A Neural Network Based Particle Swarm Optimization for the Transformers Connections of a Primary Feeder Considering Multi-objective Programming

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Abstract. A new multi-objective formulation named normalized weighting method combined with particle swarm optimization for the connections between distribution transformers and a primary feeder problem is presented. The performance of Particle Swarm Optimization can be improved by strategically selecting the starting positions of the particles by back-propagation neural network. Six important objectives are considered in this problem. These six objectives are of equal important to electric utility companies, but they are somewhat non-commensurable with each other. In view of this, a normalized weighting method for the multi-objective problem is proposed. It can provide a set of flexible solutions using particle swarm optimization by following the intention of decision makers. To increase the realism, the load and operating constraints of the system are all considered. Comparative studies on actual Tai-power systems are given to demonstrate the effectiveness of the phase load balancing and the improvement of operation efficiency for the proposed method.

1 Introduction

The distribution feeders are designed to be balanced to perfect the utilization of three phase components and loads. However, it delivers the power to the customer by one single phase only in some cases. This usually will result in unequal phase loading such that the life time of devices will deteriorate [1]. There are many researches [2] focus on the improvement of system unbalance, especially the static reactive compensator technique [2]. All of these improvement methods should add more devices to either compensation or control the system reactive needed. In this paper, we develop a powerful tool to help system planner reduce feeder loss and maintain high power quality and efficiency. No more devices are needed in this suggestion such that the economic contribution is very important.

Recently, Eberhart and Kennedy proposed a particle swarm optimization (PSO) based on the analogy of swarm of bird and school of fish [3]. The main advantages of PSO algorithm are simple concept, easy implementation, robustness to control parameters, and computational efficiency when compared with mathematical algorithm and other heuristic optimization techniques. To ensure broad coverage of the search space, the particles should be initialized so that they are distributed as better quality as

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possible throughout the space. The standard method of initialization fails to accomplish this goal, especially in high-dimensional spaces. In this paper, using a starting configuration based on back-propagation neural network (BPN) can lead to improved performance.

Therefore, this paper aims to develop a unified approach to solve connections between distribution transformers and a primary feeder by taken into account the typical daily load patterns in distribution systems. A new multi-objective formulation combined with PSO and BPN for the above problems is presented.

2 Problem Description and Formulation

In this paper, [7] is used as the calculation method to transfer the loads of distribution transformers among different kinds of connection into simple three phases loads S_a, S_b and S_c. Therefore, there are six candidate connections at most for each distribution transformers as shown in Fig. 1.

![Fig. 1. Six candidate connection method](image)

2.1 Objective Functions

The objective functions considered in this study are:

1.) Power balance index (PB): Power balance index of three phases that indicates the level of balance condition between three phases as stated below:

\[
S^h_{i,AVG} = \frac{1}{3}(S^h_{i,a} + S^h_{i,b} + S^h_{i,c}) \quad , i = 1 \sim N_i \quad PB = \sum_{h=1}^{365 \times 24} \sum_{i=1}^{N_i} \frac{\sum_{p=a,b,c} |S^h_{i,p} - S^h_{i,AVG}|}{|S^h_{i,AVG}|} \quad (1)
\]

where:

- \(S^h_{i,p}\) : complex power flowing of branch i of phase p at hour h,
- \(S^h_{i,AVG}\) : average complex power flowing of branch i at hour h,
- \(N_i\) : total number of branches.

2.) Total feeder loss (Ploss): Total feeder loss represents the economic condition of a system.

\[
Ploss = \sum_{h=1}^{365 \times 24} \sum_{p=a,b,c} \sum_{i=1}^{N_i} \frac{(P^h_{i,p})^2 + (Q^h_{i,p})^2}{|V^h_{i,p}|^2} \quad (2)
\]
where:

- $P_{loss}$: total line losses of distribution feeder,
- $P_{i,p}^h$: real power of phase p flowing out of bus i at hour h,
- $Q_{i,p}^h$: reactive power of phase p flowing out of bus i at hour h,
- $V_{i,p}^h$: voltage of phase p of bus i at hour h,
- $r_i$: resistance between buses i and i+1.

3.) Voltage deviation (VD_SUM): Voltage deviation among buses of three phases that associates with the quality condition.

$$VD\_SUM = \sum_{h=1}^{365x24} \sum_{p=a,b,c} \sum_{i=1}^{N_b} |V_{i}^{ideal} - V_{i,p}^h|$$

where:

- $N_b$: total number of buses.

4.) Zero unbalance factor (d0_SUM): Zero unbalance factor for all the buses of three phases that represents the power quality condition of a system.

$$d0\_SUM = \sum_{h=1}^{365x24} \sum_{i=1}^{N_b} |V_{0,i}^h|$$

where

- $V_{n,i}^h$: the n sequence voltage (including zero, positive and negative sequence) of bus i at hour h.

5.) Negative unbalance factor (d2_SUM): Negative unbalance factor for all the buses of three phases that also represents the power quality condition of a system.

$$d2\_SUM = \sum_{h=1}^{365x24} \sum_{i=1}^{N_b} |V_{2,i}^h|$$

6.) LCO current (ILCO_SUM): The current passing through the LCO relay equipped in substation. Obviously, to minimize the LCO current can prevent the abnormal trip of the LCO relay.

$$ILCO\_SUM = \sum_{h=1}^{365x24} ILCO_i^h = \sum_{h=1}^{365x24} |ICT_a^h + ICT_b^h + ICT_c^h|$$

where

- $ILCO_i^h$: the LCO current of a feeder at hour h,
- $ICT_p^h$: the secondary current of CT for phase p that flowing through the CB of feeder at hour h.
2.2 Operating Constraints

The voltage deviations, unbalance factors and LCO currents during each load period must lie within a permissible range for practical situation. Also, the current on each branch must stay within its ampercy limits for security reasons.

3 The Normalized Weighting Method

Most of the multi-objective programming techniques translate the objective functions into a combined single objective with weight values. This will arise one problem, the weight values are very difficult to determine because these objectives maybe vary widely in units. A better way to work with multi-objective problems is to provide a flexible NW method between the objective functions. The NW method presented here is based on this concept and will be described shortly.

3.1 Step 1

We first solve the single objective optimization problem expressed in (7). Due to its flexibility and efficiency mentioned above, a global optimization technique known as PSO [3] will be applied for such optimization applications throughout the study.

\[ \min PB \quad \text{subject to the constraints} \]  

Assume the solution of (7) is \( S_{PB} \), that is \( PB(S_{PB}) = PB_{\text{ideal}} \). Then, treat all the other objectives as a single objective optimization problem one by one to find the ideal value for each objective. The nonideal values for each objective can be found by:

\[ PB_{\text{nonideal}} = \max(PB(S_{d0_{\text{SUM}}}), PB(S_{d2_{\text{SUM}}}), PB(S_{ILCO_{\text{SUM}}})) \]  

Due to its conflicting character, this single objective optimization problem can provide the best solution for the concerned objective, denoted as subscript ideal, while the worst value of objectives are denoted as nonideal. Also, the subscript ideal denotes the attainable goal value and nonideal denotes the worst value.

3.2 Step 2

A new single objective optimization problem is formulated as follows:

\[ \min T = \sum_{\text{Obj} = PB, P_{\text{loss}}, VD_{\text{SUM}}, d0_{\text{SUM}}, d2_{\text{SUM}}, ILCO_{\text{SUM}}} W_{\text{Obj}} \frac{\text{Obj} - \text{Obj}_{\text{ideal}}}{\text{Obj}_{\text{nonideal}} - \text{Obj}_{\text{ideal}}} \quad \text{subject to the constraints} \]  

Obviously, each objective value is normalized between (0,1) in (9), it is very easy to determine the weighting factor Wobj for each objective by direct thinking. Again, the GA is employed to find the optimal solution of (9).
4 Implementation of the Neural Network Based Particle Swarm Optimization Method

Conceptually, (7,9) belong to the class of problems known as combinatorial optimization with constraints. Possible combinations grow dramatically as the number of switches increases. Recently, the use of the global optimization technique called PSO [3], to solve real world problems have aroused researchers' interest due to its flexibility and efficiency. Therefore, PSO is used as the tool for solving Eqs. (7,9) in this paper.

4.1 Brief Review of the Particle Swarm

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems [3]. The PSO technique can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods [4]. The feasibility of their method is compared with the reactive tabu system and enumeration method on practical power system, and has shown promising results [5]. Naka et al. have presented the use of a hybrid PSO method for solving efficiently the practical distribution state estimation problem [6].

4.2 Initial Population String Generated by Back-Propagation Neural Network

The particles should be initialized so that they are distributed as better as possible throughout the space. The standard method of initialization fails to accomplish this goal, especially in high-dimensional spaces. In this paper, using a starting configuration based on back-propagation neural network can lead to improved performance. Firstly, using random selection to generate some initial population and then put into the PSO to get the final solutions and evaluation values. Secondly, using these randomly guess data as the training set of BPN. The input and output layer are \( N_r \) and six neurons respectively. The hidden layer is calculated by \( \left( N_r + 6 \right) / 2 \). Finally, randomly generate 10 times of the population size and put into the BPN to get the evaluation values. Take the better solutions as the initial generation.

5 Test Study

To illustrate the performance of the proposed solution methodology, consider a system that is part of the Taipower distribution system in Taiwan. It consists of 88 load centers and each load center equipped with one distribution transformer. To evaluate the P and Q loads for this feeder during whole year, the typical load pattern include three different types such as, weekday, weekend, and Sunday are considered. Also, the load forecasting is used to predict the load in the future. The solution space includes \( 6.664 \times 10^{52} \) combinations such that PSO is used for better solution performance. The original configuration has many violations in constraints. After rearrange of
the connection between distribution transformers and a primary feeder, the constraints are all satisfied. It shows that the PSO has the ability to solve the combinatorial optimization problem well.

### Table 1. Numerical results for different strategies

<table>
<thead>
<tr>
<th>WN37</th>
<th>Multi-objective programming</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>S1</td>
</tr>
<tr>
<td>$SA_{PB}$</td>
<td>62.16</td>
</tr>
<tr>
<td>$SA_{flex}$</td>
<td>88.59</td>
</tr>
<tr>
<td>$SA_{D_SUM}$</td>
<td>84.39</td>
</tr>
<tr>
<td>$SA_{V_SUM}$</td>
<td>98.70</td>
</tr>
<tr>
<td>$SA_{I_SUM}$</td>
<td>98.90</td>
</tr>
<tr>
<td>$SA_{LCO_SUM}$</td>
<td>97.54</td>
</tr>
</tbody>
</table>

The multi-objective test results are summarized in Table 1 which according the different strategies. The satisfaction rates for each objective are defined in (10). It represents the level of satisfaction within the attainable search region for each objective. The strategy 1 denoted as S1 deal the different objectives as equal importance, and the simulation results reflect this decision correctly. All of the satisfaction rates are equally improved and and the constraints are also met the requirement. The strategies S2, S3, and S4 treat the loss, voltage deviation, and LCO current as the primary objective, respectively. Also, the strategies S5 and S6 treat two of the six objectives as the primary concern. Obviously, according to the simulation results that shown in Table 1, the proposed method can solve the multi-objective problem according to the operator’s will that represented as the weighting factor. Note that all the constraints are satisfied by the proposed method.

\[
\text{Satisfaction Rate of } PB = SA_{PB} = (\max PB - PB) / (\max PB - \min PB)
\]

### 6 Conclusion

A new multi-objective formulation for the connections between distribution transformers and a primary feeder has been presented. A normalized weighting method combined with the particle swarm optimization for solving the multi-objective problem has been presented and tested on a Taipower distribution system. The performance of Particle Swarm Optimization can be improved by strategically selecting the starting positions of the particles by back-propagation neural network. The salient feature of the proposed method lies in that it can provide an easy way to determine the weighting factors between different objectives. Results obtained show that three phase voltage, currents and loads unbalance along a feeder as well as the voltage drop, line losses and the frequency of malfunction of grounding relay can be effectively reduced.
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References