Short Term Load Forecasting Using Artificial Neural Network

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Abstract— **This paper presents a method of short term load forecasting using artificial neural network (ANN). A three layered feed-forward neural network, trained by scaled conjugate back-propagation, is used. Two models of ANN were tested and compared. The models are applied to real data from the Cape Town Control Centre.**

***Index Terms*—Artificial Intelligence, Artificial Neural Networks, Short-term load forecasting.**

I. Introduction

SHORT-term load forecasting is the prediction of electrical load demand for a period varying from the next few minutes up to a week. Short-term load forecasting plays a vital role in system operations and is the main source of information for all daily and weekly operations concerning generation commitment and scheduling. Short-term load forecast is also important for the economic and reliable operation of the power system [1].

In order to achieve high forecasting accuracy and speed, it is required to know the factors that affect the load [2]. Some of these factors are: the type and time of day, the weather conditions of the forecasting area, the season, etc. Since most days have different load profiles, it is necessary to have a day type. Time of the day is an important factor in short term load forecasting. It is required to know the forecasting time of the day because the level of demand at any time of the day is different. Therefore, the relationships between these factors and the load demand need to be determined so that the forecasts may be as accurate as possible.

Various forecasting techniques have been applied to short-term load forecasting. These techniques can be classed as classical or modern. Examples of classical methods are time series based on Box Jenkins, Multiple Linear Regression (MLR) [3]. These methods have been in use for a number of years and have shown to produce satisfactory results. However, the main problem with these methods is that they are not able to adapt to changes in weather conditions or other load affecting factors [3]. Furthermore, these methods rely heavily on past load data. However, since past load demands are not necessarily similar to future load demands, the forecasts generated by these methods may not be accurate.

Modern methods that are intelligent and able to learn and adapt to changes in the circumstances surrounding the forecasts have been developed in recent years, in order to cope with the problems experienced with classical methods. Fuzzy logic [4], expert systems [5], as well as artificial neural networks [6] are a few examples. They are collectively called Artificial Intelligence Techniques.

They have the advantage of using the knowledge of an expert and have this encoded into a set of rules that can be implemented in power systems (e.g., expert systems). In most instances, data that are ambiguous or uncertain are discarded but fuzzy logic considers these as “noisy” data. It implements human experiences through fuzzy rules embedded in the fuzzy logic system. Artificial neural networks are able to learn and adapt to the data. Artificial neural networks (ANN) learn the relationships between the variables and conclude based on that information.

This paper presents a three-layered feedforward artificial neural network for performing a short-term load forecast. Two models of ANN (ANN model 1 and ANN model 2) were tested and compared with other classical methods. The main difference between ANN model 1 and ANN model 2 is the inclusion of rainfall as an input variable to ANN model 2. The models are applied to real data from the Cape Town Control Centre. Simulation results show that ANN model 2 gives a better performance than ANN model 1.

The paper is organized as follows: Section 2 describes the typical load model as well as the typical load affecting factors. Section 3 discusses the key components of an artificial neural network. Section 4 focuses on the development of the forecasting model. In section 5, the data obtained from the Cape Town Control Centre is used to test the model that was developed. Section 6 presents the conclusions.

II. Load Model

In order to develop a forecasting model, it is required to know the typical modeling of a load as well as the load affecting factors. There are various ways of modeling the loads. The commonly used mathematical model to represent the load is additive model.

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For additive model, the typical system load at any given time is assumed to be made up of four components as follows [2]:

$$L = Ln + Lw + Ls + Lr \quad (1)$$

where

L : Total system load at any given time.

Ln : Base load and is a set of standardized load shapes for each day type that has been identified to occur throughout the year.

Lw : Weather sensitive component of the load.

Ls : load caused by special events (holidays and religious events or other rare occurrences).

Lr : signifies a random part of the load and this is known as some unexpected component which may result from industrial shutdowns, strikes by employees in the industry etc.

Load affecting factors include the day type, time of day and weather condition. Since most days have different load profiles, it is necessary to have a day type. Time of day is an important factor in short term load forecasting because it is required to know what time of day the forecast is for because the level of demand at any time of the day is different. Weather conditions are vital in short-term load forecasting as there is a variation of load demand as the conditions change.

III. Artificial Neural Network

The Artificial Neural Networks (ANN) was chosen for the implementation of the model because of its ability to approximate non-linear functions [7]. As the system load demand is highly nonlinear, the ANN is said to be a good method because it does not require an explicit model [2]. Figure 1 illustrates the structure of an artificial neuron and its components. Below is a brief description of the components (taken from [7]).

Weighting functions (input links): an adjustable representative of the input's connection strength.

Summation function: This component performs the weighted summation of the various inputs received by the neuron.

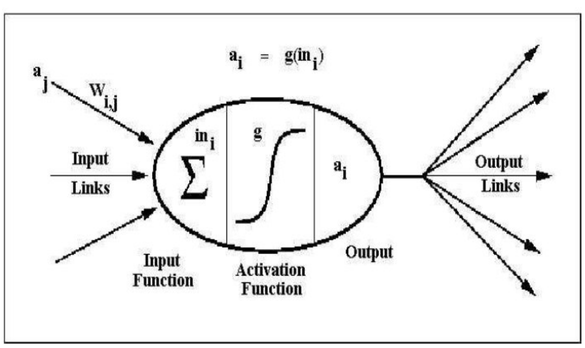

Figure 1: Artificial neuron and its components

Activation function: The output of the summation function is then taken by the transfer function. This transfer function transforms the summation output into a working output. Transfer functions that may be used are: (a) hard limiter, (b) ramping function, and (c) sigmoid functions.

Output function: Each neuron produces an output to many other neurons. In Figure1, it is represented by a_i.

Figure 2 shows the architecture of a three-layer feedforward network that is implemented in this paper. Feedforward means that the signals are propagated in a forward motion from layer to layer. The choice of the input variables, number of hidden layers, as well as the number of neurons in the hidden layers affects the results. Therefore, they need to be chosen carefully. The number of outputs represents the desired results.

As a guideline, it is suggested in [9] that the number of second hidden layer neurons should not exceed twice the number of input variables.

However, a training procedure of the neural network is able to help in choosing the adequate network configuration. The scaled conjugate gradient backpropagation training is used here.

The error at the outputs is measured by

$$error = \frac{1}{2} \sum \sum_{i=1}^{N} (T - Y)^2 \quad (2)$$

where

T: target or desired output.

Y: output from the neural network

The first derivative of the error function is propagated backwards in a direction that is conjugated to the gradient by use of a scale factor. This method is used because of its fast convergence [10].

Training is performed to find the weights that minimise the error function. The training stops when the maximum number

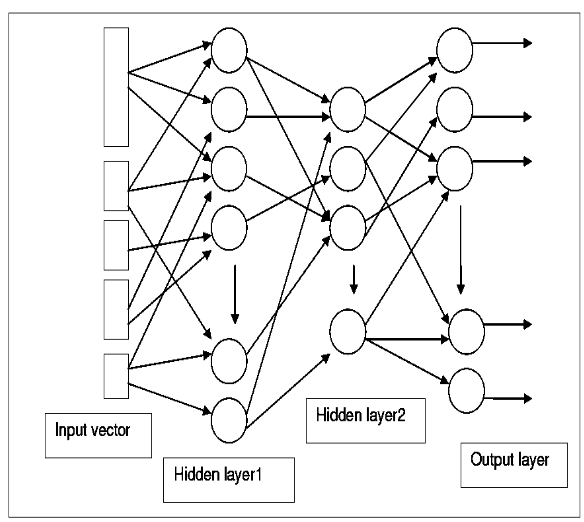

Figure 2: Three-layer feed-forward neural network

of cycles (iterations) has been reached or the performance goal has been reached.

IV. Forecasting Procedure

A three layered feedforward neural network, trained by scaled conjugate back-propagation, is used. Two three-layered neural networks were developed and tested. The main difference between ANN model 1 and ANN model 2 is the inclusion of rainfall as an input variable to ANN model 2.

A. Identification of input variables

Table 1 below shows the structure or topology of the two ANN models used in this paper. As can be seen from Table 1, the difference between model 1 and model 2 is that the previous day maximum rainfall and the forecast day maximum rainfall are used as input variable to model 2. As will be shown later, the inclusion of the rainfall as input to the ANN model 2 improves its performance.

B. Pre-processing of data

The data used in the training and validation phases was obtained from the Cape Town Control Centre. Daily half-hourly load data for the years 2004 and 2005 were obtained. The 2004 data was used to train the system and the 2005 data used for testing the network. Weather data for the corresponding years was also obtained. The data that was obtained could not be used in its actual form because the ANN model has activation functions that work optimally in a small range and had to be pre-processed.

TABLE I
Definition of ANN Inputs and Output

Model 1		Model 2	
Inputs	Description	Inputs	Description
1-48	Previous day half-hourly load demand	1-55	Same as in model 1
49-50	Previous day maximum & minimum temperature	56	Previous day maximum rain fall
51-52	Forecast day maximum & minimum temperature	57	Forecast day maximum rainfall
53-55	Previous day cloud cover (measured at 8:00 m, 14:00am and 20:00 pm)	58	Previous day type
56	Previous day type		
Outputs	Description	Outputs are the same as in model 1	
1-48σ	Forecasted half-hourly load demand		

Half-hourly load data was scaled using

$$Xn_i = (X_i - \overline{X}_i)/\sigma_i \tag{3}$$

where

Xn_i : Scaled input for day i.

X_i : Half-hourly load demand.

$\overline{X}_i$: Average load demand.

σ_i : Standard deviation

The maximum and minimum temperature is normalized by dividing both by 40º as this is the absolute maximum temperature that Cape Town receives. Cloud cover is measured in octaves where the range is from zero to eight. Zero signifies a fine weather condition and eight an overcast condition. The cloud cover data was normalized by dividing by the maximum octave, eight.

The rainfall data was normalized by dividing by the typical monthly rainfall. The day type was represented as a number with Monday being 0.1 and Sunday as 0.7 as done in reference [11].

C. Training

Weights were initialised to random values. Load and weather data (excluding holidays) for 2004 were used to train the network based on the scaled conjugate gradient back-propagation.

D. Testing the network

The data used for this process were the 2005 years half-hourly load demand, temperatures and cloud cover and rainfall as required by the models. In order to see the seasonal effect, the data was divided into seasons with January representing summer, March – autumn, July – winter, and October – spring. Three days of the last week of each month were used for the forecasting process. The days Thursday, Friday, and Saturday were selected as the forecast days.

V. Performance Evaluation

The following Mean Absolute Percentage Error (MAPE) analysis function (4) was used to assess the performance of each model

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|X_t - X_f\right|}{X_t} * 100 \tag{4}$$

In order to investigate the performance of the ANN against other classical methods, a regression based method (using Microsoft Excel) was implemented and the tool designed by the Engineer at the Cape Town Control Center was also used to compare the results.

The summary of the input-output layer neurons of the two ANN models is shown in Table 2.

TABLE II
SUMMARY OF INPUT- OUTPUT LAYER NEURONS

Model	1st hidden layer	2nd hidden layer	Output layer
1	56	15	48
2	58	20	48

A comparison between the three models, ANN model 1, ANN model 2 and the multiple linear regression method produced the following results in terms of the error analysis (see Figure 3).

The model with the best MAPE on average was ANN model 2, which had rainfall as its added variable. The error range for this model was 0.62% to 3.73% (Fig.4) compared to ANN model 1 which had an error ranging from 1.20% to 9.10%. This proves that the inclusion of more load affecting variables in the model can increase the accuracy of the forecasts.

The regression method was the worst performer as can be seen in figure 3 with an error ranging from 0.63% to 30.01%.

Figures 4 and 5 depict the performance of the two ANN models for two days, Thursday 27 October and Saturday 29 January 2005. It can be observed that ANN model2 gives a better performance than ANN model 1.

In comparison to the tool developed at the control centre, an MAPE range of 4.83% to 6.77% was obtained for the month of July 2005 using the control centre tool and an MAPE of 1.34% to 3.73% was obtained using ANN model 2.

Figure 6 shows the forecast for a Thursday in July 2005 using ANN model 2 and the control centre tool. The superiority of ANN model 2 over the Control Centre tool can be seen.

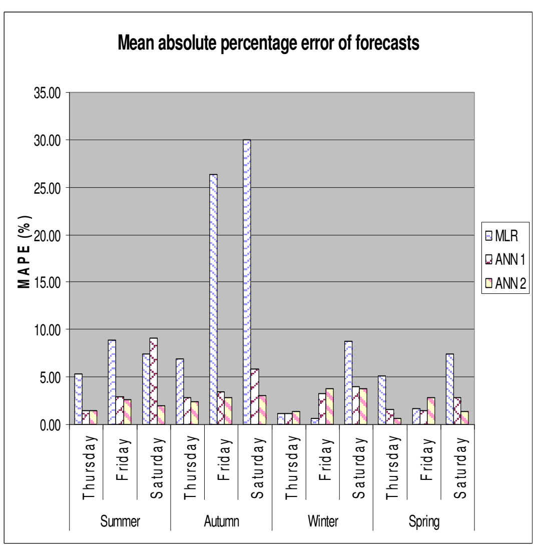

Figure 3: Mean absolute percentage error across all seasons

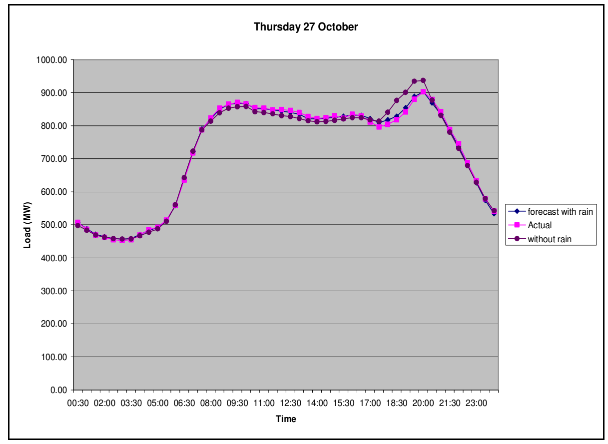

Figure 4: Forecast for Thursday 27 October 2005

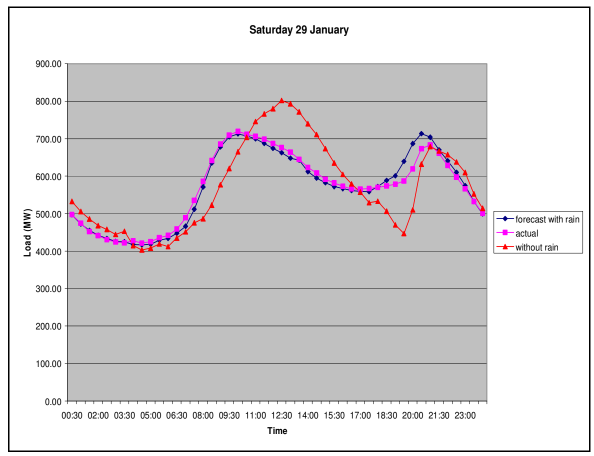

Figure 5: Forecast for Saturday 29 January

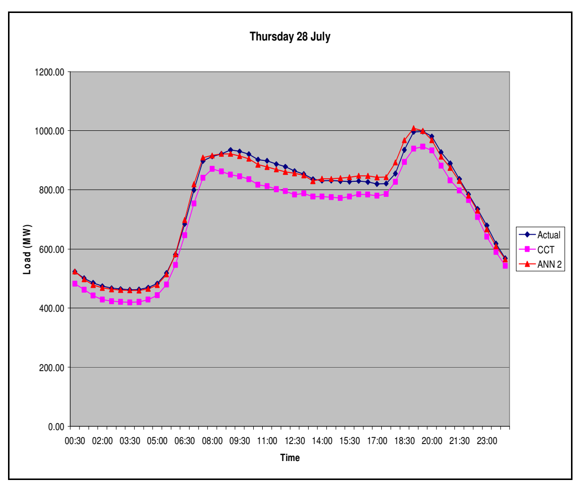

Figure 6: Forecast for Thursday 28 July 2005

VI. Conclusions

Two ANN-based short-term load forecasting methods that use a three-layer feed-forward neural network and a scaled conjugate back-propagation training algorithm have been presented in this paper. One model considers historical load data, temperature and cloud cover and the other considers rainfall as an added variable.

The ANN models perform much better than the MLR model as well as the Control Centre tool because it is able to learn from the training data, the relationships between certain variables and their effects on the load demand thereby making relatively accurate predictions.

The inclusion of more load affecting variables has a significant impact on the accuracy of the forecasts.

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