedure leaves the pair of chromosomes unchanged. Otherwise, the two chromosomes undergo crossing as follows. Suppose, the binary strings, which represent the two chromosomes, are of length *lc* and that the positions of the binary digits are consecutively numbered within [1... *lc*]. An integer number *q* is selected at random between 1 and *lc*-1. Two new strings are created by swapping all binary digits between positions $q + 1$ and lc inclusively. The process is repeated for the remaining pairs of chromosomes until the mating pool is empty. Typical values for Pc lie in the range of 0.6 to 0.95.

Mutation

The binary values of the strings are changed from true to false or vice versa with a probability Pm by the mutation operator. The variable Pm usually assumes values between 10^{-2} and 10^{-1}.

Fitness Evaluation

The fitness evaluation is given by the objective functions. This process will compare between different reproduced populations achieving the best fit to the objective functions.

Generation Process

Starting from a given population of individuals, the reproduction operator is the first to be applied. It follows the Darwinian theory of the survival of the fittest and can be considered as an artificial version of the natural selection process. The chance of an individual to be selected only depends on its fitness value. The selection process promotes the propagation of strong individuals, but it does not yield better ones. To find better solutions new stronger individuals must be created. This is the purpose of the crossover procedure. By mating reproduced individuals and, in this way combining their features, new individuals of better quality can be constructed. The action of reproduction and crossover together speculates on new better solutions created from the high quality solutions of previous generations.

Mutation enhances diversity among the population. If an individual, which represents a suboptimal solution to the optimization problem, takes over a major part of the population then the danger of premature convergence appears. A sufficiently high mutation rate can help to prevent this problem by changing the values of the binary digits at random and thus forcing diversity among the population. However, mutation rates must be kept low as in natural populations. Otherwise, good solutions would be destroyed with too high a probability. The design of the fitness function is dependent on the particular optimization problem. A fitness function design for optimal location of static shunt VAR for distribution network is described later.

Control Parameters

The values of the control parameters influence the performance of genetic algorithms. For example, the number of generations the optimization needs to converge is affected by the way the control parameters are set. The following quantities are referred to as control parameters:

- The population size np
- The chromosome length lc
- The crossover probability Pc
- The mutation probability Pm

Test runs of genetic algorithms have indicated that a high crossover rate and a small mutation rate are normally required to obtain good results. Typical values for Pc lie in the interval [0.6,0.95]. Typical values for Pm in the interval [0.01,0.1] .Values for Pc ranging close to the upper limit force convergence, while high mutation rates promote diversity among the population.

The population size must be big enough to supply sufficient genetic structures so that a wide variety of genetic material to work from is present. The population size should be set in dependency on the chromosome length. The bigger the chromosome length, the larger the solution space covered and, therefore, the bigger the population size should be.

The given proposals for the settings of the parameters can only serve as guidelines. Appropriate settings may vary significantly for different kinds of problems the genetic algorithm is used for. It is therefore advisable to run several tests with different settings and compare the performance of the genetic algorithm

2.1. GA Implementation

The representation and implementation of the GA for the optimal capacitor banks location and size is proposed in this section. Each capacitor is represented by a string C of number of binary bits. The first bit represents the state of the capacitor (1 for on, 0 for off). The remaining bits represent the capacity level of the capacitor. As an example, the string C = [1000] represents a capacitor working at minimum MVAR; C = [00000] represents a capacitor which is not operating (or not existing); the string C= [11111] represents a capacitor working at full capacity. In order to represent the type of each capacitor, a new string T is defined consisting of the concatenation of 2 strings C (thus T contains 10 bits). Therefore, let T = C1C2, where C1 represents type A of capacitor. In this way, the type of each capacitor is given by the position on the string T. For example, at a given node the string T = [1111100000] represents the situation where only one capacitor should be placed on that node, and this capacitor should be a type A working at full capacity. It is assumed, based on this representation, that a maximum of one capacitor of each type can be placed on any given node. As each string T represents the capacitor (and size) to be placed at a given node, the representation of the general location of the capacitor over the network is straightforward. A string S is defined consisting on the concatenations of 20 T strings. This sequence S contains 20 (nodes) × 10 (bits per node) = 200 bits. As any string S describes a valid placement and size configuration of capacitors over the network, therefore the string S is the chromosome used within the GA. The implementation of the GA is done with capacitors consisting of number of individuals (each one a different string S). The fitness of each individual is given by the objective function, and it also considers a penalization if the voltage or PF goes outside the allowed interval, plus another penalization if the number of capacitors exceeds 10.

The Optimal Capacitor Placement toolbox in ETAP requires an objective function and the encoding techniques between voltage regulation and PF correction. The methodology of the capacitor design in distribution system is described as follow:

1) Input the distribution system branch impedance values and the bus real and reactive power data.

2) Run the power flow calculation without any capacitor in different load levels.
3) Determine the system losses and energy losses without capacitor compensation.
4) Form a random initial chromosomes population (number of chromosomes population is usually set to 2-2.5 times the number of nodes in the network).
5) For each chromosomes population set in the previous stage, place one capacitor in the distribution system and repeat the load flow calculation. Then determine the system losses and energy losses for each chromosome.
6) For each chromosome, evaluate the objective function and the fitness value. The objective function is determined according to the difference of annual savings made from placement of the capacitors in the distribution system with the cost of capacitor placement in one year or during the planning years.
7) If chromosomes population have converged, the capacitor results for each bus is printed unless go to the next stage.
8) Select the new population based on reproduction mechanism.
9) Process the crossover and mutation on the new population.
10) Define a new population and go to step 5.

The objective of optimal capacitor placement is to minimize the cost of the system. The cost includes four parts:

- Fixed capacitor installation cost
- Capacitor purchase cost
- Capacitor bank operating cost (maintenance and depreciation)
- Cost of real power losses

The cost can be represented mathematically as:

$$\sum_{i=1}^{Nbus}(x_i C_{0i} + Q_{ci} C_{1i} + B_i C_{2i} T) + C_2 \sum_{l=1}^{Nload} T_1 P_L^l \quad (3)$$

Where:

$Nbus$ Number of Bus candidate

x_i 0/1, 0 means no capacitor installed in bus 1

C_{0i} Installation cost

C_{1i} Per kVar cost of capacitor bank

Q_{ci} Capacitor bank size in kVar

B_i Number of capacitor bank

C_{2i} Operating cost of per bank per year

T Planning period (Year)

C_2 Cost of each kWh loss

$Nload$ Load levels (Maximum, Minimum, and Average)

T_1 Time duration of load level l

P_L^l Total system loss at load level l

The main constraints for capacitor placement are used to meet the load flow constraints. In addition, all voltage magnitudes of load (PQ) buses should be within the lower and upper bars. Power Factor (PF) should be greater than the minimum. It may be a maximum power factor bar.

The constraints can be represented mathematically as:

- Power Flow solution conversion.
- $V_{\min} \le V \le V_{\max}$ and $PF_{\min} \le PF \le PF_{\max}$ for all PQ buses.

2.2. Discrete Load Variation

Plotting the discrete load variation curve of the power distribution network under evaluation is an important task to solve the optimal capacitor problem. In this study the discrete load variation curve was assumed based on the average data collected from the power system operators. The result of this assumption is presented in Table 1 and Figure 2.

Table 1 Load Duration Average Data

Months	No of Months	% of Months	Peak Load Time %	Average Load Time %	Off Peak Load %
January to March	3	25%	0%	60%	40%
April to May	2	16.67%	5%	75%	20%
June to August	3	25%	20%	75%	5%
September to December	4	33.33%	5%	65%	30%
Average			**8%**	**67%**	**25%**

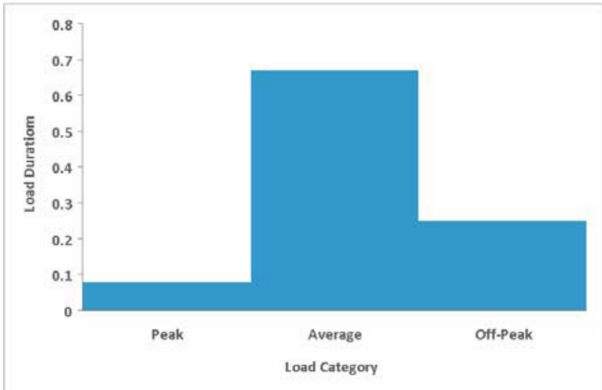

Figure 2: Discrete Load Duration

3. CASE STUDY & RESULTS

Muscat electricity network is divided into 3 main zones, as shown in Figure 3. The zones are representative of geographical areas in Muscat region. Zone 3, shown in Figure 4, is selected to implement the proposed methodology. The existing total capacitors in use are **130MVar** which are located in the 11kV side at different primary substations. First, the network is loaded in the ETAP software. Then, the GA is used to find out the optimal location and size of the capacitors to reduce the network losses. The solution showed that the actual needed capacitors in the system are 63MVar located in different locations in the network. Some of the locations are met with the existing ones and some are not. Table 2 shows the difference between the existing capacitor and the one proposed by GA at each grid point.

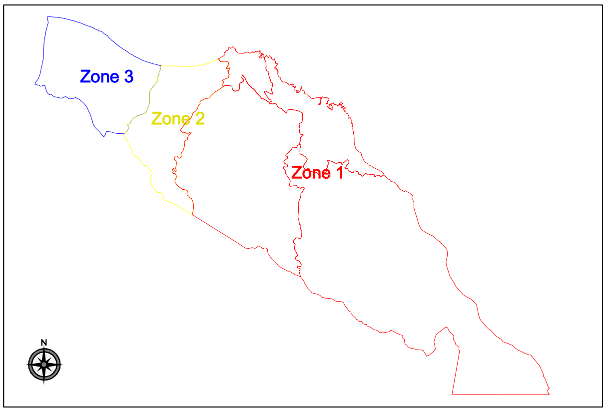

Figure 3: Geographical Overview of Zones in Muscat Region

Table 2 Existing Capacitor and GA Results

Grid Point	Existing	GA Proposal	% Difference
Mawaleh	60MVAR	24MVAR	40%
Rusail	10MVAR	12MVAR	120%
Seeb	30MVAR	8MVAR	27%
Barka	30MVAR	19MVAR	63%

Table 3 presents more detail results for Mawaleh grid showing the exciting capacitor banks and the optimal placement by GA with a difference of 40%. Figure 5 demonstrates the GA results of the optimal capacitors locations in Mawaleh distribution network.

Financially, the cost of the capacitor may be recovered within 1 to 2 years only. The calculated actual revenue collected in 5 planning years to be around 660,000 R.O (1716,000 $US) in this part of Muscat distribution network only. This amount is calculated after subtracting the capital cost of initial capacitor purchase and installation cost.

Table 3 Mawaleh Capacitor Comparison

Mawaleh Grid				
Primary Name	Existing		Optimal Capacitor Placement (GA)	
	Capacitor	Cost R.O.	Capacitor	Cost R.O.
Hail	10 MVAR	20,000	0 MVAR	0
Rusail B	0 MVAR	0	1 MVAR	2,000
Khoudh	10 MVAR	20,000	9 MVAR	18,000
Royal Flight	0 MVAR	0	1 MVAR	2,000
Mawaleh	10 MVAR	20,000	0 MVAR	0
Mawaleh A	10 MVAR	20,000	0 MVAR	0
Mawaleh B	10MVAR	20,000	3 MVAR	6,000
City Center	0 MVAR	0	0 MVAR	0
Sultan School	10 MVAR	20,000	10 MVAR	20,000
TOTAL	**60 MVAR**	**120,000**	**24 MVAR**	**48,000**
% Difference	**40%**			

4. CONCLUSION

The presented results in this paper have shown that the exiting shunt capacitor banks are over used in the studied distribution network. In addition to that, many of shunt capacitors are not correctly placed or not used. As an example, 40% only of the capacitors used in primaries connected to Mawaleh network are needed. The 60% of installed capacitors are not used or malfunctioned. In the other hand, few primaries need some shunt capacitor. The optimal placement and Mvar rating of shunt capacitor banks have been determined for the studied distribution networks using the proposed GA. The determined optimal location has reduced the system energy loss and consequently minimizes the cost of the capacitors in the system.

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REFERENCES

[1] 11. Miller, T.J.E, Reactive Power Control in electric System, (New York, John wiley & Sons Inc, 1982).

[2] 12. Barn, M.E. and WU, F.F, Optimal Capacitor Placement on Radial Distribution System, IEEE Transaction on Power Delivery, 4(1),1989, 725-734

[3] 13. Chen, c.S. SHu, C.T and yan Y.H, Optimal Distribution Feeder Capacitor Placement Considering Mutual Coupling Effect of Conductors, IEEE Transactions on Power Delivery, 10(2), 1995, 987-994

[4] 14. R. Hooshmand and M Joorabian, Optimal Choice of Fixed and Switched Capacitors for Distribution Systems by Genetic Algorithm, Department of Electrical Engineering Shahid Chamran University, Ahwaz, Iran.

[5] 15. L. Furong, J. Pilgrim, C. Dabeedin, A. Cheebo, and R. Aggarwal, Genetic Algorithms for Optimal Reactive Power Compensation on the National Grid System, IEEE Transactions on Power Systems, 20(1), 2005, 493-500

[6] 16. Robert S.Agniar, Paolo Cuervo, Capacitor Placement in Radial Distribution Network Through a Linear Deterministic Optimization Model. Electrci Engineering Department, University of Brasilia, Brazil.

[7] 17. A. Charette, J.Xu, A.Ba-Razzouk, P.Pillay, V.Rajagopalan, The Use of the Genetic Algorithm for in-situ Efficiency Measurement of an Induction Motor, IEEE Power Engineering Society Winter Meeting, 1(1), 2000, 392 - 397

[8] 18. Z.Y Dong, D.J. Hilland, V.Y. Makarov, Power System VAR Planning with Genetic Algorithm, Technical Report: EE-98015, Department Of Electrical Engineering, University of Sydney, Australia,1998

[9] Electrical Transient Analyzer Program (ETAP), www.etap.com

[10] J. H. Holland, Adoption in Natural and Artificial Systems, (Massachusetts, Cambridge, MIT Press, 1975)

[11] D.E. Goldberg, Genetic Algorithm in Search Optimization and Machine Learning, (Massachusetts, Addison-Wesley, 1989)

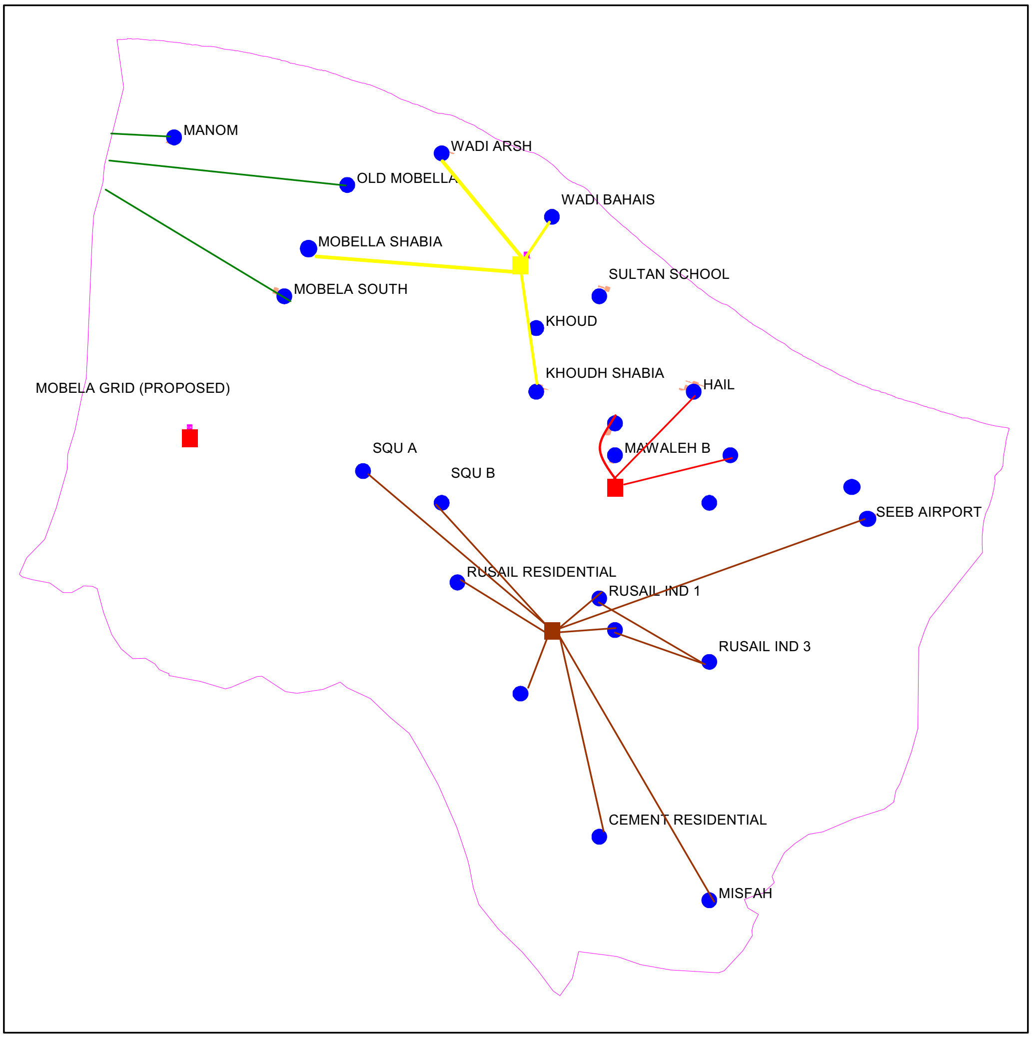

Figure 4: Zone3 33kV Network

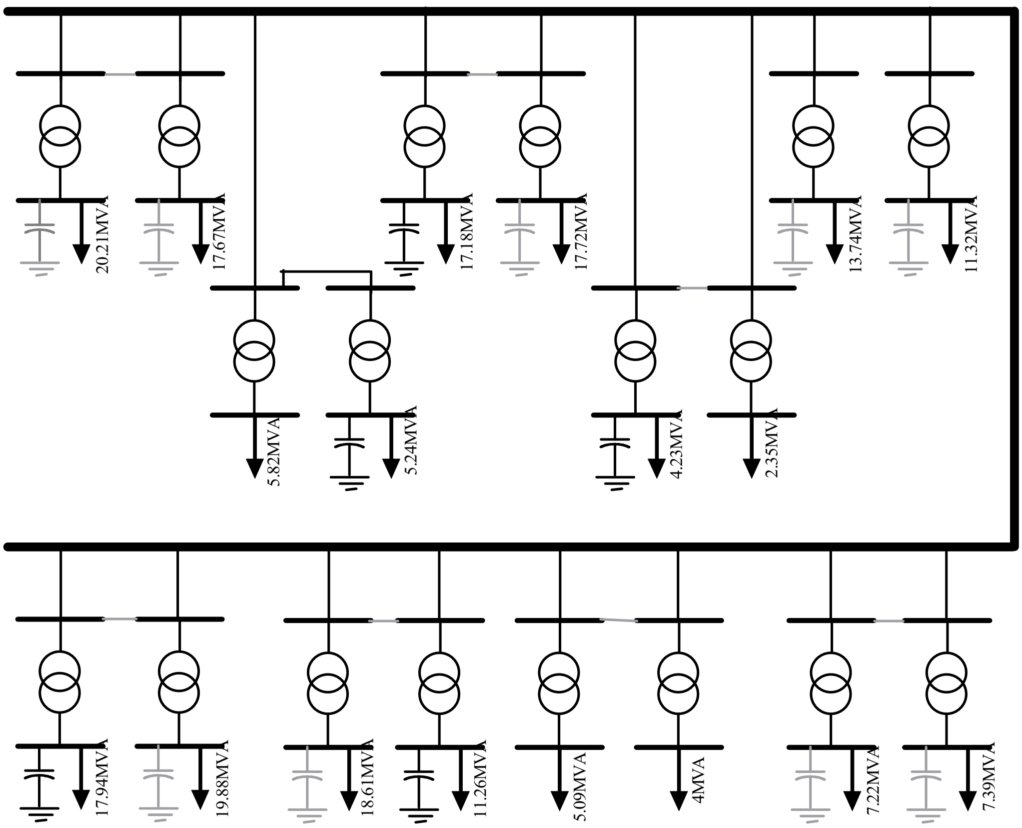

Figure 5: GA results of Capacitors Location for Mawaleh Distribution Network