Application of ANN to Load Modeling in Power System Analysis

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Abstract - Load models are very important for improving the accuracy of stability analysis and load flow studies. Various loads are connected to a power bus and their characteristics of power consumption change with voltage and frequency. Thus, the effect of voltage/frequency changes must be considered in load modeling. In this work, artificial neural networks-ANNs- were used to construct the component load models for more accurate modeling. A typical residential load was selected and subjected to a test under variable voltage/frequency conditions. Acquired data were used to construct component models by ANNs. The aggregation process of separately determined load models is also presented in the paper. Furthermore, this paper proposes a method to transform a single load model constructed by the aggregation method into a mathematical load model that can be used in traditional power system analysis software.

Keywords: load model, artificial neural network(ANN), component load model, aggregation method, dynamic load model

1. Introduction

Effective planning and operation of large electric power networks requires accurate modeling and simulation of the system. A 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 received less attention.

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

Loads are classified as static or dynamic loads. Static loads are exponential or polynomial functions of voltage and frequency. A typical dynamic load is an induction motor. In general, load modeling methods are classified as measurement approach or component based approach [5]. The measurement approach models the total load with respect to direct measurements of the load characteristics versus voltage and frequency. Determination of voltage/frequency characteristics of the load is quite difficult and time consuming because of the number of buses in an actual power system. Taking sufficient measurements to cover all conditions for all buses while maintaining high supply reliability for customers is impractical. The load model is generally determined once and often assumed applicable under various conditions including weather changes. The component based approach first separately models component loads using experimental data and later aggregates the component loads with respect to their load composition rate. The aggregate load is frequently assumed to vary according to prescribed load characteristics, such as load class distribution and load composition rate. However, power companies have insufficiently detailed customer survey data related to component load modeling.

An algorithm to estimate hourly load composition rates was developed by using load variation curves of several consumer categories for a season of the year and a day of the week and by defining the relative coefficients of each group [6]. Reasonable and practical load composition rates were estimated by a system based on the experience and knowledge of experts [6]. Both methods must assign the order of mathematical models and estimate the parameters of the model by which the component load or bus load would be characterized. However, there were difficulties related to the identification of the model order and the estimation of the parameters for the mathematical model by using measured data for large power systems. Representing the model with simple functions was also difficult due to the nonlinearity of the load characteristics.

Recently, artificial neural network (ANN) based load

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models have been reported [7-10]. An ANN, which has great potential for handling nonlinear problems, is used to construct the load model using network based techniques instead of mathematical models based on component based or measurement approaches. Unfortunately, the existing power system analysis software, PSS/E, still requires a mathematical load model rather than an ANN based load model for power system analysis. Future research should solve this problem.

The aim of this work is to construct more accurate component loads by using ANNs, to aggregate the component loads, and to transform the final load to a mathematical model for load flow calculations and stability analysis. Typical residential loads were selected and their behavior during voltage/frequency changes were recorded. Acquired data was later used to construct a component based ANN model. Component loads were later aggregated with respect to their associated composition rates. Finally, the aggregate load is transformed to a parametric form to use in power system analysis software.

2. Overview

As shown in Fig.1, this work consists of five stages and uses the component based approach to model the load for power system analysis. Typical loads are selected, and the response of component loads during voltage/frequency changes is obtained experimentally. Experimental data is later used for component load modeling by an ANN. Individual component loads are aggregated using the load composition rate to construct a single load at the load bus. Since the final form of the aggregate load model cannot be used directly in conventional power system analysis software, it is transformed to a mathematical model by a curve fitting method.

3. Data Acquisition Setup for Component Loads

The data acquisition setup, shown in Fig. 2, aims to collect and record real and reactive power of the component loads during voltage or frequency variations. The experimental setup consists of source devices, a general source and a generator, connected to typical component loads. A general source equipped with an induction voltage regulator (IVR) and frequency converter is used for the tests of small component loads. On the other hand, a generator coupled with a 10 Hp diesel engine is used for large component loads and group load.

The general source can provide a variable voltage in the range of 0.7 to 1.0 p.u. by moving the tap of the induction voltage regulator and a variable frequency in the range of

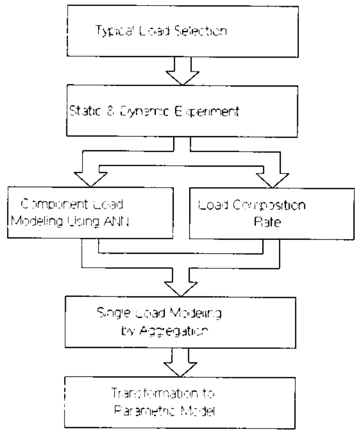

Fig. 1 Overview of this study.

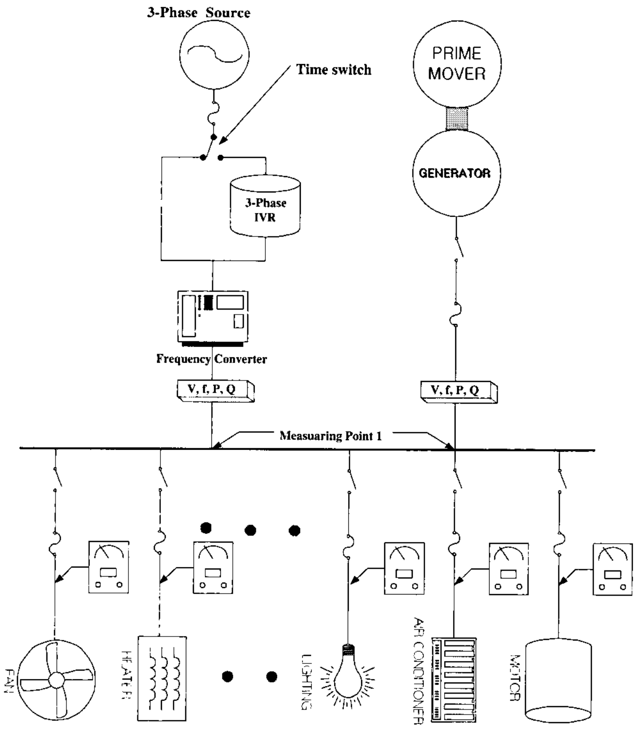

Fig. 2 Basic configuration of the experimental setup system.

0.9 to 1.0 p.u. by frequency converter. On the other hand, the generator is equipped with several control devices to attain variable voltage and frequency. A throttle valve is used to control the output frequency of the generator by changing the rotation speed of the generator and an excitation system is used to control the output voltage magnitude.

The responses of component loads to input voltage and frequency variations are measured and recorded by the power quality analyzer, which is a data acquisition system. The recorded data is used to model the component load using an ANN. The power quality analyzer is an instrument that can record three phase voltage, current, frequency, real and reactive power, and so forth. Its sampling rate is 7.68

kHz and recording cycle is 20 ms.

4. Component Load Modeling using an ANN

4.1 Artificial Neural Network

The potential benefits of neural networks, such as parallel distributed processing, high computation rates, fault tolerance, and adaptive capability have lured researchers from fields such as controls, robotics, and energy systems to seek solutions to their complicated problems. In particular, the back-propagation neural network [11] can map most linear and nonlinear relationships between input and output variables.

To train a neural network, input and output training patterns are fed to the network repeatedly. An input pattern is passed forward through each layer of the network. Outputs of the neurons are multiplied by their respective interconnection weight to arrive at the input of the neurons on next layer. At the input layer, each neuron's output is simply equal to its input. In the hidden and output layers, each neuron's output is determined by the weighted sum of its inputs and its sigmoid transfer function. Each input vector is passed forward through the network, and an output vector is calculated by

$$O = \Gamma[Wy] \tag{1}$$

where, O is the output vector calculated by the input vector and weights, y is the input (training) vector, Γ is the sigmoid transfer function matrix to generate the output for each neuron, and W is the weight matrix representing the degree of coupling between the neurons.

During training, outputs are compared with the actual recorded ones, and an error term is generated as follows.

$$E = \frac{1}{2}\|d - O\|^2 \tag{2}$$

where E is an error indicating the difference between output calculated by Eq. (1) and the desired output, d, at the output neuron. During the learning process of the ANN, the weights are updated to minimize this error, which is later fed backward through the network, from the output layer, through the hidden layer, and back to the input layer. The interconnection weights between each layer are adjusted based on the computed error and a learning rate parameter as follows.

$$W' = W + \eta\delta y^T \tag{3}$$

where W' is the updated weight matrix for minimizing the error and δ is the error signal vector of a layer. η is the learning rate for increasing the effectiveness and convergence of the error back-propagation learning algorithm.

4.2 Component Load Modeling using an ANN

The block diagram of an ANN based component load model construction is depicted in Fig. 3. Component load in the block diagram signifies a typical residential load. The ANN is fed by the input/output data obtained from the experimental setup. Real and reactive power consumptions of the load are supposed to be the responses for the input. Voltage, frequency, real power, and reactive power recorded by the data acquisition system are used as a training input/output set of the ANN to construct the component network load model. In this work, input/output patterns are constructed by Eqs. (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 training the ANN. Input pattern elements are current and past values of voltage and frequency and past active and reactive powers. The output pattern comprises the current active and reactive power consumption of the component load. We have found that past data with time lag increased the modeling accuracy of the method. Mainly because of the dynamic behavior of several load components, which analytically must be represented by a time series.

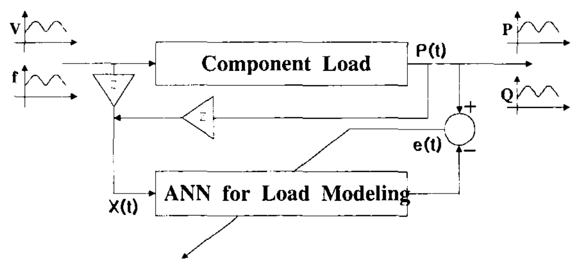

Fig. 3 Component load modeling principle by an ANN.

5. Aggregation of Component Loads

A bus/bar load is the aggregation of several component loads connected in parallel to a load bus as shown in Fig. 4. In addition, the aggregated load model should also include the effects of subtransmission and distribution lines, cables, reactive power compensation devices, LTC transformers, distribution voltage regulators, and so on. However, these effects are relatively small when compared with the component loads. The aim of this work is to validate the proposed method to model the component loads by an ANN, to aggregate the component loads with respect to associated composition rates, and to convert the final load model to a parametric mathematical model. Therefore, the auxiliary effects are neglected in this study but may be pursued in the future.

The load at the load bus can be represented as the sum of component loads given by Eq. (6) according to Tellegen's theorem [12,13].

$$P_L = \sum_{i=1}^{n} P_i \quad i = 1, 2, ... n \tag{6}$$

$$w_i = \frac{P_i}{P_L} \tag{7}$$

$$\sum_{i=1}^{n} w_i = 1.0 \tag{8}$$

where n is the number of component loads, P_L is the aggregated bus load, and P_i and w_i are the rated component load and associated composition rate, respectively. If component load models and their composition rates are given, component loads can be aggregated to form the bus load as follows:

$$P_i(v,f) = R_i \cdot P_{ANNi}(v,f) \cdot P_L \tag{9}$$

$$P_T(v,f) = \sum_{i=1}^{n} P_i(v,f) \tag{10}$$

where $P_i(v,f)$ is the real power of ith component load in terms of kilowatts or megawatts as a function of voltage and frequency. $P_{ANNi}(v,f)$ is the real power of component load i modeled by an ANN and is expressed in terms of p.u., $P_T(v,f)$ is the total bus load in terms of kilowatts or megawatts. Although similar expressions are also valid for reactive powers, they are omitted due to limited space.

The fictitious load bus and the algorithm proposed for the aggregation of component loads are shown in Fig. 4. The proposed algorithm requires the component load models and composition rates for each component. If voltage/frequency of the bus are changed, then each component load modeled by the ANN will generate its own output (active/reactive power consumption). When each output weighted value is determined according to the load composition rate of Eq. (9), component loads can be aggregated for bus active/reactive power by Eq. (10).

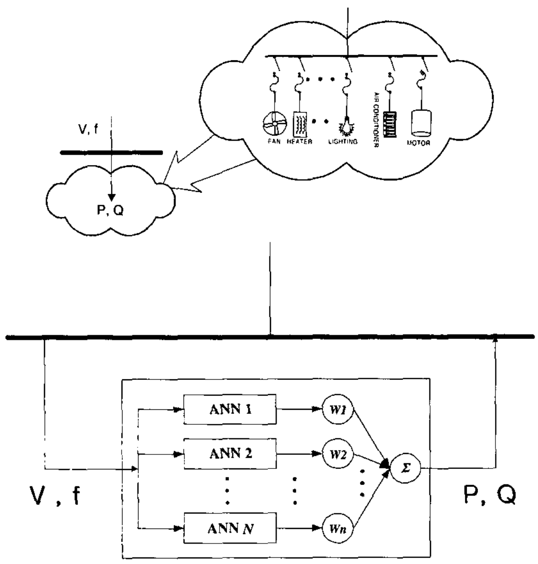

Fig. 4 Aggregation of component loads on load bus.

6. Load Modeling for Power System Analysis

As mentioned in previous sections, the final single load model is a network model and will exhibit the distinctive characteristics of the component loads. However, this final single load model can't be directly applied to the traditional power system analysis software. The developed single load is, therefore, transformed to a mathematical model as shown in Fig. 5. An example among such models is the IEEE second order equation represented by Eqs. (11) and (12) which is used in the PSS/E software package. It is a polynomial model multiplied by a linearized frequency dependence term.

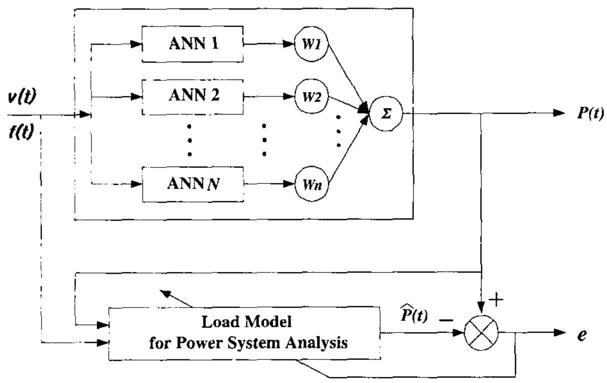

Fig. 5 Transformation of the load model.

The block named as load model in Fig. 5 denotes a process to determine the parameters p_1, p_2, p_3, K_{pf}, q_1, q_2,

q_3, and K_{qf} in Eqs. (11) and (12) by which the mathematical load will be represented. Variable voltage and frequency, $v(t)$ and $f(t)$, in p.u. are applied to the aggregated single load model as inputs, and the output, $P(t)$ and $Q(t)$, are obtained from the developed load model. The parameters of the mathematical model are estimated using the well-known least square method.

$$\hat{P}(t)=P_0[p_1+p_2\bar{V}(t)+p_3\bar{V}(t)^2](1+K_{pf}\Delta f(t)) \qquad (11)$$

$$\hat{Q}(t)=Q_0[q_1+q_2\bar{V}(t)+q_3\bar{V}(t)^2](1+K_{qf}\Delta f(t)) \qquad (12)$$

where P_0 and Q_0 are active and reactive powers at nominal voltage, V_0, $\bar{V}$ is the ratio of voltage V with nominal voltage, and Δf denotes the frequency deviation from nominal frequency f_0.

7. Case Study

7.1 Typical Component Loads

The component based approach to load modeling first requires the identification of the component loads to be modeled. In this study, component loads are selected as the most popular residential loads mainly because of the possibility of experimental realization. As shown in Table 1, the component loads are several household appliances and an induction motor to encounter a dynamic characteristic. All component loads are selected to have the same rated voltage of 220 V in the power range of 43-1127 W.

Table 1 Selected component loads.

Load	Rated Voltage	Rated Power	Units	Note
Heater	220	863	1	
Incandescent Light	220	100	6	
T V	220	43	1	
Cooker	220	815	1	
Hair Dryer	220	1,127	1	
Airconditioner	220	520	1	
Refrigerator	220	78	1	
Electric Fan	220	57	1	
Vacuum Cleaner	220	1,045	1	
Fluorescent Light	220	76	1	
Induction Motor	220	455	1	3 phase

7.2 Component Load Modeling using an ANN

To obtain the necessary data for component load modeling by an ANN, variable voltage and frequency, as shown in Fig. 6, are applied to the components.

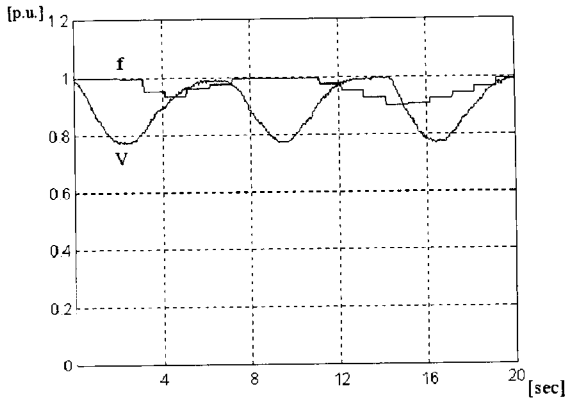

Fig. 6 Variation of voltage and frequency.

While testing the induction motor, which is the representative typical dynamic load, the shaft of the motor is coupled with a DC shunt generator whose output is connected to incandescent lights. Variable voltage and frequency, as shown in Fig. 6, are applied to the load and the real and reactive power consumptions are measured. These values are shown as solid lines in Figs. 7 and 8. To train the ANN, input/output patterns obtained from the laboratory tests and Eqs. (4) and (5) are applied. The ANN used to model the component load consists of input, hidden, and output layers comprising 7, 15, and 1 neurons, respectively. The initial learning rate is chosen to be 0.01, and then modified with respect to the squared error sum to increase the learning efficiency.

The ANN's learning of the induction motor is confirmed by data that was not used to train the network. The dotted lines in Figs.7 and 8 show the results of ANN outputs. Comparing the measured and the calculated values in Figs.7 and 8, one can easily conclude that the proposed ANN based model of the induction motor can accurately approximate the response of component load for a wide range of voltage and frequency. The average relative error is calculated to be 0.81%.

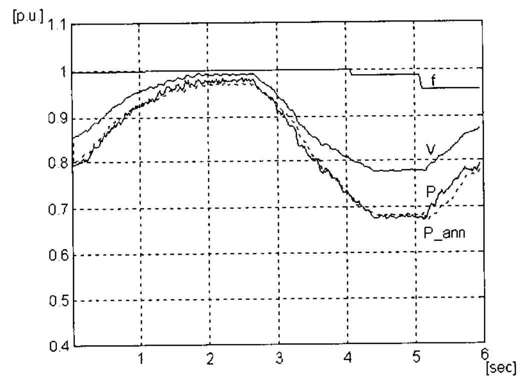

Fig. 7 Measured and modeled results for induction motor real power.

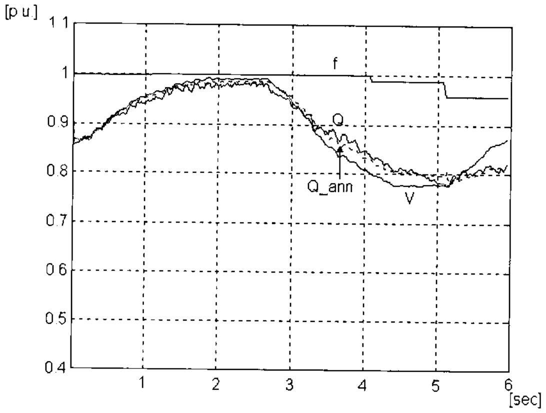

Fig. 8 Measured and modeled results for induction motor reactive power.

The average error of N measurements is defined by

$$error = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_i - X_{ann\_i}|}{X_i}\times 100 \qquad (13)$$

where X_i and X_{ann_i} denote the measured value and the output of ANN, respectively, for the ith trial. The average relative errors for other component loads are summarized in Table 2.

Table 2 Modeling error of component load.

Component Load	Modeling Error [%]	
	Active Power	Reactive Power
Heater	1.69	3.18
Incandescent Light	1.05	2.40
TV	4.13	4.39
Cooker	1.09	4.52
Hair Dryer	1.10	0.61
Airconditioner	1.50	1.33
Refrigerator	0.78	1.09
Electric Fan	1.31	2.87
Vacuum Cleaner	1.81	3.25
Fluorescent Light	0.63	0.88
Induction Motor	0.81	0.66

7.3 The Results of Component Load Aggregation

To verify the validity of the aggregation of component loads, component loads are grouped with respect to their load characteristics. In case 1, static component loads i.e., heater, incandescent light, TV, cooker, and drier are aggregated. The results for case 1 are shown in Table 3.

The second group is organized to include dynamic loads or the appliances including induction motors, such as the airconditioner, refrigerator, electric fan, vacuum cleaner, and induction motor. The results for case 2 are shown in Table 4. Finally, the two subgroups are aggregated for the total load. The results for case 3 are illustrated in Table 5.

Table 3 Static load composition rate (case 1).

Component Load	Composition Rate [%]	
	Active Power	Reactive Power
Heater	25.00	1.92
Incandescent Light	17.40	28.85
TV	1.27	45.23
Cooker	23.64	5.77
Drier	32.69	18.23
Total	3,447 [W]	10.4 [Var]

Table 4 Dynamic load composition rates (case 2).

Component Load	Composition Rate [%]	
	Active Power	Reactive Power
Airconditioner	24.13	28.54
Refrigerator	3.62	7.14
Fan	2.65	0.18
Vacuum Cleaner	48.49	21.63
Induction Motor	21.11	42.51
Total	2,155.0 [W]	1,086.0 [Var]

Table 5 Static and dynamic load composition rates (case 3).

Component Load	Composition Rate [%]	
	Active Power	Reactive Power
Heater	15.2	0.01
Incandescent Light	10.5	0.25
TV	0.75	0.30
Cooker	14.4	0.04
Hair Dryer	19.9	0.10
Airconditioner	9.10	23.9
Refrigerator	1.37	6.05
Electric Fan	1.00	0.15
Vacuum Cleaner	18.4	18.2
Fluorescent Light	1.38	15.5
Induction Motor	8.00	35.5

Figs. 9 and 10 show the measured and the calculated active and reactive powers for the first static component load grouping. Variable voltage and frequency, as shown in Fig. 9, was applied to the single aggregate static load. Active and reactive power consumptions of this load were measured and recorded by the data acquisition system. The same value of the voltage and frequency are also applied to the component loads and the results are aggregated by the ANN and composition rates. The dotted lines denote the real and reactive powers of the single load model through emulation and the solid lines denote the actual measured active and reactive powers. As can easily be realized, the ANN load model group can accurately approximate the response of the component loads for the prescribed voltage and frequency range.

The absolute errors of the first group were 1.2% for active power and 4.67% for reactive power. The error for reactive power is greater than that of the active power since the reactive power consumptions of the static loads are relatively smaller than the active power consumptions. A similar procedure is applied for the other groupings. Errors for active and reactive power for dynamic loads were 1.69% and 2.67%, respectively, and for overall loads were 0.9% and 2.2 %, respectively.

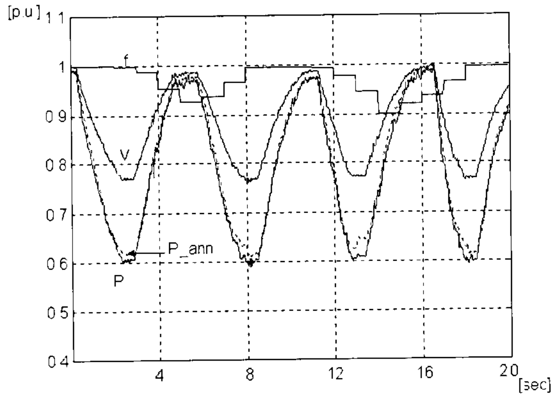

Fig. 9 Measured and calculated active powers for Case 1.

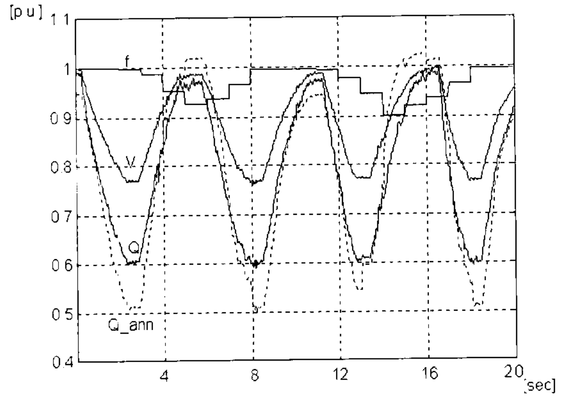

Fig. 10 Measured and calculated reactive powers for case 1.

7.4 Load Modeling for Power System Analysis

As mentioned in the preceding sections, the proposed aggregate single load obtained by the ANN has been verified as capable of approximating the load characteristics. However, it must be transformed to a mathematical model to be used in conventional power system analysis software. As stated before, the single load model is developed from the limited range of voltage and frequency. Therefore, it can be used to estimate the parameters of the IEEE second order model given by Eqs. (11) and (12).

Table 6 shows the parameters determined by the least square estimation from the data obtained using the emulation of the proposed load model, which is aggregated component load models with composition rate in each case. Estimation errors of the mathematical model are shown in Table 7 for each case. From Table 7, one can easily conclude that the proposed mathematical model is a good estimation of the response characteristics of the load. Final real and reactive power estimations are depicted in Figs. 11 and 12 together with the actual values. The differences between the measured and the estimated values increase at the end of the time scale mainly because of curve fitting difficulties for the nonlinear nature of the ANN model outputs.

Table 6 Parameters of the estimated IEEE second order model.

Case		p_1/q_1	p_2/q_2	P_3/q_3	K_{pf}/K_{qf}
Case 1	Active Power	0.1579	-0.0186	0.8325	0.2083
	Reactive	1.8368	-3.9223	3.1157	-0.6144
Case 2	Active Power	1.4899	-2.9875	2.4711	0.0658
	Reactive	0.7580	-1.0094	1.2252	0.3080
Case 3	Active Power	1.2845	-2.5290	2.2297	0.0230
	Reactive	2.0676	-4.0715	2.9932	0.0724

Table 7 Estimation errors of each case.

Case	Estimation Error [%]	
	Active Power	Reactive Power
Case 1	1.27	2.76
Case 2	0.98	1.25
Case 3	1.65	1.40

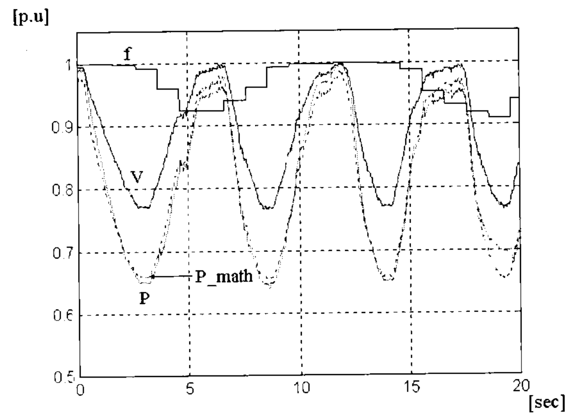

Fig. 11 Results of the developed and transformed Active power model (case 3).

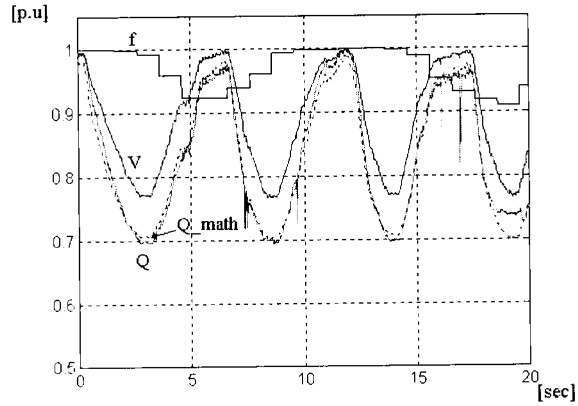

Fig. 12 Results of the developed and transformed reactive power model (case 3).

8. Conclusions

This work has addressed load modeling, which is important for power system analysis. The ANN based load models have been constructed using experimental data and were transformed into a mathematical model. The main features of this work can be summarized as follows.

First, instead of analytical methods, an ANN was used to obtain component load models. Potential benefits of ANNs for nonlinear mapping are more accurate models.

Second, an aggregation technique has been presented. The load composition rates and the component load model developed by the ANN were used to construct a single load model at the load bus.

Third, the resulting single load model was transformed to the IEEE second order model for use in traditional power system analysis software.

A case study was used to verify the validity of the proposed methods. Component load modeling using an ANN, aggregation of the component loads, and finally transformation of the load have been presented together with associated percentage of errors.

In addition, this research may be extended in two ways. First, experimental setup facilities will later be extended to cover some drawbacks that were omitted in this study. Secondly, new technology will be developed to allow the proposed ANN based load medels to be directly applied to power system analysis software without the transformation process.

Acknowledgements

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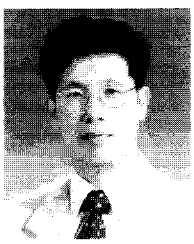

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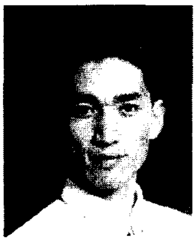

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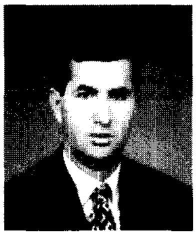

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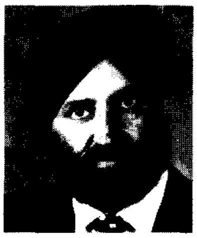

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