Load Forecasting Using Artificial Neural Network

Dissertation submitted in fulfillment of the requirements for the
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in
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Submitted by
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DECLARATION

I hereby certify that the work which is being presented in the dissertation entitled, **"Load Forecasting Using Artificial Neural Network"** in the partial fulfillment of the requirement for the award of the Degree of **Master of Engineering** in **Power Systems**, submitted to **Electrical & Instrumentation Engineering Department** of **Thapar Institute of Engineering & Technology, Patiala**, is an authentic record of my own work carried under the supervision of **Dr. Sanjay K. Jain and Ms. Navdeep Kaur**. It refers other researcher's work which is duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other university except as reported in the text and references.

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This is to certify that the above statement made by the candidate is correct and true to best of our knowledge.

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ABSTRACT

The key role of load forecasting is the power system energy management system. Load forecasting helps to diminish the production cost, spinning reserve capacity and enhance the reliability of the power system. Load forecasting is tremendously essential for financial institutions, power suppliers and other participants in electric energy market i.e. transmission, generation and distribution. The economic allotment of generation is a vital purpose of short term load forecasting.

This thesis presents a solution methodology using an artificial neural network for short term load forecasting. The inputs using for forecasting the load, i.e. Dry bulb temperature, Dew point temperature, humidity and load data. The load data is taken from the 66kv substation, Bhai Roopa, Bathinda and weather data from weather stations “IMD” Pune. The data are taken from the year 2015 and 2016. The back propagation algorithm has been implemented to minimize the error function derived on the basis of computed load and actual load. The effectiveness is also checked through its implemented under the MATLAB environment. Where, the Levenberg Marquardt algorithm is used and the performance is investigated under Multilayer Neural Network.

Key words: Short term load forecasting, Back Propagation, Levenberg Marquardt.

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ABRREVIATION

STLF	Short Term Load Forecasting
ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Variables
ARMAX	Autoregressive Moving Average with Exogenous Variables
MIMO	Multi-Input-Multi-Output
ABC	Artificial Bee Colony
EP	Evolutionary Programming
WPT	Wavelet Packet Transform
GMI	Generalized Mutual Data
LSSVM	Least Square Support Vector Machine
FARMAX	Fuzzy Autoregressive Moving Average with Exogenous Input Variables
ANFIS	Adaptive Neuro-fuzzy interface system
GPSO	Global Best Particle Swarm Optimization
BP	Back Propagation
RHONN	Recurrent High Order Neural Networks
LM	Levenberg Marquardt

NOTATIONS

e_l	Error signal at the output of neuron l
d_l	Desired response for neuron l
y_l	Functional signal appearing at the output of neuron l
$\xi(n)$	Instantaneous sum of error squares
N	Time step
w_{li}	Synaptic weight
$\Delta w_{li}(n)$	Correction applied to the weight
$v_l(n)$	Induced local field
$\varphi_l(.)$	Activation function
b_l	Bias applied to neuron l
$x_l(n)$	i_{th} element of input vector
$o_m(n)$	K_{th} element of the output vector
w	Weight of the network
d_{kp}	Desired value for the k^{th} output and the p^{th} pattern
o_{kp}	Actual value of the k^{th} output and the p^{th} pattern
N	Number of entries in training set
W	Total number of parameters (weight and bias) of the network

CHAPTER-1
INTRODUCTION

1.1 OVERVIEW

Power utilities are needed to supply reliable power to consumers. Within style stages, utilities have to be compelled to set up ahead for predictable future load development underneath totally different attainable situations. Their choices and styles will have an effect on the profit or loss of crores of rupees for his or her organizations/utilities moreover as client fulfillment and future monetary process in their space. For efficient operation and planning of utility company, correct models of power load prediction are necessary. Load forecasting is a very essential tool for an electrical utility to form necessary choices together with choices on the purchase, also for banking of power (with alternative corporations or identical state utilities or with the neighboring states), in the generation of power, in load change and development in infrastructure [1]. It is very necessary for energy suppliers as well as for other alternative participants within the electrical energy transmission, generation, distribution, and markets.

For electric utilities, accurate forecasting of load accurately plays an awfully necessary role due to exceeding cutthroat competitive surroundings shaped by the electric business deregulating. An electric company is confronted with several economists and technical operational issues, along with planning and management of a utility electric system since customers should be provided electricity of high-quality in an exceedingly efficient and safe manner [1]. Load forecasting is also beneficial for an electric utility in creating necessary selections on generating, interchanging, and buying wattage, load change. Besides this, it is important for suppliers' utility, many establishments and others concerned with the electric energy generation and regulation [2].

Load forecasting strategies can be classified into four parts i.e. very short, short, medium and long-term models in accordance with the time duration. In very-short-term forecasting, the time span may be short a few minutes whereas in long-term forecasting it may start with few years and can extend up to few decades. In dissertation work, short-term load forecasting is mainly concentrated.

With the modern phenomena of the liberation of electricity markets, STLF has acquired additional importance and larger problems. Within the atmosphere of the market, precise forecasting is that foundation of the trading of power and the damage establishment of the system to achieve the lowest electricity buying price.

1.2 LITERATURE REVIEW

There is far diversity in the load forecasting and its strategies so it's unattainable to enrich them within the restricted time duration. So, in this part of the introduction, the literature review on load forecasting and techniques is briefly summarized. This literature review about other topics is also discussed below. A revealed literature review is divided into 5 main parts:

(i) Multiple Regression Method

One of the foremost wide used statistical approaches is a regression. For load forecasting, multiple regression strategies are sometimes utilized to relate link between load utilization and alternative elements like day type, weather and client category.

Nikolic *et al.* [3] conferred that for consecutive day load forecasting there are many multiple regression models. Their models incorporate settled significances like stochastic influences, holidays like exogenous influences and average loads like the weather. [4–6] express alternative purpose of multiple regression models exercised to load forecasting.

(ii) Time Series

The time series methodology is created on the assumption that information has several internal structures resembling trends, seasonal variation or autocorrelation. Uttermost typically used traditional time series strategies are a unit ARIMA (autoregressive integrated moving average), ARMA (autoregressive moving average), ARIMAX (autoregressive integrated moving average with exogenous variables) and ARMAX (autoregressive moving average with exogenous variables). Implementations of ARIMAX models for load forecasting have been presented by Fan and McDonald [6] and Cho *et al* [7]. A unique hybrid algorithmic rule for price/load forecasting. The hybrid algorithmic rule is classed into 3 parts; versatile wavelet packet transform, multi-input-multi-output (MIMO) model and autoregressive integrated moving average (ARIMA), artificial bee colony (ABC) algorithmic rule supported time-varying coefficient and stumble generation operator that's referred to as TV-SAC. Yang *et al*. [8] used Associate in nursing evolutionary programming (EP) approach to spot the ARMAX model parameters for some unspecified time in the future so that there should be hour load demand forecast at least one week ahead. The EP could be a technique for simulating evolution and constitutes a stochastic optimal algorithmic rule. In [9] multi-input-multi-output (MIMO) model has been used for the correlation between electricity value and load. The model encompasses 3 elements referred to as wavelet packet transform (WPT), generalized mutual data (GMI) and least square support vector machine (LSSVM). A fuzzy autoregressive moving average with exogenous input variables (FARMAX) at some unspecified time in the future ahead hourly load forecasting is projected by Yang and Huang [10].

(iii) Expert System

Discussing the short-term forecasting for power grid based in Taiwan, Ho *et al*. [11] present the knowledge-based skilled system. Based on the hourly recorded data of system load and various weather parameters for five years along with the local operator's information, the forecasting has been performed. Presenting the location independent short-term forecasting technique, Rahman and Hazim [12] discussed the various factors affecting the forecasting and represented them in the parametric form as a defined rule base. Whereas, this rule base is dependent upon the location and varies accordingly. The results, considering location independent forecasting for various sites shows the approach to be fit, i.e. gives low forecasting errors. Thus, irrespective of the forecasting location, the load model, developed rule base system and the other parameters have been designed.

(iv) Fuzzy Logic

Presenting the fuzzy logic approach for load forecasting, in [13] various fuzzy based models based on the recorded data for two years, i.e. 2009-2011 have been shown. The work discusses the fuzzy logic based forecasting of the load for the off-days, i.e. holidays. The results show accurate load forecasting and thus its benefits to the power system (in terms of economic load dispatch). Overcoming the statistical forecasting approaches which included the mathematical formulation of the given problem, fuzzy logic based forecasting approach is solely dependent upon the rule base designed in fuzzy toolbox [14]. Thus, the approach proves to be robust in the area of load forecasting. Also, as discussed by [15], the drawback of various forecasting tools and approaches, i.e. absence of crisp output is a major issue. Hence, in the fuzzy logic based system; the defuzzification process depending upon the various inputs and rule base gives a crisp output value. Working on the validation of fuzzy logic based forecasting approach, the results of fuzzy depending upon the data of 1 year and for ANFIS compared with the online load data, shows MAPE to be 2.1 and 1.85. Presenting a comprehensive review of the various forecasting methodologies, [16] discusses the need, advantages and various applications of fuzzy logic based forecasting approach. Comparing the performance of fuzzy logic based system with back propagation neural network method based on historical data, shows the later to be more complex and difficult to understand in comparison to fuzzy logic models.

(v) Neural Networks

With the awareness of neural network approach in the area of forecasting, in the year 1990, the approach was first time developed for the problem of load forecasting. With parallel and distributed units for processing, the neural network can be defined as the set of arrays including series of the repetitive uniform processor while connected to the grid. In a neural network, the two important key terms are learning and training. The learning in NN can be done by various methods like interconnecting the various processors of NN with each other [17]. Using the Neuroshell-2, in [18] short-term load forecasting have been done. Based on the neural network approach and other systems like the Expert system, Grey system theory and artificial neural network [19], the short term load forecasting gives satisfactory results. Comparing the forecasting system in real time with the available data shows NN tool to be more accurate and reliable. Focusing on the advantages of back propagation type neural network in load forecasting, it can be defined as a multilayer feed forward neural network (FFNN) consisting of a nonlinear function and a transfer function.

Discussing the properties of BP, The .transfer function that can be obtained from the network will be linear or non linear input of the network depends upon the input to the network and the number of layers can also be increased up to 3 or 4 as required. It can also be fully connected or partially connected. The network of neural may be fully connected or non-fully connected. In [16] [20-22] the neural network is designed which is a three layer network having a transfer function as a nonlinear sigmoid function in the short term load forecasting. In [23] brand new technique has been utilized that is global best particle swarm optimization (GPSO) to boost the performance of ANN. To get the higher training, performance, convergence characteristics and forecast accuracy the ANN, GPSO, and BP techniques have been used. In [24] the input layer to the output layer has been planned to get the standard sigmoid function and a linear transfer function. In [25] BP model is planned. it can be understood that the results obtained from the ANN was ready to have load characteristics, even though a partially connected ANN is favorable for replacing the temperature changes. Apart from this, [25] better forecasting results can also obtained by the combination of several sub-ANN with the help of STLF approach. In [26] well planned recurrent high order neural network (RHONN). A 3-layer ANN through appropriate dimension is spare to estimate any uninterrupted non-linear function [26]. Load forecasting using a four-layer formation is enforced and the structure was reported in [11], [17], [27].

BP network can be a fair array which can see nonlinear mapping from input to output. After this, the choice of the input variable of load prediction network is of great importance. Generally, there are 2 options strategies. An expertise depends on [11], [17], [20], [24] and this option depends on statistical analysis related to ARIMA [25] and correlation analysis. Input variables are usually determined by engineering decisions and skills. In order to collect all things, the input variable can be grouped into five fundamental classes:

1. Historical loads [17-21], [24-26], [28].
2. Temperature [17-20], [24-25], [28].
3. Relative humidity [28].
4. Hour of day index [17], [20], [25].
5. Day of the week index [17], [25].

Intensive study on the effects of factors related to learning phase, bpm is presented by the authors of the motion factor [22]. He investigated a learning algorithm for adaptive training of neural networks. For the complete error function is employed in a predefined learning algorithm [29] by the principle of "forced dynamic". The rate of modification of the network weight is given priority, for reducing the error function is forced to "decay" through a shear mode. In the direct proportion of the total error, the partner approach to change the weight is in [30]. With this, the period of the postponement zone unit is very short and the risk of the crowd in the country minimum has been greatly reduced. With this, the periods of stagnation area unit a lot of shorter and also the risk of tack in native minima are greatly reduced.

ANN can only perform operations according to the trained data whereas in case of STLF the selection of training sets was quite complicated. The selection was based on the similarity of characteristics of the training pairs present in the training set must be same as those to the forecasted in that day. To get smart forecasting results, day type data should be taken under consideration. A technique is to construct the various ANNs for everyday type and fed every ANN with the corresponding day type training sets [28]. The opposite is to use only one ANN, however, contain the day type data within the input variables [17], [21], [25]. The previous uses a variety of comparatively little size networks, whereas the latter has only one network of a comparatively giant size. A typical classification given in [17] categorizes the historical loads into 5 categories. These are a Monday, Tuesday-Thursday, Friday, Saturday and Sunday/Public vacation. The traditional ways to use observation and comparison [17], [24], and was supported unsupervised ANN ideas and selects the training set automatically [11], area unit used for day type classification.

1.3 OBJECTIVE OF THESIS

The main objective of the thesis work is to develop a solution methodology and algorithm to forecast, hourly peak load; by incorporating weather conditions i.e. dew bulb temperature, dew point temperature and humidity. In this work, an attempt is made to implement the above forecast using an artificial neural network approach, i.e. backpropagation algorithm and Levenberg Marquardt algorithm. The work proposed here is allocated into three steps:

1. Data collection.
2. Development of Backpropagation algorithm and Levenberg Marquardt algorithm for hourly load forecasting for short-term load forecasting.
2. Short term load forecasting using the trained neural network the hourly load is forecasted.

1.4 ORGANIZATION OF THESIS

The thesis is organized into five chapters as shown below:-

1. Chapter 1 covers the overview, a brief summary of the literature review, objectives of thesis and the organization of thesis.
2. Chapter 2 covers short-term load forecasting in brief and methodology.
3. In Chapter 3, error back propagation algorithm and results are covered.
4. Chapter 4 summarizes the Levenberg Marquardt algorithm and the comparison between the results of single layer and multilayer network.
5. In Chapter 5, the summary of conclusions and future scope

CHAPTER- 2

SHORT TERM LOAD FORECASTING

2.1 OVERVIEW

In power system planning, generation and transmission, operation and control the load forecasting plays a crucial part [31]. Forecasting suggests that calculating active load at numerous load buses previous actual load prevalence. Application of load forecasting in planning and operation needs an exact 'lead time' additionally known as forecasting intervals. Categorization of load forecasting with respect to lead time is presented in Table 2.1.

Table 2.1. Categorization of Load Forecasting.

Nature of forecast	Lead time	Applications
Very short term	few seconds to few minutes	Scheduling of generation and distribution, power system security analysis
Short term	Half an hour to the number of hours	Unit commitment and spinning reserve allocation
Medium term	Few days to a number of weeks	Planning for seasonal peak winter, summer
Long-term	Up to one year	Planning generation growth.

There are mainly three types of categorization for load: short-term forecasting generally done from few hours to one week, medium-term forecasting is done from few weeks to a year, and long-term forecasting is done for more than one year. In an organization, it is necessary to forecast at various time horizon for various operations. These forecasts are distinct in nature. Most of the strategies employ statistical methods or artificial intelligence algorithms like fuzzy logic, regression, expert system and neural networks. From medium and long-term load forecasting, end-use econometric technique is widely used. For STLF, various strategies are employed such as fuzzy logic, different regression models, statistical learning techniques, time series, expert systems and similar day methods.

Based on historical climate observations, it is conceivable to give probability distribution of load for consecutive year peak forecast. Furthermore, weather normalized load prediction is attainable corresponding to industry practice, which would happen for normal yearly peak climate or inferior to normal peak climate conditions for a given zone. Weather-normalized load is defined as the load computed for an average of atmospheric characteristics for peak historical loads within a specific time frame. The span of this time period fluctuates starting from one utility then onto the next. A few organizations take the end thirty years historical data.

2.2 CLASSIFICATION OF LOAD FORECASTING METHODS

Load forecasting strategies are categorized into four classes [31] in terms of lead time.

- Very short-term load forecasting.
- Short-term load forecasting.
- Medium-term load forecasting.
- Long-term load forecasting.

Short-term load forecasting can use to evaluate load flows and also helpful in prohibiting overloading. Aforementioned selections prompt network reliability and decrease happening of apparatus failures and power outages. Within the deregulated economy, selections on costs supported long-term forecasting also are additional necessary than in a very non-deregulated economy once rate will increase may well be even by capital expenditure projects.

For short-term load forecasting, numerous variables must be deliberated, similar to climate data, time factors, and possible consumer’s categories whereas the medium and long-term forecasts consider the climate data and historical data, number of customers in numerous categories, the apparatuses in the zone, economic and statistic data and their forecast, the apparatus deals information and different factors. There are necessary fluctuations in load amongst the weekdays and end of the week. The load on the various weekdays can change in a different manner, for instance, Mondays and Fridays being nearby ends of the week, may have basically unexpected loads in comparison to Tuesday through Thursday. This is especially valid amid the late spring. Holidays are more crucial to forecast as compared to working days in view of their relatively rare incidence. The difference in the climate causes, the difference in the customer's amenity feeling and thus utilization several apparatus corresponding to the refrigerator, water heater, tv.

2.3 FORECASTING METHODOLOGY

Forecasting techniques can be divided into three broad categories. These include extrapolation, correlation, and the combination of both the techniques. Techniques can be subclassified as deterministic, probabilistic or stochastic.

1. Extrapolation involves fitting trend curves to basic chronological data adjusted to replicate the growing trend itself [32]. The most common curve fitting technique for fitting coefficients and exponents of a function in a very given forecast is that the methodology of least squares.

2. Correlation method based technique of forecasting relates system loads to numerous demographic and economic factors. This approach is advantageous in forcing the forecaster to know clearly the interrelation between load growth patterns and different measurable factors.

2.4 NECESSARY FACTORS FOR FORECASTING

For short-term load prediction, similar to the time factors, weather data, and potential customer categories, many variables should be considered. Medium and long-term forecasts, chronological weight and weather data, consider the number of customers in the Different categories, areas within the field and their characteristics, as well as age, economic and demographic data, and their predictions, equipment sales data, and various Factors forecasts, the appliance sales data, and different factors.

Weather conditions influence the load. In fact, a predicted weather parameter is the most important factor in short-term load forecasts. Many weather variables can be thought of as load forecast. Temperature and Humidity are the most commonly used load predictions. Most electric utilities serve clients of different sorts, such as commercial, industrial, and residential. The power usage pattern is for different customers which are related to different categories, however, in some categories, it is somewhat similar to the customers.

2.5 FORECASTING STRATEGIES

There are a variety of techniques that can be used in the STLF such as fuzzy logic, regression model, neural network, statistical learning algorithm and time series.

Statistical approaches completely require the mathematical model that can represent a dependency of load on various factors such as time, weather and customer. The mathematical model further sub-divided into two categories including additive model as well as a multiplicative model. These models further differ in various terms on the basis of load forecasted load which is considered as the multiplicative nature of various factors or addictive nature of that factor too.

2.5.1. Medium and Long-Term Load Forecasting Strategies

The previously discussed modeling approaches such as economic modeling, end-use modeling and the combination of both these approaches are used for the medium and long-term forecasting.

(i) End-use models:- This approach are utilized for the direct measurement of energy consumption on the basis of information based on several factors such as customer use, the size of the houses and the customer age [33]. Statistical information concerning customers besides the dynamics of the amendment is considered as the basis of the forecast.

(ii) Econometric models:- The electricity demand was forecasted by the effective combination of two approaches including statistical approach as well as economic theory approach. These approaches were further utilized for the representation of the relationship between the factors that affect the consumptions and the energy consumption itself. The calculation done for the measurement of relationship parameters between these approaches depends upon the least square method and sometimes time's series method.

(iii) Statistical model- Based learning the previously discussed strategies and the end user are depends upon the factor like economics and the customers etc the active participation is also needed for the various applications related to these approaches.

2.5.2. Short-Term Load Forecasting Strategies

A large type of statistical and artificial intelligence techniques are developed for short-term load forecasting.

(i) Similar day approach:- These approaches are assumed on the basis of extensive information for the days. These approaches are also considered for the forecasting of the weeks as well of the year on the basis of forecasted data which was used for the one year. The same rules are further applied for the forecasting of weekdays due to which these methodologies also consider as one of the benchmark function for the forecasted model.

(ii) Regression methods:- The regression approaches was highly utilized for the statistical techniques and the utilization of multiple regression was also done to find the hidden relations between dependent as well as independent parameters. The least square method was highly considered for these approaches including the variations in the sum of the square of expected values as well as determined one.

(iii) Time series:- This approach was also considered for the measurement and the estimation of the forecasting values. They can also be used for various factors such as electrical load forecasting and also for economics etc [34]. There were also some of the approaches that were considered for the classical time for the measurement such as Autoregressive Integrated Moving Average (ARIMA), Autoregressive Moving Average with Exogenous Variables (ARMAX), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average with Exogenouey can also be used for the various factors such as electrical load forecasting and also for economics etc.

(iv) Neural networks:- Load forecasting can also be done in quite an effective manner by the utilization of neural network for the system forecasting. The output of neural network must be linear or non-linear on the basis of the input data that can also be considered as the output of previously designed neural network [35]. The organization of neural network within the range can be accomplished by the effective use of input-output data. Sometimes feedback can also be used to improve the performance of the complete network [30]. During the implementation of a neural network for the forecasting, one should consider various parameters like the size of the neuron, relative connectivity between the layers and the elements and the utilization of uni-directional or bi-directional link within the network. Therefore, the pre-operational training neer be considered for unsupervised learning.

(v) Expert systems:- Various rules, as well as different procedure, are considered in this approach is completely related to the field of the system forecast. The rule-based forecasting was highly effective for its implementation in the load forecasting. These approaches work best whenever the data considered by the human expert for its incorporation within the software for system forecasting.

(vi) Fuzzy logic:- This technique was considered as one of the most effective methods for the mapping of the input to the output. The absence of the mathematical modeling within the system make this technique more effective in comparison to other technique as its output was highly precise [36]. For the effective utilization of Boolean logic for the digital output, fuzzy logic considered as one of the best technique for this particular application.

(vii) Support vector machines:- this technique was highly effective for the minimization of issues related to the regression and also considered one of the modern technology in the field of forecasting. It basically immerged from the statically learning theory [37]. This machine commonly utilizes linear variables for limiting the decision boundaries within the desired space.

2.6 PURPOSE OF LOAD FORECASTING

The need for load forecasting:

i. Power grid planning.

ii. Planning of transmission and distribution facilities.

iii. Power grid operation.

iv. Finance.

v. Manpower development.

vi. Grid information.

vii. Electrical sales.

CHAPTER- 3

IMPLEMENTING LOAD FORECASTING USING BP ALGORITHM

Back Propagation (BP) alludes to a wide group of ANN, whose design comprises of various interconnected layers. The learning algorithm of BP is based on the Deepest Descent technique. The proper number of hidden units limits the error of the non-linear function of high complexity. BP is a systematic technique of training multilayer ANN. It is designed on a high mathematical foundation and has excellent application potential. The networks include sensory units that represent the input layer, one or more hidden layers of calculation nodes, and the output layer of the calculation nodes. Input signals on a layer-by-layer basis propagate through the network in the forward direction. These neural networks normally allude to as a multilayer perceptrons as shown in Figure 3.1.

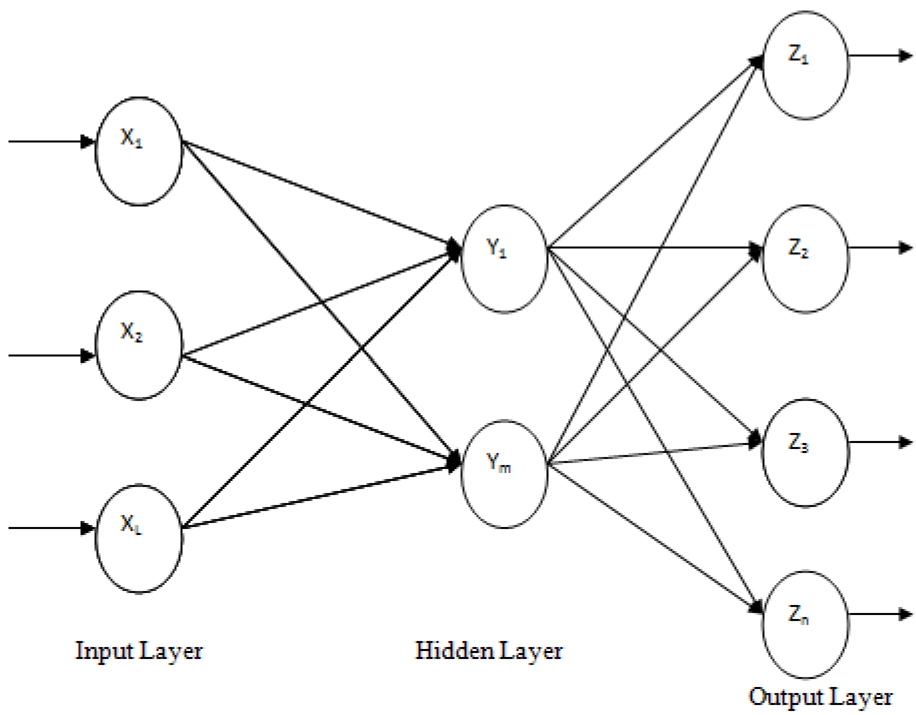

Figure 3.1 Multi-Layer Fed Forward Network.

3.1 ERROR BACK PROPAGATION

Error back propagation basically, a implementation of multilayer perceptrons in such a supervised manner with the help of comprehensive algorithm, with success to solve some difficult and different variations. This algorithm depends on the error of learning error correction. While considering the different layers of the neural network, there was basically two passes while learning error back propagation first one is the forward pass and second one is the backward pass. Within the forward pass, it was a type of activity pattern that can be applied on the sensor node of the neural network, and its effect is propagated by the layer via the network layer [38]. Finally, due to the actual response to the network, a set of output has been created. In case of forward pass, the load was considered to be mounted on the network. On the basis of error correction rule, the load was adjusted in the network in case of backward pass which was quite different from the forward pass case. Error signal can be generated by the difference of the network output and the desired output and further the generated signal was transferred within the network but in the backward direction due to which it was called error backpropagation. Back propagation method was utilized for the estimation of weight within the network [39],for the analysis of the network , this method considered the loss function with respect to output of the neural network need to be analyzed which typically means that the desired target value is known. BP is a supervised learning method. It was basically a formation of rule by the feed forward neural network by the utilization of chain rule for each layer of the network..

3.2 BACK PROPAGATION ALGORITHM

Figure 3.2 represents the flowchart of the backpropagation training algorithm for a fundamental two-layer network as appeared in Figure 3.1. The BP algorithm is briefly explained below:

The error signal at the output for l^{th}neuron at n^{th}iteration:

$$\frac{\partial \xi(n)}{\partial y_l(n)} = \sum_m e_m \frac{\partial e_m(n)}{\partial v_m(n)} \frac{\partial v_m(n)}{\partial y_l(n)} \tag{3.1}$$

Total error energy obtained

$$\xi(n) = \frac{1}{2} \sum_{j \in C} e_j^2(n) \tag{3.2}$$

The average square error energy is

$$\xi_{av} = \frac{1}{N} \sum_{n=1}^{N} \xi(n) \tag{3.3}$$

The input of the activation function with l^{th} neuron is

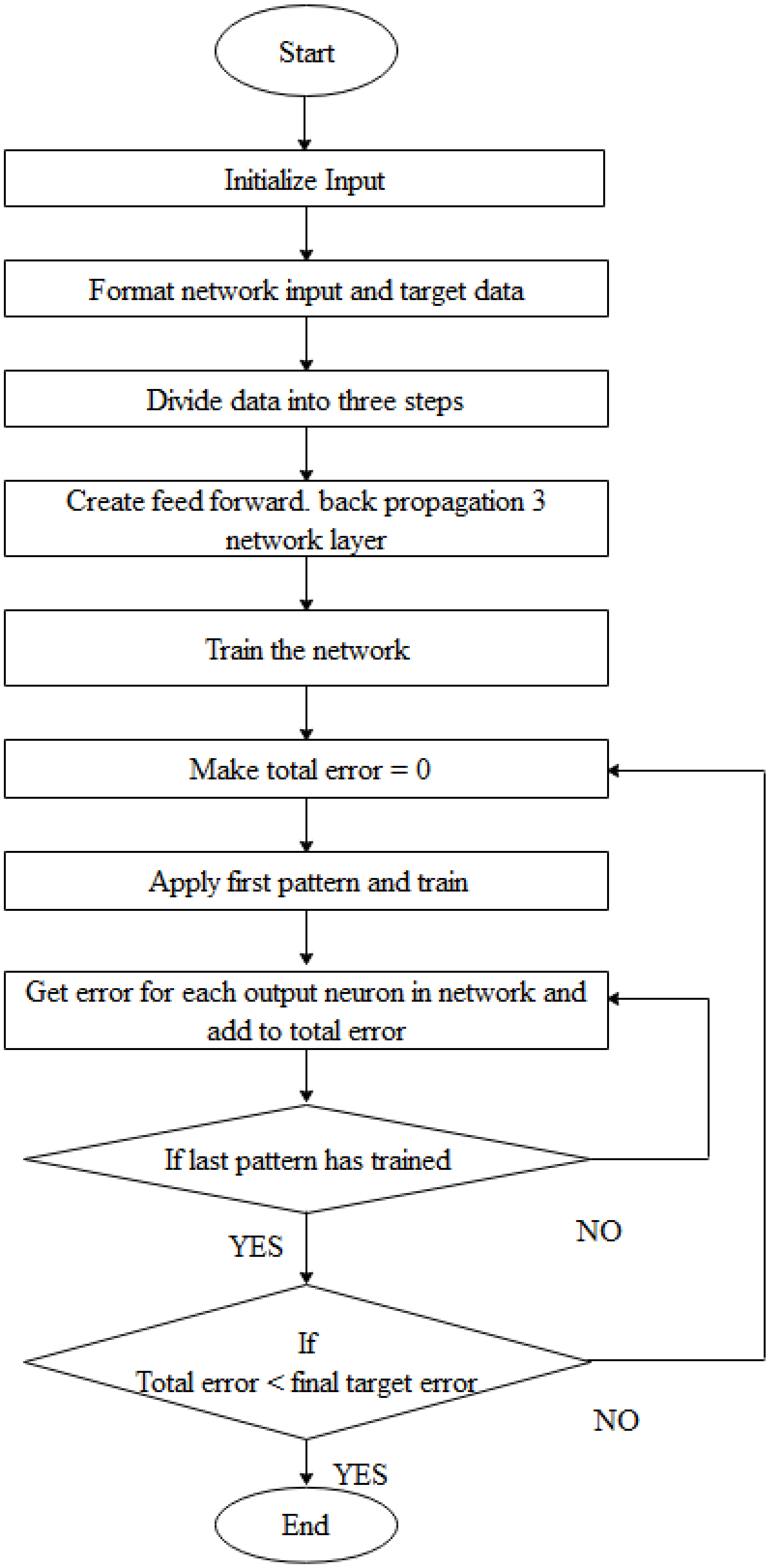

Figure 3.2 Backpropagation Flowchart

$$v_l(n) = \sum_{i=o}^{p} w_{li}(n)\, y_i(n) \tag{3.4}$$

The synaptic weight w_{l0} equals the bias b_l applied to neuron l. The functional signal $y_l(n)$ appearing at the output of l^{th} neuron at n^{th}iteration.

$$y_l(n) = \varphi(v_l(n)) \tag{3.5}$$

The chain rule is,

$$\frac{\partial \xi(n)}{\partial w_{li}(n)} = \frac{\partial \xi(n)}{\partial e_l(n)} \frac{\partial e_l(n)}{\partial y_l(n)} \frac{\partial y_l(n)}{\partial v_l(n)} \frac{\partial v_l(n)}{\partial w_{li}(n)} \tag{3.6}$$

Differentiating both sides of Eq. (3.2) with respect to $e_j(n)$,

$$\frac{\partial \xi(n)}{\partial e_l(n)} = e_l(n) \tag{3.7}$$

Differentiating both sides of Eq. (3.1) with respect to $y_j(n)$,

$$\frac{\partial e_l(n)}{\partial y_l(n)} = -1 \tag{3.8}$$

Differentiating Eq. (3.5) with respect to $v_j(n)$,

$$\frac{\partial y_l(n)}{\partial v_l(n)} = \varphi_l^{'}(v_l(n)) \tag{3.9}$$

Differentiating Eq. (3.4) with respect to $w_{ji}(n)$,

$$\frac{\partial v_l(n)}{\partial w_{li}(n)} = y_l(n) \tag{3.10}$$

Using Eqs. (3.7) to (3.10) in (3.6),

$$\frac{\partial \xi(n)}{\partial w_{li}(n)} = -e_l(n)\varphi_l^{'}(v_l(n))\, y_i(n) \tag{3.11}$$

By the delta rule

$$\Delta w_{li}(n) = -\eta \frac{\partial \xi(n)}{\partial w_{li}(n)} \tag{3.12}$$

η is the learning parameter of the backpropagation algorithm. Use Eq. (3.11) in (3.12),

$$\Delta w_{li}(n) = \eta \delta_l(n) y_i(n) \tag{3.13}$$

The local gradient $\delta_j(n)$ is defined by,

$$\begin{aligned} \delta_l(n) &= \frac{\partial \xi(n)}{\partial v_l(n)} \\ &= \frac{\partial \xi(n)}{\partial e_l(n)} \frac{\partial e_l(n)}{\partial y_l(n)} \frac{\partial y_l(n)}{\partial v_l(n)} \\ &= e_l(n) \varphi_l'(v_l(n)) \end{aligned} \tag{3.14}$$

Case 1 Neuron *l* is an output node

When neuron *l* is located in the output layer of the network, it is supplied with the desired response. Use Eq. (3.1) to compute the error signal and as shown in Figure 3.3. For the calculation of local gradient, this technique was considered as the best suitable approach by using Eq. (3.14).

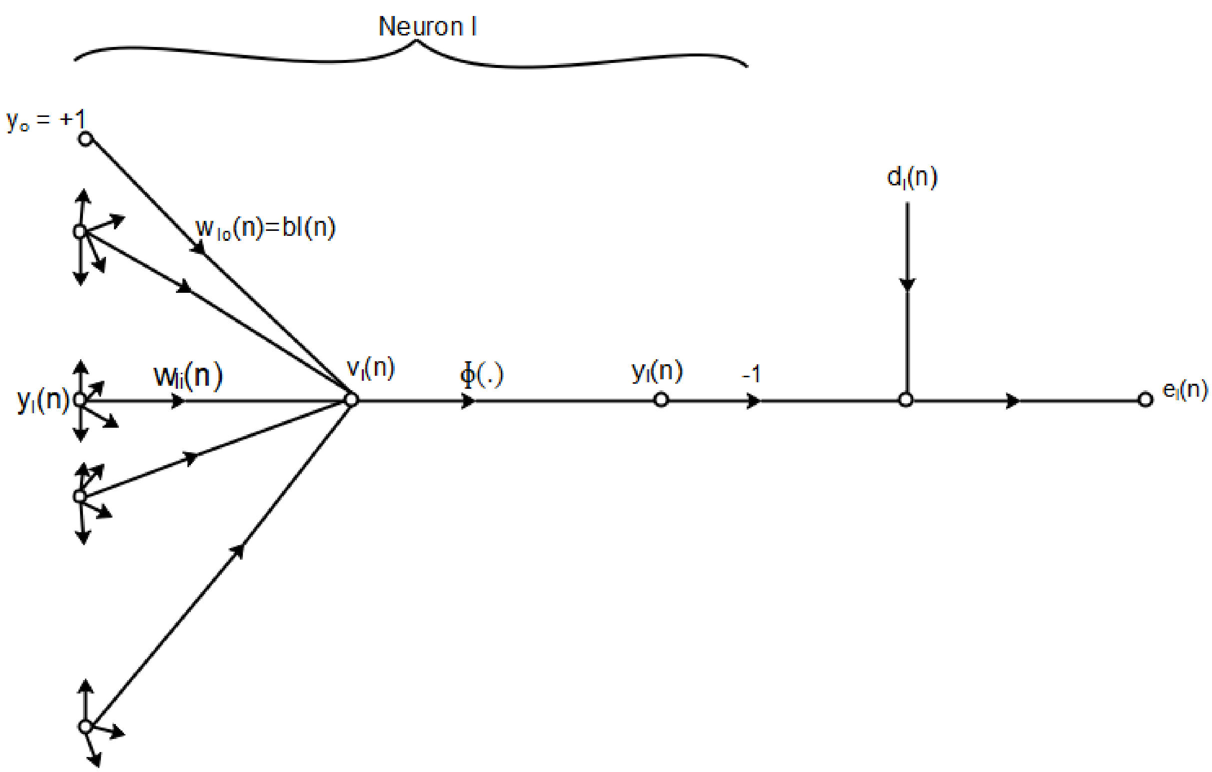

Figure 3.2 Output neuron j signal flow graph

The Case 2 Neuron *l* is a hidden node

When neuron *l* is located in a hidden layer of the network, there is no specified desired response of that neuron. Accordingly, the error signal for a hidden neuron would have to be determined in terms of the error signal of all the neurons as shown in Figure 3.4. According to Eq. (3.14) redefines the local gradient for hidden neuron *l* as

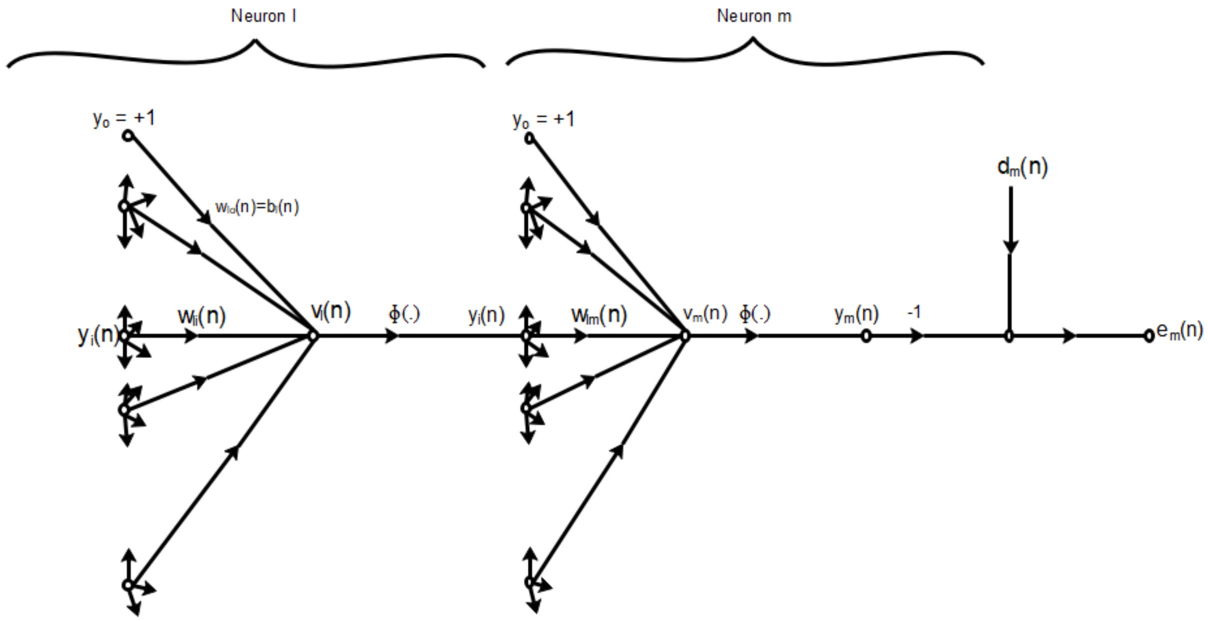

Figure 3.4 Output neuron k connected to hidden neuron j signal flow graph.

$$\delta_l(n) = -\frac{\partial \xi(n)}{\partial y_l(n)} \frac{\partial y_l(n)}{\partial v_l(n)} \tag{3.15}$$

$$\delta_l(n) = -\frac{\partial \xi(n)}{\partial y_l(n)} \frac{\partial y_l(n)}{\partial v_l(n)}, \text{ neuron } l \text{ is hidden}$$

$$\xi(n) = \frac{1}{2} \sum_{l \in C} e_m^2(n), \text{ neuron } m \text{ is an output node} \tag{3.16}$$

Differentiating Eq. (3.16) with respect to functional signal,

$$\frac{\partial \xi(n)}{\partial y_l(n)} = \sum_m e_m \frac{\partial e_m(n)}{\partial y_l(n)} \tag{3.17}$$

Using the chain rule rewriting the Eq. (3.17),

$$\frac{\partial \xi(n)}{\partial y_l(n)} = \sum_m e_m \frac{\partial e_m(n)}{\partial v_m(n)} \frac{\partial v_m(n)}{\partial y_l(n)} \tag{3.18}$$

From Fig. 3.4,

$$e_m(n) = d_m(n) - y_m(n)$$

(3.19)

$$=d_m(n)-\varphi_m\left(v_m(n)\right), \quad \text{neuron } m \text{ is an output node}$$

$$\frac{\partial e_m(n)}{\partial v_m(n)}=-\varphi'_m\left(v_m(n)\right) \tag{3.20}$$

The induced local field for neuron *m*,

$$v_m(n)=\sum_{l=0}^{p} w_{ml}(n)\,y_l(n) \tag{3.21}$$

Differentiating Eq. (3.21) with respect to $y_l(n)$,

$$\frac{\partial v_m(n)}{\partial y_l(n)}=w_{ml}(n) \tag{3.22}$$

Using Eq. (3.20) and (3.21) in (3.18),

$$\frac{\partial \xi(n)}{\partial y_l(n)}=-\sum_m e_m(n)\varphi'_m\left(v_m(n)\right)w_{ml}(n) \tag{3.23}$$

$$=-\sum_m \delta_m(n)\,w_{ml}(n)$$

Getting back propagation formula using Eq. (3.23) in (3.15),

$$\delta_l(n)=\varphi'_l\left(v_l(n)\right)\sum_m \delta_m(n)\,w_{ml}(n), \text{ neuron j is hidden} \tag{3.24}$$

(i) If neuron *l* is an output node, $\delta_l(n)$ equals the product of the derivative $\varphi'_l\left(v_l(n)\right)$ and the error signal $e_l(n)$, with the neuron j as in Eq. (3.14).

(ii) If the neuron is a hidden node $\delta_l(n)$ equals the product of the associated derivative $\varphi'_l\left(v_l(n)\right)$ and the weighted sum computed for the neuron in the output layer that is connected to neuron *l*, as in Eq. (3.24).

3.3 ACCURACY OF FORECASTS

The relative error between the actual and forecasted load demand has been obtained to ensure the accuracy of forecasts. If the error obtained is positive, it symbolizes over forecast indicating that the forecasted load is greater than that of the actual load. For negative values, the case is vice versa. The accuracy is computed by calculating the mean square error (MSE) and root mean square error (RMSE) given as follows

$$MSE = \frac{1}{N}\sum_{i=1}^{n}\left(Load_{actual} - Load_{forecasted}\right)^2 \tag{3.25}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(Load_{actual} - Load_{forecasted}\right)^2} \tag{3.26}$$

3.4 RESULTS AND DISCUSSION

Back propagation was considered as the important ingredient in the short term forecasting. For the forecasting purpose, hourly data was collected from the Punjab electricity board for the various days that helped in the training of the technique as well as for forecasting purpose and also the weather data is taken from the IMD Pune. The dew point temperature, dry bulb temperature, and humidity are taken as input and the load data is taken as the output. To train the network data, the data are divided into three parts, i.e. Validation, Training, and Testing. The BP algorithm is used to train the network and implemented in MATLAB.

The sample data for one day is given in Table A.1. The inputs dew point, dry bulb temperature, humidity and load are presented in Figure. 3.5.

(i) **Dew Point Temperature:** It was basically a temperature value at which the air losses its control over the water vapor due to which some of the air molecules converted in to the water droplet and this particular temperature was lower than the temperature.

(ii) Dry Bulb Temperature: whenever the thermometer was used for the measurement of temperature then it is called dry bulb temperature basically, it was atmospheric temperature read by the thermometer whenever it was exposed in the surrounding.

(iii) **Humidity:** it was nothing but a water droplet which was present the atmosphere but they were completely invisible for the human was basically a water molecules in the gaseous state. As humidity increases, ability of body to resist the sweating capacity reduces due to reduction in the rate of evaporation of moisture from the body**.**

With the help of the training the data the load is forecasted and presented in the Table A.2. The network is trained for 5000 iterations with the presented data. In this, the training function is ‘trainlm’ and the activation function is sigmoid. It is observed that the mean square error is

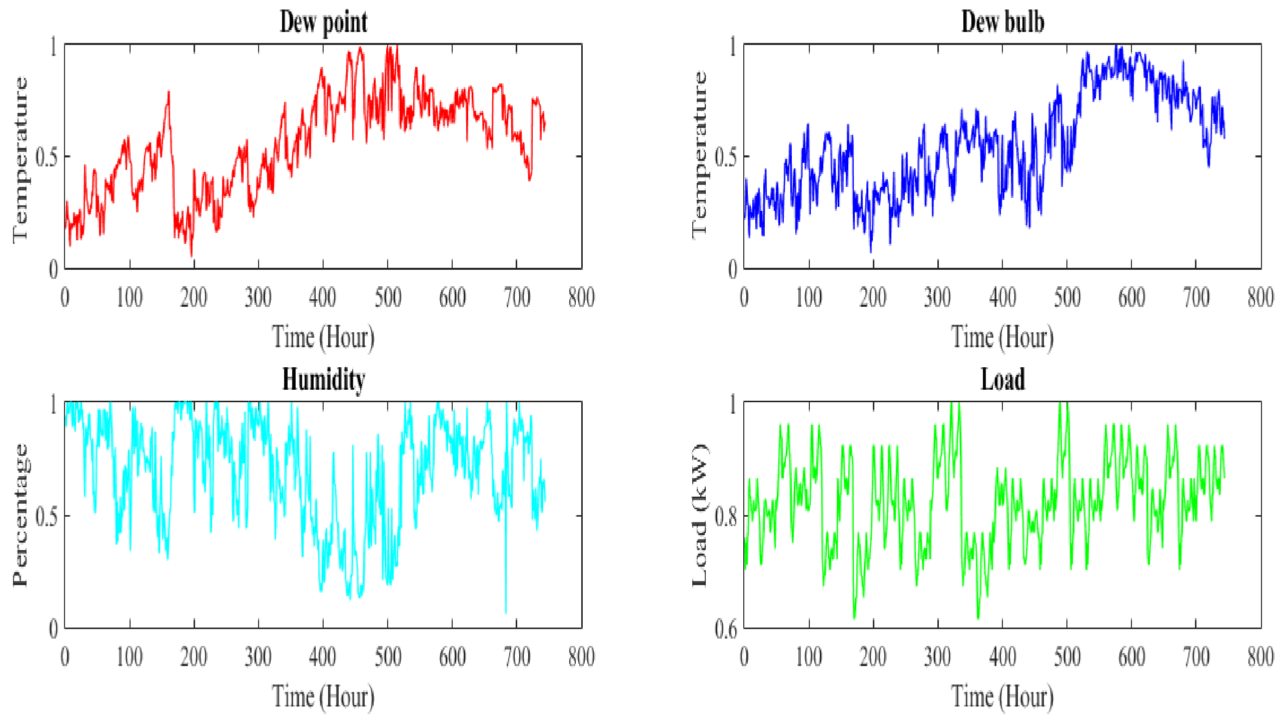

Figure 3.5 Representation of input data

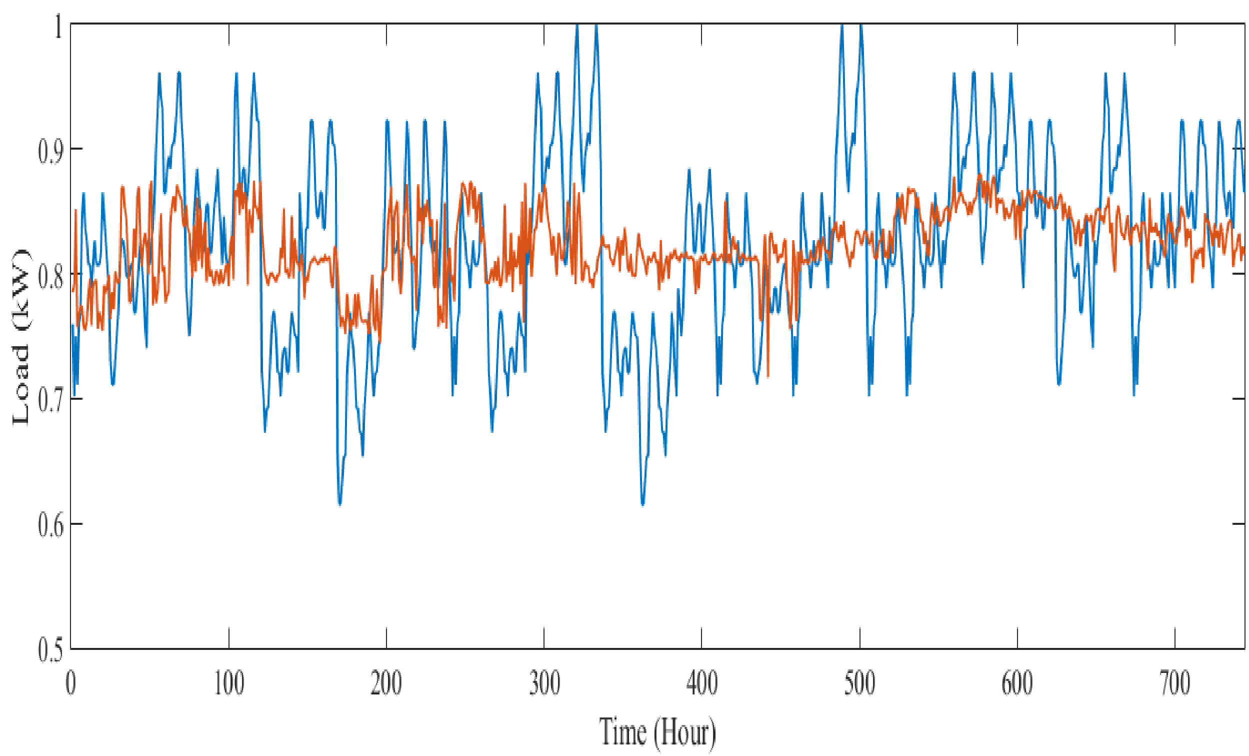

Figure 3.6 Representation of Actual and Forecasted Load

0.0061 and root mean square error is 0.0784 after training it is also observed that the actual load and forecasted load have so much variation or fluctuations as shown in Fig. 3.6. As there is a large variation between actual and forecasted load obtained by BP algorithm. So load forecasting has also been done by Levenberg Marquardt algorithm which is explained in next chapter.

Table 3.1 Input to hidden layer weights

Input layer / Hidden Layer	1		2		3		4	
	Initial weight	Final Weight	Initial weight	Final Weight	Initial weight	Final Weight	Initial weight	Final Weight
1	-0.34782	-1.80347	-0.43868	0.47153	0.405632	-0.02584	0.2499	1.263513
2	0.123935	0.289727	-0.31757	1.177436	0.200417	1.60001	-0.10008	-0.99536
3	-0.22342	-0.47633	-0.22485	0.212142	0.032243	0.102828	0.199506	0.149904
4	-0.48403	-4.87617	0.453785	9.75576	0.119968	15.20919	-0.41221	-6.54275
5	0.473032	0.825447	-0.34053	-1.09561	-0.38254	-0.31897	0.163085	-0.21496
6	-0.38572	-0.4897	-0.14099	-1.72231	-0.36486	-0.70368	-0.11197	0.995499
7	-0.27127	-0.22165	-0.16856	-0.00151	-0.08398	0.184493	-0.06536	0.093757
8	-0.38854	-2.30037	0.321911	0.745717	0.21104	-2.28622	0.294604	4.21837
9	0.473491	1.200004	-0.34527	-0.32894	0.210566	0.439223	-0.1994	-0.2442
10	-0.34622	-0.58212	0.030134	1.072627	0.109414	0.507845	-0.11479	0.000284
11	0.194902	0.107761	-0.11681	0.010768	0.25956	0.121974	0.378944	0.306346
12	-0.37715	-0.0205	0.441032	1.010085	0.084463	0.80182	0.404168	1.499915
13	0.218026	0.175655	0.451569	0.89646	-0.10817	-0.24252	0.285362	-0.13567
14	0.407962	0.463122	0.494323	1.611107	0.493919	0.628435	-0.19042	-0.81396
15	0.238622	-5.49304	-0.12286	9.250211	0.106339	9.479236	-0.4836	-2.02213
16	-0.26786	-0.81224	-0.11897	-1.98228	0.427006	0.895768	-0.33477	0.684218
17	-0.28366	-0.17115	0.169387	-0.85874	0.376344	5.69967	-0.24377	-0.81127
18	0.216537	0.29322	-0.37409	-0.74481	-0.41176	-0.17854	-0.02559	0.147388
19	0.287573	0.726257	-0.08337	-0.13256	-0.21717	0.189039	-0.11786	0.034249
20	-0.09315	4.299436	-0.37366	-5.59736	-0.44577	-4.29019	-0.46507	-1.38879
21	0.309573	-0.02732	0.008597	-1.77245	-0.34976	-0.89054	0.494925	0.765769

The short-term load forecasting is performed with the help of BP algorithm. Initially, the data for January month has been used in the normalized form. The updated values of weights have been obtained by training of network. The values of the initial and the final values of the weights between input and hidden layer are presented in Table 3.1. Table 3.2 presents the initial and final weights between hidden and an output layer. The size of neurons for input layer and hidden layer is selected as 3 and 21 respectively. The weights are initialized randomly.

Table 3.2 Hidden layer to output weights

Input Layer / Hidden Layer	1	
	Initial weight	Final Weight
1	-0.40842	-1.46514
2	0.343397	0.752626
3	0.4595	1.455527
4	0.349397	-0.06603
5	-0.35115	-4.90491
6	-0.32571	-1.71731
7	-0.14839	-1.81978
8	0.181918	-0.47673
9	0.44912	3.267875
10	-0.36074	-1.58596
11	0.453228	0.562534
12	0.327723	-0.46041
13	-0.34338	-1.77566
14	0.078922	0.182285
15	-0.45145	1.054586
16	0.493923	7.432081
17	-0.2786	-1.76668
18	0.404807	3.120187
19	0.157243	-1.12301
20	-0.10462	-1.18771
21	-0.08841	6.37731

CHAPTER 4
LOAD FORECASTING UNDER MATLAB

This chapter depicts the well-ordered strategy for training the neural network to learn from the recent one month weather and temperature data. For outlining the network architecture the MATLAB ANN toolbox is used. The selection of a suitable number of hidden layers is necessary as the increase in the number of hidden layers results in increased complexity of the ANN architecture, therefore, affecting its performance. The algorithm used for training the artificial neural network is Levenberg-Marquardt. The main problem of Levenberg-Marquardt is a selection of the hidden layer size, which is selected by hit and trial method. It trains the network quicker as compared to the BP method. Although it is more efficient it requires more memory.

4.1 LEVENBERG-MARQUARDT SOLUTION METHODOLOGY

There are five major steps to obtain the result or to train the network. The five steps are briefly explained below one by one and the flowchart is shown in Figure 4.1.

i. **Data Collection and Preparation:** The chronological data were composed for this research. The chronological load data is taken from the PSPCL, 66kV substation Bhai Roopa, Bathinda and the weather data are acquired from the internet. The one-month load data and weather data are used for the training the network.

ii. **Data Preprocessing:** Scaling of raw input data is normally important to diminish the bias caused by a various measuring unit of original input variables. The approach utilized for scaling the network input and target was to standardize the mean and standard deviation of the training set.

iii. **Network Structure Design:** The next step behind rending the training and validation data set is to outline the structure for neural networks. This has to do with choosing a network topology and the resolve of the input nodes, output nodes, number of hidden layers and the number of hidden nodes. The network topology is mostly determined based on the sort of task to be performed by the planned network. The multilayer feedforward neural networks have been effectively applied for prediction. The number of input nodes is usually set equal to the number of input variables.

The following are the input variables for this research

a) Dry bulb temperature

b) Dewpoint temperature

c) Humidity

The output of the neural network represents the forecasted load data for the forecasting day. The determination of the number of hidden layers and the number of neurons within the hidden layers is an important decision within the plan of neural networks. Too many hidden neurons cause many trainable weights, which might build a neural network to become erratic and unreliable. On the other hand, too few hidden neurons limit the learning ability of a neural network and improve its approximation performance [40]. However, there is no distinct guideline for deciding the number of neurons in the hidden layers. The usual practice is by using trial and error which cannot yield an optimum network design and therefore the method is time-consuming.

iv. **Network Training:** After the network has been outlined, the following stage is to train the network. The training of an artificial neural is an iterative method that has to do with changing the association weight. BP algorithmic rule has been generally used in the past as a fundamental learning, algorithmic rule for training feed-forward neural networks; in any case, it takes a long time in training due to the nature of gradient descent. Several techniques are utilized to enhance the execution of back propagation, among them one is by Levenberg Marquardt. Levenberg Marquardt is embraced for training the neural network amid this research. Levenberg Marquardt is the numerical optimization based technique in which performance index is to be optimized.

The performance index to be optimized for the Levenberg Marquardt is defined as

$$F(w) = \sum_{p}^{p=1}\left[\sum_{k=1}^{k}\left(d_{kp} - o_{kp}\right)^2\right] \tag{4.1}$$

Levenberg Marquardt algorithm consolidates the speed of Gauss-Newton's method and also the stability of error backpropagation algorithm during training. Once μ is large, the learning process follows the error back propagation algorithm and once μ is small, it follows the Gauss-Newton's algorithm

$$\Delta W = \left(J^T J + \mu I\right)^{-1} J^T e \tag{4.2}$$

The Jacobin matrix is known as

$$J = \begin{pmatrix} \frac{\partial F(x_1, W)}{\partial w_1} & \frac{\partial F(x_1, W)}{\partial w_{w1}} \\ \frac{\partial F(x_N, W)}{\partial w_1} & \frac{\partial F(x_N, W)}{\partial w_W} \end{pmatrix} \tag{4.3}$$

The Jacobin matrix in a neural network is N $\times$ W matrix.

v. Network Validation: After the network has been properly trained it is must be validated for its performance of generalization.

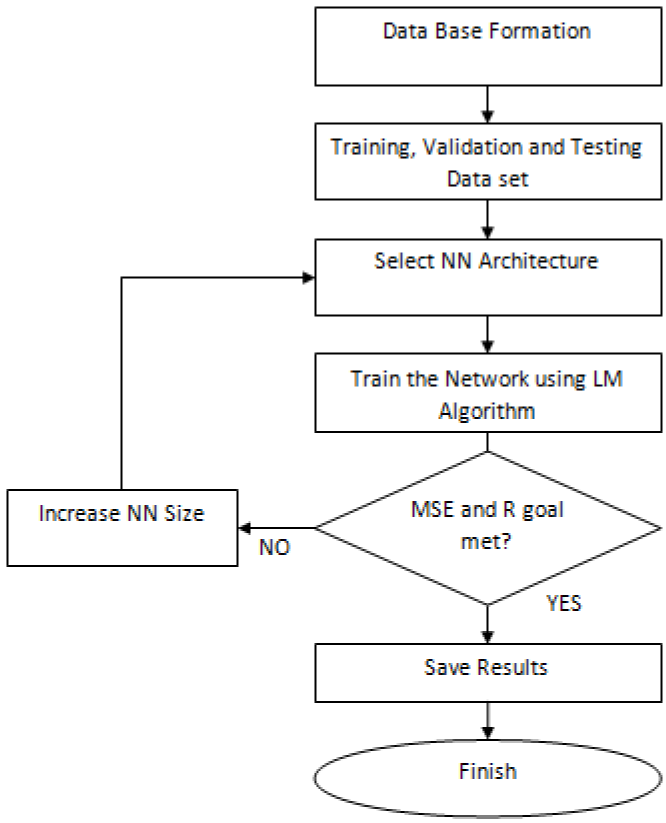

Figure 4.1 Flowchart of training and testing of ANN

4.2 LEVENBERG MARQUARDT ALGORITHM

Levenberg Marquardt Algorithm basically contains the 8 steps and that steps are discussed below:

i. Compute the Jacobin matrix

ii. Compute the error gradient

$$g = J^t E \tag{4.4}$$

iii. Approximate the Hessian using the cross product Jacobian

$$H = J^T J \tag{4.5}$$

iv. Solve $(H + \lambda I)\delta = g$, to find δ

v. Update the network weights w using δ

vi. Recalculate the sum of squared error using updated weights.

vii. If the sum of squared error has not decreased, discard the weights, increase λ using v and go to Step 4.

viii. Else decrease λ using v and stop

4.3 RESULTS AND DISCUSSION

The results of single layer feed-forward network and multilayer feed-forward network using the Levenberg-Marquardt the results are discussed. The dataset in this is divided into three parts, i.e. validation, training, and testing. The data taken for the input and output is an hourly basis of the January. The size of hidden neurons is varied for load forecasting and it is observed that less the number of hidden neuron size and result in less mean square error and root mean square error and vice versa.

4.3.1 Single layer Network

In case of single layer network, there was single input layer as well as single output layer. Further, the neurons present in the input layer received the signals at the input terminal whereas the neurons present in the output layer received the output signal in a similar way. The input cells were connected to the similar output cell by the utilization of synaptic link carrying weight with it. Due to which this was considered as the feed forward neural network as the inverse operation cannot be possible in this network. Despite of the fact that the network having two layers still it was considering as a single layer due to single output layer receiving signal from input layer [39]. The data is forecasted with different sizes of the hidden layer and the best results are observed when hidden neuron size is 3 as shown in Table 4.1. The Figure 4.2 represents the actual load and forecasted load in the hidden neuron size of three.

Table 4.1 represents the different size of the hidden neuron and error in single layer feed-forward network.

Hidden Neuron size	3	6	9	12	15	18	21
MSE	0.0063	0.0071	0.0075	0.0069	0.0071	0.0073	0.0072
RMSE	0.0796	0.0843	0.0866	0.0834	0.0843	0.0857	0.0852

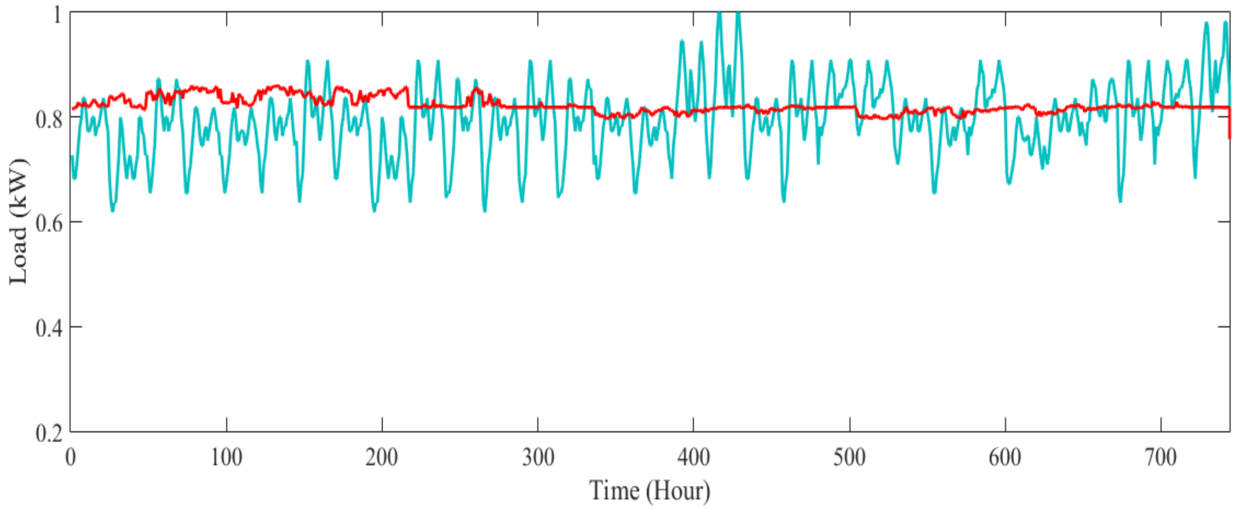

Figure 4.2. Represents the actual load and forecasted a load of hidden neuron size three.

4.3.2 MULTILAYER NETWORK

As its name indicates is formed from multilayers. So architectures of multilayer feed-forward network possessing an auxiliary layer considering between the input layer and the output layer. The hidden neurons present within the middle layer was considering for the computational purpose. The major importance of hidden layer as the computational work performed by the layer before the input signal received by the output terminal [39]. The input hidden layer weight was basically, a synaptic weight links formed by the combination of input neurons and the hidden neurons. In a similar way, whenever the output neurons formed a combination with the hidden layer neurons it was considered as the hidden output layer weight. The Table 4.2 shows that while changing the neuron size of the hidden layer the error is also changed and the Figure 4.3 shows the actual load and forecasted a load of the hidden layer having less error.

Table 4.2 represents the different size of the neuron and error in multilayer feed-forward network.

Hidden layer 1	3	6	9	12	15	18	21
Hidden layer 2	6	9	12	15	18	21	24
MSE	0.0070	0.0067	0.0071	0.0069	0.0078	0.0072	0.0075
RMSE	0.0835	0.0819	0.0843	0.0831	0.0883	0.0849	0.0866

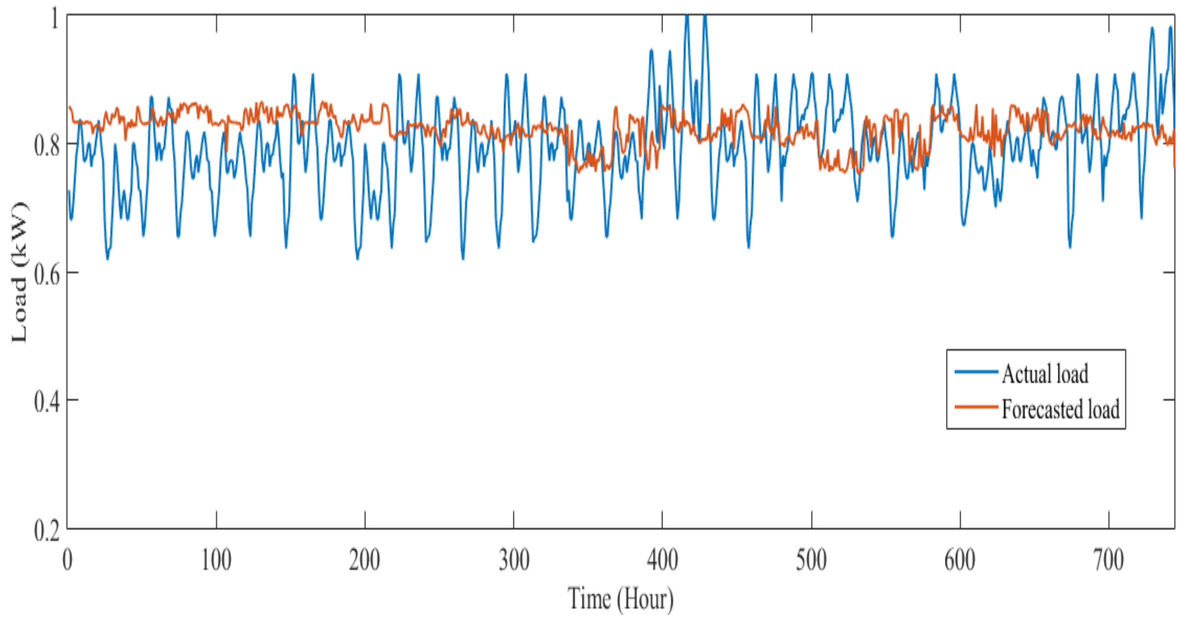

Figure 4.3. Represents the actual load and forecasted load of the hidden neuron size six and nine.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

In this work results obtained by using ANN technique for short-term load forecasting for the Bhai Roopa, Bathinda city has been analyzed. The most widely used technique in ANN is BP algorithm and LM algorithm. The forecasting has been evaluated on the basis of calculating Mean Square Error and Root Mean Square Error between the actual value and forecasted value. Three inputs namely Dew point temperature, Dry bulb temperature and Humidity have been taken as input. The effect of change in number of hidden neurons and number of hidden layers is also studied. The following observations are made:

1. The BP algorithm results into lower error compared to LM algorithm for same input.
2. One hidden layer is sufficient for the formulation of Load forecasting problem.
3. The increase in hidden neurons increases the error.

5.2 FUTURE SCOPE

1. Data processing of historical data, which might contain bad data.
2. Use clustering of data on basis of typical usage of data like weekday/ holiday/ national holiday etc.
3. Use additional parameters such as rainfall, wind, per capita income etc.
4. Use hybrid technique for the purpose.

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APPENDIX

A.1. Sample of data of the network for one day.

Table A.1. Sample of data

Date	Hours	Dew Point	Dry Bulb	Humidity	Load
1/1/2015	1	6.5	7.4	94	80
1/1/2015	2	7.7	9.4	89	75
1/1/2015	3	11.9	12.6	95	75
1/1/2015	4	10.2	10.2	100	78
1/1/2015	5	8.6	9	97	82
1/1/2015	6	8.2	9	95	86
1/1/2015	7	4.9	5.4	97	88
1/1/2015	8	4	4	100	92
1/1/2015	9	8.4	8.4	100	92
1/1/2015	10	7.2	7.2	100	89
1/1/2015	11	7.1	8	94	85
1/1/2015	12	6.5	8.2	89	85
1/1/2015	13	7.8	7.8	100	86
1/1/2015	14	9.2	10.4	92	88
1/1/2015	15	6.5	7.8	91	88
1/1/2015	16	7.8	9.8	87	84
1/1/2015	17	8.2	8.2	100	86
1/1/2015	18	9.6	10	97	86
1/1/2015	19	5.2	5.2	100	88
1/1/2015	20	10	10	100	90
1/1/2015	21	7.1	8.4	91	92
1/1/2015	22	8.6	9.8	92	90
1/1/2015	23	10.6	11	97	87
1/1/2015	24	9.6	10.8	92	85

A.2. Actual load and Forecasted load after training the BP algorithm.

Table A.2. Actual load and Forecasted load

Time (Hour)	Actual Load	Forecasted Load	Time (Hour)	Actual load	Forecasted load	Time (Hour)	Actual load	Forecasted load
1	0.7273	0.7784	39	0.7273	0.7814	76	0.6545	0.8359
2	0.6818	0.7909	40	0.7091	0.805	77	0.6909	0.8176
3	0.6818	0.8482	41	0.6818	0.828	78	0.8182	0.8381
4	0.7091	0.7702	42	0.6818	0.816	79	0.8182	0.8107
5	0.7455	0.7671	43	0.7091	0.8607	80	0.8	0.8267
6	0.7818	0.7733	44	0.7273	0.8557	81	0.7636	0.7953
7	0.8	0.7749	45	0.8	0.8373	82	0.7455	0.7976
8	0.8364	0.7667	46	0.8	0.8112	83	0.7455	0.8212
9	0.8364	0.7568	47	0.7727	0.8215	84	0.7727	0.7979
10	0.8091	0.7607	48	0.7636	0.8352	85	0.7818	0.7905
11	0.7727	0.7769	49	0.7273	0.8249	86	0.7545	0.8043
12	0.7727	0.7907	50	0.7273	0.8097	87	0.7727	0.8115
13	0.7818	0.7583	51	0.6909	0.8554	88	0.7909	0.8042
14	0.8	0.7911	52	0.6545	0.8629	89	0.8091	0.8015
16	0.8	0.7854	53	0.6727	0.7811	90	0.8182	0.8091
17	0.7636	0.7973	54	0.7091	0.815	91	0.8	0.8092
18	0.7818	0.7572	55	0.7455	0.7731	92	0.7727	0.8023
19	0.7818	0.7746	56	0.8182	0.7799	93	0.7727	0.8042
20	0.8	0.7669	57	0.8727	0.8116	94	0.7273	0.8039
21	0.8182	0.7667	58	0.8727	0.8332	95	0.7273	0.8044
22	0.8364	0.7845	59	0.8364	0.8029	96	0.6818	0.8111
23	0.8182	0.7851	60	0.8	0.8087	97	0.6545	0.815
24	0.7909	0.7953	61	0.7727	0.7722	98	0.6727	0.7993
25	0.7727	0.7974	62	0.8	0.7877	99	0.7	0.84
26	0.6818	0.7666	63	0.8	0.79	100	0.7273	0.8028
27	0.6364	0.7784	64	0.7727	0.8326	101	0.7727	0.7985
28	0.6182	0.7674	65	0.7909	0.8545	102	0.8	0.8665
29	0.6364	0.7958	66	0.7909	0.8797	103	0.8182	0.8776
30	0.6364	0.7861	67	0.8182	0.8522	104	0.8	0.8793
31	0.6818	0.8301	68	0.8455	0.8805	105	0.7545	0.8424
32	0.7273	0.7979	69	0.8727	0.8659	106	0.7545	0.8604

33	0.8	0.8675	70	0.8545	0.8654	107	0.7727	0.8613
34	0.7818	0.8739	71	0.8545	0.8857	108	0.7727	0.8651
35	0.7455	0.8402	72	0.8	0.8484	109	0.7727	0.8474
36	0.7091	0.8356	73	0.7727	0.8203	110	0.7455	0.7911
37	0.6818	0.8122	74	0.7091	0.84	111	0.7545	0.8572
38	0.7091	0.7814	75	0.6545	0.8403	112	0.7727	0.8516
113	0.8	0.841	153	0.8364	0.8075	193	0.6818	0.7961
114	0.8182	0.8716	154	0.7909	0.8218	194	0.7273	0.7946
115	0.8	0.8561	155	0.7545	0.8103	195	0.8	0.8074
116	0.7273	0.8353	156	0.7727	0.8184	196	0.7455	0.8446
117	0.6727	0.8087	157	0.8091	0.8082	197	0.7091	0.8557
118	0.6545	0.7992	158	0.8455	0.8062	198	0.6818	0.794
119	0.7091	0.8036	159	0.8818	0.806	199	0.7091	0.8314
120	0.7273	0.8017	160	0.9091	0.802	200	0.7273	0.8488
121	0.7636	0.808	161	0.8636	0.8005	201	0.7091	0.8432
122	0.8	0.8084	162	0.8182	0.8067	202	0.6818	0.7971
123	0.8364	0.8086	163	0.7909	0.8045	203	0.6818	0.7838
124	0.8364	0.8056	164	0.7273	0.8102	204	0.7091	0.7971
125	0.8182	0.8051	165	0.6818	0.7747	205	0.7273	0.8314
126	0.7727	0.8095	166	0.6818	0.7702	206	0.8	0.8374
127	0.7545	0.8076	167	0.7091	0.7688	207	0.8	0.8595
128	0.7818	0.8037	168	0.7455	0.7598	208	0.7727	0.8349
129	0.8	0.8054	169	0.7818	0.7574	209	0.7636	0.8198
130	0.8	0.8495	170	0.8	0.7877	210	0.7273	0.8156
131	0.7636	0.8004	171	0.8364	0.7664	211	0.6727	0.8226
132	0.7818	0.7952	172	0.8364	0.7567	212	0.6364	0.8201
133	0.7818	0.8007	173	0.8091	0.7631	213	0.6727	0.7848
134	0.8	0.8027	174	0.7727	0.7583	214	0.6909	0.8679
135	0.8091	0.8391	175	0.7727	0.7823	215	0.7727	0.8478
136	0.8364	0.8005	176	0.7818	0.7574	216	0.8636	0.8592
137	0.8091	0.8215	177	0.8	0.79	217	0.9091	0.8155
138	0.7727	0.8147	178	0.8	0.7698	218	0.9	0.8549
139	0.7455	0.8213	179	0.7636	0.7631	219	0.8455	0.8318
140	0.7545	0.8085	180	0.7818	0.7607	220	0.8	0.8694
141	0.6727	0.8187	181	0.7818	0.7672	221	0.8	0.86
142	0.6364	0.8074	182	0.8	0.7671	222	0.8182	0.8526
143	0.6727	0.8058	183	0.8182	0.7594	223	0.8364	0.8505

144	0.6909	0.8021	184	0.8364	0.7614	224	0.7909	0.7845
145	0.7727	0.8049	185	0.8182	0.7877	225	0.7545	0.7916
146	0.8636	0.8119	186	0.7909	0.8125	226	0.7727	0.8596
147	0.9091	0.8211	187	0.7727	0.7594	227	0.8091	0.7577
148	0.9	0.8076	188	0.6818	0.7567	228	0.8455	0.7698
149	0.8455	0.8067	189	0.6364	0.7887	229	0.8818	0.7627
150	0.8	0.8082	190	0.6182	0.7664	230	0.9091	0.7598
151	0.8	0.814	191	0.6364	0.7607	231	0.8636	0.8464
152	0.8182	0.8094	192	0.6364	0.7885	232	0.8182	0.7572
233	0.7909	0.7942	273	0.7636	0.8063	313	0.8182	0.8719
234	0.7273	0.8232	274	0.7818	0.7917	314	0.8727	0.7993
235	0.6455	0.7966	275	0.6545	0.7775	315	0.8727	0.8479
236	0.6545	0.7775	276	0.7818	0.8139	316	0.8	0.8558
237	0.6727	0.82	277	0.8	0.7986	317	0.7727	0.8049
238	0.7091	0.8278	278	0.8091	0.8446	318	0.8	0.8069
239	0.7455	0.8444	279	0.8364	0.8048	319	0.8	0.8194
240	0.8182	0.8514	280	0.8091	0.8724	320	0.7727	0.8138
241	0.8727	0.8604	281	0.7727	0.7744	321	0.7909	0.8098
242	0.8727	0.8674	282	0.6818	0.8774	322	0.7909	0.802
243	0.8364	0.8605	283	0.6545	0.8122	323	0.8182	0.7989
244	0.8	0.8849	284	0.6364	0.8249	324	0.8455	0.8017
245	0.7727	0.8393	285	0.6727	0.8446	325	0.8727	0.8058
246	0.8	0.8711	286	0.6909	0.8035	326	0.8545	0.8076
247	0.8	0.8637	287	0.7727	0.8121	327	0.8545	0.806
248	0.7727	0.8505	288	0.8636	0.828	328	0.8	0.8101
249	0.7909	0.8661	289	0.9091	0.8324	329	0.7091	0.8112
250	0.7909	0.8433	290	0.9	0.8613	330	0.7273	0.8241
251	0.8182	0.8544	291	0.8455	0.8661	331	0.6818	0.8116
252	0.8455	0.8647	292	0.8	0.8278	332	0.6818	0.8108
253	0.8727	0.8247	293	0.8091	0.8618	333	0.7091	0.8102
254	0.8545	0.8319	294	0.8182	0.8752	334	0.7455	0.8163
255	0.8545	0.8311	295	0.8364	0.8731	335	0.7818	0.8038
256	0.8	0.7979	296	0.7909	0.8703	336	0.8	0.8091
257	0.7273	0.7985	297	0.7545	0.8256	337	0.8364	0.8159
258	0.6364	0.798	298	0.7727	0.8116	338	0.8364	0.8025
259	0.6182	0.7974	299	0.8091	0.8025	339	0.8091	0.8048
260	0.6545	0.7961	300	0.8455	0.8096	340	0.7727	0.8086

261	0.7091	0.8001	301	0.8818	0.8125	341	0.7727	0.7991
262	0.7273	0.8027	302	0.9091	0.8001	342	0.7818	0.8086
263	0.7636	0.8046	303	0.8636	0.8123	343	0.8	0.8025
264	0.8	0.8051	304	0.8182	0.8108	344	0.8	0.8384
265	0.8364	0.802	305	0.7909	0.815	345	0.7636	0.8065
266	0.8364	0.8043	306	0.7091	0.8045	346	0.7818	0.8077
267	0.8182	0.8013	307	0.6455	0.8078	347	0.7818	0.81
268	0.7727	0.8566	308	0.6545	0.8098	348	0.8	0.8138
269	0.7545	0.8012	309	0.6545	0.8888	349	0.8182	0.8054
270	0.7818	0.8111	310	0.6727	0.8488	350	0.8364	0.8083
271	0.8	0.8086	311	0.7091	0.8125	351	0.8182	0.8072
272	0.8	0.8165	312	0.7455	0.7968	352	0.7909	0.827
353	0.7455	0.8161	393	0.7909	0.8065	433	0.8091	0.7277
354	0.7091	0.8158	394	0.8182	0.809	434	0.7727	0.8214
355	0.6545	0.8235	395	0.8455	0.828	435	0.7727	0.8288
356	0.6909	0.806	396	0.9455	0.8114	436	0.8	0.8236
357	0.7091	0.8078	397	0.9091	0.8276	437	0.8	0.818
358	0.7455	0.8058	398	0.8636	0.8176	438	0.7636	0.8184
359	0.7818	0.8072	399	0.7727	0.8135	439	0.7818	0.8131
360	0.8182	0.8196	400	0.7273	0.8105	440	0.7818	0.8221
361	0.8182	0.8061	401	0.6818	0.8157	441	0.8	0.8294
362	0.8	0.8071	402	0.7091	0.8123	442	0.8182	0.836
363	0.7636	0.8141	403	0.7727	0.8067	443	0.8364	0.8285
364	0.7455	0.8094	404	0.8182	0.8067	444	0.8182	0.7859
365	0.7455	0.8004	405	0.8636	0.8092	445	0.7909	0.784
366	0.7727	0.8222	406	0.9545	0.8474	446	0.7727	0.7617
367	0.7818	0.8049	407	1	0.8172	447	0.6545	0.7797
368	0.7545	0.8087	408	1	0.8138	448	0.6364	0.8219
369	0.7727	0.8069	409	0.9364	0.8094	449	0.6727	0.8108
370	0.7909	0.8068	410	0.8909	0.8167	450	0.6909	0.767
371	0.8091	0.8049	411	0.8455	0.821	451	0.7727	0.8087
372	0.8182	0.8079	412	0.8182	0.8112	452	0.8636	0.7987
373	0.8	0.8066	413	0.8909	0.8129	453	0.9091	0.8121
374	0.7727	0.8065	414	0.9	0.8067	454	0.9	0.81
375	0.7727	0.8085	415	0.8364	0.8087	455	0.8455	0.8113
376	0.7273	0.8077	416	0.8	0.8121	456	0.8	0.8072
377	0.7091	0.8063	417	0.8636	0.8157	457	0.8091	0.8156

378	0.6818	0.8094	418	0.9273	0.8151	458	0.8182	0.8112
379	0.7455	0.8114	419	1	0.8109	459	0.8364	0.8083
380	0.7727	0.8135	420	1	0.8162	460	0.7909	0.8122
381	0.8182	0.8072	421	0.9545	0.8247	461	0.7545	0.8103
382	0.8545	0.8141	422	0.9091	0.8108	462	0.7727	0.8106
383	0.8909	0.8129	423	0.8182	0.8079	463	0.8091	0.8318
384	0.9455	0.8174	424	0.7273	0.8108	464	0.8455	0.8187
385	0.9455	0.8169	425	0.6818	0.808	465	0.8818	0.81
386	0.9091	0.8101	426	0.6818	0.8143	466	0.9091	0.8177
387	0.8636	0.8066	427	0.7091	0.8079	467	0.8636	0.8205
388	0.8091	0.7908	428	0.7455	0.7728	468	0.8182	0.8239
389	0.8	0.8033	429	0.7818	0.7662	469	0.7909	0.8277
390	0.8909	0.7877	430	0.8	0.8008	470	0.7091	0.8323
391	0.8636	0.8155	431	0.8364	0.8263	471	0.7818	0.8104
392	0.8182	0.8169	432	0.8364	0.7953	472	0.7636	0.8289
473	0.7818	0.8303	513	0.9091	0.8583	553	0.7455	0.8663
474	0.7909	0.8265	514	0.8909	0.86	554	0.7455	0.8594
475	0.8182	0.8488	515	0.8727	0.8485	555	0.7727	0.8515
476	0.8818	0.8147	516	0.8545	0.8618	556	0.7818	0.8516
477	0.9091	0.8339	517	0.8182	0.8562	557	0.7545	0.847
478	0.8909	0.8295	518	0.7455	0.8462	558	0.7727	0.8439
479	0.8818	0.8353	519	0.7273	0.8582	559	0.7909	0.8528
480	0.8182	0.834	520	0.7091	0.8702	560	0.8091	0.8488
481	0.8182	0.8095	521	0.7273	0.8672	561	0.8182	0.8587
482	0.8364	0.8141	522	0.7636	0.8651	562	0.8	0.8598
483	0.8455	0.8139	523	0.8	0.8684	563	0.7727	0.8601
484	0.8364	0.807	524	0.8182	0.8638	564	0.7727	0.8728
485	0.8545	0.8135	525	0.8364	0.8557	565	0.7273	0.8755
486	0.8545	0.8192	526	0.8182	0.8621	566	0.7818	0.8749
487	0.8636	0.8301	527	0.8	0.8558	567	0.7636	0.8582
488	0.8818	0.8333	528	0.7727	0.849	568	0.7818	0.8712
489	0.9091	0.8271	529	0.7727	0.8502	569	0.7909	0.8595
490	0.9091	0.8121	530	0.7909	0.8306	570	0.8182	0.8722
491	0.8727	0.8242	531	0.8091	0.8387	571	0.8545	0.8692
492	0.8545	0.8301	532	0.8091	0.8348	572	0.8636	0.8582
493	0.8182	0.8333	533	0.7727	0.8395	573	0.9091	0.8717
494	0.7818	0.8271	534	0.7727	0.85	574	0.8909	0.875

495	0.7636	0.8121	535	0.7909	0.8563	575	0.8818	0.8706
496	0.7818	0.8242	536	0.8091	0.8393	576	0.8182	0.853
497	0.7909	0.8301	537	0.8182	0.8394	577	0.8182	0.8649
498	0.8182	0.8183	538	0.8364	0.849	578	0.8364	0.8612
499	0.8545	0.8219	539	0.8091	0.8441	579	0.8364	0.8623
500	0.8636	0.8228	540	0.7909	0.8305	580	0.8364	0.8628
501	0.9091	0.8271	541	0.7636	0.851	581	0.8545	0.8492
502	0.8909	0.837	542	0.7091	0.8483	582	0.8455	0.8557
503	0.8818	0.8459	543	0.6545	0.8474	583	0.8636	0.8554
504	0.8182	0.8535	544	0.6545	0.8516	584	0.8818	0.852
505	0.8182	0.8332	545	0.6909	0.8522	585	0.9091	0.8558
506	0.8364	0.8315	546	0.7091	0.8473	586	0.8909	0.863
507	0.8364	0.8358	547	0.7455	0.8562	587	0.8727	0.8643
508	0.8364	0.8416	548	0.7818	0.8539	588	0.8545	0.8362
509	0.8545	0.8368	549	0.8182	0.8609	589	0.8182	0.8598
510	0.8455	0.8213	550	0.8182	0.8462	590	0.6909	0.8573
511	0.8636	0.8537	551	0.8	0.8569	591	0.6727	0.8315
512	0.8818	0.8541	552	0.7636	0.8573	592	0.6727	0.8651
593	0.6909	0.8555	633	0.8364	0.8505	673	0.7909	0.843
594	0.7091	0.8507	634	0.8091	0.8499	674	0.7545	0.8239
595	0.7273	0.8586	635	0.7909	0.8557	675	0.7727	0.8356
596	0.8	0.8564	636	0.7909	0.85	676	0.8455	0.8255
597	0.8	0.8616	637	0.7727	0.8563	677	0.8818	0.8138
598	0.7818	0.8675	638	0.7636	0.8563	678	0.9091	0.8166
599	0.7636	0.8685	639	0.7455	0.858	679	0.8636	0.8205
600	0.7545	0.8644	640	0.7909	0.8461	680	0.8182	0.8236
601	0.7545	0.865	641	0.7909	0.8408	681	0.7909	0.8446
602	0.7636	0.865	642	0.8364	0.8401	682	0.7091	0.8481
603	0.7636	0.8569	643	0.8727	0.8517	683	0.7818	0.8394
604	0.7273	0.8605	644	0.8636	0.8557	684	0.7636	0.8427
605	0.7273	0.862	645	0.8545	0.8593	685	0.7818	0.8356
606	0.7455	0.8567	646	0.8182	0.8339	686	0.7909	0.8278
607	0.7636	0.8516	647	0.8091	0.8419	687	0.8182	0.8327
608	0.8	0.8474	648	0.8	0.8178	688	0.8545	0.8395
609	0.7727	0.8656	649	0.8182	0.81	689	0.8818	0.8371
610	0.7455	0.8598	650	0.8182	0.8418	690	0.9091	0.8502
611	0.7182	0.848	651	0.7909	0.8484	691	0.8909	0.8493

612	0.7	0.8557	652	0.7909	0.8431	692	0.8818	0.8485
613	0.7455	0.8531	653	0.8364	0.8323	693	0.8182	0.8137
614	0.7273	0.8509	654	0.8636	0.8294	694	0.8182	0.8285
615	0.7091	0.8558	655	0.8727	0.8254	695	0.8364	0.8228
616	0.7273	0.8558	656	0.8727	0.8346	696	0.8455	0.8338
617	0.7636	0.8413	657	0.8545	0.842	697	0.8364	0.8042
618	0.8	0.8509	658	0.8364	0.8305	698	0.8545	0.8038
619	0.8182	0.8416	659	0.8182	0.8274	699	0.8545	0.804
620	0.8364	0.846	660	0.6545	0.8379	700	0.8636	0.8038
621	0.8182	0.8605	661	0.6364	0.8375	701	0.8818	0.8038
622	0.8	0.8535	662	0.6727	0.8375	702	0.9091	0.8118
623	0.7727	0.8476	663	0.6909	0.8375	703	0.9091	0.809
624	0.7727	0.839	664	0.7727	0.8361	704	0.8727	0.7998
625	0.7909	0.8212	665	0.8636	0.8289	705	0.8545	0.8446
626	0.8091	0.8434	666	0.9091	0.8338	706	0.8182	0.8379
627	0.8091	0.8505	667	0.9	0.8521	707	0.7273	0.8343
628	0.7727	0.8137	668	0.8455	0.8333	708	0.6818	0.8221
629	0.7727	0.8434	669	0.8	0.837	709	0.7455	0.8117
630	0.7909	0.8364	670	0.8091	0.7918	710	0.7727	0.8176
631	0.8091	0.8522	671	0.8182	0.8573	711	0.8182	0.8328
632	0.8182	0.8557	672	0.8364	0.8412	712	0.8545	0.8211
713	0.9091	0.826	725	0.9182	0.8253	735	0.8455	0.8344
714	0.9545	0.8147	726	0.9818	0.8249	736	0.8636	0.8153
715	0.9818	0.8334	727	0.9818	0.8119	737	0.8909	0.8082
716	0.9091	0.8131	728	0.9091	0.8156	738	0.9091	0.8075
717	0.8364	0.8156	729	0.8545	0.8071	739	0.9182	0.8253
718	0.8091	0.8257	730	0.9091	0.8131	740	0.9818	0.8249
719	0.8636	0.8338	731	0.8364	0.8156	741	0.9818	0.8119
720	0.9091	0.8389	732	0.8091	0.8257	742	0.9091	0.8156
721	0.8455	0.8344	733	0.8636	0.8338	743	0.8545	0.8071
722	0.8636	0.8153	734	0.9091	0.8389	744	0.9091	0.8131
723	0.8909	0.8082						
724	0.9091	0.8075						

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