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Research Paper

LINE LOSS EVALUATION OF DISTRIBUTION SYSTEM USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT : *Line loss evaluation of distribution system using artificial neural network (ANN) is presented in this paper. Due to the high capability of parallel information processing of the artificial neural networks, they have most suitable for line loss evaluation of distribution system. Back propagation algorithm is adopted for training of ANN. Feeder capacities in per unit are chosen as inputs to the ANN and distribution system losses are chosen as outputs. Training data are obtained from off-line load flow studies for different system topologies and load levels are carried out and the solution are complied to form the training set. The proposed algorithm is applied to 7-feeder distribution system and numerical results are presented in this paper in order to demonstrate the effectiveness of the proposed ANN algorithm in terms of accuracy. The developed ANN model can be utilized for both off-line simulation studies for performance evaluation and on-line energy loss evaluation*

Keywords: *Distribution System, Artificial Neural Network, and Back Propagation Algorithm.*

I. INTRODUCTION

Distribution systems are the parts of the power systems that deliver energy from the area supply stations to the customers. The reliability of these systems is of same importance as those of generation and transmission systems. Any event that affects the distribution system will directly affect the consumers. Electric power being an important commodity should be effectively distributed to the consumers. For efficient and reliable power supply the losses in the distribution system should be minimum. Hence rapid and accurate evaluation of losses has gained importance. Electric utilities have considered system losses in a broad and general manner accordingly, loss calculations have been approximate. However, utilities operating in a new environment which on one hand complicate the loss calculations and on the other hand demand a fair assessment of losses. The importance of accurately and rapidly determining the losses has gained importance for many reasons including;

i) There is a continuous need by the electric utilities to improve system-operating efficiency.
ii) Electric losses are the controlling factor while evaluating alternative power system expansion plans.
iii) The current impetus in billing and rate design is to consider actual incurred cost.
iv) Losses are an important consideration in the pricing of all energy transactions among interconnected utilities.

For distribution systems, where losses would be a function of load, losses have been calculated by applying standard empirical equivalent hour loss factor equation [1, 2]. However, this method cannot be applied to systems where losses are function of generation schedule, imports, exports, wheeling and loop flow in addition to load. As the capacity, losses of a power system are complex functions of the system configuration, generation and demand pattern as well as various voltage levels at which the system is operating, a more complicated mapping capability is needed to approximate these functions. It is noted that the energy loss is the integration of capacity loss over time. As the capacity loss is changing constantly, energy loss evaluation cannot be accurate unless it is done on-line. Artificial Neural Networks (ANN) has these capabilities and is suitable to model complicated mapping relationships. It is inferred that ANN based analysis of an ac network is helpful in analyzing practical problems in modern distribution networks where the time factor (computation) and accuracy are more essential to operate and maintain the distribution system. In [3] artificial neural network based distribution system line loss estimation for sample distribution system is proposed.

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II. DISTRIBUTION SYSTEM

Distribution System is one of the most important subsystems in the power system**.** Distribution System is that part of power system which distributes power to the consumers for utilization. Distribution system gains importance because of its close proximity with the consumers and its high investment. The various components of distribution system are (i) Sub-transmission system
(ii) Distribution substation
(iii) Primary feeders
(iv) Distribution transformer
(v) Secondary circuit
(vi) Service drop.

There are two types of distribution systems, namely (i) Radial System
(ii) Loop System

(i) Radial System

The radial system gets its name from the fact that the primary feeders radiate from the distribution substation and branch into sub-feeders and laterals, which extended into all parts of the area served

(ii) Loop System

Loop System is used most frequently to supply bulk loads such as small industrial plants and medium or large commercial buildings where continuity of service is of considerable importance.

III. PROPOSED APPROACH

The proposed approach presents the application of artificial neural network for on-line and off- line loss evaluation of distribution system. The proposed approach involves following steps:
* Problem formulation
* Design of ANN for loss evaluation

IV. ARTIFICIAL NEURAL NETWORK

A typical neural network consists of a large number of elementary processing units termed as 'neurons', with each such unit connected to many others. If the numerical strength or weight of a connection between a pair of units is positive, the connection is excitatory, weight zero implies no connection and if the weight is negative, it is an inhibitory connection. Each neuron could receive several inputs X_1, X_2, - - - Xn through the connections with associated strengths W_1, W_2, - - - - - Wn. These weighted inputs of a particular neuron are combined to produce a net input to the unit. Thus the input to the unit j is given by Net_j= [W] [X]. This net signal is further processed by the activation function (F) of the neuron j to produce the output given by O_j = F (net_j)An ANN generally consists of an input layer, an output layer and one or more hidden layers with each layer having a number of neurons. The activation function of the neurons in the hidden and output layers of the network is taken as sigmoid. Training of an ANN implies the automatic adjustment of weights so that the application of a set of inputs produces the desired set of outputs. One of the popular learning algorithms is the error back propagation algorithm [4], which is based on the gradient descent technique for error reduction. In this algorithm, before starting the training process, after initializing all the weights, a set of patterns, each comprising of a normalized input vector and the corresponding desired normalized output vector are shown to the ANN. The ANN output vector obtained is then compared with the desired output vector and the weights & the bias are adjusted until the error function [4] becomes acceptably small. The training time required by the back propagation algorithm is decreased by adding a bias to each neuron in the network using momentum coefficient and learning rate parameters [4].

V. LOAD FLOW STUDIES

A load flow study is the determination of the voltage, current, power and power factor or reactive power at various points in an electric network under steady state conditions of normal operation. Load flow study gives the information, which is very essential for the continuous monitoring of current state of the system, contingency analysis, designing a new power system and for analysis of the effectiveness of the alternative plans for the future such as adding new generator sites, meeting increased load demand and locating new transmission sites. Load flow solution also gives the initial conditions of the system when the transient behavior of the system is to be studied. The principal information obtained from a load flow study is the magnitude and phase angle of the voltage at each bus and the real and reactive power flowing in each line and a clear picture of the line losses.

VI. DESIGN OF ANN FOR THE LINE LOSS EVALUATION OF A DISTRIBUTION SYSTEM

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The developed algorithm includes the following steps
(i) Preparation of suitable training data ii) Selection of suitable ANN structure (iii) Training & Evaluation of ANN.

(i) Preparation of suitable training data

It is important to appreciate that the design process is iterative. It is possible that a particular structure chosen while designing ANN may not train to a designer's satisfaction. In this situation, the structure has to be changed and the ANN should be retrained. Also, the trained network may not perform satisfactory on test data. In that situation, network structure and training data should be changed and the network retrained and tested. The training patterns should contain necessary information to generalize the problem. The preparation of a training set includes three stages; firstly, system parameters were collected and prepared for a load flow study, secondly, for different system topologies, a number of load flow studies were carried out, assuming that the state variables take values uniformly distributed in between the lower and upper limits. For the 7-feeder distribution system considered, 15 load flow solutions were carried out. The results were stored in a single text file. Finally the obtained load flow patterns were normalized between [-1, 1]. To check whether each load flow pattern obtained was healthy, a sanity check procedure was applied which examined the feasibility of a created operating condition. Impractical patterns have to be removed before the process of normalization. For the system considered only 5 practical load flow patterns were obtained. To produce a testing set consistent to the training set there is a need to keep track of normalization. The same normalizing patterns as, used in the trained data have been used in processing test data.

(ii) Selection of suitable ANN structure

The selection of the structure of the proposed network includes the selection of number of layers, choice of transfer function, number of inputs and number of neurons in each layer. A 3 layer feed forward network can be model complex mapping functions reasonably well and therefore is suggested for this application. The number of neurons in the input layer and hidden layers are decided by experimentation as, 14 & 5 respectively which involve training and testing different network configurations.

(iii) Training and Evaluation of ANN

The training of the selected network is done using training patterns and back propagation algorithm. To achieve generalization, training and testing is interleaved. Training is stopped when the mean squared error between actual outputs and desired outputs stop improving. However at that point, if the designer is not satisfied with the training and performance of the ANN, the training data and/or structure of the ANN are modified and the design process is repeated. The network can recognize input patterns only when the weights are adjusted or tuned via some kind of learning process called training. Collection of samples is divided into subsets. These subsets are presented to the network one at a time. If the outputs of these samples are known, then process is called supervised training. If the outputs are not known the process is called unsupervised training. One pass through this cycle is called epoch. The number of training samples in a subset of total samples is called epoch size. The back propagation algorithm is the most frequently used method in training the network. This is also called generalized delta rule.

GENERALIZED DELTA RULE

An error signal proportional to the difference between what the output is (reference) and what is supposed to be (target) produced. Then the weights of the network are changed in proportion to the error times the input signal, which diminishes the error in the direction of gradient.
Let the sum of the squared errors to be minimized be

$$E_p = \Sigma \frac{(t_{pm} - O_{pm})^2}{2} \qquad (1)$$

Where p = presentation number; t_{pm} = target output for y^{th} component of p^{th} pattern.
O_{pm}= actual output for y^{th} component of p^{th} pattern.
To obtain a rule for adjusting the weight the gradient of E_p with respect to the weight W_{ym} is used. Where W_{ym} is the weight between Y^{th} & M^{th} neuron. From the descent gradient algorithm, the change in weight is proportional to the gradient of error and it should be in such a direction that the error is decreasing.
Hence,

$$\Delta W_{ym} \; \alpha \; - \frac{\partial E_p}{\partial W_{ym}}$$

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$$\Delta W_{ym} \ \alpha - \frac{\partial E_p}{\partial W_{ym}} * \frac{\partial O_{pm}}{\partial O_{pm}}$$

Then, error signal is defined as

$$\delta_{pm} = -\frac{\partial E_{pm}}{\partial O_{pm}} \qquad (2)$$

Hence equation (2) becomes

$$\Delta W_{ym} \ \alpha \ \delta_{pm} * \frac{\partial O_{pm}}{\partial W_{ym}} \qquad (3)$$

This can be manipulated

$$\Delta W_{ym} = \eta * \delta_{pm} * O_{py} \qquad (4)$$

Where, η = adaptation gain = Learning rate parameter

The error signal is defined in two ways:

(i) If neuron ‘m’ is one of the output layer

$$\delta_{pm} = (t_{pm}-O_{pm}) * O_{pm} * (1-O_{pm}) \qquad (5)$$

(ii) If neuron Y is not from the output layer

$$\delta_{py} = O_{py} * (1-O_{pm}) * \Sigma\delta_{pm} * W_{ym} \qquad (6)$$

Back Propagation Algorithm

Step-1: A subset of training samples is presented to the network. The output of the neurons is computed using following equations. For each neuron in the input layer, the neuron output is the same as the neuron input for any neuron `m’ in the hidden or output layer, the neuron input is

$$Net_{pm} = W_{my} * O_{py} \qquad (7)$$

Where y = 1, 2 - - - - n. the neuron in the preceding layer

O_{py} = output of y^{th} neuron in the preceding layer.

The output of neuron `m’ is,

$$O_{pm} = \frac{1}{1+ \text{Exp}\ \{-(net_{pm} - \theta_{pm})/ \theta_{om}\}} \qquad (8)$$

Where θ_{pm} = threshold

θ_{om} = abruptness of the transition

Step-2: The sum of the squared errors is generated using equation (1).

Step-3: If the error is greater than the tolerance limit, the error signals are generated using equations (5) and (6) otherwise go to step 6.

Step-4: The change in weight is calculated using equation (4). To improve the convergence characteristic, a momentum term `α’ is introduced as follows:

$$\Delta W_{ym\ (n+1)} = \eta * \boldsymbol{\delta_{pm}} * O_{py} + \alpha[W_{ym\ (n)} - W_{ym\ (n-1)}] \qquad (9)$$

Where n = iteration count.

α = Momentum gain.

η = Adaptation gain

Then the new value of weight is

$$W_{ym\ (n+1)} = W_{ym\ (n)} + \Delta W_{ym\ (n+1)} \qquad (10)$$

Step-5: The iteration count is incremented and step1 to 4 are repeated

Step-6: Presentation number is incremented and other subsets of training samples are presented to the network. If all the subsets are over, the program is terminated.

VII. CASE STUDY AND RESULT

The 7-feeder distribution system is shown in Fig.1. The feeder capacity is 2MVA.The Table-I show the comparison of the line loss evaluation of distribution system obtained from the ANN and load flow for the 5 load flow patterns of the testing set. It can be seen that the computed losses from ANN are as accurate as those obtained from load flow studies. The results presented indicate that the proposed ANN based technique performs satisfactorily for the distribution system considered. Fig. 2 represents the developed ANN model. The proposed software model is developed using C++ language.

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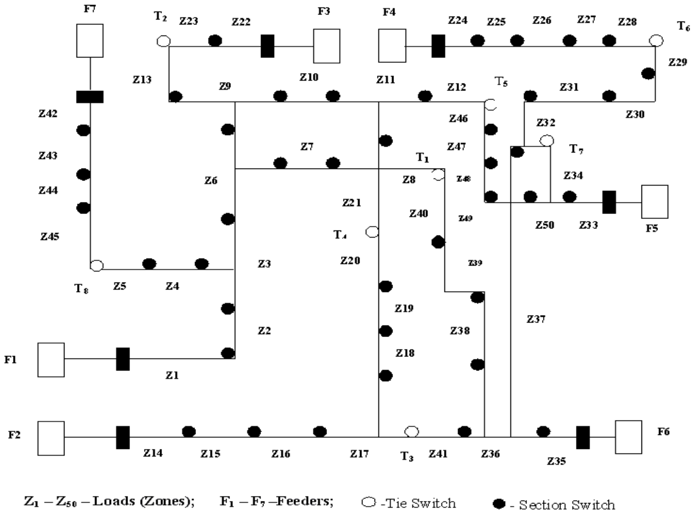

Fig.1. 11KV, 7- Feeder Distribution System

Table-I: Comparison of Line Loss Evaluation of Distribution System

Pattern	Distribution System Line loss by Load flow (MW)	Distribution System Line loss by ANN (MW)	% Error
1	**0.0528**	**0.0513**	**2.84**
2	**0.0533**	**0.0538**	**-1.12**
3	**0.0565**	**0.0548**	**3.00**
4	**0.0573**	**0.0563**	**1.74**
5	**0.0586**	**0.0583**	**0.51**

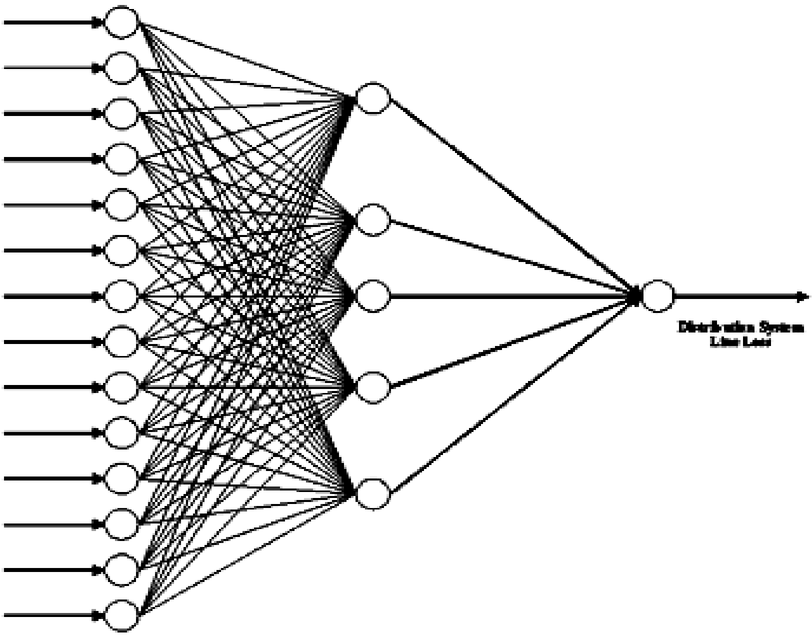

Fig.2 Developed ANN Model for 11kV, 7-Feeder Distribution System

The line loss evaluation of distribution system is presented in this paper. ANN is trained to capture the complex mapping relationships between the system losses and system topologies, operating conditions. Because of parallel information processing capability of the ANN, the proposed approach is fast and yet accurate. The proposed approach has demonstrated that the trained ANN can accurately predict the line loss through its generalization and adaptation capabilities. The results obtained were compared with those obtained from load flow studies. The margin of the error is around 3%, which appears to be within limit for practical purposes. This developed algorithm can be used for on-line evaluation of distribution system energy losses. On line calculations only include forward execution of trained network, which is supposed to be communicated to the system control center. A multi-layer feed forward neural network methodology has implemented for a 7-feeder distribution system to evaluate the distribution line loss evaluation under different operating load conditions.

VIII. CONCLUSION

The line loss evaluation of distribution system is presented in this paper. ANN is trained to capture the complex mapping relationships between the system losses and system topologies, operating conditions. Because of parallel information processing capability of the ANN, the proposed approach is fast and yet accurate. The proposed approach has demonstrated that the trained ANN can accurately predict the line loss through its generalization and adaptation capabilities. The results obtained were compared with those obtained from load flow studies. The margin of the error is around 3%, which appears to be within limit for practical purposes. This developed algorithm can be used for on-line evaluation of distribution system energy losses. On line calculations only include forward execution of trained network, which is supposed to be communicated to the system control center. A multi-layer feed forward neural network methodology has implemented for a 7-feeder distribution system to evaluate the distribution line loss evaluation under different operating load conditions.

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