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PEA Feeder Losses Calculation by Using Artificial Neural Networks

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ABSTRACT

This paper proposes the determination of technical losses in the distribution feeder system of Provincial Electricity Authority (PEA) of Thailand by using artificial neural networks (ANNs). Input features of ANNs compose of voltage, real power, reactive power and power factor. Feeder 6, Rayong 3 substation is studied. Voltage, real power, reactive power and power factor for training and testing ANNs are obtained from the Computer-Based Substation Control System (CSCS). The Power System Simulator/Advanced Distribution Engineering Productivity Tool (PSS/ADEPT) is used for simulating the load flow in the distribution system including calculating technical losses for the training and testing outputs of ANNs.

Program PSS/ADEPT has been used as the benchmark for comparing the results of ANNs. MAPE of test data of ANNs is very good (about 0.0204 %). Therefore, the engineers of PEA could use ANNs to predict the feeder losses of the distribution feeders accurately and comfortably.

Key Words: Energy and Power Systems, Power Flow Analysis

1. Introduction

The Provincial Electricity Authority (PEA) of Thailand has the duty of providing and distributing electricity to customers in many provinces except Bangkok, Nonthaburi and Samutphakarn. The service area of PEA is approximately 510,000 km^2, about 99 percent of areas in the country.

Because of the large service areas of PEA, a large number of feeder losses are occurred. In 2002, losses have been indicated as 5.5% of PEA power consumption unit [1]. It can estimate as 8,716 million baht. If PEA has an effective planning process, they can save the losses cost very much.

Power utility usually assesses the operating and planning process efficiency with the amount of power losses which are introduced from components in power systems. However, losses analysis applying the detail of system modeling is difficult to perform since voluminous data are involved. The conductor and transformer normally contribute the most of power losses in the distribution system besides the variation of feeder characteristics.

Planning of the distribution system is mostly based on the technical requirements. One of the major factors in the planning process is the amount of losses.

There are many methods to calculate losses. The total losses can be determined quickly by subtracting the total kWh sales (including unmetered sales such as street lighting) from the total kWh purchase and generation. However, these losses are the sum of technical losses and non technical losses.

An understanding of magnitude of technical losses is important for losses reduction. PEA Engineers usually determine technical losses by using the load flow program. However, it is very difficult to determine average losses because they must simulate the load flow many times to determine losses. This reason motivates the use of ANNs for feeder losses calculation.

In this paper, the ANNs are used for learning training patterns to recognize the relationship between input data and losses. The topology of ANNs, the inputs selection, training set and training method are discussed in this paper. Feed Forward Neural Networks is selected for determining feeder losses because it is effective in this area.

2. Technical Losses in Distribution Systems

Distribution systems are not 100% in efficiency. Losses are always occurred in distribution systems which can divide in 2 types as follows:

1. Technical losses are due to energy dissipated in the conductor and equipment.

2. Non technical losses or commercial losses are caused by pilferage, defective meters and errors in meter reading.

PEA determines energy losses in the distribution system by equation (1).

$$\text{Losses} = (\text{purchased unit} + \text{generated unit}) - (\text{selling unit}) \quad (1)$$

A result of equation (1) is the sum of technical losses and non-technical losses. An understanding of the magnitude of technical losses is the first step in the direction of reducing distribution losses. After that we should break them down into parts of the system as follows [2]:

1. Losses in medium voltage feeders
2. Losses in transformers
3. Losses in the accessory connection
4. Losses in low voltage feeders

This paper determined the losses of the medium voltage feeder. Although, technical losses in the medium voltage feeder can calculate by using the simple equation as I^2R but in the practical work it is very difficult to calculate it. The evaluation of losses on distribution lines is very complex because of the great variety of possible line configurations and load conditions [3]. However, the simple losses can be determined by using the load flow program.

3. Artificial Neural Networks

Artificial Neural Networks: Artificial neural networks are the mathematic representation of the biological process of the human brain. In artificial neural networks model, neurons are represented as the processing elements (PEs) connecting in parallel and series. The process of combining signals and generating the output of neurons is modeled through a transfer function. Synaptic strength of each connection is represented as weights and the change in synaptic strength is defined as the learning process [4].

Feed forward Neural Networks: Although a single neuron processing unit can handle the simple problem. Multi-layer feed-forward neural networks are essential for the complex situation. With a supervised training algorithm, an ANN which has the input layer, hidden layers and output layer can be utilized to map input patterns onto desirable output patterns [5].

Artificial Neural Network Efficiency: The efficiency of artificial neuron networks is measured by a value called the Mean Absolute Percentage Error (MAPE). It is shown as in equation (2).

$$\text{MAPE} = \sum_{i=1}^{n} \frac{1}{n} \times \left| \frac{\text{Losses}_{\text{Actual}_i} - \text{Losses}_{\text{ANN}_i}}{\text{Losses}_{\text{Actual}_i}} \right| \times 100\% \quad (2)$$

where n = Number of training or test data

$\text{Losses}_{\text{Actual } i}$ = Losses calculated by the load flow program

$\text{Losses}_{\text{ANN } i}$ = Losses calculated by ANNs.

4. Losses Calculation by Using Artificial Neural Networks

This paper determines the technical losses in PEA distribution feeder system by using Feed-Forward Neural Networks with Backpropagation algorithm. The process of this paper is shown in figure 1.

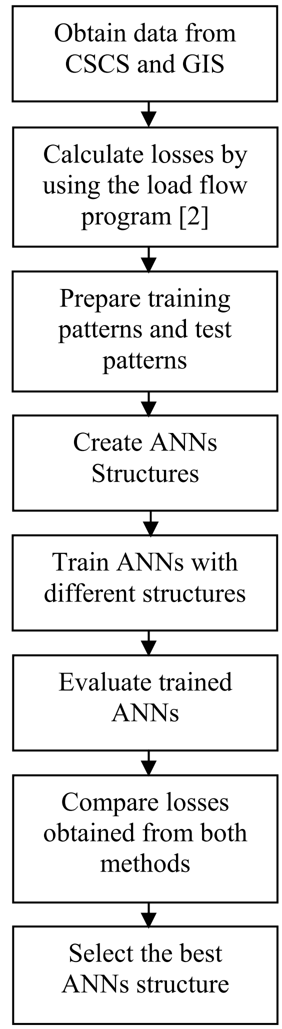

Figure 1 Process diagram of this paper

Scope of this paper: This paper studies only technical losses in the distribution feeders. The total losses of the system will be calculated in the future. The ANNs are performed base on the losses of the feeder 6 of Rayong 3 substation.

Training and Test Data Selection: Feeder 6 of Rayong 3 substation is selected to be a testing system. This feeder diagram is obtained by the GIS (Geographic Information System). The single line diagram and details of this feeder can show as in figure 2 and table 1.

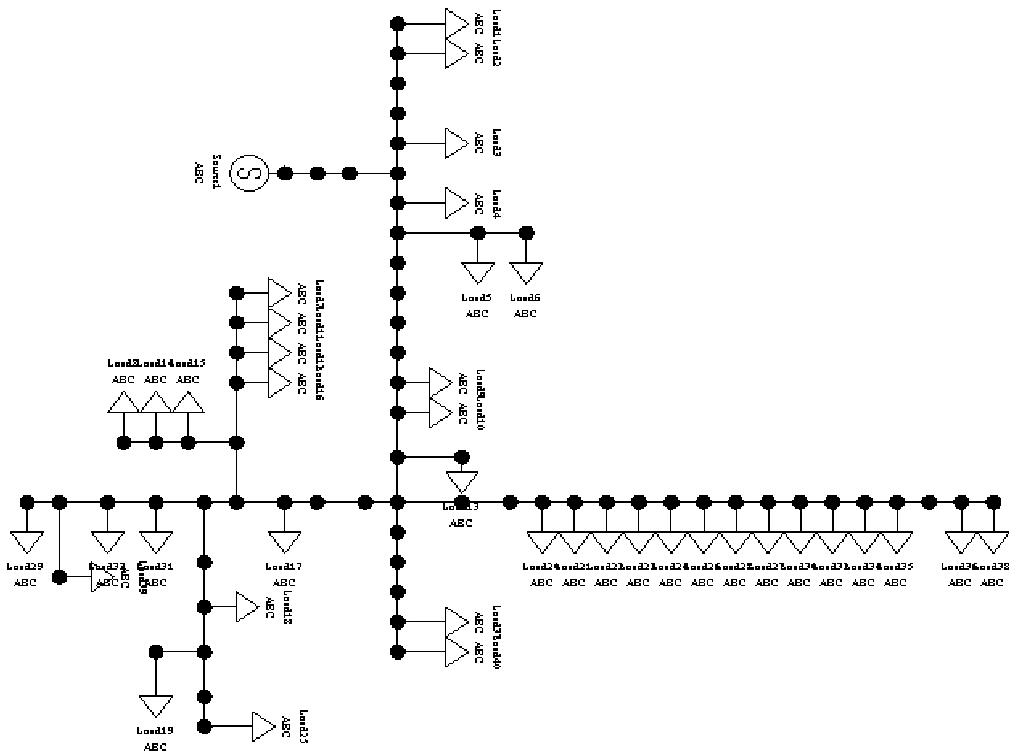

Figure 2 Single line diagram of the feeder 6 of Rayong 3 substation

Feeder	Feeder 6, Rayong 3 Substation
Load type	Residential/industrial
Conductors	185 A 0.1264 km 185 SAC 7.3338 km 185 PIC 8.4756 km 50 ACSR 0.1189 km 50 PIC 0.1851 km
Voltage level (line-line voltage)	22 kV
Configuration	Overhead Line

Table 1 Feeder details

The values of the voltage, power factor, real power and reactive power are used to train and test ANNs. These data are obtained from the CSCS (Computer-based System Control Substation). They are recorded every 30 minutes. These data are used to be input features of ANNs. The target of ANNs is the feeder losses. They are calculated by the load flow program [6]. The feeder characteristics such as the resistance, load location, line length are derived by GIS. The relationship of input data and losses can show as follows: [7], [8]

1. Effect of Real Power

Technical losses can calculate by the simple equation as follows:

$$\text{Real Power Losses} = 3I^2R \tag{3}$$

$$\text{Real Power} = 3VI\cos\theta \tag{4}$$

where
- I = Phase Current
- R = Phase Resistance
- V = Phase Voltage
- $\cos\theta$ = Power factor

Equations (3) and (4) show that increasing of the real power will introduce the larger current flow in the feeder resulting in the increasing of feeder losses. It is proposed that feeder losses are varied with the real power.

2. Power Factor

The improvement of the feeder power factor results in the decreasing of the reactive component of the current flow so that the conductor loss is reduced.

3. System Voltage

The current is increased when the voltage is increased. It is proposed that feeder losses are varied with the voltage level.

The 110 training patterns and 48 new test patterns are used to train and test ANNs. Examples of training data are shown as in table 2. Both inputs and targets used in the training process are normalized (zero mean and unity standard deviation).

Training Pattern No.	Voltage (kV)	Real Power (MW)	Reactive Power (Mvar)	Power factor	losses (kW)
1	21.7726	2.282750	1.369650	0.857493	9.621661
2	21.7726	2.282750	1.141375	0.894427	8.839714
3	21.7726	2.511025	1.369650	0.877896	11.100828
4	21.7726	2.739300	1.597925	0.863779	13.643738
5	21.7726	2.739300	1.369650	0.894427	12.720867
6	21.7726	2.967575	1.826200	0.851658	16.468466
7	21.7726	2.967575	1.597925	0.880471	15.404814
8	21.7726	2.967575	1.369650	0.907959	14.481896
9	21.7726	2.967575	1.141375	0.933346	13.699921
10	21.7726	3.195850	1.369650	0.919145	16.383775
11	21.9917	1.369650	0.913099	0.832050	3.618421
12	21.9917	1.369650	0.684825	0.894427	3.127984
13	21.9917	1.597925	0.913099	0.868243	4.515810
14	21.9917	1.826200	0.913099	0.894427	5.551333
15	21.7726	4.122377	2.054475	0.895009	28.741621
16	21.7726	4.122377	1.826200	0.914302	27.536787
17	21.7726	4.350652	2.282750	0.885510	32.702114
18	21.7726	4.350652	1.826200	0.922063	30.151681
19	21.7726	4.807202	2.739300	0.868839	41.468948
20	21.7726	5.035477	2.511025	0.894904	42.879393
21	21.7726	6.633402	4.350652	0.836193	85.218340
22	21.9917	1.369650	0.913099	0.832050	3.6184210
23	21.9917	1.369650	0.684825	0.894427	3.1279840
24	21.9917	1.597925	0.913099	0.868243	4.5158100
25	21.9917	1.826200	0.913099	0.894427	5.5513330

Table 2 25 Samples of training patterns

The Selection of Artificial Neural Networks Structure: After training patterns are prepared, the proper ANNs structure is found by increasing neurons in each hidden layer step by step using the Neural Network toolbox of Matlab program (trainlm) [9]. The proposed ANNs selection consists of the number of neurons selection in each hidden layer and choice of transfer functions. The selection of structure includes the following processes:

(i) Create the Structure of ANNs
(ii) Training of ANNs
(iii) Evaluation of trained ANNs

(i) Create ANNs Structure
Structure creation is the process to select characteristics of ANNs structure as follows:

- Number of layers selection
- Number of neurons in hidden layer selection
- Transfer functions in hidden layer selection

The first step, ANNs structures are created for training process. This paper uses the structure which it has 4 layers. The first Layer is input layer. Second and third layer are hidden layers 1 and 2. The last layer is the output layer. ANNs structures are created in many formats which in each structure has different numbers of neurons in hidden layers 1 and 2. The numbers of neurons in hidden layer 1 is varied from 2 to 10, 3 to 10 as in tables 3, 4 respectively and in hidden layer 2 is varied from 1 to 9, 1 to 8 as in tables 3, 4 respectively. Log-sigmoid and tan-sigmoid are used as transfer functions. They are shown as equations (5) and (6) respectively.

$$a(n) = \frac{1}{1 + e^{-n}} \quad (5)$$

$$a(n) = \frac{1 - e^{-n}}{1 + e^{-n}} \quad (6)$$

The transfer function of output layer is a linear transfer function. This transfer function is shown as equation (7).

$$a(n) = n \quad (7)$$

(ii) Training of ANNs
The ANNs training starts with the random of weights and biases initial value. After that, weight and bias values are adjusted to minimize error of target values. The initial weight and bias values are repeated 50 times for each structure. In each round, weights and biases are adjusted 1000 iterations.

(iii) Evaluation of trained ANNs
The best MAPE of each structure is reported for selecting the best structure. The MAPE of every structure is shown as in tables 3 and 4. The best MAPE is 0.0204. The proper ANN structure of this paper has details as in table 5 and as in figure 6. Examples of feeder losses which are determined by using the proper ANN and the load flow program are shown in table 6.

Figure 7 shows the plot of some test results obtained from PSS/ADEPT and ANNs. The results of ANNs are very close to PSS/ADEPT results.

Transfer Function		MAPE of test data (%) (Number of neurons in hidden layer 1- Number of neurons in hidden layer 2)								
Hidden 1	**Hidden 2**	**(2-1)**	**(3-2)**	**(4-3)**	**(5-4)**	**(6-5)**	**(7-6)**	**(8-7)**	**(9-8)**	**(10-9)**
tan-sigmoid	tan-sigmoid	0.1465	0.08	0.0898	0.0542	0.0597	0.0436	0.0405	0.1454	0.335
log-sigmoid	log-sigmoid	0.1578	0.088	0.0662	0.0269	0.0384	0.0204	0.0869	0.0866	0.13
tan-sigmoid	log-sigmoid	0.1524	0.0811	0.0555	0.0233	0.0551	0.1219	0.2037	0.0647	0.3253
log-sigmoid	tan-sigmoid	0.1497	0.0909	0.108	0.0438	0.0535	0.0975	0.097	0.0635	0.0635

Table 3 MAPE of test data for the format 1 structure

Transfer Function		MAPE of test data (%) (Number of neurons in hidden layer 1- Number of neurons in hidden layer 2)							
Hidden 1	**Hidden 2**	**(3-1)**	**(4-2)**	**(5-3)**	**(6-4)**	**(7-5)**	**(8-6)**	**(9-7)**	**(10-8)**
tan-sigmoid	tan-sigmoid	0.1473	0.0949	0.0548	0.0535	0.0748	0.1715	0.085	0.2518
log-sigmoid	log-sigmoid	0.1355	0.094	0.0531	0.0423	0.0443	0.0371	0.0673	0.2046
tan-sigmoid	log-sigmoid	0.1178	0.0946	0.0402	0.0378	0.0816	0.1189	0.0854	0.3305
log-sigmoid	tan-sigmoid	0.1111	0.0697	0.0541	0.0385	0.0983	0.0661	0.2443	0.6245

Table 4 MAPE of test data for the format 2 structure

Number of neurons in hidden layer 1	7
Number of neurons in hidden layer 2	6
Transfer Function in hidden layer 1	log-sigmoid
Transfer Function in hidden layer 2	log-sigmoid
Transfer Function in output layer	Linear
MAPE of test data	0.0204

Table 5 Details of selected ANN

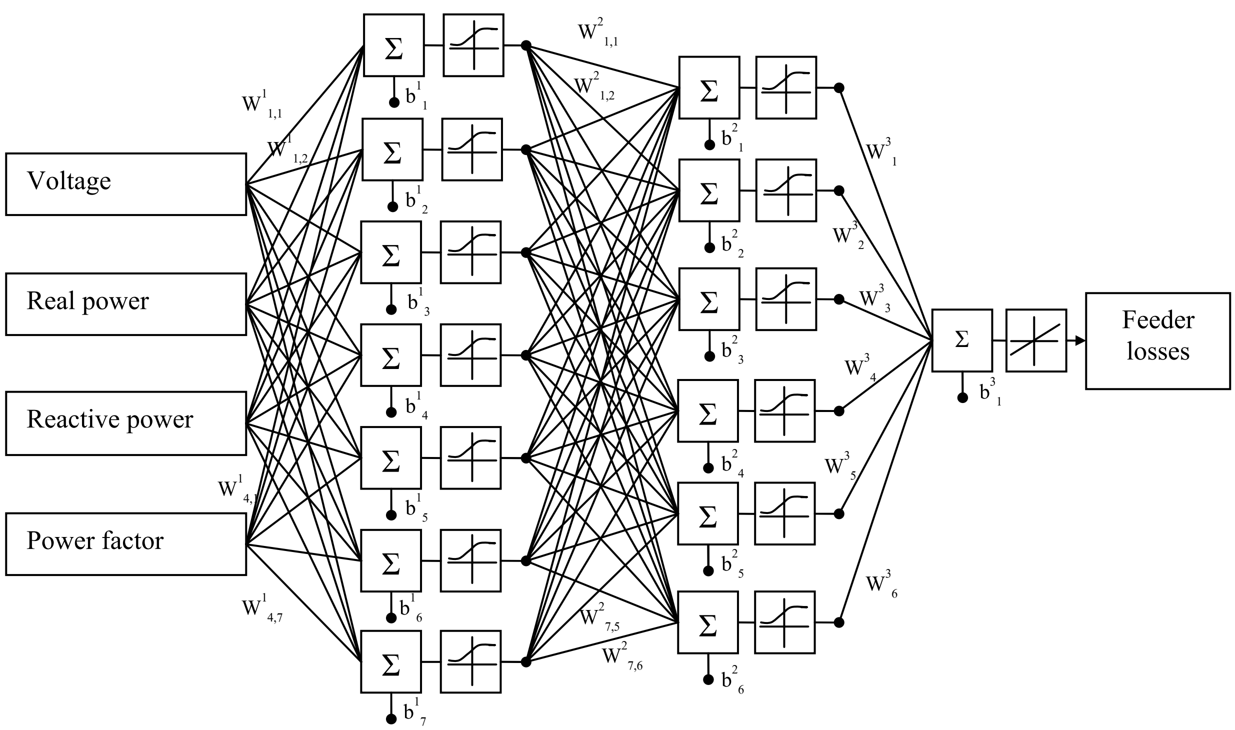

Figure 6 ANN Selected Structure

Test Data No	Feeder Losses (kW)	
	PSS/ADEPT	ANNs
1	19.618	19.618
2	18.595	18.596
3	17.708	17.709
4	25.723	25.739
5	24.295	24.294
6	23.002	23.002
7	21.844	21.845
8	20.821	20.822
9	19.934	19.935
10	29.530	29563
11	27.965	27.964
12	26.537	26.537
13	25.243	25.245
14	24.085	24.086
15	23.063	23.064
16	31.907	31.908
17	30.343	30.345
18	28.914	28.916
19	27.621	27.622
20	7.070	7.069
21	5.338	5.338
22	4.342	4.343
23	3.480	3.478

Table 6 23 samples of feeder losses which are determined by using ANNs and load flow program

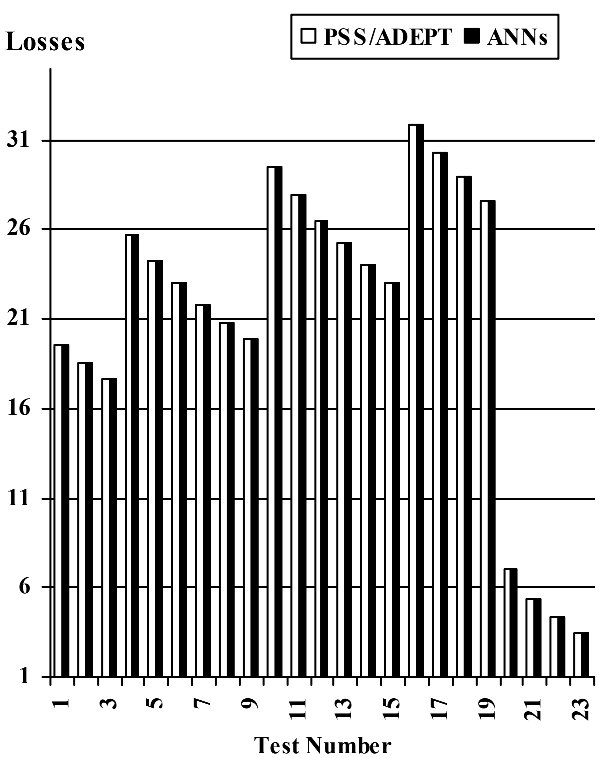

Figure 7 Plot of feeder losses calculated by using PSS/ADEPT and ANNs

5. Conclusions

An artificial neural network based feeder losses calculation is presented in this paper. Back propagation neural networks are used to adjust weight and bias values. Input data of ANNs are real power, reactive power, voltage and power factor which are derived from the CSCS. Output data, feeder losses, are calculated by using the load flow program. As the best MAPE (about 0.0204 %) of test results, PEA engineers could determine feeder losses by using ANNs because it is more convenient to analyse feeder losses than using the load flow program. ANNs are performed for losses calculation of the feeder 6 of Rayong 3 substation as an example in this paper. This method will be applied for other feeders in the future.

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