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On the Application of Artificial Neural Network in Analyzing and Studying Daily Loads of Jordan Power System Plant

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Abstract. In this paper, we propose a neural network approach to forecast AM/PM Jordan electric power load curves based on several parameters (temperature, date and the status of the day). The proposed method has an advantage of dealing with not only the nonlinear part of load curve but also with rapid temperature change of forecasted day, weekend and special day features. The proposed neural network is used to modify the load curve of a similar day by using the previous information. The suitability of the proposed approach is illustrated through an application to actual load data of Electric Power Company in Jordan. The results show an acceptable prediction for Short-Term Electrical Load Forecasting (STELF), with maximum regression factor 90%.

Keywords: artificial neural network (ANN); forecasting; multi layer perceptron (MLPs); back propagation (BP); short -term electrical load forecasting (STELF).

1. Introduction

Generally, the load of an electric utility is composed of very different consumption units. A large part of the electricity is consumed by industrial activities. Another part is of course used by private people in forms of heating, lighting, cooking, laundry, etc.

Also many services offered by society demand electricity, for example street lighting, traffic etc. Factors affecting the load depend on the particular consumption unit. The industrial load is usually mostly determined by the level of the production. The load is often quite steady, and it is possible to estimate its dependency on different production levels. In the case of private people, the factors determining the load are much more difficult to define. Each person behaves in his own individual way, and human psychology is involved in each consumption decision. Many social and behavioral factors can be found. For example, big events, holidays, affect the load. The weather is the most important individual factor, the reason largely being the electric heating of houses, which becomes more intensive as the temperature drops.

As a large part of the consumption is due to private people and other small electricity customers, the usual approach in load forecasting is to concentrate on the aggregate load of the whole utility. This is also the approach taken in this work. This reduces the number of factors that can be taken into account, the most important being considered are the temperature variation and daily status (working day or a holiday).

A lot of statistical methods such as linear regression models have been conventionally utilized [1-3] for the daily peak load forecasting. Recently, a number of artificial neural networks (ANN) approaches have been proposed and some systems are practically used in central load dispatching centers. On the other side, various daily load curve forecasting method have been proposed [4-6]. For example, linear regression models, ANN models [7-9], forecasting methods using actual load curves of some similar days of the target day. These methods construct forecasting models considering a correlation between weather conditions and a total electric load of target power system. These methods can forecast accurately for weekdays, however, cannot forecast accurately for Saturday, Sunday, national holidays, and specific holiday.

This paper proposes an ANN for short-term electrical load forecasting (STELF), time span of the forecasts will not range further than about one month ahead. Therefore, the economic and demographic factors will not be considered [10-11]. The effectiveness of the proposed method is shown by a comparison with the forecasting results of the proposed method and the actual loads.

Following a description of ANN models in the next section, an overview is given about the use of neural networks in time series prediction. In the third section, data used to train and test the implemented ANN model are described. Overall, ANN models work well for forecasting certain types of daily electrical power loads.

2. Artificial Neural Networks

ANNs have many applications, like STELF. ANN's have the ability to have knowledge of a thing never encountered before based on it's similarities with things already known. ANN's are also capable of complex function mapping and noise insensitivity. These qualities are the motivation for utilizing ANN's for STELF [12-14].

ANN's are computer algorithms which consist of highly interconnected processing elements called neurons that produce either weak, strong, or intermediate signals based on the weighted sum of the input signals they receive. These neuron output signals are either the inputs for other nodes or the outputs of the ANN. One way the ANN obtains the correct outputs is by learning from a set of examples. Fig.(1) illustrates a schematic of an ANN.

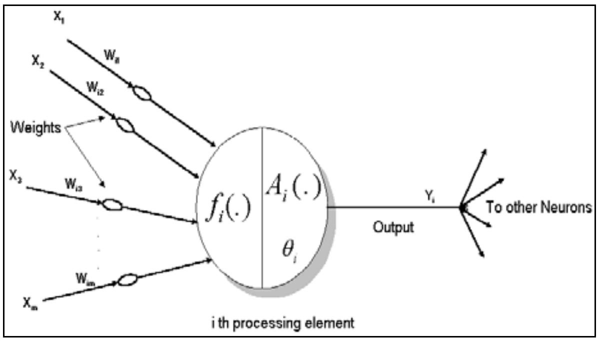

Fig.1. Simple Artificial Neuron

Multi-Layer Perceptron network is the most popular neural network type [7, 8] and most of the reported neural network short-term load forecasting models are based on it. The basic unit (neuron) of the network is a perceptron. This is a computation unit, which produces its output by taking a linear combination of the input signals and by transforming this by a function called activity function. The output of the perceptron as a function of the input signals can thus be written [7]:

$$y = \sigma\left(\sum_{i}^{n} w_i x_i - \theta\right) \quad \ldots(1)$$

where
y is the output
xi are the input signals
wi are the neuron weights
θ is the bias term (another neuron weight)
σ is the activity function

Possible forms of the activity function are linear function, step function, logistic function and hyperbolic tangent function. The MLP network consists of several layers of neurons. Each neuron in a certain layer is connected to each neuron of the next layer. There are no feedback connections. A three-layer MLP network is illustrated in Fig. (2).

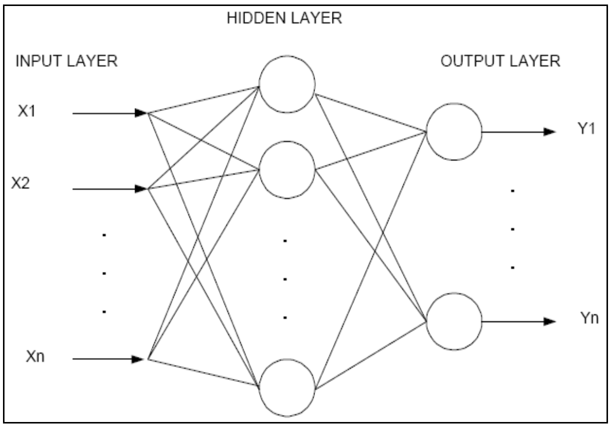

Fig.2. MLP structure.

As an N-dimensional input vector is fed to the network, an M-dimensional output vector is produced. The network can be understood as a function from the N dimensional input space to the M-dimensional output space. This function can be written in the form:

$$\mathbf{y} = f(\mathbf{x};\mathbf{W}) = \sigma(\mathbf{W}_n\sigma(\mathbf{W}_{n-1}\sigma(...\sigma(\mathbf{W}_1\mathbf{x})...))) \quad ...(2)$$

where
y is the output vector
x is the input vector
Wi is a matrix containing the neuron weights of the i:th hidden layer. The neuron weights are considered as free parameters.

The used MLP-network consists of three layers: an input layer, one hidden layer, and an output layer. The activation function used in the hidden layer is nonlinear sigmoid function (eq.3) and the activation function in the output layer is a linear function (a nonlinear-linear network) [6, 7].

$$f(x) = \frac{1}{1+\exp\left(-(x-x_o)/\theta\right)} \quad ...(3)$$

Where x is the variable value, x0 is the threshold, and θ is the slope of the sigmoid function.

3. Jordan Daily Electric Power Data

In this paper we consider a dataset containing loads from January 1, 2006 to March 31, 2007. The period from January 1, 2006 to Feb 28, 2007 is used for estimation purposes (in-sample) and the data concerning the period from March 1, 2007 to March 31 2007 is left for forecast evaluation (out-of-sample).

The data were obtained from an Electrical Power Company in Jordan. Carrying out an analysis of input variables consists in studying the contribution of each variable to the result of the forecasting model. This is always useful in practice because it makes it possible to eliminate inputs with little information to describe the output or redundancy between the variables. Fig.(3) shows the daily AM and PM loads during the in-sample period (2006), and Fig.(4) shows the daily AM and PM temperatures during the same period.

4. The Proposed Neural System for Electrical Load Forecasting

In The idea behind the use of MLP models in electric power load forecasting is simple: it is assumed that future load is dependent on various factors temperature values for (AM/PM), Days (Sat-Fri), months (Jan-Dec.) and special Events (Working day/Holiday), and the MLP network is used to approximate this dependency. The output is the target load values (for example a load value AM and PM loads of a certain day, load values of many future days, etc)

Therefore, the building of a MLP model for load forecasting can be seen as a nonlinear system identification problem. Determination of the model structure consists of selecting the input variables and building the network structure. The MLP neural network was conducted using NeuroSolution 5.0 software package, http://www.nd.com. Parameter estimation is carried out by training the network on load data of the history. The active NeuroSolutions breadboard is trained ten times and the best network weights are saved. The training results are then generated. The generated results contain the following information:

Training mean-squared error (MSE) versus Epochs.

Table showing the minimum training MSE, the epoch at which this minimum training MSE occurred, and the final training MSE.

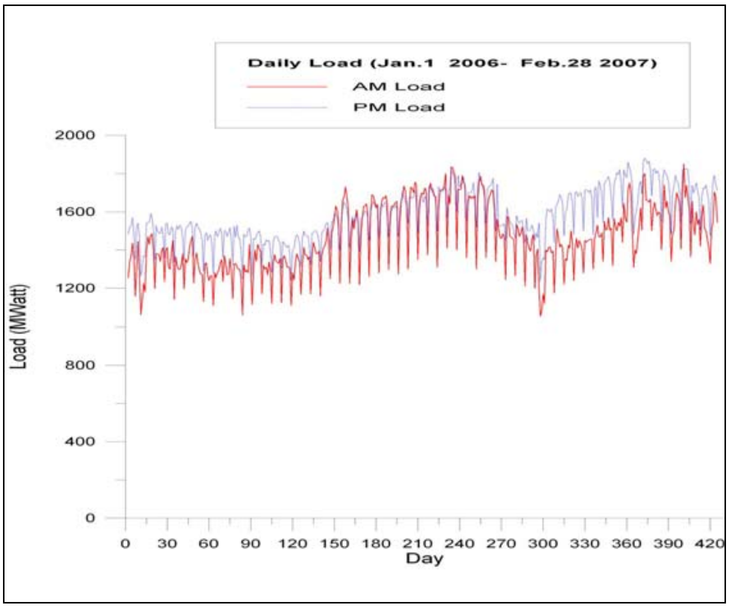

Fig.3. Daily AM/PM load

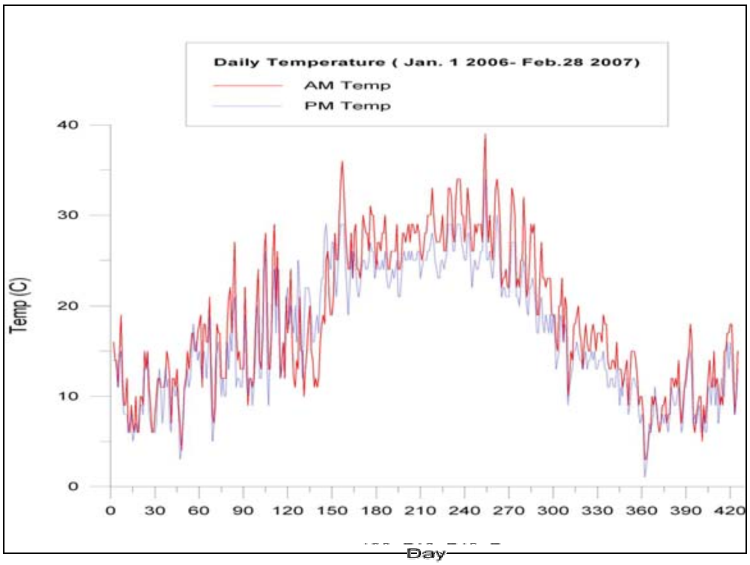

Fig.4.Daily AM/PM Temperature

This requires choices concerning the learning algorithm and appropriate training data (for period January 1, 2006 to February 28, 2007). Model validation is carried out by testing on load data, which has not been used in training (for period from March 1, 2007 to March 31, 2007)

The implemented MLP neural network consists of three-layers, the input layer have 6-inputs which are (Date dd/mm/yy, Status, AM temp., and PM temp.). The hidden layer is consisting of 10 processing elements (PEs) with a nonlinear sigmoid transfer function and bias variance 0.5. The output layer has two PEs with linear activation function.

5. Output Simulated Results

Various measures for forecasting accuracy have been taken, Mean Square Error (MSE), Normalized Mean Squire Error (NMSE), Mean Absolute Error (MAE), minimum absolute error, maximum absolute error and regression (r). Table (1) summarizes these results.

Table 1. Results Summary

Performance Measure	MW pm	MW am
MSE	2043.11975	3380.264869
NMSE	0.233209578	0.379410234
MAE	40.68898799	47.74797848
Min Abs Error	2.400411869	2.812579684
Max Abs Error	86.95226276	125.316794
r	0.877742328	0.908812838

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Fig.(5) and Fig.(6) shows a comparison between actual load (AM/PM) and the output of the implemented MLPs neural network model. This figure shows that the proposed MLPs ANN could predict the behavior of the actual load.

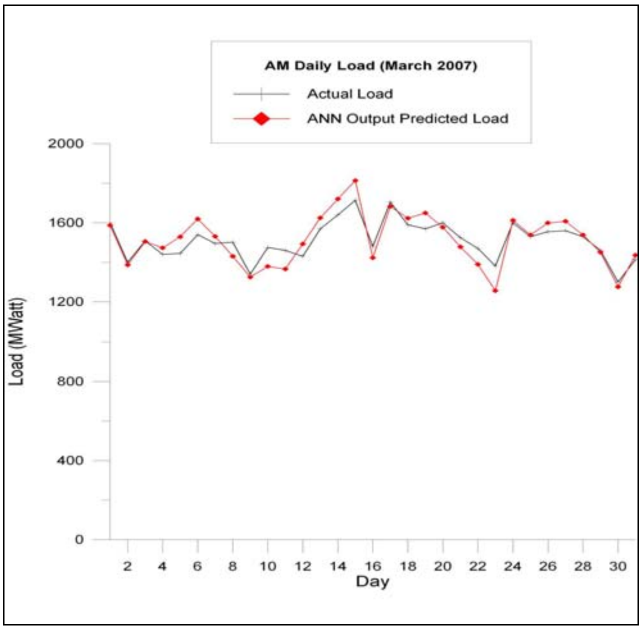

Fig.5. Actual Daily (AM) Load and ANN Output

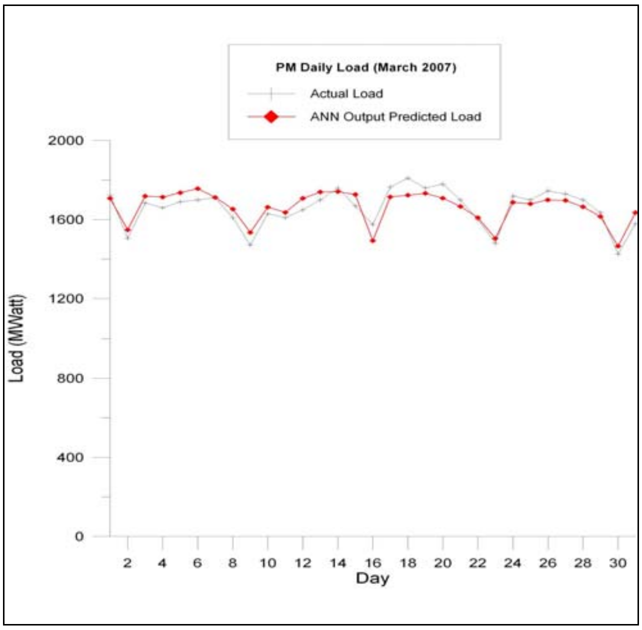

Fig.6. Actual Daily (PM) Load and ANN Output

6. Conclusions and Future Work

The Proposed MLPs ANN presents a powerful tool for decision making in electric distribution companies regarding load consuming. This is based on methodological selection of input variables and the network model. The results show a good prediction for short-term electrical load forecasting (STELF) relative to the actual electrical power load.

Since the relationship between electricity price and load is complex and dynamic, further research is needed to study how different customers' price response characteristics and locations affect load forecasting. STELF could be performed considering smaller areas and various large consumers to achieve higher forecasting accuracy by using different ANN models.

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