Multi-objective Based Optimization Using Tap Setting Transformer, DG and Capacitor Placement in Distribution Networks

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ABSTRACT
In this article, a multi-objective function for placement of Distributed Generation (DG) and capacitors with the tap setting of Under Load Tap Changer (ULTC) Transformer is introduced. Most of the recent articles have paid less attention to DG, capacitor placement and ULTC effects in the distribution network simultaneously. In simulations, a comparison between different modes was carried out with, and without tap setting of ULTC. Simultaneous DG, capacitor placement, and ULTC transformer tap setting improve the voltage profile of load buses globally. In addition, they can also reduce loss and increase Available Transfer Capability (ATC). The IEEE 41-bus radial distribution network is used to illustrate the effectiveness and feasibility of the proposed approach.

KEYWORDS: DG placement, capacitor placement, ULTC Transformer, loss reduction, voltage profile, available transfer capability, multi-objective function.

1. INTRODUCTION
The optimal placement and assignment of DG and capacitors are of the main problems in the distribution network design. The primary problem of DG and capacitors optimal placement is to study a method to reduce power loss and voltage improvement as well as increasing the ATC. There are many methods for DG and capacitor placement for different purposes. In the past decades, much attempt have been contributed to capacitor placement problem.

For example, in [1], fuzzy-genetically method for optimization is used to determine the place and the size of capacitor banks in distorted distribution systems. The fitness function reduces loss, optimized power and cost of capacitors placement, considering load voltage constraints. Capacitor placement and reconfiguration for loss reduction of distribution networks are used in [2] by an ant colony search algorithm. Also a heuristic constructive algorithm for capacitor placement in distribution systems is applied in [3].
In recent decades, different kinds of DGs have been made and different methods have been introduced for DG placement. In [4] a method for placement of a single DG on the distribution network is proposed. This method is based on the determination of most sensitive buses with voltage collapse. The analysis was done to reduce losses and improve the voltage profile and increase ATC. In [5] a multi-objective optimization method for DG placement is associated. One of the main factors in that paper is the network loss. A heuristic DG optimization method for distribution network is proposed in [6]. Moreover, the search space is reduced significantly in that work. In [7] a method to select the load buses for the DG placement based on loss reduction and voltage sensitivity improvement have been presented. An analytical approach for optimal placement of distributed generation sources in power systems is aimed to reduce loss by analytical methods in [8].

Nowadays different kinds of DGs and capacitors are simultaneously used in a lot of distribution networks. In [9] placement of DG and capacitors to reduce losses and improve the voltage profile using GA has been studied. In [10] two optimization models are proposed to improve the voltage profile. First, the DG placement problem is formulated. Then capacitor placement problem is modeled and solved.

In this paper one GA is applied to the multi-objective function including: loss reduction, load voltage profiles optimization and ATC maximization. The objective of DG and capacitor placement is to determine the placement and size of DG and capacitors. DG and capacitors are placed and the tap of ULTC transformer is set, so the system loss is reduced, load voltage profiles is improved and ATC is increased. There are some constraints on the voltage magnitude at each bus and apparent power passed through each line. It should be mentioned that in other articles less attention has been paid to simultaneous tap setting of ULTC and placement of DG and capacitors. In other articles, the ULTC is fixed to a tap in which, ULTC voltage ratio is one and there is no attempt to set adapting taps. In simulations a comparison between different modes was carried out with and without tap setting of ULTC. To show the effectiveness of the proposed method, it is applied to IEEE 41 bus radial distribution network. Simulation results show that simultaneous determination of location and size of DG and capacitors and the tap setting of ULTC transformer lead to more favorable results. The results show that the voltages in all buses remain within the desired range, loss is reduced and ATC is increased.

2. PROBLEM FORMULATION

The problem, which is formulated through a multi-objective mathematical model with three objectives, is as follows:

2.1 Determining the fitness function to decrease line loss

In the power distribution network, loss depends on two factors line resistance and line current. Variations of line resistance are low and negligible. Overall line loss is related to the current and the line current depends on system topology and loads. It is usually impossible to reduce the value of loads, but line currents can be reduced with DG and capacitors proper placement. Therefore, with optimal DG and capacitors placement, line loss can be decreased. Power flow and loss can be formulated as:
\[ P_t = V_i \sum_{j=1}^{n} Y_{ij}V_j \cos(\delta_i - \delta_j - \gamma_{ij}) \] (1)

\[ Q_t = V_i \sum_{j=1}^{n} Y_{ij}V_j \sin(\delta_i - \delta_j - \gamma_{ij}) \] (2)

Where, \( P_t \) and \( Q_t \) are active and reactive power of the \( i \)'th bus, respectively. \( V_i \) is the \( i \)'th bus voltage, \( Y_{ij} \) is the system admittance matrix element, \( \delta \) is the bus voltage angle, and \( \gamma \) is the angle of the system admittance matrix element. The first objective fitness function \( (f_1) \) is defined as:

\[ f_1 = P_{loss} = \sum_{i=1}^{n} P_{Gi} - \sum_{i=1}^{n} P_{Di} \] (3)

This fitness function shows the total line loss in the entire system \( (P_{loss}) \). \( P_{Gi} \) is the injected active power from power system to distribution network or \( i \)'th bus generated power by \( i \)'th DG. \( P_{Di} \) represents the total connected load.

2.2 Determining the fitness function to improve load bus voltages

Voltage constraint of load buses is shown as:

\[ V_{i_{\text{min}}} \leq V_i \leq V_{i_{\text{max}}} \quad i \in N_b \] (4)

\( N_b \) stands for the total number of all the buses. \( V_i \), \( V_{i_{\text{min}}} \) and \( V_{i_{\text{max}}} \) are \( i \)'th bus voltage magnitude, lower and upper boundaries of voltage magnitude of \( i \)'th bus respectively. Second fitness function is the voltage magnitude at load buses that is shown as \( (5) \). This fitness function must be decreased.

\[ f_2 = \sum_{i=1}^{N_b} (V_i - V_n)^2 \] (5)

\( V_n \) is the nominal voltage value that is considered one per-unit for all the buses in this article.

2.3 Determining the fitness function to increase ATC

ATC is one of the important factors in DG and capacitors placement in the distribution network. The capability of transmission lines is limited by ATC in the distribution network. ATC is increased because of active and reactive power injection by appropriate DG and capacitor placement. The third fitness function \( (f_3) \) is used to increase the available transfer capability that is defined as \( (6) \).

\[ f_3 = \sum_{i=1}^{n} (S_{\text{base}} - S_{i-j}) \] (6)

\[ S_{i-j} = \sqrt{P_{i-j}^2 + Q_{i-j}^2} \] (7)

\[ S_{\text{base}} = S_{1-2} = 6.9860 \text{ MVA} \] (8)

\( S_{i-j} \) is the value of apparent power flow through \( i \)'th bus to \( j \)'th bus. \( S_{\text{base}} \) is the Total Transfer Capability (TTC). \( S_{\text{base}} \) value for all lines is assumed 6.9860 MVA, which is achieved from simulation of the IEEE 41 bus system without any DG or capacitor. Maximum \( S_{i-j} \) and \( S_{1-2} \) is equal to 6.9860 MVA. Bus 1 is a substation bus. \( P_{i-j} \) and \( Q_{i-j} \) are the value of active and reactive power flow through \( i \)'th bus to \( j \)'th bus.

2.4 Multi-objective fitness function analyses using a genetic algorithm

GA invented by Holland in the early 1970’s. It is a stochastic global search
technique to optimization algorithms based on the principles of natural selection and genetic recombination. A possible solution to this problem is called an individual. An individual is represented by a computational data structure called a chromosome, which is composed of genes. The real value of a control parameter is encoded in a gene. The fitness of each individual is determined by running the GA, and examining the time required for convergence.

GAs can make possible simultaneous convergences to more than one optimum solution with a multimodal search. It is possible to adapt the genetic algorithm for determination of the global or near global optimum solution [11]. In this article, GA is applied to DG and capacitors placement and tap settings of ULTC. In addition, GA is used to determine active and reactive power values of DG and capacitors.

By proper choice of all variables using GA, multi-objective fitness function is optimized. In this paper, the multi-objective function is described as:

$$F = f_1 + f_2 - f_3$$  \(\text{(9)}\)

Where, \(F, f_1, f_2\) and \(f_3\) are multi objective fitness function, loss reduction, load voltage profiles optimization and ATC maximization, respectively. \(f_1\) and \(f_2\) should be minimized but \(f_3\) should be maximized.

3. SIMULATION RESULTS

The proposed method is applied to the IEEE 41 bus radial distribution network. The structure of the system is shown in Fig. 1. Bus 1 is a substation bus and distribution network has one ULTC transformer at the first bus. This network has 41 load buses and 40 transmission lines. Total active and reactive loads are 4.635 MW and 3.250 MVar, respectively. The parameters of the network are given in the appendix A.

![Fig. 1. Structure of the IEEE 41 bus distribution network](image)

In this paper, one DG and four capacitors are assumed to add in the network. DG and capacitor characteristics are given in the Table 1. ULTC characteristics are given in the Table 2.

<table>
<thead>
<tr>
<th>Table 1. DG and Capacitor Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number</td>
</tr>
<tr>
<td>DG</td>
</tr>
<tr>
<td>Capacitor</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2. ULTC characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tap Numbers</td>
</tr>
<tr>
<td>ULTC</td>
</tr>
</tbody>
</table>

At first stage, load flow was performed on the IEEE 41 bus distribution network. The voltage conversion ratio of the ULTC was set to one in this simulation. Power consumptions in distribution network are supplied only by the power system. At this stage, the distribution network has no DG and capacitor. Numerical values of three fitness functions are shown in Table 3.
Table 3. Numerical values of three fitness functions without DG and capacitor and ULTC tap setting

<table>
<thead>
<tr>
<th>Function</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>1.0075</td>
</tr>
<tr>
<td>$f_2$</td>
<td>1.8238</td>
</tr>
<tr>
<td>$f_3$</td>
<td>228.7923</td>
</tr>
<tr>
<td>$S_{1-2 \text{ MVA}}$</td>
<td>6.9860</td>
</tr>
<tr>
<td>$V_{\text{trans-pu}}$</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table 4. Numerical values of three fitness functions with loss reduction function

<table>
<thead>
<tr>
<th>Function $F = f_1$</th>
<th>Without ULTC tap setting</th>
<th>With ULTC tap setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>0.143</td>
<td>0.152</td>
</tr>
<tr>
<td>$f_2$</td>
<td>0.058</td>
<td>0.020</td>
</tr>
<tr>
<td>$f_3$</td>
<td>252.936</td>
<td>253.538</td>
</tr>
<tr>
<td>$S_{1-2 \text{ MVA}}$</td>
<td>2.386</td>
<td>2.310</td>
</tr>
<tr>
<td>$V_{\text{trans-pu}}$</td>
<td>1.05</td>
<td>1.00</td>
</tr>
<tr>
<td>$P_{\text{DG \text{ MW}}}$</td>
<td>2.4</td>
<td>2.6</td>
</tr>
<tr>
<td>$Q_{\text{DG \text{ Mvar}}}$</td>
<td>1.3</td>
<td>0.9</td>
</tr>
<tr>
<td>$DG \text{ Place}$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>$C_1 \text{ Place}$</td>
<td>27</td>
<td>29</td>
</tr>
<tr>
<td>$C_2 \text{ Place}$</td>
<td>29</td>
<td>32</td>
</tr>
<tr>
<td>$C_3 \text{ Place}$</td>
<td>31</td>
<td>38</td>
</tr>
<tr>
<td>$C_4 \text{ Place}$</td>
<td>38</td>
<td>41</td>
</tr>
</tbody>
</table>

Table 5. Numerical values of three fitness functions with improving voltage profiles function

<table>
<thead>
<tr>
<th>Function $F = f_2$</th>
<th>Without ULTC tap setting</th>
<th>With ULTC tap setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>0.212</td>
<td>0.250</td>
</tr>
<tr>
<td>$f_2$</td>
<td>0.006</td>
<td>0.007</td>
</tr>
<tr>
<td>$f_3$</td>
<td>251.444</td>
<td>249.511</td>
</tr>
<tr>
<td>$S_{1-2 \text{ MVA}}$</td>
<td>1.794</td>
<td>2.049</td>
</tr>
<tr>
<td>$V_{\text{trans-pu}}$</td>
<td>1.01</td>
<td>1.00</td>
</tr>
<tr>
<td>$P_{DG \text{ MW}}$</td>
<td>3.4</td>
<td>3.7</td>
</tr>
<tr>
<td>$Q_{DG \text{ Mvar}}$</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>$DG \text{ Place}$</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>$C_1 \text{ Place}$</td>
<td>30</td>
<td>32</td>
</tr>
<tr>
<td>$C_2 \text{ Place}$</td>
<td>32</td>
<td>32</td>
</tr>
<tr>
<td>$C_3 \text{ Place}$</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td>$C_4 \text{ Place}$</td>
<td>41</td>
<td>41</td>
</tr>
</tbody>
</table>

Fig. 2. Bus voltage magnitudes without DG and capacitor and ULTC tap setting

In Table 3, the network has relatively high losses. Load bus voltages are not desirable. In addition, relatively high power passes through the first lines of the network. Therefore, active and reactive power generators are needed to improve network. At second, third and fourth stages load flow was run again in two modes by adding a DG and four capacitors in the network. In the first mode, tap of ULTC was set, however in the second mode tap of ULTC was fixed to have the voltage ratio equals to one. In the all stages and modes, the GA attempts to minimize the values of $f_1$ (Eq. 3) and $f_2$ (Eq. 5) and maximize the value of $f_3$ (Eq. 6). In the second stage, although this fitness function has reduced loss, but there is no effort to improve either the bus voltage profile or to increase the ATC. Also at third and fourth stages, only one of voltage profiles or ATC is considered as a fitness function. The results are shown in Tables 4 to 5.

Main fitness functions of each stage are highlighted with gray color in tables. By comparing second columns of Tables 4 and 5, it is clear that in Table 4, losses are lower but bus voltage profiles are undesirable. Conversely, in Table 5, losses are higher and bus voltage profiles are more favorable. By adding DG and capacitors and
comparing Table 6 with two previous tables, it can be seen that with any fitness function selection, ATC is improved. In fitness function with only the ATC, the ATC is considerably improved, but loss is still considerable and the bus voltage profiles are more unfavorable. Comparison of the apparent power flow through bus 1 to bus 2, $S_{1-2}$ from all tables with Table 3, show that line current in the distribution network with DG and a capacitor is reduced significantly. Therefore, according to the mentioned results, using a mono-objective function cannot improve the network status.

Comparing second and third columns of Tables 4 to 6 indicate that approximately the similar results are obtained. Also by the same comparison, it is evident that all fitness functions with ULTC tap setting have better values without ULTC tap setting.

### Table 6. Numerical values of three fitness functions with increasing ATC function

<table>
<thead>
<tr>
<th></th>
<th>with ULTC tap setting</th>
<th>without ULTC tap setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$F$</td>
<td>254.459</td>
<td>254.471</td>
</tr>
<tr>
<td>$f_1$</td>
<td>0.167</td>
<td>0.172</td>
</tr>
<tr>
<td>$f_2$</td>
<td>0.015</td>
<td>0.021</td>
</tr>
<tr>
<td>$f_3$</td>
<td>254.459</td>
<td>254.471</td>
</tr>
<tr>
<td>$S_{1-2}$ MVA</td>
<td>1.870</td>
<td>1.874</td>
</tr>
<tr>
<td>$V_{trans-pu}$</td>
<td>1.03</td>
<td>1.00</td>
</tr>
<tr>
<td>$P_{DG}$ MW</td>
<td>3.1</td>
<td>3.1</td>
</tr>
<tr>
<td>$Q_{DG}$ Mvar</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>$DG_{place}$</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>$C_{1_{place}}$</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>$C_{2_{place}}$</td>
<td>31</td>
<td>31</td>
</tr>
<tr>
<td>$C_{3_{place}}$</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td>$C_{4_{place}}$</td>
<td>39</td>
<td>39</td>
</tr>
</tbody>
</table>

In the next stage, the relative improvement fitness function is described for all three previous functions. The multi-objective function presented in (Eq. 9) is used. In Tables 4, 5 and 6 minimum $f_1$ and $f_2$ and maximum $f_3$ are highlighted with gray color. Following equations represent minimization and maximization results:

\[
\begin{align*}
\min(f_1) &= 0.143 \\
\min(f_2) &= 0.006 \\
\max(f_3) &= 254.459
\end{align*}
\]

Considering the optimized numerical values, the differences between three mono-objective function values (equations 10 to 12) are considerable. Therefore, per-unit system is required. Equations (13 to 15) show base values of each function.

\[
\begin{align*}
\text{f}_{1\text{-base}} &= 0.143 \\
\text{f}_{2\text{-base}} &= 0.006 \\
\text{f}_{3\text{-base}} &= 254.459
\end{align*}
\]

Thus, a multi-objective function using a combination of three mono-objective functions is made. Placement results by using this fitness function are presented in Table 7. This table shows that the results in the second column are considerably better than the third column in 2nd to 6th rows. Comparing Tables 8 and 9 show the normalized values of Table 7.

By comparing the gray area of Table 4 to Table 9, it can be shown that using the multi-objective function causes to improve each of three functions to acceptable values. In the other words, it is possible to improve the overall network status by using an intelligent optimization algorithm with a multi-objective function.

Fig. 3 and Fig. 4 shows that using the proposed method, bus voltage magnitudes with ULTC tap setting are more favorable than without ULTC tap setting. Fig. 5 shows the flowchart of proposed method.
Table 7. Per unit values of three fitness functions with multi-objective function

<table>
<thead>
<tr>
<th>Function</th>
<th>with ULTC tap setting</th>
<th>without ULTC tap setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{1pu}$</td>
<td>1.109 p.u.</td>
<td>1.872</td>
</tr>
<tr>
<td>$f_{2pu}$</td>
<td>1.087 p.u.</td>
<td>1.707</td>
</tr>
<tr>
<td>$f_{3pu}$</td>
<td>1.014 p.u.</td>
<td>1.150</td>
</tr>
<tr>
<td>$f_{3pu}$</td>
<td>0.993 p.u.</td>
<td>0.985</td>
</tr>
<tr>
<td>$S_{1-2 MVA}$</td>
<td>2.468</td>
<td>2.140</td>
</tr>
<tr>
<td>$V_{trans-pu}$</td>
<td>1.02</td>
<td>1.00</td>
</tr>
<tr>
<td>$P_{DG MW}$</td>
<td>2.4</td>
<td>3.8</td>
</tr>
<tr>
<td>$Q_{DG Mvar}$</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>$DG Place$</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>$C_1 Place$</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>$C_2 Place$</td>
<td>31</td>
<td>31</td>
</tr>
<tr>
<td>$C_3 Place$</td>
<td>33</td>
<td>32</td>
</tr>
<tr>
<td>$C_4 Place$</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>

Table 8. Normalize values of three fitness functions with multi-objective function and ULTC tap setting

<table>
<thead>
<tr>
<th>Function</th>
<th>with ULTC tap setting</th>
<th>p.u. normal</th>
<th>without ULTC tap setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>1.087 p.u.</td>
<td>0.155</td>
<td>1.707</td>
</tr>
<tr>
<td>$f_2$</td>
<td>1.014 p.u.</td>
<td>0.006</td>
<td>1.150</td>
</tr>
<tr>
<td>$f_3$</td>
<td>0.993 p.u.</td>
<td>252.678</td>
<td>0.985</td>
</tr>
</tbody>
</table>

Table 9. Normalize values of three fitness functions with multi-objective function and without ULTC tap setting

<table>
<thead>
<tr>
<th>Function</th>
<th>without ULTC tap setting</th>
<th>p.u. normal</th>
<th>without ULTC tap setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>1.707</td>
<td>0.244</td>
<td>1.872</td>
</tr>
<tr>
<td>$f_2$</td>
<td>1.150</td>
<td>0.006</td>
<td>1.707</td>
</tr>
<tr>
<td>$f_3$</td>
<td>0.985</td>
<td>250.642</td>
<td>0.985</td>
</tr>
</tbody>
</table>

Fig. 3. Bus voltage magnitudes using the proposed method with ULTC tap setting

Fig. 4. Bus voltage magnitudes using the proposed method without ULTC tap setting

Fig. 5. shows the flowchart of the proposed method.

4. CONCLUSIONS

In this paper, an improved GA based method for proper placement of a DG and
capacitors and the tap setting of ULTC transformers has been proposed. The proposed algorithm is based on a new multi-objective function, which is matched with three mono-objective functions to reduce losses, improve the bus voltage profiles and to increase ATC. A multi-objective function of several per-unit Objects is created. To verify the proposed method, simulations are used based on the IEEE 41 bus distribution network. In simulations, a comparison between different modes with and without tap setting of ULTC has been shown. The capability of this method has been well shown by the results. The simulation results using multi-objective fitness function has validated the effectiveness of the proposed approach.

**APPENDIX**

A. Parameters of the IEEE 41-bus distribution systems

**Table 8. Parameters of the IEEE 41 bus radial distribution network**

<table>
<thead>
<tr>
<th>Line Index</th>
<th>To Bus Index</th>
<th>From Bus Index</th>
<th>R(ohm)</th>
<th>X(ohm)</th>
<th>bus load P(KW)</th>
<th>bus load Q(KVar)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0.0992</td>
<td>0.0470</td>
<td>100</td>
<td>60</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>1</td>
<td>0.4930</td>
<td>0.2511</td>
<td>90</td>
<td>40</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>3</td>
<td>0.3660</td>
<td>0.1864</td>
<td>120</td>
<td>80</td>
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<tr>
<td>4</td>
<td>5</td>
<td>4</td>
<td>0.3811</td>
<td>0.1941</td>
<td>60</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>5</td>
<td>0.8190</td>
<td>0.7070</td>
<td>60</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td>6</td>
<td>0.1872</td>
<td>0.6188</td>
<td>200</td>
<td>100</td>
</tr>
<tr>
<td>7</td>
<td>8</td>
<td>7</td>
<td>0.7114</td>
<td>0.2351</td>
<td>200</td>
<td>100</td>
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**REFERENCES**


A Novel Reference Current Calculation Method for Shunt Active Power Filters using a Recursive Algebraic Approach

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ABSTRACT
This paper presents a novel method to calculate the reference source current and the reference compensating current for shunt active power filters (SAPFs). This method first calculates the amplitude and phase of the fundamental load current from a recursive algebraic approach block before calculating the displacement power factor. Next, the amplitude of the reference mains current is computed with the corresponding phase voltage. Finally, the difference between the actual load current and the reference source current is considered the reference compensating current to be delivered by the SAPF. The proposed method is presented and applied to the control system of the voltage source converter of SAPFs. The performance of the proposed method in reducing harmonics and improving the power factor is examined with a SAPF simulation model. The results are compared with the instantaneous active and reactive p-q power theory as other reference generation method.

KEYWORDS: power quality, p-q theory, recursive algebraic approach, reference source current, shunt active power filter

1. INTRODUCTION
The result of industrial development and widespread use of power electronics is the increasing effects of harmonics on power systems. The use of non-linear loads such as electronic power supplies, rectifiers, and static power converters is the main factor of harmonic current generation. Most of these non-linear loads contribute also to lower power factor, reactive power burden, unbalance, and other problems that lead to low system efficiency and create serious power quality problems.

Among the miscellaneous options available for the improvement of power quality, the use of active power filters (APFs) is greatly accepted and employed as a significant option in power distribution systems to compensate current and voltage perturbations [1–2]. By using a control strategy, APF generates suitable compensating voltage/current signals that cancel the reactive power and harmonic components in the voltage/currents from the mains. The control strategy for the shunt active power filter (SAPF) comprises of reference signal extraction, control of DC capacitor voltage, and switching signal generation. The extraction of compensating current/voltage reference from the distorted
and harmonic polluted current/voltage signals forms the basis of the control strategy in the SAPF. Prior to calculating the reference source current and the reference compensating current, harmonics from the current signals have to be first detected. Harmonic current detection techniques are classified into time-based and frequency-based techniques. Some of the most commonly used techniques are described as follows.

The frequency-based techniques include conventional Fourier and fast Fourier transform algorithms [3], modified Fourier series techniques [4], discrete Fourier transform [5], and recursive discrete Fourier transform [6]. The time-based techniques include the dq method [3], instantaneous active and reactive p-q power theory [7], the synchronous detection method [8], and synchronous reference frame theory [9].

In this paper, the proposed method for calculating the reference current is compared with the popular instantaneous active and reactive p-q power theory. The simulation results were presented to compare the effectiveness of both algorithms.

2. SHUNT ACTIVE POWER FILTER

2.1. Basic compensation principle

Fig. 1 shows schematic diagram of SAPF [10], which is controlled to supply a compensating current at the point of common coupling (PCC) and to cancel current harmonics on the supply side.

The SAPF is controlled to draw/supply a compensated current from/to the utility to facilitate the elimination of harmonic and reactive currents of the non-linear load.

In order for the resulting total current drawn from the AC mains is sinusoidal, the SAPF should generate sufficient appropriate compensating current.

![Fig. 1. Connection of SAPF with non-linear load](image1)

2.2. Reference source currents

The control strategy of SAPF generates the reference current (if). The reference source current generation should be conducted correctly for optimal compensation. This current must be provided by the active power filter to compensate for reactive power and harmonic currents demanded by the load as described in Fig. 2.

![Fig. 2. Closed-loop fuzzy logic-controlled SAPF](image2)

3. PROPOSED ALGEBRAIC APPROACH TO HARMONICS CALCULATION

A sampled form of a power signal with harmonics is generally represented by the
following equation [11]:

\[
x(k) = x_0 + \sum_{n=1}^{N} A_n \cos(2\pi nf_r T_s k + \varphi_n)
\]  

(1)

where \(x_0\), \(n\), \(N\), \(f_r\), \(T_s\), \(k\), and \(\varphi_n\) are the DC component, number of harmonics, number of last harmonic, signal frequency, sampling period, number of samples, and phase of the \(n\)th harmonic, respectively. \(x(k)\) is the sampled value of the signal in the \(k\)th sequence. \(x(k)\) can be written as follows [11]:

\[
x(k) = x_0 + \sum_{n=1}^{N} \left[ a_n \cos(2\pi nf_r T_s k) + b_n \sin(2\pi nf_r T_s k) \right]
\]  

(2)

This equation calculates the values of \(x_0\), \(f_r\), \(a_n\), and \(b_n\) (for \(n=1, \ldots, N\)).

The phase and magnitude in each harmonic can be calculated using these formulas [11]:

\[
\begin{align*}
A_n(t) &= \sqrt{a_n^2(t) + b_n^2(t)} \\
\varphi_n(t) &= \begin{cases} 
\tan^{-1}(a_n(t)/b_n(t)) & : b_n(t) \geq 0 \\
\pi + \tan^{-1}(a_n(t)/b_n(t)) & : b_n(t) \leq 0 
\end{cases}
\end{align*}
\]

(3)

However, previous calculations require the signal frequency to be known. In this method, signal frequency is initially determined by the proposed algebraic method by detecting its zero crossings for the first period.

The DC value, magnitude, and the phase of harmonics can then be calculated based on the signal samples. The parameters of \(\cos(2\pi nf_r T_s k)\) and \(\sin(2\pi nf_r T_s k)\) are revealed when the values of \(f_r\), \(k\) and \(x(k)\) are known.

The values of \(x_0\), \(a_n\) and \(b_n\) should be determined. \(2N+1\) unknowns were observed, where \(N\) is the number of the last harmonic in \(x(t)\). The variables \(\cos(2\pi nf_r T_s k)\) and \(\sin(2\pi nf_r T_s k)\) are known.

Therefore, the equation can be considered as a linear equation because its variables are \(x_0, a_n\) and \(b_n\).

Accordingly, the \(2N+1\) linear equations with \(2N+1\) unknowns for the \(2N+1\) samples of \(x(t)\) can be obtained using the following formulation:

\[
X = AY
\]  

(4)

\[
X = [x(1), x(2), \ldots, x(M)]^T, Y = [x_0, a_1, a_2, \ldots, a_N, b_1, b_2, \ldots, b_N]^T
\]

where, \(M = N+1\) and \(A = [A_1, A_2, \ldots, A_{2N+1}]\) and

\[
A_1 = \begin{bmatrix}
1 & \cos(2\pi f_r (T_1)) & \cos(2\pi f_r (T_2)) & \cdots & \cos(2\pi f_r (T_{N+1})) \\
1 & \cos(2\pi f_r (2T_1)) & \cos(2\pi f_r (2T_2)) & \cdots & \cos(2\pi f_r (2T_{N+1})) \\
\vdots & \vdots & \vdots & & \vdots \\
1 & \cos(2\pi f_r (MT_1)) & \cos(2\pi f_r (MT_2)) & \cdots & \cos(2\pi f_r (MT_{N+1}))
\end{bmatrix}_{2N+1, N+1}
\]

\[
A_2 = \begin{bmatrix}
\sin(2\pi f_r (T_1)) & \sin(2\pi f_r (T_2)) & \cdots & \sin(2\pi f_r (T_{N+1})) \\
\sin(2\pi f_r (2T_1)) & \sin(2\pi f_r (2T_2)) & \cdots & \sin(2\pi f_r (2T_{N+1})) \\
\vdots & \vdots & \vdots & \vdots \\
\sin(2\pi f_r (MT_1)) & \sin(2\pi f_r (MT_2)) & \cdots & \sin(2\pi f_r (MT_{N+1}))
\end{bmatrix}_{2N+1, N+1}
\]

To solve \(Y\) the following equation is used:

\[
Y = A^{-1} X
\]  

(5)

\(A^{-1}\) must be calculated. However, A-1 is constant because A is a matrix with constant terms. Therefore, A can be calculated once. The calculation of A\(^{-1}\) can be used to solve the above equation. \(A^{-1}\) is a \(2N+1\) of the \(2N+1\) matrix, which can be written as:

\[
A^{-1} = [c_{ij}]_{2N+1, 2N+1}, (i, j = 1, \ldots, 2N+1)
\]

(6)

Based on (5) and (6), the following equation can be derived as:

\[
x_0 = \sum_{j=1}^{2N+1} c_{1,j} x(j)
\]  

(7)

\[
a_n = \sum_{j=1}^{2N+1} c_{n+1,j} x(j)
\]  

(8)

\[
b_n = \sum_{j=1}^{2N+1} c_{N+n+1,j} x(j)
\]  

(9)
One period of signal monitoring is needed to calculate $x_0, a_n$, and $b_n$. The summation and multiplication operations of 2N+1 are also required for this calculation. This calculation procedure is conducted among the samples. The method for the $k$th cycle is expressed as:

$$x_{0}^k(j + 1) = x_{0}^k(j) + c_{1,j} x(j)$$

$$a_{n}^k(j + 1) = a_{n}^k(j) + c_{n+1,j} x(j)$$

$$b_{n}^k(j + 1) = b_{n}^k(j) + c_{N+n+1,j} x(j)$$

Where $N$ is the last harmonic, $n$ is the number of harmonics, $k$ is the number of cycles, and $j$ is the number of samples in the $k$th cycle.

The initial value of any variable is zero at the beginning of any period, and the number of samples in any period starts from one, which is rendered as:

$$x_{0}^k(1) = a_{n}^k(1) = b_{n}^k(1) = 0.$$  

Thus, the DC values and harmonics are calculated after the 2N+1 sample at one period. Then, one is added to $k$, and $j$ becomes zero again until the DC values and harmonics are calculated for the $(k + 1)^{th}$ period.

This method is recursive because the variables are calculated based on their values in the previous stage at any sampling stage in a given cycle. Fig. 3 shows the flowchart of the algorithm for the recursive algebraic method.

### 4. CALCULATION OF THE REFERENCE CURRENT

#### 4.1. Instantaneous active and reactive p-q power theory

The instantaneous active and reactive p-q power theory is also known as the instantaneous power theory or p-q theory [12]. In instantaneous power theory, three-phase currents ($i_{a}, i_{b}, i_{c}$) and voltages ($v_{a}, v_{b}, v_{c}$) in the a–b–c coordinates are algebraically transformed to the $\alpha$–$\beta$ coordinates using Clarke’s transformation, as shown in the following equations [13]:

$$
\begin{bmatrix}
    v_{a} \\
    v_{\beta}
\end{bmatrix} =
\begin{bmatrix}
    2/3 & 1/2 & -1/2 \\
    0 & \sqrt{3}/2 & -\sqrt{3}/2
\end{bmatrix}
\begin{bmatrix}
    v_{a} \\
    v_{b} \\
    v_{c}
\end{bmatrix}

(11)
$$

$$
\begin{bmatrix}
    i_{a} \\
    i_{\beta}
\end{bmatrix} =
\begin{bmatrix}
    2/3 & 1/2 & -1/2 \\
    0 & \sqrt{3}/2 & -\sqrt{3}/2
\end{bmatrix}
\begin{bmatrix}
    i_{a} \\
    i_{b} \\
    i_{c}
\end{bmatrix}

(12)
$$

The instantaneous power is then calculated as follows:

$$
\begin{bmatrix}
    p \\
    q
\end{bmatrix} =
\begin{bmatrix}
    v_{a} & v_{\beta} & i_{a} \\
    v_{-\beta} & v_{a} & i_{\beta}
\end{bmatrix}

(13)
$$

$$
p = \overline{p} + \overline{\bar{p}} , q = \overline{\bar{q}} + \bar{q}

(14)$$
The entire reactive power and AC component of the active power are used as the reference power to obtain a sinusoidal current with unity power factor. The reference currents in a–ß coordinates are calculated as follows:

\[
\begin{bmatrix}
    i_a' \\
    i_\beta'
\end{bmatrix}
= \frac{1}{v_a' + v_\beta'} \begin{bmatrix}
    v_a' & -v_\beta' \\
    v_\beta' & v_a'
\end{bmatrix}
\begin{bmatrix}
    -\overline{p}' + \overline{p}_{loss} \\
    -q
\end{bmatrix}.
\]  

Here, \( \overline{p}_{loss} \) is the average value of losses in the inverter, which is obtained from the voltage regulator. The DC-link voltage regulator is designed to provide good compensation and excellent transient response. The actual DC-link capacitor voltage \( (v_{dc}) \) is measured by reference value \( (*dcV) \), and the error is processed by IT2FLC. The inputs of the IT2FLC are the capacitor voltage deviation and its derivative, whereas its output is the real power \( \overline{p}_{loss} \) requirement for voltage regulation. The reference current is calculated as shown in Eq. 17:

\[
\begin{bmatrix}
    i_{sa}^* \\
    i_{sb}^* \\
    i_{sc}^*
\end{bmatrix}
= \begin{bmatrix}
    \frac{2}{3} 1/2 & -1/2 \\
    1/2 & -3/2 \\
\end{bmatrix}
\begin{bmatrix}
    i_a \\
    i_\beta
\end{bmatrix}.
\]  

This control algorithm is illustrated in Fig. 4.

4.2. The proposed method

The source voltage should be a pure sinusoidal wave given as:

\[
v_i(t) = V_p \sin(\omega t)
\]  

The nonlinear load current is represented as:

\[
i(t) = \sum_{n=1}^{\infty} I_n \sin(n \omega t + \theta_n)
\]

\[
= I_1 \sin(\omega t + \theta_1) + \sum_{n=2}^{\infty} I_n \sin(n \omega t + \theta_n)
\]

\[
= I_1 \cos \theta_1 \sin(\omega t) + I_1 \sin \theta_1 \cos(\omega t)
+ \sum_{n=2}^{\infty} I_n \sin(n \omega t + \theta_n)
\]

\[
i_{1p}(t) + i_{1q}(t) + i_h(t)
\]

where \( I_n, \theta_n \) is the peak value of amplitude and the phase angle of the n-th harmonic current, respectively; \( n \) is a positive integer; \( I_1, \theta_1 \) is the peak value of the amplitude and the phase angle of the fundamental current, respectively; \( i_{1p}(t) \) is the component of the fundamental active current; \( i_{1q}(t) \) is the component of the fundamental reactive current; and \( i_h(t) \) is the component of the harmonics current.

A signal with unity amplitude is obtained from the source voltage using as the following equation:

\[
u(t) = \sin(\omega t)
\]  

By using the Fourier algorithm, the amplitude of the active component of the
fundamental load current can be determined as:

\[
I_{\text{smp}}^* = \frac{2}{T} \int_0^T i_L(t)u(t)dt
\]

\[
I_{\text{smp}}^* = \frac{2}{T} \left[ I_1 \cos \theta_1 \sin(\omega t) + I_1 \sin \theta_1 \cos(\omega t) + \sum_{n=2}^{\infty} I_n \sin(n \omega t + \theta_n) \right] \sin(\omega t)dt
\]

\[
= \frac{2}{T} \left[ I_1 \cos \theta_1 \sin^2(\omega t) + I_1 \sin \theta_1 \cos(\omega t) \sin(\omega t) + \sum_{n=2}^{\infty} I_n \sin(n \omega t + \theta_n) \sin(\omega t) \right] dt
\]

\[
= \frac{2}{T} \left[ I_1 \cos \theta_1 \left( \frac{1-\cos(2\omega t)}{2} \right) + I_1 \sin \theta_1 \frac{\sin(2\omega t)}{2} + \sum_{n=2}^{\infty} I_n \left\{ \cos[(n+1)\omega t + \theta_n] + \cos[(n-1)\omega t + \theta_n] \right\} \right] dt
\]

\[
= I_1 \cos \theta_1 = I_{\text{smp}}^*
\]

(21)

In this method, the peak value of the amplitude and the phase angle of the fundamental load current \((I_1, \theta_1)\) from a recursive algebraic approach block are first obtained before calculating the displacement power factor \((\cos \theta_1)\). Fig. 5 shows the schematic diagram of the \(I_1 \cos \theta_1 \) based on a recursive algebraic approach control algorithm.

\[
I_{\text{smp}}^* = I_{\text{smp}} + I_{\text{smd}}^*
\]

(24)

\[
i_s^*(t) = I_{\text{sp}} \sin(\omega t)
\]

(25)

\[
i_f^*(t) = I_f(t) - i_s^*(t)
\]

(26)

5. INTERVAL TYPE-2 FUZZY LOGIC BASED DC BUS VOLTAGE CONTROLLER

While precise knowledge of the system model is not available, FLC’s are a superior choice. The inputs of the FLC are the capacitor voltage deviation and its derivative and the output of the FLC is the
real power requirement for voltage regulation as shown in Fig.4. In this paper first, a type-1FLC is modeled and then the same configuration is chosen for the design of IT2 FLC.

For type-1FLC, the following seven fuzzy levels or sets are chosen, to convert the inputs and output variables into linguistic variables as: NB (negative big), NM (negative medium), NS (negative small), ZE (zero), PS (positive small), PM (positive medium), and PB (positive big) are chosen [13]. Membership functions (MFs) selected here for the inputs and output variables are shown in Figs 6, 7.

On the basis of the theory that in the steady state, small errors require fine control, which needs fine input/output variables and in the transient state, large errors require coarse control, which needs coarse input/output variables; rule base elements of the table are determined. Whereas both inputs have seven subsets, the elements of the rule table as shown in Table 1 are obtained [15]. The T2FLC was first introduced by Zadeh in 1970s, as an extension of the type-1 fuzzy controller [16].

As shown in Fig 8, similar to the structure of the conventional type-1 FLC, the type-2 fuzzy logic controller (T2FLC) also contains the components; fuzzifier, rule base, fuzzy inference engine and output processor which comprises of type-reducer and defuzzifier while for a type-1 fuzzy is just a defuzzifier.

The type reducer maps a type2 FLS set into a type-1 fuzzy set and defuzzifier as like as type-1 transforms a fuzzy output into a crisp output.

In the type-2 fuzzy set, the membership grade for each element is also a fuzzy set in 0 - 1, unlike the type-1 fuzzy set whose membership grade is a crisp number of either 0 or 1. The membership functions of type-2 fuzzy sets are three dimensional and include a footprint of uncertainty, as can be seen by the shaded region bounded by the lower and upper membership functions, both of which are type-1 MFs as shown in Fig 9. Normally, the T2FLC has characteristics of profound computation due to heavy computational load at the step of type reducing process.

**Table 1. Fuzzy control rule**

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<th>error (c)</th>
<th>NB</th>
<th>NM</th>
<th>NS</th>
<th>ZE</th>
<th>PS</th>
<th>PM</th>
<th>PB</th>
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</table>
A footprint of uncertainty (FOU) which displays the uncertainties in the shape and position of the type-1 fuzzy set provides an additional degree of freedom to handle uncertainties. The T2FLC can be used at the uncertain circumstances when the membership grades cannot be determined exactly [17]. To simplify the computation, the secondary membership functions can be set to either 0 or 1 so as to derive the interval T2FLC [18]. Suppose that there are M rules in the rule base, each of which has the following form

\[
\text{Rule } k : \text{IF } x_1 \text{ is } \tilde{A}_1^k \text{ and } x_2 \text{ is } \tilde{A}_2^k \text{ and } \ldots \text{ and } x_p \text{ is } \tilde{A}_p^k, \text{THEN } y \text{ is } \left[ \begin{array}{c} w^k_- \cr w^k_+ \end{array} \right].
\]

where \( k = 1,2,\ldots,M \), \( p \) is the number of input variables in the antecedent part, \( \tilde{A}_i^k \) (i= 1,2,\ldots,p , k=1,2,\ldots,M) and \( w^k_- \), \( w^k_+ \) are the singleton lower and upper weighting factors of the THEN-part. Once a crisp input \( X = (x_1, x_2, \ldots, x_p)^T \) is applied to the interval T2FLC, through the singleton fuzzifier and the inference process, the firing strength of the \( k^{th} \) rule which is an interval type-1 set can be obtained as

\[
F^k = \left[ \begin{array}{c} f^k_- \cr f^k_+ \end{array} \right], \text{ in which:}
\]

\[
f^k_- = \mu_{\tilde{A}_1^k}(x_1) \cdot \mu_{\tilde{A}_2^k}(x_2) \cdot \ldots \cdot \mu_{\tilde{A}_p^k}(x_p)
\]

(27)

\[
f^k_+ = \mu_{\tilde{A}_1^k}(x_1) \cdot \mu_{\tilde{A}_2^k}(x_2) \cdot \ldots \cdot \mu_{\tilde{A}_p^k}(x_p)
\]

(28)

\[
f^k = \mu_{\tilde{A}_1^k}(x_1) \cdot \mu_{\tilde{A}_2^k}(x_2) \cdot \ldots \cdot \mu_{\tilde{A}_p^k}(x_p)
\]

(29)

Where \( \mu(\cdot) \) and \( \mu(\cdot) \) denote the grades of the lower and upper membership functions of interval T2FLC and \( \ast \) denotes minimum or product t-norm.

The outputs of the inference engine should be type reduced and then defuzzified so as to create a crisp output. For design of the interval T2FLC for the DC voltage regulator, the same configuration as that of the conventional type-1 FLC is used (Figs. 6 and 7). There are two inputs (error and rate of error) and single output in which each set of input/output variables has similar seven linguistic variables. The fuzzy labels are negative big (NB), negative medium (NM), negative small (NS), zero (Z), positive small (PS), positive medium (PM), positive big (PB). The rules for interval T2FLC are also similar to the type 1 FLC but their antecedents and consequents are represented by the interval T2FLC. The diagonal rule table as summarized in Table 1 is constructed for the scenario in which error and change of error approach zero with a fast rise time and without overshoot. Here, the Mamdani interval T2FLC is considered and the popular center-of-sets is assigned for type-reduction method. The Karnik-Mendel algorithm is then used to obtain the type reduced set.

Here, after writing required m-codes in MATLAB for IT2FLC, Embedded MATLAB Function Block is used to incorporate into the Simulink model. The
capacitor voltage deviation $e(n)$ and its derivative $ce(n)$ are fed to the embedded MATLAB function as the inputs and the output is the real power requirement for voltage regulation.

6. ADAPTIVE-HYSTERESIS CURRENT CONTROLLER

The PWM -voltage source inverter’s voltage and current waves for phase A is shown in Fig. 10.

At point 1, when current crosses the lower hysteresis band, the transistor T1 will be switched-on. The inverter output voltage and the current will rise. In the same way, when the current touches the upper band limit at point 2 then the inverter output voltage and consequently the current will start decaying, by switch-on the transistor T4. Using the Fig. 10, the following equations can be written for the switching interval $t_1$ and $t_2$ [19].

$$\frac{d i_{fa}}{dt} = \frac{1}{L} (0.5V_{dc} - V_s)$$  \hspace{1cm} (30)

$$\frac{d i_{fa}}{dt} = -\frac{1}{L} (0.5V_{dc} + V_s)$$  \hspace{1cm} (31)

where $L =$ inductance of phase; $d i_{fa}^+$ and $d i_{fa}^-$ are the rising and falling current segments, respectively.

From the geometry of Fig. 10 can be written:

$$\frac{d i_{fa}^+}{dt} t_1 - \frac{d i_{fa}^-}{dt} t_1 = 2HB$$  \hspace{1cm} (32)

$$\frac{d i_{fa}^-}{dt} t_2 - \frac{d i_{fa}^+}{dt} t_2 = -2HB$$  \hspace{1cm} (33)

$$t_1 + t_2 = T_c = \frac{1}{f_c}$$  \hspace{1cm} (34)

Where $t_1$ and $t_2$ are the respective switching intervals and $f_c$ is the switching frequency. Adding (32) and (33) and substituting (34), it can be written:

$$t_1 \frac{d i_{fa}^+}{dt} + t_2 \frac{d i_{fa}^-}{dt} - \frac{1}{f_c} \frac{d i_{fa}^*}{dt} = 0$$ \hspace{1cm} (35)

Subtracting (33) from (32), so:

$$t_1 \frac{d i_{fa}^+}{dt} - t_2 \frac{d i_{fa}^-}{dt} - (t_1 - t_2) \frac{d i_{fa}^*}{dt} = 4HB$$ \hspace{1cm} (36)

Substituting (35) in (36), gives:

$$(t_1 + t_2) \frac{d i_{fa}^+}{dt} - (t_1 - t_2) \frac{d i_{fa}^-}{dt} = 4HB$$ \hspace{1cm} (37)

Substituting (31) in (35) and after simplifying:

$$t_1 - t_2 = \left( \frac{d i_{fa}^*}{dt} \right) / f_c \left( \frac{d i_{fa}}{dt} \right)$$ \hspace{1cm} (38)

Finally, Substituting (38) in (37), it gives:

$$HB = \left[ 0.125V_{dc} \left( 1 - \frac{4L^2}{V_{dc}^2} \left( \frac{V_s}{L} + m \right)^2 \right) \right]$$ \hspace{1cm} (39)

Hence $f_c$ is frequency of modulation, $m = \frac{d i_{fa}}{dt}$ is the slope of command current wave, $L$ is coupling inductance and $V_{dc}$ is the DC link capacitor voltage. To control the switching pattern of the inverter, hysteresis band (HB) can be modulated at different points of fundamental frequency cycle. In order to have symmetrical operation of all three phases, it is required that the hysteresis bandwidth (HB) profiles HBa, HBb and HBc will be same, but have
difference in phase. As the equation 39 demonstrates, the hysteresis bandwidth HB as a function of supply voltage, dc link voltage and reference current variations (m) can be modulated to minimize the effects of current distortion on modulated waveform. Therewith the modulation frequency is kept almost constant; the performance of PWM and shunt Active Power Filter substantially is improved. Fig.11 shows block diagram of the adaptive hysteresis bandwidth computation for phase (A).

7. SIMULATION RESULTS
The simulations conducted on the test system are shown in Fig. 12 to evaluate the performance of the SAPFs using the \( I \cos \Phi \) algorithm based on a recursive algebraic approach for generating the reference compensating currents. The test system comprises three-phase voltage source, SAPF, and an uncontrolled rectifier with R and L loads. An inductor, \( L_f \) and resistor, \( R_f \) were used to connect SAPF to the test system. The system parameters are given in Table 2.

![Image](image_url)

**Fig. 10.** Adaptive hysteresis current controller

**Fig. 11.** Block diagram of the adaptive hysteresis bandwidth computation

---

**Table 2.** Circuit parameters of SAPF

<table>
<thead>
<tr>
<th>Parameter Names</th>
<th>Numerical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source Voltage</td>
<td>312 V (peak), 50 Hz</td>
</tr>
<tr>
<td>Source Resistance and Inductance</td>
<td>0.1 ohm, 1 mH</td>
</tr>
<tr>
<td>Filter Inductance and Resistance</td>
<td>1 mH, 0.1 ohm</td>
</tr>
<tr>
<td>Load Resistance and Inductance</td>
<td>5 Ω, 1 mH</td>
</tr>
<tr>
<td>DC Capacitor</td>
<td>2500 μF</td>
</tr>
<tr>
<td>DC Capacitor Reference Voltage</td>
<td>650V</td>
</tr>
<tr>
<td>Sample Time (Ts)</td>
<td>7.14 e-6</td>
</tr>
</tbody>
</table>

Table 2 shows the circuit parameters used in the simulation while Table 3 shows the values of total harmonic distortion in percent (%), power factor, and reactive power measured at the PCC. Figure 13 show the source currents without SAPF while Figures 14 and 15 show the source currents after compensation using the p-q
theory and the proposed reference current generation using the recursive algebraic approach, respectively.

Table 3. Total harmonic distortion in percent (%), power factor and reactive power

<table>
<thead>
<tr>
<th>Method used</th>
<th>Source Current (phase a)</th>
<th>Power Factor</th>
<th>Reactive Power (Var)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before any shunt compensation</td>
<td>22.10</td>
<td>0.9537</td>
<td>4838</td>
</tr>
<tr>
<td>With recursive algebraic approach</td>
<td>2.66</td>
<td>1</td>
<td>17.29</td>
</tr>
<tr>
<td>With p-q theory</td>
<td>2.97</td>
<td>1</td>
<td>76.21</td>
</tr>
</tbody>
</table>

Fig. 13. Source currents without SAPF

Fig. 14. Source currents for SAPF with PQ theory

Fig. 15. Source currents for SAPF using the proposed method

Comparison among Figs. 13, 14 and 15 indicates that the source currents consist of fundamental current only, and the network with SAPF has fewer harmonic than the network without SAPF. Table 3 suggests that the harmonic and reactive currents are greatly reduced after compensation. The SAPF result with the reference current generation based on the recursive algebraic approach is better than SAPF with the generation system based on the p-q theory.

8. CONCLUSIONS

This paper presents a novel technique to generate the reference current for a three-phase SAPF with nonlinear loads. SAPF was simulated and its performance was analyzed in a sample power system. The results of the simulation on the test system prove that the injected harmonics are significantly reduced and power factor is improved by using the proposed algorithm based on the recursive algebraic approach. Compared with the p-q theory, the proposed approach is more effective in reducing reactive and THD to less than 3%.

REFERENCES


Improved Binary Particle Swarm Optimization Based TNEP Considering Network Losses, Voltage Level, and Uncertainty in Demand

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ABSTRACT
Transmission network expansion planning (TNEP) is an important component of power system planning. It determines the characteristics and performance of the future electric power network and influences the power system operation directly. Different methods have been proposed for the solution of the static transmission network expansion planning (STNEP) problem till now. But in all of them, STNEP problem considering the network losses, voltage level and uncertainty in demand has not been solved by improved binary particle swarm optimization (IBPSO) algorithm. Binary particle swarm optimization (BPSO) is a new population-based intelligence algorithm and exhibits good performance on the solution of the large-scale and nonlinear optimization problems. However, it has been observed that standard BPSO algorithm has premature convergence when solving a complex optimization problem like STNEP. To resolve this problem, in this study, an IBPSO approach is proposed for the solution of the STNEP problem considering network losses, voltage level, and uncertainty in demand. The proposed algorithm has been tested on a real transmission network of the Azerbaijan regional electric company and compared with BPSO. The simulation results show that considering the losses even for transmission expansion planning of a network with low load growth is caused that operational costs decreases considerably and the network satisfies the requirement of delivering electric power more reliable to load centers. In addition, regarding the convergence curves of the two methods, it can be seen that precision of the proposed algorithm for the solution of the STNEP problem is more than BPSO.

KEYWORDS: STNEP; network losses; voltage level; uncertainty in demand; IBPSO.

1. INTRODUCTION
Transmission network expansion planning (TNEP) is an important part of power system planning that its main objective is to acquire the most optimal plan for the network expansion. TNEP should satisfy the required adequacy of the lines for delivering safe and reliable electric power to load centers along the planning horizon [1, 2]. Determination of investment costs for power system expansion is a very difficult task, because costs should be determined from grid owners with agreement of a customer and considering the various reliability criteria [3]. The long-term TNEP is a hard, large-scale, and non-linear combinatorial optimization problem that generally could be classified as static or
dynamic. Static expansion determines where and how many new transmission lines should be added to the network up to the planning horizon. If in the static expansion the planning horizon is categorized in several stages, then it becomes dynamic planning [4, 5].

Most of power systems, generating plants are located far from the load centers. In addition, the planned new projects are still so far from completion. Due to these situations, the investment costs of transmission network are huge. Thus, the STNEP problem acquires a principal role in power system planning and should be evaluated carefully, because any effort to reduce the cost of transmission system expansion by some fraction of a percent allows saving of a significant amount of capital.

Garver proposed one of the first approaches for solving the STNEP problem in 1970 [6]. He formulated the problem as a power flow problem and used a linear programming algorithm to find the most direct routes from generation to loads. After his paper, much research has been done on the field of static transmission network expansion planning. Some of them are related to problem solving method. Some others proposed different approaches for the solution of this problem considering various parameters such as uncertainty [7, 8], reliability criteria [3, 9], and economic factors [10]. Also, some of them investigated this problem and generation expansion planning together [11, 12].

Chanda and Bhattacharjee [13] solved static transmission expansion planning problem in order to obtain a maximum reliable network. Reliability criteria are related to actual systems that considering them help to maintain a higher degree of reliability of the system. Later, they [14] proposed a new method for designing a maximum reliable network when failure probabilities of the lines are fuzzy in nature instead of deterministic as mentioned in Ref. [13]. However, voltage level and uncertainty in demand have not been considered in their literatures.

Grandville et al. [15] were formulated the STNEP problem by a linearized power flow model and used the Benders decomposition for its solution. However, classical decomposition approaches, e.g., Benders decomposition may fail to converge to optimal solutions due to the non-convex nature of the TNEP problem. In order to handle these non-convexities difficulties, a Benders hierarchical decomposition approach (HIPER) was proposed by Romero and Monticelli [16], where, a chain of three models represented the power network constraints. The two first models relax all the non-convexities constraints, which results in the optimal solution. Then, the non-convexities are introduced (third model). Nevertheless, the non-convexities still exist in the mathematical model used and application of this approach to networks with a large number of candidate circuits is limited by computational limitations. Binato et al. [17], presented a heuristic approach, called greedy randomized adaptive search procedure (GRASP) to solve the static transmission expansion planning problem. GRASP is an expert iterative sampling technique that due to its generality and simplicity, is a useful alternate approach that can be applied to many other kinds of decision problems. However, this technique is the most time consuming and the local search procedure used in this approach leads to some difficulties related to pruning
Lee et al. [18] adopted branch and bound (B&B) algorithm in a way to preserve the discrete nature of investments for solution of STNEP problem. However, some problems such as being too slow the convergence of algorithm regarding the problem complexity and difficult implementation are when a planner uses this algorithm. Periera and Pinto [19] proposed a technique based on sensitivity analysis for static expansion of the transmission network. But the difficulty of the proposed method is that, if the number of nodes or number of participants is large, the planning for expansion is combinatorial complicated and that makes it very difficult to find reasonable solutions within short computational time.

Romero et al. [20] presented simulated annealing (SA) for optimizing the investment costs and loss of load of the network in static transmission expansion planning. SA mimics the physical process of annealing in solids (i.e. heating up a solid, and cooling it down until it crystallizes). It is a point-to-point search method with a strong theoretical base that its ability to reach global, or near global, optimal solutions under certain circumstances (slow cooling schedules) makes it a robust optimization algorithm. However, in the hard combinational problems such as STNEP problem, both the number of alternatives to be analyzed and the number of local minimum points increase with the dimension of the network. This fact can negatively affect on computing time and solution quality of the problem. Later, Gallego et al. [21] in order to improve the performance of the SA, proposed parallel simulated annealing (PSA) approach. The objective function is the same one of Ref. [20]. The simulation results show that the proposed method gives not only faster solutions but better ones as well. But, the implementation of this method for solving large-scale, hard and highly non-linear combinational problems like long-term STNEP problem is so hard.

Al-Saba and El-Amin [22] proposed a neural network based method for the solution of the STNEP problem with considering both the network losses and construction cost of the lines. Contreras and Wu [23] included the network expansion costs and transmitted power through the lines in the objective function and the goal is optimization of both expansion costs and lines loading. However, in these papers, voltage level and uncertainty in demand have not been studied.

Braga and Saraiva [24] considered the voltage level of transmission lines as a subsidiary factor but its objective function only includes expansion and generation costs and one of the reliability criteria i.e.: power not supplied energy. Moreover, expansion plan has been studied as dynamic type and the uncertainty in demand has not been considered.

Recently, Silva et al. [25] used a genetic algorithm (GA) for solving the proposed problem of Ref. [20]. GA is a random search method that has demonstrated the ability to deal with non-convex, non-linear, integer-mixed optimization problems like the STNEP problem. Later, Silva et al. [26] introduced a Tabu search (TS) based method for optimization of investment cost in static transmission expansion planning. TS is an iterative search procedure that moving from one solution to another looks for improvements on the best solution visited. The basic concepts of TS are
movements and memory. A movement is an operation to jump from one solution to another while memory is used with different objectives such as to guide the search to avoid cycles. The simulation results for two real-world case studies (Brazilian southern and Brazilian southeastern network) have been shown that TS is a feasible and powerful technique to be applied to STNEP problem. Also, the authors have shown that the performance of TS for finding the best solutions is almost similar to GA. Thus, it can be concluded that the most important advantage of GA is its simple implementation in addition to reach the respectively good solutions.

So, in [27, 28], the expansion cost of substations with the network losses have been considered for the solution of STNEP problem using decimal codification genetic algorithm (DCGA). The results evaluation in [27] indicated that the network with considering higher voltage level saves capital investment in the long-term and become overload later. In [28], it was shown that the total expansion cost of the network was calculated more exactly considering the effects of the inflation rate and load growth factor and therefore the network satisfies the requirements of delivering electric power more safely and reliably to load centers. But, the uncertainty in demand has not been included in the objective functions.

Shayeghi and Mahdavi [29] studied the effect of losses coefficient on static transmission network expansion planning using the decimal codification based genetic algorithm. They showed that this coefficient has not any role in determining of network configuration and arrangement. However, considering its effect in expansion planning of transmission networks with various voltage levels is caused the total cost of the network (expansion and losses costs) is reduced considerably and therefore the STNEP problem is solved more exactly and correctly. Also, they [30] investigated the bundle lines effect on network losses in STNEP problem and indicated that these lines have an important role in reduction of network losses and subsequent operational costs. However, they have not investigated uncertainty in demand in their research.

Also, Zhao et al. [31] presented a multi-objective optimization model for static transmission expansion planning considering DG impacts, uncertainties of generation and load. But, they solved the problem regardless of network losses and voltage level. Finally, Mahdavi et al. [32] investigated the effect of bundle lines on static expansion planning of a multiple voltage level transmission network by DCGA. They concluded that considering the effect of bundle lines on static transmission expansion planning caused that the total expansion cost of network (expansion and operational costs) is considerably decreased and therefore the capital investment significantly saved. Moreover, it was shown that construction of bundle lines in transmission network with different voltage levels caused that the network lines is overloaded later and the network would have higher adequacy. Later they [33] considered the network losses in the problem of Ref. [32] and showed that network losses play an important role in transmission expansion planning and subsequent determination of network arrangement and configuration. However, they have not studied the uncertainty in demand in their literatures.
Although global optimization techniques like GA and TS seem to be good methods for the solution of TNEP problem. However, when the system has a highly epistatic objective function (i.e. where parameters being optimized are highly correlated), and number of parameters to be optimized is large, then they have degraded efficiency to obtain a global optimum solution and simulation process use a lot of computing time. In order to overcome these drawbacks, Shayeghi et al. [34] applied the binary PSO (BPSO) for optimization of transmission lines loading in STNEP. They found that BPSO performance is better than GA from precision and convergence speed viewpoints. BPSO is a novel population based metaheuristic that is 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. However, the standard BPSO algorithm has also some disadvantages like premature convergence phenomenon similar to the GA. Thus, in this paper, to overcome these drawbacks and considering voltage level and uncertainty in demand, expansion planning has been investigated by including network losses cost, uncertainty in demand and also the expansion cost of related substations to expansion costs, the proposed objective function is defined as follows:

$$OF = \sum_{k=1}^{NS} \left( EC_k + LC_k + \alpha \times \sum_{i=1}^{NB} r_i^k \right) \times PR_k$$  \hspace{1cm} (1)$$

$$EC_k = \sum_{l,j \in \Omega} CL_{ij} n_{ij}^k + \sum_{i=1}^{NB} \sum_{c=1}^{ST} m_i^k SC_c$$  \hspace{1cm} (2)$$

$$LC_k = \left( \sum_{i=1}^{NC} \sum_{j=1}^{NC} R_{ij}^k I_{ij}^k \right) \times K_{loss} \times 8760 \times C_{MWh}$$  \hspace{1cm} (3)$$

Where,

$$EC_k$$: Expansion cost of network in scenario $k$.

$$LC_k$$: Annual losses cost of network in scenario $k$.

$r_i^k$ : Loss of load for i-th bus in scenario $k$.

2. PROBLEM FORMULATION

Due to considering the effect of the network losses on STNEP problem in a multi voltage level transmission network under uncertainty in demand and subsequent adding the expansion cost of substations to expansion costs, the proposed objective function is defined as follows:
α: A coefficient for converting loss of load to cost ($US/MW).

PRk: Occurrence probability of scenario k.

CLij: Construction cost of transmission line in corridor i-j.

nkij: Number of new circuits of corridor i-j in scenario k.

SCC: Cost of c-th type transformer (related costs are given in Appendix A).

mik: Number of transformers that have been predicted for constructing in i-th bus under scenario k.

CMW: Cost of one MWh ($US/MWh).

Rijk: Resistance of branch i-j in scenario k.

lijtk: Flow of branch i-j in t-th year under scenario k. It is varied with respect to annual load growth and therefore depends on the time.

Kloss: Losses coefficient.

Ω: Set of all candidate corridors.

NY: Number of years after expansion to calculate the network losses. It's rate in all scenarios has been considered 10 years.

NC: Number of expandable corridors of network.

NB: Number of network busses.

ST: Number of types for constructed transformers.

NS: Number of scenarios.

The calculation method of Kloss has been given in [27]. Several restrictions have to be modeled in a mathematical representation to ensure that the mathematical solutions are in line with the planning requirements. These constraints are as follows:

\[
S^k f^k + g^k - d^k = 0 \tag{4}
\]

\[
f^k_{ij} - \gamma^k_{ij} (n^0_{ij} + n^k_{ij}) (\theta^k_i - \theta^k_j) = 0 \tag{5}
\]

\[
|f^k_{ij}| \leq \beta \cdot (n^0_{ij} + n^k_{ij}) f^k_{ij} \tag{6}
\]

\[
0 \leq n^k_{ij} \leq \bar{n}_{ij} \tag{7}
\]

N-I Safe Criterion \tag{8}

Where, (i,j) ∈ Ω and:

Sk: Branch-node incidence matrix in scenario k.

fk: Active power matrix for each corridor in scenario k.

gk: Generation vector in scenario k.

dk: Demand vector in scenario k.

θtk: Phase angle of each bus in scenario k.

γtk: Total susceptance of circuits for corridor i-j in scenario k.

\bar{n}_{ij}: Maximum number of constructible circuits in corridor i-j.

\bar{f}_{ij}: Maximum of transmissible active power through the corridor i-j which will have two different rates according to the voltage level of candidate line.

β: A coefficient for providing security margin from the loading of lines view point. This coefficient guaranties required adequacy of lines to satisfy the all of network loads at years after expansion. The goal of the STNEP problem is to obtain the number of lines and their voltage level to expand the transmission network in order to ensure required adequacy of the network along the specific planning horizon. Thus, problem parameters are discrete time type and consequently the optimization problem is an integer programming problem. For solution of this problem, there are various methods such as classic mathematical and heuristic methods. In this study, the improved binary particle swarm optimization is used to solve the STNEP problem due to simple implementation and
high precision for finding the best solutions.

3. IMPROVED BINARY PARTICLE SWARM OPTIMIZATION (IBPSO) ALGORITHM

Particle swarm optimization algorithm, which is tailored for optimizing difficult numerical functions and based on metaphor of human social interaction, is capable of mimicking the ability of human societies to process knowledge [35]. It has roots in two main component methodologies: artificial life (such as bird flocking, fish schooling and swarming); and, evolutionary computation. It lies somewhere in between evolutionary programming and the genetic algorithms [28]. As in evolutionary computation paradigms, the concept of fitness is employed and candidate solutions to the problem are termed particles or sometimes individuals, each of which adjusts its flying based on the flying experiences of both itself and its companion. Vectors are taken as presentation of particles since most optimization problems are convenient for such variable presentations. In fact, the fundamental principles of swarm intelligence are adaptable, diverse response, proximity, quality, and stability [36]. It is adaptive corresponding to the change of the best group value. The allocation of responses between the individual and group values ensures a diversity of response. The population is responding to the quality factors of the previous best individual values and the previous best group values. As it is reported in [35], this optimization technique can be used to solve many of the same kinds of problems as GA and does not suffer from any of GAs difficulties. It has also been found to be robust in solving problem featuring non-linearizing, non-differentiability and high-dimensionality. It is the search method to improve the speed of convergence and find the global optimum value of the fitness function.

PSO starts with a population of random solutions “particles” in a D-dimensional space. The ith 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 $i$ is stored as $P_i = (p_{i1}, p_{i2}, \ldots , p_{iD})$ that its best value is represented by (pbest). 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. PSO consists of, at each step, changing the velocity of each particle toward its pbest and gbest according to Eq. (9). 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 ith particle is then updated according to Eq. (10) [35, 36]:

$$v_{id}(t + 1) = \omega \times v_{id}(t) + c_1 r_1 (P_{id} - x_{id}(t)) + c_2 r_2 (P_{gd} - x_{id}(t))$$

$$x_{id}(t + 1) = x_{id}(t) + v_{id}(t + 1)$$

Where, $P_{id}$ and $P_{gd}$ are pbest and gbest. It is concluded that gbest version performs best in terms of median number of iterations to converge. However, pbest version with neighborhoods of two is more resistant to local minima. The results of past experiments about PSO show that $\omega$ was not considered at an early stage of PSO algorithm. However, $\omega$ affects the iteration number to find an optimal solution. If the
value of $\omega$ is low, the convergence will be fast, but the solution will fall into the local minimum. On the other hand, if the value will increase, the iteration number will also increase and therefore the convergence will be slow. Usually, for running the PSO algorithm, value of inertia weight is adjusted in the training process. In Eq. (9), term of $c_{i1} r_1 (P_id - x_id (t))$ represents the individual movement and term of $c_{i2} r_2 (P_gd - x_id (t))$ represents the social behavior in finding the global best solution.

Regarding the fact that the parameters of the TNEP problem are discrete time type and the performance of standard PSO is based on real numbers, this algorithm can not be used directly for solution of the STNEP problem. Thus, in order to overcome this drawback a binary based particle swarm optimization (BPSO) algorithm is used for the solution of the STNEP problem. In this method, in a D-dimensional binary solution space, the position of $i$th particle can be expressed by a D-bit binary string as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, where, $X_i \in \{0,1\}$. Since each bit $X_i$ is binary-valued, the term of $(P_id - x_id (t))$ or $(P_gd - x_id (t))$ has only three possible values 0, 1 and -1. Where,

$$P_id - x_id (t) = 1; \quad \text{if} \quad P_id = 1, x_id = 0$$
$$P_id - x_id (t) = 0; \quad \text{if} \quad P_id = 0, x_id = 0 \ or \ P_id, x_id = 1$$
$$P_id - x_id (t) = -1; \quad \text{if} \quad P_id = 0, x_id = 1$$
$$P_gd - x_id (t) = 1; \quad \text{if} \quad P_gd = 1, x_id = 0$$
$$P_gd - x_id (t) = 0; \quad \text{if} \quad P_gd = 0, x_id = 0 \ or \ P_gd, x_id = 1$$
$$P_gd - x_id (t) = -1; \quad \text{if} \quad P_gd = 0, x_id = 1$$

In Eq. (11), $t$ is the number of algorithm iterations, $t_{max}$ is the maximum number of iterations, and $\omega_{max}$ and $\omega_{min}$ are the maximum and minimum values of the inertia weight respectively. Also, the velocity $v_id (t+1)$ is a real number in $[-V_{max}, V_{max}]$. According to Eq. (10), for updating the position of the $i$th particle, the real value $v_id (t+1)$ must be added to the binary value $x_id (t)$, but this is not possible mathematically. So an intermediate variable $S(v_id(t+1))$ via the sigmoid limiting transformation is defined as Eq. (12) [37]:

$$S(v_id(t+1)) = \frac{1}{1 + e^{-v_id(t+1)}}$$

Eq. (12) maps the domain of $[-V_{max}, V_{max}]$ into the range of $[1/(1+e^{V_{max}}), 1/(1+ e^{V_{max}})]$, which is a subset of (0, 1). The value of $S (v_id (t+1))$ can be therefore interpreted as a probability threshold. A random number with a uniform distribution in (0, 1), R, is then generated and compared to $S (v_id (t+1))$. Thus, the position of the particle $i$ can be updated as follows:

$$x_id (t+1) = 1; \quad \text{if} \quad R < S(v_id(t+1))$$
$$x_id (t+1) = 0; \quad \text{if} \quad R \geq S(v_id(t+1))$$

The probability that $x_id (t+1)$ equals to 1 is $S (v_id (t+1))$ and the probability that it equals to 0 is $1 - S (v_id (t+1))$. From Eq. (11), the velocity update of the particle consists of three parts: The first term is its own current velocity of particles; the second term is cognitive part which represents the particle's own experiences; the third term is social part which represents the social interaction between the particles. With respect to Eq. (11), it is realized that best position of particles take places proportional to $pbest$. It can be seen that: when a particle's current position coincides with the global best position ($gbest$), the particle will only leave this point if the
inertia weight and its current velocity are different from zero. If the particles' current velocities in swarm are very close to zero, then these particles will not move once they catch up with the global best particle. This means that the particles have been converged to the best experience of particles and are far from the group. At this moment if these positions corresponding fitness is not the problems expected global optimal, then the premature convergence phenomenon appears. In this situation, the convergence speed will be decreased [38]. In order to overcome this drawback and improve optimization synthesis, an improved binary particle swarm optimization (IBPSO), by introducing the mutation operator often used in genetic algorithm is proposed in this paper. This process can make some particles jump out local optima and search in another area of the solution space. In this method, the mutation probability ($P_M$) is dynamically adjusted according to the diversity in the swarm. The goal with mutation probability is to prevent the BPSO to converge prematurely to local minima. It should be noted the $P_M$ is considered 0.01 in this study. Fig. 1 shows the flowchart of the improved BPSO algorithm. In this study, in order to acquire better performance of the proposed algorithm, parameters that are used in the improved BPSO algorithm have been initialized according to Table 1. It should be noted that IBPSO algorithm is run several times and then optimal results are selected.

4. SIMULATION RESULTS

The transmission network of the Azerbaijan regional electric system is used to test and evaluation of the proposed method. This actual network has been located in northwest of Iran and is shown in Fig. 2. All details of this network have been given in [32].

![Flowchart of the IBPSO algorithm](image)

**Table 1** Value of parameters for IBPSO algorithm

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem dimension</td>
<td>153</td>
</tr>
<tr>
<td>Number of particles</td>
<td>10</td>
</tr>
<tr>
<td>Number of iterations</td>
<td>1500</td>
</tr>
<tr>
<td>$C_1$</td>
<td>1.5</td>
</tr>
<tr>
<td>$C_2$</td>
<td>1.8</td>
</tr>
<tr>
<td>$C$</td>
<td>1</td>
</tr>
<tr>
<td>$\omega_{\text{max}}$</td>
<td>0.9</td>
</tr>
<tr>
<td>$\omega_{\text{min}}$</td>
<td>0.4</td>
</tr>
<tr>
<td>$v_{\text{max}}$</td>
<td>4</td>
</tr>
<tr>
<td>$v_{\text{min}}$</td>
<td>-4</td>
</tr>
</tbody>
</table>

For considering uncertainty in STNEP problem, three different scenarios with equal occurrence probabilities have been
predicted for load growth. Also planning horizon is the year 2021 (10 years ahead) and network losses is calculated from the DC load flow from planning horizon year to 10 years after it (year 2031). Therefore, for feasibility of comparing the scenarios from their effective rate on network load viewpoint, rates of network load at planning horizon with related load growth coefficients for different scenarios are given in Table 2. Value of coefficients $\alpha$ and $\beta$, and $C_{\text{MW}h}$ are considered $10^7$ SUS/MW), 40% and 33 (SUS/MWh) respectively. The proposed method is applied to the case study system and the results (lines that must be added to the network during the planning horizon year) are given in Tables 3 and 4. The first and second configurations are obtained neglecting and considering the network losses, respectively. By comparing the Tables 3 and 4, ignoring the network losses, a configuration with lower voltage level lines is proposed for expansion of the network. But if the network losses is considered, a configuration with higher voltage level lines is proposed for expansion purpose.

**Fig. 2** Transmission network of the Azerbaijan regional electric company

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Load Growth (%)</th>
<th>Load (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>5</td>
<td>3427</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>7</td>
<td>4139</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>9</td>
<td>4981</td>
</tr>
</tbody>
</table>

**Table 3** First configuration for all scenarios: neglecting the network losses

<table>
<thead>
<tr>
<th>Corridor</th>
<th>Voltage Level (kV)</th>
<th>Number of Circuits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-5</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>1-17</td>
<td>230</td>
<td>1</td>
</tr>
<tr>
<td>2-5</td>
<td>230</td>
<td>1</td>
</tr>
<tr>
<td>3-11</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>4-9</td>
<td>230</td>
<td>1</td>
</tr>
<tr>
<td>4-14</td>
<td>230</td>
<td>1</td>
</tr>
<tr>
<td>8-9</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>8-11</td>
<td>230</td>
<td>1</td>
</tr>
</tbody>
</table>

**Table 4** Second configuration for all scenarios: considering the network losses

<table>
<thead>
<tr>
<th>Corridor</th>
<th>Voltage Level (kV)</th>
<th>Number of Circuits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-5</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>1-8</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>2-5</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>2-6</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>2-7</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>3-13</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>4-5</td>
<td>400</td>
<td>1</td>
</tr>
<tr>
<td>5-6</td>
<td>400</td>
<td>1</td>
</tr>
<tr>
<td>5-7</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>5-9</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>6-13</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>7-8</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>8-11</td>
<td>400</td>
<td>1</td>
</tr>
<tr>
<td>8-18</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>9-13</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>10-11</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>11-13</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>12-18</td>
<td>230</td>
<td>2</td>
</tr>
<tr>
<td>13-14</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>13-15</td>
<td>400</td>
<td>2</td>
</tr>
<tr>
<td>15-16</td>
<td>230</td>
<td>1</td>
</tr>
</tbody>
</table>

In addition, for better analyzing of
proposed configurations, their expansion costs for different scenarios from load growth point of view are given in Tables 5 and 6. Comparison between Tables 5 and 6 shows that if network losses is neglected for solution of STNEP problem, a configuration with lower expansion cost (expansion cost of lines and substations) and higher network losses is obtained. However, considering the network losses, a plan with higher expansion cost and lower network losses is proposed for network expansion. Moreover, Tables 5 and 6 show that uncertainty in demand has no effect on expansion cost of lines while it effects on losses cost and expansion cost of substations. The reason is that expansion cost of substations from voltage level point of view and losses cost depend on loading of lines and substations. Thus, different load growths can affect on these costs. Finally, it can be said that proposed configurations by IBPSO for different scenarios are same and any loss of load is not exist. This fact reveals that proposed method has high efficiency for solution of STNEP problem. Total expansion cost (sum of expansion and losses costs) of expanded network with the two proposed configurations for different scenarios is shown in Figs 3-5.

Table 5 The costs for first configuration

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion Cost of Lines (MSUS)</td>
<td>43.4</td>
<td>43.4</td>
<td>43.4</td>
</tr>
<tr>
<td>Expansion Cost of Substations (MSUS)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Losses Cost (million SUS)</td>
<td>434.25</td>
<td>1259.25</td>
<td>3293.5</td>
</tr>
<tr>
<td>Loss of Load Cost (MSUS)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total Expansion Cost of Network (MSUS)</td>
<td>477.65</td>
<td>1302.65</td>
<td>3336.9</td>
</tr>
</tbody>
</table>

Table 6 The costs for second configuration

<table>
<thead>
<tr>
<th>Scenario Number</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion Cost of Lines (MSUS)</td>
<td>214</td>
<td>214</td>
<td>214</td>
</tr>
<tr>
<td>Expansion Cost of Substations (MSUS)</td>
<td>15.9</td>
<td>17</td>
<td>18.5</td>
</tr>
<tr>
<td>Losses Cost (million SUS)</td>
<td>45</td>
<td>125</td>
<td>321.2</td>
</tr>
<tr>
<td>Loss of Load Cost (MSUS)</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Total Expansion Cost of Network (MSUS)</td>
<td>274.9</td>
<td>356</td>
<td>553.7</td>
</tr>
</tbody>
</table>

Fig. 3 Sum of expansion costs and annual losses cost of the network for two proposed configurations under scenario 1

Fig. 4 Sum of expansion costs and annual losses cost of the network for two proposed configurations under scenario 2
Fig. 5 Sum of expansion costs and annual losses cost of the network for two proposed configurations under scenario 3

It can be seen that, for all scenarios, the total expansion cost of network with the second configuration is more than that of the first one until, about a few years after planning horizon, but afterward, the total expansion cost of network with first configuration becomes more than another one. For load growth of 5%, second one has investment return in comparison with first one about 5 years after expansion time. With rising load growth, investment return takes places earlier (for load growths of 7% and 9% this time is about 2 years and 1 year respectively). Accordingly, it can be concluded that the network losses has important role in transmission expansion planning even for low load growths.

Moreover, fitness function values of both methods for different iterations are illustrated in Fig. 6 to compare the convergence speed and precision of the IBPSO algorithm. It should be mentioned that the convergence curves only for the second configuration (considering network losses) under scenario 3, as instant, have been shown. These convergence curves show that improved BPSO by making some particles jump out local optima and search in other area of the solution space is caused that the fitness function is optimized more than BPSO one. Thus, it can be concluded that solution of desired STNEP by IBPSO is more precise and finally better than BPSO method.

Fig. 6 Convergence curves of IBPSO and BPSO for second configuration under scenario 3.

5. CONCLUSIONS

In this paper, static transmission expansion planning considering network losses, voltage level, and uncertainty in demand is studied using IBPSO algorithm. The results analysis reveals that considering the network losses in transmission expansion planning under different load growths is caused that total expansion costs and losses cost of network is decreased for long-term and mid-term. In addition, it can be said that although cost of lines with higher voltage levels are more than lines with lower voltage levels, constructing this type of lines in transmission network is caused that investment cost is considerably saved and therefore the total expansion cost is calculated more exactly. Consequently, even in networks with low load growth, network losses plays important role in
transmission expansion planning and subsequent determination of network arrangement and configuration. Finally, by comparing the results of the proposed method with BPSO, it could be concluded that although convergence speed of binary particle swarm optimization (BPSO) is more than proposed approach, however, improved BPSO, introducing the mutation operator makes some particles jump out local optima. Search in other areas of the solution space and leads in increase of the precision of algorithm for finding the more optimal solutions.

Appendix:
Costs for different types of 400/230 kV transformers are listed in Table 7.

<table>
<thead>
<tr>
<th>Rating output (MVA)</th>
<th>125</th>
<th>160</th>
<th>200</th>
<th>315</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (MS)</td>
<td>18</td>
<td>22</td>
<td>26</td>
<td>32</td>
</tr>
</tbody>
</table>

REFERENCES


Optimal Location and Parameter Settings of UPFC Device in Transmission System based on Imperialistic Competitive Algorithm

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ABSTRACT
In this paper, we present a new method to determine the optimal location and parameter settings of Unified Power Flow Controller (UPFC) for removing voltage violations and transmission lines overloading. UPFC is considered as the most powerful member of the FACTS devices, that it can control shunt and series power flow. This option gives to UPFC the power to control the voltage profile and transmission lines flow simultaneously. We used the Imperialistic Competitive Algorithm (ICA) to determine the optimal location and optimal parameter settings of UPFC to improve the performance of the power system specially removing voltage violations in the buses and solving transmission lines overloading to increase loadability in the power networks. This procedure is proposed to be applied on IEEE 14 bus system to show the validity of the method.

KEYWORDS: Imperialistic Competitive Algorithm (ICA), Loadability, Optimal Location, Optimal settings, Unified Power Flow Controller (UPFC), Voltage Profile.

1. INTRODUCTION
UPFC is applied to control the active and reactive power flow in same time, and voltage magnitude at the UPFC terminals. Also, the controller can be set to control one or more of these parameters in any combination or to control none of them. UPFC allows the combined application of phase angle control with controllable series reactive compensations and voltage regulation, and also the real-time transition from one selected compensation mode into another one to control particular system contingencies more effectively. For example, series reactive compensation may be replaced by phase-angle control or vice versa [1]-[3]. UPFC also maintain operating flexibility by its inherent adaptability in power system in variations without any hard-ware alternations [4, 5]. The mode of UPFC can be adjusted according to the required characteristic where the UPFC can work as Static VAR Compensator (SVC) to improve the network voltage profile by controlling the shunt elements of the UPFC only. And also it can work as Static Synchronous Series Compensator (SSSC) to improve the network lines loadability by controlling the series element of the UPFC only. UPFC has ability to do both of SVC and SSSC performance in a same time in
the power systems [6]-[8]. The normal operation of the power system depends on many factors as the loading conditions, the configuration of the network and the current operating point of the system. All the previous factors affect the stability and performance of the system [9, 10]. In [11] optimal placement of UPFC device is determined for enhancing transmission lines overloading issue and survey their impact on reliability of power networks and also in [12] UPFC placement is applied to study the effect of load representation in the static point of view on the performance of the UPFC in the power system.

This paper will concentrate on solving the problems of the network related to overloading of transmission lines and violation of bus voltage profile. This will be performed on the normal configuration of the system with the increasing loading pattern on the system. UPFC in such optimal placement and setting can restore the system operating condition to steady state point.

2. PROBLEM FORMULATION

The normal operation of the power network depends on many factors as the loading conditions, the configuration of the system and the current operating point of the system. All the previous factors affect the stability and the performance of the system. Some indices are used to show lines overloading and bus voltage violations. After determining the performance indices, ICA technique is applied to find the optimal location and parameters setting of the UPFC. Installing UPFC in such optimal location with such optimal parameters will remove or minimize the overloaded lines to improve power flows in the lines and bus voltage violations under increasing the loading conditions according to the proposed fitness function.

2.1 ICA Fitness Function

The target is finding the optimal location and the optimal parameters setting of the UPFC in the power system to eliminate the overloaded lines and the bus voltage violations. The main general description of the equations:

\[ \text{Min Fitness } F_t(X,U) \] (1)
Subiect to:

\[ G_t(X,U) = 0.0 \] (2)
\[ H_t(X,U) \leq 0.0 \] (3)

Where, \( F_t(X,U) \) represents the Fitness function to be minimized; \( G_t(X,U) \) represents the vector of the equality constraints corresponding to UPFC parameter bounds limits, active and reactive power generation limits, bus voltage limits, and phase angles limits; \( X \) represents the vector of the states of the power system consisting of voltage magnitude and phase angles; and \( U \) represents the vector of control variables to be optimized which the output of the process, the location of UPFC and its parameters setting.

The fitness function will be depend on some performance indices, the fitness function and the performance indices will be changed according the scope zone of interest as optimizing with overloaded lines and the bus voltage violations:

\[ F_t(X,U) = \sum_{i=1}^{N_{\text{of Lines}}} L(OL) + \sum_{j=1}^{N_{\text{of Buses}}} V(BV) \] (4)

\[ L(OL) = \begin{cases} 0, & \text{if } Si \text{ operating } \leq Si \text{ max} \\ Log \left( \frac{ΨL(OL).Si \text{ operating}}{Si \text{ max}} \right)^R, & \text{if } Si \text{ operating } \geq Si \text{ max} \end{cases} \]
\( V(BV) = \begin{cases} 0, & \text{if } 0.95 \leq \frac{V_i}{1.05} \\ \log \left( \Psi_{V(BV)} \cdot \text{abs} \left( \frac{V_i}{V_{\text{nominal}}} \right)^2 \right), & \text{otherwise} \end{cases} \) (5)

Where

- \( L(OL) \) represents the overloaded line function;
- \( S_{\text{operating}} \) represents the current volt-ampere power in line \( i \);
- \( S_{\text{max}} \) represents the volt-ampere power rate of line \( i \);
- \( \Psi_{L(OL)} \) represents the weight, is determined in order to have certain weight value for the various percentage of branch loading, also use to adjust the slope of the algorithm;
- \( R \) represents the coefficient is used to penalize more or less overloads;
- \( N_{\text{ll}} \) represents the number of lines in the system;
- \( V(BV) \) represents the Bus Voltage Violation function;
- \( V_j \) represents the voltage magnitude at bus \( j \);
- \( V_{\text{nominal}} \) represents the bus \( j \) nominal voltage;
- \( \Psi_{V(BV)} \) represents the weight is determined in order to have certain weight value for the various percentage of voltage difference, also used to adjust the slope of the algorithm;
- \( Q \) represents the coefficient is used to penalize more or less and voltage violations;
- \( N_{\text{bb}} \) represents the number of the buses in the system.

In some cases the log relations can be replaced with linear relations, according to the penalty factor of overloading and voltage violations values [13].

2.2 UPFC modeling for power flow

The UPFC could be seen to consist of two voltage source converters connecting together a common capacitor on their DC side and a unified control system. A simplified schematic representation of the UPFC is given in Figure 1.

![Fig. 1. Block Diagram of the UPFC](image)

The equivalent circuit of UPFC, which will be attached with power system equation and programmed to get the results, is shown in Figure 2. It consists of two synchronous voltage sources (SVS), which are simultaneous coordinated together to achieve the required performance mode.

![Fig. 2. UPFC equivalent circuit](image)

\[ EVR = VVR \times (\cos \delta VR + \sin \delta VR) \] (5)
\[ ECR = VCR \times (\cos \delta CR + \sin \delta CR) \] (6)

Where,

- \( V_{VR} \) the magnitude of the shunt SVS voltage.
- \( \delta_{VR} \) the value of the shunt SVS angle.
$V_{CR}$ the magnitude of the series SVS voltage.
$\delta_{CR}$ the value of the series SVS angle.

The active and reactive power equations for bus $k$ and $m$ can be combined with (5) and (6) to get:

$$P_{CR} = V_{CR} V_k \times \left( G_{km} \cos(\delta_{CR} - \theta_k) + B_{km} \sin(\delta_{CR} - \theta_k) \right) + V_{CR} V_m \times \left( G_{mm} \cos(\delta_{CR} - \theta_m) + B_{mm} \sin(\delta_{CR} - \theta_m) \right) + V_{CR} \times G_m$$

$$Q_{CR} = V_{CR} V_k \left( G_{km} \sin(\delta_{CR} - \theta_k) - B_{km} \cos(\delta_{CR} - \theta_k) \right) \quad (7)$$

$$V_k$$ and $$V_m$$: the voltage magnitude at bus $k$ and bus $m$.
$\theta_k$ and $\theta_m$: the voltage angles at bus $k$ and bus $m$.

$P_{CR}$ and $Q_{CR}$: the series SVS active and reactive powers.

$P_{VR}$ and $Q_{VR}$: the shunt SVS active and reactive powers.

$G_{mm}$, $G_{kb}$, $G_{km}$ and $G_{mk}$: the conductance elements, related to lines between buses $k$ and $m$.

$B_{mm}$, $B_{kb}$, $B_{km}$ and $B_{mk}$: the substance elements, related to lines between buses $k$ and $m$.

$G_{VR}$, $B_{VR}$, $G_{CR}$ and $B_{CR}$: the substances and conductances for shunt and series SVS.

### 3. IMPERIALISTIC COMPETITIVE ALGORITHM INTRODUCTION

Atashpaz Gargar and Lucas introduced Imperialistic Competitive Algorithm that is proposed the evolutionary process to optimize which is illustrated by imperialistic competition. Optimization is a process of making something better [14-16]. We want to find the argument $x$ in the way its analogous cost be optimum, which having function in optimization.

In this algorithm all, the countries are divided into two groups: imperialist and colonies. Imperialistic competition is the main part of this algorithm and causes the colonies to converge to the global minimum of the cost function. In continue it will be described how the imperialistic competition is modeled and implemented among empires.

#### 3.1 Flow Chart of Imperialist Competition

Figure 3 shows the flowchart of the Imperialistic Competitive Algorithm, like other evolutionary algorithm starts with an initial population. Some of the best countries in the population are selected to be the imperialist and rests are colonies. All the colonies of initial population are divided among the mentioned imperialists based on their power. After dividing all colonies among imperialists, these colonies start moving toward their relevant imperialist countries. 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. The imperialistic competition begins between all the empires. Any empire that is not able to succeed in the competition and cannot increase 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 lost in their power and ultimately they
will collapse. The movement of colonies to their relevant imperialists along with competition among empires and also 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 [15].

3.2 Generating Initial Empires

The goal of optimization is to find an optimal solution in terms of the variables of the problems. We form an array of variable values to be optimized. In GA terminology, this array is called "Chromosome" and in PSO, it's called "Particle", but here the term "Country" is used for this array. In an \( N_{\text{var}} \) dimension optimization problem, a country is a \( 1* N_{\text{var}} \) array. This array is defined by:

\[
Country = [p_1, p_2, p_3, \ldots, p_{N\text{var}}] 
\]  

(11)

The variable values in the country are represented as floating point numbers. The cost of a country is found by evaluating the cost function \( f \) at the variables \((p_1, p_2, p_3, \ldots, p_{N\text{var}})\). Then:

\[
\text{Cost} = f \left( \text{country} \right) = f \left( p_1, p_2, p_3, \ldots, p_{N\text{var}} \right) 
\]  

(12)

At the first of optimization, we generate the initial population of size \( N_{\text{pop}} \). We select \( N_{\text{imp}} \) of the most powerful countries to form the empires. The remaining \( N_{\text{col}} \) of the population will be the colonies each of which belongs to an empire. Then we have two types of countries; imperialist and colony.

To create the initial empires, we divide the colonies between imperialists based on their power.

![Fig. 3. Flow chart of the ICA](image-url)
To divide the colonies among imperialists proportionally, we define the normalized cost of an imperialist by:

$$C_n = \frac{c_n - \text{maxi} \{c_i\}}{\sum_{i=1}^{N_{imp}} c_i}$$

(13)

Where $c_n$ is the cost of $n$th imperialist and $C_n$ is its normalized cost. Having the normalized cost of all imperialists, the normalized power of each imperialist is defined by:

$$P_n = \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i}$$

(14)

The initial number of colonies of an empire will be:

$$N.C.n = \text{round}\{p_n \cdot N_{col}\}$$

(15)

Where, $N.C.n$ is the initial number of colonies of $n$th empire and $N_{col}$ is the number of all colonies. To divide the colonies for each imperialist we randomly choose $N.C.n$ of the colonies and give them to it. These colonies along with the imperialist will form $n$th empire. Figure 4 shows the initial population of each empire. As shown in this figure, bigger empires have greater number of colonies while weaker ones have less. In this figure imperialist 1 has formed the most powerful empire and has the greatest number of colonies.

3.3 Moving the Colonies of an empire toward the Imperialist

Imperialist countries started to improve their colonies. This movement is shown in figure 5 which the colony moves toward the imperialist by $x$ units. The new position of colony is shown in a darker color. The direction of the movement is the vector from colony to imperialist. In this figure $x$ is a random variable with uniform (or any proper) distribution. Then for $x$ we have:

$$x \sim U(0, \beta \times d)$$

(16)

Where $\beta$ is a number greater than 1 and $d$ is the distance between colony and imperialist. A $\beta > 1$ causes the colonies to get closer to the imperialist state from both sides.

Fig. 5. Moving colonies toward their relevant imperialist

To search different points around the imperialist we add a random amount of deviation to the direction of the movement. Figure 6 shows the new direction. In this figure, the $\theta$ is a random number with uniform (or any proper) distribution. Then:

$$\theta \sim U(-\gamma, \gamma)$$

(17)

The $\gamma$ is a parameter, which adjusts deviation from the original direction.

Fig. 6. Moving colonies toward their relevant imperialist in a randomly deviated direction
3.4 Exchanging positions of the Imperialist and Colony

While moving toward the imperialist, a colony may reach to a position with lower cost than that of imperialist. In such a case, the imperialist moves to the position of that colony and vice versa. Then algorithm will continue by the imperialist in a new position and then colonies start moving toward this position. Figure 7a illustrates the position exchange between a colony and the imperialist. In this figure the best colony of the empire is shown in a darker color. This colony has a lower cost than that of imperialist. Figure 7b shows the whole empire after exchanging the position of the imperialist and that colony.

Fig. 7a. Exchanging the positions of a colony and imperialist

Fig. 7b. Main imperialist after position exchange

3.5 Total Power an Empire

Total power of an empire is mainly affected by the power of imperialist country. But the power of the colonies of an empire has an effect, albeit negligible, on the power of that empire. We have modeled this fact by defining the total cost by:

\[ T.C.n = \text{cost(imperialist)} + \zeta \text{mean(Cost(colonies of empire))} \] (18)

Where \( T.C.n \) is the total cost of the nth empire and \( \zeta \) is a positive number which is considered to be less than 1. A little value for \( \zeta \) 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.

3.6 Imperialist competition

This competition is modeled by picking some of the weakest colonies of the weakest empires and making a competition between all empires to possess these colonies. Figure 8 shows the modeled imperialist competition each of empires will have a likelihood of taking possession of the mentioned colonies. In other words these colonies will not be possessed by the most powerful empires, but these empires will be more likely to possess them [15].

Fig. 8. Imperialist Competition

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:

\[ N.T.Cn. = T.Cn. - \maxi(T.Ci) \] (19)

Where \( T.C.n \) and \( N.T.C.n \) are total cost and normalized total cost of nth empire respectively. Having the normalized total
cost, the possession probability of each empire is given by:
\[
P_{p0} = \frac{N.T.C.R}{\sum_{i=1}^{Nimp} N.T.C[i]} \tag{20}
\]

To divide the mentioned colonies among the empires based on the possession probability of them, we form the vector \( P \) as:
\[
P = [pp1, pp2, pp3, \ldots, pNimp] \tag{21}
\]

Then we create a vector with the same size as \( P \) whose elements are uniformly distributed random numbers.
\[
R = [r1, r2, r3, \ldots, rNimp];
\]
\[
r1, r2, r3, \ldots, rNimp \sim U(0,1) \tag{22}
\]

Then we form the vector \( D \) by simply subtracting \( R \) from \( P \):
\[
D = P - R = [D1, D2, D3, \ldots, DNimp] = [pp1 - r1, pp2 - r2, \ldots, ppNimp - rNimp] \tag{23}
\]

Referring to vector \( D \) we will hand the mentioned colonies to an empire whose relevant index in \( D \) is maximum [17].

3.7 Ignooring the Weak Empires

Weak empires will eliminate in the imperialistic competition and their colonies will be divided between other empires. In this algorithm, it's assumed that an empire will be removed it when it loses all of its colonies.

3.8 Convergence

ICA will run until all the empires except the most powerful one will collapse and all the colonies will be under the rule of this unique empire. In this ideal new world all the colonies will have the same position and same costs and they will be controlled by an empire with the same position and cost as themselves.

3.9 Proposed ICA

In the ICA the colonies are coded to a country that contains variables of the problem. The configuration of the country in order to optimal UPFC consists of two types of parameters: location of UPFC and parameters setting \( V_{CR}, V_{VR} \) as decoupled model parameters of UPFC. In the figure 9 the country for the proposed algorithm has been shown.

Fig. 9. The country of Proposed ICA

The first set of countries in the colony represents the location of UPFC device in the network. This set contains the number of buses where the UPFC should be located. The second set represents the value of \( V_{CR} \) for series SVS. The range for this set is randomly generated according to the working range [0.001, 0.3]. At last, the third set represents the value of \( V_{VR} \) for shunt SVS. The range for this set is randomly generated according to the range [0.8, 1.2].

4. SIMULATION RESULTS

Matlab codes for ICA and a power flow program with MatPower to include UPFC are developed. Programmed M-Files are incorporated to include the updates for adjust the algorithm according to the required indices and terms. To show validity of the technique, it will be tested on the IEEE 14 bus system that it's shown in Figure 10. This system consists of five
generators, fourteen buses, sixteen lines and eleven loads. Because of economical aspects, we suppose the number of UPFC is set to 1 in IEEE 14 bus system. Figure 11 shows the minimization of objective function achieved by Imperialistic Competitive Algorithm in IEEE 14 bus system.

![Fig. 10. IEEE 14 bus system](image)

![Fig. 11. Convergence characteristics of ICA algorithm for IEEE 14 bus system](image)

| Table 1. Optimal location and parameter settings of UPFC in IEEE 14 bus system |
|-----------------|-----------------|------------|------------|
| Bus Number  | Bus Number | $V_{CR}$ | $V_{VR}$  |
| 7            | 9              | 0.2899    | 1.1967    |

From the Table 2-4, we can find that voltage profile is improved and active and reactive power flow in lines is optimized by placing UPFC in an optimal location with optimal parameters setting by ICA. Also for bus voltage profile, the optimal location and settings of UPFC resulted from the ICA, keep the voltage profile for all the buses in the system inside the required limit (0.95 ≤ $V_i$ ≤ 1.05) and there is not any violation in active and reactive power flow. The results show that the UPFC can significantly improve the performance of power systems with optimal location and settings. Placing UPFC in the system eliminate all of the overloaded lines and improve power flows in the system and also all of the bus voltage violations eliminated or if these violations aren't exits the algorithm able to reach the solution space to eliminate the overloaded lines and at the same time keeping the voltage profile constraint. Increasing of transmission system loadability of power system as an index to evaluate the impact of the UPFC in power system is achieved in some cases with respect to the line flow limits and the bus voltage magnitude limits.

5. CONCLUSION
The UPFC is so efficient device to improve the performance of power networks with optimal location and optimal parameter settings on an unstable power system because of load increasing. Installing UPFC in the optimal location with such optimal parameters in the power network, eliminate the overloading in the lines and removing voltage violations in the buses. ICA applied to detect the optimal location and optimal parameters settings of UPFC in the power systems. This procedure was applied for IEEE 14 bus system. The results show the efficient role of UPFC in enhancing the characteristics of the network operation.
Table 2. Bus Voltages without and with UPFC

<table>
<thead>
<tr>
<th>Bus No.</th>
<th>Voltage without UPFC</th>
<th>Voltage with UPFC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.05</td>
<td>1.05</td>
</tr>
<tr>
<td>2</td>
<td>1.05</td>
<td>1.05</td>
</tr>
<tr>
<td>3</td>
<td>1.034</td>
<td>1.032</td>
</tr>
<tr>
<td>4</td>
<td>0.982</td>
<td>1.041</td>
</tr>
<tr>
<td>5</td>
<td>1.001</td>
<td>1.027</td>
</tr>
<tr>
<td>6</td>
<td>1.051</td>
<td>1.057</td>
</tr>
<tr>
<td>7</td>
<td>0.953</td>
<td>0.986</td>
</tr>
<tr>
<td>8</td>
<td>1.049</td>
<td>1.0499</td>
</tr>
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<tr>
<td>10</td>
<td>0.887</td>
<td>0.981</td>
</tr>
<tr>
<td>11</td>
<td>0.951</td>
<td>1.079</td>
</tr>
<tr>
<td>12</td>
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<td>1.017</td>
</tr>
<tr>
<td>13</td>
<td>0.961</td>
<td>1.025</td>
</tr>
<tr>
<td>14</td>
<td>0.849</td>
<td>0.991</td>
</tr>
</tbody>
</table>

Table 3. Active power flow without and with UPFC

<table>
<thead>
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<th>Line No.</th>
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<th>Power flow with UPFC</th>
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</thead>
<tbody>
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<td>1</td>
<td>0.908</td>
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<td>0.122</td>
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<tr>
<td>5</td>
<td>0.172</td>
<td>0.258</td>
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<tr>
<td>6</td>
<td>0.117</td>
<td>0.183</td>
</tr>
<tr>
<td>7</td>
<td>0.016</td>
<td>-0.05</td>
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<tr>
<td>8</td>
<td>0.089</td>
<td>0.141</td>
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<tr>
<td>9</td>
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<td>-0.18</td>
</tr>
<tr>
<td>10</td>
<td>0.431</td>
<td>0.331</td>
</tr>
<tr>
<td>11</td>
<td>-3.68</td>
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</tr>
<tr>
<td>12</td>
<td>-1.25</td>
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<tr>
<td>13</td>
<td>-0.03</td>
<td>0.16</td>
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<tr>
<td>14</td>
<td>1.63</td>
<td>0.9</td>
</tr>
<tr>
<td>15</td>
<td>1.5</td>
<td>1.021</td>
</tr>
<tr>
<td>16</td>
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<td>0.1</td>
<td>0.2</td>
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<tr>
<td>18</td>
<td>0.74</td>
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<td>19</td>
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</tr>
<tr>
<td>20</td>
<td>0.003</td>
<td>0.01</td>
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</table>

Table 4. Reactive power flow without and with UPFC

<table>
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<th>Power flow with UPFC</th>
</tr>
</thead>
<tbody>
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</tr>
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<td>0.056</td>
</tr>
<tr>
<td>3</td>
<td>0.029</td>
<td>0.029</td>
</tr>
<tr>
<td>4</td>
<td>0.183</td>
<td>0.19</td>
</tr>
<tr>
<td>5</td>
<td>0.206</td>
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<tr>
<td>6</td>
<td>0.17</td>
<td>0.169</td>
</tr>
<tr>
<td>7</td>
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<td>-0.09</td>
</tr>
<tr>
<td>8</td>
<td>-0.02</td>
<td>-0.04</td>
</tr>
<tr>
<td>9</td>
<td>-0.11</td>
<td>-0.12</td>
</tr>
<tr>
<td>10</td>
<td>0.23</td>
<td>0.217</td>
</tr>
<tr>
<td>11</td>
<td>-0.54</td>
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</tr>
<tr>
<td>12</td>
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</tr>
<tr>
<td>13</td>
<td>0.651</td>
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<tr>
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<td>0.572</td>
</tr>
<tr>
<td>15</td>
<td>0.3</td>
<td>0.2</td>
</tr>
<tr>
<td>16</td>
<td>1.6</td>
<td>1.2</td>
</tr>
<tr>
<td>17</td>
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<td>18</td>
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</tr>
<tr>
<td>19</td>
<td>-0.3</td>
<td>-0.29</td>
</tr>
<tr>
<td>20</td>
<td>0.6</td>
<td>0.7</td>
</tr>
</tbody>
</table>

APPENDIX A
ICA parameters: $N = 100, M = 30, \zeta = 0.1, \beta = 2, \gamma = \pi/4$.

REFERENCES


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ABSTRACT
The main objective of this paper is to introduce a new intelligent optimization technique that uses a prediction-correction strategy supported by a recurrent neural network for finding a near optimal solution of a given objective function. Recently there have been attempts for using artificial neural networks (ANNs) in optimization problems and some types of ANNs such as Hopfield network and Boltzmann machine have been applied in combinatorial optimization problems. However, ANNs cannot optimize continuous functions and discrete problems should be mapped into the neural networks architecture. To overcome these shortages, we introduce a new procedure for stochastic optimization by a recurrent artificial neural network. The introduced neuro-optimizer (NO) starts with an initial solution and adjusts its weights by a new heuristic and unsupervised rule to compute the best solution. Therefore, in each iteration, NO generates a new solution to reach the optimal or near optimal solutions. For comparison and detailed description, the introduced NO is compared to genetic algorithm and particle swarm optimization methods. Then, the proposed method is used to design the optimal controller parameters for a five bar linkage manipulator robot. The important characteristics of NO are: convergence to optimal or near optimal solutions, escaping from local minima, less function evaluation, high convergence rate and easy to implement.

KEYWORDS: numerical optimization, neural networks, objective function, weight updating, five bar linkage manipulator robot.

1. INTRODUCTION
The objective of optimization is to seek values for a set of parameters that maximize or minimize objective functions subject to certain constraints. In recent years, many optimization algorithms have been introduced. Some of these algorithms are traditional optimization algorithms. Traditional optimization algorithms use exact methods to find the best solution. The idea is that if a problem can be solved, then the algorithm should find the global best solution. However, as the search space increases the objective value of these algorithms increases. Therefore, when the search space complexity increases the exact algorithms can be slow to find the global optimum. Linear and nonlinear programming, brute force or exhaustive search and divide and conquer methods are some of the most common exact optimization methods.

Calculus provides the tools and elegance for finding the optimum value of many objective functions. It quickly finds a single
optimum but requires a search scheme to find the global optimum. Continuous functions with analytical derivatives are necessary (unless derivatives are taken numerically, which results in even more function evaluations plus a loss of accuracy). If there are too many variables, then it is difficult to find all the extrema. The gradient of the objective function serves as the compass heading solution to the steepest downhill path. It works well when the optimum is nearby, but cannot deal with cliffs or boundaries, where the gradient cannot be calculated.

Other optimization algorithms are stochastic algorithms, consisted of intelligent, heuristic and random methods. Stochastic algorithms have several advantages compared to other algorithms as follows:
1) Stochastic algorithms are generally easy to implement.
2) They can be used efficiently in a multiprocessor environment.
3) They do not require the problem definition function to be continuous.
4) They generally can find optimal or near-optimal solutions.

There are several stochastic algorithms such as: Genetic algorithms (GA) (Holland, 1975), Guided Local Search (GLS) (Voudouris, 1997), Tabu Search (TS) (Glover, 1989), Variable Neighborhood Search (VNS) (Mladenovic and Hansen, 1997), Iterated Local Search (ILS) (Stützle, 1999), Simulated Annealing (SA) (Kirkpatrick et al. 1983), Greedy Randomized Adaptive Search Procedure (GRASP) (Feo and Resende, 1995), Memetic Algorithms (MA) (Moscato, 1989), Scatter Search (SS) (Cung et al. 1997), Ant Colony Optimization (ACO) (Marco Dorigo et al. 1999), Particle Swarm Optimization (PSO) (Kennedi and Eberhart 1995) and Shuffled Frog Leaping algorithm (SFL) (Eusuff, Lansey 2003), etc. These algorithms are implemented in many optimization problems and they have many applications in practical problems.

Artificial neural networks (ANNs) have been introduced as an effective tool in artificial intelligence field. Artificial neural networks have been used in many fields of science and engineering for many applications such as function approximation, prediction, pattern classification and control.

Among many types of the ANNs, the Hopfield network [1], the Boltzmann machine [2], the Mean Field Network [3], the Gaussian machine [4], the Self Organizing Map network [5] and several others can be used as optimizers. Several authors have suggested the use of the neural networks as a tool to provide approximate solutions for combinatorial optimization problems such as the traveling salesman problem [6, 7], scheduling problems [8], [9], graph problems [10], [11], Knapsack Problems [12], [13], Placement Problems [14], vehicle routing problems[15], [16], Satisfaction Problems [17], [18], Large Scale Puzzles [19], channel assignment problems [20], [21], Circuit Partitioning [22], etc.

Hopfield optimizer solves combinatorial optimization problems by gradient descent, which has the disadvantage of being trapped in local minima [23]. Mean Field, Boltzmann and Gaussian machines are stochastic in nature and allow escaping from local optima. Moreover, In order to use a neural optimizer to solve combinatorial optimization problems, one must cast problems into the neural network model. In other words, the constraints and
the objective function should be mapped in energy function of neural network. However, using this mapping procedure may require higher order neural networks for solving the problem. There is also no direct method for mapping constrained optimization problems on to a neural network except through addition of terms in the energy function which penalize violation of the constraints. In addition, SOM network is only applicable to Euclidean problems. Therefore, application of artificial neural networks for optimization problems is restricted. In fact, there are two major restrictions: 1) the problem should be discrete and 2) the problem should be mapped onto the neural network. These mappings are not possible for many problems and many of the real world optimization problems are continuous.

In this paper, a recurrent artificial neural network called neuro-optimizer (NO) is introduced to overcome the mentioned shortages of the optimizer neural networks. The neuro-optimizer is a recurrent neural network that can evaluate stochastic optimization and adjust its weights by a new unsupervised heuristic rule to achieve optimal or near optimal solutions. There is no mapping in NO procedure and any continuous problem can be easily optimized. NO has not any train or test phases, because it updates its weights during optimization process using the heuristic unsupervised rule. The proposed neural optimizer is very fast and easy to implement. These claims can be shown by using simulation results in finding the minimums of several benchmark functions. For comparison, the results of NO are compared to the results of two well known intelligent optimization methods, Genetic Algorithm (GA) [24] and Particle Swarm Optimization (PSO) [25].

PID (Proportional-Integral-Derivative) control is one of the earliest control strategies. It has been widely used in the industrial control field. Its widespread acceptability can be recognized by: the familiarity with which it is perceived amongst researchers and practitioners within the control community, simple structure and effectiveness of algorithm, relative ease and high speed of adjustment with minimal down-time and wide range of applications where its reliability and robustness produces excellent control performances. However, successful applications of PID controllers require the satisfactory tuning of three parameters (which are proportional gain (KP), integral time constant (KI) and derivative time constant (KD)) according to the dynamics of the process. Unfortunately, it has been quite difficult to tune properly the gains of PID controllers because many industrial plants are often burdened with problems such as high order, time delays and nonlinearities [26].

Traditionally, these parameters are determined by a trial and error approach. Manual tuning of PID controller is very tedious, time consuming and laborious to implement, especially where the performance of the controller mainly depends on the experiences of design engineers. In recent years, many tuning methods have been proposed to reduce the time consumption on determining the three controller parameters. The most well known tuning method is the Ziegler-Nichols tuning formula [27]; it determines suitable parameters by observing a gain and a frequency on which the plant becomes oscillatory.
Considering the limitations of the Ziegler-Nichols method and some empirical techniques in raising the performance of PID controller, recently artificial intelligence techniques such as fuzzy logic [28], fuzzy neural network [29] and some stochastic search and optimization algorithms such as simulated annealing [30], genetic algorithm [31], particle swarm optimization approach [26], immune algorithm [32] and ant colony optimization [33] have been applied to improve the performances of PID controllers. In these studies, it has been shown that these approaches provide good solutions in tuning the parameters of PID controllers. However, there are several causes for developing improved techniques to design PID controllers. One of them is the important impact it may give because of the general use of the controllers. The other one is the enhancing operation of PID controllers that can be resulted from improved design techniques. Finally, a better tuned optimal PID controller is more interested in real world applications.

This paper proposes the NO technique as a new optimization algorithm. The proposed method is applied for determining the optimal values for parameters of PID controllers. Here, we formulate the problem of designing PID controller as an optimization problem and our goal is to design a controller with high performance by adjusting four performance indexes, the maximum overshoot, the settling time, the rise time and the integral absolute error of step response. An optimal PID controller is designed for a five bar linkage manipulator robot using NO algorithm. The advantages of this methodology are that it is a simple method with less computation burden, high-quality solution and stable convergence specifications.

The rest of this paper is organized as follows. In the Section 2, the neuro-optimizer is explained in details and its optimization algorithm is described. Section 3 deals with the description of genetic algorithm and particle swarm optimization as two well known optimization algorithms. In section 4, the neuro-optimizer is compared to genetic algorithm and particle swarm optimization technique by means of simulations. Finally, the paper ends with some conclusions in Section 5.

2. BASICS OF NEURO-OPTIMIZER

Our lives confront us with many opportunities for optimization. What is the best route to work? Which project do we tackle first? When designing something, we shorten the length of this or reduce the weight of that, as we want to minimize the objective value or maximize the appeal of a product. In fact, we do optimization in our lives and this work is performed by our nervous system. If we want to find an optimum value, without any use of calculation devices, the following process may be occurred. We start with selecting a random solution in search space and then calculating its objective function value. Afterwards we select another solution and compute its objective value. Comparing these two results, we can find a better solution as third solution. Therefore, by this way, we use the results of previous solutions to determine a better solution in the next step. This process can be continued until a satisfactory solution is obtained.

Now, we try to model the mentioned human optimization process. We can use artificial neural networks. ANNs have been
introduced as a model of human neural networks. As mentioned earlier, ANNs can do two important tasks: function approximation and pattern classification. Recently there are also attempts for using ANNs in optimization problems. But there are two major restrictions, first, the problem should be discrete and second, the problem should map onto neural network that these mappings are not possible for many problems. Therefore, introducing a new human inspired tool that can easily and efficiently optimize any continuous problems is required.

With considering the mentioned assumptions about the quality of human optimization, we introduce a neuro-optimizer (NO). A neuro-optimizer is a recurrent neural network that works as a stochastic intelligent optimizer, for continuous functions. NO uses a prediction-correction strategy supported by a recurrent neural network to find an optimum of a given function. In each iteration, using an unsupervised heuristic weight updating rule, NO produces new better solutions, stochastically. The stochastic nature of NO prevents of being in any local optimum trap. Heuristic weight updating rule updates the weights to next solutions and move toward global or near global solutions, rapidly. This causes a fast convergence rate with less function evaluations. Figure (1) shows the schematic diagram of a neuro-optimizer with

\[ x = (x_1, x_2, ..., x_m) \] : A solution in search space.
\[ m \] : Dimension of the search space.
\[ Q \] : Number of neurons in the hidden layer.
\[ y = (y_1, y_2, ..., y_n) : \] Next solution generated by neuro-optimizer.
\[ w_{ij} \] : Connection weight between \( i^{th} \) neuron in input layer and \( j^{th} \) neuron in hidden layer.
\[ u_{jk} \] : Connection weight between \( j^{th} \) neuron in hidden layer and \( k^{th} \) neuron in output layer.

The outputs of neurons in hidden layer (\( z_j \)) and output layer (\( y \)) are achieved by (1) and (2), respectively.

\[ z_j = f \left( \sum_i x_i w_{ij} \right) \] (1)
\[ y_k = g \left( \sum_j z_j u_{jk} \right) \] (2)

\( f \) and \( g \) are two linear or nonlinear functions.

In this paper, we consider minimization problems and introduce the neuro-optimizer as a minimizer; one can change a maximization problem to minimization one: just slap a minus sign on the front of the objective function to change a maximization problem to a minimization one.

For a minimization problem, the proposed neuro-optimizer works as follows:

First, initial conditions are set and weight matrices are initialized with random values. Then a random solution is selected in search space. This solution is assigned to the best solution and its objective value is calculated and assigned to the best objective value. This solution is fed to NO, as input, and the output of NO is obtained by using (1) and (2). Then the objective value of the output solution is computed. If the new
objective value is less than the best one, the best objective value and the best solution are updated (replaced by new ones), otherwise no updating (replacement) occurs. Thereafter, the weights are updated by

$$w_i(n+1) = \eta_i \times w_i(n) + \beta_i \times (OBJ_{GLOBAL} - OBJ(n)) \times w_i(n) + \gamma_i \times (OBJ(n-1) - OBJ(n)) \times w_i(n) + \alpha_i \times (w_i(n) - w_i(n-1))$$

(3)

and

$$u_i(n+1) = \eta_i \times u_i(n) + \beta_i \times (OBJ_{GLOBAL} - OBJ(n)) \times u_i(n) + \gamma_i \times (OBJ(n-1) - OBJ(n)) \times u_i(n) + \alpha_i \times (u_i(n) - u_i(n-1))$$

(4)

where \(n\) is the iteration number, \(\eta_i \in [0,1]\), \(i = 1,2\) is the inertia coefficient, \(\beta_i \in [0, \beta_{\text{max}}]\) and \(\gamma_i \in [0, \gamma_{\text{max}}]\), \(i = 1,2\) are global and local learning factors, respectively (\(\beta_{\text{max}}\) and \(\gamma_{\text{max}}\) are problem dependent constants), \(\alpha_i \in [0,1]\), \(i = 1,2\) is the momentum coefficient and OBJ\((n)\) and OBJ\(_{GLOBAL}\) are the current objective function value and the best objective value calculated so far, respectively.

Then the current solution, the output of the previous input, is fed back to NO, as the new input, to generate the next solution. In fact, in each iteration, current solution is fed to NO to produce an output as the next solution and after updating the weights, the best solution and corresponding objective value, this new solution is fed back to NO as the current input to generate the next output as the next solution. Therefore, in NO procedure just one function evaluation is assessed in each iteration and there is no mapping onto the network and any continuous problem can be optimized using NO. In other words, NO just acts as a solution generator. This process continues until one of the stop conditions is satisfied.

When the process is stopped, the saved best solution is the optimum of the problem.

The pseudo-code of the neuro-optimizer procedure is as follows:

Initialization.
Generate a random solution in search space and save it as the best solution.
Calculate objective value of the solution and save it as the best objective value.
While one of the stop conditions is not true
Repeat
Insert the presented solution to NO as the input and obtain the output as the new solution.
Compute the new solution objective value: if it is better than the best objective value then replace new solution and its objective value as the best solution and the best objective value, respectively, otherwise do no replacements.
Update the weights.
End of while (if at least one of the stop conditions is true).
Export the best solution as the optimum of the problem.
End.

Remark 1. The number of hidden layer’s neurons (\(Q\)) depends on the complexity of the problem, objective value and search space (search space dimension). In general, large \(Q\) causes the algorithm to work slowly, and less \(Q\) causes to fail in local minima. A suitable value for \(Q\), is (By trial and error) \(2 < Q < 5m\), where \(m\) is the search space’s dimension.

Remark 2. The results of several simulations have shown that when the number of hidden layers exceeds of two, the convergence rate goes slower and no significant improvement is occurred. So, most of time it is suitable to select the number of hidden layers one, or at most
two. It causes to a simple, fast and easily implemented NO.

**Remark 3.** Bias terms cannot be added in input layer, because the number of neurons in input layer is fixed and is equal to search space dimension. However we can use the bias terms to hidden layer(s) that can help the diversification and escaping from local minima.

**Remark 4.** Common linear and nonlinear functions (such as pure linear, unipolar sigmoid and bipolar sigmoid functions) can be considered as the output function of neurons in hidden and output layers (f and g in (1) and (2)), with the following considerations:

a) If the variables are not constrained, then when the output function is pure linear we don’t need to renormalize the outputs of neurons to the variables range, but if we use nonlinear functions then we have to renormalize the outputs of functions to the suitable range, which is a time wasting process.

b) If linear functions are employed for the outputs of layers, the outputs of the output layer are only a linear combination of the inputs. So, the hidden layers may not help to diversification. But, if nonlinear functions are employed, a nonlinear combination of input and hidden layers make the output that the hidden layers will help to diversification and escaping from local minima trap.

Although, nonlinear functions such as sigmoid functions have better diversification characteristics than linear functions but linear functions such as pure linear function don’t need to renormalize the outputs and has less time consumption. Therefore, there is a tradeoff between diversification and time consumption. So, selecting the output functions is a problem dependant issue and can be selected by trial and error.

**Remark 5.** The major difference between artificial neural networks and neuro-optimizer is in the procedure of weight adjusting. Neuro-optimizer adjusts its weights using a new heuristic rule (Eqs. (3) and (4)). This means that neuro-optimizer has not train or test phase. There is also no mapping problem in NO.

**Remark 6.** The terms $\beta_i \times (OBJ_{GLOBAL} - OBJ(n))$ and $\gamma_i \times (OBJ_{GLOBAL} - OBJ(n))$, $i=1, 2$, are named global and local adaptive coefficients, respectively. In each iteration, the former term defines the weights changing, proportional to movement towards the global solution found so far, and the later term defines weights altering, proportional to relative improvement of presented solution with respect to the previous solution, adaptively. In other words, the adaptive coefficients decrease or increase the weights size relative to being close or far from the optimum point, respectively. The terms $\alpha_{ij} \times (w_{ij}(n) - w_{ij}(n-1))$ and $\alpha_{ij} \times (u_{ij}(n) - u_{ij}(n-1))$ are momentum statement and are known as a tool for escaping from local minima. Upper and lower limits are also considered for weight matrices to prevent the weights saturation as follows: $w_{min} < w < w_{max}$ and $u_{min} < u < u_{max}$.

**Remark 7.** The stop condition can be as follows:

a) When no improvement has been made for a certain number of iterations.
b) The maximum number of iteration has been reached.

Of course, other stop conditions can be considered depending on the problem.

**Remark 8.** For diversification in search and escaping from local minima as well as
to speed up the convergence, the following contraptions can be applied.

a) Modifying the number of hidden layers and the number of their neurons.
b) Using bias terms in hidden layer(s).
c) Using momentum in weight updating.
d) Selecting different functions in the outputs of neurons.
e) Restarting the algorithm from other (better) starter solutions.
f) Adapting other values for parameters: $\alpha, \beta, \gamma, \eta, Q, w_{\text{max}}$, and $u_{\text{max}}$.

3. GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION

3.1. Genetic algorithm

Genetic Algorithm [24] is the most famous population based method and has been applied to a large number of different types of problems. The idea stems from attempting to copy the way in which nature has evolved and selected the fittest individuals for reproduction, whilst occasionally mutating the chromosomes or genes of these individuals.

The algorithm starts with creating an initial population of solutions, and then creating a new generation, by means of probabilistically selecting parents and individuals (this may be by means of a kind of roulette wheel mechanism which biases the selection towards fitter individuals) to perform crossover, mutation and reproduction until the new population has reached the predefined population size. This process then continues until some termination condition is reached.

3.2. Particle swarm optimization

A particle swarm optimizer [25] is a population based stochastic optimization algorithm modeled after the simulation of the social behavior of bird flocks. In a PSO system a swarm of individuals (called particles) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position visited by itself and the position of the best particle in its neighborhood. When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the global best particle.

The global optimizing model proposed by Shi and Eberhart [25] is as follows:

$$v_{i} = w \times v_{i} + c_{1} \times \text{RAND} \times (P_{\text{best}} - x_{i}) + c_{2} \times \text{rand} \times (G_{\text{best}} - x_{i})$$

(5)

$$x_{i} = x_{i} + v_{i}$$

(6)

where $v_{i}$ is the velocity of particle $i$, $x_{i}$ is the particle position, $c_{1}$ and $c_{2}$ are the positive constant parameters, RAND and rand are random functions in the range [0,1], $P_{\text{best}}$ is the best position of the $i$th particle, $G_{\text{best}}$ is the best position among all particles in the swarm and $w$ is the inertial weight [25].

4. TEST RESULTS

The efficiency of NO was tested using a set of benchmark functions. To avoid any misinterpretation of the optimization results, related to the choice of any particular initial parameters, we performed each test 100 times, starting from various randomly selected solutions, inside the hyper rectangular search domain specified in the usual litterateur.

The results of NO tests performed on 11 functions listed in Appendix 1 are shown in Table 1. To evaluate the efficiency of the proposed NO algorithm, we retained the following criteria summarizing results from 100 minimizations per function: the rate of successful minimizations (RATESM), the...
average of the objective function evaluation numbers (AVERAGEOBJEN) and the average error (AVERAGEERROR). These criteria are defined precisely below.

When at least one of the termination tests is verified, NO stops and provides the coordinates of a located solution, and the objective function value OBJN.O at this solution. We compared this result with the known analytical minimum OBJANAL; we considered this result to be successful if the following inequality held:

$$\left| OBJ_{N.O} - OBJ_{ANAL} \right| < \varepsilon_{rel} | OBJ_{INIT}| + \varepsilon_{abs}$$  \hspace{1cm} (7)

where $\varepsilon_{rel} = 0.01$, $\varepsilon_{abs} = 0.0001$ and OBJINIT is an empirical average of the objective function value, calculated over typically 100 solutions, randomly selected inside the search domain, before running the algorithm. The average of the objective function evaluation numbers is evaluated in relation to only the successful minimizations and it shows the convergence rate of the algorithm. In fact, this criterion measures the speed of the algorithm and shows whether it is fast or slow. The average error is defined as the average of OBJ gaps between the best successful solution found and the known global optimum. This criterion shows the accuracy of the algorithm in finding the global optimum. As Table 1 shows, when the search space is more complicated the rate of successful minimization is decreased. Hence, NO can escape from local minima trap because of its stochastic and intelligent nature. For all functions, the average of the objective function evaluation numbers does not exceed 1000 with a suitable accuracy. This shows that the convergence of the NO is fast. For all functions, average of OBJ gaps between the best successful solution found and the known global optimum is less than 0.1. This accuracy is acceptable for many real world optimization problems.

**Table 1. Results of NO for 15 benchmark functions.**

<table>
<thead>
<tr>
<th>Benchmark function</th>
<th>RATE$_{S}$ (%)</th>
<th>AVERAGEOBJEN</th>
<th>AVERAGEERROR</th>
</tr>
</thead>
<tbody>
<tr>
<td>RC</td>
<td>96</td>
<td>285</td>
<td>0.01</td>
</tr>
<tr>
<td>ES</td>
<td>96</td>
<td>446</td>
<td>0.04</td>
</tr>
<tr>
<td>GP</td>
<td>96</td>
<td>290</td>
<td>0.015</td>
</tr>
<tr>
<td>B2</td>
<td>96</td>
<td>185</td>
<td>0.015</td>
</tr>
<tr>
<td>SH</td>
<td>94</td>
<td>318</td>
<td>0.01</td>
</tr>
<tr>
<td>RC</td>
<td>95</td>
<td>347</td>
<td>0.03</td>
</tr>
<tr>
<td>Z$_2$</td>
<td>95</td>
<td>205</td>
<td>0.035</td>
</tr>
<tr>
<td>DJ</td>
<td>95</td>
<td>272</td>
<td>0.02</td>
</tr>
<tr>
<td>H$_{3,4}$</td>
<td>83</td>
<td>361</td>
<td>0.05</td>
</tr>
<tr>
<td>S$_{1,5}$</td>
<td>81</td>
<td>467</td>
<td>0.03</td>
</tr>
<tr>
<td>S$_{1,7}$</td>
<td>80</td>
<td>445</td>
<td>0.01</td>
</tr>
<tr>
<td>S$_{1,10}$</td>
<td>78</td>
<td>431</td>
<td>0.04</td>
</tr>
<tr>
<td>R$_5$</td>
<td>80</td>
<td>688</td>
<td>0.05</td>
</tr>
<tr>
<td>Z$_5$</td>
<td>82</td>
<td>651</td>
<td>0.055</td>
</tr>
<tr>
<td>H$_{0,4}$</td>
<td>84</td>
<td>664</td>
<td>0.065</td>
</tr>
</tbody>
</table>

The performance of NO is then compared to continuous GA and PSO algorithms. The experimental results obtained for the test functions, using the 3 different methods, are given in Table 2. In our simulations, each population in GA has 20 chromosomes and a swarm in PSO has 20 particles. Other parameters of 3 algorithms are selected optimally, by trial and error. For each function, we give the average number of function evaluations for 100 runs. The best solution found by 3 methods was similar, so there were not given in Table 2. We notice that results from NO are better than results from GA and PSO methods (NO is faster than GA and PSO). This is because that NO is not a population based algorithm and it evaluates just one objective function in each iteration, while GA and PSO (and any other population based algorithms) evaluate a population of objective functions.
Table 2. Average number of objective function evaluations used by three methods.

<table>
<thead>
<tr>
<th>Function/Method</th>
<th>NO</th>
<th>GA</th>
<th>PSO</th>
</tr>
</thead>
<tbody>
<tr>
<td>RC</td>
<td>285</td>
<td>486</td>
<td>426</td>
</tr>
<tr>
<td>ES</td>
<td>446</td>
<td>920</td>
<td>903</td>
</tr>
<tr>
<td>GP</td>
<td>290</td>
<td>410</td>
<td>395</td>
</tr>
<tr>
<td>B2</td>
<td>185</td>
<td>325</td>
<td>334</td>
</tr>
<tr>
<td>SH</td>
<td>318</td>
<td>576</td>
<td>615</td>
</tr>
<tr>
<td>R2</td>
<td>347</td>
<td>657</td>
<td>633</td>
</tr>
<tr>
<td>Z2</td>
<td>205</td>
<td>620</td>
<td>622</td>
</tr>
<tr>
<td>DJ</td>
<td>272</td>
<td>601</td>
<td>556</td>
</tr>
<tr>
<td>H3,4</td>
<td>361</td>
<td>712</td>
<td>681</td>
</tr>
<tr>
<td>S4,5</td>
<td>467</td>
<td>915</td>
<td>822</td>
</tr>
<tr>
<td>S4,7</td>
<td>445</td>
<td>766</td>
<td>741</td>
</tr>
<tr>
<td>S4,10</td>
<td>431</td>
<td>792</td>
<td>816</td>
</tr>
<tr>
<td>R5</td>
<td>688</td>
<td>2516</td>
<td>2441</td>
</tr>
<tr>
<td>Z5</td>
<td>651</td>
<td>1712</td>
<td>1945</td>
</tr>
<tr>
<td>H6,4</td>
<td>664</td>
<td>1956</td>
<td>2122</td>
</tr>
</tbody>
</table>

Larger population size causes to more function evaluation numbers. So, convergence rate of GA and PSO is population size dependent while NO is not related to population.

5. APPLICATION OF NO FOR ROBOT OPTIMAL CONTROLLER DESIGN

In this section, an optimal PID controller is designed for a five-bar-linkage manipulator robot.

5.1. Problem Formulation

The PID controller is used to improve the dynamic response and to reduce the steady-state error. The transfer function of a PID controller is described as:

\[ G(s) = K_P + \frac{K_I}{s} + K_D s \]  

(8)

where KP, KI and KD are the proportional gain, integral and derivative time constants, respectively. For designing an optimal PID controller, a suitable objective function that represents system requirements, must be defined in the first step. A set of good control parameters KP, KI and KD can produce a good step response that will result in minimization of performance criteria. The optimal PID controller parameters that minimize the performance indexes are designed using the proposed NO algorithm. In the design of a PID controller, the performance criterion or objective function is first defined based on some desired specifications and constraints under input testing signal. Some typical output specifications in the time domain are overshoot, rise time, settling time, and steady-state error. In general, three kinds of performance criteria, the integrated absolute error (IAE), the integral of squared-error (ISE), and the integrated of time-weighted-squared-error (ITSE) are usually considered in the control design under step testing input, because they can be evaluated analytically in the frequency domain. It is worthy to notice that using different performance indices probably makes different solutions for PID controllers. The three integral performance criteria in the frequency domain have their own advantages and disadvantages. For example, a disadvantage of the IAE and ISE criteria is that their minimization can result in a response with relatively small overshoot but a long settling time. Although the ITSE performance criterion can overcome the disadvantage of the ISE criterion, the derivation processes of the analytical formula are complex and time-consuming [26]. The IAE, ISE, and ITSE performance criteria formulas are as follows:

\[ IAE = \int_0^\infty |r(t) - y(t)| \, dt = \int_0^\infty |e(t)| \, dt \]  

(9)

\[ ISE = \int_0^\infty e^2(t) \, dt \]  

(10)

\[ ITSE = \int_0^\infty e^2(t) \, dt \]  

(11)
In this paper, another time domain performance criterion defined by
\[
\min_k W(K) = \left(1/(1+e^{-\alpha})\right) \times (T_i + T_s) + (e^{-\alpha}/(1+e^{-\alpha})).(M_p + E_w)
\]
(12)

Where, \( K \) is \([KP, KI, KD]\), and \( \alpha \in [-5, 5] \) is the weighting factor. The optimum selection of \( \alpha \) depends on designer’s requirements and the characteristics of the plant under control. We can set \( \alpha \) to be smaller than 0 to reduce the overshoot and steady-state error. On the other hand, we can set \( \alpha \) to be larger than 0 to reduce the rise time and settling time. Note that, if \( \alpha \) is set to 0, then all performance criteria (i.e. overshoot, rise time, settling time, and steady-state error) will have the same worth.

For designing an optimal PID controller, determination of vector K with regards to the minimization of performance index is the main issue. Here, the minimization process is performed using the proposed NO algorithm. For this purpose, step response of the plant is used to compute four performance criteria overshoot (Mp), steady-state error (Ess), rise time (Tr) and settling time (Ts) in the time domain. At first, the lower and upper bounds of the controller parameters should be specified. Then the NO method is applied to find the optimal solutions.

Here, to show the efficiency and desirable performance of the proposed algorithm in designing optimal PID controllers, a well known Mechatronics application, i.e., a robot is considered. The examined robot configuration is a five-bar-linkage. Dynamic equations of the robot are described in the following subsection. Afterwards, NO algorithm for an optimum PID controller is utilized.

5.2. Dynamic equations of five-bar-linkage manipulator robot

In recent years, there has been a growing interest in the design and control of lightweight robots. Several researchers have studied the modeling and control of a single link flexible beam [34]. Fig. 2 shows the 5 bar linkage manipulator built in our robotics research lab. Also, Fig. 3 depicts the five-bar linkage manipulator schematic where the links form a parallelogram. Let \( q_i, Ti \) and \( I_i \) be the joint variable, torque and hub inertia of the \( i \)th motor, respectively. Also, let \( l_i, l_i, dCi \) and \( m_i \) be the inertia matrix, length, distance to the centre of gravity and mass of the \( i \)th link, correspondingly.

![Fig. 2. Planar presentation of robot.](image)

The dynamic equations of the manipulator are [35]:
\[
T_i = (M_{11} + I_i)^{\ddot{q}_i} + M_{12} \dot{q}_i + \frac{\partial M_{11}}{\partial q_1} \dot{q}_1 + g(m_id_i + m_d d_i + m_d I_i) \cos q_i
\]
\[
T_2 = (M_{22} + I_2)^{\ddot{q}_2} + M_{23} \dot{q}_3 + \frac{\partial M_{22}}{\partial q_1} \dot{q}_1 + g(m_id_2 + m_d d_2 + m_d I_2) \cos q_2
\]
(13)

Where, \( g \) is the gravitational constant and
\[
M_{11} = F_{11} + F_{12} + m_1 d_{i1}^2 + m_3 d_{i3} + m_4 I_i
\]
\[
M_{22} = F_{21} + F_{22} + m_2 d_{i2}^2 + m_3 l_2 + m_4 I_2
\]
\[
M_{12} = M_{21} = (m_3 d_c l_2 - m_4 d_c l_1) \cos(q_1 - q_2)
\]
(14)
It’s noticed from (13)-(14) that for 
\[ m^4 l^4 c^4 l_1^2 = m^4 l^4 c^4 l_1 \]  \hspace{1cm} (15) 

We have \( M_{12} \) and \( M_{21} \) equal to zero, that is, the matrix of inertia is diagonal and constant. Hence the dynamic equations of this manipulator will be

\[
\begin{align*}
T_1 &= (M_{11} + l_1^4) \ddot{q}_1 + g (m_1l_c_1 + m_3l_c_3 + m_4l_1) \cos q_1, \\
T_2 &= (M_{22} + l_2^4) \ddot{q}_2 + g (m_1l_c_2 + m_3l_2 + m_4l_c_4) \cos q_2 
\end{align*}
\]  \hspace{1cm} (16)

Notice that \( T_1 \) depends only on \( q_1 \) but not on \( q_2 \). On the other hand \( T_2 \) depends only on \( q_2 \) but not on \( q_1 \). This discussion helps to explain the popularity of the parallelogram configuration in industrial robots. If the condition (15) is satisfied, then we can adjust the two rotations independently, without worrying about interactions between them.

5.3. Simulation Results

Having 2 motors, the manipulator specification consisting of mass, length and centre of gravity of links are given in Table 3. The main purpose is designing an optimal PID controller for each of motors to control their rotations, with good performance. Using equation (16), five-bar-linkage manipulator robot is easily simulated using Matlab and Simulink. The block diagram of the five-bar-linkage manipulator robot with PID controller for motor 1 is shown in Fig. 4. The block diagram for motor 2 is similar to this figure. The maximum iteration of all experiments is considered equal to 200. Also, \( \alpha \) is set to 0 for all performance criteria to have the same merit in the objective function.

The following process is done to determine the optimal values of the PID controller parameters (i.e., vector K). First, the lower and upper bounds of the three controller parameters are selected as 0 and 30, respectively. Then, the network is initialized, randomly. Each solution K (the controller parameters) is sent to Matlab® Simulink® block and the values of four performance criteria in the time domain, i.e., \( M_p, \) Ess, \( T_r \) and \( T_s \) are calculated iteratively. Afterwards, the objective function is evaluated for each solution according to these performance criteria.

<table>
<thead>
<tr>
<th>Link</th>
<th>Mass (Kg)</th>
<th>Length (m)</th>
<th>C of G (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.288</td>
<td>0.33</td>
<td>0.166</td>
</tr>
<tr>
<td>2</td>
<td>0.0324</td>
<td>0.12</td>
<td>0.06</td>
</tr>
<tr>
<td>3</td>
<td>0.3702</td>
<td>0.33</td>
<td>0.166</td>
</tr>
<tr>
<td>4</td>
<td>0.2981</td>
<td>0.45</td>
<td>0.075</td>
</tr>
</tbody>
</table>

Fig. 4. Block diagram of the motor with PID controller.

Then, the procedure of NO algorithm is performed, as illustrated the pseudo-code in Section 2. At the end of any iteration, the program checks the stop criterion. When one termination condition is satisfied,
the program stops and the latest global best solution is the best solution of K.

Fig. 5 illustrates the step response without PID controllers for two motors. Figures 6 and 7 show the step response of rotation for motors 1 and 2, respectively.

Fig. 5. Step response of the robot motors without PID controller.

Fig. 6. Step response of the motor #1 rotation using NO method.

Fig. 7. Step response of the motor #2 angel using NO method.

The simulation results of the best solution are summarized in Table 4. These results demonstrate that cost function is converged rapidly. In conclusion, NO algorithm has rapid convergence characteristic and is highly effective in solving the optimal tuning problem of PID controller parameters.

Table 4. Summary of simulation results of five-bar-robot motors.

<table>
<thead>
<tr>
<th>motor</th>
<th>algorithm</th>
<th>P</th>
<th>I</th>
<th>D</th>
<th>M_p</th>
<th>T_s</th>
<th>T_r</th>
<th>E_s</th>
<th>cost</th>
<th>iteration</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NO</td>
<td>29</td>
<td>1.6</td>
<td>2.4</td>
<td>0</td>
<td>0.141</td>
<td>0.12</td>
<td>0</td>
<td>0.145</td>
<td>34</td>
</tr>
<tr>
<td>2</td>
<td>NO</td>
<td>31</td>
<td>1.5</td>
<td>2.5</td>
<td>0</td>
<td>0.193</td>
<td>0.11</td>
<td>0</td>
<td>0.161</td>
<td>30</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

In this paper, a new optimization technique based on neural networks has been introduced and it called neuro-optimizer (NO). Implemented by a recurrent neural network, NO uses a heuristic new intelligent rule to update its weights, with no supervision. The new optimization algorithm (NO) was proposed to solve the optimization problems numerically. Different benchmarks were used to illustrate the mentioned advantages. Dealing with this problem, a new time domain performance criterion for PID controller design was proposed. In all case studies, NO performed better than GA and PSO approaches which exposed NO as a promising optimization method. The optimal controller design of the five-bar-linkage manipulator robot has been considered, as a practical application. The proposed method was implemented for tuning the controller for the robot. High promising results demonstrate that the
proposed algorithm is robust, efficient and can obtain higher quality solution with better computational efficiency.

**APPENDIX A**

Some well-known benchmark functions of optimization problems:

**Branin RCOS (RC) (2 variables):**

\[
RC(x, y) = (y - (5/13)x^2 + (5/3.14)x - 6) + 10(1 - (1/28))\cos(x) + 10
\]

**B2 (2 variables):**

\[
B2(x, y) = x + 2y^2 - 0.3\cos(10x) - 0.4\cos(13y) + 0.7
\]

**Easom (ES) (2 variables):**

\[
ES(x, y) = -\cos(x)\cos(y)\exp(-(x - 3.14)^2 + (y - 3.14)^2)
\]

**Goldstein and Price (GP) (2 variables):**

\[
GP(x, y) = [1 + (x + y + 1)^2(19 - 14x + 3x^2 + 14y - 2y^2)]\times[30 + (2x - 3y)^2(18 - 32x + 12x^2 + 48y - 36y^2 + 27y^2)]
\]

**Shubert (SH) (2 variables):**

\[
SH(x, y) = \left\{ \sum_{j=1}^{5} j \cos((j + 1)x + j) \right\} \times \left\{ \sum_{j=1}^{5} j \cos((j + 1)y + j) \right\}
\]

**De Joung (DJ) (3 variables):**

\[
DJ(x, y, z) = x^2 + y^2 + z^2
\]

**Hartmann (H3,4) (3 variables):**

\[
H_{3,4}(x_j) = -\sum_{i=1}^{4} c_i \exp\left[-\sum_{j=1}^{4} a_{ij}(x_j - p_{ij})^2\right]
\]

**Shekel (S4,n) (3 variables):**

\[
H_{4,n}(X) = -\sum_{j=1}^{n} [(X - a_j)^T (X - a_j) + c_j]^{-1}
\]

3 functions were considered: S4,5, S4,7 and S4,10;

**Hartmann (H6,4) (6 variables):**

\[
H_{6,4}(x_j) = -\sum_{i=1}^{4} c_i \exp\left[-\sum_{j=1}^{6} a_{ij}(x_j - p_{ij})^2\right]
\]

**Rosenbrock (Rn) (n variables):**

\[
R_n(X) = -\sum_{j=1}^{n} (x_j^2 - x_{j+1})^2 + (x_j^2 - 1)^2
\]

**Zakharov (Zn) (n variables):**
\[ Z_n(X) = \sum_{j=1}^{n} x_j + \left( \sum_{j=1}^{n} 0.5 j x_j \right)^2 + \left( \sum_{j=1}^{n} 0.5 j x_j \right)^4 \]

ACKNOWLEDGMENT

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Optimization of Conventional Stabilizers Parameter of Two Machine Power System Linked by SSSC Using CHSA Technique

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ABSTRACT
This paper presents a method for damping of low frequency oscillations (LFO) in a power system. The power system contains static synchronous series compensators (SSSC) which using a chaotic harmony search algorithm (CHSA), optimizes the lead-lag damping stabilizer. In fact, the main target of this paper is optimization of selected gains with the time domain-based objective function, which is solved by chaotic harmony search algorithm. The performance of the proposed two-machine power system equipped with SSSC is evaluated under various disturbances and operating conditions and compared to power system stabilizer (PSS). The effectiveness of the proposed SSSC controller to damp out of oscillations, over a wide range of operating conditions and variation of system parameters is shown in simulation results and analysis.

KEYWORDS: Power System Stability, SSSC, Chaotic Harmony Search, Conventional Stabilizer, Two Machine System, LFO.

1. INTRODUCTION
Flexible AC Transmission System (FACT) is a novel integrated concept based on power electronic converters and dynamic controllers to enhance the system utilization and power transfer capacity as well as the stability, security, reliability and power quality of AC system interconnections [1]. Today’s these devices in many power systems fields have founded. More of FACTS devices have been developed from switch-mode voltage source converter configurations. They are equipped with the energy storage unit, such as DC capacitors [2]. The static synchronous series compensator (SSSC) is a kind of FACTS devices. SSSC is a member of FACTS family, which is connected in series with a power system. It consists of a voltage source converter, which injected a controllable alternating current voltage at the fundamental frequency and DC capacitor as a storage unit [3]. Although the main function of SSSC is to control the power flow but it can be used for control of dynamic stability of power system [4].

Several application fields for FACTs devices have been introduced. These fields consisting of congestion management, power flow controlling and improves dynamic stability of power systems. In some researches comparative studies between SSSC and other FACTs devices
were carried out [5-7]. Active and reactive power flow control using SSSC and other FACTS devices were investigated [8, 9] respectively. Several controlling methods for FACTS devices have been introduced. Quadratic mathematical programming for the simultaneous coordinated design of a Power System Stabilizer (PSS) and a SSSC-based stabilizer was investigated in [10]. In ref [11] fuzzy logic controller to operate SSSC in the automatic power flow control mode is used. Recently optimization techniques for obtaining parameters of controlling methods were used. These optimization techniques for achieving SSSC’s controllers have been published in following literatures. Genetic algorithm (GA) and partial swarm optimization (PSO) in [12-13] were investigated, respectively.

In this paper, a two machine system is considered as a power system. After making a linear system around the operating condition with a disturbance in different loading situation that are converted to optimizing problem. For solving these kinds of problem, several algorithms are recommended above but in this paper chaotic harmony search algorithm (CHSA) is used. By considering available parameter Δ0 as an input of lead-lag damping stabilizer this procedure is carried out. In this paper, two SSSC inputs (φ, m) and power system stabilizer (PSS) applied independently that connected to the output of the lead-lag controller. Finally, the effectiveness is shown by result evaluation and comparison of performance indices.

2. CHAOTIC HARMONY SEARCH ALGORITHM

This section describes the proposed chaotic harmony search (CHS) algorithm. First, a brief overview of the IHS is provided, and finally the modification procedures of the proposed CHS algorithm are stated [15-16].

2.1. Improved harmony search algorithm

This method is based on the concept in search of a suitable state in music. In that mean’s how a musician with different search modes to reach its desired state. To implement the above concepts in form of algorithm there will be several steps. This process generally in the form of the following five steps will be implemented [15-16].

Step 1. Initializing the problem and algorithm parameters.
Step 2. Initializing the harmony memory
Step 3. Improvising a new harmony.
Step 4. Updating the harmony memory.
Step 5. Checking the stopping criterion.

In the improved harmony search algorithm, two parameters in each iteration are changed. These parameters are pitch adjustment rate (PAR) and bandwidth (bw). The form of the changing these parameters is shown at below equations:

\[
PAR = PAR_{\text{min}} + \frac{(PAR_{\text{max}} - PAR_{\text{min}})}{NI} \tag{1}
\]

Where,

\( PAR \): pitch adjusting rate for each generation
\( PAR_{\text{min}} \): minimum pitch adjusting rate
\( PAR_{\text{max}} \): maximum pitch adjusting rate
\( NI \): number of solution vector generations
\( gn \): generation number

Also, we have:
\[ bw(gn) = bw_{\text{max}} \cdot e^{(gn - \frac{bw_{\text{min}}}{bw_{\text{max}}})} \]  

Where,  
- \( bw(gn) \): bandwidth for each generation  
- \( bw_{\text{min}} \): minimum bandwidth  
- \( bw_{\text{max}} \): maximum bandwidth

\[ x_{n+1} = f(x_n), \quad 0 < x_{n+1} < 1, \quad k=0,1,2,... \]  

It is represented as:  
\[ X_{n+1} = ax_n^2 \sin(\pi x_n) \]  

When \( a = 2.3 \) and \( x_0=0.7 \) it has the simplified form represented by:  
\[ X_{n+1} = \sin(\pi x_n) \]  

Fig.1. Flowchart of the chaotic harmony search algorithm.

2.2. Proposed method

In numerical analysis, sampling, decision making and especially heuristic optimization needs random sequences with some features. These features consist a long period and good uniformity. The nature of chaos is apparently random and unpredictable. Mathematically, chaos is the randomness of a simple deterministic dynamical system and chaotic system may be considered as sources of randomness [16]. A chaotic map is a discrete-time dynamical system which modeling in the form of below equation:

\[ x_{n+1} = f(x_n), \quad 0 < x_{n+1} < 1, \quad k=0,1,2,... \]  

3. MODELING OF THE POWER SYSTEM UNDER STUDY

System under study in this article is a two machine power system that SSSC is installed between terminal voltage of first machine and transmission line. In fact, the generators producing powers through transmission lines and SSSC to the loads delivers. SSSC with two transmission line circuit as shown in Fig.2:

Fig.2. Two machine power system equipped with SSSC

For analysis and enhancing small signal stability of power system through SSSC, dynamic relation of the system is needed. To have these relations through park transformation and ignoring the resistance...
of both boosting and exciting transformers can be achieved through following equations [14]:

\[
\begin{pmatrix}
\hat{v}_{Bd} \\
\hat{v}_{Bq}
\end{pmatrix}
= \begin{pmatrix}
0 & -x_B \\
x_B & 0
\end{pmatrix}
\begin{pmatrix}
i_{Bd} \\
i_{Bq}
\end{pmatrix}
+ \begin{pmatrix}
m \cos(\phi) v_{dc} \\
\frac{m \sin(\phi) v_{dc}}{2}
\end{pmatrix}
\]

(6)

\[
\dot{v}_{dc} = \frac{k m}{\mathcal{C}_{dc}} (\cos(\phi) \sin(\phi))
\]

(7)

Where \(v_B\) and \(i_B\) are the boosting voltage, and boosting current, respectively. \(\mathcal{C}_{dc}\) and \(v_{dc}\) are the dc link capacitance and voltage [14]. The non-linear model of the two machine power system introduced in Fig.3 and is shown in following equations:

\[
\delta_i = \omega_b (\omega_i) - 1
\]

(8)

\[
\dot{\omega}_i = \left( \frac{P_{mi} - P_{ei} - D_i \Delta \omega_i}{M_i} \right)
\]

(9)

\[
\dot{E}'_{qi} = \left( \frac{E_{fdi} + (x_{di} - x'_{di})i_{di} - E'_{qi}}{T'_{d0i}} \right)
\]

(10)

\[
\dot{E}_{fdi} = \left( \frac{-E_{fdi} + K_a (v_{refi} - v_{ti} + U_{pssi})}{T_{ai}} \right)
\]

(11)

\[
T_{ei} = E_{qi}' i_{qi} - (x_{qi} - x'_{di}) i_{di} i_{qi}
\]

(12)

By applying linearization process around the operating point on under study system, state space model of system can be achieved.

4. LEAD-LAG DAMPING STABILIZER

The eigenvalues of the linear system that are called the system modes define the stability of the system when it is affected by a small disturbance. As long as all eigenvalues have negative real parts, the power system is stable when it is subjected to a small disturbance. If one of these modes has a positive real part, the system is unstable. In this case using conventional lead-lag controller, can move the unstable mode to the left-hand side of the complex plane in the area of the negative real parts. The lead-lag damping stabilizer has the following structure:

\[
G = K_{pSS} \frac{s T_w}{1 + s T_1} \frac{1 + s T_3}{1 + s T_2} \frac{1 + s T_4}{1 + s T_4}
\]

(13)

By properly choosing the lead-lag damping stabilizer gains (\(K_{pSS}, T_1, T_2, T_3, T_4\)), the eigenvalues of system are moved to the left-hand side of the complex plane and the desired performance of the controller can be achieved. The damping controllers are designed to produce an electrical torque in phase with the speed deviation according to phase compensation method. SSSC's controllers (\(m, q\)) are two parameters that can help them, reach the above goals mentioned. The structure of SSSC based lead-lag damping controller is shown in Fig. 3.

![Fig. 3 SSSC with lead-lag damping controller](image-url)

Obtaining precise values of controller parameters (\(K_{pSS}, T_1, T_2, T_3, T_4\)) for SSSC...
controller based on the optimization algorithm is a problem of optimization. In this study for solving the optimization problem and reach the global optimal value of coefficients \( T_i \), CHS algorithm is used. By applying an impulse disturbance on the power system, parameters, and indicators, it will change. One important parameter is the frequency that speed deviation in form Integral of Time Multiplied Absolute value of the Error (ITAE) as the objective function for the algorithm is selected. The objective function is defined as follows:

\[
OF = \int_0^{t_{sim}} t|\omega_1 - \omega_2|dt
\]

(14)

In the above equations, \( t_{sim} \) is the time range of simulation. The design problem can be formulated as the following constrained optimization problem, where the constraints are the controller parameter bounds:

\[
K_{\text{PSS}}^{\text{min}} \leq K_{\text{PSS}} \leq K_{\text{PSS}}^{\text{max}} \tag{15}
\]

\[
T_1^{\text{min}} \leq T_1 \leq T_1^{\text{max}} \tag{16}
\]

\[
T_2^{\text{min}} \leq T_2 \leq T_2^{\text{max}} \tag{17}
\]

\[
T_3^{\text{min}} \leq T_3 \leq T_3^{\text{max}} \tag{18}
\]

\[
T_4^{\text{min}} \leq T_4 \leq T_4^{\text{max}} \tag{19}
\]

In order to gain constrains, all oscillation of system under all operating conditions must be damped before machine inertia coefficient \( (M_i=2H_i) \). Criteria for this damping under condition of settling time with 5% of characteristic should be less than \( 2H_i \) value. Typical ranges of the optimized parameters are \([0.01–100]\) for \( K_{\text{PSS}} \) and \([0.01–5]\) for \( T_i \). It is necessary to note that the in optimizing values of the controller parameters, algorithm must be repeated several times. Finally, values for lead-lag damping stabilizer gains are selected. Optimal values obtained for the controller parameters in normal load are shown in the Table.1.

<table>
<thead>
<tr>
<th>controller</th>
<th>( K_{\text{PSS}} )</th>
<th>( T_1 )</th>
<th>( T_2 )</th>
<th>( T_3 )</th>
<th>( T_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \varphi )</td>
<td>98.17</td>
<td>0.492</td>
<td>0.259</td>
<td>0.945</td>
<td>0.742</td>
</tr>
<tr>
<td>( m )</td>
<td>83.53</td>
<td>0.098</td>
<td>0.312</td>
<td>0.705</td>
<td>0.687</td>
</tr>
<tr>
<td>PSS</td>
<td>99.22</td>
<td>4.01</td>
<td>0.895</td>
<td>0.051</td>
<td>0.901</td>
</tr>
</tbody>
</table>

In this work, in order to acquire better performance, the parameters of CHS algorithm are showed in Table 2.

<table>
<thead>
<tr>
<th>parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>HMS</td>
<td>25</td>
</tr>
<tr>
<td>HMCr</td>
<td>0.92</td>
</tr>
<tr>
<td>PAR(_{\text{min}})</td>
<td>0.35</td>
</tr>
<tr>
<td>PAR(_{\text{max}})</td>
<td>0.65</td>
</tr>
<tr>
<td>bw(_{\text{min}})</td>
<td>(1\times10^{-5})</td>
</tr>
<tr>
<td>bw(_{\text{max}})</td>
<td>1</td>
</tr>
<tr>
<td>( a )</td>
<td>2.3</td>
</tr>
<tr>
<td>( X_0 )</td>
<td>0.7</td>
</tr>
</tbody>
</table>

5. TIME DOMAIN SIMULATION

System performance with the values obtained for the optimal conventional lead-lag controller by applying a disturbance in the second generator at \( t = 1 \) for 6 cycles is evaluated. The speed and terminal voltage deviation of generators at normal load, light load and heavy load with the proposed controller based on the \( \varphi \), \( m \) and PSS are shown in Fig (4 –5) respectively.

It is seen that the \( \varphi \)-based controller design to achieve good performance is robust, provides premier adjustment and greatly increase the dynamic stability of power systems.
To demonstrate performance robustness of the proposed method, from the performance index was used. In this work, an Integral of Time multiplied Absolute value of the Error (ITAE) is taken as the performance index that is defined as:

\[
ITAE = 1000 \int_0^T t |\Delta V_{t2}| + \frac{3|\Delta \omega_{t2}|}{3} dt
\]

(20)

Fig. 4. Dynamic responses for speed deviation of first generator with normal (a), heavy (b) and light load (c): solid (ϕ based controller), dotted (m based controller), dotted-dashed (PSS controller), dashed (without controller)

Fig. 5. Dynamic responses for speed deviation of second generator with normal (a), heavy (b) and light load (c): solid (ϕ based controller), dotted (m based controller), dotted-dashed (PSS controller), dashed (without controller)

Where \( \Delta \omega_{t2} \) and \( \Delta V_{t2} \) are speed deviation and terminal voltage deviation of the second generator, respectively. From the
Table 3, it can be received that the φ based controller is superior to the both m and PSS based controller.

**Table 3.** Values of performance index ITAE

<table>
<thead>
<tr>
<th>Controller</th>
<th>Heavy (pu)</th>
<th>Normal (pu)</th>
<th>Light (pu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without controller</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PSS based controller</td>
<td>46.78</td>
<td>56.7</td>
<td>66.35</td>
</tr>
<tr>
<td>m based controller</td>
<td>13.24</td>
<td>18.39</td>
<td>21.75</td>
</tr>
<tr>
<td>φ based controller</td>
<td>7.212</td>
<td>8.876</td>
<td>11.83</td>
</tr>
</tbody>
</table>

**Table 4.** Eigenvalues of system in normal load φ based controller

<table>
<thead>
<tr>
<th>P = 0.8 (pu)</th>
<th>Q2 = 0.149 (pu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>-19.1341</td>
<td>-18.6636</td>
</tr>
<tr>
<td>-0.0110 ± 3.6796i</td>
<td></td>
</tr>
<tr>
<td>-1.5116</td>
<td>-1.3829</td>
</tr>
</tbody>
</table>

**Table 5.** Eigenvalues of system in different operating conditions PSS based controller

<table>
<thead>
<tr>
<th>Heavy P2 = 1.2 pu</th>
<th>Normal P2 = 0.8 pu</th>
<th>Light P2 = 0.2 pu</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q2 = 0.352 pu</td>
<td>Q2 = 0.149 pu</td>
<td>Q2 = 0.009 pu</td>
</tr>
<tr>
<td>-18.3512</td>
<td>-18.6639</td>
<td>-18.2041</td>
</tr>
<tr>
<td>-18.9767</td>
<td>-19.1879</td>
<td>-18.8747</td>
</tr>
<tr>
<td>-4.3435 ± 4.3839 ± 8.0762i</td>
<td>2.3453i</td>
<td>8.0619i</td>
</tr>
<tr>
<td>-1.8169</td>
<td>-1.7481</td>
<td>-1.9641</td>
</tr>
<tr>
<td>-1.6141</td>
<td>-1.5134</td>
<td>-1.6949</td>
</tr>
</tbody>
</table>

**Table 6.** Eigenvalues of system in different operating conditions m based controller

<table>
<thead>
<tr>
<th>Heavy P2 = 1.2 pu</th>
<th>Normal P2 = 0.8 pu</th>
<th>Light P2 = 0.2 pu</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q2 = 0.352 pu</td>
<td>Q2 = 0.149 pu</td>
<td>Q2 = 0.009 pu</td>
</tr>
<tr>
<td>-18.3586</td>
<td>-18.1809</td>
<td>-18.2101</td>
</tr>
<tr>
<td>-18.9902</td>
<td>-18.6729</td>
<td>-18.9034</td>
</tr>
<tr>
<td>-1.0132 ± 1.8089i</td>
<td>-1.0753 ± 1.9249i</td>
<td>±1.8934i</td>
</tr>
<tr>
<td>-1.7604</td>
<td>-1.4375</td>
<td>-1.9187</td>
</tr>
<tr>
<td>-0.5781</td>
<td>-0.5581</td>
<td>-0.586</td>
</tr>
</tbody>
</table>

**Table 7.** Eigenvalues of system in different operating conditions

<table>
<thead>
<tr>
<th>Heavy P2 = 1.2 pu</th>
<th>Normal P2 = 0.8 pu</th>
<th>Light P2 = 0.2 pu</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q2 = 0.352 pu</td>
<td>Q2 = 0.149 pu</td>
<td>Q2 = 0.009 pu</td>
</tr>
<tr>
<td>-18.6455</td>
<td>-18.5105</td>
<td>-18.2835</td>
</tr>
<tr>
<td>-18.4112</td>
<td>-18.5105</td>
<td>-18.6498</td>
</tr>
<tr>
<td>-2.0520 ± 2.0425 ± 6.3363i</td>
<td>6.3358i</td>
<td>6.3373i</td>
</tr>
<tr>
<td>-1.8319</td>
<td>-1.9708</td>
<td>-1.5447</td>
</tr>
<tr>
<td>-1.6388</td>
<td>-1.7626</td>
<td>-1.3575</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

The chaotic harmony search algorithm was successfully used for the modeling of SSSC based conventional lead-lag damping stabilizer. In fact the design of the problem and obtain controller coefficients is converted into an optimization problem which is solved by a CHS algorithm with the time domain objective function. In this design for each of the control signals from available state variable Δω2 is used. The efficiencies of the proposed SSSC controller for improving dynamic stability performance of a power system are illustrated by applying disturbances under different operating points. Results from time domain simulation shows that the oscillations of synchronous machines can be easily damped for power systems with the proposed method. To analyze performance of SSSC’s controller one index was used. This index in term of ITAE is introduced that this index demonstrates that lead-lag with φ based damping controller is superior to both m and PSS based damping controllers.
APPENDIX

Table 8. System parameters

| Parameter                      | Value                                      
|--------------------------------|--------------------------------------------
| First generator               |                                            
| $M$                           | $6.4$ MJ/MVA                               
| $T_{do}'$                     | $6$ s                                      
| $X_d$                         | $0.8958$ pu                                
| $X_q$                         | $0.8645$ pu                                
| $X_d'$                        | $0.1198$ pu                                
| Second generator              |                                            
| $M$                           | $3.01$ MJ/MVA                              
| $T_{do}'$                     | $5.89$ s                                   
| $X_d$                         | $1.3125$ pu                                
| $X_q$                         | $1.2578$ pu                                
| $X_d'$                        | $0.1813$ pu                                
| Excitation system             | $K_{d1} = K_{d2} = 10$, $T_{d1} = T_{d2} = 0.05$ s 
| Transformers                  | $X_t = X_E = X_B = 0.1$ pu                 
| Transmission line             | $X_L = 0.5$ pu                             
| Operating condition           | $P = 0.8$ pu, $V_b = 1$ pu                 
| DC link parameter             | $V_{DC} = 2$ pu, $C_{DC} = 1$ pu          
| SSSC parameter                | $\varphi = -78.21^\circ$, $T_s = 0.05$    
|                               | $m = 0.08$, $K_s = 1$                      

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