Electricity Demand Forecasting for a Smart City

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Submitted By

Jaskaran Kaur

(Roll No. 801332010)

Under the supervision of:

Dr. Inderveer Chana

Associate Professor

COMPUTER SCIENCE AND ENGINEERING DEPARTMENT

THAPAR UNIVERSITY

PATIALA – 147004

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Certificate

I hereby certify that the work which is being presented in the thesis entitled, "*Electricity Demand Forecasting for a Smart City* ", in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Computer science* submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Inderveer Chana* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

Jaskaran Kaur

(Jaskaran Kaur)

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

(Dr. Inderveer Chana)

Associate Professor

Computer Science and Engineering Department

Countersigned by

(Dr. Deepak Garg)
Head
Computer Science and Engineering Department
Thapar University
Patiala

(Dr. S. S. Bhatia)
Dean (Academic Affairs)
Thapar University
Patiala

Abstract

With 3.3 billion people living in cities across the globe, a number that is expected to get double by 2050, the need for cities that can drive sustainable economic growth and prosperity has never been more apparent. Therefore, the world is shifting towards the "Smart Cities" i.e. a city that takes a holistic approach towards spanning infrastructure, operations and people.

Power generation and distribution infrastructure of Smart City should be built on Smart Grid technologies, which will integrate with local power demand patterns, grid supply variations and a well-defined operational process. For optimal operation of electric power plants, electricity demand must be followed by electrical generation. The production, transmission, and distribution of electricity requires possible forecasting of the electricity demand for efficient, secure and economic utilization of electrical infrastructure. Demand forecasting is also very important in order to reduce input costs and the prices of electricity. A reliable and accurate electricity demand forecasting systems are required.

This thesis presents a solution methodology using artificial neural network for monthly electricity demand forecasting. It is implemented on historical weather related data i.e. temperature, rainfall, humidity, wind speed, precipitation and historical demand data for demand forecasting and the accuracy of the result is estimated by comparing the values generated by model with actual demand. Amloh, Patiala city load data is used for training and testing collected from Amloh grid. The results obtained are compared with the results from regression model of forecasting and accuracy of neural network is better as compared to existing modules.

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Chapter 1
Introduction

With the steady growth in global population, more and more people are moving towards cities every day. World's urban population is expected to double by 2050. Expansion of geographical boundaries of urban regions, increase in number of urban centres and growth in population size including increase in population naturally, migration of people from rural area to urban areas are major factors contributing towards rapid urbanization. Urban areas are main drivers of economic growth contributing higher share of National Gross Domestic Product (GDP). In India, more than 60% of the nation's GDP is contributed by the urban population which is currently 31% of the total population of India. Therefore, there is a global imperative for developing better strategies for creation of new Smart Cities. This chapter focuses on the brief introduction of Smart Cities, followed by various characteristics of smart cities and challenges in area of smart cities. Motivation and the structure of thesis are discussed at the end of this chapter.

1.1 Smart Cities: An Overview

Smart City is a developed area with advanced technology, better infrastructure, and better integration of different technologies so as to provide good quality of living to its people [1]. In other words, a city fully equipped with basic infrastructure to provide a decent, clean and sustainable environment and a decent quality life by making use of some smart solutions. A smart city is one that is more prepared than a simple city to respond to challenges. 'Digital city', intelligent city', 'cyber Ville', 'knowledge-based city', and 'ubiquitous city' are terms that are being used for Smart City. Smart city and its major attributes are shown in Figure 1.1.

It is difficult to give a precise definition for a smart city because of the breadth of technologies implemented under the label of smart city. Deakin and Al Wear [2] list four factors contributing towards the definition of a smart city:

i. Application of a range of electronic and digital technologies to cities.
ii. Embedding ICTs in government systems.

iii. Bringing ICTs and people together to improve the innovation that they offer.

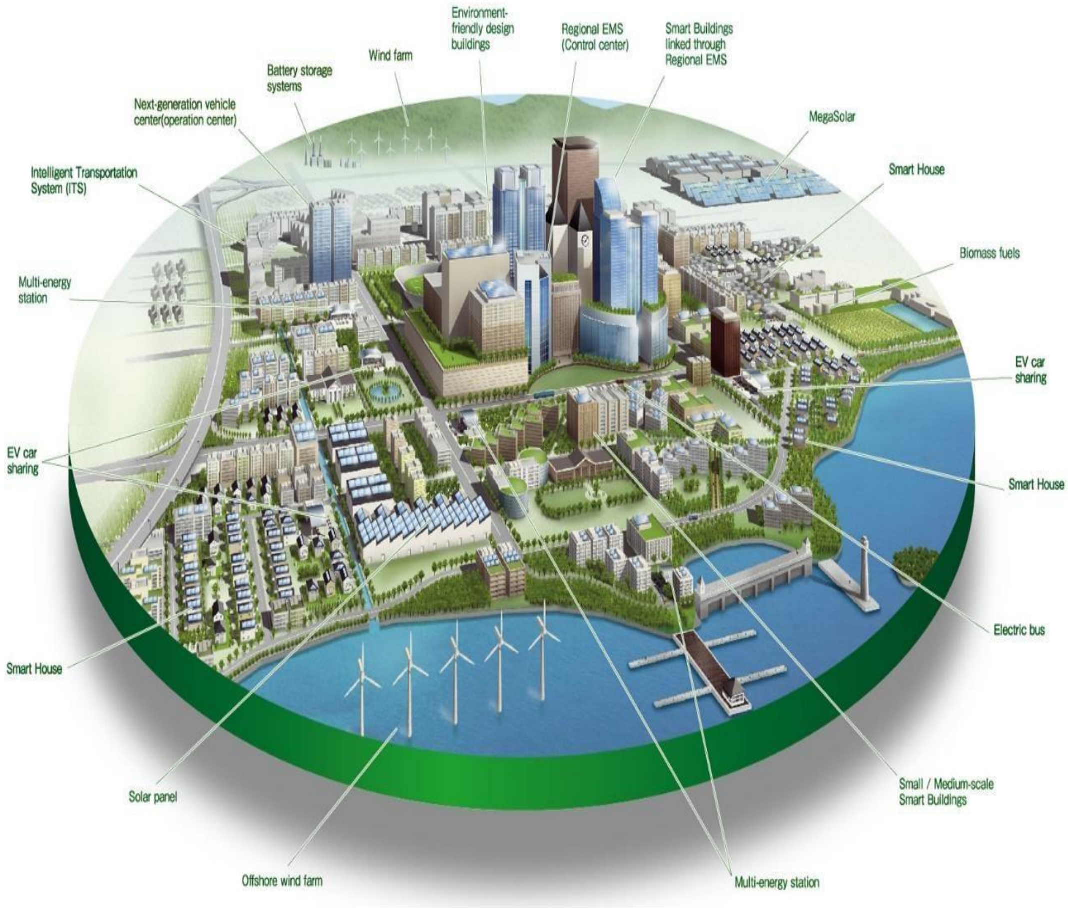

Figure 1.1: Smart city and its attributes. [1]

The interest in smart cities have been generated due to major technological, environmental and economic changes like climate change, ageing populations, economic restructuring, pressure on public finances and the move to online retail and entertainment. Economy, governance, living, security, mobility, environment and people are key areas that are required to work upon for cities to become smarter cities. Basic components like sensors, network, and smart phones are required in a smart city.

The key features of a Smart City is in the intersection among competitiveness, Capital and Sustainability .The basic model of service delivery is shown in Figure 1.2. There are five key aspects to smarter approaches:

[1] http://www.districtoffuture.eu/index.php

i. A modern digital infrastructure, combined with an open access but secure approach to public re-useable data. It enables citizens of the city to access the information they need whenever required

ii. improved citizen centric service delivery i.e. forefront placement of citizen's needs, sharing of management information, and offering internet service delivery

iii. an intelligent physical infrastructure like IOT, so that service providers can use the full range of data for management of daily service delivery and to inform strategic investment in the city

iv. an openness to learn and experiment with new business models

v. Transparency of outcomes.

Basic infrastructure of smart city includes assured water and electricity supply, efficient urban mobility and public transport, sanitation and solid waste management, robust IT connectivity, e-governance and citizen participation and safety and security of citizens. Information and communication technology (ICT) at home or at work places can play significant role to deliver smart services like smart traffic management, weather details, transportation, power, water consumption and enhanced infrastructure leading toward smarter regions and offering better quality of living.

The rise of new Internet technologies like cloud-based services, real-world user interfaces, the Internet of Things (IOT), smart meters, networks of sensors and more accurate communication, open new ways toward development of solutions to smart cities.

Some of the Smart City technologies have been implemented in Amsterdam, Southampton, Barcelona and Stockholm.

1.2 Characteristics of Smart Cities

Incredible innovations have been provided by modern technologies that can be applied in the field of sustainability. Cities in urban areas can in fact now use technology to become "Smart Cities". These Cities make use of a technological infrastructure network for monitoring various elements of a city's function.

Smart cities model can be divided into 6 common characteristics [3].Figure 1.3 shows the basic characteristics of smart city.

- Smart Governance

Smart Governance [4] is the enhanced governance that share information with the public and deliver services achieved by integrating applications and Data Centres using Information and Communication Technology. E-Services, applications, social media and many other such platforms reform the way government works and brings it closer to the public. Smart Governance should also be transparent to public. It includes the public involvement in decision-making, social and public service, and government transparency.

- Smart People

Smart people plays significant role in development of a Smart City as Smart people make Smart Cities. Smart City require people that need to be properly qualified, having affinity to lifelong learning, should be flexible, creative and socially and ethnically plural. It should include a culture of life-long learning, creativity, flexibility, social and ethnic diversity and community participation.

- Smart Transportation

No one can enjoy overcrowded and clogged cities, thus the transportation need to be reviewed to provide enhanced public transportation including railways, metros, waterways and walkways. Transportation should be innovative, sustainable and safe. It includes local and national accessibility, sustainable and safe transportation, and access to ICT-infrastructure.

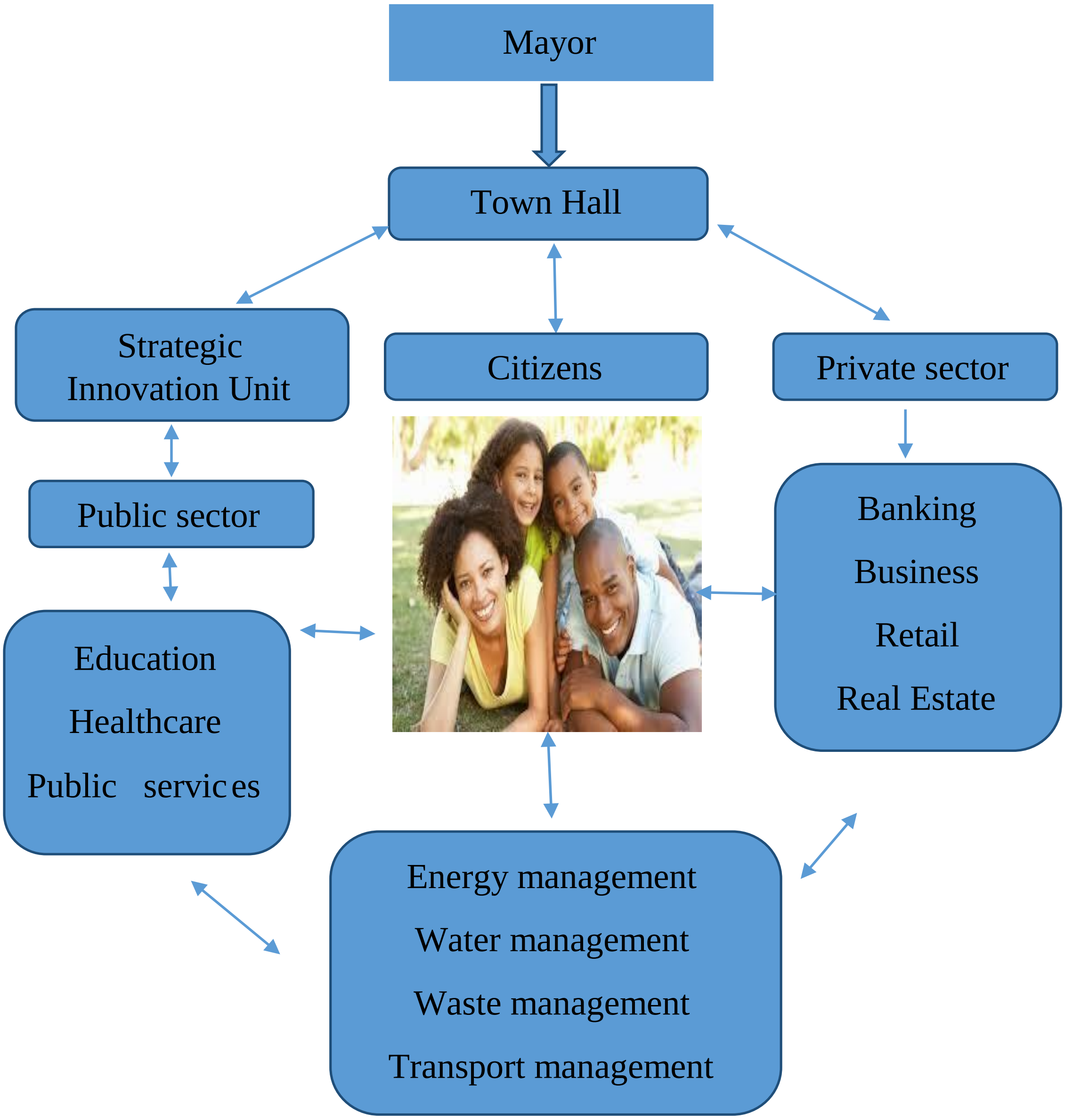

Figure 1.2. Smart City Model.

- Smart Environment

To boost up Smart Cities, sustainable and smart environment is in need. For Smart Environment focus should be on reducing waste and population, on usage of renewable resources to generate electricity and better sanitation. It aims at reduction in pollution, attracting natural conditions, sustainable resource management and increase in environmental protection.

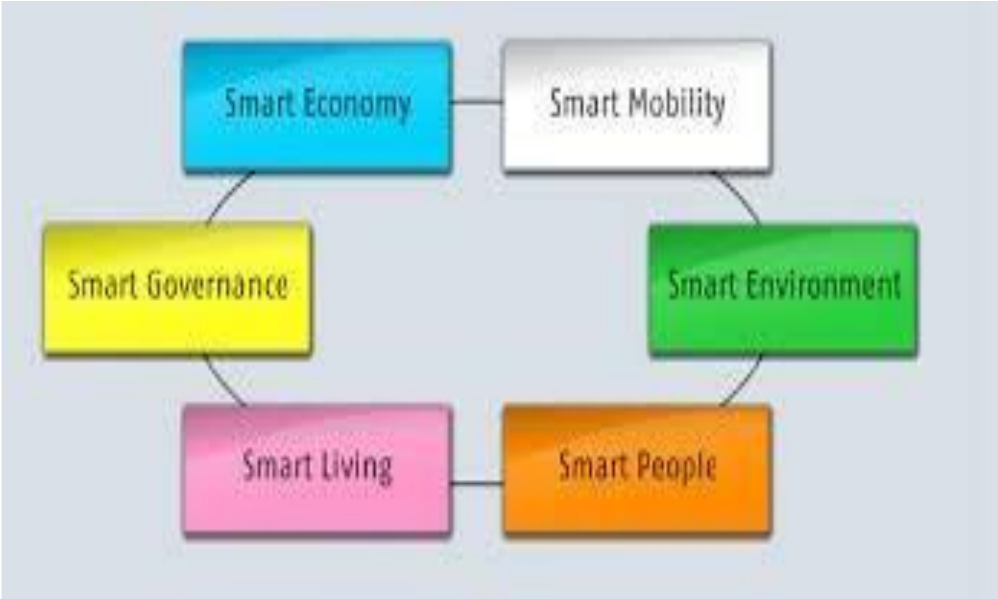

Figure 1.3 Six characteristics of smart city. [2]

- Smart Living

People are the key to development and for smart living of people better health conditions, cultural facilities, housing equality, individual safety, education and tourist attraction need to be considered. It aims at accessibility to quality housing, cultural and educational facilities, tourist attraction, quality health conditions and public safety, and social integration.

- Smart Economy

It includes productivity and entrepreneurship, flexibility in labour market, economic progression, and an overall culture of innovation.

1.3 Challenges in Developing a Smart City

Singapore, Yokohama, Seoul and Barcelona are some examples of smart cities as they efficiently use ICT to deliver services to its citizens with reduce costs and enhancing their quality of life. These cities are having intelligent physical, institutional, social and economic infrastructure to improve quality of life of its citizens by providing them safety and security, entertainment, cost efficient healthcare and quality of education.

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[2] http://sanleandronext.com/san-leandro-as-a-smart-city-a-discussion-at-east-bay-maker-labs-friday-january-10-6-p-m/

Three pillars to smart city are physical infrastructure, Institutional infrastructure and social infrastructure. Physical infrastructure includes integrated urban mobility system, sewage system, the housing stock, the energy system, sanitation facilities, waste management and drainage system. Institutional infrastructure includes the activities related to planning and management of systems. Social infrastructure refers to improvement in human capital index and emphasizing on healthcare, education and entertainment systems. To develop these three pillars the world is undergoing many challenges. Few of the challenges in building these cities includes:

- Clearances in a time bound manner

All clearances should be cleared in a time bound manner and should use online processes in order to complete the project on time. Utilities like way for laying optic fibre networks, sewerage systems, draining systems should be provided as per the time duration and cost decided by the government. For balancing quality and financial stability a regulatory body should be set up to check for all utility services to develop level playing field.

- Financing smart cities

Majority of smart city projects move through public private investment (PPP) or complete private investments. One key need is to check how these projects have to be financed. For complete realization of the potential of a city, there is requirement of investments in housing, ICT, health, electricity, education, recreation, cultural facilities, environmental facilities and sports facilities and others. A huge Initial investment may be required for preparing the city development plan and project reports for successful implementation of the scheme.

- Capacity building program

Development and construction of smart cities require huge capacity. Building such large capacity is not an easy task. Most of the ambitious smart city projects get delayed due to lack of quality manpower. Around 5 percent of the total central allocation is allocated for capacity building programs including training, education, knowledge exchange, contextual research, and a rich database. It has a multiplier effect. It helps in timely completion of projects. Therefore, capacity building need strengthening right at the beginning.

- Reliability of utility services

Reliability of utility services including electricity, telephone, water and broadband services need to be focused by all smart cities. Universal and 24*7 access to electricity is required to be provided by all smart cities. But it is not possible with the existing electricity supply and distribution system. A minimum of 100 Mbps of Internet bandwidth, fibre optic connectivity to each home, Wi-Fi in all educational and public institutions are also essentials of smart city. High quality water supply, waste management, drainage should be provided in these cities.

- Extensive usage of ICT

A sound backbone for communication is required for extensive use of ICT enabled services for example in Singapore. Smart governance structure is essential for the cities to become smart. Therefore, effective use of ICTs in order to coordinate among various departments is required by local bodies.

This means the capability to obtain services in real time using online systems and rigorous service level agreements. Online delivery of all public services, resulting in reduced visits to the local offices in a city. Security and privacy of data is also one of the major challenges faced by smart cities. These need to be taken care while planning and designing for a smart city. In this section we discussed about challenges in development of smart cities, next section will introduce to the area of electricity demand forecasting.

1.4 Forecasting electricity demand

Electricity demand forecasting is a significant tool that is used to ensure that the electricity generated by the system meet the demand and the electricity loss during transmission in the distribution network. It is an integral process in the organization, planning and operation of electricity systems. Demand forecasting helps in making important decisions related to purchase and generation of electricity [5]. It is used to control decisions like transmission, fuel allocation and off line analysis of the network.

Demand forecasting decisions implemented on time results in improvement of reliability of the network and reduce number of equipment failures. It is of vital importance for electric utilities due to fluctuation in demand and changes in weather and increase in electricity prices during peak situations, thus enabling a city to be smart enough to automatically fulfil the requirements of its citizens.

The prediction might be just for a fraction of an hour to as much as 20 years ahead for operation and planning purposes. These forecasts [6] are different in nature as well. The forecasts are divided into different categories depending upon the duration for which the demand is predicted. The various classes of prediction are shown in Table 1.1

This section discussed about electricity demand forecasting and various categories of demand forecasting based upon duration for forecast. Next section will focus upon the motivation of this research.

Table 1.1: Demand Forecasting Classification

Nature of Forecast	Duration	Applications
Very short term forecast	Few seconds to few minutes	Generation, contingency analysis for system security and distribution schedule.
Short term forecasting	Half an hour to few hours	Maintenance scheduling, spinning reserve allocation, operational planning and unit commitment.
Midterm forecasting	A few hours to few weeks	Planning for seasonal peak summer, peak-Winter.
Long term forecasting	A few months to few years	Generation growth planning.

1.5 Research Motivation

With increase in number of people moving towards cities, there is a need to find new ways to manage complexity, reduce expenses, increase efficiency and improve quality of life of urban people. As urbanisation is increasing there is a need for the cities to get smarter. Smart City is one with developed area including advanced technology, better infrastructure, better integration of different technologies and good quality of living to its citizens. Major characteristics of smart city includes, smart living, smart people, smart environment, smart mobility, smart economy and smart governance. In order to provide smart governance and smart living, the cities need to have proper waste management, water supply, proper transportation facility, healthcare and educational facilities. Proper electricity management is also crucial component of a smart city.

Growth in networks of electricity system and increase in its complexity, factors become influential in production, management of demand of electric power system. Electricity forecasting is the key factors to economic operation of electric systems.

The motivation of this research work stems as Demand forecasting is an important key for electricity management system. Precise and accurate demand forecasting helps the electric utility to make decisions like unit commitment and maintenance. Along with its importance in reducing the cost of production, it is also important for the reliability of energy systems. The load forecasting result are used by system operator to form a basis of network analysis when off-line in order to determine vulnerability of the system. Corrective actions like load shedding and electricity purchases can be performed in case of vulnerability. Power production of next day is scheduled everyday hence demand forecasting is necessary. Both under or over estimation of demand can be a cause of trouble as under prediction leads to insufficient reserve capacity preparation and, therefore, resulting in increase of the operating cost with expensive peaking units. While over-prediction leads to the unnecessary large reserve capacity which also results into the high operating costs. Though there exists numerous literatures on load forecasting since 1960s, the research work in this area is still a challenge due to its high complexity. Estimation of the future demand with the historical data is a difficulty till now, especially for the demand forecasting of days and months with extreme weather conditions. With the development recent improvement in Data Mining, mathematical and artificial intelligence tools, it has become possible for efficient results the demand forecasting results. Errors in forecasting leads to more purchasing electricity cost t to keep the electricity supply and demand balance in the real-time dispatch operation. Thus an adaptable and accurate technique is required for demand forecasting.

1.6 Organization of Thesis

Chapter 2 summarizes in detail the literature survey done to study the concept of forecasting electricity demand based upon weather variables. Chapter 3 focuses on problem statement of this thesis. This chapter also states the objectives. Chapter 4 provides solution to problem stated in the previous chapter by proposing the architecture, schematic framework model and explaining all its component. Chapter 5 demonstrates proposed framework model by implementing it using Mat Lab and Weka. Results of Experimental setup are shown. Chapter describes the conclusion, contribution of work done and future research possible.

Chapter 2
Literature Survey

In the previous chapter, the Smart Cities are discussed and characteristics of Smart city are introduced. There are many techniques for demand forecasting. Focusing on these techniques this chapter discusses the state of art and research work in the field of techniques for forecasting electricity demand. This literature review discusses existing forecasting techniques used in prediction of electricity demand. After that, this chapter discusses pros and cons of different techniques and finds out a suitable and efficient technique for electricity demand forecasting.

2.1 Research Question

This literature review incorporates the present state of the art in the field of load forecasting by purposing the answer to various present research questions.

i What is electricity demand forecasting?

ii What are the various techniques used for demand forecasting?

iii Which technique of load forecasting is more appropriate and provides justice for electricity demand forecasting with weather data and previous demand record? This literature review starts systematically with definite research questions. Various techniques for load forecasting are reviewed and compared and appropriate one is selected based upon type of dataset available and performance of various techniques.

2.2 Techniques to forecast electricity demand

In this section of the literature review, various existing techniques used for prediction of monthly demand of electricity are discussed along with various proposed forecasting techniques by different researcher and their pros and cons.

Various techniques for electricity demand forecasting have been proposed. Demand forecasting with lead-times, helps the system operator to efficiently schedule management of electricity and its allocation. Demand forecasting can provide information which is used for possible energy interchange with other utilities. For electricity providers, forecasting demand of electricity is a key activity as it is one of the most important entries for planning production and trading on the electricity markets. A good knowledge of the future electricity consumption by electricity managers stands as a central point for the reliability of the network and its investment strategies. In addition to these economic reasons, load forecasting is also useful for maintaining system security.

Many techniques have been proposed in the last few decades for electricity demand forecasting. Generally, electricity demand forecasting techniques [8] can be classified into two main categories: parametric methods and artificial intelligence based methods.

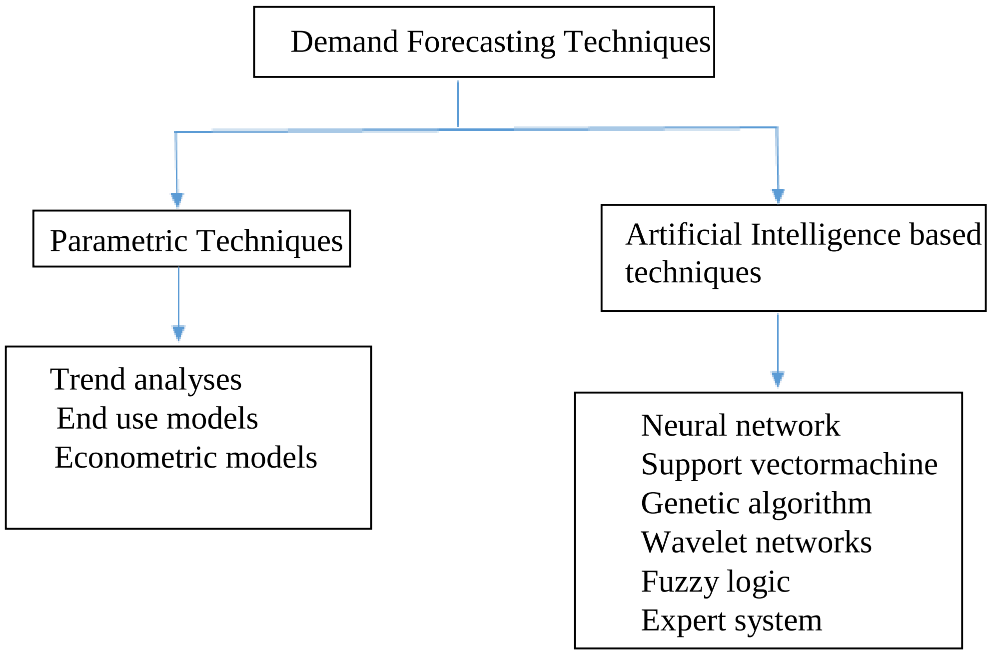


Figure 2.1. Various techniques of electricity demand forecasting

In this section of the chapter we have discussed main categories of forecasting techniques. In next section parametric model will be discussed in detail with its pros and cons.

2.2.1 Parametric Models

Parametric methods use mathematical models to relate electricity demand to its affecting factors. Estimation of parameters for the model is done using statistical techniques that are applied upon historic data of demand and its factors affecting.

Parametric model is further classified into three well-known types that are trend analysis, end use analysis and the last is econometric model.

- Trend Analysis

Trend analysis utilizes past rates of electricity demand in to the future, using techniques like hand-drawn straight lines to computer produced complex curves. These analyses of past data constitute towards the forecast. It focuses upon past changes in consumption values of electricity and utilizes it to predict future changes in the demand. Not much explanation is available for why demand acts as it does, in the past or it will in the future. Informed judgment modifies the trending. Forecasts are modified by utility forecasters depending upon information about future developments which can result in increase of future demand of electricity [6].

Table 2.1: Study of Trending Techniques used for demand forecasting

Parametric Model	**Working**	**Pros**	**Cons**
Trend Analysis	Extends past rate of electricity demand into future demand	Simple Quick Inexpensive to perform	Produces future demand. Does not allow analysing why demand behaves this way

- End Use Models

It directly estimates electricity demand by making use of extensive information available on end users like application used by customer, age of customers, house sizes etc. This statistical information related to the customer form the basis of this model forecast. It focuses on different uses of electricity in various sectors like residential, industrial and commercial sector [7]. This model works on the principle that customer demand of electricity for purposes like cooling, light and heating etc. drives the demand of electricity in a region.

Table 2.2: Study of End Use Model used for demand forecasting

Parametric Model	**Working**	**Pros**	**Cons**
End Use Model	Forecasts using extensive information present on user side	Accurate Less historic data required	Sensitive to amount and quality of end use data. Assume a constant relationship between electricity and end-use.

- Econometric models

This approach of forecasting combines statistical techniques and economic theory for forecasting electricity demand. It computes the relationship between electricity consumption and factors influencing electricity demand [8]. Time series method or least-square method are used for the estimation of relationship. It aggregates the econometric approach, when consumption in various sectors like residential, commercial, industrial, etc. is calculated as a function of economic, weather and other variables, and then computations are made using historical data.

For end use estimation the most common econometric approach is Conditional Demand Analysis (CDA) [9]. In CDA, the total household consumption is calculated as the sum of consumption of various endues plus residual or an error term [10]. Widen, et al, proposed a stochastic Markov chain model using a bottom-up approach for modelling the electricity demand in households in country like Sweden [11]. The proposed model defines that the demand of electricity depends on mainly three factors:

i. number of appliances in the house,

ii. the individual demand of electricity by these appliances and

iii. The amount of use of the appliances.

This model will be useful to develop present model due to the similarity of the consumption patterns analysed.

Table 2.3: Study of Econometric Model used for demand forecasting

Parametric Model	Working	Pros	Cons
Econometric Model	Combines statistical technique and economic theory	Provides detailed information of electricity demand. How factors affect the demand [12].	Assume the changes in electricity remain same in forecast period as in the past.

In this section we have discussed three models that fall under parametric techniques. In next section of this chapter we will compare these three techniques.

2.2.2 Comparison among different parametric models

As mentioned in the previous section of this chapter trend analysis, analyze just changes in the past years in electricity demand and utilize it to forecast electricity demand, but there is no process to explain why these changes happened. End users and behaviour of end user are not important in this model. But in end use method of forecasting, statistical information related to customers along with amount of change act as the basis for the forecast. In Economical methods, the results are estimated upon the relationship between dependent variables and factors influencing electricity consumption. Time series and least square method are used to estimate the relationship.

Comparison of these three parametric model shows that out of econometric, end use model and trend analyses, trend analysis is not as trustworthy in this method as other two models because we require a wise and knowing judge in this case, for recognition of unreal data and to omit them. In This section old methods for electricity load forecasting are described. These methods are also useful today. Next section will cover new methods, these new following methods can use for their accuracy and fast possessing system.

Table 2.4: Comparison of three parametric model for demand forecasting

Models	Pros	Cons	Authors
Trend Analysis	Fast processing and easy data availability. Many commercial tools available.	Suitable only for short-term forecasting.	[13-14]
End Use Model	It is suitable for long-term forecasting. Can simulate demand changes if consumption patterns changes or new technologies are introduced.	Model's accuracy is highly based on the information from consumers. If the consumer's sample is limited, it cannot simulate large-scale demand forecasting	[15,16]
Econometric Model	Also suitable for long-term forecasting and simulation of different scenarios of demand, implementation technologies, policy adoption and consumers' behavioural changes.	Requires historical electricity data, economic and behavioural components for the same consumers' population sample for building the model. Otherwise model's accuracy lowers.	[17-18]

2.2.3 Artificial Intelligence based Techniques

In the previous section of this chapter we discussed parametric techniques of Data Mining and compared different parametric techniques. In this section we will discuss artificial intelligence based models of Data Mining. The artificial intelligence methods of forecasting demand are further classified in to neural networks, support vector machines, genetic algorithms, wavelet networks, fuzzy logics and expert system methods.

- Artificial Neural Networks

The ability of mapping complex and non-linear relationships has resulted into increase in number of applications in demand forecasting [19]. Power system problems, like planning, analysis, control, design, protection, load forecasting, security analysis and fault diagnosis are some of the applications of ANN. Load forecasting, fault diagnosis and security analysis are most important ones. For long term load forecasting using ANN only a few studies are carried out [20], [21].

Trader H. *et al.* [22] proposed some degrees of freedom that must be iterated upon to increase the potential of an accurate demand forecast: (1) part of the database is used for training purpose and testing purpose, (2) transformations are performed on the past database, (3) specifications of ANNs architecture, (4) during training optimal stopping point and (5) relative weights to use in forecast combination. Kermanshah *et al.* [23] proposed a recurrent neural network model for long term demand forecasting. It makes use of past records to learn patterns and to project and generalize load patterns for future for an unseen data. Suita *et al.* [24] presents a system marginal price (SMP) forecasting implementation. The approach uses a three-layered ANN .

Reddy *et al.* [25] presents an approach for short term electrical load forecasting using ANN. He examines the feasibility of various mathematical models for short term load forecasting. To make these models to yield satisfactory results, various system models are formulated with combination of parameters like base load component, load inertia, day of the week, short term trends, autocorrelation, length of the past data, etc. Various modifications of Back Propagation Algorithm have been proposed by him to explore the ideal combination that will suit the forecasting need of regional electricity grids.

Many advantages offered by ANN are:

- They are extremely powerful computational devices.
- Very efficient due to massive parallelism.
- Learn and generalize from training
- Fault tolerant
- Noise tolerant

Table 2.5: Study of ANN model of load forecasting

Model	working	Pros	Cons
ANN	It performs non-linear modelling and adaptation.	Approximate very accurately, Does not require assumption of any functional relationship between load and weather variables in advance, model a multivariate problem without making complex dependency assumptions among input variables [26].	Inaccuracy of weather forecasts, difficulties in weather-load relationship modelling and implementation Problems limit the accuracy.

- Wavelet theory

Wavelet theory is introduced recently and it has received wide attention. It is a more powerful and a flexible tool that decomposes load data into different components based upon frequency. Then analyse each components characteristics thus resulting into improved accuracy. Wavelet analysis is further extended to wavelet packet analysis for better resolution [27]. Application of wavelet analysis for load prediction is investigated in several papers. Amjady N. *et al.* [28] proposed a new hybrid forecast for short term load forecasting. WT can decompose the time series effectively into its components.. Bashir Z.A et al [29] proposed a model that wavelet transformed the data during pre-processing stage and then redundant information is extracted by inserted data into neural network. It can be combined with ANN to have better forecast.

- Genetic Algorithms

Managing electricity supply is a complex task. Important of this management is forecasting future demand of a region. Genetic algorithm approach is proposed to forecast long term electricity demand. The results of its applications show success in load forecasting with minimal error [30].This class is based on natural selection, natural genetics and survival of the fittest mechanism. Fault detection, load flow problems, economic dispatch and load demand forecasting are some of the areas where GA is applied [31].

Ling S. H.*et al.* [32] presents genetic algorithm based neural network approach for short term load forecasting. This paper shows that results provided by this model provide better results as compared to traditional feed forward neural network as fewer nodes are needed in this model. Parameters of the proposed neural network are tuned by using genetic algorithms with uniform mutation.

- Fuzzy logic

Generalization of the usual Boolean logic that is used for digital circuit design is known as Fuzzy logic. Fuzzy logic is a technique for mapping inputs to outputs called curve fitting. Advantages of fuzzy logic is the absence of a need for a mathematical model for mapping inputs to outputs and also the absence of a need for precise or noise free inputs. Properly designed fuzzy logic systems with genetic conditioning can be very robust when used in field of load forecasting [33]. In many situations an exact output I required. A process called defuzzification after the logical processing of fuzzy inputs, can be used to produce such precise outputs. Parth *et al.* [34] proposed a model for short term load prediction using fuzzy logic by considering time, temperature and similar previous day load as the independent variables for short term load forecasting. Based on the time, temperature and similar previous day load, fuzzy rule base are prepared. Load data from the specific area load dispatch centre is considered for such forecast.

- Support vector machines

One of the most recent and powerful technique for regression and classification problem is Support Vector Machines (SVMs). This was originated from statistical learning theory by Vapnik's [35]. Then simple linear functions are used to create linear decision boundaries in the new space. Mohandes *et al.* [36] applied the method of support vector machines for short term electricity load forecasting. The results are in favours of SVM against the autoregressive method. Chen *et al.* [37] proposed a SVM model to predict daily electricity load demand of a month.

Li and Fang *et al.* [38] also used a SVM model for short-term load forecasting.

- Expert systems

To do accurate forecasting, rules are used by rule based forecasting which are often heuristic in nature. Expert systems, includes rules and procedures that are used by human experts in the field of their interest into a software that can then automatically make forecasts without any human assistance. The use of expert system began in the 1960's for applications like computer designing and geological prospecting. It can codify up to thousands of production rules. Ho *et al.* [39] proposed a model for short term load forecasting using knowledge-based expert system of the Taiwan power system. The developed algorithm in this paper performed better compared to the conventional Box-Jenkins method.

Rahman and Hazim [40] developed a short term load forecasting technique which is site independent.. Parameter database complements this rule base. It was tested in several sites in the United States resulting in low forecasting errors. The rules, load models and the parameters presented are designed using no specific knowledge about a particular site. The results can be improved if operators at a particular site are also consulted.

2.2.4 Comparing Artificial Intelligence based techniques

In previous section various artificial intelligence based techniques and their application were discussed. In this section we will compare these techniques. Table 2.6 will show the contrast among these techniques.

Table 2.6: Comparison of Artificial Intelligence based techniques of demand forecasting

Model	**Working**
Artificial Neural Network	Recurrent neural network learns pattern from previous year's data and project patterns and trends for future. Feed forward and back propagation neural network produces an associated output pattern when an input pattern is given. More simple and accurate then RNN.
Wavelet Analysis	Inputs are not spanned. More accurate than multi-layer neural network because of multi resolution analysis property.
Genetic Algorithms	It is a numerical optimization technique based on natural genetics. Quite promising and Produce better results in long term load forecasting. Suitable for parallel implementation.

SVM	It has non-linear mapping capabilities. Parameters if improperly determined can cause under fitting or over fitting of SVM model. Structural risk minimization is performed rather than training errors.
Fuzzy System	Fuzzy rules are combined with neural network to train ANN and to get better load demand forecasting.
Expert System	It is flexible in updating the forecasting methods and heuristic rules. It can serve as a valuable assistant to system planners in performing their annual load forecasting duties.

2.3 Factors Affecting Accurate Demand Forecast

The operation of electricity system is strongly influenced by the accuracy of demand forecast as economy and control of electric power system is quite sensitive to forecasting errors [41-42]. The four important factors affecting load forecast are:

i. Weather conditions

Electricity demand has a strong correlation to weather. To develop an efficient and accurate demand forecasting model for electricity much effort has been put to find a relationship between the weather and the demand of electricity. The change in comforts of customer due to change in weather conditions resulting in usage of appliances likes air conditioner, space heater and water heater. It also includes use of agricultural appliances for irrigation.

Table 2.7: Components of Weather of Load Forecasting

Weather Component	**Impact on demand**
Temperature (degree C)	Demand increases whenever temperature rises or lower than base line
Humidity (%)	Demand increases with increase in humidity.
Wind speed(Km/h)	Depend upon location.
Sunshine	More sunlight leads to more heat. Thus, more demand.
Rainfall (mm)	Less demand due to low irrigation requirements.

The pattern of demand differs greatly in the areas with large meteorological difference during summer and winter. Dry and wet temperature, humidity, dew point, wind speed, wind direction, sunshine and amount of precipitation are common weather parameters that influence electricity demand.

ii. Time factors

The factors related to time include the day of the week and the hour of the day. Weekdays and weekends experience different demands. Different weekdays can also behave differently particularly during summers. Forecasting demand on holidays are more difficult than non- holidays due to infrequent occurrence. The arrangement of people's daily life is reflected by the demand variation: working, leisure and sleeping time. Demand variation with time have some rules defined. The demand curve is lower on weekend than the week day curve because of less working load. Another property of the demand curve is the periodicity. Demand data contains strong periodicity daily, weekly, seasonal and yearly. Forecasting results can get benefit from better use of these properties.

iii. Economy

Electricity is also a form of commodity. Thus, utilization of electricity is also influenced by the economic situation. Demand of electricity strongly depends upon economic factors like the increase in industrialization, cost of electricity and load management policy. The relationship between electricity price and demand has become even stronger with the development of modern electricity markets.

iv. Customer class

Residential, commercial, and industrial are different types of customers served by most of the electric utilities. Customer belonging to different classes have different electric usage pattern but it is somewhat alike for customers within one class [43]. Therefore, load behaviour are distinguished on the bases of class also. Though demand of electricity is governed by number of factors as mentioned above, but studies have shown that weather is the key factor that drives the demand of electricity. The other factors like economy and time factors are important for daily demand prediction. But for long term forecasting weather variables are the major contributors.

2.4 Analysis

Conventional or parametric techniques assume, without proper justification, a linear relationship between load and weather variables. However, the functional relationship among load and weather variable is not stationary, but it depends on spatio-temporal elements. Conventional regression approach does not offer the versatility to address this kind of temporal variation. Rather, it will produce an averaged result. Therefore the required technique need to be adaptable so that efficient and accurate prediction of electricity demand can be made. Hence neural network is selected for load forecasting because it has capability of forming non-linear relationships.

Neural networks offer remarkable ability to extract meaning from complex or imprecise data. It can also be used to extract trends and patterns that are complex and difficult to be noticed by humans or other computerized techniques. A trained neural network is like an "expert" in analysing information provided to it. This provides projections to new situations and answer "what if" questions. It has many advantages like:

i. It is capable to learn how to perform tasks based on the given data .
ii. Self-Organization: It can create its own representation and organization of the information it receives during learning period.
iii. Real Time Operation: It offers parallel computations.
iv. Fault Tolerance via Redundant Information Coding

Because of above mention advantages offered by ANN and also due to database type ANN is preferred in this report for carrying out demand forecasting based on weather variables.

2.5 Conclusion

This section discussed about the research question followed by various existing and proposed models for demand forecasting and a comparison is made among all the techniques that can be used. In next chapter research gap and problem statement will be discussed followed by objectives of research.

Chapter 3
Problem Statement and Objectives

Based upon the literature survey in the previous chapter, gaps have been identified in the area of demand forecasting. Based upon the analysis of various techniques for load forecasting, problem statement for this thesis has been formulated in next section. Objectives of this thesis are entitled at the end of this chapter.

3.1 Problem Formulation

Load forecasting is one of the central functions in operation of electric power systems. The motivation for accurate demand forecasts lies in the nature of electricity to be used as a trading article and commodity. Electricity cannot be stored, therefore, the precise estimate of the future demand is necessary for management of generation and purchase in an economically reasonable way.

Therefore, there is a need to develop an efficient and precise model for demand forecasting based upon weather conditions. This work studies the applicability of neural network models on monthly load forecasting. The approach is comparative. The objective is to choose the most appropriate model(s). There are some important properties, which are considered:

i. The model should be automatic and adaptable.
ii. The model should be intended to use in many different cases (general).
iii. Updating of forecast with new data .
iv. The model should be reliable.
v. Difficult weather conditions should be taken care of.

3.2 Objectives

Electricity demand forecasting is a significant component for electricity management system. Efficient and precise demand forecasting helps in making unit commitment decisions also reduce spinning reserve capacity and reduces the generation cost and improves the reliability of the systems. Since precise and accurate demand forecasting remains a challenge, the objective of this work is to develop some new and practical algorithm and model with some up-to-date techniques to forecast demand of electricity based upon weather variables and historical demand records using suitable model of forecasting.

Due to some problems in measurement or transmission of data, the historical database might have some bad or missing data, which can degrade systems performance and affects the precision of load forecasting results. Thus, one of the objectives of this research work is to find a way to detect the missing data, and to evaluate the real data.

Thus main objectives are

i. To develop an efficient model to forecast demand of electricity based upon weather variables
ii. To find a possible method to detect the missing data.
iii. To test the model with real data.

3.3 Conclusions

This chapter discussed the research gap and research problem in detail. Then objectives of the research were discussed. Next chapter will focus upon the proposed algorithm as a solution to the problem stated in this chapter.

Chapter 4

Monthly Electricity Demand forecasting using ANN

An artificial neural network is a mathematical model inspired from biological neural networks. Neural network models are widely used in many areas like signal processing, statistics, neurophysiology, business forecasting, and engineering etc. Forecasting, rainfall prediction, speech recognition, credit card fraud detection are some of the applications of ANN. In this chapter we will discuss ANN and its application in electricity demand forecasting followed by the model for monthly electricity demand forecasting using ANN.

4.1 Artificial Neural Network

An artificial neural network is the artificial representation of the human brain which tries to simulate the process of learning. Human brain is a highly complex and offers nonlinear and parallel information processing. It has the ability to organize its neurons to perform certain computations number of times faster than the fastest digital computer existing today. It is implemented by using electronic components or by simulation in software on a digital computer. ANN is a massively parallel distributed processor which is made up of simple processing units called neurons, which has a propensity for storing knowledge and making it available for use. The procedure used to perform the learning process is called a learning algorithm, which modifies the synaptic weights of the network in a fashion to attain a desired design objective [44].

Artificial Neuron: ANN has a basic building block known as Neuron. The connection weights are adjusted between the neurons. When exposed to input pattern p, neuron u_i generates neuron inputs O_i. Then each input is multiplied with connection weight w_{ij}, which is the connection between neurons u_i and u_j. The connection weights correspond to the strength of the influence of each of the preceding neurons. After the multiplication by the connection weights, their values are added, net_{pj}. Included in the summation is a bias value θ_j to offset the basic level of the input to the activation function, f (net_{pj}), which gives the output O_j. Each neuron requiring a bias value will be connected to the same bias neuron. With the learning of neuron the bias values are then self-adjusted [45].

i. Weights
ii. Summation factors
iii. Transfer Function / Activation Function
iv. Scaling and Limiting
v. Output Function
vi. Error Function and Back-propagated Value
vii. Learning Function

Network architectures: There are three fundamental different classes of network architectures [46]

- Single-layer Feed forward Network

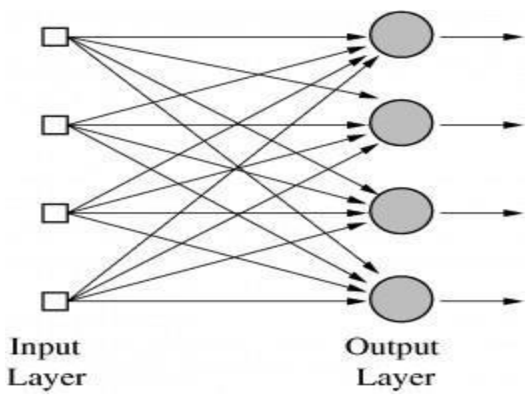


Figure 4.1. Single layer Feedforward artificial neural network[3]

This type of ANN network consists of two layers, the input layer and the output layer. The input signals are received by input layer and the output signals are received by output layer neurons. Weights are carried by the synaptic links connecting every input neuron to the output neuron. As only output layer performs the computation, therefore the network is termed single layer. Figure 4.1 shows the architecture of single layer feedforward network.

[3] http://ansonabey.hubpages.com/hub/Artificial-Neural-Network

•	Multilayer Feedforward Networks

Multilayer Feedforward Networks distinguishes itself from the previous one by the presence of multiple hidden layers, where computational nodes are known as hidden neurons. Hidden neuron intervene between the external input and the network output in some useful manner. Figure 4.2 displays the architecture for multilayer feedforward artificial neural network. The network is enabled to extract higher order statistics by adding more number of hidden layers. The input signal is applied to the neurons present in the second layer.

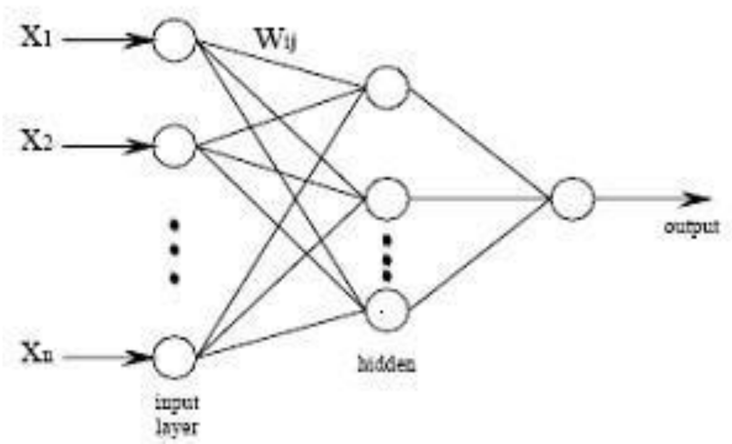


Figure 4.2. Multilayer Feedforward artificial neural network. [4]

•	Recurrent networks

A recurrent neural network is one that has at least one feedback loop. A recurrent network mainly consist of a single layer of neurons in with each neuron feeds its output signal back to the inputs of all the other neurons. Figure 4.3 shows the architecture of recurrent artificial neural network. The situation where the output of a neuron is fed back into its own input is called Self-feedback. The presence of feedback loops improves the learning capability of the network and on its performance.

[4] http://article.sapub.org/10.5923.j.ajis.20120203.02.html

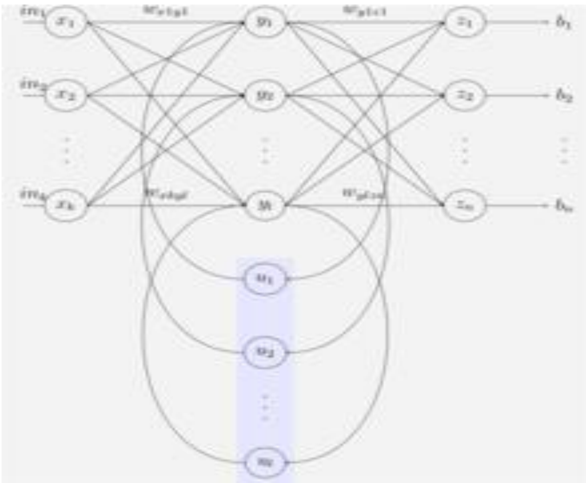


Figure 4.3. Recurrent artificial neural network. [5]

In this section we discussed different types of artificial neural networks available and how they work. In next section of this chapter we will discuss various weather parameters and their impact on electricity demand.

4.2 Weather Variables and Electricity Demand

It has been seen that weather variables are main driving factors for forecasting electricity demand. The main weather variables are dis-cussed as follows

- Temperature

The main driving factor for electricity demand forecasting is temperature [47-48]. Increasing temperature not only affects the demand but also restricts the load carrying capacity of distribution lines [49]. We first plot the monthly average demand values against the mean average temperature in India to better understand the relationship among these. This is shown in Figure. 4.4. It shows that there is a direct relationship between temperature and demand in India. During summers there is a significant cooling load that coincides with higher temperature.

[5] https://en.wikipedia.org/wiki/Recurrent_neural_network

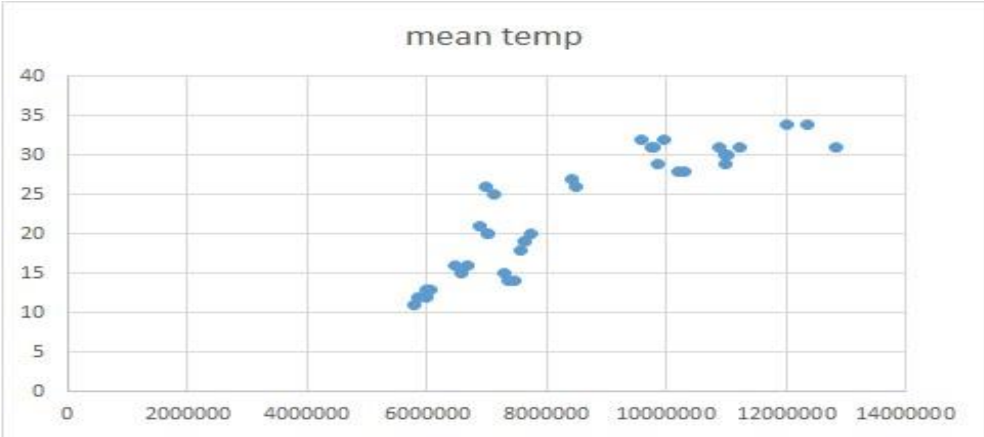


Figure.4.4. Mean monthly consumption as a function of mean average temperature.

And in winters the demand tends to be lower because there is no such load of coolers and air conditioners.

Also in extreme winters the demand rises due to increase in heating and lighting load. There is variation in correlation of demand with temperature over time due to no weather related parameters like increase in population, income etc.

- Degree Days

Degree days are categorized under two classes:

i. Cooling degree days: It measures the duration of hot weather and its severity. It is used to calculate the cooling needs [50]. Also called CDD.

ii. Heating degree days: It measures the duration of cold weather and its severity. It is used to calculate the heating needs [51]. Also called HDD.

The higher the temperature means higher is the CDD value hence more cooling is required in those days. A positive value for CDD employs electricity is required for cooling purposes whereas a positive value for HDD means electricity is required for heating purposes.

Monthly demand against HDD is shown in Figure.4.5.A weak linear correlation in shown among demand and HDD.

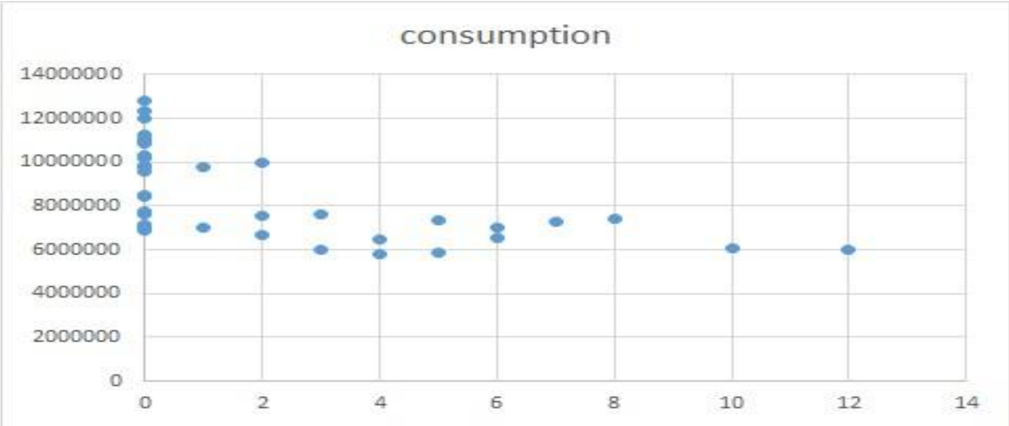


Figure.4.5. Monthly demand against heating degree days

Monthly electricity demand against CDD is shown in Figure 4.6.This is seen from the figure that there is strong correlation between value of C DD and monthly demand.

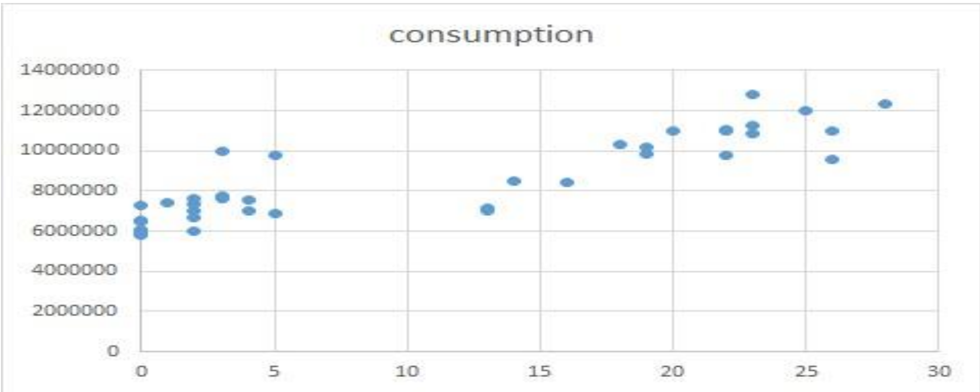


Figure.4.6. Monthly demand against cooling degree days

- Rainfall

Rainfall is also a crucial factor that mainly affects the consumption of electricity for domestic purposes. Rainfall in India is a common phenomenon especially in the months of summers as load related to lighting and air conditioning are directly affected by the rainfall in the region.

- Humidity

One of the other factors that affect the demand of electricity in a region is relative humidity. It indirectly affects the demand as increase in humidity results in increase in use of air conditioners.

Apart from these factors other factors like duration of sunshine and cloud cover[52] also drive the demand of electricity. As if duration of cloud cover is more, higher is the electricity required for lighting purposes.

4.3 ANN Technique for Monthly Demand Forecasting

The ANN technique to monthly demand forecasting has gained a great deal of interest. Its effectiveness have been reported by several researchers. The ANN techniques is applied to correlate the weather related information and the demand variations to forecast the monthly electricity demand. The advantage of ANN [53] over statistical models is that it can model a multivariate problem without making any complex dependency assumptions among input variables. The ANN can extracts the implicit nonlinear relationship among input variables by learning process from training data. The ANN used monthly historical data of the weather conditions and the load are classified according to their characteristics [54] to create a nonlinear model. Monthly demand is then forecasted by these nonlinear models.

The proposed development and implementation of new ANN based technique for monthly demand forecasting of weather sensitive loads consist of four stages. The ANN model used a multilayer neural network consisting of one input layer, two or more hidden layers and one output layer.

i. Data selection and analysis

There is no basic rule for selection of number of input variables [55]. Hit and trial method is used for data selection. The historical load data and weather data, forecasted average monthly weather and weather data are the required input parameters. Weather data include temperature (°c), humidity (%), Wind speed (km/h), rainfall (mm), and pressure. The suggested input vector to the ANN specifies weather data for the month to be forecasted, and associated load data. The demand of electricity is strongly influenced by the average monthly temperature, humidity, and wind speed [56]. Since the most recent three year load data points are considered as part of the inputs, the corresponding three year temperatures, humidity, and wind speed are included. In total, the temperature, humidity, wind speed data points, rainfall, load account for seven input variables. Climatic conditions fluctuates the demand.

ii. Pre-processing of Data

Pre-processing of data comprises normalization and handling of missing value in the historical data set. Normalization is the process of organizing data in a database and making it more flexible. The input values and the output values are normalized before training so that all the data falls within the range from 0.15 to 0.85 to prevent the simulated neurons from being driven too far into saturation. As the historic weather data is difficult to attain and also the measurement and transmission [57] of data can sometimes results into missing values in dataset. These missing values can degrade system performance thus a forward and backward difference mathematical model is applied to locate the missing values and substitute it with most appropriate values.

iii. ANN Architecture

This section describes the step by step procedures for training the neural network to learn from the recent three year monthly demand data and weather related data of Amloh as shown in Figure 4.8, in order to forecast monthly future demand. For designing the network architecture the Matlab ANN toolbox was utilized as shown in Figure 4.7. A number of ANN architectures were discussed in the previous section of this chapter and there are many other architectures of ANN. The increase in number of hidden layers results in increase in complexity of the architecture of ANN thus affecting its performance. Levenberg-Marquardt algorithm is an algorithm that is used for training an artificial neural network. It trains faster as compared to gradient decent back propagation method. It is more efficient also but require more capable memory.

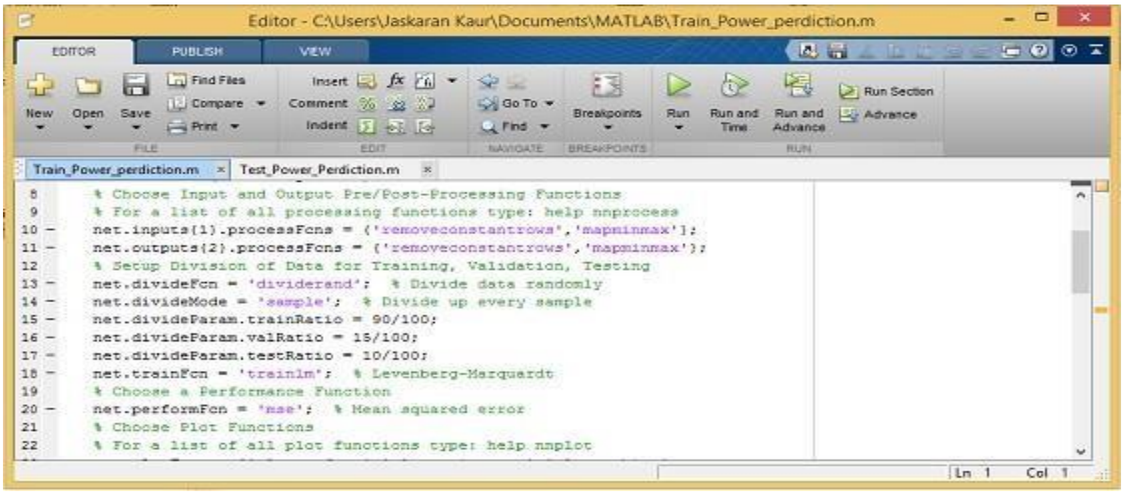
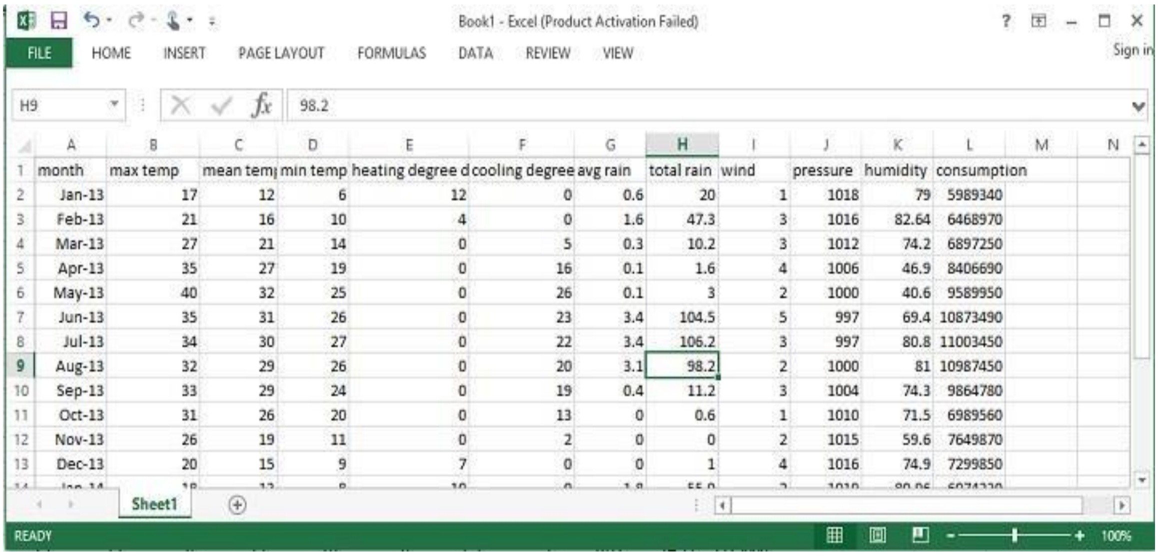


Figure 4.7. Screenshot of implementation of ANN in MATLAB.

A multilayer Feed forward Network architecture with was designed. The layers include the input layer, the hidden layers and the output layer. The input consists of monthly demand data for last three years and weather related data of these years. The output layer will be a monthly demand forecast for the utility company. The number of hidden layers in the network are determined using approach used for training epochs that is Mean squared error, since there exists no theoretical approach for calculating the appropriate number of hidden layer.



month	max temp	mean temp	min temp	heating degree d	cooling degree	avg rain	total rain	wind	pressure	humidity	consumption
Jan-13	17	12	6	12	0	0.6	20	1	1018	79	5989340
Feb-13	21	16	10	4	0	1.6	47.3	3	1016	82.64	6468970
Mar-13	27	21	14	0	5	0.3	10.2	3	1012	74.2	6897250
Apr-13	35	27	19	0	16	0.1	1.6	4	1006	46.9	8406690
May-13	40	32	25	0	26	0.1	3	2	1000	40.6	9589950
Jun-13	35	31	26	0	23	3.4	104.5	5	997	69.4	10873490
Jul-13	34	30	27	0	22	3.4	106.2	3	997	80.8	11003450
Aug-13	32	29	26	0	20	3.1	98.2	2	1000	81	10987450
Sep-13	33	29	24	0	19	0.4	11.2	3	1004	74.3	9864780
Oct-13	31	26	20	0	13	0	0.6	1	1010	71.5	6989560
Nov-13	26	19	11	0	2	0	0	2	1015	59.6	7649870
Dec-13	20	15	9	7	0	0	1	4	1016	74.9	7299850

Figure 4.8. Screenshot of weather data and previous electricity consumption data stored.

The network architecture is characterized by the pattern of connectivity. A two-step procedure is followed by output layer to determine its activity.

First, the total weighted input X_j is computed, using the formula in equation 1.

$$X_j = \sum y_i W_I \text{ ……………………(1)}$$

Where W_{ij} is the connecting weights between ith and jth layer and y_i is the activity level. Secondly, the unit calculates the activity y_j using sigmoid function of the total weighted input as shown in equation 2.

$$y_j = 1/(1+e^{-xj}) \text{ …………………..(2)}$$

Then the network computes the error E, which is defined by the expression in equation 3.

$$E = \frac{1}{2}\sum (y_i - d_i)^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

Where y_i is the activity level and d_i is the desired output of the jth unit.

The Levenberg Marquardt (lm) back-propagation algorithm consists of six computational steps.

i. It computes the error change speed with change in the activity of an output unit. This error derivative (EA) is the difference between the actual and the desired activity as shown in equation 4.

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

ii. Then it computes the error change speed with change in total input received by an output unit as shown in equation 5.

$$EI_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} * \frac{dy_j}{dx_j} = EA_j\, y_j(1-y_j) \ldots\ldots\ldots\ldots(5)$$

iii. Then it compute error changes speed with change in weight on the connection into an output unit as shown in equation 6.

$$EW_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial x_j} * \frac{dx_j}{dW_{ij}} = EI_j\, y_j \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

iv. Then it computes the error change speed with change in activity of a unit in the previous layer. This step allows back propagation to be applied to multilayer networks. The output unit activities are affected with the change in activity of a unit in the previous layer. Hence to compute the overall effect on the error, all separate effects on the output unit are add together. But each effect is simple to calculate as shown in equation 7.

$$EA_j = \frac{\partial E}{\partial y_j} = \sum_j EI_j\, W_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

v. Then it advances to compute the H matrix (equation 8) and the gradient (equation 9). This is necessary to approach second-order training speed without having to compute the Hessian matrix.

$$H = J^t J \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

$$g = J^t e \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Where J is the Jacobian matrix and e is a vector of network errors.

vi. At the end, the Levenberg Marquadt- lm algorithm uses approximation to the Hessian matrix in the following Newton-like update as shown in equation 10.

$$X_{k+1} = x_k - [J^t J + \mu I]^{-1} J^t e \ldots\ldots\ldots\ldots\ldots\ldots(10)$$

Where x_{k+1} is the updated value of the network weight and x_k is the current weight. When the scalar μ is equal to zero, this act as Newton's method, using the approximate Hessian matrix, while when μ is large, this becomes gradient descent with a small step size.

vii. Training and Testing

The fully connected multilayer ANN architecture used in this study, consist of three Layered Feed forward network that is trained using Levenberg-Marquardt algorithm which is faster as compared to gradient descent back-propagation algorithm with delta learning rule. The flowchart for training and load forecasting is shown in Figure 4.9.

The sigmoid activation function is used in ANN. The initial network connection weights are set to small random numbers commonly ranges between 0 and 0.4. The training of neural network to forecast monthly loads is based upon the classified data.

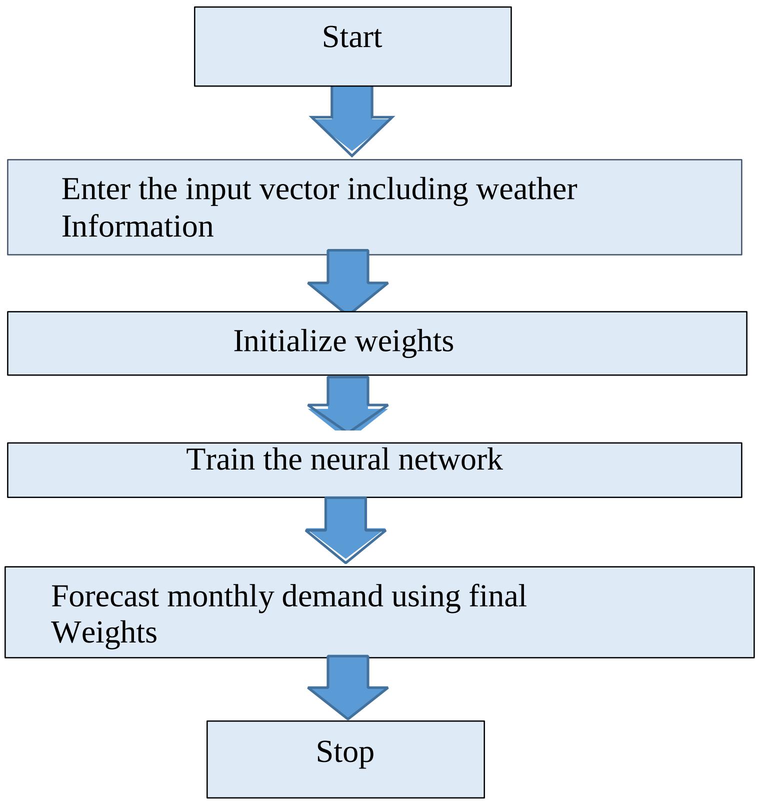


Figure.4.9 Flowchart for training and testing of ANN

4.4 Levenberg-Marquardt Algorithm

As stated in previous section of this chapter, the neural network model in this work is trained using LMA algorithm, each learning iteration (epoch) will consist of the following basic steps:

i. Compute the Jacobian (by using finite differences or the chain rule)

ii. Compute the error gradient

1. $g = J^tE$

iii. Approximate the Hessian using the cross product Jacobian

1. $H = J^tJ$

iv. Solve $(H + \lambda I)\delta = \mathbf{g}$ to find $\boldsymbol{\delta}$

v. Update the network weights **w** using $\boldsymbol{\delta}$

vi. Recalculate the sum of squared errors using the updated weights vii. If the sum of squared errors has not decreased,

a. Discard the new weights, increase $\boldsymbol{\lambda}$ using **v** and go to step 4.

Else decrease **λ** using **v** and stop.

In this section we discussed the ANN algorithm used to perform demand forecasting of electricity. The next section we discusses the measures of accuracy and performance evaluation of the model.

4.5 Accuracy of Forecasts

To ensure the accuracy of the system, the relative error between the demand of electricity generated by the model and the actual consumption are obtained on monthly basis. An over forecast is indicated by a positive value of error, which employs that the demand forecasted by the system is larger than the actual demand of electricity in the region. While, an under forecast is indicated when forecasted demand value of electricity is less than the actual demand value.

Absolute Percentage Error = $\frac{generated\ demand - actual\ demand}{actual\ demand} * 100$

Mean Absolute Percentage Error = $(1/N) \sum_{i=1}^{N} \frac{generated\ demand - actual\ demand}{actual\ demand} * 100$

4.6 Conclusions

ANN has the capability to model non-linear relationships. In this chapter we discussed ANN followed by the ANN model proposed for monthly electricity demand forecasting using weather related data. APE and MAPE are used for estimating the accuracy of the proposed model. In the next chapter we will analyze the results obtained by this model.

Chapter 5
Implementation and Results

The dissertation work has been focused on the preliminary investigation of feasibility and performance artificial neural network model to carry demand forecasting on monthly basis using weather data. Real time data that includes historical monthly load demand over 5 years, and weather data in terms of temperature humidity, wind speed, is collected for the city Amloh, Punjab. The forecasted load is compared with the actual load and average percentage error is calculated. This chapter will focus upon the results generated by the model and its accuracy.

5.1 Artificial Neural Network Model

The proposed methodology of ANN in this thesis consists of fully connected multilayer feedforward back propagation network. The network consists of input layer, hidden layer and output layer as detailed in previous chapter.

The implementation of the proposed network undergo following steps:

i. Build the training data set including historical load data and historic weather data of temperature, humidity, and wind speed that strongly influences the load.

ii. Select a multilayer feed forward back propagation network architecture hidden layers iii. Initialize the weights of connecting links to small random values to avoid saturation.

iii. Compute the activated output using summation principle at a neuron.

iv. Train the network for given number of iterations.

v. Test the trained model on the test data.

vi. Test the models forecasting accuracy on a different set of historical data and forecast accuracy is computed.

In this section the step by step procedure followed to forecast monthly electricity demand using ANN has been discussed. In the next section the tools used for implementations have been discussed.

5.2 Tools

There are number of tools available for implementation of artificial neural network. In this thesis Mat lab is being used for implementation and training of artificial neural network.

5.2.1 MATLAB

MATLAB is a high-level language and offers an interactive environment to carry out visualization, numerical computation, and programming. MATLAB can be used for analyses of data, development of algorithms, and creation of models and applications. Multiple approaches can be explored using and built-in math functions of the tools and it allows us to reach a solution faster as compared to spreadsheets and other traditional programming languages like C/C++ or Java. MATLAB offers a range of applications, including:

i. signal processing and communications,
ii. image and video processing,
iii. control systems,
iv. test and measurement,
v. computational finance,
vi. Computational biology.

Millions of engineers and scientists in academia and industry are using MATLAB, the language of technical computing. MATLAB can be used in projects such as modelling energy consumption in order to build smart power grids, development of control algorithms for hypersonic vehicles, analysing whether data to visualize intensity and track of hurricanes, and optimal dosing for antibiotics.

5.2.2 WEKA

WEKA (Waikato environment for knowledge analysis) is a suite of machine learning which consists of number of data mining algorithms to carry out tasks related to data mining. It is a free software written in java, and is developed by University of Waikato, New Zealand. The data mining algorithms present in weka can either be called by using own java code or by directly applying it to the dataset. It consists of tools that can be used to perform pre-processing of data, classification, clustering, association rules, regression and visualization of data. New schemes for machine learning can also be developed using weka.

Weka is popular suite for data mining as it offers number of advantages like:

i. It is available free of cost under GNU general public license.
ii. It includes the comprehensive collection techniques for processing and modelling of data.
iii. As it is written in java, hence offer portability and can run on any computing platform.
iv. It is easy to use due to graphical user interface

.

Figure 5.1. Graphical user interface of WEKA.

In this section we discussed the tools that are used to carry out this work. In next section we will see the results obtained by the models and also evaluate their performance on scale of APE and MAPE.

5.3 Results using ANN Model

As stated in earlier section of this chapter ANN trained using LMA algorithm based forecasting algorithm was implemented and trained using MATLAB. In this section we will discuss the results obtained by ANN model and will evaluate the system performance based upon absolute percentage error and mean absolute percentage error. Also the performance of this model is evaluated using regression model upon same data set and comparing the performance of both the models. The results obtained during testing of ANN model are shown in Figure 5.2.

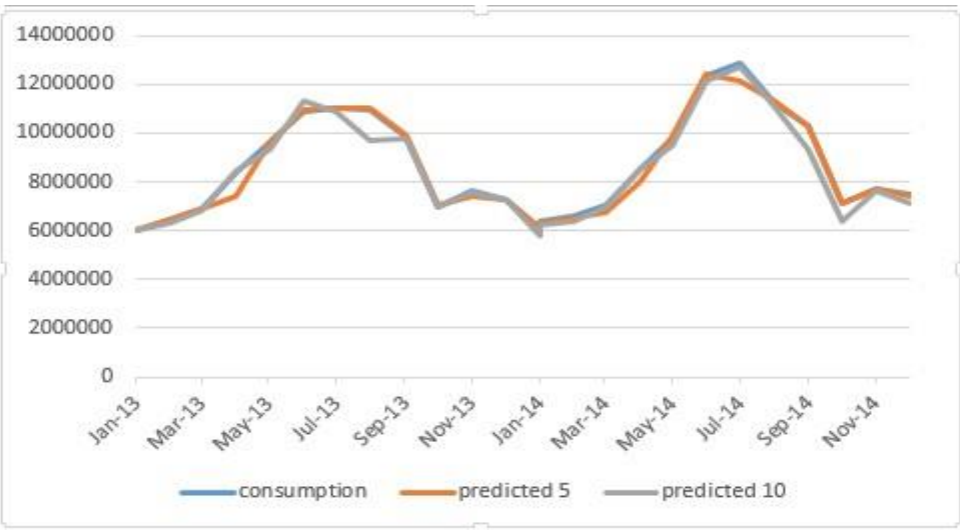


Figure 5.2. ANN generated demand values against actual values.

The performance of ANN model that is trained using LMA algorithm is evaluated by computing APE and MAPE of the results, as shown in Table 5.1. The MAPE of ANN with 5 hidden layers is 0.05 and with 10 hidden layers is 2.59. The results show that ANN model with less number of hidden layers gives better results since increase in number of hidden layers results in the increase of complexity of the system.

Table 5.1. Comparing performance of ANN model with different number of hidden layers

Actual Consumption Value	**ANN generated value(5 hidden layers)**	**APE (5 hidden layers)**	**ANN generated value(10 hidden layers)**	**APE (10 hidden layers)**
6468970	6466530	0.03	6303050	2.5
6897250	6898550	0.01	6858050	.56
9589950	9597550	0.07	9352450	2.4
10987450	11014050	0.2	9952350	9.3
7299850	7297050	0.03	7241350	.80
6551600	6569240	0.2	6388550	2.4
MAPE		0.05		2.59

The calculated values for electricity sing ANN trained using LMA algorithm are very close to the actual values using less number of hidden layers by using ANN model. The difference is due to dependency of consumption on many other non- weather related factors that are not considered while training the ANN in this model.

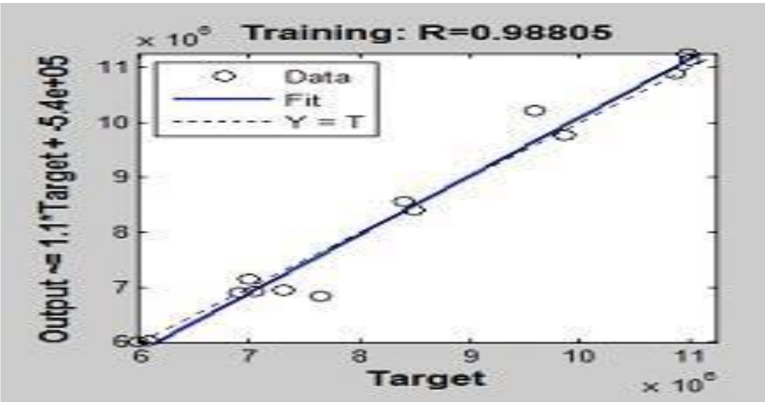


Figure 5.3. Plotting performance of ANN during training of ANN.

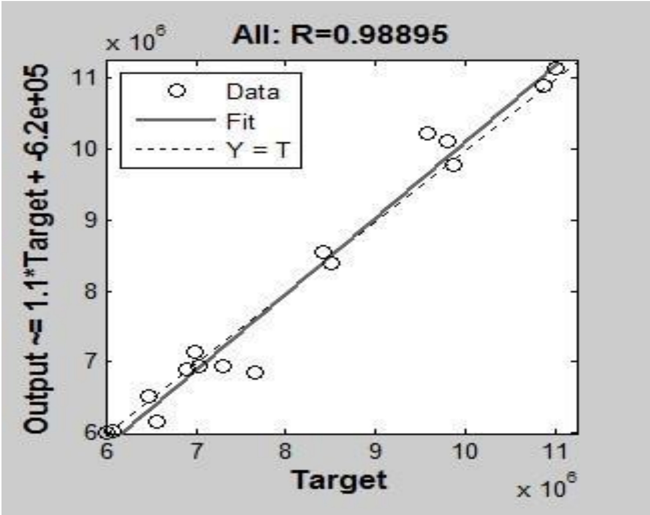


Figure 5.4. Plotting performance at all levels including training validation and testing.

Figure 5.3 and 5.4 shows the performance of ANN model during training and during all levels including training, validation and testing respectively. It shows R=0.98805 and R=0.98895 which means R is close to 1 which means satisfactory performance of the ANN model.

5.4 Regression Model and its Results

It is one of the powerful analysis technique that is used for forecasting the unknown variable value with respect to the known value of the two or more variables. The variables with known set of values are known as predictors. In other terms, multiple regression analysis is used forecast the value of variable X for known values of Y_1, Y_2….. Y_k.

Multiple regression models are one that have only one dependent variable with two or more exploratory or independent variables. Dependent variables are the variables whose values are to be predicted and independent variables are those whose values are known and are used for prediction of value of dependent variable.

Generally, the equation of multiple regression of X on Y_1, Y_2, Y_n is written as shown in equation 1.

$$X = a_0 + a_1Y_1 + a_2Y_2 + \ldots\ldots a_nY_n. \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where a_0 is the intercept, a_1, a_2 ,……a_n are known as regression coefficients and are analogous to slope. Y_1, Y_2…..Y_n are independent variables whose values are known and X is the dependent variable whose value is to be estimated.

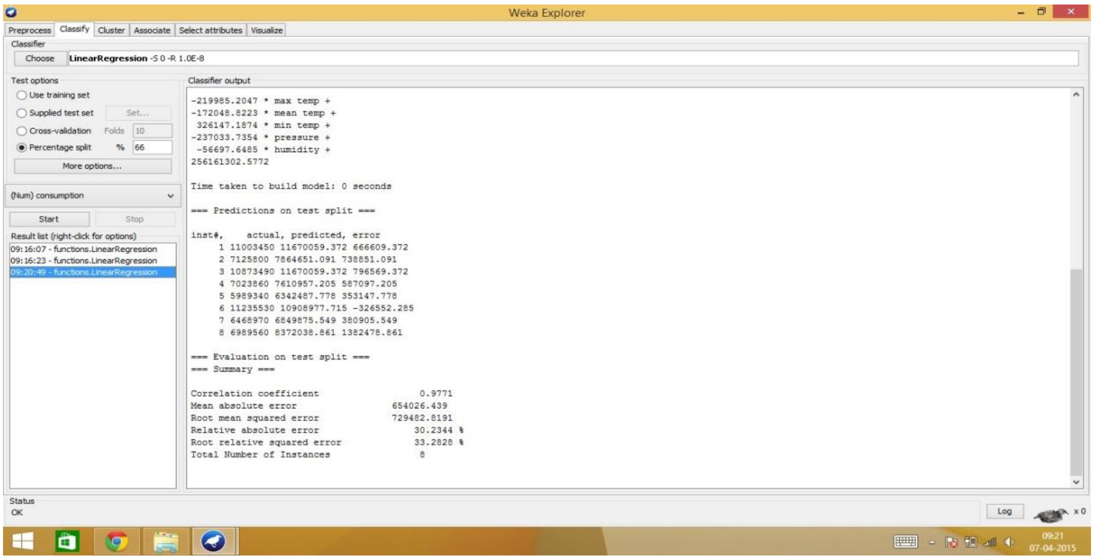
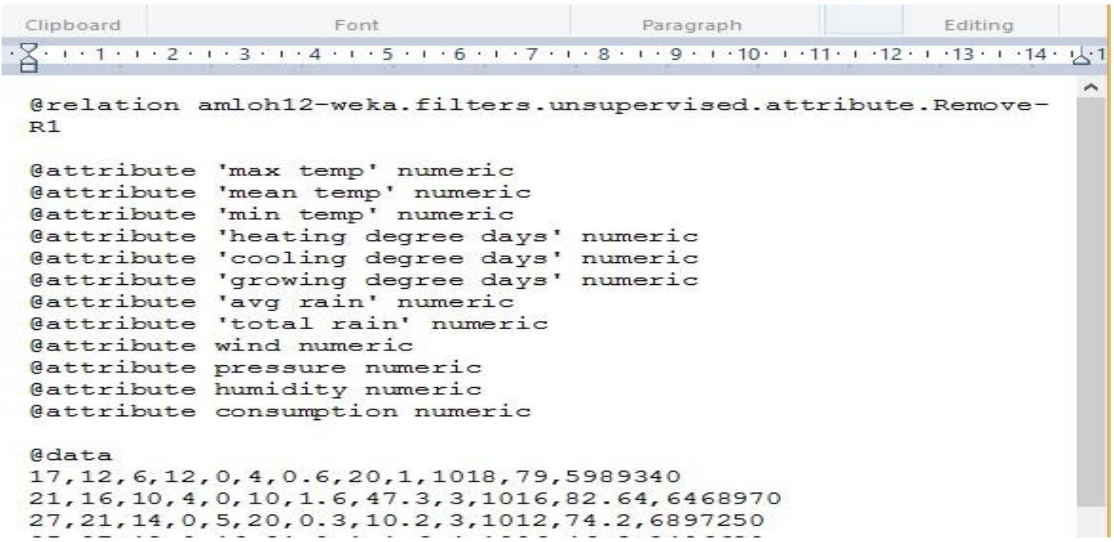


Figure 5.5. Screenshot of regression model performed using weka.

In order to load data into WEKA, it need to be to put into a weka understandable format. Attribute-Relation File Format (ARFF) is followed by weka, in which we can define the data type being loaded, and then the data itself. Only numeric oor date data can be taken in order to perform regression in weka. The ARFF file that is used with WEKA for forecasting monthly electricity demand appears below in Figure 5.6.



```
@relation amloh12-weka.filters.unsupervised.attribute.Remove-
R1

@attribute 'max temp' numeric
@attribute 'mean temp' numeric
@attribute 'min temp' numeric
@attribute 'heating degree days' numeric
@attribute 'cooling degree days' numeric
@attribute 'growing degree days' numeric
@attribute 'avg rain' numeric
@attribute 'total rain' numeric
@attribute wind numeric
@attribute pressure numeric
@attribute humidity numeric
@attribute consumption numeric

@data
17,12,6,12,0,4,0.6,20,1,1018,79,5989340
21,16,10,4,0,10,1.6,47.3,3,1016,82.64,6468970
27,21,14,0,5,20,0.3,10.2,3,1012,74.2,6897250
```

Figure 5.6. Screenshot of weather and demand data stored in arff format

In this section we discussed the regression model used for prediction, different variables used in regression. Next section will cover the methods to evaluate the performance of ANN and regression models.

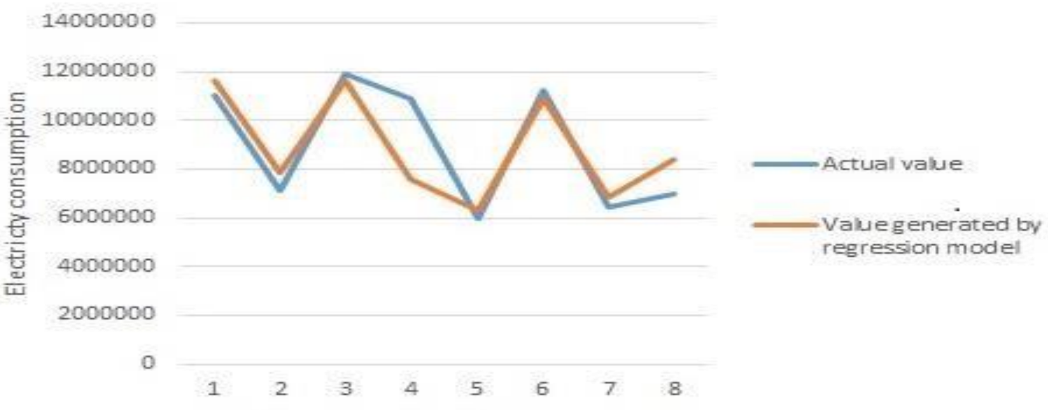


Figure 5.7.Actual electricty demand against synthetic consumption using regression model in weka.

The results generated by regression model are shown in Figure 5.7. And the closseness between values generated by regression model and actual consumption value is evaluated in Table 5.2. The MAPE of regression model is 7.15.

Table 5.2. Performance evaluation of regression model

Actual value	**Value generated by regression model**	**APE for regression model**
11003450	11670059	6.05
7125800	7864651	10.3
7023860	7690157	9.48
6468970	6849875	5.88
11235530	10908977	2.90
7023860	7610957	8.3

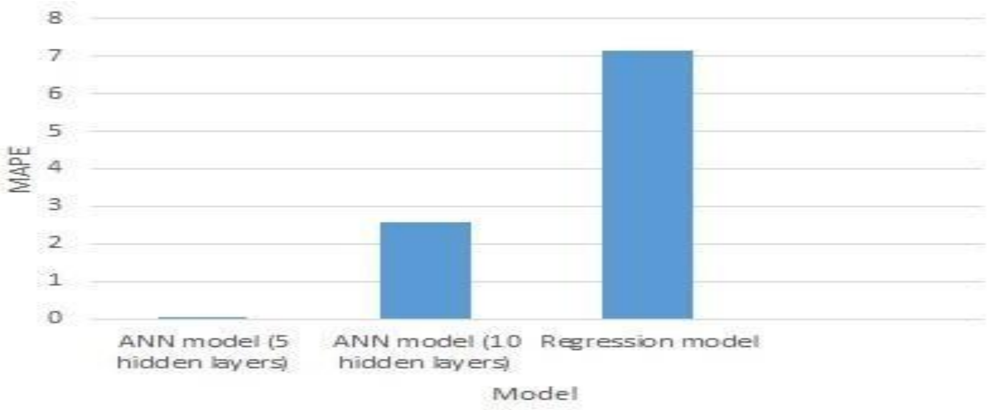


Figure 5.8. Comparison of performance of ANN and regression model for electricity demand forecasting based on weather parameters.

The performance of ANN model trained using LMA algorithm is evaluated by comparing it to the results obtained by regression model using weka and as shown in Figure 5.4. ANN performs better as compared to regression model.

Therefore, the result shows that ANN provide better performance as compared to regression model as consumption values anticipated by ANN are more closer to the real one as compared to values anticipated by regression model as shown in Figure 5.8. Moreover it is also seen that number of hidden layers should be low in order to receive better results.

5.5 Conclusion

In this chapter the proposed model and tools used for implementation followed by results obtained from ANN had been discussed. To evaluate the performance of ANN model It's performance is compared with regression model and it concluded that ANN performs better in this case. The next chapter discusses the conclusions and future scope of this work.

Chapter 6
Conclusions and Future Work

Electricity demand forecasting represents one of the main task in the planning of production of electricity as it determines the resources required to operate the electricity plants such as daily fuel consumption. It is the corner stone of planning for electric plants and networks. The literature shows that the electric load pattern is very complex. Therefore, it is necessary to develop new methods for demand forecasting to reduce the uncertainty in the predictions. This report has reported that every electricity network and electricity plant needs special forecasting method because each country is different in the factors affecting the electricity demand. In this chapter we will conclude the work followed by future scope.

6.1 Conclusions

PM Modi had announced his vision to set up 100 smart cities across the country soon after his government was sworn into power mid last year. Since then a race has been on among cities to land on the list that the ministry of urban development is compiling. The 100 smart cities mission intends to promote adoption of smart solutions for efficient use of available assets, resources and infrastructure.

For effective implementation of the energy related policies forecasting electricity consumption is quite important. In this report, the monthly electricity consumption of India is modelled as a function of weather variables like temperature, rainfall, degree days and humidity. The model is trained using monthly electricity demand data for Amloh, Punjab over the period 2009 to 2014 and the model accuracy tested against data for the period 2015. The data is pre-processed and missing values are substituted using forward and backward difference approach. These weather variables are selected using correlation coefficient. Regression analysis and ANN are used to forecast monthly consumption of electricity. It is also verified that the ANNs approach is suitable and accurate for prediction. The ANN model allows more flexible relationship between demand and weather variables as compared to multiple regression model.

The results of artificial neural network technique for monthly demand forecasting for the Amloh city, are investigated and it shows that the proposed artificial neural network technique gives a good performance and reasonable accuracy. Its reliabilities were evaluated by computing the mean absolute error between the exact and predicted values.

6.2 Future Scope

India is shifting towards Smart Cities. An outlay of Rs 98,000 crore has been allocated by the government of India for execution of hundred Smart Cities, and the Atal Mission for Rejuvenation and Urban transformation which is an urban rejuvenation programme for 500 towns and cities in next year.

Energy companies are still facing serious challenges related to generation and distribution of electricity, the competitive pressure is increasing, margins are shrinking, while new regulations introduce stricter rules in terms of environmental, health and safety standards and use of renewable resources. Electricity demand forecasting is still undergoing many challenges. Availability of weather data and electricity consumption data of certain regions is one of the major limitation. In this report only weather data is used because it is the only data available .In developing countries like India many non-weather related factors like carbon dioxide emission , per capita GDP , Gross Domestic saving, population and number of holidays also affect the consumption of electricity.

Use of such socioeconomic factors along weather variables can yield even better results. Historical extreme cases are also required in order to improve the accuracy of the forecasts. Data of such type might be obtained from analogy in other countries that have larger temperature extremes though care must be taken as the response may not be identical from one country to other country. The model presented is believed to be robust in order to predict electricity demand for number of years into the future giving reliable estimates of the relevant weather related parameters.

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Video Presentation

https://www.youtube.com/watch?v=0vjEZ5NRvAk&feature=youtu.be