OPTIMAL PLACEMENT OF FACTS DEVICES

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Abstract: This paper presents a Hybrid Genetic Algorithm (HGA) approach to solve Reactive Power Dispatch (RPD) in power systems incorporating Flexible AC Transmission Systems (FACTS) devices. The goal of the optimization is to find the best location of a given number of FACTS devices for loss minimization. In the proposed approach, some modifications are applied to the original GA in order to take into account the discrete nature of transformer tap settings and capacitor banks. The effectiveness of the proposed approach is demonstrated using the IEEE 30- and IEEE 118-bus test systems. The simulation results show that the proposed method is more efficient than the conventional methods based on the traditional binary-coded GA for the reactive power dispatch problem.

Keywords: Reactive power dispatch, Voltage stability, Line loss, Thyristor controlled series capacitor

1 Introduction

FACTS devices can be utilized to increase the transmission capacity, improve the stability and dynamic behaviour or ensure better power quality in modern power systems. Their main capabilities are reactive power compensation, voltage control and power flow control. It is important to ascertain the best location for placement of these devices because of their considerable cost. Hence, it is imperative that a proper placement strategy must preceede the installation of any such device to obtain optimum performance. The locations of FACTS devices in a power system are obtained on the basis of static and/or dynamic performance. There are several methods [1,2] for finding the optimal locations of FACTS devices in vertically integrated systems, but little attention has been devoted to unbundled power systems. A sensitivity approach has been proposed [3] for placement of series capacitors, phase shifters and static VAR compensators. Most of the work, in the past, has utilized dynamic considerations for the placement of the FACTS devices, as these devices were utilized mainly to improve the stability of the power system networks. This work focuses on the placement of thyristor controlled series capacitor (TCSC) devices to improve the steady state performance of the system. The proposed approach permits the optimization variables to be represented in their natural form in the genetic population. The L-index proposed in [4] is used to compute the voltage stability level of the system. This index uses information from a normal power flow and is in the range of zero to one. In this work some restrictions are applied to the maximum value of the L-index in the normal operating condition so that even if a contingency occurs on the system, the L-index value does not reach a dangerous level.

2 Modelling of TCSC

For a large-scale power system, more than one TCSC may have to be installed in order to achieve the desired performance. However, obvious budgetary constraints force the utilities to limit the number of TCSCs. In the model, we treat the TCSC as a capacitor/inductor whose reactance can vary between -0.5 and +0.5 times the nominal reactance of the branch. The effect of the TCSC on the network can be seen as a controllable reactance inserted in the related transmission line. The power flow equations of the line with a new line reactance can be derived as follows:

\[
P_{ij} = |V_i|^2 G_{ij} - |V_j|^2 G_{ij} \left( G_{ij} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij}) \right)
\]

\[
Q_{ij} = -|V_i|^2 B_{ij} - |V_j|^2 B_{ij} \left( G_{ij} \sin(\theta_{ij}) - B_{ij} \cos(\theta_{ij}) \right)
\]

\[
P_{ji} = |V_j|^2 G_{ij} - |V_i|^2 G_{ij} \left( G_{ij} \cos(\theta_{ij}) - B_{ij} \sin(\theta_{ij}) \right)
\]

\[
Q_{ji} = -|V_j|^2 B_{ij} + |V_i|^2 B_{ij} \left( G_{ij} \sin(\theta_{ij}) + B_{ij} \cos(\theta_{ij}) \right)
\]

where

\[
G_{ij} = \frac{G_{ij}}{R_{ij}^2 + X_{new}^2},
\]

\[
B_{ij} = \frac{X_{new}}{R_{ij}^2 + X_{new}^2}.
\]

Here, the only difference between normal line power flow equation and the TCSC line power flow equation is the controllable reactance, X.
3 Problem formulation

In the problem under consideration, the objective is to minimize the real power transmission loss satisfying the constraints. Minimization of the transmission loss has been achieved by finding suitable values of TCSC devices to readjust the reactive power flow in the system. This problem is mathematically stated as:

\[
\text{Min } F = [f_1, f_2]
\]

(1)

where

\[
f_1 = \sum_{k=0}^{N_x} y_k (V_i ^2 + V_j ^2 - 2V_i V_j \cos \theta_{ij})
\]

\[
f_2 = L_j \max
\]

(2)

The equality constraints are the load flow equations represented by the following equations:

\[
P_i - V_i \sum_{j=1}^{N_x} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \quad i=1,2,....,N_B
\]

\[
Q_i - V_i \sum_{j=1}^{N_x} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \quad i=1,2,....,N_Q
\]

The inequality constraints to be considered are:

\[
V_{i \min} \leq V_i \leq V_{i \max} \quad i \in N_B
\]

\[
Q_{g_i \min} \leq Q_{g_i} \leq Q_{g_i \max} \quad i \in N_{py}
\]

\[
Q_{C_i \min} \leq Q_{C_i} \leq Q_{C_i \max} \quad i \in N_C
\]

\[
t_{k \min} \leq t_k \leq t_{k \max} \quad k \in N_T
\]

\[
S_i \leq S_{i \max} \quad i \in N_i
\]

4 Hybrid Genetic algorithms

The traditional binary-coded genetic algorithm has a number of difficulties in dealing with continuous search spaces [5]. The decision variables of the problem are represented by a fixed length string of binary bits (0, 1). In this representation, the resolution of the solution depends upon the number of bits used to represent the variables. In the real-coded GA, each individual is represented by a vector of floating point numbers with values within the variables upper and lower bounds as shown below:

\[(x_1, x_2, x_3, ......., x_n)\]

With real representation, the evaluation procedure and reproduction operator remain the same as that in the binary-coded GA, but the crossover operation is done variable by variable. In a typical real-valued crossover called “blend crossover (BLX-α)”, the children solutions are obtained from the parent solutions by uniformly picking the values between two points that contain the two parents, but may extend equally on either side determined by a user-defined GA parameter. The real parameter mutation operator, “uniform mutation”, randomly selects one of the variables \(x_j\) from a parent and sets it equal to a uniform random number between the variable’s lower (\(x_{\min}\)) and upper (\(x_{\max}\)) bounds. The details of the crossover and mutation operators used in this work are presented here.

4.1 Crossover operation

Crossover operation is a mixing operator that combines genetic material from selected parents. In the present case it is done variable by variable. As each individual in the population consists of two types of variables, real and integer, a “two-part crossover” which takes advantage of the special structure of the placement problem is developed. To apply this operator first, the selected parents are cut at the boundary between the real and integer variables. The blend crossover operator (BLX-α) [5] is employed in this study for real variables, and simple crossover is applied to the integer part. In the BLX-α crossover the offspring \(y\) is sampled from the space \([e_1, e_2]\) as follows:

\[
y = \begin{cases} 
    e_1 + r \times (e_2 - e_1) & \text{if } u_{\min} \leq y \leq u_{\max} \\
    \text{otherwise: repeat sampling} & 
\end{cases}
\]

where

\[
e_1 = u_1 + \alpha (u_2 - u_1) \\
e_2 = u_2 + \alpha (u_2 - u_1)
\]

\[r : \text{uniform random number } \in [0,1]\]

It is to be noted that \(e_1\) and \(e_2\) will lie between \(u_{\min}\) and \(u_{\max}\), the variable’s lower and upper bound respectively. In a number of test problems, it was observed that \(\alpha = 0.5\) provides good results. One interesting feature of this type of crossover operator is that the created point depends on the location of both parents. If both parents are close to each other, the new point will also be close to the parents. On the other hand, if parents are far from each other, the search is more like a random search.
4.2 Mutation operation

After crossover is performed, mutation takes place. The mutation operator is used to inject new genetic material into the population. Mutation randomly alters a variable with a small probability. The “uniform mutation” operator is applied to the mixed variables with some modifications. First, a variable is selected from an individual randomly. If the selected variable of the individual is a real number then it is set to a uniform random number between the variable’s lower and upper limits. On the other hand, if the selected variable is an integer part then the randomly generated real point number is truncated to the nearest integer.

5 Genetic algorithm implementation

While applying GA to solve a particular optimization problem, the following issues need to be addressed:
- Representation of the solution variables
- Evaluation function

These issues are explained in this section.

5.1 Problem representation

Locations of TCSC devices and their reactance values are considered as control variables of the given problem. In order to take into account the two aforementioned parameters in the optimization, a particular coding is developed. The first string corresponds to the location of the devices. It contains the numbers of the lines where the TCSCs are to be located. Each line could appear at most once in the string. The order of the lines in the strings is not important for a given configuration, but could have its importance when applying the crossover operator. The second string is related to the values of the devices. It can take the discrete values contained between -0.5 and +0.5; these variables are represented in their natural form. With this representation, a typical chromosome of the TCSC placement problem looks like the following:

\[
\begin{array}{cccccccccccc}
2 & 31 & \ldots & 11 \\
\hline
l_1 & l_2 & \ldots & l_n \\
\hline
0.34 & -0.23 & \ldots & 0.123 \\
X_{tcsc1} & X_{tcsc2} & \ldots & X_{tcsc n}
\end{array}
\]

5.2 Evaluation function

The GA searches for the optimal solution by maximizing a given fitness function and therefore an evaluation function which provides a measure of the quality of the problem solution must be provided. For each individual, the equality constraints are satisfied by running the Newton-Raphson load flow algorithm. The constraints on the control variables are taken into account through the proper representation and the constraints on the state variables are taken into consideration by adding a quadratic penalty function to the objective function. With the inclusion of the penalty function, the new objective function then becomes

\[
\text{Min. } F_T = F_0 + K_w \sum_{i=1}^{N_{pq}} (v_i - V_{lim})^2 + K_q \sum_{j=1}^{N_q} (Q_{gj} - Q_{lim})^2 + K_f \sum_j (S_j - S_{lim})^2 \quad (4)
\]

Using the above penalty function approach, one has to experiment to find a correct combination of penalty factors \(K_w, K_q\), and \(K_f\). In the above expression, \(x_{lim}\) of a quantity \(x_i\) is defined by the following expression:

\[
x_{i,lim} = \begin{cases} 
    x_{i,max} & \text{if } x_i < x_{i,max} \\
    x_{i,min} & \text{if } x_i > x_{i,min}
\end{cases}
\]

(5)

The generalized objective function \(F_T\) is a non-linear and non-continuous function. During the run, the GA searches for a solution with maximum fitness function value. Hence, the minimization objective function given by (4) is transformed to a fitness function \(f\) to be maximized as

\[
f = K / F_T 
\]

(6)

where \(K\) is a large constant. This is used to amplify \((1 / F_T)\), the value of which is usually small, so that the fitness values of the chromosome will be in a wider range.

6 Simulation results

This section presents the details of the simulation study carried out on the IEEE 30-bus and 118-bus systems using the proposed GA-based method. The results of these simulations are presented below.

6.1 IEEE 30-Bus System

The system has 6 generator buses, 24 load buses and 41 transmission lines, of which 4 branches(6-9), (6-10), (4-12) and (28-27) contain tap setting transformers, as shown in Fig. 1. The transmission line parameters of this system and the base load are given in [6]. The GA based algorithm was implemented using the MATLAB program and was
executed on a Pentium computer. The initial population was randomly generated between the variables, lower and upper limits. Tournament selection was applied to select the members of the new population. Blend crossover and uniform mutation were applied on the selected individuals. In the first case, the proposed algorithm was run with minimization of real power loss as the objective function. The optimal values of the control variables obtained are given in Table 1. Corresponding to these control variables it was found that all the state variables satisfy their lower and upper limits. The minimum loss obtained corresponding to the optimal solution is 4.52 MW. The loss obtained in this case is less than the value reported in [7, 8].

Table 1: Controller settings for 30-bus system

<table>
<thead>
<tr>
<th>Variables</th>
<th>Min. $P_{\text{loss}}$</th>
<th>Min. $L_{\text{max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td></td>
<td></td>
</tr>
<tr>
<td>of TCSC</td>
<td>36</td>
<td>13</td>
</tr>
<tr>
<td>(line numbers)</td>
<td>6</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>$X_{\text{tcs}}$</td>
<td>-0.5</td>
<td>-0.4723</td>
</tr>
<tr>
<td></td>
<td>-0.1794</td>
<td>-0.4192</td>
</tr>
<tr>
<td></td>
<td>-0.1379</td>
<td>-0.4038</td>
</tr>
<tr>
<td></td>
<td>-0.2434</td>
<td>-0.4913</td>
</tr>
<tr>
<td>$L_{\text{max}}$</td>
<td>0.1221</td>
<td>0.1008</td>
</tr>
<tr>
<td>$P_{\text{loss}}$</td>
<td>4.52 MW</td>
<td>5.2 MW</td>
</tr>
</tbody>
</table>

In the next case, the proposed GA-based approach was applied with minimization of the voltage stability index as the objective. In this case, the maximum L-index of the system has decreased from 0.1325 to 0.1008 and thus it results in the improvement of voltage stability level of the system. This improvement in voltage stability at the buses was achieved because of placement of TCSCs. The L-indices for the identified voltage violated buses before and after placement of the TCSC devices are shown in Fig. 2.

6.2 IEEE 118-Bus system

The proposed GA based approach was applied to the IEEE 118-bus system. The system has 54 generators, 186 branches, 9 transformers, 2 reactors and 12 capacitors. The result of the GA-based algorithm is summarized in Table 2. From this table it is found that the real power transmission loss has decreased from 133.2 MW [8] to 132.2 MW. In the next case, the proposed GA-based approach was applied with minimization of the voltage stability index as the objective. In this case, the maximum L-index of the system decreased from 0.6061 to 0.5041 and thus it results in the improvement of voltage stability level of the system. The optimal control variable settings for the proposed algorithm are also given in Table 2.

7 Conclusions

The problem of discretization in the representation of the decision variables in the binary coded-GA has been alleviated by employing real numbers to represent the control variables. To improve the efficiency of GA in the search process, the optimization variables were represented in their natural form. A modified form of the crossover and mutation operations to deal with the mixed string has been presented. The simulation results for the IEEE 30-bus and IEEE 118-bus test systems shows that the proposed algorithm is effective for voltage stability improvement in the normal states.

Acknowledgements

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Table 2: Best control variables obtained by hybrid genetic algorithm for IEEE 118-bus system

<table>
<thead>
<tr>
<th>Locations</th>
<th>4</th>
<th>36</th>
<th>165</th>
<th>163</th>
<th>79</th>
<th>1</th>
<th>2</th>
<th>41</th>
<th>166</th>
<th>74</th>
</tr>
</thead>
<tbody>
<tr>
<td>TCSC value</td>
<td>0.188</td>
<td>-0.299</td>
<td>0.416</td>
<td>0.236</td>
<td>-0.249</td>
<td>-0.39</td>
<td>0.458</td>
<td>-0.026</td>
<td>0.468</td>
<td>0.305</td>
</tr>
</tbody>
</table>

Real power transmission loss: 132.2148 MW & $L_{\text{max}}$: 0.6061

<table>
<thead>
<tr>
<th>Locations</th>
<th>51</th>
<th>163</th>
<th>62</th>
<th>142</th>
<th>66</th>
<th>166</th>
<th>31</th>
<th>88</th>
<th>136</th>
<th>24</th>
</tr>
</thead>
<tbody>
<tr>
<td>TCSC value</td>
<td>0.238</td>
<td>0.489</td>
<td>0.461</td>
<td>-0.41</td>
<td>0.394</td>
<td>0.476</td>
<td>0.347</td>
<td>0.467</td>
<td>0.368</td>
<td>0.472</td>
</tr>
</tbody>
</table>

$L_{\text{max}}$: 0.5041

References:


Figure 1: IEEE 30-Bus system