SHORT-TERM LOAD FORECASTING FOR JORDAN'S POWER SYSTEM

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ABSTRACT

One of the requirements for the operation and planning activities of an electrical utility is the prediction of load for the next hour to several days out, known as Short Term Load Forecasting (STLF). Artificial neural network (ANN) techniques have been applied to various subjects in the electrical power system area including electric load forecasting. This paper presents an application of (ANN) to the weekly load forecast problem of Jordan National Power System (JNPS). The ANN is trained with the load patterns corresponding to the forecasting hours and the forecasted load is obtained. Time Series Regression (TSR) modifies the initial forecasted load. A Neural Network (NN) model for the prediction of the seven-day ahead peak load of Jordan power system is developed. For the purpose, Nonlinear Autoregressive (AR) modeling, using simple Back-propagation NNs architecture, is used. This model was trained using two weeks data window for the most recent daily peak loads. The model treated the peak load at weekdays and weekends altogether. The results showed that the model has satisfactory results for one hour up to a week prediction of JNPS load. The average absolute percent error for the generated forecasts using this model was 0.5%.

INTRODUCTION

Various operations of electric utilities, such as unit commitment, energy transfer scheduling, coordination of energy management programs with the system resources, system maintenance, and fuel supply scheduling, require load forecast. Some of these operations require weekly load forecast, such as unit commitment and energy management operations.

In Jordan, the Jordanian government has recently taken several steps towards the deregulation and privatization of the electricity sector. Based on the new regulations, private electricity power generation is now possible, although with some limitations on purely Independent Power Producers (IPPs). This process adds a significant importance to the electric load forecasting.

Several electric power companies, including National Electricity Power Company in Jordan (NEPCO), are now forecasting electric loads based on conventional methods. However, since the relationship between loads and factors influencing these loads is nonlinear, it is difficult to identify its nonlinearity by using conventional methods. Most of papers deal with 24-h-ahead load forecasting or next day peak load forecasting. These methods forecast the demand power by using forecasted temperature as forecast information. But, when the temperature curves change rapidly on the forecast day, loads change greatly and forecast error would be going to increase [1].

To solve this forecast problem, different techniques have been used. Many of these techniques fall in the time series approaches [2-6]. The statistical time series methodologies, through for the analysis may require large databases, are more accurate than other statistical approaches such as regression, exponential smoothing and state space techniques [3]. However, the statistical time series techniques are suitable for short lead time forecasts (up to one or two days). Therefore, when applied to longer lead time forecasts, such as weekly load forecasts, their accuracy deteriorates. This can be explained by the fact that higher lead-time forecasts have higher forecast error covariance [7].

There are other approaches that have been used to solve the load forecast problem. These approaches are based on heuristics and expertise such as knowledge based expert system [8-11] and fuzzy systems [12-13]. Recently, various works have been reported based on the artificial neural network approaches leading to the solution of the load forecast problem [14-17]. However, many of these networks have complex architecture, huge databases, and developed for short lead-time predictions.

A work of Weekly Electrical Peak Load Forecasting based on ANN has been done for a certain region of Jordanian power system [20]. For that region, historical Load data of 1991 were collected manually. Nowadays, data are recorded and collected digitally and have no personal mistakes.

Typically, load forecasting can be long-term, medium-term, short-term or very short-term. This paper addresses the application of the artificial neural networks to the one-week lead time peak load prediction problem. The proposed Neural Network (NN) models have simple architecture and require small data depth for their NN training. The paper is presented as follows: section 1 presents a standard multi-layered Back-Propagation Neural Network (BP-NN), section 2 presents the developed ANN model for Jordan Power System, section 3 presents results and their discussion, and the conclusion is presented finally.

1. Muti-layered BP-NN

Artificial neural networks are the information-processing systems that are based on generalization of human cognition. Since their emergence, these systems have been used in many fields and applications. Description of these NNs can be found in many text books [18-19]. NNs are characterized by:

1. Architecture describing the connection among its processing units, i.e. Neurons.
2. Activation, (transfer) functions that map the weighted input signals of these processing units to output signals, i.e. neurons models.
3. Training (learning) algorithm for determining the weights of the connections between these processing units [18]. The work in this paper has been based on using a structured three-layer Back-propagation NN.

The Back-propagation method used to train the network was based on the Gradient Descent Optimization (GDO) technique applied to the cost function (J) is defined by the Sum of the Squares of Errors (SSE) of the network input-output training set as:

$$J = \frac{1}{2}\sum_{n=1}^{N}(y(n) - \hat{y}(n))^{T}(y(n) - \hat{y}(n)) \qquad (1)$$

where: N-number of input-output pairs in the training database, T-transpose operator, y(n)-actual output, and $\hat{y}(n)$ is estimated network output.

The Back-propagation method with GDO technique for minimizing the SSE cost function for the NN with one hidden layer is as follows:

1. Choose appropriate initial weights for the hidden layer, V, and the output layer, W.

2. Propagate through the network all the input layer from the input-output pairs in the training database and calculate the corresponding output in each unit in the hidden layer and in the output layer as:

Hidden Layer:

$$Z_j = f_h\left(\sum_{i=0}^{q} V_{ji} X_i\right) \quad j = 1,\ldots, p \qquad (2)$$

where,

f_h is hidden layer activation function, X is input units vector including the Bias, p is maximum number of neurons in the hidden layer, and q is number of the units in the input layer including the Bias.

Output Layer:

$$y(k) = f_o\left(\sum_{j=0}^{p} W_{kj} Z_j\right) \quad k = 1,\ldots, m; \qquad (3)$$

where F_0 -output layer activation function, Z-hidden layer outputs vector including the bias, and m is maximum number of neurons in the output layer.

3. Calculate the error information term for each unit, k, in the output layer as:

$$\delta_k = (y(k) - \hat{y}(k))\, f'_o \quad k=1,\ldots,m \qquad (4)$$

where,

f'_o is derivative of the output layer activation function.

4. Calculate the weight correction for all units of the output layer as:

$$\Delta W_{jk} = \alpha\, \delta_k\, Z_j \quad j=0,1,\ldots,p;\ k=1,\ldots,m., \qquad (5)$$

α = learning rate, Z_j = the j^{th} output in the hidden layer.

5. Calculate the error information terms in each unit, j. in the hidden layer by Back-propagation of the output error information, from the output layer as:

$$\delta_j \quad (\overset{m}{\underset{k \;\; 1}{}} \delta_k W_{jk}) f_h \qquad j \quad 1,.......,p \qquad (6)$$

F' is the derivative of the hidden layer activation function

6. Calculate the weight correction term for all units in the hidden layer as:

$$\Delta V_{ji} \quad \alpha \, \delta_j X_i \qquad j \quad 1,....p; \; i \quad 0,1,...,q \qquad (7)$$

7. Update the weight for the output layer and the hidden layer as:

$$\begin{array}{l} W_{jk}(new) \quad W_{jk}(old) \quad \Delta W_{jk} \\ and \\ V_{ij}(new) \quad V_{ij}(old) \quad V_{ij} \end{array} \qquad (8)$$

8. Repeat step 2 to step 7 until meeting the stopping condition.

2. Developed NN Model

Statistical analysis, from the past experience, has been used to identify the most influential variables on the targeted one week lead time forecasts. Weather variables are not considered in the developed NN models as their values could not be obtained with reasonable accuracy one week ahead. Therefore, only statistical trends in the changes in peak load are captured from the smallest most recent database. An NN model has been developed based on non-linear autoregressive (AR) time series modeling.

This NN model treats together the peak loads of both weekdays and weekends. However to capture the difference in peak loads in both weekdays and weekends, indicator variables have been introduced. The mathematical model for the peak load at time step n, y(n), becomes:

$$y(n) = F(y(n-1), \ldots\ldots, y(n-L), I_d, I_e) + e(n) \qquad (9)$$

where:

F-non-linear function with autoregressive variables and indicator variables, I_d- indicator variable for weekdays, I_e - indicator variable for weekends, and e(n) is white noise.

Two indicator variables have been used in the model as to capture, from the continuous peak load process,the imposed effect of weekdays and weekends variations. In this NN model formulation, the input layer altered as: Input Layer: y(n-1), y(n-L), I_d, I_e, Bias. All the Bias values in the model have been assumed as ones.

3. Results and Discussion

Application results of the developed NN model is obtained using historical peak load data of an electric utility in the area for the late period of 2005 and the full of 2006. Starting with the 2005 data for the prediction of January 1st, 2006, the neural network was trained using the most recent two weeks database. Once the network has been trained, the seven-day ahead, peak forecast was calculated using the NN weights. As "new" observation of peak load of January 1st, 2006 become available, the forecast error was calculated. Then, the window moved one step to include this "most recent" peak load data of January 1st, and to drop the oldest peak load from the database. The NN was retrained to adapt for the effect of the "new" observation data for updating the weights before calculating the next weekly load forecast of January 2nd. This mechanism has been repeated until generating the one-week lead-time forecasts for the full year of 2006. The actual load and generated forecasts are displayed for both weekdays in Figure1 and weekends in Figure 2. The Percent Error (PE) of these generated forecasts, are displayed in Figures 3 and 4.

The NN model has been developed using an MS-windows based Matlab software. The weekdays NN has been trained with SSE=0.002 and 10000 iteration steps (epochs). The network was retrained 365 times as moving from one day to the next as explained earlier. However, the NN weights were expected to vary smoothly in most case since the training started using previous available

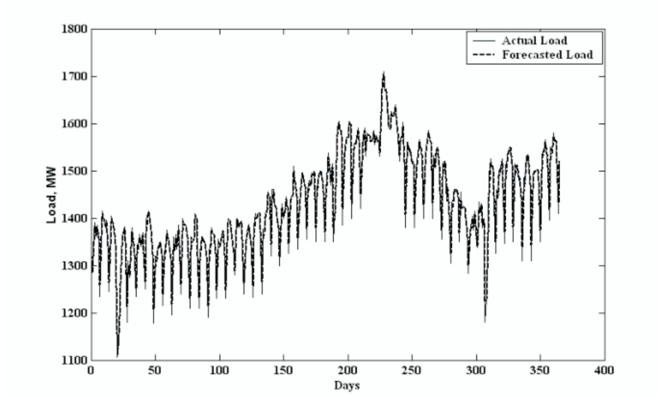

Figure 1. Weekdays One-Week Lead-Time Forecast

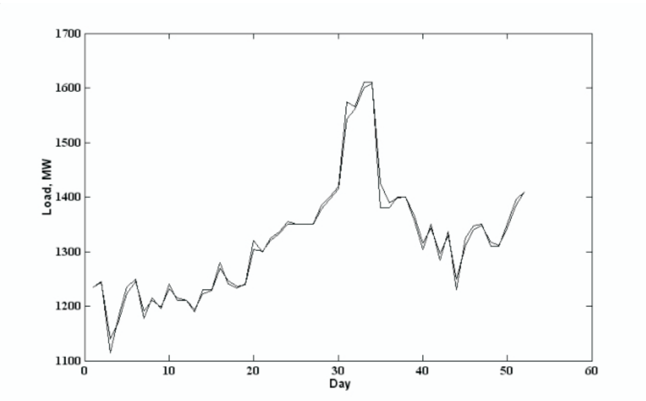

Figure 2. Weekends One-Week Lead-Time Forecast

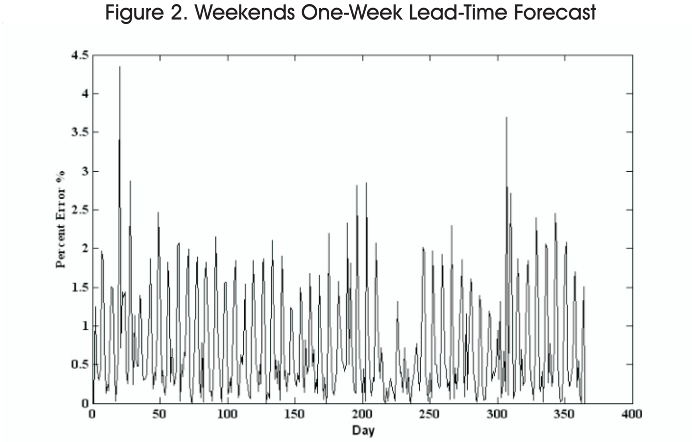

Figure 3. All Weekdays Forecast Percent Errors

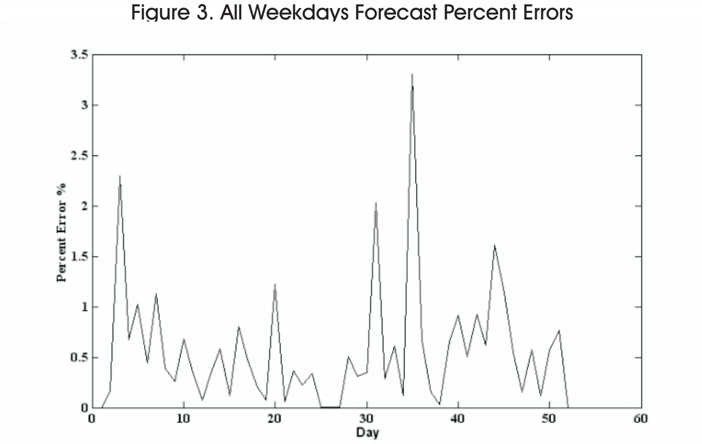

Figure 4. All Weekends Forecast Percent Errors

weight. For retraining the model using the previous weights, it took only 1 epoch. That was not always the case with all data points as some "new" data patterns did not follow the previous patterns and took larger number of steps for NN retraining.

The used peak load data has been pre-processed by scaling it (to per unit values) by a number slightly larger than the expected yearly peak load, i.e., 1000 MW.

The forecasting errors displayed in Figures 3 and 4 have been analyzed based on the Average Absolute Percent Error (AAPE) defined as:

$$AAPE = \frac{1}{M}\sum_{i=1}^{M}\frac{|ActualPeak - PredictedPeak|}{ActualPeak}\times 100 \qquad (10)$$

Where M is the number of predicated peak loads, e.g. Days of the month.

A summary of the Average Absolute Percent errors (AAPE) of the generated forecasts for all months of the year is shown in Table 1. These results have been displayed on a month bias to demonstrate the accuracy and consequently the validity of the model under seasonal variations. The summary shows that the Model outperforms very good in all months of the year. Though these results are generated for specific utility these have better accuracy than one-weak peak load predications generated using other statistical and expert system methods as reported in [6].

The largest AAPEs are in October, January, and February months. This can be explained by the fact that in October 2006 is Ramadan. Special treatments or separate modeling for generating predictions in Ramadan should be considered. The next largest average errors are in January and February. This can be explained by the fact that both of Al-Adha and Christmas Feasts occurred in these months in 2006. The data in feast holidays are treated as normal weekdays and weekends. This

$y(k) = f_o(\sum_{j=0}^{p} W_{kj} Z_j)$	Average Absolute Percent Error		
Month	Weekdays	Weekends	Total week
Jan	0.5970	0.7047	0.6114
Feb	0.5860	0.5686	0.5837
Mar	0.4797	0.4027	0.4694
April	0.4220	0.5657	0.4412
May	0.4272	0.5610	0.4450
June	0.3933	0.2037	0.3680
July	0.5244	0.2920	0.4934
Aug	0.4520	0.4757	0.4552
Sep	0.4447	0.1254	0.4021
Oct	0.5588	0.9183	0.6061
Nov	0.3626	0.6076	0.3953
Dec	0.4966	0.4754	0.4938
Average	0.4787	0.5167	0.4838

Table 1. Average Absolute Percent Weekly Peak Load Forecast Errors for All Months of the Year

contributed to errors in the trained network weights and the generated forecasts when such data are involved. These results also show that it would be more accurate for the tested utility data to treat peak loads at weekdays and weekends with the introduction of indicator variables.

Conclusion

An application of artificial neural networks to the weekly peak load forecast problem has been presented. ANN model with simple architecture has been developed. The generated one-week lead-time peak load forecasts using this model are accurate with an AAPE of only 0.5%. These results also show that it would be more accurate for the tested utility data to treat peak loads at weekdays and weekends together. Special treatments or separate modeling for generating predictions in Ramadan month and feast holidays should be considered.

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