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Artificial Neural Network Based Reconfiguration Of Electrical Distribution Network

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ABSTRACT

In order to find the network topology that minimises system power loss, reduces node voltage deviation, and improves load balancing among feeders while maintaining branch current within designed limits, the electrical distribution network must be reconfigured using a complex combinatorial optimization process. In order to address network reconfiguration issues, this research provides an artificial neural network (ANN)-based methodology. The fuzzy-based and genetic algorithm (GA)-based optimization approaches are used to build the training set for ANN. The 33 bus test system is subjected to the proposed ANN technique. According to test results, the suggested ANN model enables quick and precise network design under various load scenarios.

Key words: Electric Distribution Network, Fuzzy Inference System, Genetic Algorithm,Multi-objective optimization,Radial distributionSystem,Recon figuration.

1. INTRODUCTION

Power distribution structures are normally configured radially, however the act of establishing or last switches or safetygadgets can likelyextrade the topology of such structures. In this context, the community is reconfigured to keep its radial topology and additionally to lessen electricity losses on the feeders, to beautify the voltage profile for customers, and to boom the reliability levels. Though there are numerous alternatives consisting of reconfiguration, capacitor placement, load feeder balancing, and disbursedtechnology for lowering losses and enhancing voltage profile in a distribution system, reconfiguration is the maximum favored techniqueas itcalls for no greatersystem to be established and is price effective. In current years, sizeablestudies has been carried out for loss minimization withinside thelocation of community reconfiguration of distribution structures. Various algorithms are proposed and examined for community reconfiguration.

Merlin et al. [1] first proposed a reconfiguration of the distribution system. To determine the minimum loss configuration, he used a branch-and-bound optimization technique. Based on Merlin et al. [1], Shirmohamadi et al. [2] We propose a heuristic algorithm. This method also creates an optimal flow pattern in the network by closing all network switches and opening one after the other. This helped us make many approximations to the algorithm of Merlin et al. [1] Overcome. A heuristic algorithm based on power flow is proposed by Goswami et al. [3] Suggestions. To determine the distribution system configuration, Civanlar et al. [4] developed a simplified formula. To obtain a globally optimal, or at least nearly globally optimal solution for reconfiguration of distribution networks, Chiang et al. [5, 6] and Jeon et al. [7] Proposed solution using simulated annealing. But it is very time consuming. Jiang et al. [8] presented algorithms for switch reconfiguration and capacitor control in power distribution systems using simulated cooling techniques. Lee et al. [9] proposed a power exponent-based approach using heuristic rules for resistive loss reduction. Aoki, et al [10] have altogether different approach for this problem.They have formulated it as a discrete optimization problem.Fereidunianetal[11]have comeout with altogether different approach for distribution network reconfiguration algorithm. Wagner, et al [12] has presented comparisonof various methods which are applied to network reconfiguration for loss reduction. Manyother researchers such as Hsiao, et al [13], Jeon, et al [14], Shin, et al [15], Hsiao [16], Lin, etal [17], Das [18] and Hong, et al [19] etc. have proposed different approaches for network reconfiguration.

Because of their numerous applications in fields including image processing, pattern recognition, associative memory, and combinational optimization, neural networks have attracted a lot of recent academic attention. Numerous criteria must frequently be taken into account when solving engineering optimization challenges [20]. In order to minimise or maximise many objective functions at once in this condition, it is formulated as a nonlinear constrained multi-criteria optimization problem. Different classes of optimization issues are undoubtedly one of the most promising areas for using artificial neural networks.

Neural networks have recently received a lot of academic attention due to their many applications in areas such as image processing, pattern recognition, associative memory, and combinatorial optimization. When solving a technical optimization problem, a number of factors usually have to be considered [20]. To simultaneously minimize or maximize many objective functions under such circumstances, it is formulated as a multi-criteria nonlinear optimization problem. Using artificial neural networks to solve various classes of optimization problems is perhaps one of the most promising applications. His two-step approach based on ANNs for reconfiguring power distribution systems to minimize losses was first proposed by Kim et al. [twenty one]. To address the challenges associated with training on large amounts of data, it has been proposed to divide the delivery network into load zones. Dividing the load into multiple categories, with the load levels reported by Kashem M. et al., significantly reduced the number of load patterns and increased computational speed. Divided into 7 categories. [twenty two].

The use of ANN can greatly shorten the time required for distribution network reconfiguration because the flow computation is not necessary. The quickest approach for reconfiguring a distribution network, in terms of speed. Artificial neural networks are highly parallelizable when implemented on hardware and disturbance-resistant. However, the availability of training samples determines how accurate results generated by an ANN algorithm are.

2. Artificial Neural Network Approach For Re-Configuration Of Electrical Distribution Network

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

The multiple objectives considered for optimizationare

- Minimization of thesystem powerloss.
- 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 giveninthefigure1.

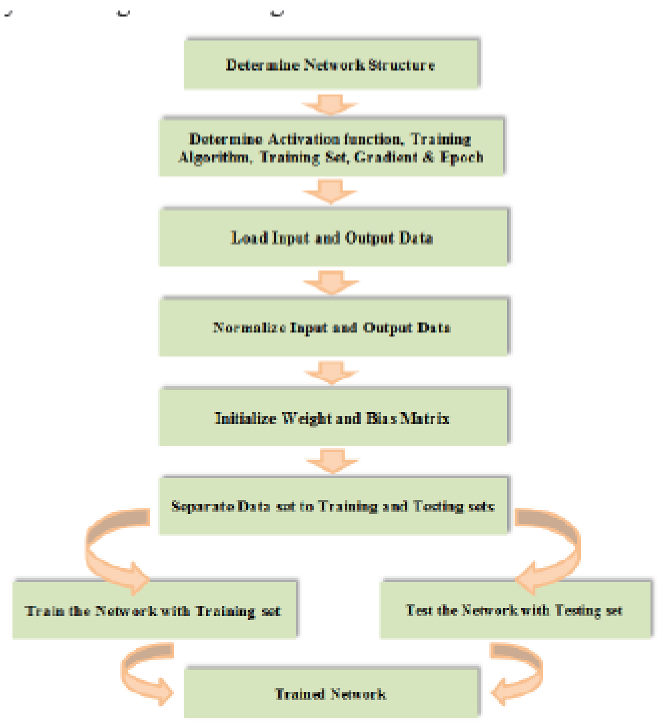


Figure1DesignStepsforANN.

At the core of all artificial neural networks is their structure. This is the first step where we need to determine the input layer, the number of hidden layers, and the output layer. Indicates the number of inputs to the artificial neural network and the number of outputs from the artificial neural network. The details of the proposed neural network structure are given in the next section. The next step in design is to specify the activation function, training algorithm, and training set. The different activation functions and different training algorithms that can be used were described in the previous section. The proposed system uses a sigmoidal activation function and a backpropagation learning algorithm. More details are provided in the next section. The weights in the network can be initialized randomly or using normalized input and output data. A neural network is trained using a training set and its performance is tested using a test set. This process is repeated until an acceptable output is obtained. After that, this trained network is ready to use. More details on the training set and training algorithm are provided in the next section.

2.1. Design of Artificial Neural Network

A lot of time and function modules are needed for the design of an artificial neural network and for evaluating its performance. On the basis of the trained knowledge, the artificial neural network-based network reconfiguration approaches map the nonlinear relationship between the load patterns and the associated ideal system topologies and choose the best system topology in accordance with the current load pattern. By training an artificial neural network, the relationship between load patterns and the related switching states in the network is mapped into the network.

The load pattern of the network's buses must be the neural network's input. Depending on the load buses in the system, each system may thus require a distinct artificial neural network system. Again, the number of load buses will determine the size of the training set. The overall combination number will increase by *m*p, where m is the number of load levels, if a given distribution system has p load buses and each load bus changes its load separately. As a result, *m*p will increase the size of the training set, making it impossible to train artificial neural networks. Therefore, the load buses are divided into a number of distinct load groups in order to decrease the number of inputs to the neural network and the size of the training sets.

2.1.1. LoadGroups

For proposed system the loads of the network are divided into three load groups such asresidential, commercial and industrial. By considering only three load groups, the number ofload combination is reduced to m^3, where m is number of load levels.

LoadGroups

After studying load curve of different load groups, 5 load levels are taken for the study. It isgiven 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 setrequired 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 overtrained network and too less training set may result in accurate results.

Table1LoadLevels

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

2.1.2. **Structure of Artificial Neural Network Model**

Figure 2 depicts the suggested artificial neural network architecture. Before the input layer of an artificial neural network comes the computational layer. It receives the load status from each bus and computes the overall load for each category, such as residential, industrial, and commercial. Next, its percentage in relation to peak load is calculated. The neural network will receive this load % from the three load groups as input. Input layer will therefore have three neurons. It is now possible to obtain an exact online estimate of each type of load at each bus in the system because to advances in measuring and transmitting technologies.

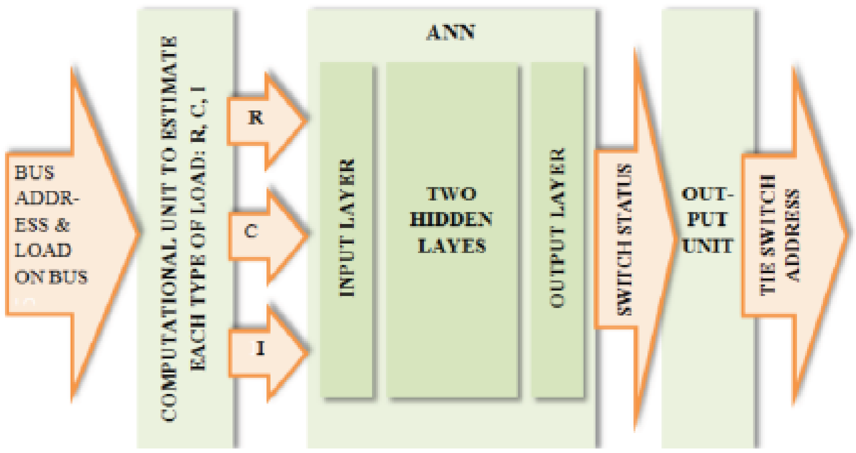


Figure2ArchitectureofProposedANN

The current system uses two hidden layers. You have flexibility in choosing the number of neurons in the hidden layer. The higher the number of neurons, the more memory occupied by the neural network. As the number of neurons increases, the classification process overfits, which is good for the training set but not for the unknown data. Current work has been tested on a 33-bus system. For the 33-bus test system, the number of neurons used initially in each hidden layer is: 20. It is then tuned by trial and error for optimal performance. We find that using 10 neurons in each layer system gives the best results. The output of this system is the switching status of the connection switch and split switch of the network to be investigated. This is the optimized network configuration recommended for your input load. The current test system has

37 neurons in the output layer.

*2.1.3 **Training data for Artificial Neural NetworkModel***

Applying the supervised back propagation learning algorithm trains the neural network model. Each training set has an optimum switch state that corresponds to the input load level. A training set can contain a maximum of 53 load combinations and accompanying switch statuses because the proposed system uses 5 load levels.

The training of an artificial neural network is key to its success. There are 53 different load combinations and accompanying switch statuses for the proposed paradigm training set. However, the challenge here is finding the best and most optimal switch combination for the chosen load level. The analysis of the published work reveals that optimization performance differs from method to method. Once more, performance changes depending on the load level. Here, a novel method for choosing the training set is suggested in order to get over this issue.

Given the variety of paradigms provided for reconfiguring electrical distribution networks, it is feasible to select a few that perform the best. The performance of each of the 125 combinations is then assessed. The best output from each of the paradigms chosen for comparison will then be added to the training set for each combination. The best results at a specific load combination achieved by using multi-objective optimization of the electrical distribution system using fuzzy inference system [23] and Fuzzy-genetic approach for reconfiguring the electrical distribution system [24] are used for the current study to design the training set. These two methods optimise the electrical distribution network across multiple objectives. Using the two methods indicated above, load flow results may be produced for all 125 load combinations. It may be utilised as a practiseset.

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

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

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

WhereLR_{ij},is percent loss reduction for that paradigmiatloadcombinationj

and,

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

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

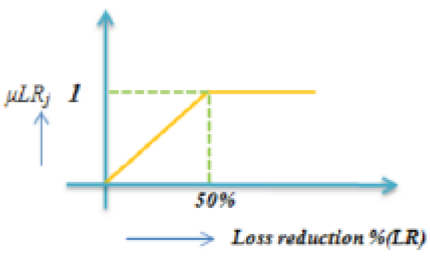
Total degree of satisfaction *Tds*is then calculated for paradigm *i*and load *j* as,$Tds_{ij}=\mu LR_{ij+}\mu VD_{ij}$ (4)

And training data selected for load combination *j* will befrom the paradigmfor which*Tds*is maximum as,

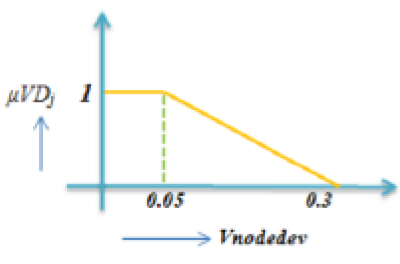
$$\text{Trainingdata}(j)=\text{maximum}(Tds_i), \qquad (5)$$

Where,*i*indicatesparadigmsavailableforcomparison.

The membership function for load reduction(μLR) and node voltage deviation are shown in figure3.



(a) Loss Reduction



(b) Node Voltage Deviation

According to its design, if loss reduction is 50% or above, LR=1, and if node voltage variation is less than 0.05 p.u., VD=1.

This strategy is particularly adaptable since it gives users the freedom to choose the optimum training data from a variety of different optimization techniques. It guarantees the best workout regimen.

Testing data are required to validate artificial neural network training. A significant amount of testing data can be made available by selecting various load combinations, which will aid in validating the suggested neural network.

2.2 **Realization of ProposedArtificial Neural Network Paradigm**

Figure4shows steps followed to implement multi-objective reconfiguration of electrical distribution network using artificialneural network.

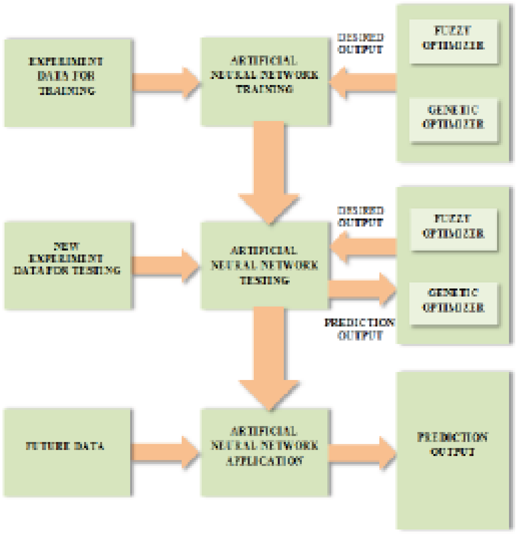


Figure4 Reconfiguration of Electrical Distribution Network usingANN

First, 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 network output and target output is used as the performance function. An impulse gradient descent algorithm was used for training the backpropagation network to speed up convergence. The number of hidden layer neurons is empirically tuned for optimal performance of the network. The trained network is tested using new input vectors that were not used to train the artificial neural network model, and the results are compared with simulation results obtained for these new test input vectors. If the global error is not within bounds, the network is retrained. Once the network is sufficiently trained, it is ready to use.

The parameters of the proposed system are shown in Table 2. The proposed system is implemented using MATLAB and the Artificial Neural Networks Toolbox.

Table2DesignParametersofANN

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 paradigmfor33bustest system are given in thetable3.

Table 3

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

Electrical distribution networks can be reconfigured using artificial neural networks to improve various performance metrics. The system that is being described here is relatively straightforward, and it can be simply trained using the outcomes of any applicable optimization technique. It guarantees that the network configuration will be the most effective configuration for all load scenarios.

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