A Genetic Algorithm Approach to Voltage-VAR Control in Systems with Distributed Generation

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Abstract: This paper presents a case study that highlights the influences which the connection of distributed generation sources may have over the solutions of reactive power compensation and voltage control already existing in a given network. The problem of voltage-reactive power control to minimize energy losses was solved by changing the number of capacitor banks located in buses and changing the tap position of the HV/MV transformer from the system, via a genetic algorithm based method.

Key-Words: Genetic algorithms, Distributed generation, Voltage-var control, Renewable sources

1 Introduction

The need for diversification of primary energy sources, given the depletion of the existing resources, which generates increased costs, and also the problem of greenhouse gas emissions generated by fossil fuels, made scientists to focus on new solutions for power generation from renewable sources.

The importance of ‘green energy’ is increasing on the energy markets around the world. The last EU climate and energy regulations package requires, besides a 20% reduction in emissions of greenhouse gases and an energy consumption reduction by another 20% by means of increasing efficiency, that 20% of EU energy consumption to come from renewable sources [1].

In the Romanian power system, excepting hydroelectricity, only the wind energy can be considered as a usable renewable resource. A recent discussion document released by the National Energy Regulation Authority (ANRE) presents the commitment of the Romanian TSO to integrate in the system a wind generation capacity of more than 2400 MW (approved projects), with an estimated limit of 2660 MW [2].

Currently, promoting renewable energy sources and their implementation through distributed generation scheme is an important issue in the electrical energy field.

Distributed generation (DG) involves the production of electricity nearby the consumption points, from low power sources (<50MW). In [3], distributed generation is defined as an electric power source connected directly to the distribution network, or at the consumer. Distributed generation units include small gas turbines, micro turbines, fuel cells, solar and wind energy etc.

Connecting DG units involves several issues, especially in distribution networks that were not originally designed to include such sources. In addition, others problems can occur, like: high initial investment cost, environmental issues and unpredictability of the delivered energy, technical issues regarding the short circuit current on the transmission line. For solving these problems, several types of optimization techniques can be employed, such as: optimal placement and capacity of DG units, minimizing losses and improving power system voltage levels; voltage-var control (VVC); minimizing investment costs and the total cost for energy losses in distribution network.

The VVC represents an important problem for the power systems, which requires appropriate regulation for the contribution of DG units to the VVC, such as: maintaining a constant value of reactive power at the connection point by using capacitor banks (CBs), a constant power factor etc.

Reactive power control flow problems can be solved using traditional techniques like linear programming [4], or new optimization techniques: evolutionary algorithms, neural networks, genetic algorithms. In [5], the VVC problem is solved using an evolutionary approach consisting of an elitist genetic algorithm with secondary population. A heuristic algorithm is presented in [6] for the problem of optimal placement of reactive power sources in distribution networks. Metaheuristics techniques were highly used in the last years to solve complex problems. Some metaheuristics techniques are: evolutionary algorithms, genetic algorithms (GA), evolutionary programming, particle swarm optimization and ant colony optimization. Because VVC requires solving several problems such as improving the system power factor and voltage levels or reducing energy losses, genetic algorithms or evolutionary algorithms are...
often used in practice, which significantly reduces the computing time for finding the optimal solutions.

This paper presents a case study which highlights the influences which the connection of DG sources may have over the solutions of reactive power compensation and voltage control used in the network. Four cases are analyzed, a base case in which a wind power source is not connected to the network and three cases in which a wind power source is connected to the network (the production profile is different for each case). VVC is accomplished by changing the tap of the transformer in the substation through which the plant is connected to the system and by modifying the number of CBs located at the buses. For each case, the optimal solution for VVC is identified using genetic algorithms.

2 Genetic Algorithms

Genetic algorithms (GA) are metaheuristic search algorithms based on the principles of genetics and natural selection, which were used for solving various optimization problems, from control problems [7] to image processing [8]. Their main advantages are that they encode the variables of the optimization function in a straightforward manner, the searching process explores the searching space in parallel using the criteria of natural selection, and the direction of movement is based on the fitness function evaluation. A disadvantage of the GA might be premature convergence to local minima.

GAs can be used only for the types of problems where solutions can be represented by chromosome. The GA starts by randomly generating a population of solutions, which will be improved through a repetitive application of mutation, crossover and selection operators. Besides these genetic operators there is another one, named elitism [9]. Elitism is used to make a copy of the best chromosome from the current population in the next population. This is a simple, but efficient technique.

The selection is used to choose the chromosomes from the current population that will form the next generation. The existing selection methods use probabilistic rules of survival. Individual solutions are selected through a fitness-based process, where the more adapted solution is typically more likely to be selected. The selection methods include the roulette wheel selection and the tournament selection [10].

The crossover is the most important genetic operator used by GAs. Two parent chromosomes are chosen to form two offspring chromosomes, which pass into the next generation, with a given probability. Several crossover operators may be used: one-point crossover, two-point crossover and uniform crossover [11].

The mutation is a genetic operator used to maintain genetic diversity from one generation to the next and helps to prevent the population from stagnating in a local optimal solution. Mutations occur with a certain probability, called mutation rate, usually quite low.

The generic diagram of the GA is presented in Fig. 1.

3 Reactive power compensation

The VVC problem in electrical networks is quite complex, requiring time and effort to find appropriate strategies. VC is carried out at different levels in the system by controlling the generation, the consumption and the reactive power flow.

The reactive power control has as main objectives reducing losses, maintaining voltage within acceptable limits for both normal and emergency operations scenarios and increasing transmission capacity.

Considering a radial network which supplies a consumer where a reactive power source K will be connected, the achieved reduction in power losses is called the energy equivalent of reactive power, which is bigger if the difference between the total and the compensated reactive power is bigger.

\[
k_Q = \frac{\Delta P_k - \Delta Q_k}{Q_k} = \frac{2Q_k}{U_n^2} R \left[\frac{\text{kW}}{\text{kVA}}\right]
\]

Eq. (1) shows that the efficiency of reactive power compensation is proportional to the electrical distance between the compensation device and existing reactive power sources.

VVC is a nonlinear optimization problem. As key variables for voltage control, the voltages of the compensated buses and of the HV/MV transformer tap position are used. The voltage control problem is often encountered when connecting DG units to MV and LV distribution networks. The distribution systems were designed to transfer electricity from a small number of large units of production to a large number of distributed loads, with unidirectional power flow. When a DG unit is connected, the power flow becomes bidirectional and the bus voltages will rise. For keeping the voltages inside the admissible limits, restrictions will be enforced.
when a DG unit is connected to a distribution network: for example, maintaining a fixed power factor in operation. The effects of DG on VVC can be reduced through proper coordination between the distributed generation units and the transformer tap position, so connecting the DG is achieved without unnecessary restrictions.

4 Case study

A radial 26 bus and 25 lines distribution network, with a wind turbine placed in bus 15 was considered (Fig. 2). Its electrical characteristics are presented in Table 1. Table 2 shows the rated power of the transformers connected in the MV buses.

The connection to the system is made through a HV/MV transformer, with on-load tap changing voltage regulation. The LV network is connected through the MV/LV transformers.

Consumers are defined by the rated power of transformers from the substations. For the HV source bus, the load profile for the day of analysis is known (Fig. 3). Then, for every hour, the load is distributed between buses proportional with the rated power of the transformer.

\[ P_{h,j} = P_{h}^{ST} \sum_{k} \frac{S_{nom,j}}{S_{nom,k}} \quad j = 1,2,... \]  

Related with the load profile of the system from Fig. 3, 3 types of load intervals are considered: peak (6, 7, 8, 9, 14, 15, 16, 17, 18, 19), valley (20, 21, 22, 23, 24, 1, 2, 3, 4, 5) and rest of hours (10, 11, 12, 13). The tap position of the HV/MV transformer is considered related with these intervals. Thus, it is considered that the tap position can have only 3 values, one for each interval.

Capacitor banks, as reactive power sources, can be installed in the network, by convention only in MV buses. The CBs have a fixed capacity \( Q_{BC} = 2.5 \, \text{kVAR} \) and, according to the analyzed interval (they will be used only on the peak hours).

![Fig.2 The one-line diagram of the test network](image)

![Fig.3 The load profile for analyzed day](image)

<table>
<thead>
<tr>
<th>Bus i</th>
<th>Bus j</th>
<th>S[nMVA]</th>
<th>R[Ω]</th>
<th>X[Ω]</th>
</tr>
</thead>
<tbody>
<tr>
<td>02</td>
<td>03</td>
<td>10000</td>
<td>0.276</td>
<td>4.4</td>
</tr>
<tr>
<td>03</td>
<td>04</td>
<td>160</td>
<td>58.125</td>
<td>81.373</td>
</tr>
<tr>
<td>04</td>
<td>05</td>
<td>250</td>
<td>32.256</td>
<td>90.149</td>
</tr>
<tr>
<td>05</td>
<td>06</td>
<td>400</td>
<td>17.125</td>
<td>36.149</td>
</tr>
<tr>
<td>06</td>
<td>07</td>
<td>630</td>
<td>9.7959</td>
<td>36.814</td>
</tr>
<tr>
<td>07</td>
<td>08</td>
<td>1000</td>
<td>5.56</td>
<td>23.347</td>
</tr>
</tbody>
</table>

No restriction is imposed over the amount of reactive power produced by the CBs installed in the MV buses, because only a limited number of CBs can be installed at one bus, low enough for not exceeding the reactive power consumption of that bus.

For finding the optimal solution for reactive power compensation by placing CBs at the buses while determining the optimal operation tap of the HV/MV transformer, it is defined an optimization problem that seeks to minimize the daily energy losses under an adequate voltage profile in the network and for admissible values of the current on the lines.
The optimization problem is defined as:

$$f(t, k) = \sum_{h=1}^{24} \sum_{b \in B} R_{h,b} \cdot I_{h,b}^2 = \min$$

with the restrictions:

$$U_{\min} \leq U_{i,h} \leq U_{\max} \quad i \in N$$
$$I_{h,b} \leq I_{\max,b} \quad b \in B$$

where \( t \) and \( k \) are two vectors describing the combinations of operating taps \( (t) \) and CBs \( (k) \) placement at buses.

For solving the optimization problem described in (3) using genetic algorithms, it is required to represent possible solutions using chromosomes. For this purpose, taking into account the possibilities of tap control and CBs placement described above, it is considered a generic chromosome, presented in Fig.4.

![Fig. 4 – The structure of a GA chromosome](image)

The first 3 genes encode the transformer’s tap for the peak, valley and rest hours, and the remaining five groups of two genes store information about the buses where CBs are placed and the number of CBs placed in that bus. It is considered that only 5 buses are eligible for var compensation and a maximum number of 10 CBs can be placed at one bus. The adjustment step of the transformer is between ± 9*1.25%.

The presence of the wind turbine located in bus 15 it is considered in 4 different scenarios:

- base case: the wind turbine not connected;
- case I: the wind turbine connected to the network, having the same production profile during the analysis day (Fig.5a) and loaded at 30% of its rated power;
- case II: the wind turbine connected, having a higher production profile in the first half of the day (50% of its rated power) and a lower production profile in the rest (10% of its rated power), (Fig.5b);
- case III: the wind turbine connected, having a lower production profile in the first half of the day (10% of its rated power) and a higher production profile in the rest (50% of its rated power), (Fig.5c).

For the cases in which the wind turbine is connected to the network, two variants for its rated power are considered: (a) \( S_{\text{nom}} = 2 \times 2 \text{ MW} \), (b) \( S_{\text{nom}} = 2 \times 1 \text{ MW} \).

For modelling the participation of the wind turbine in the voltage control, the bus 15 was considered a PV bus, and for computing the steady state of the system, the Newton-Raphson method was used. Using this method instead of a direct method (where the loads could be represented by currents and the voltage control in bus 15 doesn’t exist) has two effects: the computing time is increased and the risk of divergence appears, correlated with unwanted voltage levels.

For all the 4 cases, the energy losses evolution for the optimal chromosome for 100 generations and the evolution of the number of capacitor banks used for reactive power compensation are presented, in Fig. 6, 7 and 8. It can be seen that, in most cases, the energy losses could be smaller if the algorithm was ran for more than 100 generations, because the fitness function is not saturated. Still, the energy losses are decreasing over the generations and the number of CBs placed in the buses is close to the maximum available, which means that the algorithm used for reactive power compensation has good performances, with optimal solutions.

Table 3 presents the optimal chromosome, found by the GA, the energy losses and minimum and maximum voltage variation for all 4 cases. The best results, meaning the smaller power and energy losses, were obtained when the two wind power turbines are connected to the network at rated power \( S_{\text{nom}} = 1 \text{ MW} \). Also, it can be seen that the wind power sources have an influence on energy losses in the system, which are higher when the wind turbines are not connected to the network.

Table 4 presents the daily energy losses values computed for each case using both the optimal solution identified in that case (on the table’s diagonal) and the optimal solutions identified for the other analyzed cases (out of the table’s diagonal).

The absence of the values for the case IIb corresponds to some divergent regimes of Newton-Raphson method. As it can be seen from Table 4, the solution of integrating the DG unit in the MV network can increase the energy losses, fact that can be seen from comparing the energy losses values in the 2 scenarios: two wind turbines with 2 MW and 1MW rated power.

In Table 4, on every row are indicated the daily energy losses values computed for each case using both the optimal solution identified in that case (on the table’s diagonal) and the optimal solutions identified for the other analyzed cases (out of the table’s diagonal).
Table 3. Chromosome structure, energy losses and minimum and maximum voltage variation for all 4 cases

<table>
<thead>
<tr>
<th>Cases</th>
<th>Optimal chromosome</th>
<th>Energy losses [MWh]</th>
<th>dV min (%)</th>
<th>dV max (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic case</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Case I</td>
<td>a -1 -3 0 9 8 10 9 11 6 8 10 14 9</td>
<td>0.6619</td>
<td>3.0915</td>
<td>3.6936</td>
</tr>
<tr>
<td></td>
<td>b -1 -3 -2 1 1 1 1 0 4 1 0 8 9 7 8 9 9</td>
<td>0.1837</td>
<td>3.3744</td>
<td>3.7264</td>
</tr>
<tr>
<td>Case II</td>
<td>a 0 -3 0 8 9 5 1 0 9 1 0 1 2 9 1 1 1 0</td>
<td>0.3120</td>
<td>3.2812</td>
<td>3.7163</td>
</tr>
<tr>
<td></td>
<td>b -1 -3 -3 7 1 0 4 1 0 5 6 1 1 8 6 1 0</td>
<td>0.2155</td>
<td>3.1393</td>
<td>3.6996</td>
</tr>
<tr>
<td>Case III</td>
<td>a -1 -3 -2 7 9 9 8 5 1 0 1 2 1 0 6 7</td>
<td>0.258</td>
<td>3.77</td>
<td>3.9962</td>
</tr>
<tr>
<td></td>
<td>b -1 -4 -2 1 1 1 0 4 9 7 6 1 2 1 0 5 1 0</td>
<td>0.1880</td>
<td>3.5208</td>
<td>3.7444</td>
</tr>
</tbody>
</table>

Table 4. Energy losses computed by using the optimal chromosome from one case in the others cases

<table>
<thead>
<tr>
<th>Compute losses for:</th>
<th>Using the optimal chromosome for:</th>
</tr>
</thead>
<tbody>
<tr>
<td>case I.a</td>
<td>case I.b</td>
</tr>
<tr>
<td>0.2208</td>
<td>0.2187</td>
</tr>
<tr>
<td>case II.a</td>
<td>case II.b</td>
</tr>
<tr>
<td>0.2283</td>
<td>0.2196</td>
</tr>
<tr>
<td>case III.a</td>
<td>case III.b</td>
</tr>
<tr>
<td>0.2187</td>
<td>0.2187</td>
</tr>
<tr>
<td>case I.b</td>
<td>case II.a</td>
</tr>
<tr>
<td>0.1854</td>
<td>0.1837</td>
</tr>
<tr>
<td>case II.b</td>
<td>case III.a</td>
</tr>
<tr>
<td>0.2233</td>
<td>0.2198</td>
</tr>
<tr>
<td>case III.b</td>
<td>case III.b</td>
</tr>
<tr>
<td>0.1918</td>
<td>0.1878</td>
</tr>
</tbody>
</table>
row. On each column are presented the energy losses for the optimal chromosomes identified in each case. In principle, for each case, in Table 4, the optimal solutions are located on the diagonal, except the cases I.a and III.a, when better compensation solutions exist. For the case I.a, (Fig.7a), the most probable cause for which the global minimum was not identified is because the searching process stopped in a local minimum. On the other hand, for case III.a, the searching process is unsaturated, and a higher number of generations would have certainly enabled a superior solution.

Similar tables could be made for the minimum and maximum values of voltage deviations from the network. The computed values have shown insignificant variations in the voltage variation limits for a given case. So, Table 5 shows the minimum and maximum percentage values of voltage deviation from the buses in the network, found for each case, which, as it can be seen, are inside the ±5% admissible variation.

In conclusion, it can be said that the presence of the wind turbines and their rated power affects both the VVC solutions and voltage and power losses levels in the network, good results being achieved when the wind power sources are connected to the network. Connecting wind power sources to the MT network contributes to energy losses reduction and the improvement of the voltage levels in the network, but the best solutions for voltage-reactive power control should be correlated with the connection scenario of the distributed generation sources (location and production capacity).

4 Conclusions

The reactive power compensation problem with the aim to minimize energy losses was solved in the paper using genetic algorithms. The paper presented a study case for a radial distribution network to which two wind power sources are connected. Four cases are analyzed, one basic case in which the wind power sources are not connected to the network and 3 cases in which the wind power sources are connected to the network (the production profile is different for each case), and the voltage-var control was realized by changing the transformer’s tap and the number of capacitor banks installed in the buses.

It was noted that the presence of wind power sources, more specific their rated powers, affects the solutions of voltage-var control.

As an advantage of genetic algorithms, it can be said that, starting from a set of solutions generated randomly, an optimal solution can be found, for which the power losses are minimal, with no previous information available.

References:


