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Expert System Based Power Loss Analysis of a Distribution System

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Abstract: The knowledge of power loss in an electrical distribution system is necessary to implement the strategies such as reactive power compensation and optimal system configuration. This necessitates the use of efficient feeder loss model. Power loss of distribution system is obtained by integrating the power loss of all feeders. This study presents a novel approach to analyze the real and reactive power loss of a distribution feeder using Artificial Neural Network (ANN) and GA based power loss model. Three phase load flow analysis is executed to find the sensitivity of feeder power loss with the variation in temperature, feeder power loading, conductor length and total capacity of distribution transformers and accordingly simulated data sets are generated for neural network training by way of varying these parameters. The parameters are tuned by genetic algorithm. Simulation results show that the power loss derived by using the ANN-GA model is rather consistent to that solved by the three-phase load flow analysis with an average percentage error of 3.33 and 2.16% for real and reactive power loss, respectively.

Key words: Artificial Neural Network (ANN), genetic algorithm, software, simulation, parameters, India

INTRODUCTION

In power system, the distribution system losses have become more and more of concern because of the growth of load demand and wide area it covers. The primary and secondary conductors and transformers contribute most of the power loss of distributed system. The knowledge of power loss of a distribution system is great concern for distribution engineers to implement the strategies such as reactive power compensation, optimal system configuration, etc. (Chen *et al*., 1994). This necessitates the use of efficient feeder loss model. Power loss of distribution system is obtained by integrating the power loss of all feeders. So far to the best of the knowledge, the research reported in different published literatures, researchers do not consider the effect of temperature in analyzing the feeder loss. In the power loss model of a distribution feeder using Artificial Neural Network (ANN) (Kang *et al*., 2006) temperature was not considered as an input parameter.

This motivates to develop a feeder loss model which would be sensitive to the temperature. Accordingly this study presents a novel approach to analyze the real and reactive power loss of a distribution feeder using ANN-GA based power loss model (ShangDong and Xiang, 2006). The conventional loss analysis by applying the detailed system modeling is difficult and impractical to be performed since voluminous data are involved (Kartalopoulos, 2005). In the present study, single input representing the total feeder length of both primary and secondary feeder is selected as an input parameter for ANN modeling where the length of primary feeder remained fixed and the length of the secondary feeder is varied. Three other factors which are feeder power loading, temperature and total capacity of distribution transformers are also selected as input parameters for ANN modeling.

For analyzing the feeder loss, a three phase distribution feeder model has been simulated using ETAP 5.00 software and 320 data sets of feeder loss have been determined by way of varying feeder loading, feeder length, temperature and total transformer capacities. These simulated data sets are used for training, validation and testing the ANN model. Simulation results show that the power loss derived using the ANN model is rather consistent to that solved by the three-phase load flow analysis with an average percentage error of 4.33 and 3.16% for real and reactive power loss, respectively (Haykin, 2001).

MATERIALS AND METHODS

Generation of experimental data

Feeder length data: To illustrate the power loss analysis of distribution feeder, an 11 kV overhead primary feeder is simulated using ETAP 5.00 software as shown in Fig. 1. In Table 1, specifications of real cables are shown which are used for simulation purpose. Secondary feeders

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Table 1: Specification of feeders

Types of cable	Conductor size for Al 3 core (mm^2)	Voltage rating (kV)	A.C resistance in Ω/km	No. of wires per conductor	Current rating (Ampere)	Overall diameter (mm)	Weight of cable (kg km^{-1})
Primary	3×240	11/11 kV(UE)	0.162	30	390	95	7340
Secondary	3×70	3.8/6.6 kV(E)	0.572	12	180	48	2760

Table 2: Sets of transformer capacity

No. of set	Total transformer capacity in MVA (Sum of transformer capacities connected to bus no. 5, 8, 11, 14 and 17)	Transformer capacity in MVA connected to bus no. 5	Transformer capacity in MVA connected to bus no. 8
1	1.63	0.40	0.40
2	2.46	0.40	0.63
3	2.69	0.63	0.63
4	3.36	0.63	0.63
No. of set	Transformer capacity in MVA connected to bus no. 11	Transformer capacity in MVA connected to bus no. 14	Transformer capacity in MVA connected to bus no. 17
1	0.10	0.1	0.63
2	0.40	0.4	0.63
3	0.63	0.4	0.40
4	0.10	1.0	1.00

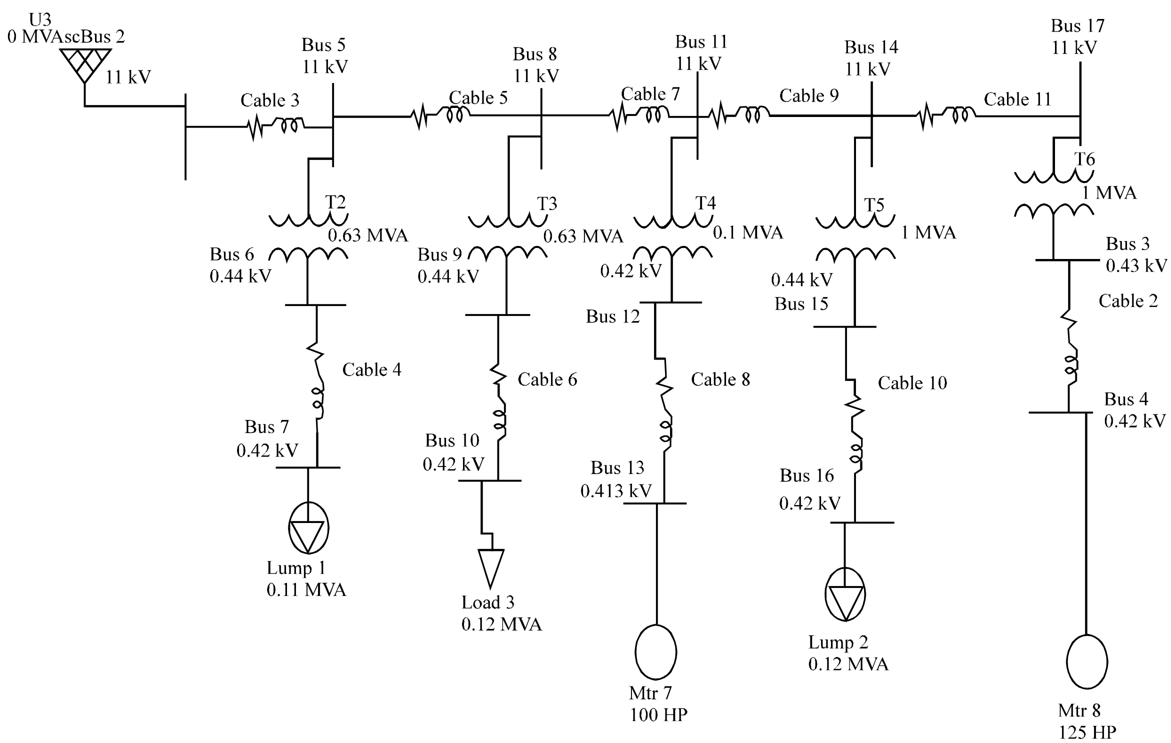

Fig. 1: Test feeder

connected from the secondary side of the transformers are directly supplying the load to the customers. The length of the primary feeder is remained fixed at 5 km whereas the length of the secondary feeder is varied from 0.25-1 km. Thus, the total length of the primary feeder and secondary feeder is varied from 5.25-6 km.

Distribution transformer ratings: There are four distribution transformers having capacities 0.1, 0.4, 0.63 and 1.0 MVA selected for simulation and the inputs to NN structure in respect of transformer capacity is either of the set 1-4 as shown in Table 2.

Temperature: Temperature is a parameter on which feeder loss depends and is varied from 5-45°C in the steps of 5°C during computer simulation.

Generation of experimental data using ETAP 5.00 software: Three-phase load flow analysis is executed using ETAP 5.00 software to find the parameters to which

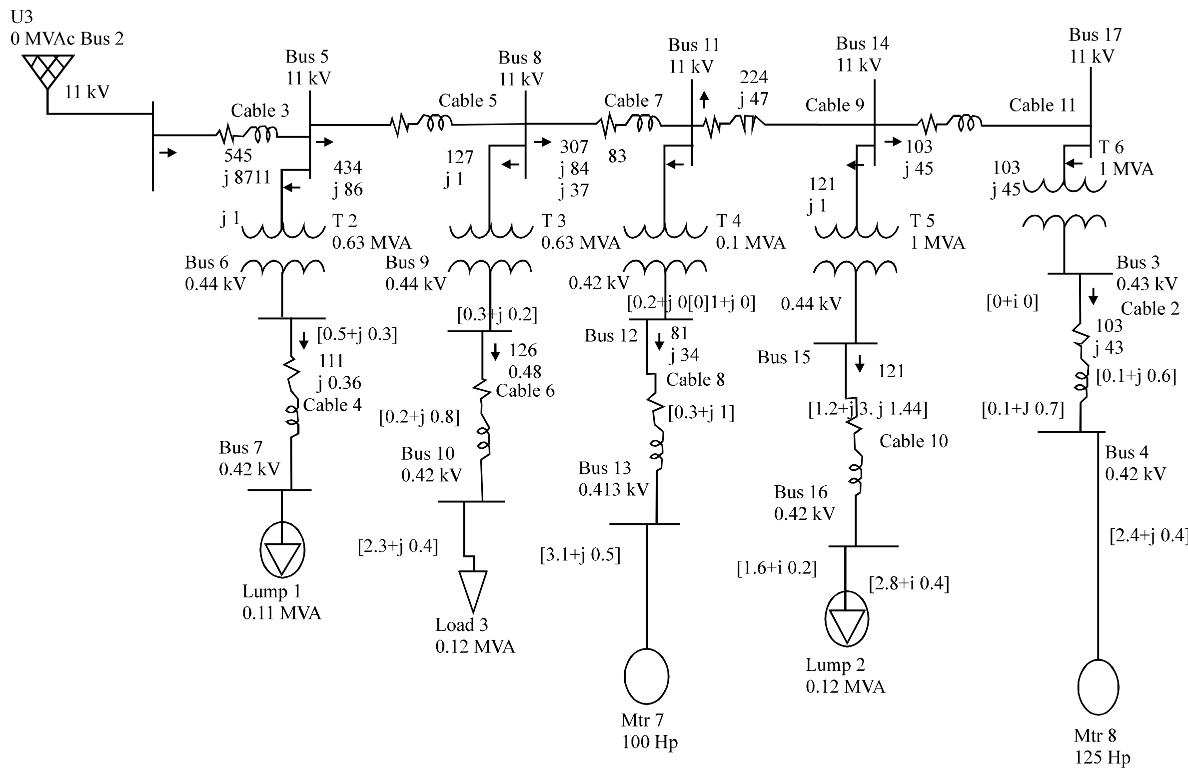

Fig. 2: Load flow of test feeder

the feeder loss is sensitive. It is found that feeder loss is sensitive to the variation in power loading, conductor length, temperature and total capacity of distribution transformers. Load on the feeders remained fixed whereas feeder loading is changed by way of varying conductor length, temperature or total capacity of distribution transformers. As such the power loss of distribution feeder is derived according to the key factors of feeder loading, conductor length, temperature and total capacity of distribution transformers. By this way, 320 data sets are generated for Neural Network (NN) training to derive the ANN based power loss model as shown in Fig. 2. These simulated data sets are used to train, validate and testing the NN structure.

Neural network application

Selection of training cases: One of the important uses of NN is function approximation. The main characteristic of this is that the function that should be approximated is given not explicitly but indirectly through a set of input-output pair as a training set. This data set can easily be obtained from the experiments. In the present study, experiments are basically the execution of three-phase load flow analysis, 320 times using ETAP 5.00 software by way of varying feeder loading, temperature, total transformer capacities and total feeder length.

Accordingly 320 data sets are generated among which 260 data sets are used for training, 40 for validation and 20 for testing the NN model.

Network structure: The NN structure used is a three layered feed-forward neural network trained by back propagation algorithm based on Levenberg-Marquardt approach. This NN structure comprises an input, a hidden and an output layer. The processing units of the hidden and output layers have a non-linear hyperbolic tangent transfer function and identity transfer function, respectively. Each layer is connected to the layer above it in a feed forward manner. The input layer has five inputs viz. feeder loading in kW and kVAR, conductor length, temperature and total capacity of distribution transformers. The output layer has two nodes viz. feeder loss in kW and kVAR. For normalizing the input data in required range [-1, 1] following equation is used:

$$L_N = 2\times\frac{L-\min(L)}{\max(L)-\min(L)}-1 \quad (1)$$

where, L_N is the normalized value, L the actual value, min (L) the minimum value and max (L) the maximum value. The training parameters viz. learning rate is set as 0.1 and error goals are set as 0.1 kW and 0.1 kVAR. The neurons in the hidden layer are selected heuristically and the network is trained with error goal. Processing with this NN structure is carried out in two phases. During 1st phase, training of NN structure with training data is performed to obtain approximate nonlinear input output mapping. The mapped network in the form of free parameters (weights) is stored in the NN structure in a distributed manner. These weights give a functional relationship between input and output data. The optimum NN structure is 5-12-2, i.e., five inputs, twelve hidden layer and two output neurons. Weights of trained network between input and hidden layer are shown as:

[-0.0685	-0.0255	0.2465	0.0006	0.1371
-3.2466	0.9779	1.3741	4.2904	0.0153
-1.0963	-3.9562	2.0985	-4.9542	-0.0595
-0.0671	-0.1352	-0.1236	-0.6811	-0.0271
-0.3242	0.1619	-0.1668	0.0046	0.0347
0.4226	1.0189	-0.6380	-1.0358	-0.0985
1.7847	1.8067	-2.8415	2.2710	-4.7297
-0.1512	-0.1537	-0.2282	-0.0775	-0.1230
0.0704	-0.0601	-0.2448	-0.0687	0.0631
-0.0493	-0.6806	0.0331	1.6488	-0.0808
-1.5821	-3.8209	3.6130	-4.5087	-3.9944
0.9848	-0.2376	0.3863	0.1764	-1.3527]

for future testing with new test data not seen before by the network. The implementation of neural network model and GA is carried out using Matlab neural network toolbox. GA based bias weights of trained network at hidden layer are [0.6600, 1.8609, -2.4993, 0.4732, 0.2587, -0.2928, 1.1818, 0.3395, 0.1623, 0.9610, -5.0190, -1.7029].

Transpose of the matrix containing weights of trained network between hidden layer and output node shown is as:

[1.0881	0.1326
0.02320	0.0162
0.02320	0.0522
0.20360	-0.3745
-0.8021	-0.2882
0.3955	0.2509
0.0037	0.0020
-0.0300	-0.1313
-2.6616	-0.7896
0.3039	-0.4414
0.0023	-0.0044
0.0529	0.0081]

Bias weight of trained network at output layer are [-0.1082, 0.3192].

RESULTS AND DISCUSSION

Average percentage feeder loss error is used as a measure of performance for the NN structure. Average percentage feeder loss error E_{av} is defined as:

$$E_{av} = \frac{1}{N}\sum_{i=1}^{N}\left[\left|\frac{Y_a(i) - Y_f(i)}{Y_a(i)}\right|\right] \times 100 \qquad (2)$$

Where:

N = The number of test data cases

$Y_a(i)$ = ith actual feeder loss value as obtained by running the load flow using ETAP 5.00 software

$Y_f(i)$ = ith feeder loss value at the output node of NN structure

Feeder loss for twenty test data not seen before by the network is obtained by this trained ANN model as shown in Fig. 3 and 4. It is found that the feeder power loss derived by using the ANN model is rather consistent to that solved by the three-phase load flow analysis in ETAP 5.00 software with an average percentage error of 4.33 and 3.16% for real and reactive power loss, respectively.

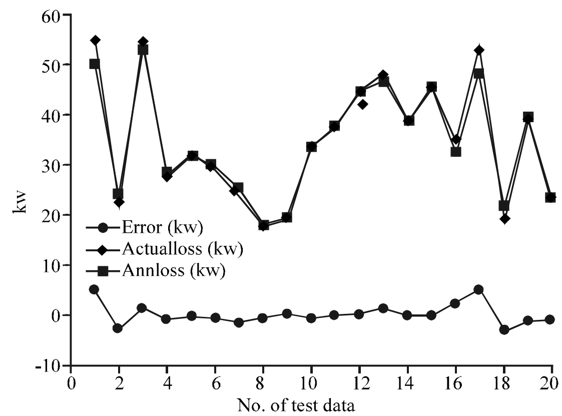

Fig. 3: Comparison of real power loss, solved by three phase load flow analysis using ETAP 5.00 software and by ANN model

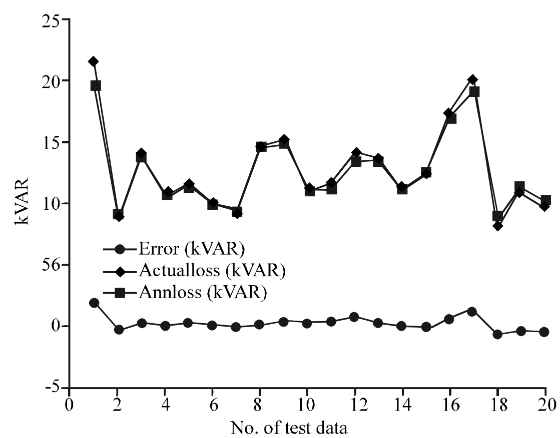

Fig. 4: Comparison of reactive power loss, solved by three phase load flow analysis using ETAP 5.00 software and by ANN model

CONCLUSION

This study has presented a simple and systematic method to develop an ANN-GA based model to analyze the real and reactive power loss of a distribution feeder. This study identifies the effect of ambient temperature in power loss calculation of a distribution feeder since, variation in ambient temperature introduces the changes in load demand and system loss.

From the results, it can be concluded that ANN-GA technique can be successfully used to calculate feeder's total power loss by knowing only the parameters feeder length, transformer capacities installed in that feeder, feeder power loading and ambient temperature. Power loss of whole distribution system can be obtained by integrating the power loss of all feeders. The operational efficiency of distribution system can be effectively estimated by the proposed method.

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