© IJCIRAS | ISSN (O) - 2581-5334
May 2020 | Vol. 2 Issue. 12

# ARTIFICIAL NEURAL NETWORKS APPROACH BASED SHORT TERM ELECTRIC LOAD FORECASTING

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**Abstract**

***The term load prediction refers to the projected load requirement using systematic process of defining load in sufficient quantitative detail so that vital power system expansion decisions can be made. In recent years, there is an emphasis on Short-Term Load Forecasting (STLF), the essential part of power system planning and operation. Rudimentary operating functions such as unit commitment, economic transmit, and unit preservation can be performed efficiently with a precise forecast. Short-term forecasting can assist in predicting the flow and making decisions that prevent overloading. This paper implements the STLF as a 24-hour forecast whose result is an hourly electric forecast. This paper uses the method of Artificial Neural Network (ANN) to create a STLF process. The inputs to the ANN are load profiles of one month previous days and the weather variables of that days. Correlation analysis between load and weather variables will be used for all predictor input data to the ANN to optimize in size and accuracy. MATLAB programming language is used to implement this system.***

***Keyword: Electricity Load Forecasting, Short Term Load Forecasting, Artificial Neural Networks, ANN.***

## 1.INTRODUCTION

Accurate models for electric power load forecasting are necessary to developing a utility is the company's operations and planning. Load estimate assists an electric utility to make vital including purchases decisions and generating electricity, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets [3]. At present, there is no substantial energy storage in the electric transmission and distribution system. For best power system operation, electric generation must follow electrical load demand. The generation, transmission, and distribution accessories require some means to forecast the electrical load, so they can utilize their electrical infrastructure efficiently, secure and economically viable. Generation utilities use electrical load forecasting techniques to schedule their generational resources to meet a future load demand. Transmission utilities use electric load forecasting methods to optimize the power flow on the transmission network to decrease congestion and overloads. Distribution utilities there are not many benefits in short term electric load forecasts as their distribution systems are predominantly radial with predictable maximum load demands. Therefore, the distribution systems are sized conservatively and short term payroll changes have little impact on the distribution system. Load forecasting refers to projected load requirement using systematic process of defining load in enough quantitative detail so that vital power system decisions can be made. A total forecast is obtained by combining forecasts for various classes of customers such as residential commercial, industrial and others. The load forecasting can be divided into following four types [1].

- Very short-term load forecast: These are required for on line operation and control of system. The time ranges from a few second to a minute.
- Short-Term Load Forecast (STLF): Short-term load forecast have special important in operation, control and techno commercial decisions. It is made on hourly to a day ahead.
- Medium-term load forecast: It ranges from a week ahead to a six months. Generally energy estimates are made in this range. Energy sales and fuel purchase agreements are based on these forecasts.

- Long-term load forecast ranges from a year to 20 years. Theses in general are estimate of peak demand in future years. It is very much needed in system generation and transmission planning.

Short-term load forecasting plays a vital role in power systems. Accurate short-term load forecasting has a significant influence on proper system operational efficiency such as unit commitment, annual hydro thermal maintenance scheduling, hydro thermal coordination, demand side management, interchange evaluation, security assessment and other purposes. Progress in the accuracy of short-term load forecasts can result in significant financial savings for utilities and generators. Short-term load forecasting can help to predict load flows and to make decisions that can prohibit overloading. Timely implementations of such decisions lead to the improvement of network trusted and to reduced event of equipment failures and blackouts [1].

## 2. LOAD FORECASTING METHODS

Some of the methods that have been proposed and implemented to create STLF are:

1. Multiple Linear Regression
2. Stochastic Time Series
3. Support Vector Machines
4. Similar-day Approach
5. State Space Method
6. Knowledge-based Expert Approach
7. Artificial Neural Network (ANN)
8. Fuzzy Logic

Methods 1-5 use statistical means to arrive at a forecast solution. The algorithm for method 6 selects a reference day based on a set of rules and reshapes this day's electric load curve using other sets of rules specific to the system under study. Method 7 ANN uses an algorithm that combines previous system load and weather data and predicts a future load pattern. The ANN is trained with an input data set to estimate a target data set. Load forecasting is an innate nonlinear problem and the structure of an ANN is suited for nonlinear modeling [2]. These eight methods will be explored further with the focus on ANN as the preferred method for calculating the STLF for power distribution system. The algorithm will be the best to produce a STLF with low percent error. Many accounting and artificial intelligence methods have been developed for short-term forecasts.

## 3. ARTIFICIAL NEURAL NETWORKS (ANN)

Work on artificial neural network (ANN) has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the ordinary digital computer. The brain is very complex, nonlinear and parallel information processing system. It has the ability to organize its structural constituents, known as neurons, so as to perform sure computations many times faster than the fastest digital computer in existence today [5].

In recent years, artificial neural network is the load forecasting class of algorithms which is used most widely. A reaction to the query in Life and Physical Science more papers were returned, in a single year, on "neural network" than on "support vector"; ARIMA; "similar days"; or ARMA, terms together with "load forecasting". For example, in 2011, there were 170 papers which included both terms "load forecasting" and "neural network", while there were only 58 papers which included both terms "load forecasting" and "support vector", which positioned "support vector" based algorithms in second place [4]. Neural networks are popular probably because of their simple and traditional usages in which the no user needed to go to complex depths in order to achieve a relatively good solution to the problem. High usage may not necessarily mean that neural networks are the best algorithm in overall performance [4].

### *3.1. Neural Network Definition*

A neural network is a machine designed to design the brain for a particular task.The network is implemented by electronic components or software on a digital computer.The neural network is a highly competitive distributed processor composed of simple adaptive units. It has the natural ability to store test knowledge and to use it. It resembles the brain in two respects:

- Knowledge is acquired through a learning process from the network itself.
- Used to store knowledge gained on the advantages of the Interneuron connection, known as synaptic weight.

The procedure used to process the learning process is called the learning algorithm. The function is to systematically adjust the weight of the network to achieve the desired design goals [5].

### *3.2. History of ANN*

The neural network was recently developed for simulator development. However, this field was established before the advent of computers and survived at least one major setback.The modern development of neural network was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. They have developed a mathematical model of a sensor cell that follows "all - or none at all" rule. Due to the availability of such simple units and the synaptic connections, they are organized and run consistently, and they show that the organized network is essentially calculating any kind of computation.This was a very significant result and it is generally agreed that the disciplines of neural network and of an artificial intelligence were born.Significant improvements have been made in the use of low cost computers. After the initial enthusiasm, the field became disappointing and frustrating.During this period when funding and professional support was minimal, important advances were made by relatively few researchers.[5]

### *3.3. Biological Model of Human Brain*

The name neural networks was came from the analogy of a mathematical model and neurons in the human brain. The human nervous system may be viewed as a three stage system as in the following figure. These receptors turn electrical signals from the human body or from the outside environment into sensory stimuli. The effectors turn electrical signals emitted by the neural network into sensible responses as system outputs. [5].

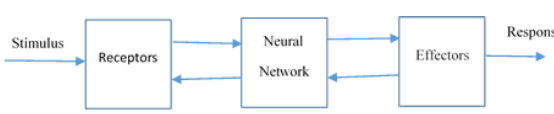


*Figure 1 . Block Diagram of a Human Nervous System*

### *3.4. Mathematical Model of a Neuron*

A neuron model is a basic information management unit for the functioning of the neural network. The block diagram of Figure 2 shows the model of a neuron, which is the basic design of neural network. The three basic components of a neuron model are:

- A set of weights, each of which is characterized by a strength of its own. The $x_j$ signal connected to the sensor cell increases $w_{kj}$ weight. The weight of the artificial neuron has positive and negative values as well.
- An adder for summing the input signals, weighted by the respective weights of the neuron.
- An activation function for limiting the amplitude of the output of a neuron. It is also referred to as squashing function which squashes the amplitude range of the output signal to some finite value [5].

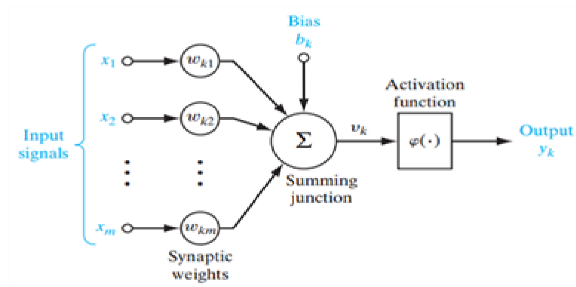


*Figure 2. Model of a Neuron*

In mathematical terms, may describe a neuron k by writing the following pair of equations:

$$v_k = \sum_{j=1}^{m} w_{kj} x_j \quad (1)$$

and

$$y_k = \varphi(v_k + b_k) \quad (2)$$

### *3.5. Network Architectures*

There are three fundamental different classes of network architecture:

- Single-layer Feedforward Networks

An input layer of main nodes that projects onto an output layer of neurons, but it's not mutual. This network is strictly a feed forward type. In single-layer network have been only one input and one output layer. Input layer is not counted as a layer since no mathematical calculations take place at this layer [5].

- Multilayer Feedforward Networks

  The second tier of a Feed forward neural network distinguishes itself by the existence of one or more confidential layers, whose computational nodes are correspondingly called hidden neurons. The function of hidden neuron is to interfere between the external input and the network output in some useful custom. By adding hidden layers, the network is enabled to extract higher order statistics. The input signal is involved to the neurons in the second layer. The output signal of second layer is used as inputs to the third layer, and so on for the rest of the network [5].
- Recurrent Networks

  There is at least one feedback loop in the neural network that is triggered. A recurrent network may contains of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Self-feedback refers to a status where the output of a neuron is fed back into its own input. The presence of feedback loops has a profound impact on the learning capability of the network and on its performance [5].

## 4. INPUT DATA COLLECTION

Data collection is an important activity in any type of research. Inaccurate or insufficient data can impact the results of a study and ultimately lead to invalid or bad results. A good predictive system requires variables that are strongly correlated with load. The selection of the input variables is rather done unrighteous, based on the relevance analysis and sometimes on suggestions made in previous works and experience. Literature report that among all other weather related factors, temperature has the most notable dependency in load variation. The load data spreadsheet contains the electrical load for my city recorded in the previous one hour (hour-by-hour). Additional columns were added to the original load data spreadsheet to indicate day-of-week and serial date as these values were also required as inputs to the ANN.

### *4.1. Defining Time-Lagged Data*

As a result, it was essential that previous load values were used as inputs to the ANN. Additional column vectors were created from the original input data to store time lagged load data. If $d$ represents the forecast day, and $t$ represents the current forecasted hour, then the time-lagged input load data is as shown in Table 4.1.

| **Forecast-Day Lag** | **1-Day Lag** | **2-Day Lag** | **3-Day Lag** | **. . .** | **1-Week Lag** |
|---|---|---|---|---|---|
| n/a | kW(d-1,t) | kW(d-2,t) | kW(d-3,t) | . . . | kW(d-7,t) |
| kW(d,t-1) | kW(d-1,t-1) | kW(d-2,t-1) | kW(d-3,t-1) | . . . | kW(d-7,t-1) |
| kW(d,t-2) | kW(d-1,t-2) | kW(d-2,t-2) | kW(d-3,t-2) | . . . | kW(d-7,t-2) |
| kW(d,t-3) | kW(d-1,t-3) | kW(d-2,t-3) | kW(d-3,t-3) | . . . | kW(d-7,t-3) |
| kW(d,t-4) | kW(d-1,t-4) | kW(d-2,t-4) | kW(d-3,t-4) | . . . | kW(d-7,t-4) |
| . . . | . . . | . . . | . . . | . . . | . . . |
| kW(d,t-23) | kW(d-1,t-23) | kW(d-2,t-23) | kW(d-3,t-23) | . . . | kW(d-7,t-23) |

**d**: forecast day, **t**: current forecasted hour

**Table 4.1 Time-Lagged Input Load Data**

### *4.2. Correlation Analysis*

List of input data variables available for use in ANN. Correlation analysis was performed on the input data to make it better the ANN's training and load forecasting methods. Correlation analysis applied to the input data in an effort to reduce the amount of data to only what is necessary. This analysis identified which input data is correlated to the actual load data and which data was neglected. This analysis also helped to select the amount of time needed for service information. The coefficient can range between -1 and +1 where -1 indicates a high negative correlation, 0 means no correlation, and +1 for a high positive correlation. Table 4.2 shows the definition of strength of correlation coefficients and Table 4.3 shows the sample calculation for correlation coefficient between current electric load and 1-hour ago electric load using the equation (3). The result shows that the relationship between these two variables is strong relationship.

| Strength of Association | Coefficient, r | |
|---|---|---|
| | **Positive** | **Negative** |
| Strong | 0.5 to 1.0 | -0.5 to -1.0 |
| Moderate | 0.3 to 0.5 | -0.3 to -0.5 |
| Weak | 0.1 to 0.3 | -0.1 to -0.3 |

**Table 4.2 Strength of Correlation Coefficient, r**

The minimum correlation coefficient value (0.7, strong relationship coefficient) is defined in the simulation code. This value can be increased or decreased to allow less or more input data types, based on their correlation coefficients, to be presented to the ANN.

| No | X | Y | X2 | Y2 | X*Y |
|---|---|---|---|---|---|
| 1 | 41.91 | 45.04 | 1756.76 | 2028.98 | 1887.97 |
| 2 | 39.67 | 41.91 | 1573.90 | 1756.76 | 1662.82 |
| 3 | 37.79 | 39.67 | 1428.15 | 1573.90 | 1499.25 |
| 4 | 37.67 | 37.79 | 1419.02 | 1428.15 | 1423.58 |
| 5 | 39.45 | 37.67 | 1556.40 | 1419.02 | 1486.12 |
| 6 | 39.58 | 39.45 | 1566.69 | 1556.40 | 1561.53 |
| 7 | 44.70 | 39.58 | 1998.43 | 1566.69 | 1769.44 |
| 8 | 46.87 | 44.70 | 2197.08 | 1998.43 | 2095.40 |
| 9 | 55.11 | 46.87 | 3036.72 | 2197.08 | 2583.00 |
| 10 | 58.46 | 55.11 | 3417.21 | 3036.72 | 3221.35 |
| 11 | 57.74 | 58.46 | 3333.35 | 3417.21 | 3375.02 |
| 12 | 53.88 | 57.74 | 2902.67 | 3333.35 | 3110.56 |
| 13 | 53.45 | 53.88 | 2857.32 | 2902.67 | 2879.90 |
| 14 | 54.61 | 53.45 | 2982.05 | 2857.32 | 2919.02 |
| 15 | 55.45 | 54.61 | 3074.93 | 2982.05 | 3028.14 |
| 16 | 55.59 | 55.45 | 3090.29 | 3074.93 | 3082.60 |
| 17 | 57.49 | 55.59 | 3305.18 | 3090.29 | 3195.93 |
| 18 | 59.30 | 57.49 | 3516.73 | 3305.18 | 3409.31 |
| 19 | 62.31 | 59.30 | 3882.21 | 3516.73 | 3694.95 |
| 20 | 61.56 | 62.31 | 3789.28 | 3882.21 | 3835.46 |
| 21 | 58.38 | 61.56 | 3408.27 | 3789.28 | 3593.73 |
| 22 | 54.97 | 58.38 | 3021.46 | 3408.27 | 3209.04 |
| … | ……. | ……. | ……. | ……. | ……. |
| … | ……. | ……. | ……. | ……. | ……. |
| … | ……. | ……. | ……. | ……. | ……. |
| 667 | 53.49 | 59.02 | 2861.33 | 3483.00 | 3156.90 |
| 668 | 51.10 | 53.49 | 2611.12 | 2861.33 | 2733.36 |
| 669 | 51.40 | 51.10 | 2641.67 | 2611.12 | 2626.35 |
| 670 | 47.11 | 51.40 | 2219.29 | 2641.67 | 2421.29 |
| 671 | 40.91 | 47.11 | 1674.00 | 2219.29 | 1927.46 |
| 672 | 35.48 | 40.91 | 1258.80 | 1674.00 | 1451.63 |
| Total | 30242.31 | 30251.87 | 1420090.45 | 1420860.63 | 1414078.84 |
| **r** | 0.89165 | | | | |

**Table 4.3 Sample Calculation for Correlation Coefficient between X (Electric Load) and Y (1-Hour Ago Electric Load)**

Correlation coefficient, r

$$= \frac{n\sum XY - \sum X \sum Y}{\sqrt{[n\sum X^2 - (\sum X)^2] * [n\sum Y^2 - (\sum Y)^2]}} \quad (3)$$

## 5. IMPLEMENTATION AND RESULTS

The results that implement in various 24-hour load forecasts using trained ANN. Scatter plots for the forecasted inputs are presented to visually see the correlations and trends between the predictors and the load. A list of forecasted results 24 hours a week for each season is listed. The Maximum Percent Error column in Table is the highest integer error value obtained for all hours from the 24-hour load forecast day. The ANN cannot predict these events, so a one or two hour outage on a major distribution feeder will have a significant impact on the resulting error. If these events did not occur, then the error would have been much less. Figures 3 through 5 are plots showing the forecasted and actual load profiles.

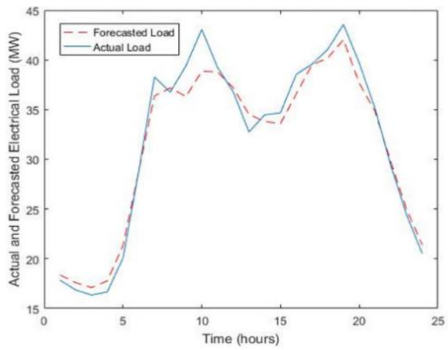


*Figure 3. Forecasted and Actual Load Profile*

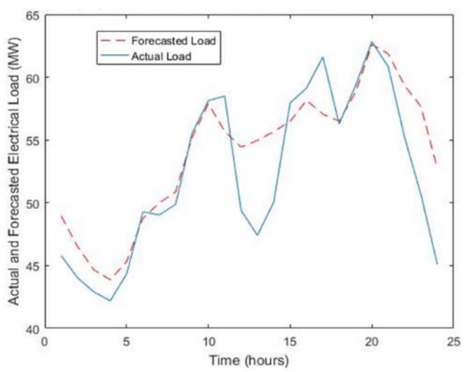


*Figure 4. Forecasted and Actual Load Profile for May*

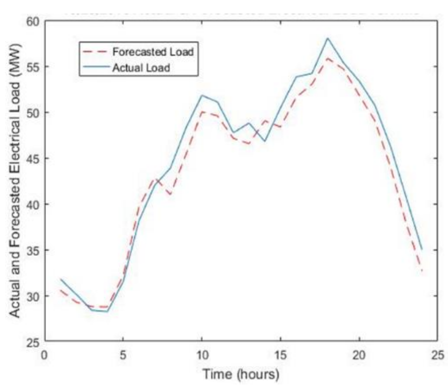


*Figure 5. Forecasted and Actual Load Profile for October*

The hourly forecasted load, actual load, and absolute percent errors associated with each forecasted load profile in Figures 3 through 5. The higher absolute percent errors occurred during the hours when the load profile approached the peak, peaked, and left the peak. The higher error value on May 21 (Holiday), 2016 occurred during minimum load levels. All ANNs were trained on four weeks (28 days) of input data. This value was selected by trial and error to determine the minimum number of weeks of training that would lead to the wrong estimate. Limiting the training input data to a small number of weeks keeps the data within the same season, and so the use of Pearson's correlation coefficient is justified since the weather input variables in a specific season had linear relevance with the load values in that same season.

If the input data set was too large, the ANN could not generalize its output, and the resulting forecast error would increase. Increasing the number of hidden-layer neurons increased the program runtime because the weights and biases of each neuron have to be calculated and the best during network training. A very complicated network could not generalize on the out-of-sample data set and would over-fit the in-sample data. The MATLAB program ANN training runtime typically take 1 minute when using a minimum correlation coefficient of 0.7, four training weeks, 70:15:15 training ratio and 10 hidden layer neurons.

## 6.CONCLUSION

There must be a goal for every power system manager to have their power system operate efficiently, securely, and economically. The main objective of this thesis is to provide power system planners with an accurate and reliable short term load forecasting (STLF) system which may assist to optimize power system operations.

The result of this neural network model used for one day ahead short-term load forecasting for Myauk Pyin Substation (Mandalay) shows that this system has a good performance and reasonable prediction accuracy was achieved. The results suggest that ANN model with the developed structure can perform good prediction with the least error and so this feed forward neural network could be an important tool for STLF. Thus, this short-term electric load forecasting system provides the inside operations in making power system operational decisions.

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