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RECONFIGURATION OF ELECTRICAL DISTRIBUTION NETWORK USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Electrical distribution network reconfiguration is a complex combinatorial optimization process to find the network topology that minimizes system power loss, reduces node voltage deviation, improves load balancing among feeders while maintaining branch current within designed limits. This paper presents artificial neural network (ANN) based approach to solve network reconfiguration problems. The training set for ANN is generated from the fuzzy based and genetic algorithm (GA) based optimization approach. Proposed ANN method is applied to 33 bus test system. Test results specify that proposed ANN model provides fast and accurate network configuration for different load conditions.

Key words: Electric Distribution Network, Fuzzy Inference System, Genetic Algorithm, Multi-objective optimization, Radial distribution System, Reconfiguration.

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1. INTRODUCTION

Power distribution systems are usually configured radially, but the act of opening or closing switches or protection devices can possibly change the topology of such systems. In this context, the network is reconfigured to maintain its radial topology and also to reduce power losses at the feeders, to enhance the voltage profile for customers, and to increase the reliability levels. Though there are many options such as reconfiguration, capacitor placement, load feeder balancing, and distributed generation for reducing losses and improving voltage profile in a distribution system, reconfiguration is the most preferred method because it requires no extra equipment to be installed and is cost effective.

In recent years, considerable research has been conducted for loss minimization in the area of network reconfiguration of distribution systems. Various algorithms are proposed and tested for network reconfiguration.

Merlin, et al [1], first proposed reconfiguration for distribution system. For determining minimum loss configuration he used a branch-and-bound-type optimization technique. Based on the method presented by Merlin, et al [1], Shirmohammadi, et al [2], presented heuristic algorithm. In this method also, the optimum flow pattern in the network is established by closing all of the network switches and then opening it one after another. This helped overcoming many approximations of Merlin, et al [1] algorithm.

The heuristic algorithm based on power flow is proposed by Goswami, et al [3]. To determine a distribution system configuration, simplified formula is developed by Civanlar, et al [4]. To obtain global optimal or, at least near global optimal solutions for reconfiguration of distribution network Chiang, et al [5,6] and Jeon, et al [7] have proposed solution techniques, using simulated annealing. But it is very time consuming. Using simulated annealing technique Jiang, et al [8] have presented an algorithm for switch reconfiguration and capacitor control of distribution system. Lee, et al [9] has proposed a performance index based approach using heuristic rule for resistive loss reduction. Aoki, et al [10] have altogether different approach for this problem. They have formulated it as a discrete optimization problem. Fereidunian et al [11] have come out with altogether different approach for distribution network reconfiguration algorithm. Wagner, et al [12] has presented comparison of various methods which are applied to network reconfiguration for loss reduction. Many other researchers such as Hsiao, et al [13], Jeon, et al [14], Shin, et al [15], Hsiao [16], Lin, et al [17], Das [18] and Hong, et al [19] etc. have proposed different approaches for network reconfiguration.

In recent years, neural networks have been a subject of intense research activities due to their wide applications in different areas, such as image processing, pattern recognition, associative memory, and combinational optimization. In engineering optimization problems there often exists several criteria, which must be considered in a conflicting situation [20]. This situation is formulated as a nonlinear constrained multi-criterion optimization problem where not a single objective function but several functions are to be minimized or maximized simultaneously. One of the most promising applications of artificial neural networks is probably in the area of different classes of optimization problems.

Network reconfiguration for minimizing system power loss, branch current constraint violation and maximizing voltage stability, is the determination of switching options that optimizes multiple objectives for a particular set of loads on the distribution systems. It is performed by altering the topological structure of distribution feeders. Network reconfiguration for time varying loads is a complex and extremely nonlinear optimization problem which can be effectively solved by artificial neural network.

Kim et al. first proposed a two-stage algorithm based upon ANNs for distribution system reconfiguration for loss minimization [21]. To avoid the difficulties associated with training large sets of data, it was proposed that the distribution network be divided into load zones. Kashem M. et al. [22] divided the load into different categories and load level was divided into seven categories, which greatly reduced the number of load patterns and also improved the calculation speed.

As the flow calculation is not required, the use of ANN can significantly reduce the time of distribution network reconfiguration. From the point of speed ANN is the fastest method for distribution network reconfiguration. Artificial neural networks have the robustness for disturbance and the massive parallelism for the hardware implementation. However, the accuracy of results based on ANN algorithm depends on the provision of training samples.

2. ARTIFICIAL NEURAL NETWORK APPROACH FOR RE-CONFIGURATION OF ELECTRICAL DISTRIBUTION NETWORK

Paradigm based on artificial neural network is proposed here to reconfigure power distribution network taking multiple objectives in to consideration for optimization.

The multiple objectives considered for optimization are

- Minimization of the system power loss.
- Minimization of deviation of node voltages.
- Branch Current Constraint
- Load Balancing

Design steps for proposed artificial neural network based multi-objective network reconfiguration system are given in the figure 1.

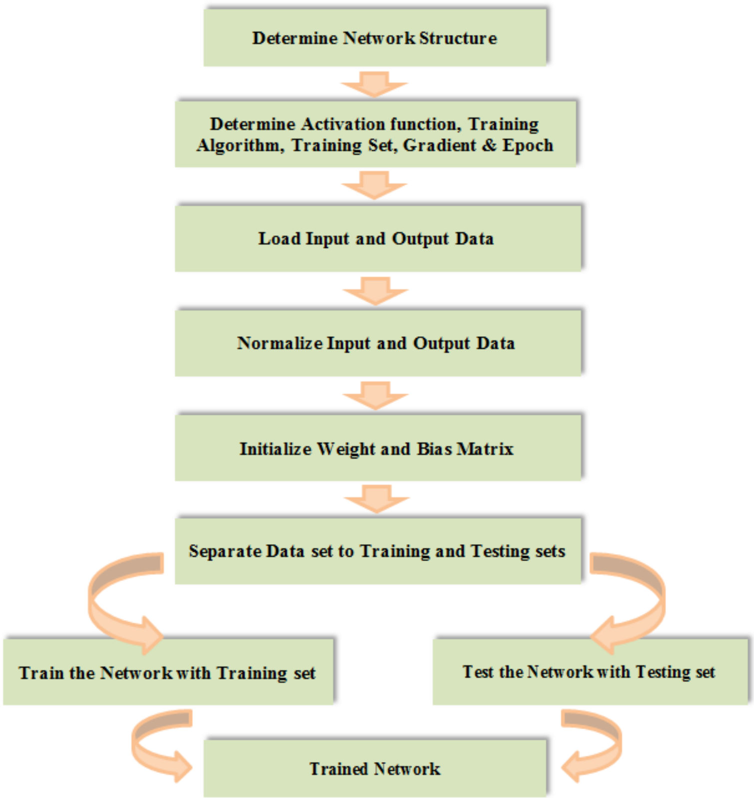


Figure 1 Design Steps for ANN.

Core of any artificial neural network is its structure. It is the first step where it is necessary to *determine* input layer, number of hidden layers and the output layer. It specifies number of inputs to the artificial neural network and number of outputs from artificial neural network. Details of the proposed neural network structure are discussed in next section.

Next step in the design is to decide activation function, training algorithm and training set. Various activation functions which may be utilized and different training algorithms are discussed in previous section. For proposed system sigmoid activation function and back propagation learning algorithm is used. Its details are discussed in following section. Weights in network may be initialized randomly or normalized input and output data is used to initialize it.

The neural network is trained using training set and its performance is tested with testing set. Process is repeated till acceptable output is obtained. Then this trained network is ready for use. Details of training set and training algorithm is discussed in the following section.

2.1. Design of Artificial Neural Network

Design of artificial neural network and evaluation of its performance requires a lot of time and function modules. The artificial neural network based network reconfiguration techniques map the nonlinear relationship between the load patterns and the corresponding optimal system topologies and determine the most appropriate system topology according to the current load pattern on the basis of the trained knowledge. The relationship, between load patterns and the corresponding switching states in the network, is mapped into an artificial neural network by training it.

The input to the neural network must be the load pattern of buses in the network. In such case every system may require different artificial neural network system depending on the load busses in the system. Again size of training set will depend on number of load buses. If given distribution system is composed of p load busses and each load bus changes its load independently, the total combination number will be increased by m^p, where m is number of load levels. Thus size of training set will be increased by m^p, which makes it impossible to train artificial neural networks. Therefore, to reduce number of inputs to neural network and size of training sets, the load busses are grouped into several independent load groups

2.1.1. Load Groups

For proposed system the loads of the network are divided into three load groups such as residential, commercial and industrial. By considering only three load groups, the number of load combination is reduced to m^3, where m is number of load levels. Type of load assumed in present work for particular load bus in 33 bus test system is given in appendix A.

2.1.2. Load Groups

After studying load curve of different load groups, 5 load levels are taken for the study. It is given in table 1. So, there will be $5^3 = 125$ load patterns and corresponding network topology for each load pattern. This will be the training vector for the neural network.

Dividing load levels into load groups will significantly reduce number of training set required for neural network. It has to be noted that success of any artificial neural network depends on the accuracy and amount of training data and. Sometimes large training set may lead to over trained network and too less training set may result in inaccurate results.

Table 1 Load Levels

Load Level	Actual load (In % of Peak Demand)	Estimated Load (In % of Peak Demand)
1	<=50	50
2	51 – 65	60
3	66 – 75	70
4	76 – 85	80
5	86 – 100	100

2.1.3. Structure of Artificial Neural Network Model

The proposed artificial neural network architecture is shown in figure 2. There is computational layer before input layer of artificial neural network. It receives status of loads at every bus and then computes total load of different type i.e. residential, industrial and commercial. Then its percentage as compared to peak load is determined. This load percentage of three load groups will be input to the neural network. It means input layer will have 3 neurons. With modern measuring and transmitting technology it is possible to get accurate and online estimate of each type of load at bus in the system.

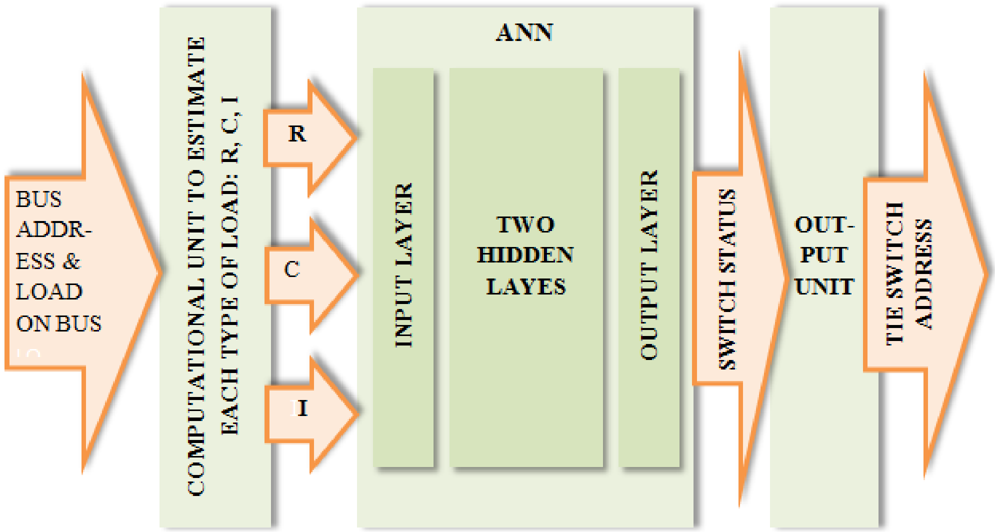


Figure 2 Architecture of Proposed ANN

In present system 2 hidden layers are used. There is flexibility in choosing number of neurons in hidden layers. More the number of neurons more will be the memory occupation by neural network. More number of neurons makes process of classification over trained and it may be good for training set but bad for unknown data. Present work is tested with 33 bus system. For 33 bus test system, numbers of neurons used to start with in each hidden layer are 20. Then they are adjusted by trial and error to get optimized performance. It is seen that with 10 neurons in each layer system is giving best results.

The output of the present system is switch status of tie and sectionalization switches of the network under study. It will be the suggested optimized network configuration for input load. For present test system 37 neurons will be present in output layer.

2.1.4. Training data for Artificial Neural Network Model

Neural network model is trained by applying the supervised back propagation learning algorithm. Each training set has input load level and corresponding optimized switch status. In proposed system 5 load levels are used, so training set will have maximum 5^3 load combinations and corresponding switch status.

Success of artificial neural network depends on its training. For proposed paradigm training set has 5^3 load combinations and corresponding switch status. But difficulty here is to get most appropriate and optimized switch combination for selected load level. From the study of reported work it is seen that from method to method optimization performance varies. Again the performance varies for different load levels. To overcome this limitation a novel approach is proposed here for selection of training set.

As there are different paradigms reported for electrical distribution network reconfiguration, it is possible to choose few best performing paradigms. Then for all 125 combinations its performance is evaluated. Then for each combination the best possible output from all of the paradigms selected for comparison will be added in training set. For present study to design training set the best results at particular load combination achieved by using multi objective optimization of electrical distribution system using fuzzy inference system [23] and Fuzzy-genetic approach for reconfiguration of electrical distribution system [24] are used. Both of these approaches perform multi-objective optimization of electrical distribution network. Load flow results can be obtained for all 125 load combinations using mentioned two approaches. It can be used as training set.

To choose best configuration for particular load condition fuzzy membership function is defined for total loss reduction *(μLR_i)* and minimum node voltage deviation (μVD_i), *i* indicates paradigm referred. It is defined as :

$\mu LR_{i,j}= 1$ for $LR_i>=50$ (1)

$\mu LR_{i,j}= LR_{ij}/100$ for $LR_{ij}<50$, (2)

Where LR_{ij}, is percent loss reduction for that paradigm i at load combination j

and,

$\mu VD_{ij}=(1-Vnode(min)_{i,j})$, (3)

Where $Vnode(min)_{ij}$ is minimum node voltage for paradigm *i* at load combination *j*.

Now,

Total degree of satisfaction *Tds* is then calculated for paradigm *i* and load *j* as,

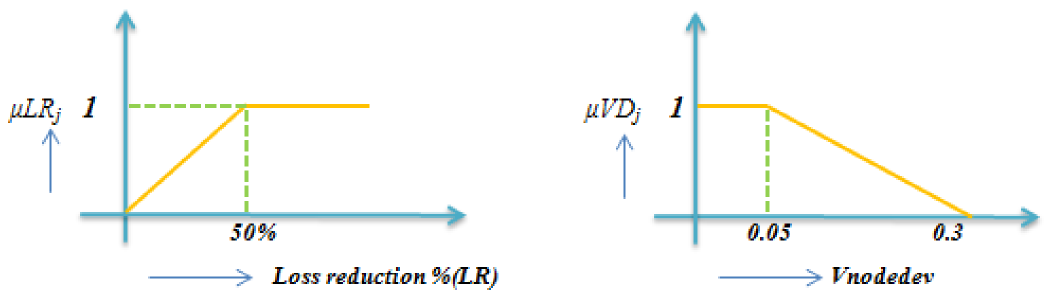
$Tds_{ij} = \mu LR_{ij} + \mu VD_{ij}$ (4)

And training data selected for load combination *j* will be from the paradigm for which *Tds* is maximum as,

Training data(j) = maximum(Tds_i), (5)

Where, *i* indicates paradigms available for comparison.

The membership function for load reduction (µLR) and node voltage deviation are shown in figure 3.



(a) Loss Reduction (b) Node Voltage Deviation

Figure 3 Training set selection

It is designed that if loss reduction is 50 percent or more then $\mu LR=1$, similarly if node voltage deviation is less than 0.05 p.u then $\mu VD=1$.

This approach is very flexible as it has liberty to select best training data obtained from among number of different optimization methods. It assures most appropriate training set.

To validate training of artificial neural network it is necessary to have testing data. By choosing different load combinations sufficient amount of testing data can be made available which will help validating proposed neural network.

2.2. Realization of Proposed Artificial Neural Network Paradigm

Figure 4 shows steps followed to implement multi-objective reconfiguration of electrical distribution network using artificial neural network.

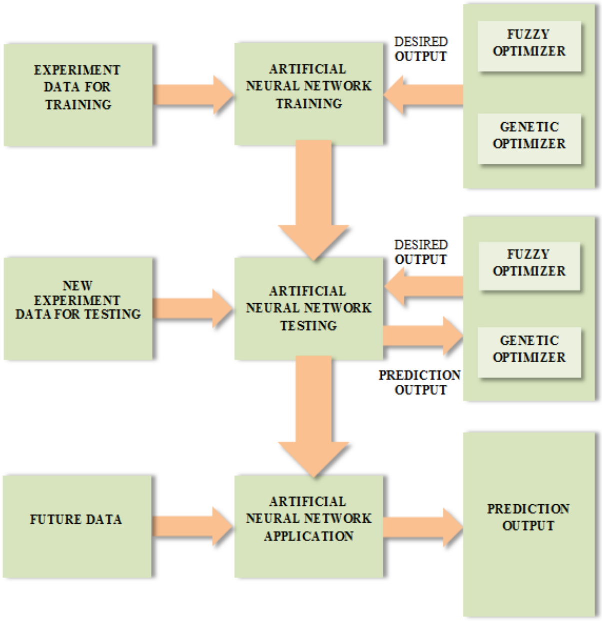


Figure 4 Reconfiguration of Electrical Distribution Network using ANN

To start with, the network weights and biases are initialized to random values. During training, the weights and biases are iteratively adjusted to minimize the network performance function. The mean-squared-error between the network outputs and target outputs is used as the performance function. To provide faster convergence, gradient descent algorithm with momentum has been employed for training the back propagation network. The number of neurons in the hidden layer is adjusted empirically to obtain the optimum performance of the network.

The trained network is tested with new input vectors which were not used for training the artificial neural network model, and the results compared with the simulation results obtained for these new test input vectors. The network is retrained if the global error is not within the specified limit. Once the network is satisfactorily trained, it is ready for use. The design parameters for proposed system are give in the table 2. Proposed system is implemented using MATLAB and artificial neural network tool box.

Table 2 Design Parameters of ANN

Test System	Input Layer Neurons	Hidden Layer Neurons		Output Layer Neurons	Training Set	Epoch	Training Rate
		Layer 1	Layer 2				
33 Bus	3	20	20	37	125	100	0.001

3. RESULTS

Results achieved using proposed paradigm for 33 bus test system are given in the table 3.

Table 1

Load Combination	Parameters	Before Reconfiguration	After Reconfiguration
R:100 C:100 I: 100	Tie Switch	33,34,35,36,37	7,9,14,32,37
	Power Loss	210.667 kW	139.536 kW
	Min. Node Voltage	0.90 p.u.	0.94 p.u
R:70 C:60 I: 70	Tie Switch	33,34,35,36,37	7,10,32,34,37
	Power Loss	90.94 kW	56.48 kW
	Min. Node Voltage	0.93 p.u	0.96 p.u
R:60 C:80 I:100	Tie Switch	33,34,35,36,37	7,10,14,36,37
	Power Loss	150.24 kW	92.0156 kW
	Min. Node Voltage	0.91 p.u	0.94 p.u
R: 50 C: 50 I: 50	Tie Switch	33,34,35,36,37	7,10,14,36,37
	Power Loss	50.39 kW	30.5791 kW
	Min. Node Voltage	0.91 p.u	0.94 p.u

For load level 1, where residential commercial and industrial load is at 100% of its total load the loss has reduced by around 38% compared to that of loss before reconfiguration. Similarly minimum node voltage has increased to 0.94 p.u from 0.90 p.u. It clearly shows improvement in network parameters after reconfiguration.

Similar improvements are seen in other load combinations where residential, commercial and industrial load is at different levels.

4. CONCLUSIONS

Using artificial neural network it is possible to reconfigure electrical distribution network to optimize its performance parameters. The system proposed here is very simple and can be trained easily by using results achieved by any suitable optimization method. It assures that for all load conditions, network configuration will be the most optimized configuration.

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APPENDIX A (R: Residential, C: Commercial, I: Industrial)

Bus No.	Load Type	Bus No.	Load Type	Bus No.	Load Type	Bus No.	Load Type
2	R	10	R	18	I	26	R
3	R	11	C	19	R	27	R
4	R	12	C	20	C	28	R
5	C	13	C	21	C	29	C
6	C	14	I	22	C	30	C
7	I	15	R	23	C	31	I
8	I	16	R	24	I	32	I
9	R	17	R	25	I	33	R