V/VAR Control for the Iraqi National SHV Grid by Optimum Placement of SVC using Genetic Algorithm

H. A. Hassonny
Mechanical, Electrical and Industrial Engineering
Brandenburg Technical University/Cottbus/Germany

K. Pfeiffer
Distributed energy System and Storage Technology
Brandenburg Technical University/Cottbus/Germany

Firas M. Tuaimah
Electrical Engineering Department/ College of Engineering
Baghdad University/Iraq

ABSTRACT
The reactive power control has as its main objectives for reducing losses, increasing transmission capacity, and maintaining voltage within acceptable limits.

This paper suggests using SVC (Static VAr Compensator) for Iraqi National Super High Voltage (SHV) Grid System (400 kV). The aim is to improve voltage profile across the load nodes and enhance system stability as well as to reduce active power losses, which depends greatly on how these devices are placed in the system. The general problem to optimally determine the locations and sizes of SVC's to be installed by following an optimization approach. GA, as one of the heuristic methods, will be used to solve the optimization problem.

Keywords
Static VAr Compensator, Genetic Algorithm, FACT.

1. INTRODUCTION
The most common requirements for coordinated V/VAr control are the load compensation, controlling transformer and line loading, minimizing active power losses, and controlling the power factor.

Load compensation is the management of reactive power sources to improve power quality, i.e. voltage profile and power factor. The reactive power flow is controlled by installing shunt compensating devices (capacitors/reactors) at the load end resulting in a proper balance between generated and consumed reactive power [1].

In addition to shunt capacitors and reactors, Static VAr Compensators (SVC's) are also commonly used for compensation for several reasons. Installing an SVC at one or more suitable points in the network can increase the transfer capability by increasing the maximum flow through transmission lines. Also, reduce power losses while maintaining a smooth voltage profile under different network conditions [2].

The purpose behind installing SVC's is crucial in deciding where to install them and the sufficient number and size of each SVC. The locations of SVC's have a significant impact on power flow control performance.

In this paper, SVC was proposed to reduce the active power loss and solve voltage fall problem for the Iraqi National SHV Grid system during heavy reactive power conditions.

The locations and sizes in MVAr of these devices will be calculated by means of one of the optimization algorithm, namely, "Genetic Algorithm" (GA).

Nowadays, GA is one of the commonly used methods to solve several optimization problems. GA can be used only for the types of problems where solutions can be represented by chromosome. GA starts by a randomly generated population of solutions, which will be improved through a repetitive application of mutation, crossover, and selection operators. Individual solutions are selected through a fitness-based process, where the more adapted solution is typically more likely to be selected [3].

MATLAB programming language will be used to simulate the power system and apply GA to find the best buses in the grid for installing a proposed number of SVC's and the size of each SVC.

Optimization tools are used for adjusting the power flows in a power network to achieve optimal values of predefined objectives. Some objectives are related to minimizing costs, while some others consider the stability and the quality of power systems. It should be noticed that optimization tools suggest the global setting of control such as capacitors, reactors, transformer tap, and so on. This setting conflicts sometimes with the local regulation assignment of these devices. Therefore, it is required to disable one function in some cases giving the priority to the other [4].

Two objectives are considered in this work for the Iraqi power grid: The active power losses and voltage deviation minimization.

The unit transformers in the grid will be modelled considering the tap changers. The reason is to observe the reactive power values at generators terminals, and hence, to guarantee that the reactive power capabilities limits of the generators are not violated.

2. GENETIC ALGORITHM
Genetic Algorithm (GA) is a powerful stochastic search and optimization technique. It is the most commonly known type of evolutionary computation methods [5]. GA encodes the variables of the optimization function and runs a searching process that explores the searching space in parallel. The searching mechanism starts with an initial set of solutions generated randomly, called "*Population"*, which satisfy the equality and inequality constraints of the problem. Each individual solution in the population is called "C*hromosome*". The movement of the algorithm towards the global point is directed by fitness function evaluation of the chromosomes. GA uses the criteria of natural selection to evolve the chromosomes through successive iterations called "G*enerations*". New chromosomes (offspring) are formed by crossover and/or mutation operators. And by continuous evaluation of each chromosome during each generation, and using selection techniques, a new generation is formed. This way, the chromosomes with high fitness have high probabilities to be selected and survive over many generations while other chromosomes will be rejected. Thus, GA

converges to the best chromosome that may represent the optimum solution to the problem [6].

3. GENETIC OPERATORS

3.1 Individual (Chromosome)

An individual within a population represents a single solution to the optimization problem at hand. It is also called a chromosome and represented by a binary bit string, real number, or a string of symbols [7]. The representation of the variables in GA environment is called "Genotype" which is the encoding of the solution. While the representation of these variables in the search space of the function is called "Phenotype". The location of a gene within a chromosome is called "Locus" and it defines a particular characteristic represented by this gene. While the values of the genes are called "Alleles" [6]. The number of chromosomes in population defines the population size which was chosen equal to (60).

3.2 Encoding

Encoding means how individuals are represented in GA. It is the first step used in genetic computation and before applying genetic operators. Several methods are used to encode the individuals to obtain this representation [8]. Binary coding was used to represent the chromosomes in this paper. The decision variables are represented as strings of binary numbers and some constraints were included in the coding process.

The variables of the introduced problem embrace the locations of SVC's and the sizes of SVC's. For the locations of SVC's, the number of nominated buses is (13) noticing that SVC's will be installed only at *PQ* buses. Therefore, 4 bits binary string is sufficient to represent the location of each SVC and all obtained solutions that are greater than (13) will be discarded.

The number of bits for the size of SVC representation is calculated using the following formula:

$$R_Q = \frac{Q_{SVC_{min}} - Q_{SVC_{max}}}{2^n + 1} \qquad (1)$$

where R_Q is the precision of injected reactive power changes and *n* is number of bits required for SVC size representation.

The precision R_Q was chosen equal to 5 MVAr, then, 5 bits are required to represent the size of the SVC.

3.3 Crossover (Recombination)

The use of crossover is the main distinguishing feature of a GA [3]. By crossover operator, the information of two parents' genotypes is merged to produce one or two offspring genotypes. The new population, after this process may contain better individuals. The choice of what parts of each parent are combined is random, as well as the way of combining these parts. In other words, crossover is a stochastic operator, where a random appointing of crossover sites in the individual strings is implemented. The values following the selected cross site are swapped between the two strings.

The crossover process will/will not occur depending on the value of crossover probability (P_c). The crossover probability (P_c) was chosen equal to (1) in this work and the crossover was applied at multiple points within each chromosome.

3.4 Mutation

The process of replacing the gene value (allele) by another is called "Mutation". The new value usually is a random value. Mutation maintains diversity in the population and the aim is to explore the whole search space to prevent the algorithm to be trapped in a local minimum. The crucial point here is to specify the mutation probability (P_m) which defines how often the mutation process will occur. As the mutation probability (P_m) increases, a large part of chromosome will change. For instance, if P_m is 100%, the whole chromosome will be changed, if it is 0%, nothing is changed. It can be noted that if the mutation probability is large, the search will be faster, while the diversity of population will be less. This leads to more convergence toward some local optima [7] & [9]. The better performance has been obtained by P_m equal to (0.03).

3.5 Selection

It is the process of choosing the chromosomes from the population to contribute in crossover and mutation processes that lead to produce new offspring [6]. It is usually based on the fitness value, where parents are selected according to their fitness. In other words, the individual that has high fitness value will have more chance to be selected. The idea behind this is to select the best chromosomes from the parents in the hope that combining them will produce better offspring chromosomes. Therefore, selection is responsible for transferring the individuals that have higher fitness to the new population. Chromosomes are selected randomly from the initial population to be parents for reproduction. In this paper, Roulette Wheel Selection was used.

4. OPTIMIZATION OBJECTIVES

The performance of GA was studied on the SVC localization problem and the aim is to reduce the active power loss and voltage deviation. Hence, it is a multiobjective optimization problem.

4.1 Power Losses

Active power loss of the transmission lines is one of the common objectives of optimization problems in electrical power systems. The power loss (P_L) of a transmission line is calculated by the following equation:

$$P_L = G_{ij}\left[|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos(\delta_i - \delta_j)\right] \qquad (2)$$

Or the total active power loss of transmission lines [10]

$$P_L = \sum_{L=1}^{N_L} [|V_i|^2 + |V_j|^2 - 2|V_i||V_j|\cos(\delta_i - \delta_j)]\, Y_{ij}\cos\theta \quad (3)$$

where N_L is the number of lines in the system, Y_{ij}, θ are the magnitude and angle of line (L) admittance respectively, $|V_i|$, $|V_j|$ are voltage magnitudes at bus i and j respectively, and δ_i, δ_j are voltage angles at bus i and j.

4.2 Voltage deviation

Voltage deviation is an indication for the security of power systems and it is a measure for the quality of service [11]. The following formula is used to calculate voltage deviation of the buses from their specified values [12]:

$$V_D = \sum_{i=1}^{N_b} \frac{|V_{ref} - V_i|}{V_{ref}} \qquad (4)$$

The reference voltage for *PQ* bus is one and for *PV* bus the voltage magnitude is fixed, thus, the equation becomes

$$V_D = \sum_{i=1}^{N_b} |V_{ref} - V_i| \qquad (5)$$

5. Objective Function

Not like single objective problems, multiobjective problems have no unique solution. A set of acceptable optimal solutions exists and is called "*Pareto Front*". The vector of decision variables called "*Pareto Optimal*" and the operator selects the preferred solution from the Pareto set [13].

Several methods were introduced for solving multiobjective problems using single objective approximation such as weighted sum, ε-constraint, weighted metrics, Benson, lexicographic, etc. [14]. In this work, the weighted sum method is used and is explained below.

The weighted sum method changes a weight multiplier among the objectives in the objective function to obtain the Pareto front. Then, the multiobjective optimization problem will take the following general form:

$$F(x,u) = w_1 f_1(x,u) + w_2 f_2(x,u) + \cdots + w_m f_m(x,u)$$

$$0 \le w_i \le 1$$

$$\sum_{\mathrm{i}=1}^{m} \mathrm{w_i} = 1$$

The problem is solved several times for a different weight coefficients combination to find multiple solutions [14] & [15].

Fitness function is used to normalize the objective function of the optimization problem normally to a range of 0 to 1. Fitness function maintains uniformity over various problem domains. It is in this way, a quality measure of genotypes. The selection of an individual for crossover process will depend on the fitness value calculated by fitness function of this individual in the population.

Before formulating the objective function for this work, it is important to note the following:

- The two objectives (power loss and voltage deviation) have different ranges of magnitudes, where total voltage deviation (V_D) is much less than total power loss (P_L)
- The two objectives have – but not necessarily - an opposite effect on each other, since minimizing one of them leads to increasing in the other, and vice versa.

Consequently, the objective function must consider these two cases. The first case can be overcome by normalizing the two values. The second one makes necessary to define a feasible space for the weight factors, in a way that, if the given weight multipliers lead to make one objective exceeds the desired limit, then, these weight multipliers are defined as infeasible space.

According to the above considerations, objective function will take the following form:

$$O_{\mathrm{F}} = w_1 \frac{P_L - P_{L_{min}}}{P_{L_{max}} - P_{L_{min}}} + w_2 \frac{V_D - V_{D_{min}}}{V_{D_{max}} - V_{D_{min}}} \qquad (6)$$

6. PROBLEM CONSTRAINTS

Most of the optimization problems are constrained problems. The constraints are divided into equality and inequality constraints as was indicated by equation (4.2) and (4.3). The equality constraints are the active and reactive power equalities which are represented by the following power flow nonlinear equations:

$$P_{Gi} - P_{Di} = |V_i| \sum_{n=1}^{N_b} |V_n| \left[G_{in} \cos(\delta_i - \delta_n) + B_{in} \sin(\delta_i - \delta_n)\right] \qquad (7)$$

$$Q_{Gi} - Q_{Di} = |V_i| \sum_{n=1}^{N_b} |V_n| \left[G_{in} \sin(\delta_i - \delta_n) - B_{in} \cos(\delta_i - \delta_n)\right] \qquad (8)$$

The inequality constraints include the limits on all control variables such as bus voltage constraints, generators reactive power constraints, capacitors and reactors reactive power capacities constraints, the transformer tap position constraints, and so on. Mathematically, the inequality constraints can be defined as in the following equations:

$$V_{i\,min} \le V_i \le V_{i\,max} \qquad i = 1, \ldots, N_b \qquad (9)$$

$$P_{Gi\,min} \le P_{Gi} \le P_{Gi\,max} \qquad i \in slack\ bus \qquad (10)$$

$$Q_{Gi\,min} \le Q_{Gi} \le Q_{Gi\,max} \qquad i = 1, \ldots, N_G \qquad (11)$$

$$Q_{SVC_{min}} \le Q_{SVC\,i} \le Q_{SVC_{max}} \qquad i = 1, \ldots, \mathrm{N_{SVC}} \qquad (12)$$

$$I_l \le I_{l\,max} \qquad l = 1, \ldots, N_L \qquad (13)$$

Where V_i is the bus voltage magnitude, N_b is the number of buses in the system, P_G is the active power of the generator, Q_G is the reactive power of the generator, N_G is the number of generators in the system, Q_{SVC} is the reactive power of SVC, N_{SVC} is number of SVC's, I_l is the current flow through the transmission line, and N_L is the number of transmission lines in the system.

In additional to the above constraints, the algorithm restricted to the following parameters:

- Number of SVC devices that will be installed = 4
- The minimum and maximum limits of each SVC chosen as in follows:

$$-75\ \mathrm{MVAr} \le \mathrm{Q_{SVC\,i}} \le 80\ \mathrm{MVAr} \qquad \mathrm{i} = 1, \ldots, 4$$

- Only one SVC is allowed to be installed at a nominated bus.
- The SVC devices can be installed only at load buses (*PQ*). The slack bus and *PV* buses are excluded.
- The SVC's are considered to be reactive power controlled (inject the set point MVAr).
- Population size (number of individuals N_{ind}) = 60
- Maximum number of generations GEN_{max} = 80

GA calls the load flow calculations subroutine for each individual to calculate its fitness. For each step of weighting coefficients increment the program is repeated several times and the most common obtained solution is considered.

7. RESULTS

The optimization problem was solved for the Iraqi national SHV grid system. The grid includes 24 buses. The number of stations that comprise generation units (*PV* buses) is 11. While the load buses (*PQ*) are 13 and these are the nominated buses for the installation of SVC's. Since, in this work, the network is modelled starting from generators terminals, i.e. the unit transformers were included, the busbar before the transformers (from generators side) were considered to be the *PV* node. While the busbar after the transformers were considered as *PQ* node. For the generators located at one station and have different voltage setting, they were modelled separately and considered being connected to separate nodes.

For the above considerations, the number of *PV* buses became 13 and the number of *PQ* buses was 24.

In this paper, six cases were taken for the weight multipliers (w_1, w_2), as shown in Table 1 For the cases 1 and 6, only one objective is considered because one of the two multipliers is zero. Then, the minimum possible active power loss is obtained from installing SVC's according to the results from case 6. In the same way, the minimum voltage deviation is obtained from installing SVC's according to the results from case 1.

Table 1. Selected weights for the two objectives

w_1	0	0.2	0.4	0.6	0.8	1
w_2	1	0.8	0.6	0.4	0.2	0

where w_1 is the weight coefficient for active power loss (P_L) and w_2 is the weight coefficient for voltage deviation (V_D).

Table 2 shows the nominated buses for the 4 SVC's by GA for the mentioned six cases and Table 3 shows the size of each SVC. Table 4 shows the resulted voltage deviation and active power loss for each case.

Table 2. Nominated buses for SVC's obtained by GA for each case of weight coefficients

Case No.	w_1	w_2	SVC_1 Node	SVC_2 Node	SVC_3 Node	SVC_4 Node
case1	0	1	2	7	8	13
case2	0.2	0.8	2	7	12	13
case3	0.4	0.6	1	7	12	13
case4	0.6	0.4	1	2	7	12
case5	0.8	0.2	1	2	7	12
case6	1	0	1	2	7	12

Table 3. Obtained sizes of the 4 SVC's by GA in each case

Case No.	SVC_1 (MVAr)	SVC_2 (MVAr)	SVC_3 (MVAr)	SVC_4 (MVAr)
case1	-70	80	80	80
case2	-65	80	80	75
case3	80	80	80	60
case4	80	-70	80	80
case5	80	-65	80	80
case6	80	-60	80	80

Table 4. Calculated voltage deviation and active power loss for each case

Case No.	V_D (p.u.)	P_L (MW)
case1	0.143	8.7570
case2	0.147	8.6655
case3	0.165	8.5280
case4	0.202	8.3080
case5	0.204	8.3054
case6	0.206	8.3050

The values in Table 4 represent the non-dominated solutions and can be represented by pareto optimal front. In all the cases, voltage deviation and active power loss were reduced in comparison to the uncompensated system. That means, all the solutions in Table 3 satisfy the goal and the operator can choose one of these solutions depending on the importance of each objective.

From Table 2, it can be seen that bus 7 appears in all cases as a nominated bus for installing the SVC. Bus 2 and bus 12 appear in 5 cases and bus 1 appears in 4 cases. This may also help to decide which case among the studied six cases is chosen. In other words, the cases that combine these buses (1, 2, 7, and 12) are preferred for being chosen. The same thing can be said regarding the size of SVC.

Figure 1 shows the pareto front for the two objectives and Figure 2 visualizes, in three dimension, the value of the two objectives against the value of the fitness function for the six cases.

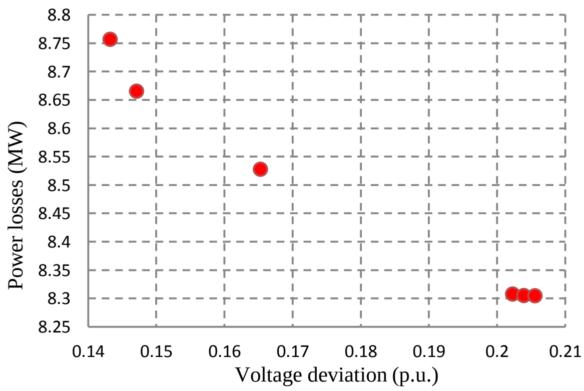

Figure 1. Pareto front for the two objectives

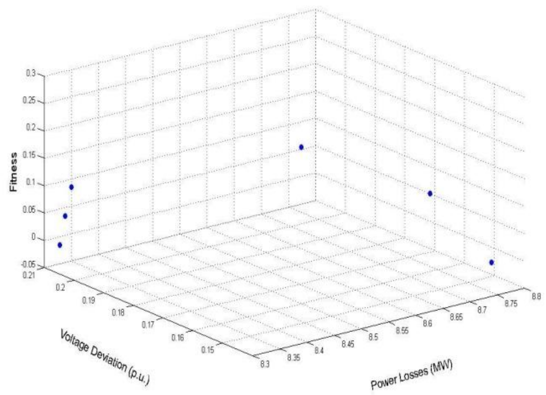

Figure 2. The two objectives versus fitness function value

In the SVC localization problem, it was noticed that the algorithm find the solution after around 40 generation. Nevertheless, the number of generations in each case is set to be 80 to explore all search space and prevent the algorithm from falling in local minima. For the case number 4, the evolution of the best individual (minimum objective function value) for each generation of GA is shown in Figure 3 and Figure 4 shows bus voltage magnitude in (*p.u.*) for all cases.

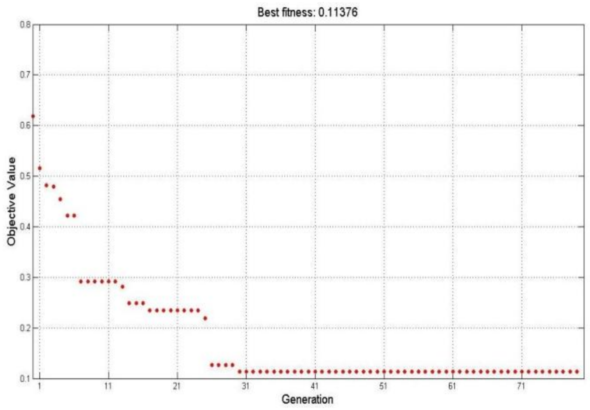

Figure 2. Best individual evolution for each generation in GA

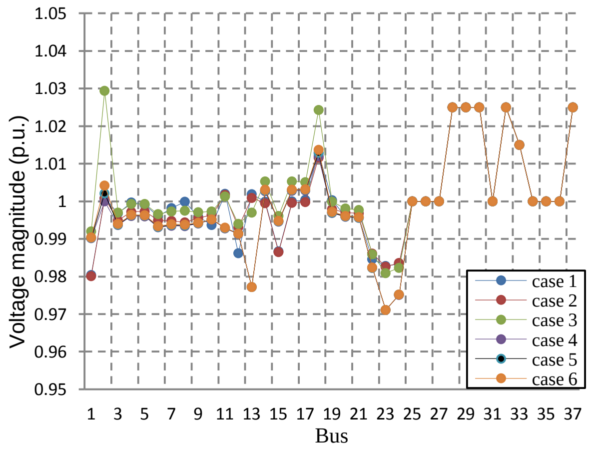

Figure 2. Bus voltage magnitude in (p.u.) for all cases

In term of reducing operation costs and from economical view, reducing active power loss is more important than reducing voltage deviation, while reducing voltage deviation is important in term of improving service quality. As a conclusion, the resulted active power loss and voltage deviation before and after installing the SVC's according to case 4 are indicated in Table 5.

Table 5. Results of power loss and voltage deviation for optimized and unoptimized system

Objective	Unoptimized	SVC installed
power loss (MW)	8.88117	8.30804
%	-	6.45%
voltage deviation (p.u.)	0.3568	0.20227
%	-	43.31%

Figure 5 shows the bus voltage magnitude of the system before and after installing the 4 SVC's according to the locations and sizes obtained from case 4.

8. CONCLUSION

In this work, GA was proposed as an algorithm to find the best locations and sizes of SVC devices. The algorithm was applied on the Iraqi National SHV Grid system. Considering the unit transformers in the grid modelling made the algorithm restricts to the exact reactive power limits of the generators taking into account the added or absorbed reactive power by the transformers.

GA was used to solve the multiobjective optimization problem. The application of the algorithm successfully found the optimum location and the size of each SVC to reduce the active power losses of the grid as well as to enhance voltage profile by reducing voltage deviation from its nominal value for all load nodes. This was done by the reactive power support of SVC devices.

The following points were concluded from the overall results:

1. The algorithm tends to find the best size of each SVC to minimize the objective function, therefore, the obtained sizes were mostly hit the proposed limits of SVC's.
2. With the proposed number and sizes of SVC's, it has been noticed that the reduction in voltage deviation is significantly higher than the reduction in power loss.

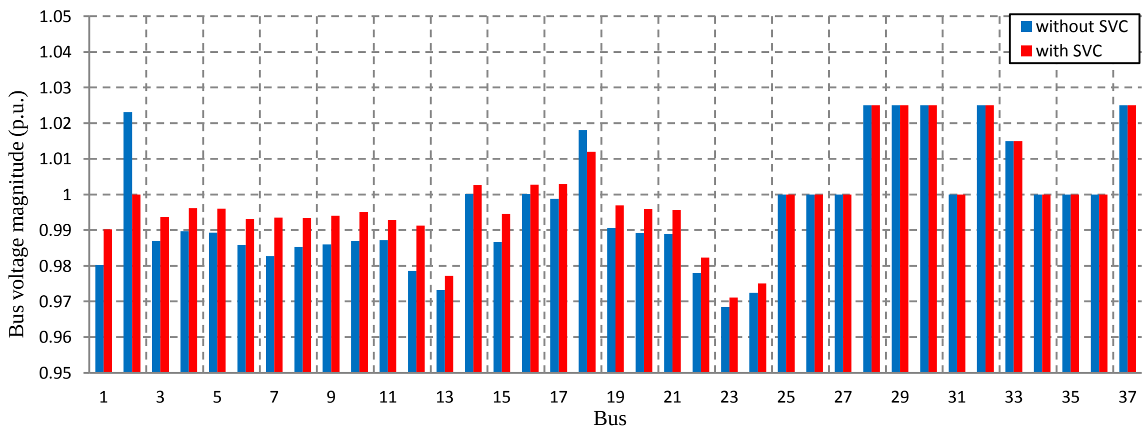

Figure 2. Bus voltage magnitude of the system before and after installing 4 SVC's according to case 4

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