Load Model Effect Assessment on Optimal Distributed Generation Sizing and Allocation Using Improved Harmony Search Algorithm

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ABSTRACT
The operation of a distribution system in the presence of distributed generation systems has some advantages and challenges. Optimal sizing and siting of DG systems has economic, technical, and environmental benefits in distribution systems. Improper selection of DG systems can reduce these advantages or even result in deterioration in the normal operation of the distribution system. DG allocation and capacity determination is a nonlinear optimization problem. The objective function of this problem is the minimization of the total loss of the distribution system. In this paper, the Improved Harmony Search (IHS) algorithm has been applied to the optimization problem. This algorithm has a suitable performance for this type of optimization problem. Active and reactive power demands of the distribution system loads are dependent on bus voltage. This paper verifies the effect of voltage dependent loads on system power characteristics. The load model has an inevitable impact on DG sizing and placement. The proposed algorithm implemented and tested on 69-bus distribution systems and the impact of voltage dependent load models are demonstrated. The obtained results show that the proposed algorithm has an acceptable performance.

KEYWORDS: Distributed generation, improved harmony search, DG sizing and siting, load model.

1. INTRODUCTION
DG systems are small power sources that connect to distribution systems. With the increasing demand for electrical power and the technical, economic, and environmental constraints in the construction of new power plants and new transmission lines, DG can efficiently respond to system requirements. DG has predominant specifications. DG’s features are listed below:
- DG facilitates the finding of optimal locations for small resources.
- DG has various technologies that help the distribution system planner to select the appropriate technology (such as wind turbine, gas turbine, solar, fuel
cell, and so forth) according to the system’s requirement.
- Installing DG systems close to the load causes a reduction in power losses, deferral, or postponement of generation, and transmission or distribution system expansion.
- DG provides the least cost solution to power system problems, such as distribution system over load or voltage problems [1, 2].
- DG provides a reserve service, black start service, and intentional islanding operation for the faultless section under fault conditions and increases system reliability [2].
- During peak load, when electricity prices are at their highest, DG can supply loads and avoids wholesale electricity purchase [3].
- DG improves the voltage profile of the distribution system and enhances power quality.

The DG benefits in distribution systems can be summarized as: economic, technical and environmental advantages. In recent research, different aspects of these benefits have been verified [3–5]. To achieve these benefits, special attention must be given to DG placement and sizing. Improper sizing and siting of DG can cause a rise in voltage in some load buses, power flows from the low voltage into the medium voltage grid because of increased DG units, reduction in the effectiveness of protection equipment, creation of operational difficulties under certain conditions and also causing power quality problems and increasing power loss [6].

Different methods have been proposed for optimal location and sizing of DG systems. The main objective for DG placement is to minimize the losses of power systems. However, other objectives such as voltage profile [2] and reliability [1] improvement, cost minimization [3–5] and maximizing DG capacity and penetration level [7] have been considered in different studies too.

System loss reduction has the most important direct and indirect economic and technical benefits. For this reason, in some countries the regulator sets a loss target and rewards distribution network operators (DNO) if their real losses are lower than the loss target [8]. In references [3–5, 9], the loss reduction effect has been translated into economic terms and the economic effects of the loss reduction in the distribution system have been considered.

In order to attain the aforementioned benefits, the optimal DG size and location should be selected. For this purpose, many interesting algorithms and solutions have been developed. The solution methods vary from one application to another. The algorithms with more objectives and constraints need more data and the implementation of such algorithms is difficult. The differences concern the problems of assumptions, methodology, constraints, and cost functions. The DG planning problem can be a mixed integer nonlinear optimization problem. References [10–14] addressed analytical approaches to DG sizing and placement problems. Wang and Nehrir [10] proposed an analytical method to place the DG in order to minimize the power loss of the system. In this method, the optimal bus is selected based on the admittance matrix and this method only optimizes location and considers the size of the DG as fixed. Acharya et al. [11] used a methodology for single DG placement in order to minimize the total power losses. In this research, an
approximate formula for loss calculation and optimal DG capacity at all buses suggested. The best location was obtained from the loss sensitivity factor. Gozel and Hocaoglu [12] propose an analytical method for calculating the loss sensitivity factor and the optimal single DG location and capacity without the use of the admittance matrix. In reference [13], an iterative method has been used for the minimization of the total system losses, voltage drops, and system short circuit levels. This algorithm is based on placing DG at all acceptable buses and the calculation of the cost function. In analytical methods, the process of finding the best candidate location is exhaustive and they sought to optimize only the DG’s real power output. Analytical method is appropriate for single DG sizing and placement optimization.

The problem of optimal DG location and sizing is divided into two sub problems, consisting of optimal DG location and suitable capacity. This problem combines discrete, that is, potential bus locations, and continuous, that is, DG sizing, variable, in a single optimization problem. This combination imposes a difficulty to most optimization techniques and it considerably increases the feasible search space size. As mentioned above, some of the analytical methods only consider location for optimization and assume DG capacity to be fixed or propose a single DG system for optimization. Multiple DG systems have good performance in increasing distribution system efficiency. Applied optimization techniques should be capable of handling multiple DG sizing and siting.

Meta-heuristic and evolutionary algorithm techniques, such as the genetic algorithm (GA), and related techniques, such as particle swarm optimization (PSO), ant colony (AC), simulated annealing (SA) and Tabu search (TS) optimization, have been used to solve this type of optimization problem.

Khalesi et al. [9] applied an approach based on dynamic programming to place and size DG in a distribution system in order to minimize power loss of the system and enhance reliability. In reference [15], a hybrid GA and a PSO technique are presented for optimal location and sizing of DG. The cost function is to minimize the distribution system losses, improve the voltage profile, and increase voltage stability. The PSO algorithm has been used in reference [16] for loss minimization by optimal DG placement and sizing.

Abu-Mouti and El-Hawary [17] have implemented the artificial bee colony (ABC) algorithm for multiple and single DG sizing and siting; the objective function is power loss minimization in the distribution system.

According to the above-mentioned research, meta-heuristic and evolutionary algorithms have appropriate performance for multiple and single DG placement and sizing in distribution systems. In this paper, the improved harmony search (IHS) algorithm has been used for this optimization problem.

The harmony search (HS) algorithm is a new algorithm, which is based on using the musical process of searching for a perfect state of harmony. This method uses a stochastic random search that, in this algorithm, the need for derivative information eliminates. The HS algorithm has been successfully applied for various power system optimization problems. Srinivasa Rao et al. [18] implemented the HS algorithm for a large-scale distribution
system reconfiguration optimization problem. The results show that the proposed algorithm can converge to the optimum solution quickly with better accuracy compared to other optimization methods. Khazali and Kalantar [19] applied the HS algorithm to an optimal reactive power dispatch problem. In references [20–23], the HS algorithm was used for an economic power dispatch optimization problem. The HS algorithm has good performance and appropriate characteristics for the above mentioned optimization problems. Following this research and the acceptable results of the HS algorithm for optimization problems, in this paper the HS algorithm method is applied to optimal DG sizing and placement problems.

In several of the DG planning studies, the loads are modeled as constant power sinks, that is, independent of the feeder voltage magnitude. The load in the distribution system is divided into three categories, being residential, commercial and industrial. These three load types are voltage dependent, and active and reactive power components respond differently to variations in voltage. Considering the effect of voltage dependent loads has a main impact on distribution system planning studies. In reference [24] it has been shown that the load model has a considerable effect on the total loss of the distribution system, active and reactive intake power at the main substation. Load models are major deciding factors in reconfiguration studies. In references [25, 26], the effect of load models on DG planning has been verified. Singh et al. [25] have shown the effects of different load type models, such as residential, commercial, industrial, and mixed loads, at the presence of the DG on active and reactive intake power and system losses. An iterative method for optimal single DG sizing and placement considering the load model has been applied. The results displayed that the load models significantly affect the DG capacity and location, intake power and system losses.

In reference [26], an exhaustive and GA based multi objective optimization method for DG sizing and siting, considering the load model, has been presented. The objectives are voltage deviation, real power loss, reactive power loss, and line loading. The results show that load model plays an important role in DG siting and sizing, individual indices, and the overall objectives. It has been verified that the GA method has good performance in comparison to the exhaustive method, especially in a large-scale distribution system.

In this paper, optimal DG sizing and placement considering different load models is presented. The IHS algorithm has been applied for optimization. Power loss minimization is a cost function and other system limitations, such as bus voltage magnitude, feeder current capacity, and maximum and minimum DG capacity, have been considered as constraints. The effect of the load model on the distribution system power flow has been respected. According to the influence of these loads on distribution system losses, installed DG capacities and locations are prospected to be dependent on the load model.

The next section of this paper describes the mathematical formulation of the voltage dependent load model, Section 3 highlights the objective function and constraints of the optimization problem, and Section 4 introduces the IHS algorithm and related parameters. The simulation results are
presented in Section 5 and the conclusion is given in Section 6.

2. VOLTAGE DEPENDENT LOAD MODEL

Conventionally, in most distribution system planning researches, it is presumed that active and reactive power demands are specified constant values, and loads are voltage independent. In actual distribution systems, different categories and types of loads, such as residential, industrial, and commercial, might be present. The nature of these types of loads is such that their active and reactive powers are voltage dependent. Moreover, load characteristics have considerable effects on load flow solutions and system power losses.

The voltage dependent load models can be mathematically expressed as:

\[ P_L = P_{L0} V^\alpha \]  
\[ Q_L = Q_{L0} V^\beta \]  

Where \( \alpha \) and \( \beta \) are active and reactive power exponents respectively. \( P_L \) and \( Q_L \) are the values of real and reactive powers, while \( P_{L0} \) and \( Q_{L0} \) are the values of active and reactive powers at nominal voltages, respectively. \( V \) represents the voltage magnitude at each bus. For practical application, the evaluation of coefficients \( \alpha \) and \( \beta \) requires field measurement and parameter estimation techniques. In reference [27], common values for the exponents for different static load models have been presented. In practical distribution systems, loads are not explicitly residential, industrial, or commercial. Each busload can be a mix of residential, commercial, and industrial loads. The voltage dependent load model can therefore be expressed as follows:

\[ P_L = \rho P_{L0} V^\alpha + \sigma P_{L0} V^\alpha + \tau P_{L0} V^\alpha \]  
\[ Q_L = \rho Q_{L0} V^\alpha + \sigma Q_{L0} V^\alpha + \tau Q_{L0} V^\alpha \]  

\[ \rho, \sigma \text{ and } \tau \text{ are the percentages of residential, commercial and industrial loads at each load bus respectively.} \]  
\[ \rho + \sigma + \tau = 1 \]  

The values of the real and reactive power exponents used in the present work for industrial, residential, and commercial loads are given in Table 1 [26].

<table>
<thead>
<tr>
<th>Load type</th>
<th>( \alpha )</th>
<th>( \beta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Industrial</td>
<td>0.18</td>
<td>6</td>
</tr>
<tr>
<td>Residential</td>
<td>0.92</td>
<td>4.04</td>
</tr>
<tr>
<td>Commercial</td>
<td>1.51</td>
<td>3.04</td>
</tr>
</tbody>
</table>

According to Table 1, the voltage exponent (\( \beta \)) of the reactive load is quite high in most of the load types when compared to the real power exponent (\( \alpha \)), especially for industrial loads; therefore, consideration of the voltage dependency of the reactive load is necessary for DG planning studies.

3. MATHEMATICAL FORMULATION FOR OPTIMIZATION

It is necessary to note the importance of DG allocation and the sizing problem. The non-optimal installation of DG units in the distribution system can result in increasing system losses, increasing system operation costs, and increasing voltage in some load buses and, therefore, an
undesirable effect on the distribution system. Therefore, the use of an algorithm that could effectively analyze the influence of DG sizing and siting on system characteristics is necessary for the distribution system planner. The main reason for mal operation of the distribution system in the presence of DG refers to the basic assumption of the distribution system. Traditionally, distribution systems have been designed for radial application. By inserting DG into a traditional distribution system this assumption may be violated. Fig. 1 represents a 3-D diagram of typical power loss versus size of DG at each bus in a distribution system. According to Fig. 1, for an installed DG at a specified bus the size of DG is increased and the system losses are decreased to a minimum value. To achieve further increases in DG capacity, the losses start to increase with the high capacity DG, the losses reach values in excess of the base case. This problem can arise in all distribution systems if the size and location of the DG is not optimal.

3.1. Objective functions

In Fig. 2, a sample two-bus system including a DG unit has been depicted. The objective of this problem is to find the optimal capacity and location for a pre-specified number of DG units that minimize the total active power losses of a radial distribution system network. The mathematical formulations of the mixed integer nonlinear optimization problem for the DG unit application are as follows. The objective function is to minimize the total system real power loss:

\[ \text{obj. Function} = \min \, P_{\text{Loss}} \]  

(6)

The real power losses of \( N_B \) - bus distribution system is as follows:

\[ P_{\text{loss}} = \sum_{i=1}^{N_B} \sum_{j=1}^{N_B} \left[ \alpha_{ij}(P_iP_j + Q_iQ_j) + \beta_{ij}(Q_iP_j - P_iQ_j) \right] \]  

(7)

Where,

\[ \alpha_{ij} = \frac{R_{ij}}{V_iV_j} \cos(\delta_i - \delta_j) \]  

(8)
Fig. 2. Single-line diagram of a two-bus system.

\[
\beta_{ij} = \frac{R_{ij}}{V_i V_j} \sin(\delta_i - \delta_j)
\]

(9)

\( V_i \) and \( \delta_i \) are voltage and voltage angle of bus \( i \), respectively. \( Z_{ij} = R_{ij} + jX_{ij} \) are elements of the bus impedance matrix corresponding to buses \( i \) and \( j \). The \( P_i \) and \( Q_i \) are the active and reactive power at bus \( i \), respectively, which is the difference between active and reactive power generation \((P_{gi}, Q_{gi})\) and the active and reactive power load at that bus \((P_{Li}, Q_{Li})\):

\[
P_i = P_{gi} - P_{Li}
\]

(10)

\[
Q_i = Q_{gi} - Q_{Li}
\]

(11)

3.2. Constraints

Power flow equations in the network must be satisfied throughout the optimization process. These equations can be mathematically expressed as follows:

\[
P_{gi} - P_{Li} = \sum_{j} V_j V_{ij} [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)]
\]

\( ; \)For \( i = 1 \) to \( N_B \)

(12)

\[
Q_{gi} - Q_{Li} = \sum_{j} V_j V_{ij} [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)]
\]

\( ; \)For \( i = 1 \) to \( N_B \)

(13)

\( Y_{ij} = G_{ij} + jB_{ij} \) are elements of the bus admittance matrix corresponding to buses \( i \) and \( j \). The delivered active power at the main substation \((P_{\text{intake}})\) to the distribution system can be expressed as the following relation:

\[
P_{\text{intake}} = \sum_{i = 1}^{N_B} P_{oi} |V_i|^2 + P_{\text{loss}} - \sum_{i = 1}^{N_B} \mu_i P_{gi}
\]

(14)

Similarly, the total system reactive power \((Q_{\text{intake}})\) can be given by following relation:

\[
Q_{\text{intake}} = \sum_{i = 1}^{N_B} Q_{oi} |V_i|^2 + Q_{\text{loss}} - \sum_{i = 1}^{N_B} \mu_i Q_{gi}
\]

(15)

If DG exists at bus \( i \) the value of \( \mu_i \) is 1 else \( \mu_i \) is zero. All of the equality constraints have been considered in the power flow program. In addition to the equality constraint, this problem has some inequality constraints. These constraints have been considered and added to the algorithm procedure by using penalty factors in the objective function. If these constraints are violated, the value of the penalty factor increases and the related answers removed. The inequality constraints are presented below:

DG penetration level limitation

\[
\sum_{i = 1}^{N_{DG}} P_{gi} \leq \gamma (\sum_{i = 1}^{N_B} P_{Li})
\]

(16)

\( \gamma \) is the penetration level of DG and is a number between 1 and 0. According to this limitation, the installed DG capacity should be less than the sum of the load demand. \( N_{DG} \) is the total number of installed DG units.

Bus voltage limitation
Bus voltage magnitudes of the distribution system should be kept at acceptable levels.

Thermal limit

\[ |S_{ij}| \leq S_{ij}^{\text{max}} \]  

\( S_{ij} \) is the apparent power flow at distribution system lines between bus i and j. Active and reactive power generation constraint of the distributed generator:

\[ 0 \leq P_{gi} \leq P_{gi}^{\text{max}} \]  

\[ Q_{gi}^{\text{min}} \leq Q_{gi} \leq Q_{gi}^{\text{max}} \]  

The operating limits constraints are represented by the generator’s capability curves. For a conventional synchronous generator the capability of absorbing or generating reactive power is limited by the minimum excitation limit and by the need to provide a sufficient thermal limit (i.e., field and armature current limits) as showed by the capability curve in Fig. 3. Similar limitations exist for generated active and reactive power, and absorbed reactive power for other types of DG.

**4. IHS ALGORITHM**

Recently, a new meta-heuristic optimization algorithm, HS, that is conceptualized using the musical improvisation process of searching for a perfect state of harmony, was developed by Geem et al. [28]. In the HS algorithm there is a memory which stores the solution vectors, as shown in Equation (21). Each musician improvises using three possible choices: (1) playing any famous note exactly from his or her memory, known as the harmony memory consideration rate (HMCR); (2) playing a note in the vicinity of the previous selected note, known as pitch adjustment rate (PAR); (3) selecting a note randomly. Geem et al. [28] formalized these three musicians’ choices into the HS algorithm’s process and the three options respectively became three rules of the algorithm in the generation of a new solution: harmony memory consideration, pitch adjustment, and random selection.

\[
HM = \begin{bmatrix}
x_1^1 & x_2^1 & \ldots & x_D^1 \\
x_1^2 & x_2^2 & \ldots & x_D^2 \\
\vdots & \vdots & \ddots & \vdots \\
x_1^{HMS} & x_2^{HMS} & \ldots & x_D^{HMS}
\end{bmatrix}
\]  

4.1. Harmony memory consideration rule

The harmony memory consideration rule can be considered as elitism, that is, a kind of exploitation or intensification. In fact, this rule makes the algorithm concentrate on potential regions that have already been identified by the exploration component of the algorithm and aims to increase the convergence speed. Algorithms using a harmony memory and HMCR apply this rule. In harmony memory, the algorithm stores the best solutions that have already
been identified and, in order to use this solution effectively, the algorithm adopts an HMCR. This should be considered a high degree of elitism as it can lead to premature convergence and trap the algorithm in the local optimum, but the algorithm, escapes from this premature convergence. The algorithm is generating a new solution, which means that a group of multiple harmonies can be used in parallel to generate a new harmony. In this way the algorithm creates an efficient balance between parallelism (exploration) and elitism (exploitation).

4.2. Random selection rule

The random selection rule is one of the exploration components of the HS algorithm. As is clear from its name, this is not an intelligent rule; in fact, it is used to increase the diversity of the solutions. It can be helpful when the algorithm is trapped in the local optimum because it can help the algorithm to escape from premature convergence but not significantly. A value for each decision variable is selected by the algorithm, either from harmony memory with an HMCR probability or randomly from its domain with a \((1-\text{HMCR})\) probability, and, just for those that have been selected from harmony memory, the algorithm applies the pitch adjustment rule. The random selection rule is applied by Equation (22), where \(UB_i\) and \(LB_i\) are the upper bound and the lower bound of the \(i^{th}\) variable respectively, and \(\text{rand()}\) is a random number between 0 and 1. The random selection rule is just used for exploration; hence, there is no combination of exploration and exploitation in this rule.

\[
x_i^{\text{new}} = LB_i + \text{rand()} \times (UB_i - LB_i)
\]  

(22)  

4.3. Pitch adjustment rule

The HS algorithm uses PAR and pitch bandwidth (bw) to apply the pitch adjustment rule. By applying this rule, the HS algorithm slightly changes the value that is selected from harmony memory by the harmony memory rule. The PAR is used to control the degree of pitch adjustment and the algorithm with a \(\text{PAR} \times \text{HMCR}\) probability adds a small random number \((\pm \text{rand()} \times \text{bw})\) to the value that has been already selected from harmony memory. Here \(\text{rand()}\) is a random number with the range of \([0,1]\). As mentioned earlier, this rule, which is considered to be an exploration component, makes the algorithm slightly change the values of the decision variables that are sorted in the harmony memory with a \(\text{PAR} \times \text{HMCR}\) probability. This act helps the algorithm to search around the good solutions and increases the convergence speed of the algorithm. In fact, this rule in early iterations should work as a global searcher and in the final iterations should work as a local searcher. The serious drawback of the HS algorithm arises from here because Geem et al. [29] have selected a fixed bw for all generations of the algorithm. However, this rule is used as an exploration component in the HS algorithm but it makes the algorithm search in the vicinity of the solutions that have been sorted in harmony memory, in all generations of new solutions. Hence, it can be a kind of exploration that is named local search. To improve the performance of the algorithm and eliminate this serious drawback of the HS algorithm, Mahdavi et al. [30] proposed a new variant of HS, named the IHS algorithm. The IHS dynamically increases the pitch adjustment rate and decreases
pitch bandwidth, respectively. IHS tries, by choosing a low PAR and a wide bandwidth in early iterations, to increase the exploration of the algorithm and gradually, by increasing the PAR and decreasing the bw, tries to exploit the global optimum or the closest to it in the vicinity of the best solutions that have been sorted in harmony memory. Therefore, they dynamically update PAR and bw according to the following equations:

\[
P_{AR}(t) = P_{AR_{\min}} + \frac{(P_{AR_{\max}} - P_{AR_{\min}})}{Max_{\_Iter}} \times t
\]

Where

\(P_{AR}(t)\) Pitch adjusting rate for each generation

\(P_{AR_{\min}}\) Minimum pitch adjusting rate

\(P_{AR_{\max}}\) Maximum pitch adjusting rate

\(Max_{\_Iter}\) Number of solution vector generations

\(t\) Iteration number

And

\[
bw(t) = bw_{\max} \times e^{\ln\left(\frac{bw_{\min}}{bw_{\max}}\right) \times \left(\frac{P_{AR_{\max}} - P_{AR_{\min}}}{Max_{\_Iter}}\right)}
\]

Where

\(bw(t)\) Bandwidth for each generation

\(bw_{\min}\) Minimum bandwidth

4.4. IHS for optimal DG sizing and placement

As mentioned before, in this paper IHS has been applied in order to solve the addressed problem. Fig. 4 shows the overall procedure of the applied IHS for the optimal DG unit sizing and placement. The steps of the algorithm are presented as follows:

Step 1) Initializing the harmony memory which represents the solutions of the problem, \(x^j, j = 1, 2, ..., HMS\), \(x^j\) consists of two sections. The first section comprises the integer numbers and displays the DG unit’s location and the second section comprises a continuous number between 0 and \(P_{g_{\max}}\).

Step 2) Calculating the fitness value of each solution in the HM by using the objective function of the problem \(f(x^j)\). The objective function is the total distribution system losses. A power flow program has been applied for each solution \((x^j)\) in order to compute the losses. As mentioned above, for constraint handling of the problem, in this paper a penalty function, has been used.

Step 3) Improvising a new harmony \(x_{new}^i\) as follows:

\[
\text{For } (i = 1 \text{ to } D) \text{ Do}
\]

\[
\text{If } (\text{rand()} < HMCR) \text{ The (memory consideration)}
\]

\[
x_{new}^i = x_j^i
\]

Where

\(j \in (1, 2, ..., HMS)\)

\[
\text{If } (\text{rand()} < PAR) \text{ Then (pitch adjustment)}
\]

\[
x_{new}^i = x_{new}^i \pm \text{rand()} \times bw
\]

\[
\text{End If}
\]

Else

\[
\text{ (random selection)}
\]

\[
x_{new}^i = LB_i + \text{rand()} \times (UB_i - LB_i)
\]

\[
\text{End If}
\]

\[
\text{End For}
\]

Step 4) Updating the HM that means if
\( f(x^{new}) < f(x^{end}) \) then \( x^{new} = x^{end} \) and sort the memory.

Step 5) Updating the algorithm’s parameters using (23) and (24)

Step 6) if \( Max\_\text{Iter} \) is reached, returning the best harmony vector found so far; otherwise going to Step 2.

Since meta-heuristic algorithms are very sensitive to the range of parameters, a series of experiments has been carried out to obtain the best values of the parameters. Table.2 shows the values of the applied parameters in the proposed IHS which have been used in all of the experiments in this paper.

**Table 2. Applied parameters of proposed IHS**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMS</td>
<td>5</td>
</tr>
<tr>
<td>Max _ \text{Iter}</td>
<td>1000</td>
</tr>
<tr>
<td>HMCR</td>
<td>0.9</td>
</tr>
<tr>
<td>( PAR_{\text{max}} )</td>
<td>0.99</td>
</tr>
<tr>
<td>( PAR_{\text{min}} )</td>
<td>0.01</td>
</tr>
<tr>
<td>( bw_{\text{max}} )</td>
<td>( (UB_i - LB_i) / 20 )</td>
</tr>
<tr>
<td>( bw_{\text{min}} )</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

**5. TEST SYSTEM AND SIMULATION RESULTS**

The proposed algorithm has been implemented by MATLAB software. In order to verify the performance of the proposed algorithm for DG sizing and siting applications, a 69-bus distribution test system has been applied. Fig. 5 shows a single-line diagram of a 69-bus distribution system. The total active and reactive powers of this system are 3.80 MW and 2.69 MVAR respectively. The technical information of the test system is presented in reference [31]. According to the IEEE Standard for Interconnecting Distributed Resources with Electric Power Systems [32], the application of DG as a P.V. bus is not preferred. DG units normally inject a constant amount of real and reactive power.

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**Fig. 4. The IHS algorithm**

All DG units are considered with a pre specified power factor and injected power. Two case studies for investigation of the proposed algorithm have been applied. In the first one, the proposed method has been
applied in a test system without considering the load model and the results have been compared with other methods in order to verify the capability of the proposed algorithm. In the second one, the proposed algorithm has been applied for DG determination, considering different load type models, that is, residential, commercial, industrial and mixed loads.

5.1. Case1 – DG sizing and siting without considering the load model

In order to verify the performance of the proposed algorithm, this algorithm has been implemented for single and dual DG sizing and placement in a 69-bus test system. Table 3 shows the 69-bus distribution test system specification before inserting the DG unit. System power loss before DG unit installation is 0.225+ 0.1022i and the minimum bus voltage is 0.909185 p.u. at bus number 65. The IHS optimization algorithm has been used for single and multiple (two) DG sizing and allocation. Table 4 shows the optimization results, including the optimal value of the objective function (system losses), DG unit capacity and DG unit location. The results have been compared with two other powerful optimization methods, being, the PSO and ABC methods. The operating power factor of the DG unit is assumed to be 0.85 and the leading and penetration level is 0.7, that is, the total installed DG unit capacity is less than 70% of the total active load. According to Table 4, the system power losses decrease from 0.225 MW to 0.0239 in the case of a single DG unit installation and losses decrease to 0.008 MW in the presence of two DG units. The optimal DG unit location for a single DG unit is bus 61 and for two DG units buses 61 and 17.

Installing DG units considerably improves the voltage profile. In the case of a single DG unit installation, the minimum voltage of the bus increases from 0.909 p.u. to 0.9725 p.u. and increases to 0.9936 p.u. in the case of a two DG unit installation.

The results of Table 4 show that proposed method has a good performance in DG sizing and siting applications. With regard to other algorithms, this method also has a good speed for solving this problem. Fig. 6 shows the convergence diagram of this method for single and dual DG units. The proposed optimization algorithm can be used for further numbers of DG units. The voltage profile of a 69-bus distribution system has been depicted in Fig. 7. According to Fig. 7, in the presence of two DG units, the voltage profile of the distribution system considerably improves in comparison to the case of a single DG unit. Generally, it is observed that optimal insertion of DG into a distribution system can significantly decreases the total system
losses and improves the voltage profile.

5.2. Case 2 – DG sizing and sitting considering the load model

As mentioned in Section 2-1, the distribution system loads are mainly categorized into residential, industrial, and commercial loads. These types of loads are voltage dependent.

Mathematical expressions of voltage dependent loads have been given in Equations (1) and (2), Table 1 also represents the voltage exponents of different types of load model. Fig. 8 clearly shows the variation of $P_{\text{intake}}$, $Q_{\text{intake}}$, the total active and reactive load and the total active and reactive power losses of the distribution system for different types of load. These variations are due to the voltage dependency of the distribution loads. According to Table 1, the reactive power of an industrial load has the biggest dependency on voltage; this relevance can be seen in Fig. 8 as can other types of load dependency. According to the power flow results of the voltage dependent load model, in this case active and reactive power demand decreases were compared to a constant load. Table 5, shows the detailed results of DG sizing and siting for different types of load models and also the power characteristics of the distribution system. The operating power factor of the DG unit and the penetration level is similar to the previous case study, that is, 0.85 leading and 0.7, respectively.

**Table 3.** 69-bus system specification without installation of DG unit

<table>
<thead>
<tr>
<th>System loss (MW, MVAR)</th>
<th>Pintake (MW)</th>
<th>Qintake (MVAR)</th>
<th>Total active load (MW)</th>
<th>Total reactive load (MVAR)</th>
<th>Vmin (p.u)</th>
<th>Vmax (p.u)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.225+0.1022i</td>
<td>4.0264</td>
<td>2.7972</td>
<td>3.8014</td>
<td>2.695</td>
<td>0.9091 @ Bus 65</td>
<td>1 @ Bus1</td>
</tr>
</tbody>
</table>
Table 4. Optimization results for a 69-bus distribution system

<table>
<thead>
<tr>
<th>DG Number</th>
<th>Method</th>
<th>System Losses (MW)</th>
<th>DG Location</th>
<th>DG Capacity (MW)</th>
<th>Vmin (p.u)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single DG</td>
<td>Proposed method</td>
<td>0.023865</td>
<td>61</td>
<td>1.904308</td>
<td>0.972539 @ Bus 27</td>
</tr>
<tr>
<td></td>
<td>PSO [16]</td>
<td>0.0239</td>
<td>61</td>
<td>1.90422</td>
<td>0.9725 @ Bus 27</td>
</tr>
<tr>
<td></td>
<td>Artificial Bee Colony (ABC)[17]</td>
<td>0.02392</td>
<td>61</td>
<td>1.873</td>
<td>0.972297 @ Bus 27</td>
</tr>
<tr>
<td>Two DGs</td>
<td>Proposed method</td>
<td>0.008</td>
<td>61, 17</td>
<td>1.768, 0.5121</td>
<td>0.993641 @ Bus 65</td>
</tr>
<tr>
<td></td>
<td>PSO [16]</td>
<td>0.0136</td>
<td>61, 21</td>
<td>1.582, 0.322</td>
<td>0.9862 @ Bus 65</td>
</tr>
<tr>
<td></td>
<td>Artificial Bee Colony (ABC)[17]</td>
<td>0.00799901</td>
<td>61, 17</td>
<td>1.785, 0.51</td>
<td>-</td>
</tr>
</tbody>
</table>

In voltage dependent load models, increasing the voltage of load buses causes an increase in active and reactive power demand. In the case of two DG units, the total active and reactive power of the load is higher than a single DG unit. In this case, voltage increases more than with a single DG unit so that active and reactive power demand is higher. According to Table 5, the maximum difference between the cases without DG and with a single DG unit for total active power load belongs to the commercial load and the maximum difference for reactive load belongs to the industrial load. Referring to Table 1, commercial and industrial loads have the highest dependency on the voltage of the load. The difference in total active load for the commercial load is 0.2 MW. The difference in total reactive load for the industrial load is 0.5 MVAR. According to Tables 4 and 5, considering load models, the optimal capacity of a single DG unit and two DG units differ from the case of a constant load. This implies that the consideration of load model has an important effect on DG capacity and location. For two case studies, one with and one without consideration of the load model, the location of the DG unit is similar but for other case studies or different assumptions, the load model absolutely has an impact on DG location. In the case of installing DG in a distribution system, the DG supply portion of the distribution system loads so that the injected active and reactive power from the main substation to distribution system, that is, $P_{\text{intake}}$ and $Q_{\text{intake}}$, decrease.

6. CONCLUSIONS

This paper presented an algorithm using the IHS optimization method for optimal DG sizing and siting. Optimal DG sizing has important effects on the economic operation and appropriate performance of a distribution system. Improper sizing and siting of DG can jeopardize the normal operation of the distribution system and cause undesirable effects. This problem is formulated as nonlinear optimization with continuous variables for DG capacity and discrete control variables for DG location. The IHS algorithm has good capability for...
most of the continuous optimization problems. The obtained results show appropriate performance of this method compared to other approaches and its implementation is not very hard or complicated. Mathematical modeling of voltage dependent loads i.e residential, commercial and industrial loads has been presented. Simulation results showed that voltage dependent load models have a significant effect on total active and reactive power losses of a distribution system. Optimal DG sizing and siting considering the load model have been verified and the results have been compared to a constant load model. The obtained

<table>
<thead>
<tr>
<th></th>
<th>P\text{intake}</th>
<th>Q\text{intake}</th>
<th>Total active load</th>
<th>Total reactive load</th>
<th>P\text{loss}</th>
<th>Q\text{loss}</th>
<th>DG capacity</th>
<th>DG location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without DG</td>
<td>4.0264</td>
<td>2.7972</td>
<td>3.8014</td>
<td>2.695</td>
<td>0.225</td>
<td>0.1022</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Res.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With single DG</td>
<td>1.924</td>
<td>1.4865855</td>
<td>3.78007</td>
<td>2.63155</td>
<td>0.0229</td>
<td>0.01403</td>
<td>1.8701</td>
<td>61</td>
</tr>
<tr>
<td>with two DGs</td>
<td>1.521349</td>
<td>1.2673094</td>
<td>3.782929</td>
<td>2.6655</td>
<td>0.00782</td>
<td>0.00827</td>
<td>1.7551, 0.5143</td>
<td>61, 17</td>
</tr>
<tr>
<td>Without DG</td>
<td>3.82249</td>
<td>2.3533</td>
<td>3.6517</td>
<td>2.2744</td>
<td>0.17079</td>
<td>0.0789</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Diff.</td>
<td>1.89849</td>
<td>0.8667145</td>
<td>-0.12837</td>
<td>-0.35715</td>
<td>0.1485</td>
<td>0.06487</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Ind.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With single DG</td>
<td>1.946265</td>
<td>1.4562133</td>
<td>3.79724</td>
<td>2.603149</td>
<td>0.022225</td>
<td>0.01398</td>
<td>1.8732</td>
<td>61</td>
</tr>
<tr>
<td>with two DGs</td>
<td>1.529842</td>
<td>1.2428153</td>
<td>3.7993</td>
<td>2.64588</td>
<td>0.007742</td>
<td>0.00823</td>
<td>1.7633, 0.5139</td>
<td>61, 17</td>
</tr>
<tr>
<td>Without DG</td>
<td>3.94621</td>
<td>2.183</td>
<td>3.771</td>
<td>2.1023</td>
<td>0.17521</td>
<td>0.0807</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Diff.</td>
<td>1.999945</td>
<td>0.7267867</td>
<td>-0.02624</td>
<td>-0.500849</td>
<td>0.152985</td>
<td>0.06672</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Com.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With single DG</td>
<td>1.91548</td>
<td>1.4943518</td>
<td>3.766541</td>
<td>2.64131</td>
<td>0.022143</td>
<td>0.01396</td>
<td>1.873204</td>
<td>61</td>
</tr>
<tr>
<td>with two DGs</td>
<td>1.521331</td>
<td>1.2676705</td>
<td>3.783294</td>
<td>2.6661</td>
<td>0.007837</td>
<td>0.008279</td>
<td>1.7607, 0.5091</td>
<td>61, 17</td>
</tr>
<tr>
<td>Without DG</td>
<td>3.730399</td>
<td>2.41677</td>
<td>3.565438</td>
<td>2.34037</td>
<td>0.164961</td>
<td>0.0764</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Diff.</td>
<td>1.814919</td>
<td>0.9224182</td>
<td>-0.201103</td>
<td>-0.30094</td>
<td>0.142818</td>
<td>0.06244</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Mix.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With single DG</td>
<td>1.9503</td>
<td>1.4710975</td>
<td>3.79</td>
<td>2.611</td>
<td>0.0222</td>
<td>0.01401</td>
<td>1.8619</td>
<td>61</td>
</tr>
<tr>
<td>with two DGs</td>
<td>1.52404</td>
<td>1.2474799</td>
<td>3.79548</td>
<td>2.652</td>
<td>0.00776</td>
<td>0.0082</td>
<td>1.758, 0.5212</td>
<td>61, 17</td>
</tr>
<tr>
<td>Without DG</td>
<td>3.8921144</td>
<td>2.250309</td>
<td>3.71948</td>
<td>2.17064</td>
<td>0.1726344</td>
<td>0.079669</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Diff.</td>
<td>1.9418144</td>
<td>0.7792115</td>
<td>-0.07052</td>
<td>-0.44036</td>
<td>0.1504344</td>
<td>0.065659</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Diff.=(without DG)-(with single DG)
results highlight that voltage dependent load models have an impact on the power and voltage characteristics of a distribution system, also that voltage dependent load models influence the optimal capacity and location of installed DG. Consequently, in order to improve DG planning results, assessment of the effects of voltage dependent load models is necessary.

REFERENCES


A PSO-Based Static Synchronous Compensator Controller for Power System Stability Enhancement

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ABSTRACT
In this paper Power system stability enhancement through static synchronous compensator (STATCOM) based controller is investigated. The potential of the STATCOM supplementary controllers to enhance the dynamic stability is evaluated. The design problem of STATCOM based damping controller is formulated as an optimization problem according to the eigenvalue based objective function that is solved by a particle swarm optimization (PSO) algorithm. The controllers are tuned to simultaneously shift the lightly damped and un-damped electro-mechanical modes of machine to a prescribed zone in the s-plane. The results analysis reveals that the designed PSO based STATCOM damping controller has an excellent capability in damping the power system low frequency oscillations and enhance greatly the dynamic stability of the power system.

KEYWORDS: STATCOM, Particle swarm optimization, damping controller, Dynamic stability.

1. INTRODUCTION

Intensive progress in power electronics has enabled application of flexible AC transmission system (FACTS) devices in high voltage transmission networks. The main aim of FACTS devices is normally steady-state control of a power system but, due to their fast response, FACTS can also be used for power system stability enhancement through improved damping of power swings [1]. Static synchronous compensator (STATCOM) is a member of FACTS family that is connected in shunt with the system. It replaces the bulky reactive elements of conventional static var compensator (SVC) by a solid-state synchronous voltage source. The STATCOM is based on the principle that a voltage-source inverter generates a controllable AC voltage source behind a transformer-leakage reactance so that the voltage difference across the reactance produces active and reactive power exchange between the STATCOM and the transmission network. Several trials have been reported in the literature to dynamic models of STATCOM in order to design suitable controllers for power flow, voltage and
damping controls [2, 3]. Wang [4] presents the establishment of the linearized Phillips–Heffron model of a power system installed with a STATCOM. Wang has not presented a systematic approach for designing the damping controllers. Further, it seems no effort have been made to identify the most suitable STATCOM control parameter, in order to arrive at a robust damping controller. Intelligent controllers have the potential to overcome the above-mentioned problems. Fuzzy-logic-based controllers have, for example, been used for controlling a STATCOM [5]. The performance of such controllers can further be improved by adaptively updating their parameters. Although using the robust control methods [6], the uncertainties are directly introduced to the synthesis, but due to the large model order of power systems the order resulting controller will be very large in general, which is not feasible because of the computational economical difficulties in implementing. The PSO algorithm can be used to solve many of the same kinds of problems as GA and does not suffer from of GA’s difficulties. The PSO is a novel population based meta heuristic, which utilize the swarm intelligence generated by the cooperation and competition between the particle in a swarm and has emerged as a useful tool for engineering optimization. Unlike the other heuristic techniques, it has a flexible and well-balanced mechanism to enhance the global and local exploration abilities. This algorithm has also been found to be robust in solving problems featuring non-linearing, non-differentiability and high-dimensionality [7-11].

In this study, the problem of robust STATCOM based damping controller design is formulated as an optimization problem and PSO technique is used to solve it. The aim of the optimization is to search for the optimum controller parameter settings that improve the dynamic system performance. The effectiveness of the proposed controller is demonstrated through eigenvalue analysis and nonlinear time-domain simulation studies to damp low frequency oscillations under different operating conditions. Results evaluation shows that the proposed damping controller achieves good robust performance for a wide range of operating conditions and disturbance.

2. OVERVIEW OF PARTICLE SWARM OPTIMIZATION

The PSO method is a population-based one and is described by its developers as an optimization paradigm, which models the social behavior of birds flocking or fish schooling for food. Therefore, PSO works with a population of potential solutions rather than with a single individual [7]. Its key concept is: potential solutions are flown through hyperspace and are accelerated towards better or optimum solutions. Its paradigm can be implemented in simple form of computer codes and is computationally inexpensive in terms of both memory requirements and speed. The higher dimensional space calculations of the PSO concept are performed over a series of time steps. The population is responding to the quality factors of the previous best individual values and the previous best group values. It has also been found to be robust in solving problem featuring non-linearing, non-differentiability and high-dimensionality [8-10].

The PSO starts with a population of random solutions “particles” in a D-dimension space.
The \( i \)th particle is represented by \( X_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \). Each particle keeps track of its coordinates in hyperspace, which are associated with the fittest solution it has achieved so far. The value of the fitness for particle \( i \) (pbest) is also stored as \( P_i = (p_{i1}, p_{i2}, \ldots, p_{iD}) \). The global version of the PSO keeps track of the overall best value (gbest), and its location, obtained thus far by any particle in the population. The PSO consists of, at each step, changing the velocity of each particle toward its pbest and gbest according to Eq. (1). The velocity of particle \( i \) is represented as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{iD}) \). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest. The position of the \( i \)th particle is then updated according to Eq. (2) [11]:

\[
v_{i_d} = w \times v_{i_d} + c_1 \times \text{rand()} \times (P_{i_d} - x_{i_d}) + c_2 \times \text{rand()} \times (P_{gd} - x_{i_d})
\]

\[
x_{id} = x_{id} + cV_{id}
\]

Where, \( P_{id} \) and \( P_{gd} \) are pbest and gbest. The positive constants \( c_1 \) and \( c_2 \) are the cognitive and social components that are the acceleration constants responsible for varying the particle velocity towards pbest and gbest, respectively. Variables \( r_1 \) and \( r_2 \) are two random functions based on uniform probability distribution functions in the range \([0, 1]\). The use of variable \( w \) is responsible for dynamically adjusting the velocity of the particles, so it is responsible for balancing between local and global searches, hence requiring less iteration for the algorithm to converge [7]. The following weighting function \( w \) is used in Eq. (1):

\[
w = w_{\text{max}} - \frac{w_{\text{max}} - w_{\text{min}}}{\text{iter}_{\text{max}}} \times \text{iteration}
\]

Fig.1. Flowchart of the proposed PSO technique

3. DESCRIPTION OF CASE STUDY NETWORK

Figure 2 is a single machine infinite bus power (SMIB) system installed with a STATCOM. The synchronous generator is delivering power to the infinite-bus through a double circuit transmission line and a STATCOM. The system data is given in the Appendix. The system consists of a step down transformer (SDT) with a leakage reactance XSDT, a three-phase GTO-based voltage source converter, and a dc capacitor [4].

The VSC generates a controllable AC voltage source \( v_{\text{VSC}}(t) = V_0 \sin(wt - \phi) \) behind the leakage reactance. The voltage difference between the STATCOM bus AC voltage, \( V_L(t) \)
and \( v_0(t) \) produces active and reactive power exchange between the STATCOM and the power system, which can be controlled by adjusting the magnitude \( V_0 \) and the phase \( \phi \). The dynamic relation between the capacitor voltage and current in the STATCOM circuit are expressed as [4]:

\[
I_{dc} = I_{lod} + j I_{loq} \\
V_v = c V_d (\cos \phi + j \sin \phi) = c V_d \angle \phi \\
\dot{V}_{dc} = \frac{I_{dc}}{C_{dc}} (I_{lod} \cos \phi + I_{loq} \sin \phi)
\]

(4) \hspace{1cm} (5) \hspace{1cm} (6)

\[\text{Where for the PWM inverter } c=mk \text{ and } k \text{ is the ratio between AC and DC voltage depending on the inverter structure, } m \text{ is the modulation ratio defined by the PWM and the phase } c \text{ is also defined by the PWM. The } C_{dc} \text{ is the dc capacitor value and } I_{dc} \text{ is the capacitor current while } i_{lod} \text{ and } i_{loq} \text{ are the d- and q-components of the STATCOM current, respectively.}
\]

\[\text{The dynamics of the generator and the excitation system are expressed through a third order model given as [10]:}
\]

\[
\Delta \delta = \omega_0 \Delta \omega, \\
\Delta \omega = (-\Delta P_e + \Delta \omega) / M, \\
\Delta E_i = (-\Delta Q_e + \Delta E_i) / T_A, \\
\Delta \dot{E}_{fd} = \left( K_A (\Delta v_{ref} - \Delta v) - \Delta E_{fd} \right) / T_A
\]

(15) \hspace{1cm} (16) \hspace{1cm} (17) \hspace{1cm} (18)

\[\text{Where, } X_T, x_d' \text{ and } x_q \text{ are the transmission line reactance, d-axis transient reactance, and q-axis reactance, respectively. A linear dynamic model is obtained by linearizing the nonlinear model round an operating condition. The linearized model of power system as shown in Fig.1 is given as follows:}
\]

\[
E_{al} = (-E_{al} + K_a (V_{al} - V_i)) / T_a
\]

(10)

\[\text{The expressions for the power output, terminal voltage, and the d-q axes currents in the transmission line and STATCOM, respectively, are:}
\]

\[I_{al} = \frac{(1 + \frac{X_{td}}{X_{SOT}}) x_d' - \frac{X_{td}}{X_{SOT}} m V_{al} \sin \phi - V_i \cos \phi}{X_{al} + X_{td} + \frac{X_{td}}{X_{SOT}} (1 + \frac{X_{td}}{X_{SOT}}) x_d'}
\]

(11) \hspace{1cm} \frac{X_{td} m V_{al} \cos \phi + V_i \sin \phi}{X_{SOT}}

(12)

\[I_{loq} = \frac{m V_{al} \cos \phi - (x_d' + X_{td}) i_{loq}}{X_{SOT}}
\]

(13)

\[I_{lod} = \frac{m V_{al} \cos \phi - (x_q' + X_{td}) i_{lod}}{X_{SOT}}
\]

(14)
\[ \Delta V_i = K_s \Delta \delta + K_p \Delta E_{q}^{1} + K_{vdc} \Delta V_{dc} + K_{vc} \Delta c + K_{vq} \Delta \phi, \]  

\( (22) \)

\( K_1, K_2, \ldots, K_9, K_{pu}, K_{qu} \) and \( K_{vu} \) are linearization constants. The block diagram of the linearized dynamic model of the SMIB power system with STATCOM is shown in Fig. 3.

The power oscillation damping (POD) controller is designed to produce an electrical torque in phase with the speed deviation according to phase compensation method. The structure of POD controller is given in Fig. 4. This controller may be considered as a lead-lag compensator. It comprises gain block, signal-washout block and lead-lag compensator. The block diagram of STATCOM dc voltage PI controller with power oscillation damping stabilizer is shown in Fig. 5. The DC-voltage regulator controls the DC voltage across the DC capacitor of the STATCOM.

In the proposed method, we must tune the STATCOM controller parameters optimally to improve overall system dynamic stability. To increase the system damping to electromechanical modes, an eigenvalue-based objective function is considered as follows:

\[ J = \sum_{j=1}^{NP} \sum_{i>\sigma_0} (\sigma_{ij} - \sigma_0)^2 \]  

\( (23) \)

Where, \( \sigma_{ij} \) is the real part of the \( i \)th eigenvalue of the \( j \)th operating point. The value of \( NP \) is the total number of operating points for which the optimization is carried out. The value of \( \sigma_0 \) determines the relative stability in terms of damping factor margin provided for constraining the placement of eigenvalues during the process of optimization. The proposed approach employs PSO to solve this optimization problem and searches for an optimal set of controller parameters. The optimization of controller parameters is carried out by evaluating the objective function as given in Eq. (23), which considers a multiple of operating conditions. The operating conditions are given in Table 1. Figure 6 illustrates the block diagram of STATCOM ac voltage PI controller with a power oscillation-damping stabilizer. In our implementation, the value of \( \sigma_0 \) is taken as \(-2\).

In order to acquire better performance, number of particle, particle size, number of iteration, \( c_1, c_2, \) and \( c \) is chosen as 30, 7, 50, 2, 2 and 1, respectively. In addition, the inertia weight, \( w \), is linearly decreasing from 0.9 to 0.4. The final values of the optimized parameters with objective function, \( J \), are given in Table 2.

\[ \text{Fig.4. Power oscillation damping controller} \]
The electromechanical modes and the damping ratios obtained for nominal and heavy operating conditions both with and without proposed controllers in the system are given in Table 3. When stabilizer is not installed, it can be seen that some of the modes are unstable (highlighted in Table 3). Moreover, it is also clear that the system damping with the proposed PSO based STATCOM damping controller is significantly improved.

Table 3. System eigenvalues with and without controller.

<table>
<thead>
<tr>
<th>Type of controller</th>
<th>Nominal</th>
<th>Heavy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without controller</td>
<td>-0.196 ± i3.389,</td>
<td>0.256 ± i4.49,</td>
</tr>
<tr>
<td></td>
<td>-0.058</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td>-97.87, -2.761,</td>
<td>-3.3718, -96.643</td>
</tr>
<tr>
<td></td>
<td>-0.066</td>
<td>-0.066</td>
</tr>
<tr>
<td>C based controller</td>
<td>-3.095 ± i4.78,</td>
<td>-2.966 ± i3.28,</td>
</tr>
<tr>
<td></td>
<td>-1.404</td>
<td>-1.316</td>
</tr>
<tr>
<td></td>
<td>-131.62, -0.1086</td>
<td>-133.37, -0.1094</td>
</tr>
<tr>
<td></td>
<td>-0.609</td>
<td>0.90</td>
</tr>
<tr>
<td>φ based controller</td>
<td>-2.106 ± i3.964,</td>
<td>-2.089 ± i3.73,</td>
</tr>
<tr>
<td></td>
<td>0.469</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>-2.62 ± i3.28,</td>
<td>-2.623 ± 0.012</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>-96.582</td>
</tr>
<tr>
<td></td>
<td>0.886</td>
<td>-96.644</td>
</tr>
<tr>
<td></td>
<td>0.84</td>
<td></td>
</tr>
</tbody>
</table>

5.2. Nonlinear time domain simulation

In this section, the performance of the proposed controller under transient conditions is verified by applying a 6-cycle three-phase fault at t=1 sec, at the middle of the L3 transmission line. Permanent tripping of the faulted line clears the fault. The system response to this disturbance is shown in Fig. 7. It can be seen that the proposed controller has good performance in damping low frequency oscillations and stabilizes the system quickly.

5. CONCLUSIONS

A method of designing a power oscillation-damping controller for a STATCOM has been proposed. The design problem of the controller is converted into an optimization problem, which is solved by a PSO technique. The robust design has been found to be very effective for a range of operating conditions
of the power system. The eigenvalues analysis and nonlinear time domain simulation results show the robustness of the proposed controller and their ability to provide good damping of low frequency oscillations. Moreover, the φ-based stabilizer provides better damping characteristics and enhances greatly the first swing stability compared to the C-based stabilizer. Results demonstrate that the overshoot, undershoot, settling time and speed deviations of the machine are greatly reduced by applying the proposed methodology based tuned controller.

**Fig.7.** Speed deviation (Δω) at (a) Nominal (b) Light and (c) Heavy loading; Solid (φ based controller) and Dashed (C based controller).

### APPENDIX

The nominal parameters are listed in Table 4.

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Generator</td>
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<td>$X'_g = 0.3 \text{pu}$</td>
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<td>$T_a = 0.05 \text{s}$</td>
<td></td>
</tr>
<tr>
<td>Transformers</td>
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<td>$X_{av} = 0.1 \text{pu}$</td>
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</tr>
<tr>
<td>DC link parameter</td>
<td>$V_{dc} = 1 \text{pu}$</td>
<td>$C_{dc} = 1 \text{pu}$</td>
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</tr>
<tr>
<td>STATCOM parameter</td>
<td>$C = 0.25$</td>
<td>$\varphi = 52^\circ$</td>
<td></td>
</tr>
</tbody>
</table>

| $K_s = 1$                | $T_s = 0.05$          |

### REFERENCES


Using Neural Network to Control STATCOM for Improving Transient Stability

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ABSTRACT
FACTS technology has considerable applications in power systems, such as; improving the steady state performance, damping the power system oscillations, controlling the power flow, and etc. STATCOM is one of the most important FACTS devices used in the parallel compensation, enhancing transient stability and etc. Since three phase fault is widespread in power systems, in this paper STATCOM is used to improve the transient stability of power system when three phase fault occurred. Neural Network has been used for adjusting the gain of the supplementary controller of STATCOM. The simulation performed in MATLAB / Simulink software. Simulation results showed when STATCOM combines with proposed Neural Network based supplementary controller; the transient stability of power system improves.

KEYWORDS: FACTS, STATCOM, Artificial Neural Network (ANN), Power Oscillation Damping.

1. INTRODUCTION
The Stability is main Characteristics and requirements of the dynamical systems. Common phenomenon and stability in a power network divided into two categories, namely the turbulence intensity and duration that remain in the system. The first division including: steady state, dynamic and transient stability. Steady state stability is stability of power system under very little disturbances, transient stability is stability of power system under large disturbances and dynamic stability is stability of power system under disturbance that is resolved via plant controller like voltage and frequency Controllers. In the second division, the phenomenon of the power grid is divided according to time duration remained in the network. There are many control systems in a power system that their aim is to supply necessary power to consumers in the desired Frequency and voltage. Another role of control systems eliminates the rapid transient Fluctuations and create stability in the system when it deals with disturbances. This control system can be divided into two categories: Control systems in a plant and control systems in transmission lines. The control system of transmission lines helps to maintain the voltage, frequency level and control of amount active power and reactive power [1]. One of the technologies
that makes optimum use of lines and systems and maintains power system stability is FACTS technology. This technology was introduced in 1986 by the Institute EPRI [2]. STATCOM is one of the FACTS devices which operate in parallel with the system. STATCOM is used for voltage control by compensating an appropriate amount of reactive power in the early years but in recent years it has been considered to reduce the power grid fluctuations. This is done by using appropriate controller. Some previous studies showed that using an additional control system is an effective method to reduce fluctuations. Some of them have been used in a simple PI controller. Other researchers have used fuzzy logic for improving the performance of the controller. The fuzzy logic calculates the appropriate gain [3-4]. In this paper, to achieve greater and faster oscillation damping, the amount gain of additional controller is calculated by the neural network. With this controller, the STATCOM is able to reduce oscillations quickly when the three-phase to ground fault occurs in the system. Simulation is done in MATLAB, for three cases: I-system without STATCOM, II-system with STATCOM without additional controller, III-system with STATCOM with additional controller. Simulation results showed that the system with STATCOM with additional controller that its gain was calculated by the neural network has a faster and better damping.

2. TRANSIENT STABILITY

In a power system, transient stability is the ability of a system to maintain stability, and oscillation damping after a severe disturbance. Disturbances in power systems such as the removal of equipment, changes in load and short circuit lead to increase the generator rotor angle. So system response is affected by the non-linear relationship between power and load angle. The relationship between power and angle in a power system can be expressed as follows:

$$P = \frac{V_s V_r}{X} \sin(\delta)$$  (1)

Where $V_s$ is Terminal voltage of the transmitter, $V_r$ Terminal voltage of the receiver, $X$ is Line impedance, $\delta$ is angle between the voltage of the transmitter of receiver or load angle. According to equation (1), the curve of power-angle load is similar to Fig. 1:

According to this curve (fig. 1), when the fault occurs in a synchronous machine, Electromagnetic torque is suddenly reduced and the amount transferred power can be significantly reduced, while the mechanical power remains constant. So the rotor is accelerated and load angle increases from $\delta_1$ to $\delta_2$. Generator absorbs energy accelerators that it is shown with the area $A_1$. After eliminating the fault in point related to the angle $\delta_2$, transferred power increased from Mechanical power and generator begins to decrease the acceleration. In this case angle $\delta$
increased more. Due to the kinetic energy stored in the machine and it reaches to the maximum angle $\delta_m$ and established balance between energy accelerators and energy reducing acceleration. Energy reducing acceleration is shown with the area $A_2$. The area between the curve of power and line of Mechanical power named Transient stability margin that shown with $A_{\text{margin}}$ [5]. Parallel compensation instruments such as STATCOM with appropriate control in the connection point can support the voltage. The result showed increased ability of the transfer system after the fault. Therefore it increases the transient stability. With parallel compensation maximum power will be equal below:

$$P_{\text{max}} = \frac{2V_s V_e}{X}$$

(2)

Fig. 2 shows the power-angle curve in the presence a STATCOM.

The STATCOM is based on a solid state synchronous voltage source which generates a balanced set of three sinusoidal voltages at the fundamental frequency with fast amplitude and phase angle control. The configuration of a STATCOM is shown in Fig. 1. Basically it consists of a voltage source converter (VSC), a coupling transformer and a DC capacitor. STATCOM is used for voltage support in a power system. When the voltage drop occurs in the system, it caused a rapid adjustment of the voltage at the connection point with a reactive power injection. Thus it prevents the system from instability [6].

![Diagram of STATCOM](image)

Fig. 3. Structure of STATCOM

4. ARTIFICIAL NEURAL NETWORK

Nowadays with the advancement of technology and use of computer systems in complex calculations, intelligent computer systems and artificial intelligence have a greater importance. Neural networks have been devised in accordance with the nervous system; this means that a neural network is composed of several elements called neurons. These neurons communicate with other neurons; the connections between neurons are weighted. The weight is considered as important parameters in neural network training. Generally neural networks are trained so that a particular input leads to a specific output in the output layer neural network. The multilayer PERCEPTRON network (MLP) and back propagation network...
approaches have a privileged position in technology of neural network. The back propagation method is achieved with training rules WIDROW-HOFF. In multilayer networks and the decision function can be derived. In this method, input and network output and desired output are used for network training until Network output is closer to the desired output. Multilayer feed word neural network has the ability to specify input and output relationships by learning back propagation algorithm [7]. In this paper a feed-forward artificial network with online training is used to calculate the gain of controller added to the control system of STATCOM online. This network has two layers which are shown in Fig. 4.

Fig.4. Model of two-layer neural network

The input network can be the machine speed changes, frequency changes, angle load of generator changes.

5. TIME DOMAIN SIMULATION

The one line diagram of the two-machine test system that is simulated in MATLAB SIMULINK is shown in Fig.5. Parameters of generators, lines and STATCOM are parameters used in toolbox MATLAB. Time domain simulation is performed on the system with a three phase fault applied at the sending end of the circuit. Duration time of this fault is 0.1 s. In this study STATCOM is used to control reactive power exchange with the network.
The input signal of the additional controller will be selected from error between desired and actual load angle of machine 1 (M1), also in this simulation, to adjust the weights of neural network we used the difference between the reference voltage and bus voltage of STATKAM as another input of additional controller. Neural network by adjusting the inputs calculates the desired gain for an additional controller. The controller output is added to the difference between the reference voltage and bus voltage of STATKAM input. In this way, Bus voltage of STATCOM is controlled to help damping system oscillations. In fact when the angle changes are positive, STATCOM increases voltage of connection point to grid and when the angle changes are negative, reduces it. So it causes an increase in transient stability of the system. In this paper we used three cases of simulation; case I: system without STATCOM, case II: system with STATCOM without additional controller, case III: system with STATCOM with additional controller. Results of system response for each control mode are shown in Fig.8. Injected Reactive power by STATCOM in tow case is shown in Fig.9. According to figures, it is clear that employing artificial neural networks to determine the gain of additional controller will increase the damping widely.

6. CONCLUSIONS

In this paper we have shown that the STATCOM has a positive effect on transient stability. Then with using an additional controller that its gain calculated with artificial neural network, we can see that ANN improved the performance of STATCOM.
Furthermore Computer simulations showed the advantage of this method to improve the STATCOM performance on transient stability of the power system.

REFERENCES


Voltage Flicker Parameters Estimation Using Shuffled Frog Leaping Algorithm and Imperialistic Competitive Algorithm

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ABSTRACT
Measurement of magnitude and frequency of the voltage flicker is very important for monitoring and controlling voltage flicker efficiently to improve the network power quality. This paper presents two new methods for measurement of flicker signal parameters using Shuffled Frog Leaping Algorithm (SFLA) and Imperialist Competitive Algorithm (ICA). This paper estimates fundamental voltage and flicker magnitudes and frequencies with proposed methods. The goal is to minimize the error of the estimated magnitudes and frequencies via a designed fitness function. At first, we introduce voltage flicker and its measuring techniques. Then voltage flicker model is analyzed. At the next part, a review of SFLA and ICA is presented. These methods will be applied to a test voltage signal and the results are be analyzed.

KEYWORDS: Voltage flicker signal, Flicker magnitude and frequency measurement, Shuffled Frog Leaping Algorithm (SFLA), Imperialist Competitive Algorithm (ICA).

1. INTRODUCTION
Voltage flicker is "the impression of unsteadiness of visual sensation induced by a light stimulus whose luminance or spectral distribution fluctuates with time". Voltage fluctuations are a systematic variations or a series of random changes in the voltage envelope. Cyclic flicker is repeatedly occurring over perhaps an extended period and is caused by periodic voltage fluctuations due to the operation of loads such as arc furnaces. Random changes in the voltage magnitude (non-cyclic flicker) refer to occasional voltage fluctuations due to operations such as the starting of large motors. Exhaustion of human eyes, malfunction of electronic controllers and protection devices, reduction the life span of the electronic, incandescent, and cathode ray tubes are in the result of voltage flicker. Thus, it is necessary to measure voltage flicker parameters in the power grid and evaluate them for designing suitable control devices to eliminate voltage flicker. Up to now, many techniques have been presented for digital analysis of voltage flicker parameters. Some of these techniques are listed as follows:
1. Techniques based on fast Fourier transform (FFT) [1,2].
2. Kalman Filtering technique [3, 4]
3. Wavelet transforms technique [7, 8]
4. Least Absolute Value state estimation technique (LAV), [6]

The conventional techniques have some deficiencies. Main disadvantage of applying either FFT or FFT prune techniques is the assumption of stationary signals. The application of such algorithms on non-stationary signals may lead to inaccurate results. Kalman filtering technique is a difficult method because of its large mathematical burden and needs to accurate adjustment for its parameters. The wavelet transform method involves computational complexity and it has difficult process of choosing the candidate wavelet. The main disadvantage of the LAV state estimation technique is the assumption of knowing the flicker frequency in advance, which is not a realistic assumption. Moreover, it has slow convergence, which makes this algorithm not attractive for on-line tracking and implementation.

This paper presents two new methods for measuring flicker signals magnitude and frequency. For this aim, the methods based on SFLA and ICA optimization techniques are used. The goal is to minimize the error in estimated parameters. The proposed methods are tested with a flicker signal and the ability of these methods to measure the flicker magnitude and frequency is verified. At the end, these two methods are compared.

2. VOLTAGE FLICKER MODEL

Mathematically, voltage flicker signal is shown as follows [2, 5]:

\[
V(t) = A_0 + \sum_{i=1}^{m} A_{fi} \cos(w_{fi}t) + \phi_{fi}) \cos(w_0t + \phi_0) 
\]

Where \(V(t)\) is the instantaneous voltage magnitude at time \(t\), \(A_0\) is the fundamental voltage amplitude, \(w_0\) the power frequency, \(\phi_0\) the phase angle of fundamental voltage, \(A_{fi}\) the amplitude of voltage flicker, \(w_{fi}\) the frequency of voltage flicker, \(\phi_{fi}\) the phase angle of voltage flicker and \(m\) is the number of flicker modes.

In Eq. (1), the power frequency \(w_0\) is known, the problem is to estimate \(A_0, A_{fi}, w_{fi}, \phi_0, \phi_{fi}\) with proposed methods. In general, Eq. (1) is written as:

\[
Z(t) = F(t, x) + e(t) 
\]

Where \(Z(t)\) is the measurement \(N*1\) matrix. This matrix is given by measurement of digital signal samples with a suitable sampling frequency. \(F(t, x)\) is the \(N*1\) information matrix given by Eq. (1) and is the function of time \(t\) and unknown variables. \(e(t)\) is the \(N*1\) error matrix associated with the estimation of unknowns \(x\). The error at each time step is calculated by:

\[
e_i(t) = V_{i\text{ actual}}(t) - V_{i\text{ calculated}}(t) 
\]
fundamental voltage amplitude, flicker amplitude, frequency and phase angle. The goal is to minimize the error between actual voltage and calculated voltage by accurately estimating the optimum value of unknowns of the voltage flicker equation.

3. A REVIEW OF SFLA AND ICA ALGORITHMS

3.1 SFLA algorithm [9]

A mimetic meta-heuristic called the shuffled frog-leaping algorithm (SFLA) has been developed for solving combinatorial optimization problems. The SFLA is a population-based cooperative search inspired by natural behavior of a group of frogs when seeking for the location that has the maximum amount of available food. The algorithm contains elements of local search and global information exchange. At first, an initial population of N frogs is created randomly. Then the frogs are sorted in a descending order according to their fitness. Then, the frogs divided into “m” memeplexes in such a way that the first frog goes to the first memeplex, the second frog goes to the second memeplex, the m\(^{th}\) frog goes to the m\(^{th}\) memeplex and the (m+1)\(^{th}\) frog goes back to the first memeplex. This algorithm continues until N\(^{th}\) frog. The SFLA performs simultaneously an independent local search in each memeplex using a particle swarm optimization like method. Within each memeplex, the frogs with the best and worst fitness are identified. During each memeplex evolution, the worst frog leaps toward the best frog. The position of the worst frog in each memeplex is updated as follows:

\[ D = r \left( x_b - x_w \right) \]  (4)

\[ x_w(\text{new}) = x_w + D, \left( |D| < D_{\text{max}} \right) \]  (5)

Where “r” is a random number between 0 and 1, \( x_b \) and \( x_w \) are position of the frogs with best and worst fitness respectively and \( D_{\text{max}} \) is the maximum allowed change of frog’s position in one jump. After a defined number of memeplex evolution steps, the virtual frogs are shuffled and reorganized into new memeplexes. To provide the opportunity for random generation of improved information, random virtual frogs are generated and substituted in the population if the local search cannot find better solutions. The flowchart of SFLA is showed in figure (1).

3.2 ICA algorithm [10]

Imperialist competitive algorithm is an evolutionary algorithm for the optimization problems, which is inspired by imperialistic competition of the countries of the world. Like other evolutionary algorithms, ICA starts with an initial population (countries in the world). Some of the best countries in the population are selected to be the imperialists and the rest, forms the colonies of these imperialists. All the colonies are divided among the imperialists based on their power, which is inversely proportional to colonies costs. Afterwards these colonies start moving toward their relevant imperialist country by \( x \) units.\( x \) is a random variable with uniform (or any proper distribution). Thus, \( x \) is as follows:

\[ x \sim U(0, \beta * d) \]  (6)

Where \( \beta \) is a number greater than 1 and \( d \) is the distance between colony and imperialist. The direction of the movement is the vector from colony to the imperialist. The total power of an empire depends on
both the power of the imperialist country and the power of its colonies. We will model this fact by defining the total power of an empire by the power of imperialist country plus a percentage of mean power of its colonies. Then the imperialistic competition begins among all the empires.

![](image)

**Fig.1. Flowchart of SFLA algorithm**

Any empire that is not able to succeed in this competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of powerful empires and a decrease in the power of weaker ones. Weak empires will lose their power and ultimately they will collapse. The movement of colonies toward their relevant imperialists along with competition among empires and the collapse mechanism will hopefully cause all the countries to converge to a state in which there exist just one empire in the world and all the other countries are colonies of that empire. In this ideal new world, colonies have the same position and power as the imperialist. The best country in this world is the optimum response. The flowchart of ICA is shown in figure (2).

Total cost of an empire computes as follows:

\[
T.C_n = \text{Cost(imperialist}_n) + \xi \times \text{mean(Cost(colonies of empire}_n))
\]  
(7)

Where \(T.C_n\) is the total cost of \(n^{th}\) empire and \(\xi\) is a positive number which is considered to be less than 1. A little value for \(\xi\) causes the total power of the empire to be determined by just the imperialist and increasing it will increase the role of the colonies in determining the total power of an empire. In this paper, the value of 0.1 for \(\xi\) is used. We model imperialistic competition by just picking some (usually one) of the weakest colonies of the weakest empires and giving them (that) to an empire that have most chance to possess these (this) colonies. Based on their total power, in this competition, each of empires will have a chance to take possession of the mentioned colonies. To start the competition, first, we find the possession probability of each empire based on its total power. The normalized total cost is simply obtained by Eq. (8):
Where $T.C_n$ and $N.T.C_n$ are respectively total cost and normalized total cost of $n^{th}$ empire. The possession probability of each empire is given by:

$$p_{p_n} = \frac{N.T.C_n}{\sum_{i=1}^{N_{imp}} N.T.C_i}$$

(9)

To divide the mentioned colonies among empires based on the possession probability of them, we form the vector $P$ as follows:

$$P = [p_{p_1}, p_{p_2}, p_{p_3}, \ldots, p_{p_{N_{imp}}}]$$

(10)

Then we create a vector with the same size as $P$ whose elements are uniformly distributed random numbers.

$$R = [r_1, r_2, r_3, \ldots, r_{N_{imp}}]$$

(11)

where $r_1, r_2, r_3, \ldots, r_{N_{imp}} \sim U(0,1)$

Then we have $D$ vector as follows:

$$D = P - R = [D_1, D_2, D_3, \ldots, D_{N_{imp}}]$$

$$= [p_{p_1} - r_1, p_{p_2} - r_2, \ldots, p_{p_{N_{imp}}} - r_{N_{imp}}]$$

(12)

The mentioned colonies will be given to an empire whose relevant index in $D$ is maximum.

3.3 Fitness function

Fitness function is responsible for evaluation of the solution at each step. For reaching to the minimum error ($e_i$), we should consider a suitable fitness function.
for these optimization algorithms. The fitness function that is used in this paper is given in Eq.(8):

\[
SS = \frac{\sum_{i=1}^{N} e_i(t)^2}{N}
\]

(13)

Where \( e_i \) is calculated by Eq. (3) and \( N \) is the number of samples. To reach to optimum estimates of flicker parameters, we should minimize \( SS \) with SFLA and ICA methods.

4. RESULTS

4.1 Case study one

We consider a sample voltage flicker model according to Eq. (14) to test proposed methods:

\[
V(t) = [1 + 0.1 \cos(2\pi 5t)] \cos(2\pi 50t)
\]

(14)

Where \( v_0(t) = 1 * \cos(2\pi 50t) \) is the carrier signal and \( v_1(t) = 0.1 * \cos(2\pi 5t) \cos(2\pi 50t) \) is voltage flicker.

<table>
<thead>
<tr>
<th>Optimization Algorithm</th>
<th>( A_0 )</th>
<th>( A_{f1} )</th>
<th>( w_{f1} )</th>
<th>Run time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SFLA</td>
<td>0.9501</td>
<td>0.1489</td>
<td>8.80</td>
<td>61</td>
</tr>
<tr>
<td>ICA</td>
<td>0.95</td>
<td>0.15</td>
<td>8.8</td>
<td>6.8</td>
</tr>
</tbody>
</table>

4.2 Case study two

\[
V(t) = [0.95 + 0.15 \cos(2\pi 8.8t)] \cos(2\pi 50t)
\]

(15)

The number of samples is 50 and sampling frequency is 200Hz. Proposed methods are applied to this sample voltage signal. The results are given in table (2):

As it is seen from tables (1) and (2), proposed methods estimates unknown parameters of voltage flicker with error less than 1\%. With the same number of samples, Shuffled Frog Leaping Algorithm estimates fundamental voltage amplitude and flicker amplitude and frequency in about 6.6 seconds, but Imperialist Competitive Algorithm estimates those parameters in about 7 seconds. So Imperialist Competitive Algorithm convergence to the optimum
parameters very faster than Shuffled Frog Leaping Algorithm.

These two optimization methods have excellent results for the flicker parameters estimation problem when the number of samples is more than 20 and sampling frequency is more than 100Hz. With increasing the number of samples and sampling frequency, SFLA and ICA gives best results for this problem.

Imperialist Competitive Algorithm results is better than Shuffled Frog Leaping Algorithm, as the flicker parameters estimation error in ICA technique is about zero (based on the number of samples and sampling frequency and the number of imperialists and colonies, it may have slightly error but it is less than 0.5% ).

5. CONCLUSIONS

Two new methods for measurement of flicker signal parameters (magnitudes and frequencies) are proposed in this paper. These proposed approaches estimates fundamental voltage amplitude and flicker amplitude and frequency with high accuracy. The proposed algorithms are tested with two sample voltage flicker signals and the results are presented. In addition, these two methods are compared and the effect of the number of samples and sampling frequency has analyzed. The results verify high efficiency of Shuffled Frog Leaping Algorithm (SFLA) and Imperialist Competitive Algorithm (ICA) in estimating of voltage flicker parameters.

REFERENCES


The Intelligent Modeling of Human Hand Motion Using Magnetic Based Techniques

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ABSTRACT
With increasing use of robots instead of human in industrial, medicine and military applications etc. the importance of research on designing and building of robots is increasing. In this paper various methods of the human hand motion simulation has been investigated and we used one of most common method named Data-gloves which extract data from hand and then we simulated hand motion during several processing stages. At first step we designed and built circuits to digitize analog data received from sensors and we sent them to computer. Then we received extracted data in MATLAB and processed them to simulate bending of the wrist and fingers joints graphically. In this method we mapped data linearly to 0-90 and rotate points around relative Coordinate axis in the specific conditions. Results show that we can simulate hand motion in real time with low cost, lowest error and without complex and expensive equipments.

KEYWORDS: Hand motion simulation, Data-Glove, Data extraction circuit, simulation in MATLAB.

1. INTRODUCTION
Nowadays using robots to replace human resources is widely used. Sometimes the robots are pre-programmed to perform specific and common tasks. But in some conditions such as critical tasks, unpredictable environment and complex situations the human role and his so fast dissension making cannot be completely eliminated and his direct and continuous control is necessary. Then we need some kind of robots that imitate human motion. Considering the importance of simulation, so many ways is presented to simulate human motion. The main difference in the simulation models is due to differences in methods of data extraction. Different data extraction techniques can be grouped into three general approaches: Data extraction by data gloves - Data extraction by image processing - Data extraction from electromyogram signals. Here we describe these methods more detailed.
2. VARIETY OF DATA EXTRACTION METHODS FOR HAND SIMULATION

2.1. Data extraction by Data-Glove

Data-Glove is made of many sensors to digitize hand motion and provides more natural relationship between man and robot [1]. In comparison with other input devices such as keyboard, mouse and joystick it provides more detailed and complex information. Data-Gloves are known with commercial brands such as Sayre Glove, MIT LED Glove, Digital Data-Entry Glove, Data-Glove, Dexterous Hand-Master, Power Glove, Cyber Glove, VPL Glove and Space Glove [2]. There are different types of Data-gloves and in this paper we point out to some of most important types of them. One of the most common type of Data-gloves are the gloves that use variable resistance to bending (strain gauge). Tekscan[3] company has made a combination of strain gauge sensors with linear output to detect amount of the fingers bends. Thus using neural networks and other methods for linearization of nonlinear data is not needed.

In other types of Data-Gloves the infrared transmitter receiver sensors are used to detect bending of the fingers (Fig. 2) [1]. In these sensors transmitter is connected to receiver through a pipe which is route of the infrared waves. These sensors are placed in the joints of the Data-glove fingers and with bending of the joints pipe bends. Infrared transmission path are changed and therefore it will cause decreasing received infrared waves in receiver.

These data are non-linear so in several calibration steps and using neural networks they are converted to linear data. In other types of Data-Gloves the sensors composed of orthogonal coils are used [4]. In this method one of the coils as a transmitter is located on the hand and six of them are used as receiver are located on the fingertips and wrist (Fig. 3). Against previous methods, instead of measuring bending of the joints, hand motion detection is done with finding of position of fingertips.

These data are non-linear so in several calibration steps and using neural networks they are converted to linear data. In other types of Data-Gloves the sensors composed of orthogonal coils are used [4]. In this method one of the coils as a transmitter is located on the hand and six of them are used as receiver are located on the fingertips and wrist (Fig. 3).

![Fig. 1. Strain gauge sensors with linear output](image-url)
Against previous methods, instead of measuring bending of the joints, hand motion detection is done with finding of position of fingertips. In this method processing unit provides electromagnetic waves in environment by transmitter sensor that cases magnetic induction in receiver sensors. Processing unit with measuring this induction in receiver sensors and processing them, can identify position and rotation of the fingertips.

2.2. Data extraction by image processing

In this method, by using a camera, various parameters of hand are investigated. In this model based on the various factors hand motion is detected. A method for detecting motions is based on the reorganization of the edges [5]. In this method a classifier named Haar is trained during a relatively long time. This classifier classifies the extracted data and using Adaboost algorithm in Matlab during five image processing stages, image edges are detected and virtual hand is controlled (Fig. 4).

2.3. Data extraction by electromyogram signals

In this method the nerve signals of brain is used to control the robot [8][9][10][11][12][13]. As shown in Fig.6 (a) and Fig.6 (b), in this method electromyogram signals sent by the brain is
received by sensors. Received signals were processed and various characteristics such as frequency, power, energy, Fourier series coefficients or a combination of them, etc. for identifying the type, pressure and direction of motion is extracted from marrow. Then the extracted information is classified and will be sent to the controller for controlling an artificial organ. Finally by the user visual feedback can be more carefully controlled artificial organs. Above steps briefly is shown in Fig. 7.

![Fig. 5. Marker-settings for hand movements][6]

![Fig. 6(a). Surface EMG sensors][7]

![Fig. 6(b). Revised EMG signals][8]

![Fig. 7. Block diagram of the cybernetic hand control mechanism][9]

3. PRESENTED SIMULATION

3.1. Data extraction and sending to computer

Simulation performed by us is based on Data-gloves using sensors varies with the bending (strain gauge) with a linear output and large resistance range. In this paper, we measured and simulated the bending of the 7 joints of hand. Therefore 7 sensors are embedded in the specified locations. The strain gauge sensor output voltage is very small therefore; by the circuit shown in fig. 8 we mapped output voltage range of strain gauge sensors to the range of 0-5 volts. In this circuit $R_2=R_{12}=10K, V_x=4.21, R_2/R_{11}=1.25$ and $R_1=24k$ [14]. As shown in fig. 8, sensors No. 1, 2, 3 and 4 are measuring the bending of the index, middle and ring fingers around the x axis and No. 7 sensor measuring the bending of...
the wrist around the x axis and No. 5,6 sensors are measuring the bending of the Thumb around the y and z axis. Then the analog extracted data is converted to digital data by the Atmega32 microcontroller that sampling rate is selected to be 172.688 KHz. In next step digital data must be sent to the computer. Therefore they are placed in UDR register and the start, parity and stop bits are added to them and data is send from Atmega32 as asynchronous in 9600 bond rates. In order to send data can be used in the computer we use the MAX232chip and its output is sent to COM port of the computer by RS232 interface. Related circuit to the extraction, digitization, sending and conversion to computer-usable data for one sensor is shown in Fig.9.

![Fig.8. Positions of the sensors on the data glove](image)

3.2. Receiving data in MATLAB

At this stage we will receive data sent from the circuit in MATLAB [15][16][17]. And with processing the data a virtual hand is controlled according to the received data. As mentioned digital data from seven sensors installed on the Data-glove will be sent to the computer and these data are stored in a 1*7 matrix. Members of this matrix are the numbers in the range of 0-5 volts [14]. Since the bending angle of the virtual hand joints should be in the range 0-90 degrees thus, we linearly map the received data to 0-90.

3.3. Rotation one point around another point

For rotation the P point with coordinates \([x \ (2) \ y \ (2) \ z \ (2) \ 1]\) around the axis of coordinates x, y or z to size 0, coordinates of P point must be multiplied respectively to the matrix of Rx, Ry or Rz. For example, rotation around x axis is as follows:
M. Asghari, M. A. Badamchizadeh, M. E. Akbari: The Intelligent Modeling of Human Hand Motion Using …

**Fig. 10.** P point rotation around x axis

\[
R_x = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & \cos \Theta & -\sin \Theta & 0 \\
0 & \sin \Theta & \cos \Theta & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
R_y = \begin{bmatrix}
\cos \Theta & 0 & \sin \Theta & 0 \\
0 & 1 & 0 & 0 \\
-\sin \Theta & 0 & \cos \Theta & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
R_z = \begin{bmatrix}
\cos \Theta & -\sin \Theta & 0 & 0 \\
\sin \Theta & \cos \Theta & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
\begin{align*}
[X_{\text{new}}(2) & \ Y_{\text{new}}(2) \ Z_{\text{new}}(2) \ 1] \\
= & \begin{bmatrix}
1 & 0 & 0 & -X(1) \\
0 & 1 & 0 & -Y(1) \\
0 & 0 & 1 & -Z(1) \\
0 & 0 & 0 & 1
\end{bmatrix}
\end{align*}
\]

But for rotation P point around transmitted x axis to O = [x (1) y (1) z (1) 1] point, we perform as follows:

**Fig. 11.** rotation P point around transmitted x axis to O point

\[
M = \begin{bmatrix}
1 & 0 & 0 & -X(1) \\
0 & 1 & 0 & -Y(1) \\
0 & 0 & 1 & -Z(1) \\
0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
[X_{\text{new}}(2) \ Y_{\text{new}}(2) \ Z_{\text{new}}(2) \ 1] = \left( \text{Inv}(M) \right) * R_x * M \\
* \begin{bmatrix}
X(2) & Y(2) & Z(2) & 1
\end{bmatrix}
\]

First, to hand graphical simulation we define the points and to build base state for four fingers virtual hand we connect the points to each other as shown in fig.12. Bending angle of the Joints in the Ground state is 0 degree.

Considering the relations mentioned in rotation one point around another point, the manner and amount of the bending of the joints in the simulation can be described as follows: point No.1 rotation around point No.2 along the x axis indicates joints bending in point No.2 and Rotation Point.

**Fig. 12.** Virtual hand in base position

No. 1 and 2 around point No.3 indicate joints bending in point No.3. Thus, with mapping values from sensors to the angles and assigning these angles to amount of point's rotation, the joints bending of the visual hand is controlled. It is obvious when a point is rotated, also dependent points to rotated point must be rotated. Otherwise length of rotated finger will change and the
simulation will be incorrect. For example, when the virtual hand is bent at point No.10 all other points must also be rotated around the point No.10. Summarizes of all needed steps to simulation are shown in fig 13. Some states of the simulated virtual hand are shown in fig.14.

4. CONCLUSIONS

In this paper, using sensors variable with bending, bending of the user’s fingers measured. After digitization of analog extracted data and sending them to the computer, in MATLAB they were mapped to the range 0-90 degrees. Then by the related relations in rotation one point around another point we simulated and controlled the motion of the virtual hand. According to the results observed that virtual hand quickly, smoothly and carefully repeats hand motion of the user. In the future we will simulate hand motion in

all degrees of freedom by our method and also using electromyogram waves and we will extend it to simulate all movement parts of body.

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FACTS Control Parameters Identification for Enhancement of Power System Stability

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ABSTRACT
The aim of this paper is to investigate a novel approach for output feedback damping controller design of STATCOM in order to enhance the damping of power system low frequency oscillations (LFO). The design of output feedback controller is considered as an optimization problem according with the time domain-based objective function which is solved by a honey bee mating optimization algorithm (HBMO) that has a strong ability to find the most optimistic results. The effectiveness of the proposed controller are tested and demonstrated through nonlinear time-domain simulation studies over a wide range of loading conditions. The simulation study shows that the designed controller by HBMO has a strong ability to damping of power system low frequency oscillations. Moreover, the system performance analysis under different operating conditions show that the $\varphi$ based controller is superior to the $C$ based controller.

KEYWORDS: FACTS, STATCOM, Honey Bee Mating Optimization, Damping Controller, Low Frequency Oscillations, Power System, Dynamic Stability

1. INTRODUCTION

One of the most important aspects in electric system operation is stability of power systems. By the development of interconnection of large electric power systems, low frequency oscillations have become a serious problem in power system. This oscillation occur as result of a sudden increase in the load, loss of one generator or switching out of a transmission line during a fault [1]. Once started, they would continue a long period of time. In some cases, they continue to grow, causing system separation if no adequate damping is available. In recent years, flexible AC transmission system (FACTS) devices are one of the most effective ways to improve power system operation controllability and power transfer limits. Through the modulation of bus voltage, phase shift between buses, and transmission line reactance, FACTS devices can cause a substantial increase in power transfer limits during steady-state [2]. These devices are addition to normally steady-state control of a power system but, due to their fast response, FACTS can also be used for power system stability enhancement through improved damping of power swings [3]. The real power flow with primary function of FACTS devices, can be
regulated to reduce the low frequency oscillation and enhance power system stability. Static synchronous compensator (STATCOM) is a member of FACTS family that is connected in shunt with the system. From the power system dynamic stability viewpoint, the STATCOM provides better damping characteristics than the SVC as it is able to transiently exchange reactive power with the system, so it can improve oscillation stability better than SVC[4], because of it’s greater reactive current output capability at depressed voltage, faster response, better control stability, lower harmonics and smaller size, etc[5]. The STATCOM is based on the principle that a voltage-source inverter generates a controllable AC voltage source behind a transformer-leakage reactance so that the voltage difference across the reactance produces active and reactive power exchange between the STATCOM and the transmission network. Several trials have been reported in the literature to dynamic models of STATCOM in order to design suitable controllers for power flow, voltage and damping controls [6]. Wang [7] established the linearized Phillips-Heffron model of a power system installed with a STATCOM and demonstrated the application of the model in analyzing the damping effect of the STATCOM. Further, no effort seems to have been made to identify the most suitable STATCOM control parameter, in order to arrive at a robust damping controller. Intelligent controllers have the potential to overcome the above mentioned problems. Fuzzy-logic-based controllers have, for example, been used for controlling a STATCOM [8].

The performance of such controllers can further be improved by adaptively updating their parameters. Also, although using the robust control methods[9], the uncertainties are directly introduced to the synthesis, but due to the large model order of power systems the order resulting controller will be very large in general, which is not feasible because of the computational economical difficulties in implementing. In general, for the simplicity of practical implementation of the controllers, output feedback controller with feedback signals available at the location of the each controlled device is most favourable[10,11]. HBMO algorithm can be used to solve many of the same kinds of problems as GA[8] and does not suffer from of GA’s difficulties. The honey bee is one of the social insects that can just survive as a member of colony. The activity of honey bee suggests many characteristics like together working and communication.

In this paper, the optimal tuning of the output feedback gains for the STATCOM based damping controller is considered as an optimization problem and HBMO technique is used for searching optimized parameters. The effectiveness and robustness of the proposed controller is demonstrated through the eigenvalue analysis ,nonlinear time-domain simulation studies to damping low frequency oscillations under different operating conditions and network structure. Results evaluation show that the HBMO based tuned damping controller achieves good performance for a wide range of operating conditions, and the $\phi$ based controller is superior to the C based controller.

### 2. Honey Bee Mating Optimization

The honey bee is one of the social insects that can just survive as a member of colony. The activity of honey bee suggests
many characteristics like together working and communication. A honey bee colony normally includes a single egg-laying queen with which it’s life-span is more than other bees; that with depend upon that seasons usually have more than 60,000 workers or more. A colony may contain a queen during it’s life-cycle. That is named monogynous one. Only the queen is fed by “royal jelly.” “Nurse bee” take care of this gland and feed it to queen. The royal jelly causes the queen bee biggest bee in the hive. Several hundred drones live with queen and its workers. Queen bee life-span is about 5 or 6 years, whereas rest of the bees, specially worker bees, oven their period of living do not reach to 1 year. The drones die after mating process.

The drones act in father function in the colony, that are haploid and amplify or multiply their mother’s genome without changing their genetics combinations, but mutation. So, drones are agents that anticipate one of the mother’s gametes and by the sake of that female can do genetically like males. Broods, that be cared by workers, improve from fertilized or unfertilized eggs. They represent potential queens and prospective drones respectively. In marriage process, the queens in mating period, their mate flight of the nest to the far places.

Insemination ends with the gradual death of drones, and by the sake of that queens receive the “mating sign.” Any drone can take part in mating process just one time, but the queens mate several times. These features make bee mating very interesting among insects. A drone mates with a queen probabilistically using an annealing function like this:

\[ \text{Prob}(D,Q) = \exp(-\Delta f / S(t)) \]  

Where \( \text{Prob}(D,Q) \) is probability of adding drone’s sperm D to queen’s spermatheca \( Q \), \( \Delta(f) \) is perfect difference of fitness D and queen, and \( S(t) \) is speed of the queen at time t. The mating is high either when queen’s speed level is high, or when drone’s fitness is equal with queen’s. After every transition, speed of queen will decrease according to the following equations:

\[ s(t+1) = \alpha \times s(t) \]  
\[ E(t+1) = E(t) - \gamma \]

Where: \( \alpha \) is a factor \( \epsilon(0,1) \) and \( \gamma \) is the amount of energy, \( E(t) \) reduction after each transition. The algorithm starts with three user-defined parameters and one predefined parameter. The predefined parameter is the number of workers \( W \), representing the number of heuristics encoded in the program. The three user-defined parameters are the number of queens, the queen’s spermatheca size representing the maximum number of mating per queen in a single mating flight, and the number of broods that will be born by all queens. The energy and speed of each queen at the start of each mating flight is initialized at random. A number of mating flights are realized. At the commence of a mating flight, drones are generated randomly and the queen selects a drone using the probabilistic rule in Eq. (1). If mating done successfully, storing of drone’s sperm in queen’s spermatheca occur. using of combination of drone’s and queen’s genotaypes, generate a new brood, which can be improved later by employing workers to conduct local search. Main difference (or one of them) HBMO algorithm from classic evolutionary algorithms that is storing of many different
drone’s sperm in spermatheca by queen cause which the queen use of them to create new solution for fittest of broods, which gives the possibility to have fittest broods more. The rule of workers is brood caring and for the sake of that they are not separated of population and used to grow the broods that produced by queen. Every worker has different capability for production in solutions

3. POWER SYSTEM MODELING

A single machine infinite bus power (SMIB) system installed with a STATCOM in Figure 1 is adopted in this paper to demonstrate the proposed method. The synchronous generator is delivering power to the infinite-bus through a double circuit transmission line and a STATCOM. The system data is given in the Appendix. The system consists of a step down transformer (SDT) with a leakage reactance XSDT, a three phase GTO-based voltage source converter, and a dc capacitor [7].

![Fig. 1. SMIB power system equipped with STATCOM](image)

The VSC generates a controllable AC voltage source behind the leakage reactance. The voltage difference between the STATCOM bus AC voltage, \( V_{L(t)} \) and \( V_{0(t)} \) produces active and reactive power exchange between the STATCOM and the power system, which can be controlled by adjusting the magnitude \( V_0 \) and the phase \( \phi \).

The dynamic relation between the capacitor voltage and current in the STATCOM circuit are expressed as [7]:

\[
\bar{I}_{Lo} = I_{Lo_d} + jI_{Lo_q} \tag{4}
\]

\[
V_o = cV_{dc} (\cos \phi + j \sin \phi) = cV_{dc} \angle \phi \tag{5}
\]

\[
V'_{dc} = \frac{I_{dc}}{C_{dc}} = \frac{c}{C_{dc}} (I_{Lo_d} \cos \phi + I_{Lo_q} \sin \phi) \tag{6}
\]

Where for the PWM inverter \( c = mk \) and \( k \) is the ratio between AC and DC voltage depending on the inverter structure, \( m \) is the modulation ratio defined by the PWM and the phase \( c \) is also defined by the PWM. The \( C_{dc} \) is the dc capacitor value and \( I_{dc} \) is the capacitor current while \( i_{Lo_d} \) and \( i_{Lo_q} \) are the d-and q-components of the STATCOM current, respectively.

The dynamics of the generator and the excitation system are expressed through a third order model given as[7, 8]:

\[
\delta = \omega_s (\omega - 1) \tag{7}
\]

\[
\omega = (P_m - P_e - D \Delta \omega) / M \tag{8}
\]

\[
E'_{s} = (-E_{s} + E_{d})/T_{\omega} \tag{9}
\]

\[
E_{d} = (-E_{d} + K_f (V_{set} - V_{s})) / T_{\omega} \tag{10}
\]

The expressions for the power output, terminal voltage, and the d-q axes currents in the transmission line and STATCOM, respectively, are:

\[
I_{\omega_d} = \frac{(1 + \frac{X_{lb}}{X_{sof}})X_{lb}}{X_{sof}} \frac{mV_{dc} \sin \phi - V_{s} \cos \phi}{X_{d} + X_{lb} + \frac{X_{d}}{X_{lb}} (1 + \frac{X_{lb}}{X_{sof}}) x_{q}'} \tag{11}
\]

\[
I_{\omega_q} = \frac{\frac{X_{lb}}{X_{sof}} mV_{dc} \cos \phi + V_{s} \sin \phi}{X_{d} + X_{lb} + \frac{X_{d}}{X_{lb}} (1 + \frac{X_{lb}}{X_{sof}}) x_{q}} \tag{12}
\]
\[ I_{los} = \frac{\epsilon' - (x'_d + X_d)I_{d} - mV_p \sin \phi}{X_{s0}} \]  
\[ I_{los} = \frac{mV_p \cos \phi - (x'_d + X_d)I_{d}}{X_{s0}} \]  
\[ X_d = X_T + \frac{X_l}{2}; \quad X_{lb} = \frac{X_l}{2} \]

Where: \( X_T, x'_d \) and \( x_q \) are the transmission line reactance, d-axis transient reactance, and q-axis reactance, respectively. The linearized model of this case is given in [8].

### 4. OUTPUT FEEDBACK DAMPING CONTROLLER

A power system can be described by a Linear Time Invariant (LTI) state space model as follows [12]:

\[ \dot{x} = Ax + Bu \]
\[ y = Cx \]

Where \( x, y \) and \( u \) denote the system linearized state, output and input variable vectors, respectively. \( A, B \) and \( C \) are constant matrixes with appropriate dimensions which are dependent on the operating point of the system. The system modes define the stability of the system when it is affected by a small interruption. As long as all eigenvalues have negative real parts, the power system is stable when it is subjected to a small disturbance. An output feedback controller has the following structures [13]:

\[ u = -G y \]

Substituting (18) into (16) the resulting state equation is:

\[ \dot{x} = A_c x \]

Where, \( A_c \) is the closed-loop state matrix and is given by:

\[ A_c = A - B G C \]

Only the local and available state variables \( \Delta \omega, \Delta P_e \) and \( \Delta V_t \) are taken as the input signals of each controller, so the implementation of the designed stabilizers becomes more feasible. By properly choosing the feedback gain \( G \), the eigenvalues of closed-loop matrix \( AC \) are moved to the left-hand side of the complex plane and the desired performance of controller can be achieved [5].

#### 4.1 HBMO-Based output feedback damping controller design

Two control parameters of the STATCOM (\( \phi \) and \( C \)) are to modulation in order to produce the damping torque. The two control parameters of the STATCOM (\( \phi \) and \( C \)) modulated in order to produce the damping torque. Since the selection of the output feedback gains for mentioned STATCOM based damping controller is a complex optimization problem. Thus, to acquire an optimal combination, this paper employs HBMO to improve optimization synthesis and find the global optimum value of objective function. In this study, an Integral of Time multiplied Absolute value of the Error (ITAE) is taken as the objective function. For our optimization problem, objective function is time domain-based objective function:

\[ J = \sum_{i=1}^{N_p} \int_{0}^{t_{sim}} \left| \Delta \omega \right| dt \]

Where, the \( t_{sim} \) is the time range of simulation and \( N_p \) is the total number of operating points for which the optimization is carried out. The design problem can be formulated as the following constrained optimization problem, where the constraints are the controller parameters bounds:
Minimize $J$ Subject to:

$$G_1^{\text{min}} \leq G_1 \leq G_1^{\text{max}}$$

$$G_2^{\text{min}} \leq G_2 \leq G_2^{\text{max}}$$

$$G_3^{\text{min}} \leq G_3 \leq G_3^{\text{max}}$$

The proposed approach employs HBMO to solve this optimization problem and search for an optimal set of controller parameters. The optimization of controller parameters is carried out by evaluating the objective function as given in equation (21), which considers a multiple of operating conditions. The operating conditions are given in Table 1.

<table>
<thead>
<tr>
<th>Loading conditions</th>
<th>$P_e$(pu)</th>
<th>$Q_e$(pu)</th>
<th>$X_L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>nominal</td>
<td>0.8</td>
<td>0.15</td>
<td>0.3</td>
</tr>
<tr>
<td>light</td>
<td>0.2</td>
<td>0.01</td>
<td>0.3</td>
</tr>
<tr>
<td>heavy</td>
<td>1.2</td>
<td>0.4</td>
<td>0.3</td>
</tr>
</tbody>
</table>

In order to acquire better performance, size of spermatheca, number of variables, maximum number of mating flight, $N_{\text{queen}}$, $N_{\text{brood}}$ and $N_{\text{workers}}$ is chosen as 50, 5, 30, 1, 50 and 1000, respectively. The final values of the optimized parameters with objective function, $J$, are given in Table 2.

<table>
<thead>
<tr>
<th>Optimized Parameter</th>
<th>$C$</th>
<th>$\varphi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_1$</td>
<td>195.69</td>
<td>118.44</td>
</tr>
<tr>
<td>$G_2$</td>
<td>2.9721</td>
<td>1.4633</td>
</tr>
<tr>
<td>$G_3$</td>
<td>1.7249</td>
<td>1.6796</td>
</tr>
</tbody>
</table>

5. NONLINEAR TIME-DOMAIN SIMULATION RESULTS

In this section, the performance of the proposed controller under transient conditions is verified by applying a small disturbance of 0.2 pu input torque is applied to the machine at $t = 1$ sec. The study is performed at three different operating conditions. The results are shown in Figures 2 and 3. It is also clear from the figures that the first swing stability is greatly improved with the coordinated design approach. The time domain simulation was performed and the consequent results reveal the suitable damping function of the HBMO based designed controller.
6. CONCLUSIONS

The honey bee mating optimization (HBMO) algorithm has been successfully applied to the optimal designing of the STATCOM with output feedback damping controller. The design problem of the selecting output feedback is converted into an optimization problem which is solved by a HBMO technique with the time domain-based objective function. The robust design has been found to be very effective for a range of operating conditions of the power system. The effectiveness of the proposed STATCOM controllers for improving transient stability performance of a power system are demonstrated by a weakly connected example system subjected to severe disturbance. The nonlinear time-domain simulation results show the robustness of the proposed controller and their ability to provide good damping of low frequency oscillations. Moreover, the $\phi$-based stabilizer provides better damping characteristics and enhances greatly the first swing stability compared to the C-based stabilizer.

APPENDIX A

System Data

<table>
<thead>
<tr>
<th>Generator</th>
<th>$M=8MJ/MV$</th>
<th>$T_{d0} = 5.044$ s</th>
<th>$X_p = 1$ pu</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_q = 0.6$ p.u.</td>
<td>$X'_q = 0.3$ pu</td>
<td>$D = 0$</td>
<td></td>
</tr>
<tr>
<td>Excitation System</td>
<td>$K_s = 50$</td>
<td>$T_s = 0.05$ s</td>
<td></td>
</tr>
<tr>
<td>Transformers</td>
<td>$X_p = 0.1$ pu</td>
<td>$X_{S0} = 0.1$ pu</td>
<td></td>
</tr>
<tr>
<td>Transmission Line</td>
<td>$X_p = 0.4$ pu</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DC link Parameter</td>
<td>$V_{dc} = 1$ pu</td>
<td>$C_{dc} = 1$ pu</td>
<td></td>
</tr>
<tr>
<td>STATCOM Parameter</td>
<td>$C = 0.25$</td>
<td>$\phi = 52^\circ$</td>
<td></td>
</tr>
</tbody>
</table>

REFERENCES


A Novel Heuristic Optimization Methodology for Solving of Economic Dispatch Problems

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ABSTRACT
This paper presents a biogeography-based optimization (BBO) algorithm to solve the economic load dispatch (ELD) problem with generator constraints in thermal plants. The applied method can solve the ELD problem with constraints like transmission losses, ramp rate limits, and prohibited operating zones. Biogeography is the science of the geographical distribution of biological species. The models of biogeography explain how a organisms arises, immigrate from an environment to another and gets eliminated. The BBO has some characteristics that are shared with other population based optimization procedures, similar to genetic algorithms (GAs) and particle swarm optimization (PSO). The BBO algorithm mainly based on two steps: migration and mutation. The BBO has some good features in reaching to the global minimum in comparison to other evolutionary algorithms. This algorithm applied on two practical test systems that have six and fifteen thermal units, results of this paper are used to see the comparison between performances of the BBO algorithm with other existing algorithms. The result of this investigation proves the efficiency and good performance of applying BBO algorithm on ELD problem and show that this method can be a good substitute for other algorithms.

KEYWORDS: biogeography-based optimization, economic load dispatch, prohibited operating zone, ramp rate limits.

1. INTRODUCTION
Economic load dispatch is one of the important problems in power system. The purpose of economic load dispatch is to seek the best answer for minimizing total generation cost of power generation units because of increment of fossil fuel cost in thermal plants [1]. Until this moment various methods applied on ELD problem. Previously some traditional methods like Lagrangian multiplier [2] and lambda iteration method [3] have been applied to ELD problem but these methods were failed to solve the ELD problem because the characteristic of modern power plants is very nonlinear due to constraints like ramp rate limits, valve-point loadings, and multi-fuel options. However this problem should
be solve considering power demand, prohibited operated zones and transmission losses in practical systems thus conventional methods cannot reach to global optimum for obtaining minimum generation cost. For solving this problem Wood and Wollenberg introduced dynamic programming method but this method is not good for large systems because simulation time is increases with increasing of system size. Recently all of power system experts focused on artificial intelligence algorithms specially evolutionary algorithms like particle swarm optimization (PSO) [4], genetic algorithm (GA) [5], ant colony optimization (ACO), improved tabu search [6], and Clonal algorithm [7], simulated annealing (SA) [8], evolutionary programming (EP) [9] all of this algorithms applied on ELD problem successfully. All of these algorithms are classified as iterative algorithms and have some parameters that influence on quality of convergence. GA and SA used for solving ELD problem, GA is faster than SA because GA has parallel seek ability in comparison to SA. PSO method was invented in 1990, this method have less parameters than other high performance evolutionary algorithms therefore have high speed convergence. DE was invented by price and stone and it has three steps: selection, crossover and mutation. This method has high speed in finding global optimum but DE fail when the dimension of system increases.

Recently a new population based evolutionary algorithm has been invented by Simon, based on biogeography [10]. This has better properties than other evolutionary algorithms hence can be employing in power system optimization problems. Biogeography is way of natural for species distribution on the earth. In BBO algorithm a good solution for a problem considered as a habitat with high HSI and a poor solution considered as a habitat with low HSI. A good solution tends resist to any changes but a poor solution has a tendency to copy good properties from a good solution. Good properties remain in the high HSI habitat and at the same time appear in low HSI habitats as a new feature. This accepting of good features from good solutions may help the low HSI habitats to be a high HSI habitat. Similar to PSO and GA, BBO has the feature of sharing information between solutions. The BBO algorithm has some advantages in comparison to other algorithms. In BBO and PSO each solution stay survive to the end of optimization procedure but in most of evolutionary based algorithms, solutions die at the end of each generation. In some of evolutionary due to crossover step, good solutions lose their efficiency but in BBO don’t have crossover step [10].

The paper is organized as follows: Section 2 introduces the problem formulation. Section 3 then describes the BBO algorithm. Detailed process of using the BBO method to solve the ELD problems are presented in Section 4, Section 5 shows two application cases using the proposed method to solve the ELD problems and the results have been compared to recently published results and found to be superior.

2. FORMULATION OF ELD WITH GENERATOR CONSTRAINTS

The objective of ELD problem is minimizing total generation (fuel) cost in the power system so that reach to the best generation between power plants and
specially satisfying some practical constraints:

2.1 Power balance condition

\[ \sum_{i=1}^{m} P_i = P_D + P_L \]  

(1)

\[ P_L = \sum_{i=1}^{m} \sum_{j=1}^{m} P_i B_{ij} P_i + \sum_{i=1}^{m} B_{0i} P_i + B_{00} \]  

(2)

In (1) \( P_i \) is generation of each generator. The \( P_D \) is total power demand. \( P_L \) is transmission loss and can be expressed with B-coefficient matrix. Formula (1) means that all of generators in addition to provide power demand of consumers are responsible for providing transmission loss of lines.

2.2 Generator constraints

\[ P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}} \]  

(3)

Each generator has specific interval for power generation and cannot generate more or less than specified values.

2.3 Ramp rate limit limitations

a) If power generation increases

\[ P_i - P_i^{0} \leq UR_i \]  

(4)

b) If power generation decreases

\[ P_i^{0} - P_i \leq DR_i \]  

(5)

For each power plant, output power is limited to above constraints. Which \( UR_i \) is the up ramp limit of \( i \)th generator and \( DR_i \is the down ramp limit of the generator. With applying ramp rate limit constraints and generator constraints we can reach below formulation

\[ \text{Max}(P_i^{\text{min}}, P_{i0} - DR_i) \leq P_i \leq \text{Min}(P_i^{\text{max}}, P_{i0} + UR_i) \]  

(6)

2.4 Prohibited operating zones

The prohibited operating zones are the ranges confines of generator power that working in this range might create vibrations in turbine shaft and cause some detriments because of opening and closing of valves. Therefore, generators must avoid operation in these regions. If we consider prohibited operating zones constraints and generator limit constraints, we can assume that, practical formulations can provided as mentioned below:

\[ P_i^{\text{min}} \leq P_i \leq P_i^{l} \]

\[ P_{i,j-1}^{u} \leq P_i \leq P_{i,j}^{l} ; j = 2,3,\ldots,n_i \]  

(7)

\[ P_{i,n_i}^{u} \leq P_i \leq P_i^{\text{max}} \]

In above formula, \( j \) is number of prohibited operating zones of \( i \)th generator. \( P_{i,j-1}^{u} \) is the upper limit of \((j - 1)\)th prohibited operating zone of \( i \)th generator and \( P_{i,j}^{l} \) is the lower limit of \( j \)th prohibited operating zone of \( i \)th generator. \( n_i \) is the total number of prohibited operating zone of \( i \)th generator.

3. PROPOSED TECHNIQUE

3.1 Biogeography

Biogeography shows a model of migrating a type of living thing from an island to another. And it shows the overthrow and rise of living things in an environment [10]. Habitat is an island that is physically separated from other islands. a factor that is important for a habitats is HSI (habitat suitability index). This factor shows that how a habitat is suitable for living. The environment that is suitable for live has a high HSI and vice versa. Some
Factors can impress the quality and quantity of HSI and there are SIV (suitability index variable). These variables can regard as an independent variable and HSI can be calculated on the basis of SIV’s. Temperature, diversity of vegetation, rain downfall and etc are examples of SIV’s. Habitats that have high HSI can have large number of living things and habitats that have low HSI, have small number of living things [10]. Habitats with high HSI, because of their large number of creature, have many species that they can migrate to other habitats. Transferring creatures from one habitat to another is called emigration. The process of entering creatures to a habitat from another habitat is called immigration. Thus a habitat with high HSI has a high emigration rate and habitat with low HSI has high immigration rate. This immigration of creatures from high HSI habitats to low HSI habitats can enhance the HSI of this habitat because the HSI of habitat is directly proportional to creatures variety. Fig.1 gives a full model of immigration rate and emigration rate [10]. In the immigration figure we can see that maximum immigration rate occurred when there are no creatures in the habitat. If there are small numbers of creatures in the habitat, large number of living things can enter to the habitat and consequently immigration rate is high. When number of creatures in the habitat goes up and habitat becomes populated, small number of creatures can leave their own habitats and consequently emigration rate increases. The maximum emigration rate occurs when the number of creatures is $S_{\text{max}}$. In the figure 1 the immigration and emigration lines are in form of straight lines but these lines might be more complicated lines. Calculation of immigration an emigration values in BBO algorithm is so important. Immigration and emigration rate have a important role in selecting those SIV’s that migration process should be apply on them.

With regard to immigration and emigration diagrams in figure 1, we can extract the following formulas [10]:

$$\mu_k = \frac{Ek}{n} \quad (8)$$

$$\lambda_k = \hat{I}(1 - \frac{k}{n}) \quad (9)$$

Where $\mu_k$ is emigration rate for $k$ number of creatures and $\lambda_k$ is immigration rate for $k$ number of creatures.

If $E = \hat{I}$, with combining of (8) and (9) will results

$$\mu_k + \lambda_k = E \quad (10)$$

3.2 biogeography based optimization

This section refers to application of biogeography based optimization in solving problems and surveying different parts of this algorithm. The basis of BBO algorithm is based on two main parts: 1 – Migration

2 – Mutation

Migration

In BBO algorithm a population is selected as a solution. This solution can represent as
a vector of real numbers that each real number is a SIV in BBO algorithm [11]. The fitness of each solution can be calculated with its objective function. This fitness is the same HSI in BBO algorithm. In BBO solutions with high HSI represents a good solution and solution with low HSI represents a bad solution. The information of habitats probabilistically shares between other habitats using emigration rate and immigration rate of each solution. Each solution can modify on basis of $P_{\text{mod}}$, modification probability of each solution. In BBO one solution $S_i$ is selected for modification and then using immigration rate of that solution, is decided that modification be imposed on which SIV in that solution. Emigration rate of other solution is used for choosing a SIV that with that SIV, modification will be apply and then a SIV will select randomly to migrate to the solution $S_i$. In BBO algorithm an elitism process is included to prevent deterioration of best solution during the migration. In this process, a number of best solutions are transferred to next iteration without migration procedure [11].

**Mutation**

Sudden changes in climate of one habitat or other incidents will cause the sudden changes in HSI of that habitat [11]. In BBO algorithm this situation can be model in the form of sudden changes in value of SIV. The probability of any organism can be calculated by the following equation (11).

$$P = \frac{1}{\lambda + \mu + \mu_{s+1}P_{s+1}}$$

(11)

Each member of one habitat has its own probability. If this probability is too low, then this solution has high chance to mutate. In the same manner if probability of a solution is high that solution has a little chance to mutate. Consequently solutions with high HSI and low HSI have a little chance to development a better SIV in the next iteration. Unlike high HSI and low HSI solutions, medium HSI solutions have a greater chance to development better solutions after mutation procedure. In the following equation mutation rate of each solution can be calculated [10].

$$m(s) = m_{\text{max}} \left( \frac{1-P_s}{P_{\text{max}}} \right)$$

(12)

At this stage $m_{\text{max}}$ is a parameter that is determined by the user. At this stage there is also a elitism to prevent the answers from getting worse after mutation procedure. In this case if a SIV is selected for mutation operation, one authorized random number is substituted.
3.3 BBO algorithm

The process of the IPSO algorithm for solving ELD problems can be summarized as follows:

Step 1: Initializing BBO parameter as mentioned below

- $P_{mod}$ - modification probability
- $P_{max}$ - mutation probability
- $m_{max}$ - maximum mutation rate
- $I$ - maximum immigration rate
- $E$ - maximum emigration rate
- Lower bound and upper bound for immigration probability.
- $dt$ - step size for numerical integration
- $N$ - number of habitats
- $m$ - number of SIV’s
- $p$ - elitism parameter
- Maximum number of iteration

After initializing parameters, SIV Initial values must be generated in their feasible intervals using random numbers.

Step 2: For example, assume that we are applying this algorithm on following function:

$$f(x) = \sum_{i=1}^{m} \cos x$$  \hspace{1cm} (13)

SIV’s should be generated in the allowed range. Due to the number of habitats $N$ and SIV’s $m$ the Habitat matrix can form as below. Each row of habitat matrix represents a solution for problem.

$$H = \begin{bmatrix}
x_{11} & x_{12} & x_{13} & x_{14} & \ldots & x_{1m} \\
x_{21} & x_{22} & x_{23} & x_{24} & \ldots & x_{2m} \\
x_{31} & x_{32} & x_{33} & x_{34} & \ldots & x_{3m} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
x_{N1} & x_{N2} & x_{N3} & x_{N4} & \ldots & x_{Nm}
\end{bmatrix}$$  \hspace{1cm} (14)

Step 3: Calculation of HSI quantity for each solution of habitat matrix as follows:

$$HSI_1 = [\cos x_{11} + \cos x_{12} + \cos x_{13} + \cos x_{14} + \ldots + \cos x_{1m}]$$

$$HSI_2 = [\cos x_{21} + \cos x_{22} + \cos x_{23} + \cos x_{24} + \ldots + \cos x_{2m}]$$

$$HSI_3 = [\cos x_{31} + \cos x_{32} + \cos x_{33} + \cos x_{34} + \ldots + \cos x_{3m}]$$

$$\vdots$$

$$HSI_N = [\cos x_{N1} + \cos x_{N2} + \cos x_{N3} + \cos x_{N4} + \ldots + \cos x_{Nm}]$$

Step 4: Selection stage

Select $p$ number of the best solutions in each iteration and Move them to the next iteration.

Step 5: Migration operation [11]

Migration operation is used for modifying habitats those are selected probabilistically. If our goal is to modify habitat $H_i$ with replacing habitat $H_j$, the probability of election of $H_i$ is proportional to immigration rate $\lambda_k$ and the probability of election of $H_j$ is proportional to emigration rate $\mu_k$. The migration procedure can be demonstrated as follows:

Select a habitat $H_i$ with probability proportional to $\lambda_i$

If $H_i$ is selected

For $j = 1$ to $N$

Select another habitat $H_j$ with probability proportional to $\mu_i$

If $H_j$ is selected

Randomly select an SIV from habitat $H_j$

Replace a random SIV in $H_i$ with that selected SIV of $H_j$

End

End

End

After applying this operation on selected habitats, feasibility of each habitat should
be reviewed. If any of habitats is not suitable after migration, this procedure must be repeated on the habitat to achieve the desired result. After applying migration procedure on selected habitats, HSI values must be computed again.

**Step 6:** Mutation operation [11]

Mutation operation is applied on each selected habitat as follow and then quantity of HSI for each habitat must be computed again.

For $i = 1$ to $N$

For $j = 1$ to $m$

Use $\lambda_i$ and $\mu_i$ to compute probability of $P_i$ using (11)

Select SIV $H_i(j)$ with probability proportional to $P_i$

If $H_i(j)$ is selected

Replace $H_i(j)$ with a randomly generated SIV in its feasible region

End

End

End

After above operation feasibility of habitats should be checked and if it’s not a feasible solution the operation should be done again to enrich the feasible solutions.

**Step 7:** Go to step – 3 for next iteration.

The algorithm ends after a certain number of iterations.

### 4. SOLUTION OF ELD PROBLEM WITH BBO ALGORITHM

In this section, a new method is presented for solving ELD problems. The main goal of ELD is obtaining the values of each generator in range of allowed values. What is important is that this algorithm is able to satisfy certain constraints like ramp rate limit and prohibited operating zones. The procedure of BBO algorithm can be presented as follows:

1) Initializing SIV’s

The Output power of each generator is assumed as a SIV in this algorithm. Each SIV should be chosen in the range of its authorized. In this algorithm $N$ is the number of solutions and $m$ is the number of generators.

2) Checking feasibility of habitats

After generating random numbers with regard to generator provisions (3),(6), we should check the constraint (1) to have a feasible solution for ELD problem.

3) Calculating HSI

HSI value should be computed to each row of habitat matrix considering each individual’s objective function. In ELD problem HSI represents the total fuel cost of each solution. For example if we have $m$ generators with their own cost functions, HSI represent the summation of fuel cost of each generator.

4) Selection stage

At this stage, according to the HSI values obtained for each solution, $p$ number of best solutions that they have best fuel cost are kept without modifying on them and transferred to next iteration.

5) Migration

Applying migration procedure on those SIV’s of each non-elite habitats. This procedure is work probabilistically as mentioned before.

6) Mutation

After updating probability of each habitat from (11), mutation procedure is performed on non-elite habitats as mentioned before.

### 5. SIMULATION RESULTS

In order to validate the proposed method, we employed the BBO approach for ELD problems in a 6 unit system and a 15 unit system. In these cases, the ramp rate limits
Table 1: Best simulation results of 6-unit system

<table>
<thead>
<tr>
<th>Generator</th>
<th>Power Output (MW)</th>
<th>Methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>447.1828</td>
<td>474.81</td>
</tr>
<tr>
<td>G2</td>
<td>173.1249</td>
<td>178.64</td>
</tr>
<tr>
<td>G3</td>
<td>264.2082</td>
<td>262.21</td>
</tr>
<tr>
<td>G4</td>
<td>138.4957</td>
<td>134.28</td>
</tr>
<tr>
<td>G5</td>
<td>165.8612</td>
<td>151.90</td>
</tr>
<tr>
<td>G6</td>
<td>86.5572</td>
<td>74.18</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>1275.43</td>
</tr>
</tbody>
</table>

Table 2: Best simulation results of 15-unit system

<table>
<thead>
<tr>
<th>Generator</th>
<th>Power Output (MW)</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>450.951</td>
<td>415.31</td>
</tr>
<tr>
<td>G2</td>
<td>402.951</td>
<td>359.72</td>
</tr>
<tr>
<td>G3</td>
<td>127.5847</td>
<td>104.42</td>
</tr>
<tr>
<td>G4</td>
<td>129.6629</td>
<td>74.98</td>
</tr>
<tr>
<td>G5</td>
<td>357.8484</td>
<td>380.28</td>
</tr>
<tr>
<td>G6</td>
<td>415.6189</td>
<td>426.79</td>
</tr>
<tr>
<td>G7</td>
<td>463.4147</td>
<td>341.32</td>
</tr>
<tr>
<td>G8</td>
<td>61.8705</td>
<td>124.79</td>
</tr>
<tr>
<td>G9</td>
<td>34.3134</td>
<td>133.14</td>
</tr>
<tr>
<td>G10</td>
<td>48.0068</td>
<td>89.26</td>
</tr>
<tr>
<td>G11</td>
<td>30.2575</td>
<td>60.06</td>
</tr>
<tr>
<td>G12</td>
<td>74.5209</td>
<td>50.00</td>
</tr>
<tr>
<td>G13</td>
<td>26.7615</td>
<td>38.77</td>
</tr>
<tr>
<td>G14</td>
<td>15.3425</td>
<td>41.94</td>
</tr>
<tr>
<td>G15</td>
<td>15.5912</td>
<td>22.64</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>2654.4671</td>
</tr>
</tbody>
</table>

Total generation cost 32558.7261 33113 32858 32568.54 32798.69 32775.36 32751.39
and prohibited zones of the units were taken into account in the practical application. The obtained results are compared with the reported results. The BBO approach was implemented in MATLAB software. In each case study, 50 independent runs were made for each of the optimization methods. The parameters of BBO are selected as following: $P_{\text{mod}}= 1; m_{\text{max}} = 0.05; l= 1; E= 1$ and $p = 2$. In these case studies, the stopping criterion iteration maximum was 500 generations. The population size was 50 to different case studies.

5.1 Case study I: Six unit system

The system contains six thermal generating limits, 26 buses and 46 transmission lines. The load demand is 1263 MW. The characteristics of the six thermal units are given in [12]. The network losses are calculated by B matrix loss formula [12]. The best solutions using the proposed optimizer are shown in Table 1 that satisfies the generator constraints. It can be evident from Table 1 that the technique provided better results compared with other reported evolutionary algorithm techniques. It is also observed that the mean cost using the proposed approach is less than the reported minimum cost using some of other methods.

5.2 Case study II: Fifteen unit system

The system contains 15 thermal units whose characteristics are given in [12]. The load demand of the system is 2630MW. The loss coefficients matrix was shown in the [12]. In this second case, the results of numerical simulation of tested BBO method are shown in Table 2 that also satisfy the system constrains. It can be seen from Table 2 that the BBO perform better than the PSO, GA, ES, SPSO, PC_PSO and SOH_PSO methods in terms of solution quality.

6. CONCLUSIONS

In this paper, a BBO algorithm is applied to solve the ELD problem with non smooth cost function with constraints of the prohibited zones and ramp rate limits. To enrich the searching behavior and to avoid being trapped into local optimum, BBO technique is used, which is a novel population-based search technique. The proposed approach has produced results comparable or better than those generated by other algorithms and the solutions obtained have superior solution quality. The results obtained for both the cases were always comparable or better that the earlier best reported results. From this limited comparative study, it can be concluded that the BBO can be effectively used to solve ELD problems.

REFERENCES


