LMBP를 이용한 주거용 부하의 동특성 모델링

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Dynamic Modeling of Residential Load Using LMBP

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Abstract - Load models are important for improving the accuracy of stability analysis and power flow studies. Load characteristics change for different voltages and frequencies. In this research, ANN is used to construct the load model. Characteristics of some residential loads are tested under various voltage and frequency conditions. Acquired data are used to construct load models by ANN. Experiments and modeling results are presented in conclusions.

1. INTRODUCTION

Typical power system is composed of generation, transmission, distribution and utilization (load) parts. Although other parts of the system have been well researched and several models have been developed, load models have not received the same amount of attention.

It is difficult to obtain a good load model to improve the accuracy of stability analysis and load flow calculations in power systems [1-2]. A typical load bus is connected to various loads with different characteristics, each load exhibiting different patterns of energy consumption depending upon the voltage and/or frequency of the systems. Thus, the effects of the varying voltage/frequency must be included in load modeling[3-4].

In general, load modeling methods are classified into measurement approach and component-based approach [5]. Measurement approach models the total load with respect to direct measurements of the load characteristics with respect to voltage and frequency. Determination of voltage/frequency characteristics of the load is difficult and time consuming due to the number of buses in the actual power systems. It is also impractical to take sufficient measurements to cover the conditions for all buses maintaining high supply reliability for customers. The load model is generally determined once and often assumed applicable under several different conditions including the weather changes. Component-based approach first aims at separate modeling of component loads by using experimental data and later aggregates the component loads with respect to their load composition rates. Itis frequently assumed that the aggregate load varies according to some prescribed load characteristics as load class distribution and load composition rate vary. However, power companies do not have sufficiently detailed data related to component load modeling.

Recently, artificial neural network (ANN) models based the load have been reported[6-8]. ANN, which has great potential to handle nonlinear problems, isused to construct the load model by network-based techniques instead of mathematical models based on a component-based or a measurement approach.

Variable Learning rate Back Propagation (VLBP) had been used in past researches[8]. VLBP algorithm requires long training time and the selection of a total of five parameters. The choice of the parameters can affect the convergence speed and is dependent on the program. The Levenberg-Marquardt (LMBP) algorithm is probably the fastest method known for training multiplayer networks of moderate size. It requires to select two parameters, but the algorithm does not appear to be sensitive to the parameter selection. Thus, using of LMBP algorithm makes modeling process become faster and simpler.

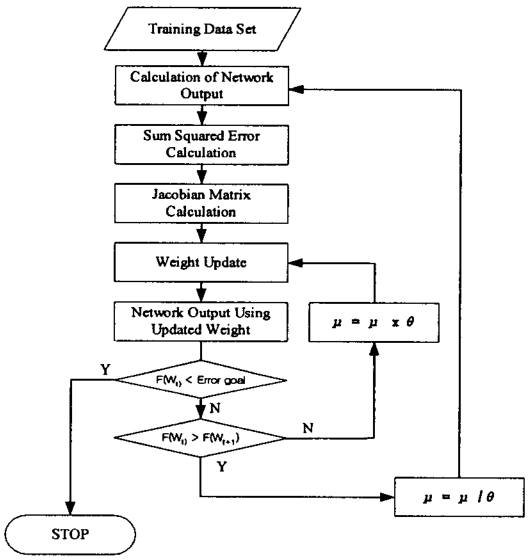
The aim of this work is to construct an accurate load model by using ANNs. Some residential loads are selected and their characteristics against voltage/frequency change are recorded. Acquired data are later used to construct ANN model. The LMBP algorithm is selected for this work.

2. ANN Load Model

2.1 ANN with LMBP Learning Rule

Levenberg-Marquardt back-propagation (LMBP) learning rule is used in this paper. LMBP algorithm is a variation of Newton's method that is designed for minimizing the sum of squares of other nonlinear functions. This is very well suited to neural network training where the performance index is the mean squared error. LMBP learning algorithm is probably the fastest known method for training.

The key drawback of the LMBP algorithm is the storage requirement. The LMBP algorithm must store the approximate Hessian matrix. When the number of parametersis very large, it may be impractical to use the LMBP, where a few of parameters are needed in this work.



<Fig. 1> LMBP Iteration

The LMBP algorithm is shown in Fig. 1.

First step of LMBP learning rule is calculation of the sum of squared errors over all inputs using (1).

$$F(W)=\sum_{q=1}^{Q}(t_q-O_q^o)^T(t_q-O_q^o) \\ =\sum_{q=1}^{Q}e_q^T e_q=\sum_{i=1}^{N}(v_i)^2 \tag{1}$$

Where, $e_{j,q}$ is the jth element of the error for the qth input an d target pair.

$$\mathbf{J}(\mathbf{x})=\begin{bmatrix} \frac{\partial e_{1,1}}{\partial w^1_{1,1}} & \frac{\partial e_{1,1}}{\partial w^1_{1,2}} & \cdots & \frac{\partial e_{1,1}}{\partial w^1_{S^1,R}} & \frac{\partial e_{1,1}}{\partial b^1_1} & \cdots \\ \frac{\partial e_{2,1}}{\partial w^1_{1,1}} & \frac{\partial e_{2,1}}{\partial w^1_{1,2}} & \cdots & \frac{\partial e_{2,1}}{\partial w^1_{S^1,R}} & \frac{\partial e_{2,1}}{\partial b^1_1} & \cdots \\ \vdots & \vdots & & \vdots & \vdots & \\ \frac{\partial e_{S^M,1}}{\partial w^1_{1,1}} & \frac{\partial e_{S^M,1}}{\partial w^1_{1,2}} & \cdots & \frac{\partial e_{S^M,1}}{\partial w^1_{S^1,R}} & \frac{\partial e_{S^M,1}}{\partial b^1_1} & \cdots \\ \frac{\partial e_{1,2}}{\partial w^1_{1,1}} & \frac{\partial e_{1,2}}{\partial w^1_{1,2}} & \cdots & \frac{\partial e_{1,2}}{\partial w^1_{S^1,R}} & \frac{\partial e_{1,2}}{\partial b^1_1} & \cdots \\ \vdots & \vdots & & \vdots & \vdots & \end{bmatrix} \tag{2}$$

Second step of LMBP is the calculation of Jacobian matrix.

After the calculation of Jacobian matrix, weight of ANN is up dated by (3).

$$W_{k+1} = W_k - [J^T(W_k)J(W_k) + \mu_k I]^{-1} J^T(W_k) v(W_k) \tag{3}$$

Where, J is the Jacobian matrix and V is the sum of squared errors.

Sum of squared errors is recomputed using updated weights. If the new sum of squares is smaller than that of computed before the weight update, then we divide μ by θ, and go back to first step. If the sum of squares is not reduced, then we multiply μ by θ and go back to weight update step. Iteration is continued until the sum of squared error reaches error goal.

3. Case Study

3.1 Neural Network Construction

ANN is fed by the input- output data obtained from the experimental setup. The real and the reactive power consumptions of the load are the responses for the input. Voltage, frequency, the real power and reactive power recorded by data acquisition systems are used as a training input-output set of the ANN to construct the load model. In this work, input-output patterns are constructed by (4) and (5).

$$x(t) = [v(t), v(t-1), v(t-2), f(t), f(t-1), f(t-2), p(t-1)] \tag{4}$$

$$O(t) = [p(t)] \tag{5}$$

Where $x(t)$ and O(t) are the input and output vectors used for the training of ANN.

Input pattern elements are the current and past values of voltage and frequencies and the past active or reactive powers. Output pattern comprises the current active and reactive power consumption of the component load. We have found that past data with time lag increases the modeling accuracy of the method. It was mainly because of the dynamic behavior of several load components, which are analytically needed to be represented by time series.

Generally, structure of the ANN is constructed of more than three layers; input, output, and hidden layer. But, the precise method for structure determination has not yet been presented. Therefore, it is constructed by the several trials and errors. The 7-20 numbers of hidden neurons are tested. ANN shows the best performance with 10 hidden neurons. The maximum number of iterations used in this work is chosen as 500 iterations.

3.2 Modeling Results

ANN shows the excellent approximation ability for an induction motor 1. Comparison between the measured and the calculated values is made in Fig. 2, which concludes that the proposed ANN based model of an induction motor can accurately approximate the response of component load in the wide range of voltages and frequencies. Average error was 0.9954/0.8220 for active/reactive power.

The average error of N measurements is defined by:

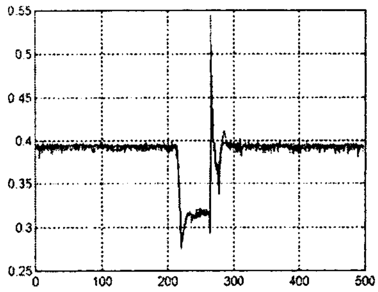
$$E_a = \frac{1}{N}\sum_{q=1}^{N}\frac{|X_q - X_{ann_q}|}{X_q} \times 100 \tag{6}$$

The average relative errors for other component loads are summarized in Table 1.

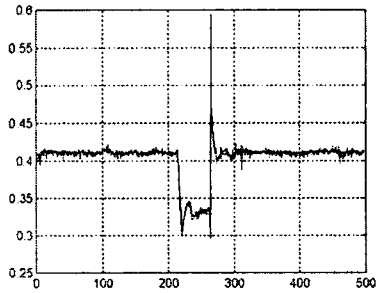
Because Heater, Incandescent light, and Hair dryer are resistive load, Reactive power was disregard.

<Table 1> Modeling Error of Loads

Component Load	Modeling Error	
	Active power	Reactive power
Heater	1.1500	-
Incandescent light	1.1523	-
Hair dryer	1.6667	-
Electric fan	2.1250	2.7006
Induction motor 1	0.9954	0.8220
Induction motor 2	6.4614	2.6124
Pump	2.2453	13.4479



(a) Active Power



(b) Reactive Power

<Fig. 2> Modeling results of Induction motor 1

4. Conclusions

This work has addressed load modeling, which is important for power system analysis. The ANN based load models have been constructed by using the experimental data, instead of the analytical methods. ANNs for nonlinear mapping are used to obtain more accurate models.

Also, a case study has been used to verify the validity of the proposed method. The proposed LMBP algorithm makes the training process more robust and faster. Estimation results show that ANNs are suitable for load modeling.

For further research, the development of the updated device to experiment load characteristic, and the application of the developed ANN load model of power system analysis is required.

[Acknowledgement]

This work has been supported by KESRI(R-2005-7-061), Which is fun ded by MOCIE(Ministry of commerce, industry and energy).

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