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SHORT TERM LOAD FORECASTING USING EMPIRICAL MODE DECOMPOSITION AND ARTIFICIAL NEURAL NETWORK: A CASE STUDY OF KATHMANU VALLEY, NEPAL

By

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A THESIS

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The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled **"SHORT TERM LOAD FORECASTING USING EMPIRICAL MODE DECOMPOSITION AND ARTIFICIAL NEURAL NETWORK: A CASE STUDY OF KATHMANDU VALLEY,NEPAL"** submitted by Mr. Narayan Aryal, in partial fulfilment of the requirements for the degree of Master of Science in Renewable Energy Engineering.

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ABSTRACT

Short-term Electric Load Forecasting is an important aspect of power system planning and operation for utility companies. Short Term Load Forecasting (STLF) has always been one of the most critical, sensitive and accuracy demanding factors of the power systems. An accurate STLF improves not only the system's economic viability but also its safety, stability and reliability. The research presented in this work supports the argument of hybrid model based on Artificial Intelligence (AI) and Empirical Mode Decomposition (EMD) techniques in short-term load forecasting.

In this research work, a hybrid short term load forecasting model based on EMD and Feed Forward Back Propagation (FFBP) algorithm of artificial neural network was developed. With the application of hybrid model the load demand for Sunday 22, 2076 B.S is forecasted and the result is compared with the actual data by calculating the Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) between the actual and forecasted load. The MAD value of 8.53MW and MAPE of 4.82% is found between the original and forecasted load.

The correlation factor analysis between the IMFs, residue and the original load data which is decomposed using EMD technique is carried out and the most informative IMFs are chosen to further forecast the load. The correlation between the original load and the residue is found to be 0.93 while the correlation between the IMFs and the input is very low which less than 0.2. The load is forecasted taking the residue as the input, in this case the MAD is found to be 3.27MW and the MAPE 1.79%.The model is compared with the basic FFBP algorithm of ANN. The output of both the model is compared by calculating the MAD and MAPE between the actual and the forecasted load. The EMD based hybrid model after Correlation Factor Analysis decreases the MAD by 75.95% and MAPE by 80.15% compared to basic FFBP model.

For the validation of model it is used to forecast the load of New York Network for July 1, 2004 and the output is compared to other well known hybrid model such as WTNNEA, WGMIPSO and IEEMD-BPNN. The proposed EMD-FFBP model gives the MAPE of 4.34 % which is higher than the MAPE value obtained by other hybrid models, but it is within the limit of acceptance.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
STLF	Short-Term Load Forecasting
NEA	Nepal Electricity Authority
FFBP	Feed Forward Back Propagation
LNN	Linera Neural Network
BPC	Butwal Power Company
MAPE	Mean Absolute Percentage Error
MAD	Mean Absolute Deviation
MSE	Mean Square Error
RMSE	Root Mean Square Error
MA	Moving Average
WMA	Weighted Moving Average
ES	Exponential Smoothing
INPS	Integrated Nepal Power System
MAED	Model for Energy Demand Analysis
LDC	Load Dispatch Centre
EMD	Empirical Mode Decomposition
CFA	Correlation Factor Analysis
NYN	New York Network

CHAPTER ONE: INTRODUCTION

1.1 Background

Load forecasting is a complex phenomenon. For underdeveloped country and developing country it has became a matter of high uncertainty (Hamza, et al., 2002). The power consumption of any specific area basically depends upon several factors including time, social, economical, and environmental factors by which the pattern will form various complex variations (Almeshaiei, et al., 2011). Social (such as behaviour) and environmental factors are big sources of randomness (noise) found on the load pattern. Diversity and complexity in demand pattern is developing complicated short term load forecasting methods. However for the short term load forecasting phenomena the environmental and climatic factors are not considered at all.

Development planning of electrical power systems starts with load forecasting. Accurate load planning can be useful in appropriate expansion and development of power plants and transmission and distribution devices. Forecasting annual peak load demand and annual energy demand for a number of years ahead has a vital role in the context of generation, transmission and distribution network planning in a power system. Short Term Load Forecasting (STLF) plays an important role in electrical power systems in term of policy planning and budget allocation (Fullerton, et al., 2015).The power system expansion planning starts with the forecast of anticipated load requirement. Accurate load forecast can be helpful in developing a power supply strategy and development plan, especially for developing countries where the demand is increased with dynamic and high growth rate.

Over- or underestimation can greatly affect the revenue of the electric utility industry. Overestimation of the future load may lead to spending more money in building new power stations to supply this load. Moreover, underestimation of load may cause troubles in supplying this load from the available electric supplies and produce a shortage in the spinning reserve of the system that may lead to an insecure and unreliable system. Therefore, an accurate method is needed to forecast loads.

The growth in electricity consumption in many developing countries has outstripped existing projections, and accordingly, the uncertainties of forecasting have increased (Hongyi Hu & Xiong, 2013). Variables such as economic growth, population, and efficiency standards, coupled with other factors inherent in the mathematical development of forecasting models, make accurate projection difficult.

Nepal Electricity Authority (NEA) in the apex body for generation, transmission and distribution of electric power all over the country through its integrated Nepal power system (INPS). INPS is the interconnection of all the generating stations, transmission lines and all the distribution lines. The generating station may be either privately owned or owned by NEA itself. Transmission system in context of Nepal consists of all the transmission network of 66 and 132 KV either cross boarder or inside the country.

The electric load consumption of Kathmandu valley is almost 26 percent of the total load consumption of national grid distribution system and the consumption pattern resembles with the overall consumption pattern of the national grid which is shown in Figure 1.1. Accurate forecasting of this huge amount of load consumption certainly helps in the planning and execution of day to day activities of system operation department of Nepal Electricity Authority.

Table 1.1 Average Load of INPS and Kathmandu valley for the different date of year 2075

Date/month	Baishak 16	Bhadra 16	Poush 16	Falgun 16
Average load of INPS in MW	786.1	936.9	862.86	701.6
Average load of Kathmandu valley in MW	201.0	187.8	265.97	197.42
percentage of Kathmandu valley load consumption	26	20	31	28

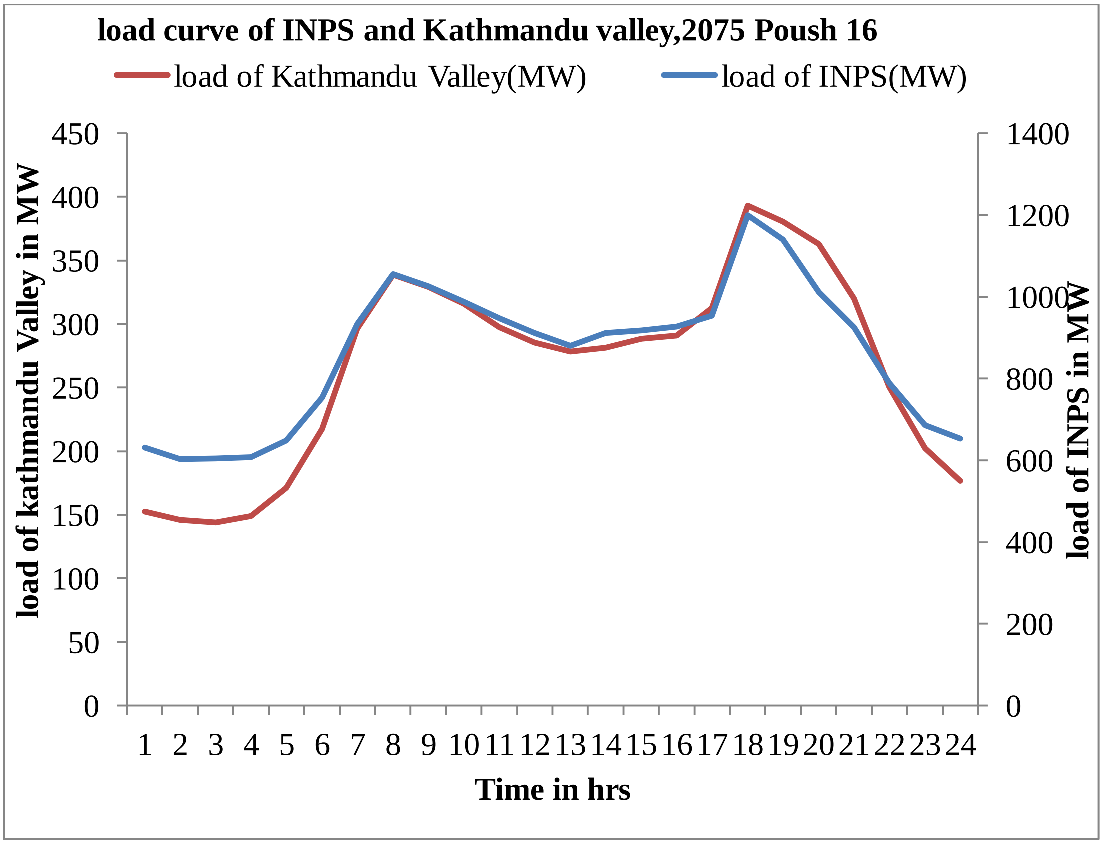

Figure 1.1 Load of Kathmandu valley and INPS

Kathmandu valley is being fed by Balaju, Mathatirtha, Baneshowar, Bhaktapur, Patan, Teku, K-3 and Syuchatar substations. The power input to the valley consists of the power generated By Trisuli, Devighat, Chilime, Tadi, Aankhukhola, Mailung, Khimti ,Sipring, Jiri, Chanrawati, Kuthali-Bukhari, Bhotekoshi, Sunkoshi, Sunkoshi Khola, Bhairabkunda, Chaku, Lower Chaku, Middle Chaku, Indrawati, Baramchi and Upperhadi power houses. Power in/out flow through Marsyangdi-Syuchatar 132 KV ,KL2-Matatirtha 132 KV, KL1-syuchatar 66 KV and khimit-Dhalkebar 132 KV transmission line are considered to find out the load consumption of Kathmandu valley only.

1.2 Power System Load Forecasting

A secure and highly reliable source of electricity is an essential part of our modern society. Providing a reliable supply of electricity at the lowest possible price would require (among other things) sufficient generation to exactly meet customers fluctuating demand and system losses. One way that facilitates achieving this exact match between demand fluctuation (say, on an hourly basis) and energy generation is to estimate the demand in advance. In principle this can be done using known demand patterns and the factors affecting demands. For long and medium-term demand estimation, factors such as economic growth, gross domestic product, purchasing power of people along with many other factors including economical, demographical and social and load composition have to be taken into account while for short term estimation metrological factors are considered. In a broad sense, this practice of anticipating the future load demand is commonly referred to as “Load forecasting”.

Load forecasting is an area of great economic value to the electrical power utility. It is also a problem to be tackled on a daily basis. Reliable forecasting tools would enable power utilities to plan for peak demand to achieve more economical unit allocation, scheduling and pre-dispatching.

The lead time in load forecasting ranges from a few minutes ahead for security assessments, to several years for long economic operations and planning. This could constitute a very short and a very long-term frame for power systems load forecasting

1.3 Load Dispatch Practice in Nepal

It is because of monopoly market that prevails in Nepal in case of electricity distribution no such efficient, accurate and widely accepted load dispatching techniques has been utilized. NEA, perform load dispatch all across the county via its integrated system of transmission and distribution line leaving behind very few area of Syangja and Pyuthan. Load Dispatch Centre (LDC) of system operation department of NEA is fully responsible for load dispatch. Power trading, power plant operation, loading of transmission line ,flow of power along with co-ordination for shutdowns of generating units and substation equipment is perform by LDC . The management of demand and supply side depends upon the operator choice. Instant decision made by the system operator’s plays role in power dispatch. Trading of power to other private electricity company and cross-border is not in practice till now so no such economical and technical analysis is done before the load dispatch all across the country.

1.4 Scope of Work

Load dispatch procedure of Nepal does not follow the technical procedure of anticipating the load demand of an hour or a day ahead because our power dispatching environment does not have any competitive market. Application of STLF technique and working accordingly will help for more reliable and optimized operation of our power system. Some of the research work has been done in his field for study purpose but not adequate technology has been adopted to verify the accurateness of the model developed. For minimizing this research gap in the demand forecasting this research will play vital role.

1.5 Rationale

This thesis is important to find out a day ahead load demand of Kathmandu Valley via the new tool and techniques developed and utilized so far.

Nepal electricity authority is the apex body for the generation, transmission and distribution of electricity across the country via its integrated system. Knowledge of Short term load demand of national utility plays vital role in planning for the future planning and execution of power project with fixing the target of national planning in this sector. State restructuring of our country will definitely demand the regional dispatch centre according to the provincial state. The establishment of regional load dispatch centre will force for the unbundling of power sector of Nepal .Unbundling of power sector increases the market competition. Competition will be in both reliable power supplies along with the cost of energy to the end use consumer. The cost and reliable supply both demand the accurate planning tool to be implemented.

The outcome of independent research guided by university will help to suggest policy maker and power dispatcher for the application of technique of STLF in coming days in power sector.

1.6 Problem Statements

STLF will play important role in forecasting an hour to a day ahead load demand of any geographical to sectoral region. Various regional grids will demand power from the National grid and their own Power plant according to their instant need. For this purpose there should be an accurate model of load forecasting which will give idea of load demand.

NEA to the date being the sole entity of power dispatcher to the entire consumer does not feel the requirement of STLF technique for managing load and demand. But with the establishment of provincial grid and unbundling of power system STLF will come in account.

This research will play role in selecting appropriate model for short term load forecasting in our case and will contribute in near future for our nation as their will be reform in power sector .

1.7 Objectives

1.7.1 Main Objective

To design a hybrid short term load forecasting model based on empirical mode decomposition and feed forward back propagation neural network and predict short term load of Kathmandu valley, Nepal.

1.7.2 Specific Objectives

The specific objectives of the research are as follows:

- To develop basic Feed Forward Back Propagation (FFBP) neural network model and hybrid model based on EMD and neural network for Short Term Load Forecasting.
- To forecast the day ahead 24 hours load demand of Kathmandu Valley with basic FFBP neural network and hybrid STLF model and compare the result.
- To validate the result with actual data.

1.8 Research Limitations

- Data provided by NEA is not verified by any other similar agencies, data recording technology being manual there remains chance of human error while recording the data.
- Factors influencing short term load like temperature, humidity, precipitation, holidays, emergencies etc are not incorporated in this research.

CHAPTER TWO: LITERATURE REVIEW

For good operation of power system and reliable supply of electric load accurate and efficient load forecasting techniques plays vital role. Number of research has been done in this field to find out the accurate and appropriate model of forecasting. As STLF is largely dependent upon human behaviour and the meteorological condition it has became the field of curiosity for the researcher to work in this field. Many research paper and report has been published in this domain over the past decades. Literature review covered in this topic primarily focus on the literature and research published in the field of STFL all across the world. In context of our country all the study and research done by different sectors in the field of load forecasting are closely studied .Research and papers published according to the techniques of STLF are included in separate topic.

2.1 Load Forecasting Categories

Broadly speaking, the very first question in a forecasting task is “How far in advance the forecast is needed?” There is a natural lead time for any process. Under normal circumstances, according to the forecasting period and purposes, load forecasting can be classified as long-term load forecasting, medium-term load forecasting, and short-term load forecasting.

Usually, the load and power consumption can be predicted by adopting this different time-scale forecasts. The long-term load forecast period is generally 10 to 15 years or even longer. The prediction target is usually the regional load capacity or the annual electricity consumption. The prediction purpose is to provide the base data for the power grid planning that help determine the grid operation mode and annual maintenance plans. The main factors affecting long-term load forecasting are national economic development, population, industrial restructuring and national tariff policy and so on.

The medium-term load forecast period is generally 5 or 6 years. The prediction target usually is the load capacity of a region or the monthly electricity consumption. The forecast data generally indicates cyclical growth and each month of one year consists with the similar growth pattern. The prediction purpose is to arrange monthly maintenance plan, operation mode, reservoir operation plans and coal transportation plans. The main factors affecting medium-term load forecasting come from production planning from large users, weather conditions, industrial restructuring situations and national tariff policy and so on. The short-term load forecast period is generally 24 or 48 hours or even one week. The prediction target usually is the load capacity of a region or the daily and weekly electricity consumption data. The forecasting data generally indicates daily or monthly periodicity and the same date type of one year that follows the similar periodic pattern. The prediction purpose is to arrange day forecast for power generation projects as well as suspending or restarting power plans. The main factors affecting short-term load forecasting are week type, weather conditions and national tariff policy and so on.

2.2 Short-Term Load Forecasting

Since the mid-1960's numerous researchers have studied the problem of short-term load forecasting and provided moderately accurate and efficient load forecasting methods to tackle this problem. The main motivation for this considerable amount of research on this topic centred on the cost saving that could be realised with the improved accuracy of forecasting**.**

The selection of appropriate methods, based on the factors affecting STLF, is an optimisation problem because the influence of the factor depends upon the model selected for forecasting. For short term load forecasting historical data and other relevant data, such as weather and the type of day are used. In terms of lead time, short-term load forecasting is usually done for 24 hours ahead when the weather data and other parameters for the following day become available.

2.2.1 Characteristics of Short-Term Load

Short-term load basically defined as the load of a day or an hour ahead is highly unpredictable in many of the case. This load depends upon weather to unpredictable condition that arises day to day in our life and varies largely because of the human daily activities. Although the load is highly fluctuating in nature some of the basic characteristic is shown by it. Below are the characteristics of short-term load.

Uncertainty: It is uncertain to know the future development of the load because the changes are related with a lot of factors that is also constantly developing and changing. Although several of these factors can be predicted, the remaining is difficult to predict, which makes our prediction results uncertain.

Conditionality: The future load change occurs under the necessary conditions and the assumed conditions when predicting it. The necessary condition is the ability to predict the essential rules of change in load, and prediction results obtained in this case are usually effective. In many cases, the load change in the future is difficult to determine. That is why the assumed conditions exist. Assumed conditions are based on some certain research and obtained through repeated analysis.

Temporality: The short-term load forecasting is conducted by applying scientific prediction method during a certain period of time scale, such as minutes, hours and days. In this way, the temporality is one important feature of the short-term load forecasting.

Multi-scheme: In various environments, sometimes it is necessary to predict the future load trends according to the uncertainty and conditionality of the short-term load forecasting. Thus, variety of short-term load forecasting method is developed. The load forecasting is conducted based on the real-time data. The short-term load forecast model might fail to fulfil its function while the load characteristics change over time. Therefore, to ensure an accurate prediction during the change in load characteristics, it is necessary to choose an appropriate short-term load forecasting methods and make corresponding adjustments based on the previous short-term load forecasting model.

2.2.2 Influencing Factors of Short-Term Load Forecasting

The system load is complicated and diverse since it is affected by different social and natural conditions. These social factors include energy utilization, agricultural structure, national policy, the rate of economic growth, population growth, social conditions, national holiday system, development level of science and technology. Natural factors consist of the complex and diverse changes in the weather, natural disasters, season changing and so on. Since the short-term load forecast has a shorter time interval during the prediction, the main factors including the level of social progress, national policies, the use of energy and the changing of the seasons and other natural factors, has less impact on the short-term load forecasting. Usually there are four main factors that can impact the short-term load forecast.

Meteorological Condition: Weather is the most important independent variable for load forecasting. The effect of weather is most prominent for domestic and agricultural consumers, but it can also alter the load profile of industrial consumers. Load forecasting models use weather forecast and other factors to predict the future load, thus to minimize the operational cost. Weather is often cited as the tipping point that can cause unreliability in the system by decreasing the efficient supply of power. Temperature can also alter the conductivity of the transmission lines. Thus temperature can affect the overall carrying capability of the transmission lines. High temperature can increase not only the resistance of the transmission lines, but also it can alter the reactance of line, due to temperature induced expansion of the length of transmission line.

The weather factor include the following

- Temperature
- Humidity
- Precipitation
- Wind speed and wind chill index
- Cloud cover and light intensity

Holidays: Typically, holidays such as New Year, Dashain, Christmas, Eid and weekend usually poses a certain impaction the load changes of power system. This is mainly because during the holidays, the power consumption is considerably reduced by most enterprises and other high-power industrial load. On the contrary, the main component of the power system loads includes the service industries, such as residential electricity consumption, commercial electricity, catering industry. So, the overall power consumption level is dramatically reduced.

Emergencies: Several urgent factors cause the interference of the power load, such as: unexpected incidents, unplanned overhaul, large electricity load fluctuations and limitation of electricity consumption. Therefore, it is useful to conduct the corresponding processing about the historical load data.

In short, the short-term load forecasting accuracy level is the outcome of the combined effect of a variety of influencing factors. For short-term load forecasting, the right technology must be applied to address those associated influencing factors in order to achieve the precise and scientific short-term load forecasting. However, the impact that influencing factors have on the future load change are usually difficult to be defined by using a specific function expression. Meanwhile, the impact of short-term load forecasting factors may be correlated with each other. All of these conditions undoubtedly increase the difficulty of short-term load forecasting.

2.3 Forecasting Techniques

With the advancement in technology and the requirement of highly accurate forecasted output various forecasting techniques are being used in power industries now-a day's which give the accurate result. The basic forecasting techniques are described below.

Similar Day Approach: Similar day approach is based on searching historical data of days of one, two or three years having the similar characteristics to the day of forecast. The characteristics include similar weather conditions, similar day of the week or date.

Regression Based Approach: Linear regression is a technique which examines the dependent variable to specified independent. The independent variables are firstly considered because changes occur in them unfortunately. In load forecasting, the dependent variable is usually load of the electricity because it depends on production which on the other hand depends on the independent variables.

A Regression method for Self-described in (papalexopolous, et al., 1990)considers the Iran network load which is highly non-linear in nature depends to some extent in temperature. The relationship is found using simple regression between load and temperature. This gives some idea of climatic condition affecting the electrical load.

N.Amral, C.S. Ozveren and D king has developed a model of STLF for forecasting the demand of the south Sulawesi's (Sulawesi Island - Indonesia) power system (Amral, et al., 2007). This paper uses a multiple linear regression investigation for the STLF of the demand. Weather along with other parameters like week day also effect the demand of load is clearly described in the paper.

M. Matijas, M. Cerjan and S. Krajcar describe about not only the model chosen will affect the accuracy of load forecasting but the factors that affect the load also play role in the accuracy of forecasting model(Matijas, et al., 2011).

A.D. Papalexopoulos and T.C. Hesterberghas incorporated the weight of factor influencing load by using regression based least square method (Papalexopoulos & Hesterberg, 1990).

Time Series Analysis: Time series forecasting is based on the idea that reliable predictions can be achieved by modelling patterns in a time series plot, and then extrapolating those patterns to the future. Using historical data as input, time series analysis fits a model according to seasonality and trend. Time series models can be accurate in some situations, but are especially complex and require large amounts of historical data

A paper by B. Krogh, E. S. de Llinas and D. Lesser presents a short-term load forecasting algorithm for Energy Control Centre applications. Regression techniques are combined with Auto Regressive Integrated Moving Average (ARIMA) models to produce week ahead hourly MW load forecast values. The results of many case studies have also been presented (Krogh, et al., 1982).

A paper by Martin T. Hagan and Suzanne M. in ref (Martin & Suzzane, 1987) recommend Box and Jenkins time series statistical models, as the suitable time –series model of load forecasting. Drawback of this model i.e. the non-linearity of both load and temperature parameters and simple way to eliminate it has be described.

Several other papers(Espinoza, et al., 2007), (Kiartzis, et al., 1997) used the autoregressive, autoregressive with moving Average, threshold autoregressive and periodic autoregressive models to provide effective Solutions to the short term load forecasting problems.

Expert Systems: An expert system is a computer program, which has the ability to act as an expert. This means this computer program can reason, explain, and have its knowledge. The load forecast model is built using the knowledge about the load forecast domain from an expert in the field (Gorr, et al., 1994).

In a paper by S. Rahman and R. Bhavnagar (Saifur, et al., 1988) an algorithm based on expert systems to obtain the hourly load forecasts was proposed. In the paper analysis of monthly load and same month weather data and the relationship between the parameters are analysed. The paper also obtains the effect of load variation based on the day of the week factor, and other factors that affect the load.

Fuzzy Logic: Fuzzy logic based on the usual Boolean logic which is used for digital circuit design. In Boolean logic, the input may be the truth value in the form of “0” and “1”. In case of fuzzy logic, the input is related to the comparison based on qualities.

A time series prediction method for the nonlinear system using the fuzzy system and the genetic algorithm was proposed in (Kang, et al., 2006) .

The paper (Kiartzis, et al., 2000) presents the development of a hybrid technique using the fuzzy logic and expert systems used for short term load forecasting to forecast the maxima and minima of the daily electrical load curve.

A new technique for short-term load forecasting in an electrical market scenario which is moving towards deregulation and dwelling with competitive pricing schemes using fuzzy logic method was described in (Khotanzad, et al., 2002)

A fuzzy inference system was designed for short term load forecasting in (Chenthu Pandian, et al., 2006). The parameters of temperature and time were taken as the inputs to the fuzzy system and the load forecast value formed the output of the fuzzy controller.

Linear regression model using the fuzzy logic which combated the effect of seasonal variations was described in (AlKandaria, et al., 2004)

Artificial Neural Network: Neural networks with their useful properties can perform many functions including load forecasting. In load forecasting application, the basic role of an ANN is to provide a prediction of power system demand for the next few hours, day(s) or week(s).

There are number of good reasons to substantiate the superiority of a neural network-based load forecasting over conventional forecasting techniques. First, there are no specific rule and /or transfer function required to describe the relationship between the load variation and other parameters such as weather information.

A paper by (Yuhang Yang, 2011) describes an efficient approach of short term load forecasting using ANN techniques. In this study the load curve of a time interval before the target hour is regarded as the training data and the data are normalized before training. Experiment carried out for Duke Energy Carolina is found satisfactory.

Study carried out by Anil K Pandey, Kishan Bhushan Sahay, M. M Tripathi and D Chandra (Pandey, et al., 2104) describes the ANN techniques of forecasting short-term load of UPPCL, India. Data from UPPCL, April 2014 to June 2014 are used for training ANN algorithm. The only input data used is load.

A paper (claudio, et al., 2008) include electricity price as the main influencing factor of load. A day ahead load is forecasted in this paper using the electricity price as the influencing factor of short term load demand.

A paper by (LU, et al., 2004) data are separated in two forms linear and non-linear. Non linear data are dealt by ANN while the linear data are dealt by ARIMA. Combination of both ARIMA and ANN is used to study the forecasted load

In a reference (Bansal, et al., 2018) ANN based forecasting algorithm MLP has been studied and proved to be the potential technique for this challenging job.

(Mollaiy, et al., 2015) Describes hybrid method using ANN technology is described. A case study of Thailand and Turkey was done. The result is hybrid method found more accurate than single one.

(Bhattacharyyan, et al., 2004) Carried out study of North Vietnam using feed forward neural network with back propagation algorithm. The result shows that ANN technique for short-term load forecasting problem is very useful with near accurate result.

(Sheikh, et al., 2012) Multilayer perception technique of ANN is used. Error is found in the range i.e. MAPE 1 to 1.5

(Sun, et al., 2015) Describe the approach the forecasting the load at distribution-level using ANN technique

Weather profile is also predicted using ANN technique and its effect has been studied (Zhu, et al., 2017) .

Hybrid Models: Several hybrid models has been developed and used in the field of load forecasting for short medium and long term. The combination of more than one technique helps to reduce the error between the forecasted load and actual load.

(Amjady & Keynia, 2009) had developed a hybrid model based on wavelet transform and neuro evolutionary algorithm (WTNNEA) for short term load forecasting and used to forecast the load of North American Electric Utility.

(Bahrami, et al., 2014) had developed a wavelet transform and grey model improved by practical swarm optimization (WGMIPSO) and used the model to forecast the load of New York City .

Improved Ensemble Empirical Mode Decomposition and Back Propagation Neural Network model has been developed by (YU, et al., 2016). Eastern Slovakian Electricity Corporation load had been forecasted by using this model.

Seasonal autoregressive integrated moving average (SARIMA) and Back propagation neural network (BPNN) model had been developed by (Yang, et al., 2013) and South Australia State of electricity load had been forecasted.

2.4 Nepal Study

Government of Nepal, water and energy commission secretariat has forecasted electricity demand up to 2040 (WECS, 2017). Model for Energy Demand Analysis MAED has been used in this study. Three scenarios of economic development have been taken into consideration - (i) Business as usual (4.5% GDP growth rate), (ii) Reference (7.2% GDP growth rate), and (iii) High growth (9.2% GDP growth rate). An extra analysis has been done with various policy interventions, e.g. 100% of the cooking with electricity and 75% of water heating with electricity in urban areas by 2020, metro in cities by 2025, etc., at 7.2% and 9.2% GDP growth rate. The planning period of 25 years has been taken into consideration, which gives electricity demand forecast for the period of 2015-2040.

Energy demand projection up to 2030 using a MAED based approach is carried out by Nepal investment board in 2068 (NIB, 2068).The model present a framework for evaluating the impact on energy demand by certain changes in the overall macroeconomic picture of a nation as well as the standard of living of population. Demand for energy is disaggregated into a various end use categories. The total demand for energy is combined into four different energy consumer sector viz. industry (agriculture, construction, mining and manufacturing), transportation, service and household.

Nepal electricity authority, system planning department on 2015 has published a report on demand forecasting up to year 2033/34 AD (NEA, 2015). Demand of energy is divided into three categories; domestic, irrigation and industrial commercial and other sector. Mathematical equation is formulated to forecast the consumption scenario of energy in three different models and the load is forecasted based upon it.

Table 2.1 Load Forecast (NEA, 2014/15)

FY	Peak Load(MW) Previous Forecast	Peak(MW) Base case	Peak(MW) Optimistic Case
2013/14	1303.9	1201	1202
2014/15	1426.4	1286.1	1310.6
2015/16	1542.6	1422.8	1400.5
2016/17	1653.7	1559.7	1561.5
2017/18	1837.1	1742.2	1800.6
2018/19	2018.8	1903.3	2003.5
2019/20	2208.7	2071.5	2220.3
2020/21	2361	2203.8	2408.6
2021/22	2523	2378.9	2652.6
2022/23	2695.4	2562.1	2744.7
2023/24	2888.1	2764.5	3024.9
2024/25	3109	2978.3	3330.1
2025/26	3345.5	3203	3661.6
2026/27	3597.6	3439.5	4022
2027/28	3866.4	3688.7	4414.5
2028/29	4168.8	3971.7	4866.7
2029/30	4493.2	4280.7	5371.2
2030/31	4841.4	4614.4	5930.4
2031/32	5216.4	4974.9	6550.3
2032/33	5621.8	5364.5	6779.9
2033/34		5785.3	7491

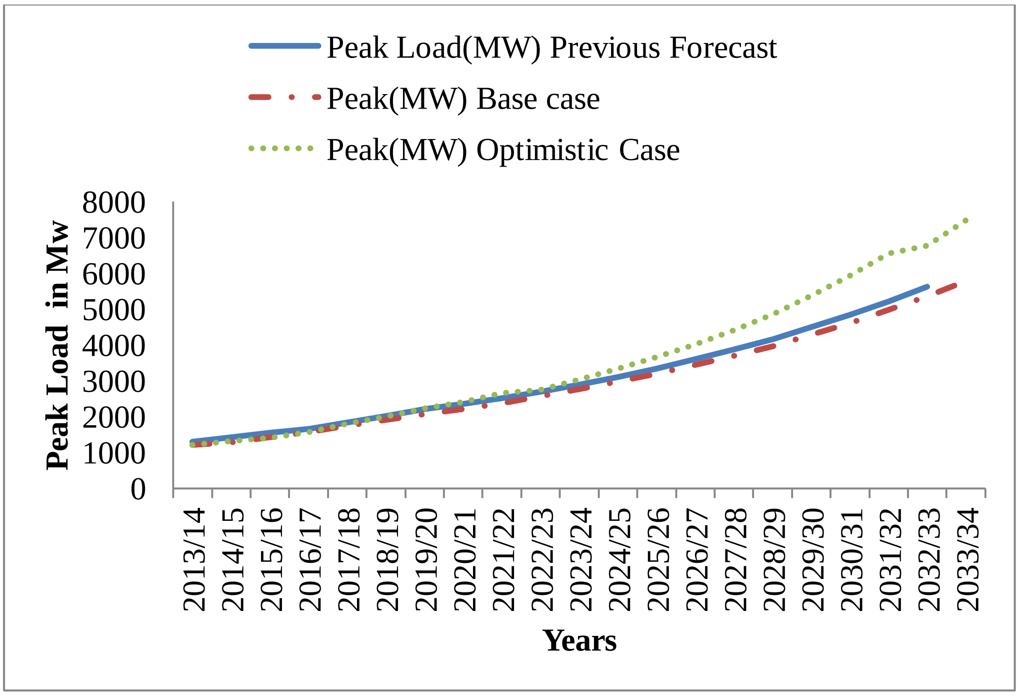

Figure 2.1 Load Forecast (NEA, 2014/15)

some university level study has been carried out in short term load forecasting using ANN and other conventional technique but this study doesn’t compare the result between the various technique of ANN .

2.5 Research Gap

In context of Nepal unbundling of power system is not yet been implemented. NEA, an undertaking of Government of Nepal is the only one institution for power generation, transmission and distribution. Although Private sectors are involved in power generation but for evacuation of power they are fully dependent with NEA governed by the power purchase agreement between them. In some district of Nepal like Pyuthan and Syangja, Butwal Power Company (BPC) has distributed its generated power to some extent to local consumer. Some part of the very remote area of Nepal has been electrified by micro hydro and some stand alone small power plant of NEA. STLF i.e. forecast of an hour or a day ahead load which plays vital role in managing load distribution to the consumer at distribution level has been widely utilized all over the world by distribution companies is not in practise in context of Nepal in both private and government sector. So for application levels no such research activities have been carried out in the area of short term load forecasting. As mentioned above all the agencies of Nepal has studied the long term demand forecast and no any single research or analysis could be found in STLF by any agencies of Nepal. Some studies have been done by the university's student for the fulfilment of the requirement in Master and Bachelor level. Some traditional method along with the pre-defined model of ANN that is multilayer Perceptron has been utilized to forecast the short term load demand of Kathmandu valley with and without considering the factors affecting the load demand. Because of very few study in the field of short-term load forecasting using artificial neural network and other hybrid model there remains some question regarding finding out the suitable model among the various models. This opportunity is utilized in this research where the hybrid model of ANN incorporating empirical mode decomposition technique has been selected among the different model and the load for a day ahead has been forecasted.

CHAPTER THREE: METHODOLOGY

3.1 Problem Formulation

Since the decisions in power system and energy planning needs to be done with accurate load anticipation, the forecasted loads affect in several planning strategies. Particularly, STLF assist in day to day operation. Thus, if forecasting can be done with appropriate method for hourly loads of a day, short term planning could have been more easy and efficient.

3.2 Literature Review

This step has been done in chapter two. All the available literature has been studied which are required to meet our need. In addition during this stage, several forecasting approaches were studied and compared.

3.3 Research methodology

Different model of STLF has been studied and implemented all over the world for short term load forecasting. Similar day approach to the modern artificial intelligence has been studied and implemented all over the world in various power grid companies. Power grid companies also select or develop the model according to their best suit. In case of Nepal, STLF is not implemented in real day to day operation of power system because of which no such model and technique is in use for our power system. Some study has been done in this sector in university level for the fulfilment of course necessities.

In this research two different analytical technique of load forecasting are examined by calculating MAPE and MAD between the actual and forecasted load. Both technique uses feed forward back propagation neural network algorithm for data training and forecasting. First technique use the basic ANN model to forecast the load using its FFBP algorithm, while second technique decomposed the original data by using empirical mode decomposition technique and the denoising of data are carried out by calculating the correlation between the original and decomposed data before used as input for load forecasting.

Data collection and processing of data for training purpose of ANN is done using MATLAB programming. The basic framework of research methodology is shown in Figure 3.1.

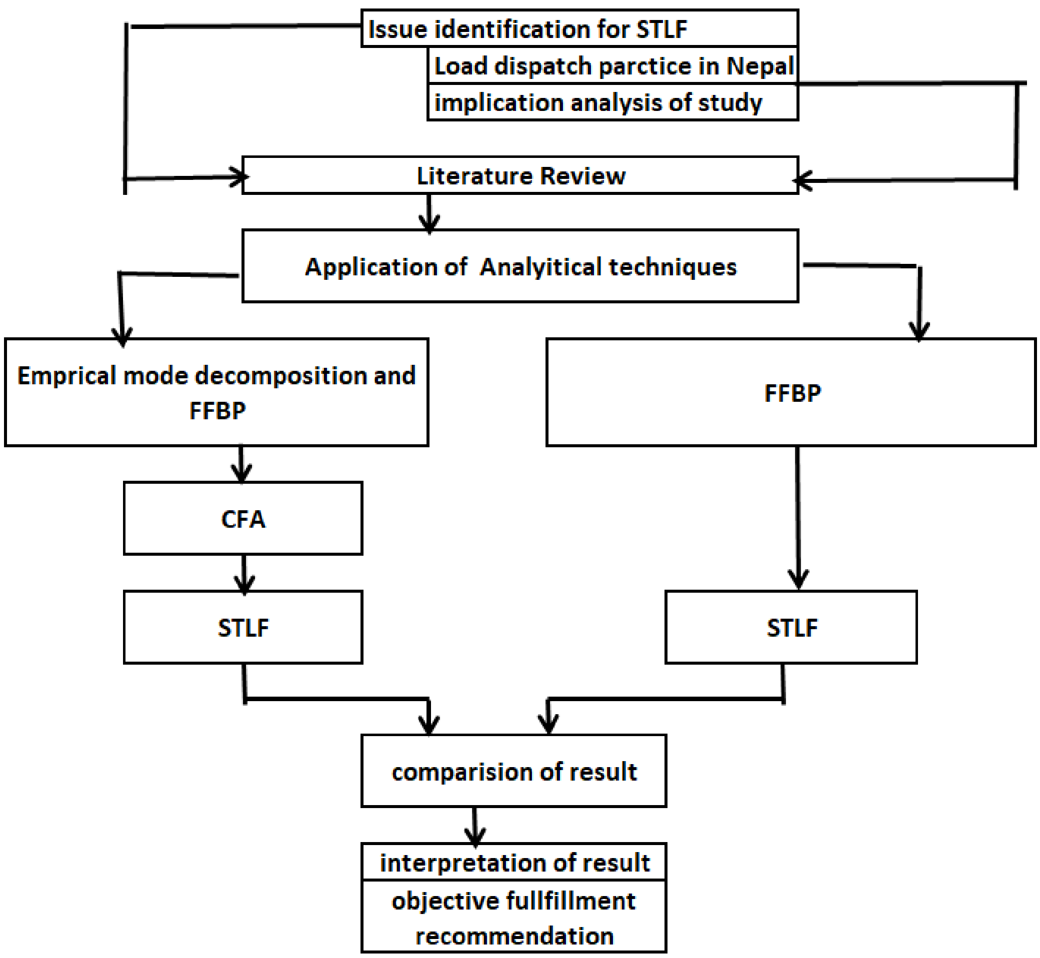

Figure 3.1 Research Methodological Framework

3.4 Analysing Techniques

Data analysis is a process of inspecting, cleansing, transforming and modelling data with the goal of discovering useful information. The empirical mode decomposition and the feed forward back propagation techniques are used to analyze and forecast the load data.

3.4.1 Empirical Mode Decomposition

The EMD is a time domain signal processing method for analyzing non-linear and non-stationary signal in which the signal is decomposed into several simpler forms, called Intrinsic Mode Functions (IMFs). Huang et al. (1998) proposed this process. A number of IMFs can be decomposed from the input load signal by the process known as sifting. The IMFs have two properties:

(a) The extreme between zero crossings must differ at most by one or equal

(b) Its mean value obtained by averaging upper and lower envelop is zero.

The system load is a random non-stationary process composed of thousands of individual components. The system load behaviour is influenced by a number of factors, which can be classified as: economic factors, time, day, season, weather and random effects. Thus, EMD algorithm can be very effective for load demand forecasting. The EMD algorithm is described below.

1 With a given time series signal x (t), create its upper u (t) and lower l (t) envelopes by a cubic-spline interpolation of local maxima and minima.

(2) Find the mean of the envelopes as m (t) = [u (t) + l (t)]/2.

(3) Take the difference between the data and the mean as the proto-IMF, h (t) =x (t) − m (t).

(4) Check the proto-IMF against the definition of IMF and the stoppage criterion to determine if it is an IMF.

(5) If the proto-IMF does not satisfy the definition, repeat step 1 to 5 on *h* (*t*) as many time as needed till it satisfies the definition.

(6) If the proto-IMF does satisfy the definition, assign the proto-IMF as an IMF component, c (t).

(7) Repeat the operation step 1 to 7 on the residue, r (t) = x (t) −c (t), as the data.

(8) The operation ends when the residue contains no more than one extreme.

Finally the original TS signal is decomposed as:

$$X(t) = \sum_{j=1}^{n} c_j + r_n$$

Where the number of functions n in the set depends on the original TS signal.

Mathematically the operation of empirical mode decomposition is as follows:

$x(t)-m_{1,1}(t)=h_{1,1}(t);$

$h_{1,1}(t)-m_{1,2}(t)=h_{1,2}(t);$

…

…

$h_{1,k-1}(t)-m_{1,k}(t)=h_{1,k}(t)$;

$h_{1,k}(t)=c_1(t)$,

in which the indices indicate the iteration of the same step. From this operation, we can see that

$x(t)-m_{1,1}(t)=h_{1,1}(t)$;

$h_{1,2}(t)=h_{1,1}(t)-m_{1,2}(t)=x(t)-(m_{1,1}+m_{1,2})$;

…

…

$h_{1,k}(t)=h_{1,k-1}(t)-m_{1,k}(t)=x(t)-(m_{1,1}+m_{1,2}+\ldots+m_{1,k})$;

$c_{1(t)}=x(t)-(m_{1,1}+m_{1,2}+\ldots+m_{1,k})$.

this is the step to extract the first IMF component. Subsequently, we have

$x(t)-c_1(t)=r_1(t)$;

$r_1(t)-c_2(t)=r_2(t)$;

…

…

$r_{n-1}(t)-c_n(t)=r_n(t)$; Equation 3.1

$x(t)-\sum_{j=0}^{n} c_j(t)=r_n(t)$.

Therefore,

$r_1(t)=\sum_{j=1}^{k_1} m_{1,j}$

From Equation 3.1, we have

$c_2(t)=r_1-r_2=\sum_{j=1}^{k_1} m_{1,j}-\sum_{j=1}^{k_2} m_{2,j}$

Similarly,we have

$$c_i(t)=r_{i-1}-r_i=\sum_{j=1}^{k_1} m_{1-1,j}-\sum_{j=1}^{k_2} m_{i,j}$$

Thus, the entire IMF component, other than the first one, is the sums of spline functions. With this form, the basis formed in terms of IMFs through EMD can be shown to be complete automatically, for

$$x(t)=\sum_{j=1}^{n} c_j+r_n$$

$$=x(t) - \sum_{j=1}^{k_1} m_{1,j}-(\sum_{j=1}^{k_1} m_{1,j} - \sum_{j=1}^{k_1} m_{2,j})+\ldots+(\sum_{j=1}^{k_{n-1}} m_{n-1,j}-\sum_{j=1}^{k_n} m_{n,j})-\sum_{j=1}^{k_n} m_{n,j}$$

$$=x(t)$$

From this operation we can see that IMFs could sum up to the original signal precisely.

The flow chart of extraction of IMFs from a original signal is show in Figure 3.2 .

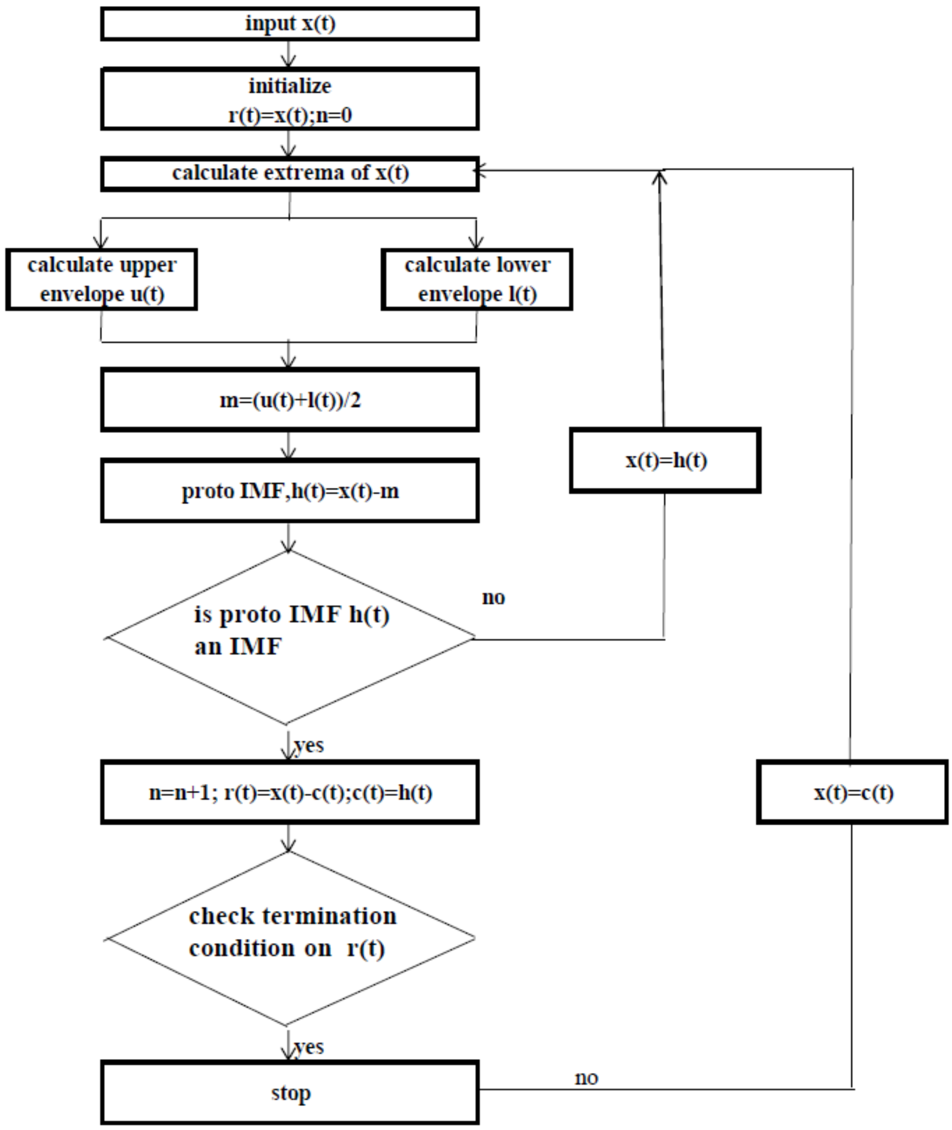

Figure 3.2 Flow chart of empirical mode decomposition

3.4.2 Feed Forward Back Propagation Neural Network

A neural network is a group of connected I/O units where each connection has a weight associated with its computer programs. It helps to build predictive models from large databases. This model builds upon the human nervous system. It helps to conduct image understanding, human learning, computer speech, etc.

Back-propagation is the essence of neural net training. It is the method of fine-tuning the weights of a neural net based on the error rate obtained in the previous epoch (i.e., iteration). Proper tuning of the weights allows to reduce error rates and to make the model reliable by increasing its generalization.

Back propagation is a short form for "backward propagation of errors". It is a standard method of training artificial neural networks. This method helps to calculate the gradient of a loss function with respects to all the weights in the network. Figure 3.3 shows how the input and the error are propagated in feed forward back propagation neural network algorithm.

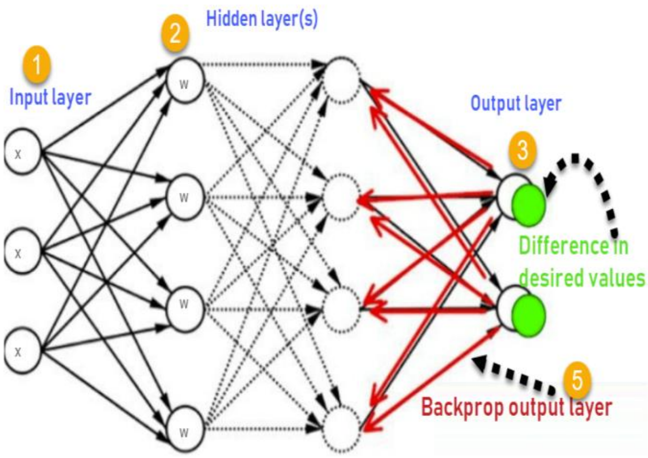

Figure 3.3 Schematic diagram of feed forward back propagation neural network.

The working procedure of feed forward back propagation neural network algorithm can be described as:

- Inputs X, flow through the preconnected path.
- Input is modeled using real weights W. The weights are usually randomly selected.
- Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
- Calculate the error in the outputs.
- Error = Actual Output – Desired Output.
- Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased, repeating the process until the desired output is achieved.

3.5 Analysis of load curve of Kathmandu valley

In order to know the variation of load with time and to understand the consumption pattern of Kathmandu valley the load curve of Kathmandu valley, taking the reference date of past two years of two different month are drawn. 2074 B.S and 2075 B.S are taken as the reference year while the month Baishak and poush are taken as the reference month to analyze the consumption pattern of Kathmandu valley.

The daily load consumption follows the same pattern in both of the year for the month poush as shown in Figure 3.4. The morning peak being in between 7:00 to 8:00 am and the evening peak at 18:00 to 19:00 pm. The peak of 2075 is slightly greater than that of 2074. The peak load demand of 2075 poush is 361 MW while it is 341 MW in the year 2074 B.S for the same month. The peak demand increases by almost 6 percentages.

The trend of load consumption of two consecutive years for the month Baishak is same. The load curve in Figure 3.5 shows the consumption pattern of load for the month of Baishak for the two consecutive years. The morning peak being in between 7:00 to 8:00 am and the evening peak at 19:00 pm. The peak load demand of 2075 is 279.87 MW while it is 250.7 MW in the year 2074 B.S the peak demand increases by 11 percentages.

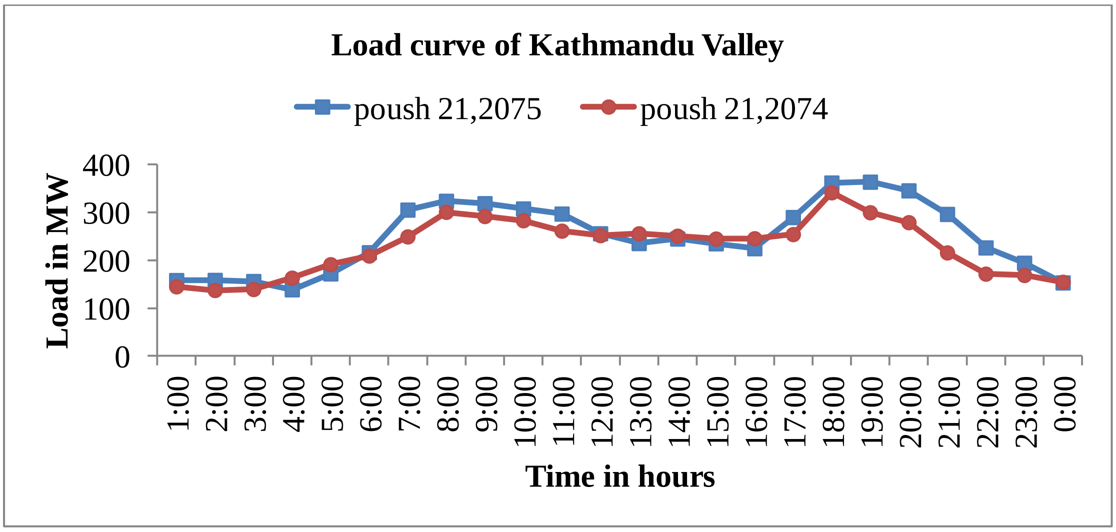

Figure 3.4 Load curve of Kathmandu Valley of the month Poush

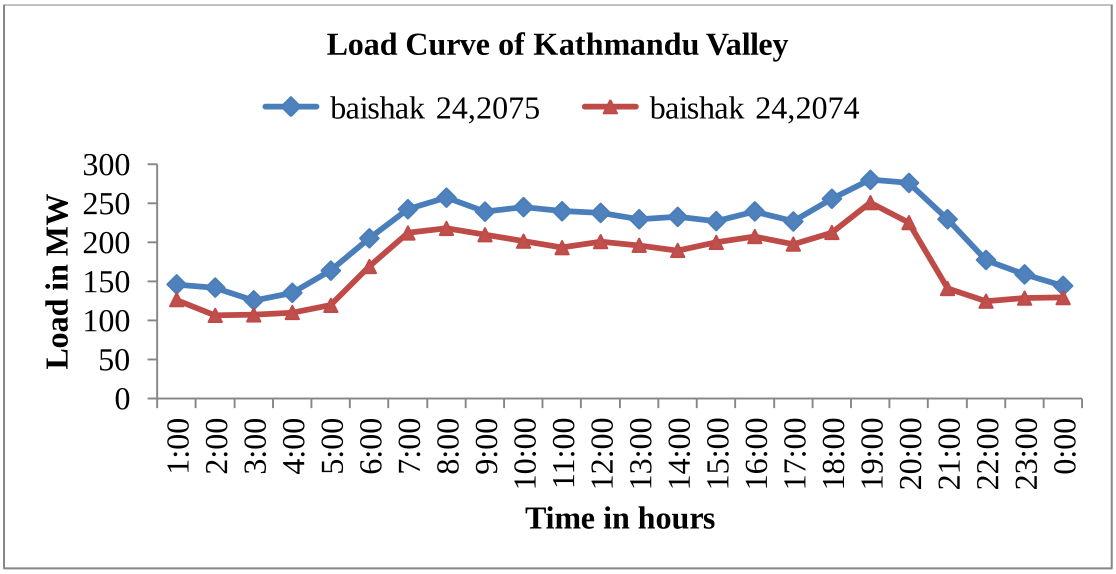

Figure 3.5 Load Curve of Kathmandu Valley of the month Baishak

The Figure 3.6 shows the combined seven days load curve of Kathmandu valley of the month poush. The consumption pattern of all seven days is almost same and the daily morning and evening peak occurs almost at the same time for all the days. The load started to increase at first reach the morning peak and comes down to the almost steady value for the day time. It starts increasing after 5:00 pm reach the evening peak around 6 pm to 6:30 pm and again start to decrease and comes to the steady value.

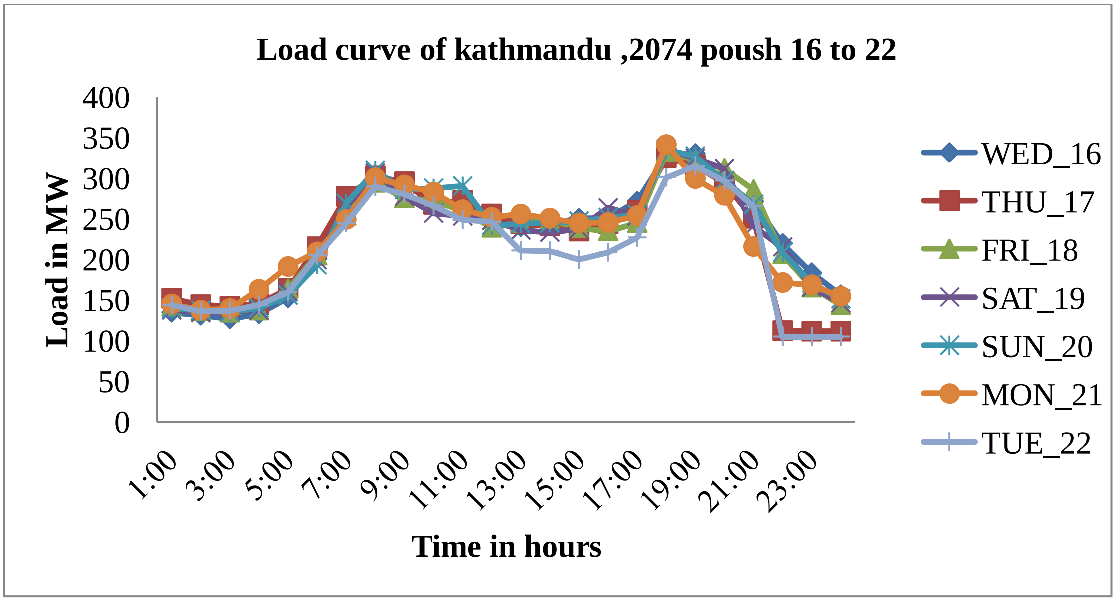

Figure 3.6 Seven days Load curve of Kathmandu Valley.

Figure 3.7 shows the daily average and peak load of Kathmandu valley for the month Baishak of 2075. The peak load is almost 75 MW greater than that of average load of each day. The average peak load is found to be 281 MW while the average of daily average load is 206 MW. The maximum peak load reaches to 326 MW where as the maximum average load reaches to 257 MW.

For the month of poush of the same year 2075, the peak load is almost 90 MW greater than that of average load of each day. The average peak load is found to be 356 MW while the average of daily average load is 266 MW. The maximum peak load reaches to 387 MW where as the maximum average load reaches to 283 MW.

The maximum peak load of Baishak is 326 MW whereas it is 387 MW for the month poush also the average consumption on poush is greater than that of Baishak. It shows that the load consumption increases as the temperature decreases in Kathmandu Valley.

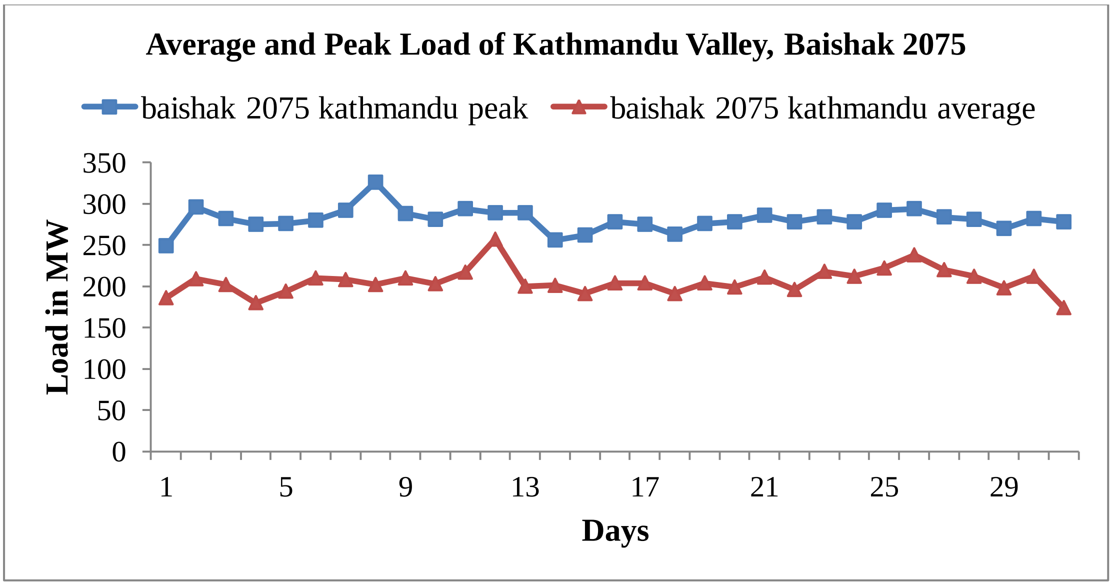

Figure 3.7 Daily average and Peak load of Kathmandu Valley for the month Baishak, 2075.

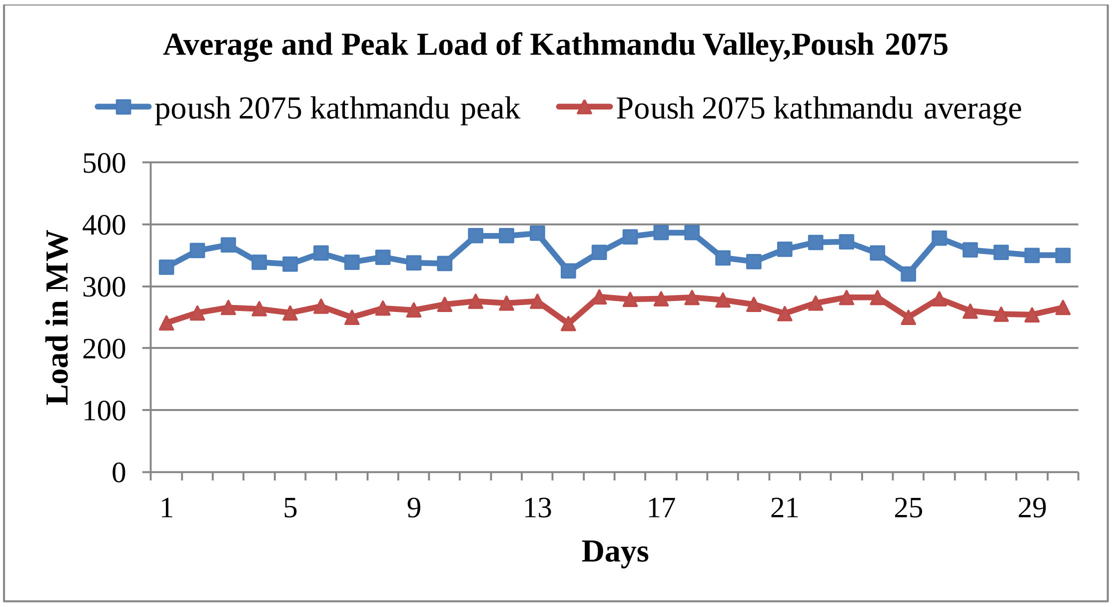

Figure 3.8 Daily average and Peak load of Kathmandu Valley for the month Poush, 2075.

Figure 3.9 shows the variation of daily peak of INPS and Kathmandu valley for the month of Baishak, 2075. The peak for the month is almost constant for both INPS and Kathmandu valley. The average peak load of INPS is 1191 MW while that of Kathmandu valley is 281 MW.

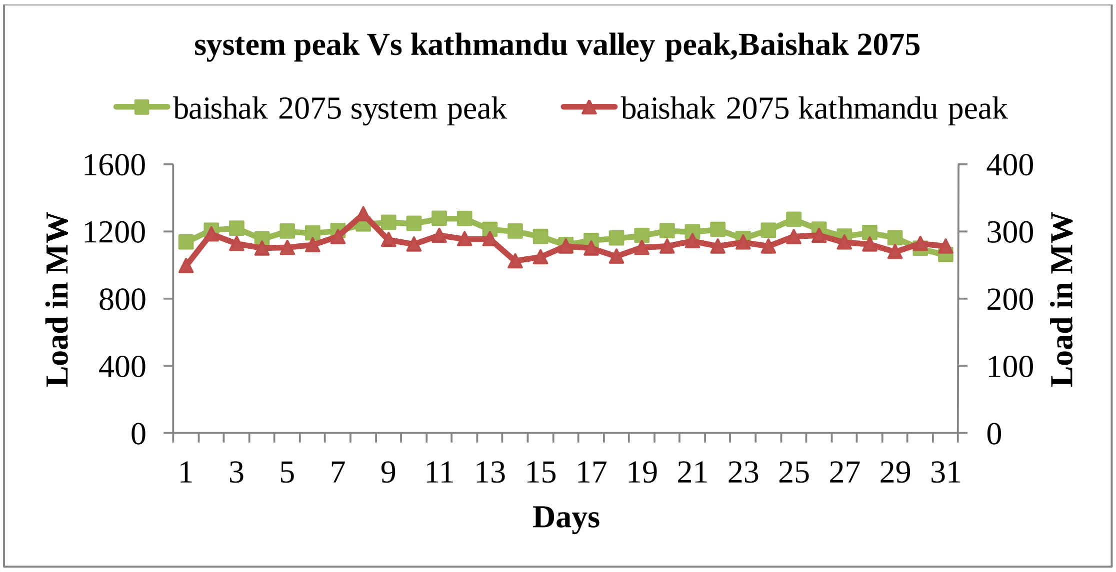

Figure 3.9 System peak Vs Kathmandu valley peak for the month of Baishak, 2075

From the above analysis it can be inferred that the load of Kathmandu Valley is increasing but it follows the same pattern of consumption for both the year and two different months. Also the daily load curves are almost same for working and off days. The system peak and Kathmandu valley peak occurs almost in same time. Therefore developing a model for load forecasting of particular day can helps to understand the load forecasting trend of other six days. Also from the analysis in Table 1.1 and the load data analysis of Kathmandu Valley we can understand the load demand of overall INPS.

3.6 Data Collection

The hourly load of Kathmandu valley from 2074 Baishak to 2076 has been taken from the load recorded at Load Dispatch Centre (LDC) of Nepal Electricity Authority. The data obtained had been recorded manually in LDC and substations containing single excel sheet for daily load.

3.7 Data Set For Testing and Training

Testing requires and independent data set. The network should be tested using another data set, which is one that has not been used in training. A simple way which is generally in practice is to prepare a test data set is to divide the available data into two parts, one for training and next for testing.

In this research work 24 hours load data of hourly sampling time is of Baishak's Sundays (3,10,17,24,31) 2074 B.S, data of Baishak's Sunday (2,9,16,23,30) 2075 B.S and data of Baishak's Sunday (1,8,15) 2076 B.S are used for training purpose. All together 312 data points are used for training and the load is forecasted using this training data for the date for Baishak 22, 2076 B.S. The data set for testing is of Baishak 22, 2076 B.S.

3.8 Hybrid STLF model

To reduce the instability of the original load series, EMD is used to decompose the original load series into a numbers of IMFs and one residual. Then these components are forecast by FFBP neural network respectively, such that the tendencies of these components can be predicted. Finally, aggregation of the prediction results of all components through NN produces, the final forecasting result for the original electric load series, this model can be denoted by EMD–FFBP. Figure 3.10 shows the algorithm of hybrid ANN model for short term load forecasting. However, all IMFs are not effective for load forecasting. Therefore, in order to select effective IMFs, Correlation Factor Analysis CFA as proposed in (Kumar, et al., 2018) is carried out. The quantity measures the correlation coefficient between each IMF and the original signal. If the correlation coefficient is too small, then the IMF may be primarily considered to be a redundant or noisy component. The CFA can be formulated as in equation below.

$$\boldsymbol{\lambda} = \frac{\sum_{n=1}^{N}[\mathbf{x}(t)C(t)]}{\sqrt{[\sum_{n=1}^{N}\mathbf{x}(t)^2 \sum_{n=1}^{N}\mathbf{c}(t)^2]}} \qquad \text{Equation 3.2}$$

Where x (t) the original signal, c (t) is an IMF and N is total number of sampling points.

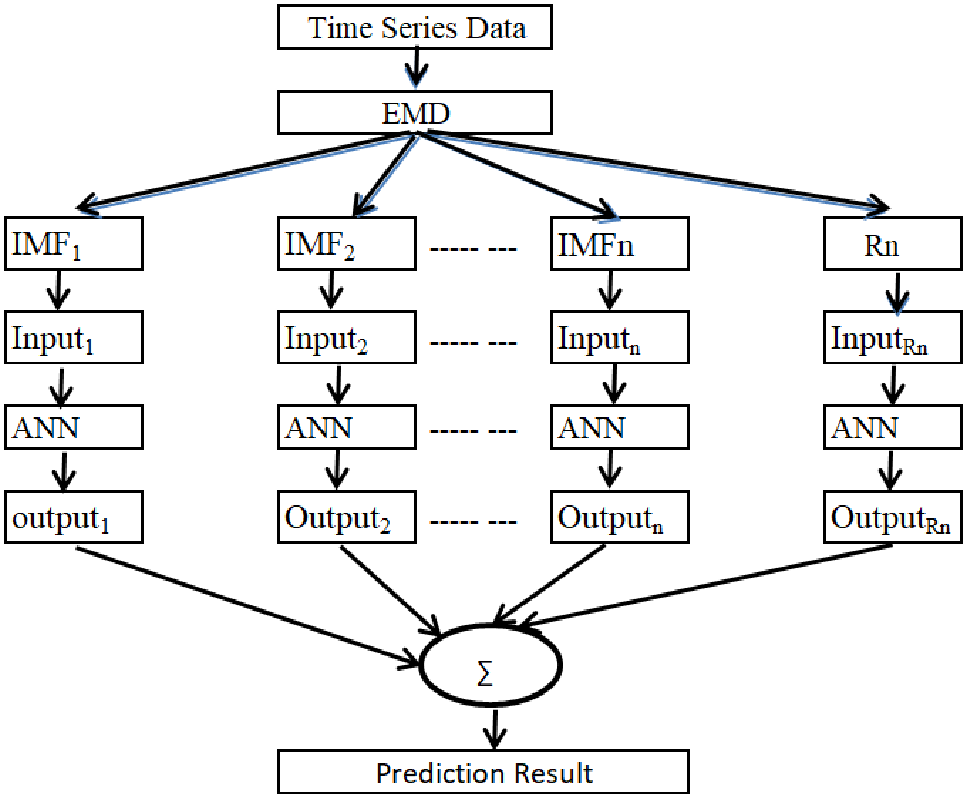

Figure 3.10 A hybrid ANN model for STLF

3.9 Forecasting and Validation

Next, the day ahead hourly load of Baishak 22, 2076 B.S is forecasted by using the hybrid network developed. The forecasted load is presented in the Results and Discussion Section. The results (the forecasted loads) were compared with real data of same period provided by NEA. In order to evaluate the performance of the network, model validating techniques like Mean Absolute percentage Error (MAPE) and Mean Absolute Deviation (MAD) were used. Then finally, a conclusion is reached upon regarding the whole research. These all are mentioned in chapter four.

The statistical formula for calculation of MAPE and MAD are as follows

Mean Absolute Deviation (MAD)

Mean absolute Deviation express accuracy in the same units as the data so it helps to conceptualize the amount of error

$$\text{MAD}=\frac{\sum_{i=1}^{n}|A-F|}{n} \qquad \text{Equation 3.3}$$

Mean Absolute Percentage Error (MAPE)

Mean absolute percentage error express accuracy as a percentage of error. Because this number is a percentage, it can be easier to understand than the other statistics. For example, if the MAPE is 5 that it is understood the forecast is off by 5%.

$$\text{MAPE} = \frac{\sum_{i=1}^{n}(|A-F|)/n}{n}\times 100 \qquad \text{Equation 3.4}$$

CHAPTER FOUR: RESULTS AND DISCUSSION

As stated earlier in methodology load forecasting is done by the feed forward propagation algorithm of ANN and the hybrid model which includes the empirical mode decomposition of original input signal to its number of components and residue and then forecasting with the same algorithm of ANN. Although short term load depends upon temperature, humidity, holidays and greatly to the human behaviour in our study we include time of the day, day of the week and the load as the input parameters for both forecasting techniques.

4.1 Forecasted load with basic ANN Model

Table 4.1 shows the actual and forecasted load of 2076/01/22, Sunday by feed forward back propagation algorithm of ANN. The input being the actual load of Sunday for the month of Baishak of the year 2074, 2075 and 2076 and the load is forecasted for 22nd of Baishak 2076.

The largest deviation of 56.85 MW is found in the hour 5:00 am while the smallest deviation of 0.2 MW is found at 15:00 pm, peak of 295 MW occurs at 19:00 pm for the forecasted load which is 311.14 MW at the same time in actual.

Table 4.1 Result obtained by forecasting through basic FFBP model.

Time(Hours)	actual load in MW	forecasted load by basic ANN in MW
1:00	128.34	134.58
2:00	123.84	136.00
3:00	122.04	171.47
4:00	123.54	178.10
5:00	138.64	195.49
6:00	181.44	218.48
7:00	223.34	233.24
8:00	243.84	239.09
9:00	242.44	240.99

Time(Hours)	actual load in MW	forecasted load by basic ANN in MW
10:00	247.24	241.57
11:00	251.14	241.75
12:00	247.84	241.84
13:00	240.94	241.96
14:00	243.24	242.31
15:00	243.54	243.34
16:00	250.34	246.28
17:00	266.14	253.07
18:00	253.94	252.00
19:00	311.14	295.00
20:00	287.29	288.63
21:00	255.74	252.26
22:00	162.64	172.83
23:00	137.54	132.00
0:00	101.54	116.58

4.2 Forecasted load with Hybrid ANN model

The hybrid ANN model as discussed in the methodology is the combination of empirical mode decomposition technique and ANN for the load forecasting. The input for this model is also the same as discussed in 4.1. The input load is decomposed to its intrinsic mode function and residue by using EMD algorithm. Each IMFs and residue are than forecasted separately and combined forecasted result is obtained.

Figure 4.1 shows the decomposition of original load input into its IMFs component and Residue. The original signal is decomposed into 9 IMFs component and one residue.

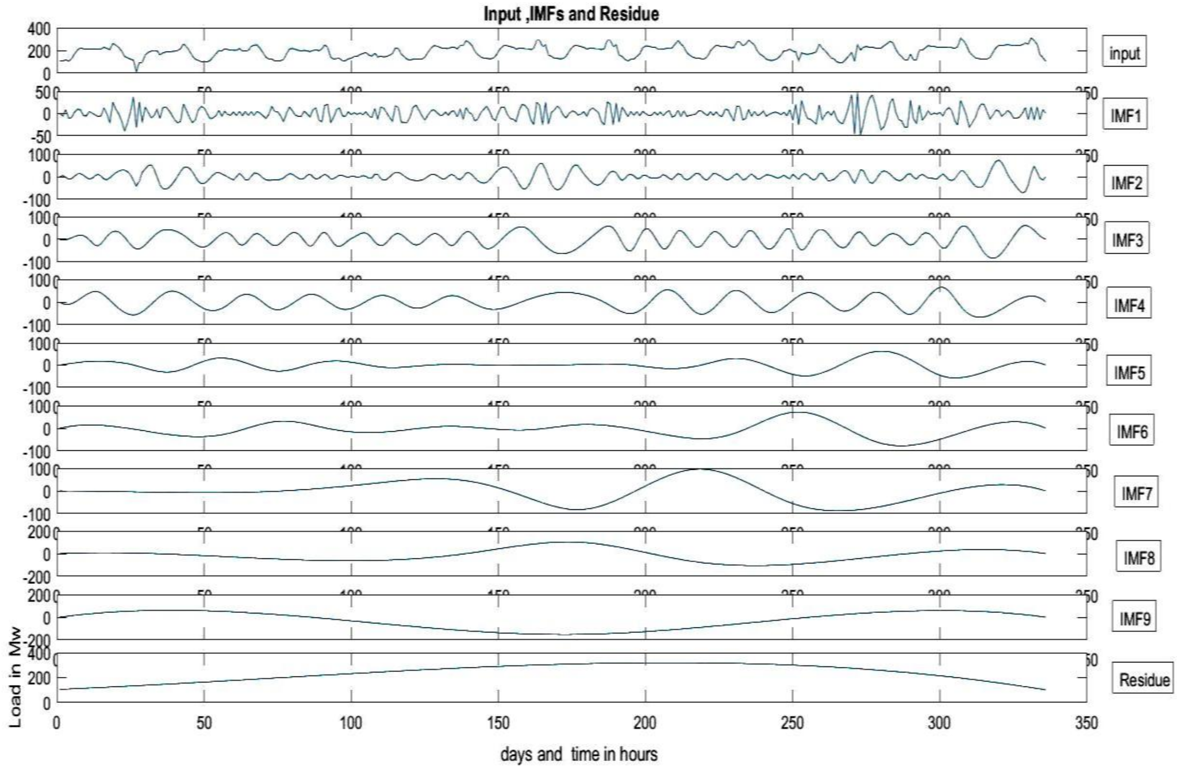

Figure 4.1 Actual load decomposed into number of IMFs and Residue

Load forecasting of individual IMFs is done using the same FFBP algorithm of ANN. Table 4.2 shows the forecasted load of IMFs and Residue extracted by EMD algorithm. The total forecasted load is obtained by the summation of the forecast of individual IMFs and residue.

Table 4.2 forecasted load of IMFs, Residue and Total forecasted load

Load Forecast of Individual IMF and Residue in Mw										Total Forecast in Mw
IMF1	**IMF2**	**IMF3**	**IMF4**	**IMF5**	**IMF6**	**IMF7**	**IMF8**	**IMF9**	**Residue**	
4.71	-9.19	-42.29	-40.58	13.14	13.74	12.72	15.23	28.51	125.83	121.81
3.55	-9.88	-44.39	-43.07	18.03	13.76	12.83	15.25	28.78	121.11	115.96
3.11	-9.87	-44.11	-43.95	17.98	13.77	12.85	15.26	28.85	121.20	115.09
3.21	-8.45	-39.52	-43.02	16.89	13.77	12.85	15.28	28.90	122.31	122.21
3.61	-2.11	-22.96	-39.05	7.68	13.77	12.82	15.32	28.98	131.49	149.54
3.88	10.83	-1.81	-33.70	-43.48	13.77	12.79	15.36	29.03	182.59	189.26
3.88	18.63	7.63	-30.47	-73.56	13.77	12.78	15.37	29.05	222.64	219.73
3.52	19.80	13.55	-25.42	-92.69	13.76	12.79	15.39	29.11	251.73	241.54
2.70	16.06	17.66	-16.13	-102.94	13.74	12.80	15.42	29.20	241.91	230.43
2.22	4.30	15.07	-9.98	-103.12	13.73	12.81	15.45	29.27	252.03	231.78
2.61	-6.93	0.92	-6.29	-74.19	13.73	12.81	15.46	29.29	252.08	239.48
3.99	-10.92	-16.48	-0.30	-62.30	13.71	12.83	15.48	29.33	251.16	236.50
5.19	-12.00	-23.05	4.66	-43.46	13.70	12.86	15.51	29.39	242.29	245.08
5.39	-12.22	-23.99	6.14	-63.54	13.69	12.87	15.52	29.43	252.38	235.66
4.74	-12.12	-21.60	6.04	-43.56	13.68	12.88	15.53	29.45	252.42	257.47
3.70	-11.37	-10.56	4.22	-62.56	13.68	12.89	15.55	29.48	251.51	246.55
3.23	-7.77	11.23	-0.60	-75.56	13.68	12.92	15.58	29.52	265.61	267.85
3.11	4.34	23.79	-5.15	-103.55	13.67	12.94	15.59	29.54	252.66	246.95
3.05	19.67	26.74	-8.93	-111.54	13.68	12.96	15.60	29.55	309.69	310.48
2.81	23.36	26.37	-16.59	-113.48	13.70	13.00	15.62	29.58	282.75	277.12
1.88	17.33	21.84	-24.37	-93.42	13.72	13.03	15.64	29.60	252.86	248.10
-0.11	1.22	5.78	-28.80	-32.40	13.73	13.03	15.65	29.61	161.91	179.63
-0.69	-9.63	-17.10	-35.06	-3.37	13.74	13.03	15.66	29.61	142.91	149.10
2.37	-12.30	-27.54	-40.89	20.67	13.77	13.02	15.69	29.58	108.86	123.23

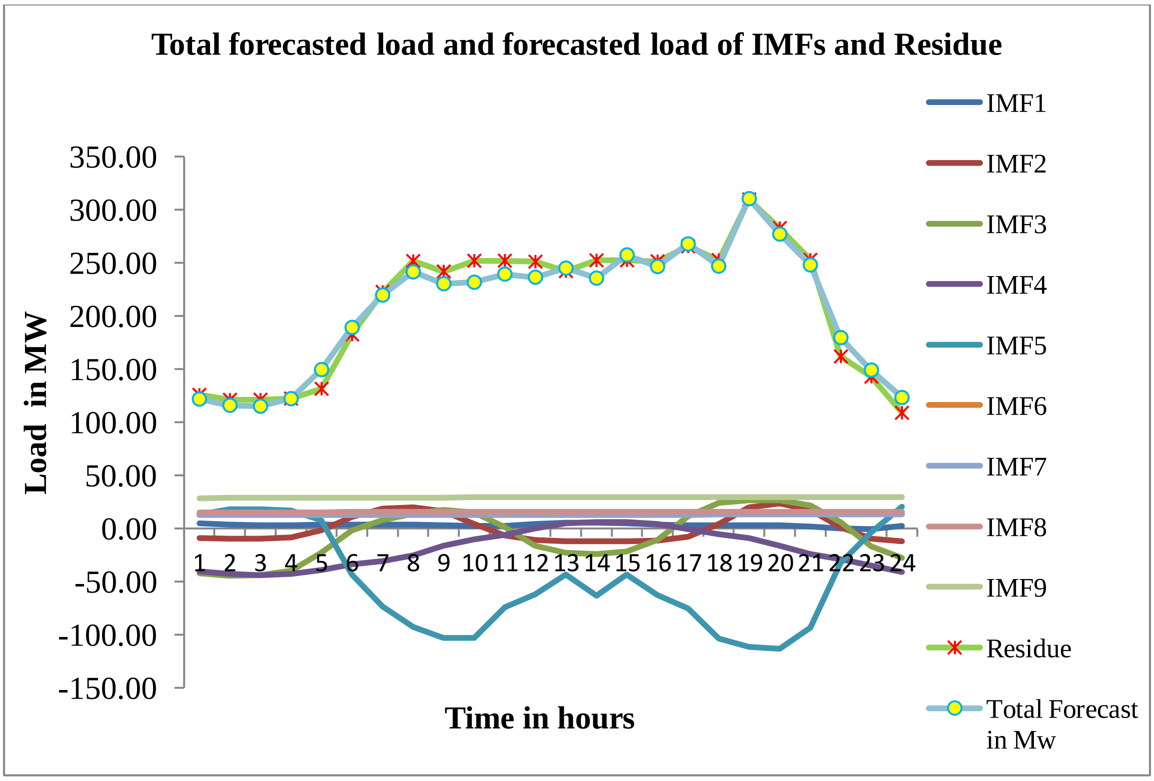

Figure 4.2 forecasted loads of IMFs, Residue and total forecasted load

From the Figure 4.2 it can be seen that the forecasted load of residue resembles with the total forecasted load obtained by summing the forecast of individual IMFs and residue. The forecasted load of IMFs is far below the actual load.

Table 4.3 Result obtained by forecasting by hybrid ANN model

Time(Hours)	**actual load in MW**	**forecasted load by hybrid ANN model in MW**
1:00	128.34	121.81
2:00	123.84	115.96
3:00	122.04	115.09
4:00	123.54	122.21
5:00	138.64	149.54
6:00	181.44	189.26
7:00	223.34	219.73
8:00	243.84	241.54
9:00	242.44	230.43
10:00	247.24	231.78
11:00	251.14	239.48

Time(Hours)	actual load in MW	forecasted load by hybrid ANN model in MW
12:00	247.84	236.50
13:00	240.94	245.08
14:00	243.24	235.66
15:00	243.54	257.47
16:00	250.34	246.55
17:00	266.14	267.85
18:00	253.94	246.95
19:00	311.14	310.48
20:00	287.29	277.12
21:00	255.74	248.10
22:00	162.64	179.63
23:00	137.54	149.10
0:00	101.54	123.23

4.3 Forecasted load with Hybrid ANN model after CFA analysis

The EMD algorithm decomposes the input time series load data into nine numbers of IMFs and a residue. Table 4.2 shows the total forecast load including all the IMFs and the residue. As all the IMFs does not contain the meaningful selection of most relevant IMFs and residue is done by calculating the correlation factor between the input and IMFs. The result of correlation factor is shown in Table 4.4. From this analysis we can conclude that the residue contain the most relevant information compare to other intrinsic mode functions. So in this case residue is the input parameter.

Table 4.4 correlation factor analysis between the Input and IMFs

IMFs/Residue	Input
IMF1	0.03
IMF2	0.05
IMF3	0.15

IMFs/Residue	Input
IMF4	0.13
IMF5	0.01
IMF6	-0.16
IMF7	-0.01
IMF8	-0.2
IMF9	-0.35
Residue	0.93

Table 4.5 shows the actual and forecasted load. The load is forecasted by taking the residue only. The maximum difference of 9.14 MW at 14:00 and the minimum difference of 0.53 MW at 17:00 are noticed. The peak load forecasted is 309.69 MW at 19:00 which is 1.45 MW less compared to the original peak load.

Table 4.5 Result obtained by forecasting by hybrid ANN model after CFA analysis

Time(Hours)	actual load in MW	Forecasted load by hybrid model after CFA analysis in MW
1:00	128.34	125.83
2:00	123.84	121.11
3:00	122.04	121.20
4:00	123.54	122.31
5:00	138.64	131.49
6:00	181.44	182.59
7:00	223.34	222.64
8:00	243.84	251.73
9:00	242.44	241.91
10:00	247.24	252.03

Time(Hours)	actual load in MW	Forecasted load by hybrid model after CFA analysis in MW
11:00	251.14	252.08
12:00	247.84	251.16
13:00	240.94	242.29
14:00	243.24	252.38
15:00	243.54	252.42
16:00	250.34	251.51
17:00	266.14	265.61
18:00	253.94	252.66
19:00	311.14	309.69
20:00	287.29	282.75
21:00	255.74	252.86
22:00	162.64	161.91
23:00	137.54	142.91
0:00	101.54	108.86

4.4 Comparison of Outputs by Different Models

Table 4.6 shows the comparison of forecasted and actual load by calculating the error parameters. The mean absolute deviation and mean absolute percentage error are calculated between the actual load and forecasted load by two different models.

The MAD between the actual and forecasted load by basic ANN is found to be 13.6 MW while for the hybrid model it decreases to 8.53 MW similarly the MAPE between the actual and forecasted load by basic ANN is 8.53% while it reduces to 4.82% for the hybrid model.

The error reduces to 3.27 MW for MAD and 1.79% to MAPE after forecasting the load using hybrid model after selecting the most informative IMFs and residue.

From these values it can be inferred that the error is reduced when we apply the hybrid model after denoising the input load rather than basic ANN model only. Therefore the final forecasted load is the output of the hybrid model after denoising the input load data.

Table 4.6 Error of Different Model

Model	MAD	MAPE
ANN	13.6	9.02
Hybrid ANN	8.53	4.82
Hybrid ANN after CFA analysis	**3.27**	**1.79**

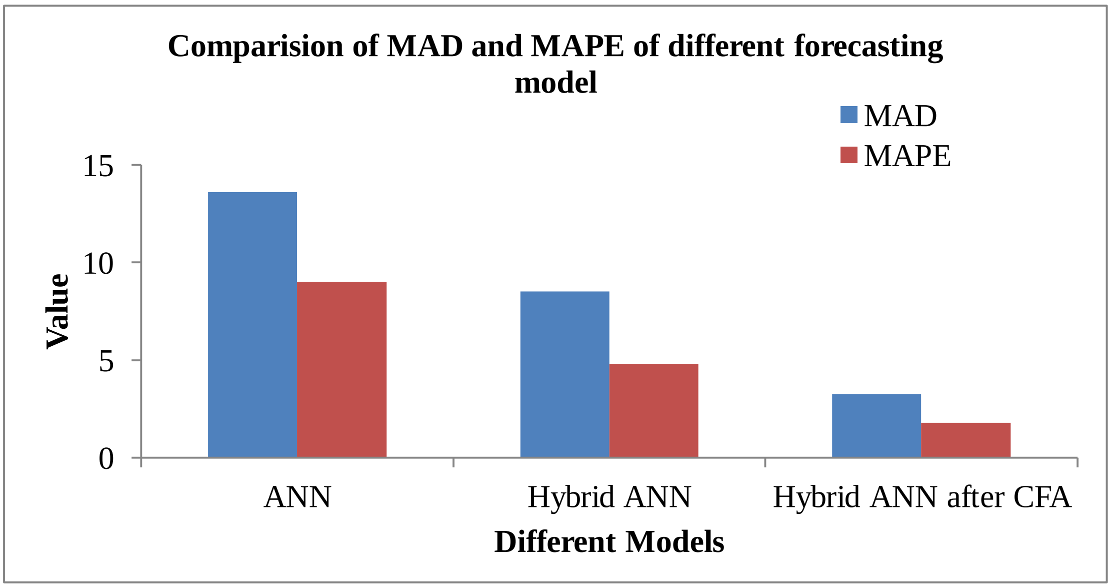

Figure 4.3 Comparison of MAD and MAPE of different forecasting models.

4.5 Forecasted load vs. Actual Load: Comparison

The forecasted loads obtained from the model developed and the real loads taken from the concerned department needs to be compared. Table 4.7 shows the hourly actual load and the forecasted load of 2076, Baishak 22. Loads are plotted in the same line diagram to observe the deviation from actual load and to identify the load pattern. The load pattern as seen in Figure 4.4 follows the same pattern for both the actual and forecasted load. It can be observed that there was very small variation among actual load and forecast loads at each hour. The forecasted loads approximately coincide with the actual loads.

Table 4.7 Actual load and forecasted load by ANN and hybrid ANN model

Time(Hours)	actual load in MW	forecasted load by hybrid ANN in MW
1:00	128.34	125.83
2:00	123.84	121.11
3:00	122.04	121.20
4:00	123.54	122.31
5:00	138.64	131.49
6:00	181.44	182.59
7:00	223.34	222.64
8:00	243.84	251.73
9:00	242.44	241.91
10:00	247.24	252.03
11:00	251.14	252.08
12:00	247.84	251.16
13:00	240.94	242.29
14:00	243.24	252.38
15:00	243.54	252.42
16:00	250.34	251.51
17:00	266.14	265.61

Time(Hours)	actual load in MW	forecasted load by hybrid ANN in MW
18:00	253.94	252.66
19:00	311.14	309.69
20:00	287.29	282.75
21:00	255.74	252.86
22:00	162.64	161.91
23:00	137.54	142.91
0:00	101.54	108.86

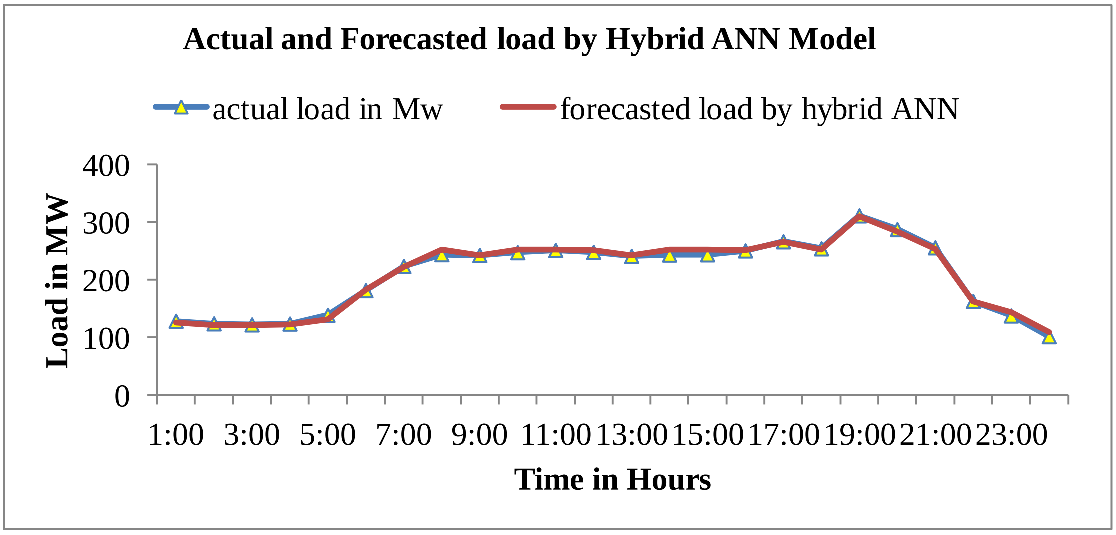

Figure 4.4 Actual load and forecasted load by hybrid ANN model

4.6 Research Validation

In literature section, we have discussed about the various hybrid model developed for short term load forecasting.

To further examine the proposed EMD–BPNN forecasting model, the electric load data of New York networks (NYISO, 2004) are used. The load data include the readings for 1 h per sampling point. The results of the proposed EMD–FFBPNN are compared with the results of other well-known hybrid models, WTNNEA, WGMIPSO and IEEMD-BPNN presented by (Amjady & Keynia, 2009), (Bahrami, et al., 2014) and (YU, et al., 2016), respectively, to forecast the load of July 1, 2004 of New York Network. For this purpose, the load data of the previous 10 days are used to forecast the electric load on July 1, 2004.The forecast results of the EMD–FFBP and the result obtained by other methods are shown in Table 4.8.

Table 4.8 Actual load forecasted load for the power system of New York for July 1, 2004

Time(Hours)	actual load (MW)	Forecasted load in MW by different models			
		WTNNEA (Amjady & Keynia, 2009)	WGMIPSO (Bahrami, et al., 2014)	IEEMD-BPNN (YU, et al., 2016)	**EMD-FFBP**
1:00	5650	5766.45	5585.08	5664.3	5942.94
2:00	5439	5681.63	5362.49	5419.9	5545.07
3:00	5325	5210.55	5256.19	5297.08	5346.02
4:00	5315	5508.26	5247.9	5319.93	5247.01
5:00	5505	5675.96	5423.21	5986.41	5249.11
6:00	6044	6282.63	6039.49	6109.32	5950.87
7:00	6840	7077.63	6884.31	6783.96	6951.58
8:00	7505	7393.55	7565.75	7450.97	6952.47
9:00	7988	7879.55	8047.9	7960.99	6954.38
10:00	8268	8160.55	8279.92	8281.18	7855.94
11:00	8461	8389.21	8462.96	8453.26	7956.70
12:00	8554	8448.55	8578.1	8548.84	7957.92
13:00	8645	8876.63	8684.34	8645.75	8359.75
14:00	8705	8601.55	8745.89	8723.82	8560.74
15:00	8743	8640.55	8793.68	8759.71	8961.29
16:00	8735	8633.55	8797.86	8705.03	8662.53
17:00	8562	8461.55	8655.77	8498.52	8864.30
18:00	8105	8005.55	8173.87	8158.56	8665.20
19:00	7780	7887.26	7824.22	7863.76	7965.73
20:00	7627	7529.55	7623.56	7662.93	7666.89
21:00	7526	7489.07	7523.02	7464.21	6968.42
22:00	7192	7096.55	7164.08	7120.25	6969.17
23:00	6691	6192.63	6645.03	6699.6	6969.73
0:00	6175	6232.63	6103.53	6247.14	6970.98

Table 4.9 shows the MAPE between the actual and forecasted load of NYN for July 1, 2004 by different four hybrid models. In the method purposed by (Amjady & Keynia, 2009) the MAPE for July 1, 2004 is 1.93%. Similarly the value is 0.682% and 0.533 % for the method purposed by (Bahrami, et al., 2014) and (YU, et al., 2016) respectively. The purposed EMD-FFBP model gives the MAPE value of 4.34 % for the same data.

Table 4.9 MAPE value of different model for the load forecast of July1, 2004 of NYN

MODEL	MAPE
WTNNEA (Amjady & Keynia, 2009)	1.93
WGMIPSO (Bahrami, et al., 2014)	0.682
IEEMD-BPNN (YU, et al., 2016)	0.533
EMD-FFBP	**4.34**

Figure 4.5 shows the actual and forecasted load by four different models for July 1, 2004 of New York City. The maximum and minimum deviation for the model purposed by (Amjady & Keynia, 2009) was found to be 498.37 MW (23:00pm) and 36.93 MW (21:00pm) .The maximum deviation of 93.77 MW (17:00pm) and 481.41 MW (5:00am) was found for (Bahrami, et al., 2014) and (YU, et al., 2016) respectively, while the minimum deviation of 1.96 MW (11:00am) and 0.75MW (13:00pm) for the above two model respectively. In the purposed EMD-FFBP model the maximum deviation of 1033.62 MW (9:00am) and minimum deviation of 21.02 MW (3:00am) was seen.

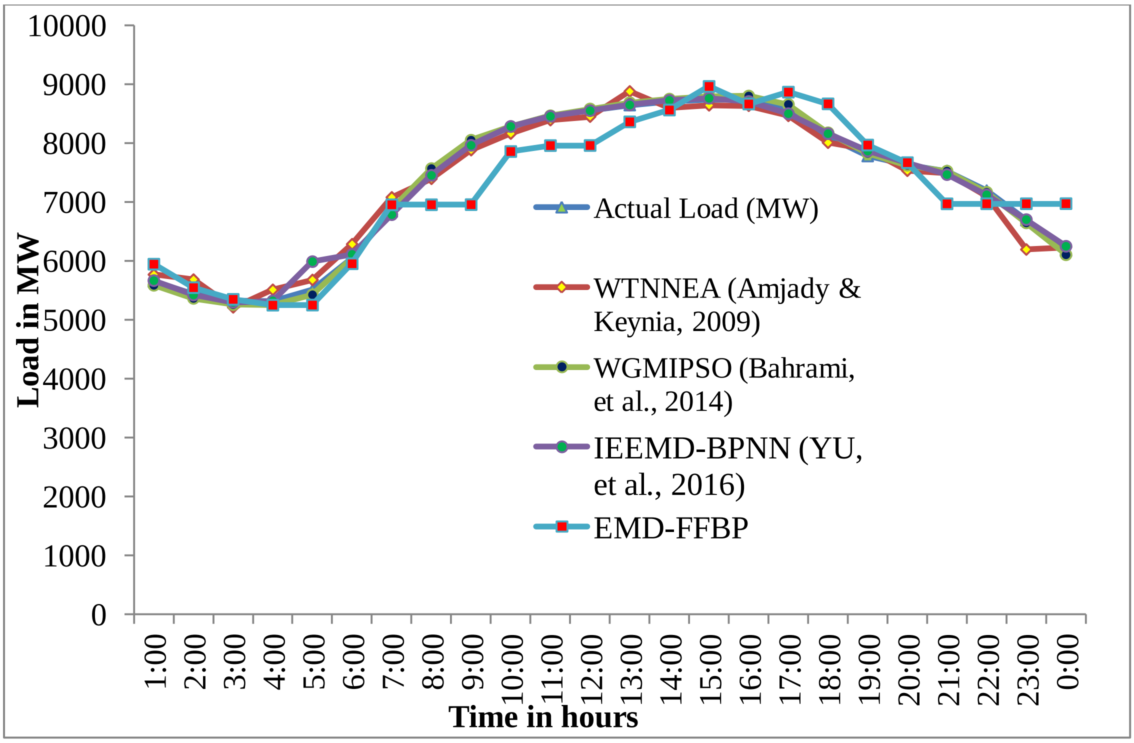

Figure 4.5 Actual and forecasted load value obtained by four methods for July 1, 2004 of New York Network.

From the above analysis it can be concluded that although the proposed EMD-FFBP neural network model gives the MAPE value higher among the other hybrid model for the same day load forecast, the forecast accuracy of the proposed EMD–FFBP neural network model is within the acceptable limit (Yang, et al., 2013).

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 Conclusion

- A hybrid short term load forecasting model was developed incorporating Empirical Model Decomposition and Artificial Neural Network.
- The hybrid model is used to forecast the day ahead 24 hours load of Kathmandu Valley for the desired day. The mean absolute deviation between the actual load and forecasted load is 3.27 MW while the MAPE is 1.79%. The EMD-FFBP model reduces the MAPE by 80.15% and MAD by 75.95% compared to basic NN model.
- The results of proposed EMD–FFBPNN are compared with the results of other well-known hybrid models, WTNNEA, WGMIPSO and IEEMD-BPNN presented by (Amjady & Keynia, 2009), (Bahrami, et al., 2014) and (YU, et al., 2016), respectively, to forecast the load of July 1, 2004 of New York Network. The proposed EMD-FFBP model gives the MAPE of 4.34% which is higher than the MAPE value obtained by other hybrid models, but it is within the limit of acceptance.

The hybrid artificial neural network model gives the satisfactory result of short term load forecast showing the robustness of the method to model non-linear load data.

5.2 Recommendation

- This research can help to make important decisions in the field of scheduling, contingency analysis, load flow analysis in power system, and can be useful for the energy utility companies for trading energy on the basis of future load demand in dynamic energy markets.

- This research is limited to Kathmandu Valley for academic purpose. If the recording of the past data can be done properly of others stations of Nepal, similar forecasting can be carried out for whole country.

- There is space for researcher in other hybrid model comprising of Neural Network and check whether the hybrid model could forecast more accurately than basic Neural Network model.

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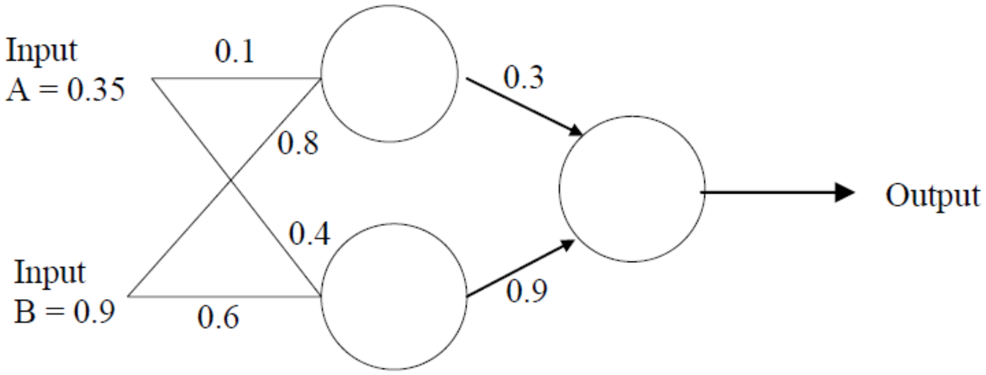
APPENDIX A: Feed Forward Back Propagation Algorithm mathematical calculation



Assume that the neurons have a Sigmoid activation function and
(i) Perform a forward pass on the network.
(ii) Perform a reverse pass (training) once (target = 0.5).
(iii) Perform a further forward pass and comment on the result.
Answer:
(i)
Input to top neuron = (0.35x0.1)+(0.9x0.8)=0.755. Out = 0.68.
Input to bottom neuron = (0.9x0.6)+(0.35x0.4) = 0.68. Out = 0.6637.
Input to final neuron = (0.3x0.68)+(0.9x0.6637) = 0.80133. Out = 0.69.
(ii)
Output error δ=(t-o)(1-o)o = (0.5-0.69)(1-0.69)0.69 = -0.0406.
New weights for output layer
$w1^{+}$ = w1+(δ x input) = 0.3 + (-0.0406x0.68) = 0.272392.
$w2^{+}$ = w2+(δ x input) = 0.9 + (-0.0406x0.6637) = 0.87305.
Errors for hidden layers:
δ1 = δ x w1 = -0.0406 x 0.272392 x (1-o)o = -2.406×10^{-3}
δ2= δ x w2 = -0.0406 x 0.87305 x (1-o)o = -7.916×10^{-3}
New hidden layer weights:
$w3^{+}$=0.1 + (-2.406×10^{-3} x 0.35) = 0.09916.
$w4^{+}$ = 0.8 + (-2.406×10^{-3} x 0.9) = 0.7978.
$w5^{+}$ = 0.4 + (-7.916×10^{-3} x 0.35) = 0.3972.
$w6^{+}$ = 0.6 + (-7.916×10^{-3} x 0.9) = 0.5928.
(iii)
Old error was -0.19. New error is -0.18205. Therefore error has reduced.

APPENDIX B: Error Calculation between the Actual and Forecasted Load

Time(Hours)	actual load (A)	forecasted load by hybrid ANN (F)	abs(A-F)	abs(A-F)/A
1:00	128.34	125.83	2.51	0.02
2:00	123.84	121.11	2.73	0.02
3:00	122.04	121.20	0.84	0.01
4:00	123.54	122.31	1.23	0.01
5:00	138.64	131.49	7.15	0.05
6:00	181.44	182.59	1.15	0.01
7:00	223.34	222.64	0.70	0.00
8:00	243.84	251.73	7.89	0.03
9:00	242.44	241.91	0.53	0.00
10:00	247.24	252.03	4.79	0.02
11:00	251.14	252.08	0.94	0.00
12:00	247.84	251.16	3.32	0.01
13:00	240.94	242.29	1.35	0.01
14:00	243.24	252.38	9.14	0.04
15:00	243.54	252.42	8.88	0.04
16:00	250.34	251.51	1.17	0.00
17:00	266.14	265.61	0.53	0.00
18:00	253.94	252.66	1.28	0.01
19:00	311.14	309.69	1.45	0.00
20:00	287.29	282.75	4.54	0.02
21:00	255.74	252.86	2.88	0.01
22:00	162.64	161.91	0.73	0.00
23:00	137.54	142.91	5.37	0.04
0:00	101.54	108.86	7.32	0.07
			MAD	**MAPE**
			3.27	**1.79**

APPENDIX C: Input Load Data for Neural Network Training

time In	load data in MW for different data of 2074,2075,2076 Sunday											
hours/Date	2074-01-03	2074-01-10	2074-01-17	2074-01-24	2074-01-31	2075-01-02	2075-01-09	2075-01-16	2075-01-23	2075-01-30	2076-01-01	2076-01-08	2076-01-15
1:00	106	123	102	126	110	123	130	130	121	134	123	99	113
2:00	105	114	97	106	109	125	130	130	108	133	113	92	167
3:00	119	103	99	107	125	121	126	126	122	127	111	95	117
4:00	104	93	110	110	133	125	129	129	122	127	119	120	116
5:00	128	95	139	119	145	140	148	148	146	145	133	151	201
6:00	170	160	169	169	147	181	192	192	169	195	159	183	201
7:00	205	182	200	212	164	219	227	227	223	224	198	104	224
8:00	222	194	196	218	174	241	245	245	240	246	199	250	242
9:00	215	200	214	210	181	240	240	240	238	240	212	203	237
10:00	212	199	209	201	160	228	234	234	231	232	193	229	238
11:00	214	159	202	193	149	218	228	228	231	236	190	235	227
12:00	211	178	202	201	175	219	212	212	215	231	110	228	232
13:00	213	186	200	196	142	216	220	220	215	222	178	228	226
14:00	214	189	217	190	149	228	220	220	212	225	171	223	226
15:00	214	191	197	200	143	229	216	216	217	274	166	219	225
16:00	227	193	198	207	146	214	215	215	224	273	172	220	224
17:00	218	200	199	198	158	241	207	207	223	242	176	241	219
18:00	208	215	236	213	173	241	218	218	255	256	189	259	231
19:00	262	258	247	251	223	287	288	288	287	289	255	280	307
20:00	246	234	248	225	216	271	289	289	257	271	221	268	288
21:00	226	196	219	141	168	244	233	233	231	247	198	211	245
22:00	194	153	180	125	145	193	250	250	181	192	167	169	185
23:00	148	122	141	128	121	161	159	159	157	164	135	145	159
0:00	136	112	126	129	115	144	148	148	142	150	126	118	136

APPENDIX D: Kathmandu Peak and System Peak Data Of 2075 Baishak And Poush

Days	Baishak 2075 Kathmandu peak laod MW	Baishak 2075 System peak load MW	Poush 2075 Kathmandu peak	poush 2075 System peak in MW	Baishak 2075 Kathmandu average in MW	Poush 2075 kathmandu average in MW
1	249	1136	331	1138	186	241
2	296	1206	358	1192	209	257
3	282	1218	367	1182	202	266
4	275	1154	339	1189	180	264
5	276	1201	336	1180	194	257
6	280	1190	354	1170	210	268
7	292	1204	339	1103	208	250
8	326	1243	347	1190	202	265
9	288	1253	338	1213	210	262
10	281	1247	337	1205	203	271
11	294	1277	382	1232	217	276
12	289	1276	382	1235	257	273
13	289	1211	386	1223	200	276
14	256	1201	325	1158	201	240
15	262	1169	355	1203	191	283
16	278	1121	380	1208	204	279
17	275	1145	387	1191	204	280
18	263	1160	387	1210	191	282
19	276	1175	346	1219	204	278
20	278	1203	340	1216	199	271
21	286	1197	360	1162	211	256
22	278	1211	371	1218	196	273
23	284	1157	372	1220	218	282
24	278	1206	354	1216	212	282
25	292	1271	320	1128	222	250
26	294	1212	378	1233	238	280
27	284	1171	359	1218	220	260
28	281	1192	355	1149	212	255
29	270	1161	350	1211	198	254
30	282	1099	350	1169	212	266
31	278	1061			174	

APPENDIX E: NEA, Load Dispatch Centre Peak Data Record

LOAD DISPATCH CENTRE

Peak Load Detail

Date: 2075 Asoj 31 Wednesday, October 17, 2018

To copy Load, Frequency and time to Daily Report (No Need to enter):

Load (MW)	952.30	953.60	955.10	967.50	966.60	973.18	969.60	966.50	960.00
Frequency (Hz)	49.968	49.989	49.898	50	49.986	49.973	50	50	50
Time	18:15	18:20	18:25	18:30	18:35	18:40	18:45	18:50	18:55
.						PEAK			

TIME / POWER HOUSE	18:15	18:20	18:25	18:30	18:35	18:40	18:45	18:50	18:55
KHIMTI	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0
UMRS	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
BKPC	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Upper Madi	24.7	24.7	24.7	24.7	24.7	24.7	24.7	24.7	24.7
CHILIME	22.0	22.0	22.0	22.0	22.0	22.0	22.0	22.0	22.0
Sanima Mai	22.0	22.0	22.0	22.0	22.0	22.0	22.0	22.0	22.0
L-Modi	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
JHIMRUK	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
INDRAWATI	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5
BIJAYPUR	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
OTHERS IPP	190.0	190.0	190.0	190.0	190.0	190.0	190.0	190.0	190.0
TOTAL IPP	**371.7**	**371.7**	**371.7**	**371.7**	**371.7**	**371.7**	**371.7**	**371.7**	**371.7**
KALI GANDAKI-A	95.8	95.1	96.1	96.1	96.2	96.1	96.2	95.9	96.3
M - MRS	72.5	71.0	72.8	72.5	72.1	72.6	72.0	71.3	71.9
MARSYNGDI	71.6	71.7	71.9	71.6	71.9	71.6	71.8	71.7	71.4
TRISHULI	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6	11.6
DEVIGHAT	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0
SUNKOSHI	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2	10.2
GANDAK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MODI	14.0	14.0	14.0	14.0	14.0	14.0	14.0	14.0	14.0
PUWA	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2	6.2
CHAMELIYA	29.0	29.0	29.0	29.0	29.0	29.0	29.0	29.0	29.0
KL-I	15.0	14.7	14.7	14.7	14.7	14.7	14.7	14.7	14.7
KL-II	7.1	7.1	6.6	7.8	7.1	7.1	7.1	7.1	7.2
SMALL HYDRO	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1	3.1
TOTAL NEA HYDRO	**345.1**	**342.7**	**345.2**	**345.8**	**345.1**	**345.2**	**344.9**	**343.8**	**344.6**
IMPORT									
TANAKPUR	17.0	17.0	18.0	18.0	22.0	22.0	22.0	22.0	22.0
KATAIYA	50.1	49.1	48.8	49.7	49.5	48.1	48.7	48.0	47.0
MUJAFFARPUR	78.8	90.6	82.9	87.8	79.0	87.2	83.9	86.1	84.4
RAMNAGAR	12.0	12.0	12.0	12.0	15.0	15.0	15.0	15.0	12.5
RAXAUL 132 kV	52.6	45.5	51.5	57.5	59.3	59.0	58.4	54.9	52.8
OTHERS IMPORT	25	25	25	25	25	25	25	25	25
TOTAL IMPORT	**235.5**	**239.2**	**238.2**	**250**	**249.8**	**256.3**	**253**	**251**	**243.7**
THERMAL									
MULTI FUEL	0	0	0	0	0	0	0	0	0
HTD DIESEL	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
TOTAL THERMAL	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
EXPORT									
RAMNAGAR	0	0	0	0	0	0	0	0	0
RAXAUL	0	0	0	0	0	0	0	0	0
TOTAL EXPORT	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
TOTAL	**952.3**	**953.6**	**955.1**	**967.5**	**966.6**	**973.2**	**969.6**	**966.5**	**960.0**
FREQUENCY	**49.97**	**49.99**	**49.90**	**50.00**	**49.99**	**49.97**	**50.00**	**50.00**	**50.00**
LOAD SHEDDED	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
TOTAL LOAD	**952.3**	**953.6**	**955.1**	**967.5**	**966.6**	**973.2**	**969.6**	**966.5**	**960.0**

APPENDIX F: NEA, Load Dispatch Centre Daily load Data Record

	Night Shift(Contd..)										*Morning Shift*						*Day Shift*								
Hrs. **Source**	01:00	02:00	03:00	04:00	05:00	05:30	06:00	06:30	07:00	07:30	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	17:30	18:00	18:30	19:00	19:30
Khimti	57.8	57.8	58.5	57.9	58.0	58.3	58.3	58.0	56.9	56.8	57.8	57.5	48.0	48.0	48.0	48.0	50.5	51.0	57.0	60.0	60.0	55.0	56.0	56.0	55.0
Upper Marsyangdi	25.3	25.3	25.3	25.4	48.2	49.3	49.3	49.3	49.3	49.3	49.4	49.3	49.5	49.2	44.1	49.3	49.0	48.8	48.9	48.8	48.9	48.6	48.6	48.3	48.6
Bhotekoshi	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Upper Madi	13.6	13.6	13.6	13.5	13.6	13.7	13.7	13.6	13.6	13.6	13.5	13.6	13.6	13.6	16.6	13.5	13.6	13.5	13.6	13.6	13.6	13.6	13.6	13.6	13.6
Chilime	20.8	19.7	19.7	19.7	19.7	19.7	19.7	19.7	19.7	19.7	19.0	19.0	19.0	19.6	19.6	19.7	19.4	19.6	19.4	19.4	19.4	19.4	19.4	19.4	19.4
Sanima Mai	12.8	12.8	12.8	12.8	12.8	12.8	12.8	12.8	12.8	12.8	12.0	12.0	12.0	12.0	12.0	12.0	12.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0	11.0
Lower Modi	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Jhimurk	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
Indrawati	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5	6.5
Bijayapur	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other IPP Total	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0	150.0
Total IPP	**306.3**	**305.2**	**305.9**	**305.3**	**328.3**	**329.8**	**329.8**	**329.4**	**328.3**	**328.2**	**327.7**	**327.4**	**318.1**	**318.4**	**316.3**	**318.5**	**320.5**	**317.4**	**323.4**	**326.3**	**326.4**	**321.1**	**322.1**	**321.8**	**321.1**
KGA	109.0	101.0	91.0	65.0	83.4	95.6	95.6	90.3	92.0	96.0	91.2	95.0	76.3	79.0	71.0	93.2	97.4	113.0	116.0	116.0	144.0	142.0	144.0	143.0	142.0
Middle MRS	49.5	49.8	50.4	50.0	45.2	71.6	71.6	50.4	49.4	71.6	58.9	50.4	49.0	49.6	43.5	76.3	45.6	46.1	45.9	60.6	66.0	67.8	66.3	66.0	65.3
MRS	70.2	70.2	70.2	70.0	69.6	70.4	70.4	60.0	70.1	70.0	70.0	61.0	61.3	61.7	61.7	61.8	55.6	46.7	46.9	69.5	69.6	70.0	69.3	69.3	70.0
TRI	16.	16.	16.	16.	16.	16.	16.	16.	16.	16.	16.	16.	16.	16.	16.	17.	16.	17.	17.	17.	17.	17.	17.	17.	17.

	Night Shift(Contd..)										Morning Shift						Day Shift								
	8	8	8	8	7	6	6	6	8	9	9	7	9	6	4	2	9	1	2	2	2	2	2	2	2
DEVI	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
SUN	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
GDK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MODI	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0
PUWA	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5	4.5
CHM	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	9.0	25.0	25.0	25.0	25.0	18.0	18.0	18.0	15.0	15.0	15.0	15.0	15.0	30.0	30.0	25.0
Other NEA Small	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5
Total ROR	**294.1**	**286.4**	**277.0**	**250.4**	**263.5**	**302.8**	**302.8**	**265.9**	**276.9**	**301.1**	**301.6**	**285.1**	**265.5**	**268.9**	**247.6**	**303.5**	**270.5**	**274.9**	**278.0**	**315.3**	**348.8**	**349.0**	**363.8**	**362.5**	**356.5**
KL1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.6	54.0	30.0	15.0	0.0
KL2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	20.3	14.5	6.5	0.0
Total STORGE	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**12.6**	**74.3**	**44.5**	**21.5**	**0.0**
TNKPR	0.0	0.0	0.0	0.0	11.0	13.0	15.0	16.5	16.5	17.2	17.2	16.5	15.5	15.8	0.0	0.0	0.0	0.0	0.0	0.0	17.5	25.0	24.5	23.3	22.8
BHNTBRI	1.6	0.0	0.0	22.3	28.0	33.3	42.0	54.8	52.0	98.0	101.0	93.1	95.3	99.1	90.6	59.2	56.8	61.8	67.9	90.0	142.0	145.0	137.0	129.0	127.0
MUJAFFARPUR	31.8	31.4	39.0	35.0	32.2	42.0	97.0	113.0	134.0	120.0	135.0	105.0	114.0	110.0	92.0	110.0	107.0	106.0	120.0	136.0	148.0	131.0	127.0	125.0	94.0
RAMNAGAR	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	6.0	5.0	5.0	5.0	5.0
RAXAUL 132	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	49.5	55.1	53.2	56.3	51.8	54.0	50.7	47.6	43.4	53.6	54.2	52.6	53.2	44.0	48.9	48.0	52.6
NANPRA																									
BHRWA																									

	Night Shift(Contd..)										***Morning Shift***						***Day Shift***								
JAN-JAL																									
RAJBRJ																									
INRWA																									
Others	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	10.0	10.0	10.0	10.0	10.0
Total IMPORT	**36.4**	**34.4**	**42.0**	**60.3**	**74.2**	**91.3**	**157.0**	**187.3**	**255.0**	**293.3**	**312.4**	**276.9**	**282.6**	**284.9**	**239.3**	**222.8**	**213.2**	**227.4**	**248.1**	**289.6**	**376.7**	**360.0**	**352.4**	**340.3**	**311.4**
MULTI F	0.0		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
HTD DIE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
MRS DI	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total DIESEL	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Total Load Shedded/Trip	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
T0TAL	**637**	**626**	**625**	**616**	**666**	**724**	**790**	**783**	**860**	**925**	**942**	**889**	**866**	**872**	**803**	**845**	**804**	**820**	**850**	**931**	**1065**	**1104**	**1083**	**1046**	**989**
RMNGR	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
RAXAUL	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
OTHER	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total EXPORT	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
HZ	50.0	50.0	49.9	50.0	49.9	49.8	49.8	49.9	49.9	49.9	50.0	49.9	50.0	50.0	50.1	50.0	50.0	49.9	49.9	49.9	49.9	49.9	49.9	50.0	50.0
HTD 132KV	130.0	130.0	130.0	131.0	129.0	128.0	128.0	129.0	129.0	128.0	128.0	129.0	128.0	128.0	129.0	129.0	129.0	129.0	129.0	129.0	128.0	128.0	130.0	130.0	130.0
SUI 132KV	131.0	132.0	132.0	132.0	130.0	129.0	129.0	129.0	129.0	127.0	127.0	129.0	128.0	128.0	129.0	129.0	129.0	129.0	129.0	129.0	128.0	128.0	129.0	129.0	129.0
DUBI 132KV	124.0	125.0	125.0	127.0	126.0	125.0	125.0	130.0	129.0	126.0	130.0	122.0	122.0	123.0	123.0	132.0	130.0	127.0	127.0	127.0	129.0	129.0	127.0	129.0	129.0
LAMO 132KV	137.0			138.0	137.0	136.0	136.0	135.0	134.0	134.0	134.0	135.0			135.0	135.0	136.0								

	Night Shift(Contd..)										***Morning Shift***						***Day Shift***								
KG-A 132KV	**136.0**	**136.0**	**136.0**	**135.0**	**136.0**	**135.0**	**135.0**	**135.0**	**133.0**	**132.0**	132.0	133.0	133.0	133.0	134.0	133.0	133.0	134.0	133.0	133.0	132.0	132.0	135.0	134.0	134.0
SUI 66KV	**66.0**	**66.3**	**66.3**	**66.1**	**65.4**	**65.7**	**65.7**	**64.5**	**64.5**	**64.1**	63.7	64.7	64.5	64.4	64.7	64.7	64.9	64.8	64.5	64.5	64.5	64.5	65.0	65.2	65.2
Lamahi 132 KV																									
Dhalkebar 132 KV	**132.0**	**133.0**	**133.0**	**135.0**	**134.0**	**133.0**	**133.0**	**135.0**	**135.0**	**135.0**	135.0	135.0	135.0	135.0	136.0	135.0	136.0	135.0	135.0	135.0	134.0	134.0	134.0	135.0	135.0
Tanakpur Hz																									

Others IPP Detail

U Hewa	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40
Sipring	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36	4.36
Upper Mai	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77	5.77
Aandhi Khola	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87	9.87
Api Hydro	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39	6.39
Aankhu	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Jogmai	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47	4.47
Mai Cascade	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22	3.22
Daraudi A	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23	5.23
Mailung	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08	3.08
Siuri	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5	3.5

	Night Shift(Contd..)										***Morning Shift***						***Day Shift***								
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Tadi	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50	4.50
U Hugdi	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30	3.30
Mardi	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91	3.91
Mai khola	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09	3.09
Hewa	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40	7.40
Radhi	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43	4.43
Tungun Thosne	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14
Baramchi	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02	2.02
Charanawati	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Khudi	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Bhairavkunda	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76	1.76
Chakukhola	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Piluwa	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05	2.05
U Puwa-I	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15	2.15
Chhyangdi	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58	1.58
Daram Khola	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08	1.08

	Night Shift(Contd..)										***Morning Shift***						***Day Shift***								
Sanima Sunkoshi	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37	2.37
Ridikhola	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81	1.81
Jiri Khola	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09
Khani Khola	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
Lower Chaku	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mid Chaku	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kuthali Bukhari	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Thoppalkhola	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
Patikhola	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Phemekhola	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Chhotekhola	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44	0.44
U Hadikhola	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Lower Piluwa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mewa Khola	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
Seti II	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
Sisnekhola	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
Solar KUK	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.4	0.4	0.4	0.5	0.6	0.6	0.6	0.6	0.5	0.4	0.3	0.3	0.0	0.0	0.0	0.0

	Night Shift(Contd..)										***Morning Shift***						***Day Shift***								
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Belkhu Khola	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
Rairang	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Salinadi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Syange	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Thapa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chake	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12	2.12
Sikless	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44	7.44
Mai Sana Casc	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12	4.12
Total Capacity	127.74	127.74	127.74	127.74	127.74	127.74	127.74	127.74	128.14	128.14	128.14	128.14	128.24	128.34	128.34	128.34	128.34	128.24	128.14	128.04	128.04	127.74	127.74	127.74	127.74
IPP Total	125.19	125.19	125.19	125.19	125.19	125.19	125.19	125.19	125.58	125.58	125.58	125.58	125.68	125.77	125.77	125.77	125.77	125.68	125.58	125.48	125.48	125.19	125.19	125.19	125.19

Other NEA Small

TATOPANI	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
PANAUTI	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
SETI	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5

	Night Shift(Contd..)										*Morning Shift*						*Day Shift*								
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FEWA	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
TINAU	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
SUNDARIJAL	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64	0.64
Other NEA Small	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54	3.54

2075 Kartik 30 [2018/11/16] Friday	1.0	2.0	3.0	4.0	5.0	5.5	6.0	6.5	7.0	7.5	8.0	9.0	10.0	11.0	12.0	13.0	14.0	15.0	16.0	17.0	17.5	18.0	18.5	19.0	19.5
Kathmandu Load	**127.6**	**122.0**	**120.4**	**120.7**	**140.1**	**161.0**	**159.0**	**219.3**	**243.9**	**259.4**	**275.1**	**239.6**	**231.7**	**231.6**	**227.1**	**210.1**	**211.3**	**211.7**	**219.3**	**260.9**	**298.3**	**305.3**	**296.3**	**279.0**	**253.2**
MRS-SYU	71.7	71.7	72	71.9	88.3	112	93	94	94	111	100	93.9	92.1	92.9	88.6	88.7	88.8	89.1	89.3	105	107	108	107	106	107
KL2-MATA	-85.8	-88.5	-90	-88	-86	-90	-75	-30	-14.6	-16	9.2	-17	-15	-15.9	-14.1	-31	-31.2	-31.4	-30.1	-13	6	4	5	5	-15
KL1-SYU	-13.1	-14.9	-16	-17	-16	-15	-13	1.6	11.3	11.2	12.4	9.7	10.8	10.4	8.6	7.5	6.9	6.4	6.7	12.6	29	42.3	32.3	16	10.2
DHALK--KHIMTI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

APPENDIX G: Load forecasting of Poush 22, 2076 B.S by the hybrid model.

Load data to Kathmandu Valley 2076 poush-15 to 22 (LDC, NEA).

poush-15	poush-16	poush-17	poush-18	poush-19	poush-20	poush-21	poush-22
176.14	177.04	177.04	155.64	173.54	161.24	168.24	162.04
169.14	167.04	167.04	157.64	172.64	156.64	163.64	159.74
163.64	163.84	163.84	159.84	170.54	157.24	150.94	154.94
168.96	169.06	169.06	168.86	212.06	160.76	170.96	163.06
186.66	188.36	188.36	193.86	214.46	182.96	191.96	185.16
261.97	259.57	259.57	260.17	252.27	242.47	249.17	244.97
303.27	300.47	300.47	345.57	329.77	334.07	317.97	326.57
355.37	393.27	393.27	393.47	376.17	383.37	405.37	350.57
348.97	368.27	368.27	384.17	357.27	359.67	394.16	389.87
342.27	370.47	370.47	409.27	367.27	360.57	387.17	392.87
345.57	358.77	358.77	367.77	360.37	373.27	377.17	364.67
331.37	344.27	344.27	388.27	333.27	348.57	380.47	366.87
328.57	322.57	322.57	407.77	324.57	328.27	340.57	344.77
325.77	320.57	320.57	401.67	334.67	339.07	335.17	348.77
348.77	350.07	350.07	402.47	325.57	347.77	356.17	345.17
355.17	345.87	345.87	393.77	347.77	350.77	348.47	372.57
367.57	341.67	341.67	422.07	366.87	375.37	383.07	403.27
434.17	440.37	440.37	449.57	436.17	452.07	449.67	453.87
422.37	445.97	445.97	427.57	427.97	451.17	454.37	433.97
411.47	385.57	385.57	400.87	400.47	409.67	429.67	409.97
365.67	344.87	344.87	364.87	361.17	381.97	365.77	353.77
294.17	264.47	264.47	284.77	283.67	308.17	302.2	272.87
231.07	224.27	224.27	225.87	257.57	228.07	228.6	225.07
197.37	197.07	197.07	188.97	195.47	195.97	188.7	182.07

The empirical mode decomposition of input data that decomposes the data into seven numbers of IMFs and residue. The correlation coefficient between the input data, IMFs and the residue is as shown in table.

Input /IMFs	Input
IMF1	0.03
IMF2	0.03
IMF3	0.19
IMF4	0.00
IMF5	-0.11
IMF6	-0.25
IMF7	-0.33
Residue	0.94

The load forecast of Kathmandu valley for poush 22, 2076 B.S taking the residue as the input parameter gives the result as shown in table below.

Time(Hours)	actual load (A)	forecasted load by hybrid ANN (F)	abs(A-F)	abs(A-F)/A
1:00	162.04	171.22	9.18	0.06
2:00	159.74	151.22	8.52	0.05
3:00	154.94	165.22	10.28	0.07
4:00	163.06	171.22	8.16	0.05
5:00	185.16	201.21	16.05	0.09
6:00	244.97	231.21	13.76	0.06
7:00	326.57	301.21	25.36	0.08
8:00	350.57	331.21	19.36	0.06
9:00	389.87	371.21	18.66	0.05
10:00	392.87	385.22	7.65	0.02
11:00	364.67	341.24	23.43	0.06
12:00	366.87	361.28	5.59	0.02
13:00	344.77	331.35	13.42	0.04
14:00	348.77	346.47	2.30	0.01
15:00	345.17	351.64	6.47	0.02
16:00	372.57	381.88	9.31	0.02
17:00	403.27	408.13	4.86	0.01
18:00	453.87	422.36	31.51	0.07
19:00	433.97	402.54	31.43	0.07
20:00	409.97	402.66	7.31	0.02
21:00	353.77	342.73	11.04	0.03
22:00	272.87	302.77	29.90	0.11
23:00	225.07	202.79	22.28	0.10
0:00	182.07	202.81	20.74	0.11
			MAD	**MAPE**
			14.86	**5.26**

APPENDIX G: Program code of EMD in Matlab.

Main

```
close all;
clear all;
clc;

load('data1.mat')
signal=num(1:192);
n = 10;
imf = workdata_friday_function(signal);

subplot(11,1,1), plot(signal),title('Input ,IMFs and
Residue'),ylabel('load in Mw')
for i=1:n
  subplot(n+1,1,i+1),plot(imf(i,:));
end

subplot(10,1,10), plot(c);
```

Function

```
function imf = emd(x);

c = x(:)'; % copy of the input signal (as a row vector)
N = length(x);

%-------------------------------------------------------------
------------
% loop to decompose the input signal into successive IMF

imf = []; % Matrix which will contain the successive IMF, and
the residue

while (1) % the stop criterion is tested at the end of the
loop

   %----------------------------------------------------------
---------------
   % inner loop to find each imf

   h = c; % at the beginning of the sifting process, h is the
signal
   SD = 1; % Standard deviation which will be used to stop the
sifting process

   while SD > 0.3
      % while the standard deviation is higher than 0.3
(typical value)

      % find local max/min points
      d = diff(h); % approximate derivative
```

```
      maxmin = []; % to store the optima (min and max without
distinction so far)
      for i=1:N-2
         if d(i)==0                        % we are on a zero
            maxmin = [maxmin, i];
         elseif sign(d(i))~=sign(d(i+1))   % we are straddling
a zero so
            maxmin = [maxmin, i+1];        % define zero as at
i+1 (not i)
         end
      end

      if size(maxmin,2) < 2 % then it is the residue
         break
      end

      % divide maxmin into maxes and mins
      if maxmin(1)>maxmin(2)              % first one is a max
not a min
         maxes = maxmin(1:2:length(maxmin));
         mins  = maxmin(2:2:length(maxmin));
      else                                % is the other way
around
         maxes = maxmin(2:2:length(maxmin));
         mins  = maxmin(1:2:length(maxmin));
      end

      % make endpoints both maxes and mins
      maxes = [1 maxes N];
      mins  = [1 mins  N];


      %-------------------------------------------------------
------------------
      % spline interpolate to get max and min envelopes; form
imf
      maxenv = spline(maxes,h(maxes),1:N);
      minenv = spline(mins, h(mins),1:N);

      m = (maxenv + minenv)/2; % mean of max and min
enveloppes
      prevh = h; % copy of the previous value of h before
modifying it
      h = h - m; % substract mean to h

      % calculate standard deviation
      eps = 0.0000001; % to avoid zero values
      SD = sum ( ((prevh - h).^2) ./ (prevh.^2 + eps) );

   end

   imf = [imf; h]; % store the extracted IMF in the matrix imf
   % if size(maxmin,2)<2, then h is the residue

   % stop criterion of the algo.
   if size(maxmin,2) < 2
```

```
      break
   end

   c = c - h; % substract the extracted IMF from the signal

end

assignin('base','c',c);

return
```

APPENDIX H: Program code of NN in Matlab.

```
clear clc;
data=xlsread('data.xlsx');
 P=data(1:168,1:2);
 T=data(1:168,11);
 a=data(169:192,1:2);
 s=data(169:192,11);
 [pn,minp,maxp,tn,mint,maxt]=premnmx(P',T');
 [an,mina,maxa,sn,mins,maxs]=premnmx(a',s');
net=newff(minmax(pn),[7 1],{'tansig','tansig'},'traingdm');
 net.trainParam.epochs=1994;
 net.trainParam.lr=0.3;
 net.trainParam.mc=0.6;
 net=train (net,pn,tn);
  y=sim(net,an);
  t=postmnmx(y',mins,maxs);
 figure;
plot(1:24,s,'r', 1:24,t,'b--');
title('feed forward backpropagation-sunday' );
xlabel('Hours');
ylabel ('Load');
legend('Actual','Forcasted
```