A NEW DISTRIBUTION SYSTEM RECONFIGURATION APPROACH USING PARTICLE SWARM OPTIMIZATION AND NEURAL NETWORK

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Abstract: This paper uses artificial intelligent algorithms for reconfiguration of the distribution network. The problem is formulated as an optimization problem where the objective function to be minimized is the power losses, and the constraints are nodal voltage magnitude limits, branch current limits, Kirchhoff's current law (KCL), Kirchhoff's voltage law (KVL) and the network radiality condition. While the state (on-off) of the tie switch is considered as control or independent variable, the nodal voltage magnitude, branch current are considered as state or dependent variables. These state variables are continuous whilst the switch state is an integer (binary) variable. The problem being a mixed-integer programming one because of the state of switch (on=closed=1 or off=open=0), a Binary Particle Swarm Optimization (BPSO) and Neural Network are used separately to solve this problem. The effectiveness of proposed method is demonstrated through an example.

1 INTRODUCTION

The energy in the system is wasted in the form of power losses at the distribution level. Recent advances in distribution automation technology have made it possible to reduce these losses by applying loss minimization techniques on a real time basis.

At the HV and MV levels, the load is usually three-phase and balanced, although large single or dual phase loads can be connected. Each feeder in a distribution system usually supplies a mix of residential, commercial and sometimes industrial consumers with varying needs depending on the season of the year (Chen and Cherng, 2000); (Liu et al., 1989). Because of load changes and the diversity of loads being *on* or *off*, the three phase imbalances may be substantial. Balancing is accomplished by selecting the phase of the supply for each load so that the total load is distributed as evenly as possible between the phases for each section of the feeder. The balancing procedure must consider all possible combinations of phase loads connecting to three phases. There are a number of benefits that make efficient load phase balancing a worthwhile objective. Balancing reduces feeder losses for the phases as the square of the current magnitude. Loading on a feeder section is synonymous with the most heavily loaded phase so that, in the case of significant imbalance, feeder capacity is used inefficiently. Balancing between phases tends to equalize the phase loading by reducing the largest phase peak load while increasing the load on the other phases. This equates to releasing feeder capacity that can be used for future load increases without reinforcing feeder conductors. Released feeder capacity provides more reserve loading capacity for emergency loading conditions.

Balancing not only reduces feeder losses, but also improves voltage on a feeder by equalizing the voltage drops in each phase along the feeder. It is realistic to assume that the benefits in improved use of feeder capacity and voltage quality are significant in terms of the value of reduction in loss except when loading is already high (Ukil et al., 2006).

In past, many studies based on traditional heuristic algorithms have been carried out on network and feeder (Zhu, 2009); (Alexandre et al., 2009). The problems were formulated and solved to control the switching of sectionalize and tie switches so as to achieve a better efficiency. However, they

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did not guarantee the optimal solution although they provide high quality suboptimal solution.

Recently new methods based artificial intelligent such as genetic algorithm (GA) have been used in the distribution network reconfiguration (Zhu, 2009). However, it has been shown in general that PSO algorithm can provide better optimal solution than GA (Zhu, 2009); (Yu et al., 2009) and it is also requires lower computational time than GA (Zhu, 2009).

From the above background, the authors in this paper have used a Binary particle swarm optimization (BPSO) algorithm for the distribution network reconfiguration loss minimization. Neural network algorithm is used also in order to validate the results obtained by BPSO algorithm.

2 PROBLEM DESCRIPTION AND FORMULATION

2.1 Network Reconfiguration

The distribution system is the final stage in the transfer of power to individual customers. Typically, it commences from the sub transmission station transformers, and normally will consist of two levels primary distribution or medium voltage level (Alexandre et al., 2009); (Siti et al., 2007).

There are two types of switch in primary distribution systems: normally closed switch connects line sections, and normally open switch on the tie-lines which connects two primary feeders, or two substation or loop-type laterals. Network reconfiguration (or feeder reconfiguration) is the process of altering the topological structures of the distribution feeders by changing the open /closed status of the sectionalizing and tie switches (Alexandre et al., 2009), (Siti et al., 2007).

In general, distribution loads shows different characteristics according to their corresponding distribution lines and line sections. Therefore, load levels for each time period can be regarded as non identical. In the case of a distribution system with some overloaded to less loaded feeders. The maximum current which the feeder conductor can take may be considered as the reference. Nevertheless, the transfer of load must be such that certain predefined objective is satisfied. In this case, the objective is to ensure the network has minimum real power loss.

The solution objective for a feeder is to obtain a set of rearrangement of the connected loads at each node (or consumer point) such that the objective function is minimized. This is a non-linear problem that will involve a number of trial and errors. It is hereby proposed to solve this problem, where iteratively, as changes are made, a method is used to sense the relative loading of the phases, and another method is used to edge towards the minimized objective.

2.2 Mathematical Model for Optimal Network Reconfiguration

This mathematical model has been discussed in (Zhu, 2009); (Alexandre et al., 2009), (Siti et al., 2007).The objective function to be minimized is the total active power losses and is expressed in terms of branch current as given below:

$$\text{Min } P_L = \sum_{l=1}^{NB} k_b R_b I_b^2 \quad b \in NB \tag{1}$$

where P_L, k_b, R_b, I_b and NB are respectively, the total active power losses, the tie switch state of the branch b ($k_b = 1$ if branch b is closed and $k_b = 0$ if branch b is open), resistance and current magnitude of the branch b, and NB is the total number of branches.

The operating constraints of the network are given as follows:

2.2.1 Inequality Constraints

These constraints are nodal voltage and branch current limits.

$$0.95p.u. \le V_i \le 1.05p.u. \tag{2}$$

$$k_b I_b \le I_b^{\max} \tag{3}$$

where V_i is the voltage magnitude at node i, $I_b^{\max}$ (1.pu. in this paper) is the maximum branch current.

2.2.2 Equality Constraints

The fists equality constraint is the Kirchhoff's current law (KCL), given as follows:

$$h_i(I, b) = 0 \;\; i \in N \tag{4}$$

The second equality constraint to be satisfied is the Kirchhoff's voltage law (KVL), given as follows:

$$h_i(V, b) = 0 \;\; i \in N \tag{5}$$

Another equality constraint is the one that ensure the radiality condition of the network. This means that the number of branches in the network must be smaller than the number of nodes by one unit ($k_b NB = N - 1$) (Zhu, 2009). This can be expressed by the following equation:

$$\phi(k_b) = 0 \tag{6}$$

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2.3 Feeder Test System

In this case the suggestion is that the 66 kV be fed at both ends instead of at one end only, since the total voltage drop can be considerably reduced without increasing the cross section of the conductor, and also taking into account that the ends of distribution are supplied with equal voltage. The system distribution can be fed at both ends with the equal voltage. Let S represent the sectionalizing switch and T represent the tie switch as shown in Figure 1.

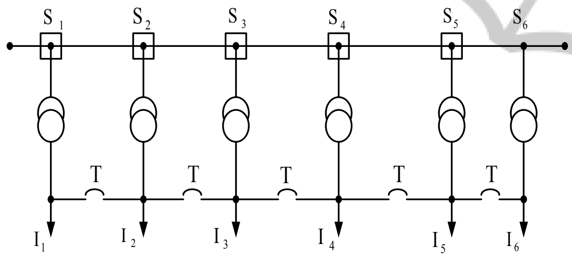

Figure 1: Network representation.

3 PROPOSED METHODS

3.1 Classical PSO

Particle swarm optimization is an intelligent algorithm developed by Kennedy and Eberhart in 1995 as an alternative to genetic algorithm (GA) (Zhu, 2009). The PSO algorithm motivation was the social behaviour such as bird flocking and fish schooling. This algorithm was used to solve many nonlinear hard optimization problems (Zaraki and Othman, 2009). The main advantage of the PSO over traditional optimization algorithm is the fact it does not need any gradient information about the objective function when search for the global optimal solution (Zhu, 2009); (Zaraki and Othman, 2009). Another advantage is the fact that it less dependent on the initial starting point in the search space (Numbi et al., 2011). Over other intelligent algorithms such as GA, PSO can be easier to program, to modify, inexpensive in terms of memory and even computation time, etc. (Zhu, 2009); (Mantawy and Al-Ghamdi, 2003). The general PSO algorithm for real-valued numbers is explained as follows:

From an initial position, a swarm of particles starts flying in the search space exploring optimal points. Each particle position represents a potential solution. Therefore, the performance of each particle position is evaluated by the fitness function which is the objective function in this work. Our problem having minimization purpose, the best particle is the one with lower fitness value. During the flight (iterations), the best experiences (positions) for each particle is stored in its memory and called personal best (Pbest). The lowest value of all the Pbests, determines the global best (Gbest) of the swarm.

The velocity and the position of each particle are updated using respectively, the following equations:

$$V_i^{t+1} = wV_i^t + C_1 r_1 \left(X_i^{pbest} - X_i^t \right) + C_2 r_2 \left(X_i^{Gbest} - X_i^t \right) \tag{7}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{8}$$

with

w: The Inertia weight (0.729 for clerc's constriction method) (Eberhart and Yuhui, 2001)

C_1, C_2: Acceleration coefficients (1.49445 for clerc's constriction method) (Eberhart and Yuhui, 2001)

r_1, r_2: Two separately generated uniformly distributed random numbers in the range [0, 1] added in the model to introduce stochastic nature.

3.1.1 Proposed Fitness of the Binary Particle Swarm Optimization (BPSO)

With the purpose of dealing with constraints, all the constraints given by (2)-(6) are penalized in the main objective function given by (1). Exterior penalty terms are used here. Since our problem has binary control variables which are the states of tie switch (on=1 or off=0), these tie switch states are treated first as continuous number (real-valued number) between 0 and 1. Secondly, the conversion of continuous number to binary number is done as follows:

-if the value of the particle position (tie switch state) is less than 0.5 then this is set to zero,

-if the value of the particle position is greater than 0.5 then this set to one,

-otherwise, the PSO is reinitialized.

Therefore, the fitness of each particle in the swarm is given as a penalty functions as expressed below:

$$
\begin{aligned}
F(X_i) = {} & k_b R_b I_b^2 + \mu_1 \sum_{b=1}^{NB} \left\{\max\left(0, k_b - k_b^{\max}\right)\right\}^2 + \\
& \mu_1 \sum_{b=1}^{NB} \left\{\max\left(0, k_b^{\min} - k_b\right)\right\}^2 + \mu_2 \sum_{i=1}^{N} \left\{\max\left(0, V_i - V_i^{\max}\right)\right\}^2 + \\
& \mu_2 \sum_{i=1}^{N} \left\{\max\left(0, V_i^{\min} - V_i\right)\right\}^2 + \mu_3 \sum_{b=1}^{NB} \left\{\max\left(0, k_b I_b - I_b^{\max}\right)\right\}^2 + \\
& \mu_4 \sum_{i=1}^{N} \left\{h(I,k)\right\}^2 + \mu_4 \sum_{i=1}^{N} \left\{h(V,k)\right\}^2
\end{aligned}
\tag{9}
$$

with

$\mu_1 \ldots \mu_4$ the penalty factors or coefficients for each constraint violations. In order to reduce the number of these penalty factors, all of them have been set to a value of 10000.

The flowchart of BPSO is shown in figure 2 given below:

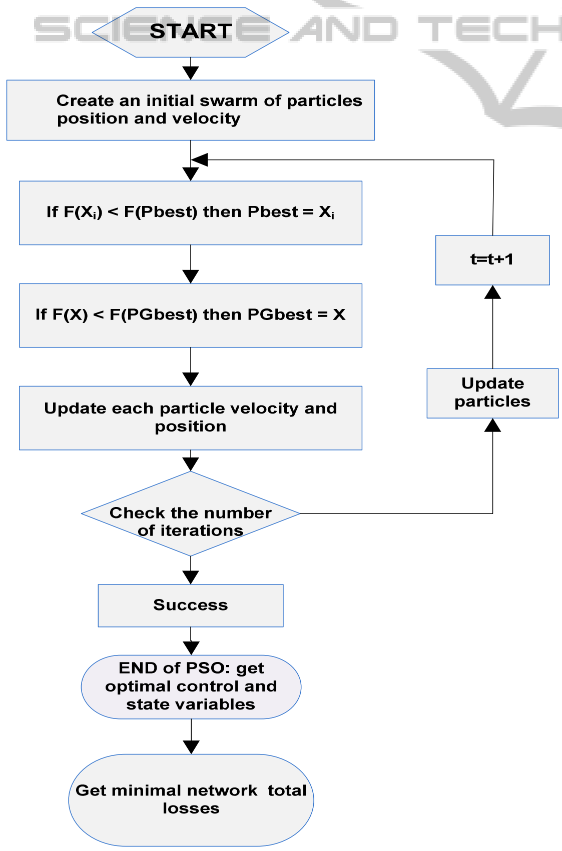

Figure 2: Flowchart of PSO algorithm.

3.2 Neural Networks

In the proposed strategy in this paper, the neural network must control the switch-closing sequence of each branch to achieve the minimum power loss which will lead to the distribution network reconfiguration. The inputs to the neural network are the unbalanced branch currents while the outputs are the switch closing sequences for each node.

The input layer of the network contains N input neurons, N being the number of unbalanced branch currents to be controlled. The following column vector has been assumed as the input:

$$C_{SW} = \left[I_{b1} \ldots\ldots\ldots\ldots I_{bN}\right]^T \tag{10}$$

The output of the network is in the range {0,1} for each switch, i.e., indicating which switch must be open or close to reduce the power loss in the network.

3.2.1 Neural Network Structure

For this application, we used the radial basis network. Experiments with the back propagation and the radial basis networks indicated faster training and better convergence for the latter. Radial basis networks may require more neurons than the standard feed-forward back propagation networks, but often they can be designed in a fraction of the time needed to train the standard feed-forward networks. They work best when many training vectors are available. The Matlab® neural network toolbox (Math Works; release 13) has been used for the implementation. We experimented with different kinds of radial basis networks, but a generalized regression neural network (GRNN) produced the best result (Ukil et al., 2006). Such a network is often used for function approximation. It consists of a radial basis layer and a special linear layer (Ukil et al., 2006).

3.2.2 Neural Network Training

We have used the neural network-based operation for the test data in the following structure: real and simulated data for network presented in figure 1. The real data set consisted of unbalanced network. The test data set contained average load current values per load in a specific network of the country for the different times of each day in a month. We selected a specific network as our test data for each specific time, and we tested our result on 500 sets of data. We consider the loads to be equally distributed per phase, that is, we assume that the load flow distribution in a loop is an optimal flow; the corresponding network power losses will be minimal. Thus the basic idea of the optimal flow pattern is to open the switch of the branch that has minimal current value in loop, with the optimal flow pattern were to compute load flow of initial radial network, it will follow by the closing of all normal switches to produce loop networks, this will continue by computing the equivalent injection current at all nodes in loops through injecting current method, and the replacement of the branch impedance by corresponding branch resistance in the loop and then compute the optimal flow, the network will have a new reconfiguration by opening a switch branch that has a minimal current value in loop. And can again recomputed the load flow for the remained network, this will end by opening the next branch switch, and repeat the previous step discussed above, until we have the radial network.

4 RESULTS AND DISCUSSION

The following case illustrates the loss reduction through network reconfiguration of the tested system of a 6 bus radial distribution. To evaluate the proposed techniques, it has been applied to 6 bus radial distribution system loss reduction. The results obtained from the combination PSO, and as been validated by Neural Network with the control of the tie switch, it shows that it succeed in finding the global solution with a high probability in the system as represented in table 1

Table 1: Results of 6 bus radial distribution network reconfiguration.

Description		Initial State	PSO	Neural Network
Tie Switch open		Switch 1-2	Switch 3-2 Switch 3-5	Switch 3-2 Switch 3-5
Total Power Loss (MW)	Best	-------------	0.0096525	0.009652
	Average	----------	0.00117044	0.00117044
	Worst	0.0095452	0.0035428	0.0035428
Average Power Loss Reduction (%)			62.23	62.23
Minimum Voltage Magnitude (p.u.)		0.894	0.978	0.978

5 CONCLUSIONS

Loss reduction is very important complement to network and feeder reconfiguration. In this paper the network and feeder reconfiguration problem was formulated as loss minimization problem with the view for its solution to control different switches placed in the network. Two MATLAB based solution methods have been proposed and demonstrated. First is the PSO and the other is neural network-base technique. The proposed methods were successfully tested. From the practical point of view these method can be very effective as several model based approaches usually take very long running time. The PSO has been found more suitable and faster compared to neural network. But both methods gives good results on loss reduction in the network.

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