Day-Ahead Load Forecasting using Artificial Neural Network

Pradipsinh A. Chauhan 1 Jyoti R. Iyer 2
1 P.G Student 2 Associate Professor
1, 2 Department of Electrical Engineering
1, 2 L.D. College of Engineering, Ahmedabad, India

Abstract—Load forecasting is an important component of power system energy management system. Short-term load forecasting (STLF) with lead time of the few minutes to several days is required for the several decision making in the electric utility. These decisions include economic scheduling of generating capacity, scheduling of fuel purchase, maintenance scheduling, unit commitment and planning for energy transactions. In this paper artificial neural network (ANN) is used for short-term load forecasting. Multilayer Back propagation network is used for day ahead (i.e. Next day) load forecasting. Neural network is trained by back propagation algorithm with gradient descent. Load data is collected from GETCO (Gujarat energy Transmission Corporation) 66/11kv distribution substation, Navagam. The load data of Bareja (medium sized town), urban feeder is taken.

Key words: Short-Term Load Forecasting (STLF), Artificial Neural Network (ANN), Back Propagation Network (BPN)

I. INTRODUCTION

Accurate models for load forecasting are essential to operation and planning of a utility company. Load forecasts can be divided into four categories: very short-term forecasts which are usually from few seconds to few minutes, short term forecasts which are usually from one hour to one week, medium term forecasts which are usually from a week to a year, and long term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility company. Also, with the deregulation of the electric utilities, load forecasting is even more important.

Many techniques have been proposed for STLF during last few decades such as linear multiple regression, time series approach, general exponential smoothing, kalman filtering, expert system etc.[1,2]. Time series models employ the historical data for extrapolation to obtain the future hourly loads. The limitation of these models is that the load trend is stationary and that weather information or any other factors that contribute to the load behaviour cannot be fully utilised.[2]. Regression models analyse the relationship among loads and other influential factors such as weather and customer usage behaviour. The main drawback is that these models require complex modelling techniques and heavy computational efforts to produce reasonably accurate results.[2]. The expert system models are discrete and logical in nature, and use the knowledge of a human expert to develop rules for forecasting. However, transforming the knowledge of an expert to a set of mathematical rules is often very difficult.

Neural Networks (NNs) have succeeded in several power system problems, such as: planning, control, analysis, protection, design, load forecasting, security assessment, and fault diagnosis. Among which last three are the most popular. The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990[2-8]. Neural networks are essentially non-linear circuits that have the demonstrated capability to do nonlinear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs.

This paper present ANN for day-ahead load forecasting. Three layer feedforward(or BPN) is used. Training algorithm used is backpropagation and learning mechanism for weight optimisation is gradient descent method.

II. LOAD CHARACTERISTIC

System load can be considered as highly nonlinear function of several factors.

\[ L = f(\text{Previous load, Weather, Time, Special, Price, Random}) \]

Where, \( f(\cdot) \) is a highly nonlinear function

Weather factors covers temperature, humidity, precipitation, wind speed, cloud cover and light intensity etc. Time factors influencing the load are time point of the day, holiday, weekday/weekend property and season property. Electricity is a commodity. The economic factors also affects the utilization of this commodity. Economic factors, such as the degree of industrialization, price of electricity and load management policy have some impacts on the system load growth/decline trend. Special events such as religious or cultural celebration also are source of random disturbance. Diwali, Id and Christmas and other religious events are the examples of special events. Similarly India Vs Pakistan cricket match also lies in the category of special days and is another source of random disturbance, causing huge spikes in the load curve due to increased usage of T.V.

III. ARTIFICIAL NEURAL NETWORK

By definition neural network (NN) is a massively paralleled highly interconnected network of large number of processing elements called neurons in architecture inspired by the human brain. These neurons are interconnected with weighted unidirectional connection as in Fig.1. Each neuron is composed of multiple inputs, one output and activation function. The inputs carry the weighted output of other directly connected neurons. The incoming information of neuron is processed by the associated nonlinear activation function (such as sigmoid function). The output is then distributed to other neurons as inputs. Connection strengths (or weights) are allowed to adjust during training stage.
**Day Ahead Load Forecasting using Artificial Neural Network**

**I. Introduction**

Most common, as a rule ANN has three layers of neuron: input, hidden and output. Number of neuron in input layer corresponds to the number of inputs to the NN. These layer consists of passive nodes, i.e which do not take part in actual signal modification, but only transmit the signal to the following layer. Hidden layer has arbitrary number of layers with arbitrary number of neurons. The nodes in these layer take part in actual signal modification hence they are active nodes. Output layer as has many neurons as number of output and nodes in these layer are also active node. A variety of ANN configurations have been developed for different applications. The number of inputs, the number of hidden nodes, transfer functions and training methods affect the performance of ANN and hence need to be chosen carefully [9, 10].

**II. ANN Model**

ANN works through the optimized weight value. The method by which optimized weight value are attained is called learning and these process is called training of ANN. Backpropagation is the most frequently used algorithm for training ANN (By David Rumelhart et.al). The learning algorithm behind backpropagation is the kind of gradient descent method. The gradient descent algorithm adapts the weights according to gradient of error w.r.t weight as

\[ \Delta W_{ij} \propto -\frac{\partial E}{\partial W_{ij}} \]

\[ \Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} \]

Where, \( E \) = the error at the output neuron

And \( \eta \) = constant of proportionality = learning rate

Step given below shows the general procedure for back propagation[10]

1) Initialize all network weights with small random numbers between -1 and +1.
2) A first pattern is presented to the network (i.e., the input values).
3) The input is propagated through the network to give an output
4) The actual output is compared with the desired (target) output and an error function is defined (that we have to minimise).
5) The errors are propagated back though the network to determine the amount by which to update the weights.
6) Update the weights.
7) Repeat from step-2 for each pattern (when all patterns have been used we say one epoch (iteration) has completed).
8) Continue until for one epoch, all outputs for each pattern are within the tolerance.
9) Then we can say the network is trained and can be tried on test data.

A typical operation of ANN can be classified into two stage a) training stage and b) testing stage. The training stage is conducted by using various data sets which includes the respective inputs and the corresponding outputs (targets). After the network is properly trained, the testing stage will start. A set of test data is then applied to the network at this stage. Afterward, the performance of the network is analyzed. There are number of performance measures used such as mean squared error (MSE), sum squared error (SSE), root mean squared error (RMSE), mean absolute percentage error (MAPE) etc.

**V. METHODOLOGY**

A. Proposed ANN Model:

Multilayer feedforward network (Back propagation network) with 32 inputs and 24 outputs (hourly load of next day) is used for day ahead load forecasting.

1) Parameters of Neural Network:

- Number of layers: 3 (input layer, hidden layer, output layer)
- Number of input variables: 32
- Number of hidden neurons: 32
- Activation function of hidden layer: sigmoidal with \( \lambda = 1 \)
- Activation function of output layer: sigmoidal with \( \lambda = 1 \)
- Training algorithm: Back propagation with gradient descent
- Learning rate(\( \eta \)): 0.6
- Momentum term(\( \alpha \)): 0.3
- Number of output neurons: 24 (Hourly load of next day)
- Number of training set in each epoch (iteration): 398
- Number of epoch for training: 1935

2) Input Vector Configuration:

Number of inputs : 32

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hourly load of previous day to the forecast day</td>
<td>24</td>
</tr>
<tr>
<td>Max. &amp; min. temperature of previous day to the forecast day.</td>
<td>2</td>
</tr>
<tr>
<td>Max. &amp; min. temperature of the forecast day</td>
<td>2</td>
</tr>
<tr>
<td>Day of week</td>
<td>3 bits</td>
</tr>
<tr>
<td>Holiday</td>
<td>1 bit (If holiday then 1 otherwise 0)</td>
</tr>
<tr>
<td>Total</td>
<td>32</td>
</tr>
</tbody>
</table>

Table 1: Input Vector Configuration

The load and temperature values are normalised using the equation

\[ \text{Normalised value} = \frac{\text{actual value} - \text{min. value}}{\text{max. value} - \text{min. value}} \]
B. Results:
The network was trained with 14 months data (from June 2013 to July 2014) and performance of the developed model was tested for last six days of the July month. The final converged weights are used to test this six input pattern (unseen inputs). Numerical simulation (MATLAB code) is developed on MATLAB R2010a. Fig. 2 shows plot of error rate w.r.t number of training epochs.

Fig. 2: Number of Epochs Vs Errorrate

Fig. 3 shows day ahead load forecasts for six test days and its comparison with actual load.

The load forecast was compared to the actual load data and the error is calculated. The mean absolute percentage error (MAPE) is used to evaluate the performance of these models. MAPE is defined as

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_{\text{actual } i} - P_{\text{predicted } i}}{P_{\text{actual } i}} \right| \times 100
\]

Where, \( N \) = total number of hours or samples points and \( i = 1,2,3,\ldots,24 \).

Table 2: shows the actual and predicted load for first test day.

<table>
<thead>
<tr>
<th>Hours</th>
<th>Actual Load</th>
<th>Predicted Load</th>
<th>% Error</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1314.39</td>
<td>1320.29</td>
<td>-0.449602</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1262.82</td>
<td>1207.91</td>
<td>4.348159</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>1193.97</td>
<td>1182.67</td>
<td>0.946373</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1205.61</td>
<td>1159.79</td>
<td>3.799915</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1186.32</td>
<td>1132.14</td>
<td>4.566950</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1205.49</td>
<td>1140.45</td>
<td>5.395054</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1355.40</td>
<td>1251.88</td>
<td>7.636949</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>1339.62</td>
<td>1313.83</td>
<td>1.924777</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>1370.07</td>
<td>1266.64</td>
<td>7.549168</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>1340.25</td>
<td>1319.06</td>
<td>1.580974</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1461.63</td>
<td>1410.14</td>
<td>3.522683</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>1578.54</td>
<td>1496.62</td>
<td>5.189538</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>1607.76</td>
<td>1427.43</td>
<td>11.215848</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>1586.55</td>
<td>1493.02</td>
<td>5.894662</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>1396.56</td>
<td>1485.21</td>
<td>-6.347787</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>1525.68</td>
<td>1462.16</td>
<td>4.163363</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>1540.89</td>
<td>1437.41</td>
<td>6.715177</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>1612.71</td>
<td>1486.04</td>
<td>7.854304</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>1490.67</td>
<td>1434.26</td>
<td>3.783779</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>1405.80</td>
<td>1465.01</td>
<td>-4.212325</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>1728.57</td>
<td>1743.03</td>
<td>-0.836584</td>
<td></td>
</tr>
<tr>
<td>21</td>
<td>1700.85</td>
<td>1630.26</td>
<td>4.150033</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>1550.82</td>
<td>1553.62</td>
<td>-0.181058</td>
<td></td>
</tr>
<tr>
<td>23</td>
<td>1486.89</td>
<td>1451.49</td>
<td>2.380624</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Comparison of Actual and Predicted Load

MAPE for other test day respectively are 5.34, 2.99, 3.009, 4.38, 5.48.

VI. Conclusion

This paper present the application of neural network for short-term load forecasting. The result obtained shows
reasonable prediction accuracy, suggesting suitability of BPN for short-term load forecasting.

REFERENCES


