A NEW TECHNIQUE
OF
LOAD FORECASTING FOR AN ISOLATED AREA

by

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A Thesis

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DECLARATION

This is to certify that this work has been done by me and it has not been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Forecasted electrical loads are the core information required in many processes, especially in power system expansion planning process. Several techniques are available to forecast the loads of an area for a future period. The pattern of load growth over the past are the basic requirements for all of these techniques. However, in an isolated rural area historical load data may not be available either because, the electricity might not be a source of energy in the past in that area or the available data may not be representative ones, rather suppressed load demands. First, research presents a technique [27, 28] of forecasting loads for an isolated area. This technique identifies the factors responsible for the development of electrical loads. The correlation of each of these factors with the load growth is determined. The technique selects one or more areas with the characteristics similar to those of an isolated area. The forecasted loads of this area are derived from the selected area should be such that its history must be known. It develops a relation between the load dependent factors of the selected area/areas with those of an isolated area. The forecasted loads of the selected area/areas using the relation developed from the load dependent factors. The methodology is applied to an isolated area of Bangladesh. However, there is no conceptual difficulty in applying the methodology to forecast the loads of any isolated area.

To realize a relationship between the load dependent variables and the demand which may be highly nonlinear, a relatively new technique, using artificial neural network, capable of solving a non-linear mapping, is investigated. The inherent parallelism of neural network captures the past trend of the event and make projection of the best guess. The study shows encouraging result on forecasting the loads of an isolated area, using the neural network method.

CONTENTS

LIST SYMBOLS

AD = Average Demand

AL = Agriculture Land in percent of Total Area

DT = Distrance from Local Town

L_C = Commercial Load

L_D = Domestic Load

L_I = Industrial Load

L_{IR} = Load for Irrigation

LR = Adult Literacy Rate

MD = Maximum Demand

PI = Per capita Income

POP = Population

RL = Road Length

ABBREVIATIONS

ACRE	= Area Coverage Rural Electrification
BADC	= Bangladesh Agriculture Development Corporation
BBS	= Bangladesh Bureau of Statistics.
BEPP	= Bangladesh Energy Planning Project
BPDB	= Bangladesh Power Development Board
BPN	= Backpropagation Network
BSCIC	= Bangladesh Small and Cottage Industries Corporation
CHT	= Chittagong Hill Tracts
GDP	= Gross Domestic Product
GEP	= Generation Expansion Planning
GNP	= Gross National Product
IBA	= Institute of Business Administration
MIS	= Management Information System
NN	= Neural Network
PBS	= Palli Bidhyut Samity
RE	= Rural Electrification
REB	= Rural Electrification Board
RES	= Rural Electrification System
SCPSCS	= South Carolina Power Systems and Combined Systems

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CHAPTER - 1

INTRODUCTION

1.1 INTRODUCTION

Electrical energy consumed in a society and its economic development are correlated. The ultimate goal of the economic development of a society/country is to improve the quality of life. One of the measure of quality of life in a community or a country is the amount of energy it consumes [1]. Electrical energy is widely used in modern societies because of its sophistication in use, high efficiency and low cost of transmission from one place to another.

In generation expansion planning as well as in distribution planning, load forecasting is an essential step. The importance of accurate forecast in planning is that, it ensures the availability of supply of electricity, as well as providing the means of avoiding over and under utilization of generating capacity and making the best possible use of capacity. Obviously, errors in forecasting can lead to bad planning which will be costly. Too high forecast lead to more plants than are required which will be an unnecessary capital expenditure. Too low forecast prevents optimum economic growth and lead to the installation of many costly an expensive-to-run generators. These costs will finally be born by consumers.

With the increase of population, industry and rapid urbanization, the demand for electricity increases very rapidly. Many of the factors, on which the growth of electrical load depends, are random in nature. The incorporation of this randomness in load forecasting makes this task difficult.

Load forecasting did not receive as much attention in the past as it deserved, because the fuel supply especially hydrocarbons were cheap and abundant, and could find funds for erecting enough gas/oil generating plants at relatively short load lines. From the last few years, the situation has changed and the load forecasting is getting more attention than before.

In 1977, Sachdev et al.[2] presented a bibliography on load forecasting. This bibliography listed the papers on load forecasting from 1975 to 1978. In 1980, the load forecasting working group of IEEE [3] also presented a bibliography on load forecasting. This paper covers the list of the articles which deal with the general philosophy of load forecasting and it contains a short summary of each listed article.

In many countries, especially in developing ones, the major portion of the population live in remote and isolated areas. In term of electrical energy use, isolated areas are those areas which can not be connected with the main electrical grid system due to economic or technical reasons. The economic and technical incapability of connecting isolated areas with the main grid may evolve from the distance between the grid and the isolated area or inconvenient connecting zones.

In the future planning of any power sector; generation, transmission or distribution system, the forecast load during the planning period is the core information on which the plan based. A plan would be effective if forecasted load becomes closer to the realistic value. Researchers have developed numerous techniques [4-7] for forecasting loads. All this techniques require the past history of the load. However, in under-developed or isolated areas the historical pattern of the load may not be available. Indeed it can be the case that even when an electrical supply is available it may be totally inadequate and therefore, the history of demand does not reveal the true demand of the consumers. This is particularly the case in isolated areas.

Some isolated areas may be industrially or commercially important and they might have developed their own electric power systems. However, this will not be the case for every isolated area and areas exist where electric power is not freely available. This research is not concerned with those areas rather it deals in the forecasting of load of electrically isolated places.

The present research presents, a methodology to forecast the loads of an isolated area, where the history of load is not available or the history may not represent the realistic demand of electricity. The proposed methodology is based on the identification of factors on which electrical load growth depends. Areas are selected whose histories of load growth are known and the load growth deciding factors are similar to those of the isolated area.

The forecasting of load of an isolated area is an uncertain problem with previous methods as described earlier and the mathematical analysis can not be implemented properly. But the neural network method [8] is most suitable and being used for this kind of uncertain problem. So, in the present study neural network method is used to forecast the loads of an isolated area.

This proposed methodology is applied to Sandwip, an isolated area of Bangladesh. But this concept would be applied to forecast the loads in any isolated area of any other country, where a past history of electrical load demand is not available and at present there is no electricity and also there is no possibility of connecting the area with the main land grid system.

1.2 BACKGROUND

Load forecasting plays an important role in the electric power industries. Load forecasting is the prediction of the electrical load upon a given system at a future time. The forecast may be made for any size of system and for any point in future time. Time scales for which it is necessary to have forecasts of electricity consumption and demand fall into three groups: the long term, for the period covering seven years onwards; the short term to medium term, for the period covering upto seven years; and the short term, which covers the time scale of upto one day ahead [9].

The short term is necessary in planning the level and mix of generating capacity that will be used to support actual demand, and the sequence in which power stations are brought into operation. The short to medium forecasts are used in preparing; operating plans, financial planning and tariff setting. The long term forecasts of electricity consumption and demand are used in the planning of investment in generating capacity and the development of fuel supplies [9]

Load forecasting procedures can be classified into five broad categories [9]: subjective, univariate, multivariates, end user and combination. Using the subjective approach, forecasts can be made on a subjective basis using judgement, intuition, commercial knowledge and any other relevant information. Forecasts may or may not take the past information into consideration. Univariate forecasts are based entirely on the past observation in a given series.

Hussien et al. [10] presented a simple algorithm for precise short term load forecasting. The technique is based on a adaptive model incorporating hourly loads and weather information. Similar short term forecasting was made by Hossain et al. [11], using pattern recognition technique. In forecasting hourly loads, the latter work incorporated a lead time of one to three hours. Irisarri et al. [12] have also attempted to forecast the load on short term basis using, a transfer function model developed on the basis of load and temperature profiles which are obtained from historical data. A micro-computer based on-line load forecasting technique has been developed [13] by Keyhani and Miri. The technique is based on two different load profiles, one is weather-sensitive and other is non-weather sensitive. The technique is found to be superior than one based on composite load profile. A method of extrapolating has been described [14] by Willis and Tram. The method combines two previously used methods of extrapolation in a manner in which one reinforces the other. The authors claim that the new method is more accurate and dependable than other extrapolation procedures. The technique is described with flowchart for computer implementation and it requires less data. This technique also offers an excellent combination of accuracy and simplicity.

Willis et al. [15] have also described a new method using clustering of historical load at the small area level. This paper has presented an algorithm for forecasting the load. This method has significant performance advantages over normal curve fitting time methods and can be complemented on most computer.

In our country, different all types of forecasting have been used by different organizations. Several organizations have forecasted [16] for Bangladesh Power Development Board (BPDB). The Institute of Business Administration (IBA) has made a forecast for the BPDB in June, 1981. It was a time series approach in Power Market Survey.

The Bangladesh Energy Planning Project (BEPP) under the Planning Commission has made a survey and has forecasted for various sectors (petroleum, coal etc.) including electric power [17 - 19].

The Power System Master Plan of BPDB assumes annual growth rate of power demand. It is used to make a power demand forecast for BPDB.

Tram et al.[20] have forecasted the load through data collection and coding cost and also the impact on accuracy of different types of data. A test on data source collection method and forecast accuracy have been carried out to identify critical elements and costs of data preparation.

An investigation is made by Willis [21]. In this research, the impact of small area load forecast errors on the planning of a power distribution system has been investigated. It is shown that traditional error measures are inadequate as indicator to forecast quality.

Willis et al. [22] research have presented to improve the extrapolation of load growth. Three different concepts for improving load forecasting are given in this paper. A computer combining method has also been described in the same paper.

A load management analysis is presented by Mcrae et al. [23]. The technique is capable of forecasting the amount of load reductions. The load reduction forecasting technique is expected to improve the load management, operation, planning and future performance.

Campo and Ruiz [24] have introduced an adaptive, weather sensitive, short term load forecast algorithm that has been developed for two South Carolina Power Systems and Combined Systems (SCPCS). A detail correlation study is performed to identify the most relevant weather variables. Different models are used for Summer and Winter, since different weather variables are found to be relevant in both seasons. An adaptivity is also attained through careful message of Kalman filtering and Baysicen techniques.

Chong and Malhami [25] have presented a methodology for predicting load at a point in the system, starting from elementary component of load models. The methodology consists of three key steps: modelling of elementary component loads, classification of homogenous (similar) groups, and aggregation of the load models in each homogenous group, using statistical techniques. The methodology is illustrated with cold load pick-up. The evaluation of the fraction of `on' spare heaters has also been developed.

1.3 OBJECTIVES OF THE RESEARCH

Review of literature clearly reveals that a technique of load forecasting for an isolated area either without the history of load growth or any electricity has not been attempted [4-6] so far. The main objective of this research is to develop a technique for forecasting the load demand of an isolated area, where there is no electricity at all and the target area can not be connected with the main grid system, because of technical or economics reasons.

1.4 THESIS ORGANIZATION

Recognizing the work that has already been done in the field of load forecasting, this research is applied to analyze a generation plan of an isolated area. As the forecasted load during the plan period is essentially required for the analysis of a generation plan, this research mainly develops a technique to forecast the loads of an isolated area.

Chapter 1 presents, the general introduction , background or brief review of similar research works and the thesis organization.

Different load forecasting approaches, types of load forecasting and forecasting models are presented in chapter-2.

Chapter 3 presents, the methodology of load forecasting by Dr. A. Hoque. In this chapter, the different factors on which the load growth usually depends are also identified and finally a mathematical model is developed for forecasting the loads.

Data for load forecasting including definition and specification of variables, data sources, data collection, and data process are described in chapter-4. The simulation results in tabular form are also presented in this chapter.

Chapter 5 presents, the backpropagation trained neural network including its algorithm and architecture. The detail formulation of backpropogation algorithm is also described in this chapter.

The forecasting of load by neural network is presented in chapter-6. In this chapter, approach of the network, training data, network size and learning parameters are also presented. The results obtained as weights of the network are given in different tabular forms. The forecasting results with short discussions are also presented in this chapter.

Finally, the observations and conclusion are presented in chapter-7. The recommendations for further research scope are also described in this chapter.

CHAPTER - 2

LOAD FORECASTING TECHNIQUES

2.1 INTRODUCTION

Load forecasting is simply a systematic procedure for quantitatively defining future loads. Forecasts of both system peak load and energy can be made. Power system expansion planning starts with a forecast of anticipated future load requirements. Estimates of both system peak demand and energy requirements are crucial to effective system planning. Since electricity is a product that cannot be stored in large quantities, its generation must follow instantaneous demand variations. This implies that not only the total amount of electricity during a certain period of time (energy), but also the maximum demand within that time (peak power or peak load) is relevant for the planning and operation of generation, transmission, and distribution facilities.

Demand forecast is used to determine the capacity of generation, transmission and distribution system additions; and energy forecast determines the type of facilities required. For example, if demand and energy forecasts show that the system requires large demand addition but comparatively small energy addition, then it can be decided, in all probability, that the system requires a peaking generating unit to be installed. The energy and demand are interrelated by load factor. The load factor is of considerable economic and technical importance, because it measures the extent of utilization of electricity supply system facilities.

The accuracy of load forecast is crucial to any electric utility, since it dictates the timing and characteristics of major system additions. Errors in load forecasts have serious consequences. Although compensating decision on the basis of regular forecast reviews are possible, the error may still impose significant costs. An under estimation of future demand results in inability to meet it. This may lead to insufficient reliability of supply and load shedding with manifold negative effects for the customers (lost production, damage of equipments, inconvenience etc.). A low load forecast also results in loss of revenue. On the other hand, an overestimate of future load can result in severe financial problems due to excessive investment in an electric plant that is not fully utilized.

In this chapter, the general load forecasting approaches and different methodologies are discussed in detail. The importance of load forecasting has been discussed in the previous paragraphs. The factors which are to be considered in choosing a particular forecasting method are also discussed. The load models discussed are econometric and time series models. Linear and non-linear econometric models and non linear time series models have been discussed. To show the level of confidence (how closely the demand data generated by each model approximates the known demand data) of different models, statistical parameters such as Error, Percentage Error, Sum of Errors have been discussed.

2.2 APPROACHES TO LOAD FORECASTING

Decision to use a particular method for load forecasting can be based on the following questions:

(A) Should the peak demand be forecasted using forecasted energy and load factor, or should it be forecasted separately ?

(B) Should the total forecast be determined by combining forecasts of appropriate load components, or should the total forecast be directly obtained from historical total load data ?

(C) Should the simple forecasting methods be used, or should a more formal mathematical procedure be investigated ?

Loads can broadly be classified as residential, commercial, industrial, and other, although consumers in a particular group may not have characteristics unique to that group. Load demand of different groups can be forecasted, and the total system load demand forecast can be obtained by adding forecasts of different groups.

Because of the unavailability of necessary historical data in our country, the approach (B) mentioned above, to obtain total load forecast by combining forecasts of different groups of consumers, cannot be performed.

2.3 TYPES OF LOAD FORECASTING

Depending on the time horizon, the electricity demand forecast can be classified [7] as day to day, immediate, short-term, medium-term and long-term load forecasting.

(1) Day to Day Forecast: This type of forecast is generally done for generator scheduling during various parts of the day. However, this program may be done for a week also.

(2) Immediate Forecast: This type of forecast generally covers a period of maximum one year and serve for the planning of system operation, such as, generating plant commitment and maintenance scheduling.

(3) Short-term Forecast: This type of forecast generally ranges from 1 to 5 years and serves for the planning of distribution system expansions. It is also used to review and - if necessary - to adjust the generation and transmission expansion with the help of crash program. A typical example is the installation of package gas turbine in order to meet unexpected load increments. Besides, short-term load forecast serves for the planning of resources, required by electric power utilities to expand and operate their systems.

(4) Medium-term Forecast: This type of forecast covers a range of 5 to 15 years and are used for the detailed planning of individual generation and transmission projects by means of feasibility studies.

(5) Long-term Forecast: Most power projects have long lead time from the beginning of studies to the commissioning. Th long term forecasts for a period of 15 to 25 years are necessary in master plan studies to establish the optimum program of generation and transmission projects required to

cope with the growing demand. The long-term load forecasts are also needed for the formulation of the national energy policy, since electric power is an important element of the overall energy sector.

2.4 FORECASTING MODELS

A model is a representation of reality; not any representation but one prepared as a function of the decisions to be taken. For example, a control centre map for an interconnected power system both represents the geographical reality of a country but more precisely it also represents in one case its anatomic aspect and in other its power supply aspect. The signs used on the map constitute information noted solely as a function of the decisions to be taken: optimizing power transmission.

The preparation of a model, therefore, requires the selection of the significant elements of reality and the ordering of these according to the range of decisions to be taken. It also requires the selection of as few elements as possible so as not to encumber the decision making. A forecasting model is, therefore, an information instrument subordinated to a decision instrument.

2.4.1 General Classification

If forecasting is to make any sense, there must be a functional relationship between the electricity demand as dependent variable and one or more extraneous independent, or explanatory variables.

To establish the assumed relationship in mathematical form, various statistical methods, such as regression analyses by means of the least-squares technique, are usually used. A general classification of forecasting models is relatively difficult as there are many hybrids and variants. Nevertheless, taking the independent, explanatory variable(s) criterion, the following main groups can be distinguished:

2.4.1.1 Trend models

In the trend models, time serves as the explanatory variable for the development of electricity demand. The basic underlying trend is derived from historic demand data with the help of the time series regression analysis. This trend is then either extrapolated for the future or modified on the basis of qualitative judgment and experience. Trend models can be used for both global and sectoral, and short-term, medium-term and long-term forecasts.

2.4.1.2 Econometric models

Instead of, or in addition to time, other explanatory variables, mostly or macroeconomic types, are introduced. Simple correlation models consist of a single equation which expresses the relationship between the electricity demand and one to three macroeconoic explanatory variables, such as GDP and population. Complex models use the sectoral approach to forecast the electricity demand with different explanatory variables for each sector (domestic, industrial, etc.). Time-series and cross-section regression analyses, elasticity coefficients, input-output tables, etc. are used to determine the parameters of the model equations. The forecast of the future electricity demand, projections of the various explanatory variables must then be available.

2.4.1.3 Use of different models

The trend models generally consider the particular country in isolation, i.e. the underlying trend is derived with the help of a time-series regression analysis from its historic data. Some econometric models use the same approach, while others replace it or extend it by international comparisons based on a cross-section regression analysis.

Using the least-square technique, the regression equation is derived from the time series of historic demand data. To avoid an exaggerated effect of short term cyclical variations, the time series must be long enough.

Generally, exponential functions producing constant annual growth rates are used to fit the historic data and to extrapolate the underlying trend for the future. By logarithmizing, the exponential form is transformed into linear form so that the trend can be plotted as a straight line.

In recent years, there have been signs of an increasing price-elasticity of demand as a result of frequent tariff increases, induced by the oil price escalation as well as of an approaching saturation point of demand for certain consumer groups. These signs have made it unlikely for many countries that a sustained annual growth rate of demand can be maintained in the long run. As a matter of fact, other mathematical functions than the purely exponential ones have sometimes turned out to reflect better, both the past development and future growth potential.

The trend extrapolation based on exponential or other mathematical functions implies the assumption that all events and forces which determined the historic demand growth will continue to operate with the same effect in the future. If this assumption is deemed to be unrealistic, the underlying trend has to be modified for the extrapolation. The modification requires an interpretation of the likely developments and changes in consumption patterns, as well as, in the economy with respect to its structure, urbanization, population, overall economic growth, etc. In this type of model, the modification of the underlying trend is qualitative - based on the judgment and experience of the forecaster, which consequently have a major impact on the forecasting accuracy.

2.5 SIMPLE CORRELATION WITH MACRO-ECONOMIC VARIABLES

These methods are based on the relationship between the electricity demand and general economic development. Experience from many countries confirms that the use of electricity - and of energy in general - is to a large extent dependent on the overall economic growth, total population, etc. The higher the level of production and income in an economy, the higher is usually the use of electricity in industry, commerce and households. To measure the general economic development of a country, Gross National Product (GNP) figures at constant prices (i.e. exclusive of inflation) are usually used.

There are basically two methods to express mathematically this relationship. The first one, consists of the regression analysis of the time series of historic electricity demand and GNP, industrial output, population data, etc. Parameters of that regression function (linear, exponential, etc.) are calculated which are deemed to fit best the underlying electricity demand/GNP, industrial output, population trend, etc. The higher the correlation coefficient, the better is the past development of electricity demand and GNP, industrial output, population; described by the selected regression equations. By inserting projected GNP, industrial output, and population values into the equation, an electricity demand forecast can then be prepared.

The second method, relies upon the so-called Gross Domestic Product (GDP) - elasticity coefficient of electricity demand. The coefficient is a ratio between the growth rate of electricity demand and that of GDP. The growth rates should be related to a longer period rather than a single year in order to eliminate short-term variations. An elasticity coefficient of more than one indicates that electricity demand grows faster than GDP, while an elasticity coefficient smaller than one reflects an underproportional increase of the demand in comparison to the GDP. If the analysis of historic data shows that there was a more or less constant elasticity coefficient, its value can be applied to the projected GDP growth rate. The result is a forecast growth rate of electricity demand. A similar procedure is possible when a clear trend of the elasticity coefficient can be deduced from the historic data.

Compared with the trend models, the correlation methods replace time by GNP, and other economic and demographic parameters such as: total industrial output, population, etc. This means that while the trend models assume that all macroeconomic and other relevant factors will act in the same way as in the past, the correlation methods assume that all the factors will be self-compensating except GNP, industrial output, and population. They are, therefore, recommendable only if there are no major changes to be expected in the patterns of electricity use, electricity tariffs, structure of the economy, etc., which would modify the parameters of the regression equation of the elasticity coefficient. Furthermore, the success of the correlation methods depends to a large extent on the ability to predict accurately the future GNP, industrial output and population levels.

CHAPTER- 3

ISOLATED AREA LOAD FORECASTING TECHNIQUE BY DR. A. HOQUE

3.1 INTRODUCTION

In the future planning of any power sector, generation, transmission or distribution, the forecasted load during the planning period is the core information. A plan would be effective if the forecasted load becomes closer to the realistic value. Researchers have developed numerous techniques [4-7] for forecasting the loads. All these techniques require the history of load growth over the past. However, in an isolated area the history of load growth may not be available. Recall that, an isolated area is a place where the electrical consumers can not be connected with the main grid system either because of technical reasons or economic reasons.

Some isolated areas may be industrially or commercially important and they might have developed their own electric power systems. However, it may not be the case for every isolated area. There may exist some isolated areas where electric power might not have even developed and the question of history of electrical load growth does not arise. This chapter presents a methodology [27, 28] to forecast the loads of an isolated area where the history of load is not available, if it does, the information does not represent the realistic demand of electricity.

The methodology that have been developed by A.Hoque [27, 28] is based on the identification of the factors on which electrical load growth depends. Area/areas with the known load deciding variables similar to those of the isolated area are selected to evaluated the contribution of load deciding variables. A suitable area in which the load deciding variable are similar to those of the typical isolated area and whose hourly load data are known is selected. The average loads of the selected area and the typical isolated area are estimated. Then the load of the typical isolated area is derived from the load of the selected area. This methodology is applied by using the data available for some selected Rural Electric Societies called Palli Bidhyut Samitys (PBSs) of Bangladesh. The main objective and priority selection critria of the Rural Electrification Program of Bangladesh have also been mentioned in the Annexure-1.

3.2 ISOLATED AREA LOAD FORECASTING TECHNIQUE BY DR. A. HOQUE

A linear regression analysis (LRA) was adopted to develop a method of load forecasting.

The method (LRA) starts with the identification of factors on which load growth depends. These factors may be different for different types of loads. Usually electric loads are domestic, commercial, industrial and irrigation.

The domestic load may be function of population and standard of living of people. The variation of standard of living is caused by per capita income and adult literacy rate. All these factors are time varying quantities. The domestic load, L_D may then be expressed as,

$$L_D(t) = f_1\,(P(t), LR(t), PI\,(t\,)) \quad \ldots\ldots \quad (3.1)$$

where, $P(t)$ = Population at time t.

$LR(t)$ = Adult literacy rate at time t.

$PI(t)$ = Per capita income at time t.

However, industrial load may depend on the per capita income, inland communication in per unit area of total area, distance from local town, literacy rate and agricultural land in per unit area of total area. This industrial load, L_I may then be express as

$$L_I(t) = f_2(P(t), RL(t), DT(t), AL(t)) \quad \ldots \quad (3.2)$$

where, $RL(t)$ = Inland communication length per unit area at time t.

$DT(t)$ = Distance from local town

$AL(t)$ = Agricultural land in percent of total area at time t

In some isolated areas, instead of inland communication, communication across the sea may be the major type of communication. In that case the communication must be included the sea route length also.

The commercial load, L_C mainly depends on per capita income and inland communication and distance from local town. This type of load may be expressed as

$$L_C(t) = f_3(PI(t), RL(t), DT(t)) \quad \ldots \quad (3.3)$$

The load for irrigation, L_{IR} mainly depends on agricultural land in per unit area of the total area and per capita income. This type of load may be expressed as

$$L_{IR}(t) = f_4\,(AI\,(t), PI(t)) \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots \quad (3.4)$$

The total electrical load demand, $L(t)$ in an isolated area is the sum of the above four types of loads. That is ,

$$L(t) = L_D\,(t) + L_I\,(t) + L_C(t) + L_{IR}(t) \quad \ldots\ldots \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots \quad (3.5)$$

Therefore, the load of an isolated area may be expressed as

$$L(t) = f(P(t), LR(t), PI(t), RL(t), AL(t), DT(t)) \quad \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots \quad \ldots \quad (3.6)$$

Although Eq. (3.6), expresses that the load is a function of six time dependent variables. However, all variables will not contribute equally to the generation of load. Let X_1 , X_2 , X_3 ,X_4 ,X_5 and X_6 represent the weighting factors by which each time varying factor $P(t)$, $LR(t)$, $PI(t)$, $RL(t)$, $Al(t)$ and $DT(t)$ respectively contributes towards the load growth. The weighting factors, [X] are also random in nature. They may vary with different areas. Now the load can be expressed as

$$[L(t)] = [X]\begin{bmatrix} P(t) \\ LR(t) \\ PI(t) \\ RL(t) \\ AL(t) \\ DT(t) \end{bmatrix} \quad \ldots\ldots \qquad (3.7)$$

Solving the Eq. (3.7), the weighting factors [X] can be determined as

$$[X] = \begin{bmatrix} P(t) \\ LR(t) \\ PI(t) \\ RL(t) \\ AL(t) \\ DT(t) \end{bmatrix}^{-1} [L(t)] \quad \ldots\ldots \qquad (3.8)$$

Now each element of X_i, the row vector of [X], may be obtained from the relation

$$X_i = \sum_{j=1}^{M} X_i^j P_j \quad \ldots\ldots \qquad (3.9)$$

Where, M is the number of isolated areas considered to generate the distribution of X_i and P_j is the probability that the value of X_i^j will occur. Since, the contributions of different areas in the evaluation of the load of an isolated area may be different in reality, therefore, the values of P_j 's may be different.

CHAPTER - 4

DATA FOR LOAD FORECASTING

4.1 INTRODUCTION

The quality of data is important in determining the accuracy, credibility and acceptability of any forecast. There are two main use of data in forecasting. Firstly, data is used to determine the pattern of behaviour of some variables, based on historical observations. The various time series approaches to forecast are methodologies for using data in this fashion. Increasing the amount of data generally increases the accuracy of forecast, but not necessarily is direct proportion to the amount of data.

Secondly, data is used to provide future values of independent variables, included in a causal model. This usage often requires that those independent variables be forecasted before they can be part of the input to such a causal model. It is often necessary to examine several alternative independent variables and to include those that give suitable results and that can most easily be predicted in the future.

As such, issues concern with specifying, procuring, preparing and handling of data for forecasting are of fundamental importance. It is essential that data processing must be done with full care.

4.2 DEFINITION AND SPECIFICATION OF VARIABLES IN FORECASTING

Most work on forecasting tends to assume that the variable to be forecasted is known and well defined. While that may be the case for on going situations in which a forecasting method has been applied in the past, but in a new situation this may not necessarily be true. Thus a first step in forecasting is to decide just; what is to be forecasted and how best to be defined that variable ?

The decision, as to the appropriate variable to be forecasted, depends largely on the needs of the planner. The contribution that the forecast will make to the planner to determine the time span that should be covered by each value of the variable, the level of detail requirement, the frequency with which it is required, the required level of accuracy, the appropriate segmentation of variable and the value of the forecast. Because of the importance of each of these aspects to the definition of appropriate variables for forecasting, all of these aspect are discussed very briefly.

4.2.1 Time Covered by Each Data Value

Most of the factors, involved in a real situation, can be viewed as taking place in a continuous manner. However, for planning purposes, it is necessary to define some period of time and to summarize the value of each variable for that time period.

4.2.2 Level of Detail Requirement

During the definition phase of forecasting, determining just what level of detail is required, saves substantial costs in general collection of data. It indicates, the most detailed level of collection also to be done.

4.2.3 Frequency of Data Use

The frequency with which data is collected is related to the time period covered by each value of the variable. For example, load forecasting used in generation expansion planning, generally requires yearly peak load and other economic and demographic factors of that corresponding year.

4.3 DATA SOURCES

In general, for forecasting purposes, data can be collected either from primary or secondary sources.

Primary data sources include all forms of original data collection. These data can be collected, for example, by taking direct readings. On the other hand, secondary sources are defined as the data in the accounting records of various organizations. For our thesis, the question of obtaining data from primary sources do not arise as most of the required data are either the peak value or the cumulative value of a particular fiscal year. Therefore, various secondary sources are used for data collection.

All data collected from Rural Electrification Board (REB), Bangladesh; Statistical Year Books of Bangladesh, Bangladesh Bureau of Statistics (BBS); Bangladesh Population Census, District Series, BBS; Report on Traffic Engineering Division, Roads and Highways Department, Government of Bangladesh; Graphosman's New Atlas; etc.

4.4 DATA COLLECTION

In Bangladesh, Rural Electrification Programme is implemented under the Area Coverage Rural Electrification (ACRE) system. Each of the electrified area is managed by an independent co-operative society known as Palli Bidhyut Samity (Rural Electric Society), PBS. Starting from 1981, forty five (45) PBSs have been electrified upto 1995-96. Maximum demand and average demand of electricity for all the energized PBSs for the year 1995-96 and their respective load deciding variables are shown in Table 4.1.

Table 4.1 Load and Load Dependent Factors for All PBSs*:

Sl. No.	Name of PBSs	Area (Km^2)	POP (1000)	LR (%)	PI (TK.)	AL (%)	RL (Km/Km^2)	DT (Km)	MD (MW)	AD (MW)
1	Dhaka-1	959	998	34.95	5291	73.57	0.11	40	37.35	32.41
2	Tangail-1	1313	1280	32.70	4504	84.43	0.09	15	21.94	13.52
3	Comilla - 1	1577	2004	29.43	4587	78.16	0.12	28	15.50	13.02
4	Chandpur	1704	2032	36.09	4587	77.98	0.04	24	10.52	8.80
5	Hobigonj	1734	1093	25.60	5045	59.04	0.17	22	8.28	7.64
6	Moulivibazar	2799	1376	30.85	5045	45.38	0.12	20	11.26	8.04
7	Pabna-1	1456	1213	27.13	3728	81.70	0.14	25	7.50	4.26
8	Pabna-2	915	706	24.60	3728	68.10	0.12	30	5.00	4.48
9	Sirajgonj	1309	1180	25.35	3728	85.67	0.17	25	16.70	10.27
10	Jessore-1	1616	1476	33.62	4949	75.97	0.22	20	17.17	12.78
11	Jesspre-2	1681	1455	34.67	4949	77.68	0.13	25	11.50	9.77
12	Natore-1	1261	926	28.28	4313	72.71	0.14	14	10.90	6.46
13	Natore-2	1176	938	25.14	4313	65.21	0.21	16	7.40	6.63
14	Mymensing-1	2248	2202	26.93	4199	73.18	0.20	15	20.13	11.29
15	Feni	1581	1579	40.34	3935	66.53	0.19	20	11.94	11.36
16	Joypurhat	1696	1176	30.37	4793	80.26	0.12	22	7.40	4.79
17	Dinajpur-1	2863	1879	28.31	4698	79.17	0.22	23	10.60	7.89
18	Rangpur-1	2317	2298	24.24	4793	72.57	0.08	20	12.12	8.04
19	Satkhira-1	1843	1268	31.72	5627	67.93	0.28	16	8.13	6.53
20	Pirojpur	2213	1660	49.02	4842	69.51	0.22	20	1.22	1.11
21	Kushtia	1621	1502	25.80	4755	61.71	0.32	30	9.80	7.90
22	Jamalpur	2125	2125	19.19	5194	61.49	0.01	18	11.90	5.64
23	Rangpur -2	1240	1389	28.06	4232	71.07	0.24	19	6.50	4.78
24	Bogra	1839	1780	29.48	4793	81.62	0.33	14	16.36	12.36
25	Chittagong -1	1748	1810	34.81	7689	41.21	0.26	20	8.63	7.13
26	Thakurgaon	2535	1378	29.98	4698	54.69	0.15	16	15.50	6.82
27	Madaripur	1755	1544	30.65	4908	78.57	0.27	17	4.45	4.08
28	Barisal-2	1733	1411	42.32	4842	71.27	0.29	16	8.81	7.98
29	Chittagong-2	2108	1521	41.86	7689	41.29	0.23	19	12.85	10.31
30	Bagerhat	1862	1335	52.42	5627	68.01	0.27	20	3.45	2.89

Table 4.1 Load and Load Dependent Factors for All PBSs(Contd.):

Sl. No.	Name of PBSs	Area (Km^2)	POP (1000)	LR (%)	PI (TK.)	AL (%)	RL (Km/Km^2)	DT (Km)	MD (MW)	AD (MW)
31	Noakhali	2294	2135	36.11	3935	69.69	0.14	17	7.05	6.69
32	Meherpur	1343	1006	26.80	4755	71.93	0.25	32	6.65	4.88
33	Narsingdi-1	909	1563	31.56	5271	70.01	0.11	56	19.87	15.89
34	Kishoregonj	1638	1796	21.46	4199	69.38	0.24	20	9.64	8.09
35	Narsingdi-2	1271	1549	25.94	5291	72.08	0.13	70	8.62	6.31
36	Naogaon	2041	1409	27.93	4313	63.23	0.16	25	12.34	7.22
37	Sylhet	2054	1621	37.28	5045	57.67	0.19	30	8.13	5.63
38	Laxmipur	885	977	37.80	3953	66.47	0.18	12	5.82	4.19
39	Barisal-1	1501	1089	39.92	4842	72.33	0.07	20	2.14	1.89
40	Patuakhali	2446	1277	40.21	5010	70.03	0.07	22	2.91	2.56
41	Manikgonj	1378	1176	26.70	5292	70.02	0.09	66	10.89	5.90
42	Comilla-2	1507	2027	34.85	4587	76.77	0.08	32	6.97	4.46
43	Cox's Bazar	2276	1324	20.56	7689	40.38	0.15	26	7.13	6.68
44	Dinajpur -2	1400	856	28.60	4698	63.07	0.21	30	3.70	2.01
45	Netrokona	2810	1731	26.00	4199	69.01	0.14	30	3.05	2.07
**	Sandwip	762	272	35.00	7689	60.10	0.22	50		

POP Population (1000),

LR Adult Literacy Rate (%),

PI Per capita Income (Tk.),

AL Agricultural Land (Percentage of Total Area),

RL Road Length (Km/ $(Km)^2$),

DT Distance from Local Town (Km),

MD Maximum Demand (MW), 1995-96,

AD Average Demand (MW), 1995-96.

* **Sources:**

1. Management Information System (MIS), REB, 1995-96,
2. Annual Reports, Rural Electrification Board (REB) ,1986-96,
3. Statement of Load Shedding, REB, 1995-96,
4. Statistical Pocket-books Bangladesh, Bangladesh Bureau of Statistics (BBS), 1993-96,
5. Statistical Year Books of Bangladesh, BBS, 1981-95,
6. Bangladesh Population Census, District Series, BBS, 1995-96,
7. Report on Traffic Engineering Division, Roads and Highways Department, Government of Bangladesh, 1995-96,
8. Graphosman's New Atlas, Eds. Amanat Ullah Khan and Mosharraf Hossain, Pub-lished by Graphosman, 1996.

** An Isolated Area whose Load to be Forecasted.

4.5 DATA PROCESS

A close observation of the data of Table 4.1, shows that there are closeness among the factors of some areas, however, the peak demand varies widely. Similarly, the peak demands of some areas have closeness, however, other different factors of these areas vary widely.

For the purpose of present analysis, a group of six (6) PBSs having similar Adult Literacy Rate have been selected for estimating the contribution of load deciding variables and the relevant data are shown in Table 4.2. Note that, all the PBSs grouped in Table 4.2 are belongs to almost similar Adult Literacy Rate..

Table 4.2 : Data of PBSs of Almost Similar Adult Literacy Rate

Sl. No.	Name of PBSs	POP (1000)	LR (%)	PI (TK.)	AL (%)	RL (Km/ Km^2)	DT (Km)	MD (MW)	AD (MW)
01	Jessore-2	1455	34.67	4949	77.68	0.13	25	11.50	9.77
02	Comilla-2	2027	34.85	4587	76.77	0.08	32	6.97	4.46
03	Sylhet	1621	37.28	5045	57.67	0.19	30	8.13	5.63
04	Chittagong-1	1810	34.81	7689	41.21	0.26	20	8.63	7.13
05	Chandpur	2032	36.90	4587	77.98	0.04	24	10.52	8.80
06	Noakhali	2135	36.11	3935	69.69	0.14	17	7.05	6.69

POP Population (1000),

LR . Adult Literacy Rate(%),

PI Per capita Income (Taka),

AL Agricultural Land (Percentage of Total Area),

RL Road Length (Km/ $(Km)^2$),

DT Distance from Loacl Town (Km),

MD Maximum Demand (MW), 1995-96,

AD Average Demand (MW), 1995-996.

4.6 SIMULATION RESULTS

The data of Table 4.2 are used to evaluate [X] for maximum demand and average demand. The evaluated values of weighting factors are given in Table 4.3 and Table 4.4 respectively and computer print-outs are shown in Annexure 2.

Table 4.3 Weighting Factors of Load Growth Deciding Variables for Maximum Demand *:

X1 (Population)	X2 (Adult Literacy Rate)	X3 (Per Capita Income)	X4 (Agricultural Land)	X5 (Road Length)	X6 (Distance from town)
-0.0066928683	0.4929097029	0.001404639	0.0657156982	-23.05500755	-0.1964103942

Table 4.4 Weighting Factors of Load Growth Deciding Variables for Average Demand :

X1 (Population)	X2 (Adult Literacy Rate)	X3 (Per Capita Income)	X4 (Agricultural Land)	X5 (Road Length)	X6 (Distance from town)
-0.0061490992	0.4663190417	0.001250615	0.0874380245	-18.24708481	-0.3223288502

Table 4.3 and Table 4.4 show that the weighting factors evaluated for different load deciding variables are not same. This clearly indicates that the load growths do not depend equally on all factors. This is, because some factors are

very sensitive to the development of maximum/average demand while the others are not.

It is observed from Table 4.3 and Table that the value of the weighting factor relating to adult literacy rate is the highest while that relating to percapita income is the lowest. However, it observed from Table 4.2 the maximum demand of Jessore-2 is the highest among other PBSs, but the literacy rate is the lowest. It is also observed from Table 4.1 that maximum demand Jessore-1 is higher than Jessore-2, but its literacy rate is lower.

If we put the value of weighting factors to Jessore-1 PBS whose literacy rate is similar to Sandwip, then we get the following results as shown in Table 4.5

Table 4.5 Result Obtained for Jessore-1 PBS

Name of PBSs	Maximiu Demand (Actual, MW)	Maximum Demand by Weighting Factor (MW)	Average Demand (Actual, MW)	Average Demand by Weighting Factor (MW)
Jessore-1	17.17	9.64	12.78	8.97

It is observed from Table 4.5 that the actual demands (maximum and average) varys widely from the calculated demands for this particular case due to some undesireable negative effects on Population, Road Length (Communication) and Distance from Loacl Town.

Again we put the value of weighting factors to an isolated area, Sandwip, then we get the following forecasted results which is shown in Table 4.6 i.e. our forecasted result.

Table 4.6 Forecasted Load of an Isolated Are, Sandwip

Name of PBSs	Forecasted Maximiu Demand (MW)	Forecasted Average Demand (MW)
Sandwip	15.29	9.39

CHAPTER-5

BACKPROPAGATION TRAINED NEURAL NETWORK

5.1 INTRODUCTION

This chapter explains the backpropagation algorithm and utilizes the algorithm to develop an artificial neural network for the load forcasting of an isolated area. It also describes the development of a theoritical back ground on artificial neural network, its learning algorithm and sensitivity of different parameters on convergence of the network. A neural network module for implementing the proposed load forecasting is presented in this chapter.

5.2 BACKPROPAGATION ALGORITHM

Backpropagation [8] is one of the most widely-used learning algorithms to train multi-layer feed forward neural networks. Its weight update procedure is intuitively appealing, because it is based on a relatively simple concept. If the network gives the wrong answer, then the weights are corrected so that the error is lessened and as a result future responses of the network are more likely to be corrected. When the network is given an input, the updating of activation values propagates forward from the input layer of the processing units, through each internal layer, often called hidden layer, to the output layer of processing units. The output units then provide the network's correction mechanism, starts with the output units and backpropagates backward through each hidden layer to the input layer, hence the term back-error propagation, or back-propagation.

5.2.1 Architecture of Backpropagation Network (BPN)

Backpropagation network (BPN) is a layer, feed forward network that is fully interconnected by layers. There are no feed back connections. A typical three layer backpropagation architecture is shown in Fig. 5.1. When signal patterns are applied to the input layer of the network, it propagates upwards towards the output layer through the interconnections (commonly called weights) of the middle layer, known as hidden layer. Outputs of the hidden layer are then propagation forward through the weights between hidden and output layer, and an output pattern is generated. This output pattern is then compared to the desired output, and an error signal is computed for each output unit. The error signals are then transmitted backward from the output layer to each node in the intermediate layer that contributes directly to the output. However, each unit in the intermediate layer receives only a portion of the total error signal, based roughly on the relative contribution, the unit made to the original output. This process repeats, layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Based on the error signal received, connection weights are then updated by each unit to cause the network to converge toward a set that allows all the training patterns to be encoded.

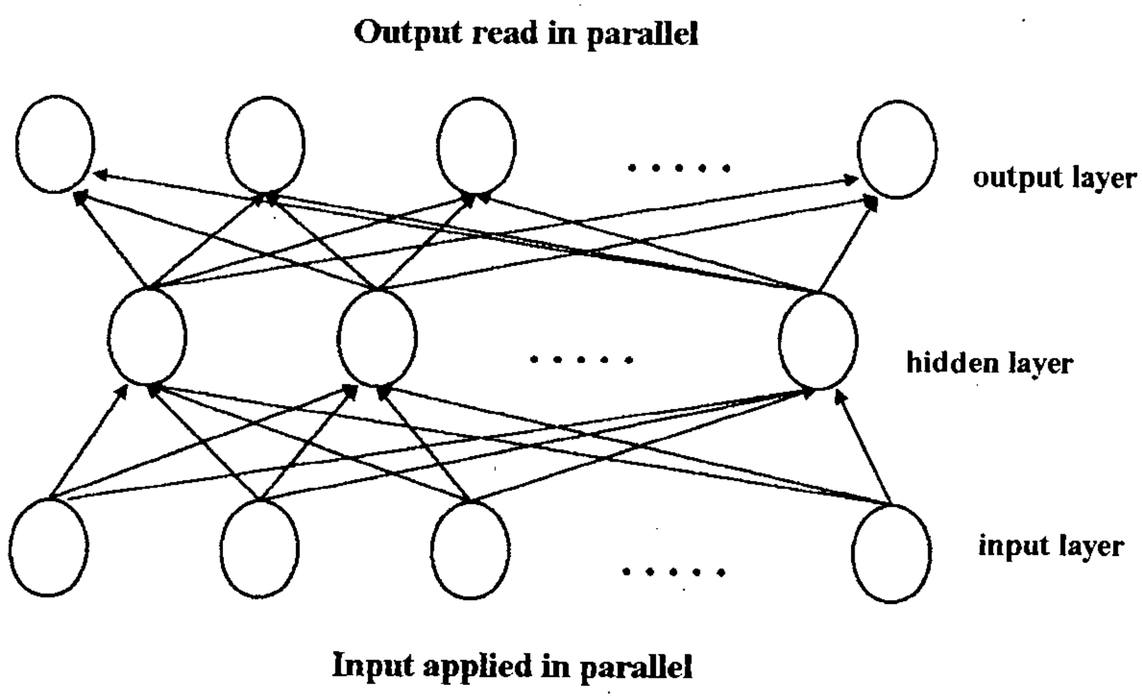

Figure 5.1 A typical three-layer backpropagation network architecture

The significance of this process is that, as the network trains, the nodes in the intermediate layers organize themselves such that different nodes learn to recognize different features of the total input space. After training, when presented with an arbitrary input pattern, the units of the hidden layers of the network will respond with an active output which is very close to the target value.

As the signal propagates through the different layers in the network, the activity pattern present at each upper layer can be thought of, as a pattern with features that can be recognized by units in the subsequent layer. The output pattern generated can be thought of, as a feature map that provides an indication of the presence and absence of many different feature combinations at the input. The total effect of this behavior is that the BPN provides an effective means of allowing the total system to examine data patterns that may be untrained and to recognize the corresponding output.

Several researchers have shown that during training, BPNs tend to develop internal relationships between nodes so as to organize the training data into classes of patterns. This tendency can be extrapolated to the hypothesis that all the hidden units are somehow associated with specific features of the input pattern as a result of training. Exactly, what association it may or may not be evident to the human observer. What is important is that the network has found an internal representation that enables it to generate the desired outputs when given the training inputs. This same internal representation can be applied to inputs that are not used during training. The network will classify these, previously unseen inputs, according to the features they share with the training examples.

5.2.2 Formulation of Backpropagation Algorithm

In the following, a detailed derivation of backpropagation learning rule is represented. The learning rule is also known as generalized delta rule (GDR). Figure 5.2 is the repetition of Figure 5.1 where suffix are included to serve as the reference of the discussion.

The network will be trained to learn a functional mapping, $\mathbf{y} = \phi(\mathbf{x}) : \mathbf{x} \in \mathbf{R}^N, \mathbf{y} \in \mathbf{R}^M$. A set of P vector pairs of the function are $(\mathbf{x}_1, \mathbf{y}_1), (\mathbf{x}_2, \mathbf{y}_2), \ldots (\mathbf{x}_P, \mathbf{y}_P)$. Considering the mapping to be nonlinear and multidimensional, the iterative version of the simple least square method, called **steepest descent technique**, will be employed.

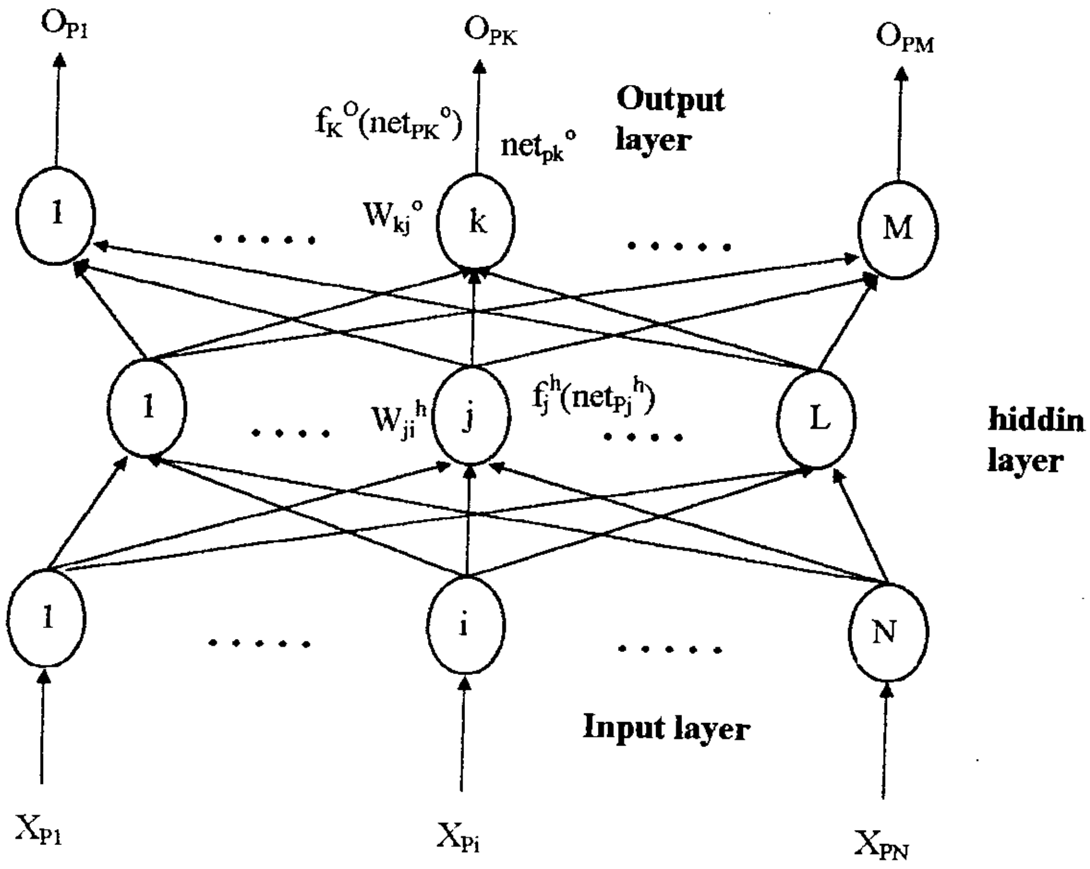

Figure 5.2 The BPN network with suffix

An input vector, $\mathbf{x_P} = (x_{P1}, x_{P2}, \ldots x_{PN})$, is applied to the input layer of the network. The input units distribute the values to the hidden layer units. The net input to the j-th hidden unit is

$$net_{Pj}^h = \sum_{i=1}^{N} w_{ji}^h . x_{pi} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \qquad (5.1)$$

where, w_{ji}^{h} is the weight on the connection from the i-th input unit. The "h" superscript refers to quantities on the hidden layer. For a defined activation function of this node, the output of this node will be

$$i_{Pj} = f_j^h(net_{Pj}^h) \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5.2)$$

The equations for the output nodes are

$$net_{Pk}^{o} = \sum_{j=1}^{L} w_{kj}^{o}.i_{Pj} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5.3)$$

$$O_{pk} = f_k^o(net_{Pk}^{o}) \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5.4)$$

where the"o" superscript refers to quantities on the output layer. The initial set of weights represents a first guess as to the proper weights for the problem.

The error value at a single output unit "k" is defined as, δ_{Pk} = **(y_{Pk} - O_{pk})**, where the subscript "p" refers to the p-th training vector, and $\mathbf{y_{Pk}}$ is the desired output value. The error that is minimized by the GDR is the sum of the squares of the errors of all the output units,

$$E_P = 0.5. \sum_{k=1}^{M} \delta_{Pk}^{2} \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (5.5)$$

To determine the direction in which, to change the weights, negative of the gradient of $\mathbf{E_P}$, $\nabla \mathbf{E_P}$, with respect to the weights, w_{kj} is calculated. Then, the weights can be adjusted in such way, so that the total error is reduced.

Considering only for the k-th output unit, the component of ∇E_P is calculated separately,

$$E_P = 0.5.\sum_k (y_{Pk} - O_{pk})^2 \quad \dots \quad \dots \quad \dots \quad (5.6)$$

$$\frac{\partial E_P}{\partial w_{kj}^o} = -(y_{Pk} - O_{Pk}).\frac{\partial f_k^o}{\partial (net_{pk}^o)}.\frac{\partial (net_{Pk}^o)}{\partial w_{kj}^o} \quad \dots \quad \dots \quad (5.7)$$

The last factor in Eq. (5.7) is

$$\frac{\partial (net_{Pk}^o)}{\partial w_{kj}^o} = \frac{\partial}{\partial w_{kj}^o}\sum_{j=1}^{L} w_{kj}^o.i_{pj} = i_{pj} \quad \dots \quad \dots \quad \dots. \quad (5.8)$$

Combining Eqs. (5.7) and (5.8), the negative gradient is

$$-\frac{\partial E_P}{\partial w_{kj}^o} = (y_{Pk} - O_{Pk}).f_k^{o\prime}(net_{Pk}^o).i_{Pj} \quad \dots \quad \dots \quad (5.9)$$

Thus the weights of the output layer are updated according to

$$w_{kj}^o(t+1) = w_{kj}^o(t) + \Delta_P.\ w_{kj}^o(t) \quad \dots \quad \dots \quad \dots \quad (5.10)$$

$$\Delta_p.w_{kj}^o = \eta.(y_{Pk} - O_{pk}).f_k^{o\prime}(net_{Pk}^o).i_{Pj} \quad \dots \quad \dots \quad (5.11)$$

The factor η is called the learning rate parameter. It is usually kept below 1.0.

The weight update Eq. (5.10) can be reformed by defining a quantity,

$$\partial_{Pk}{}^{0} = (y_{Pk} - O_{Pk}).f_k{}^{o\prime}(net_{Pk})$$

$$\text{or} \quad = \partial_{Pk}.f_k{}^{o\prime}(net_{Pk}{}^{o}) \qquad \dots \quad \dots \quad \dots \quad (5.12)$$

The weight update equation thus becomes,

$$w_{kj}{}^{o}(t+1) = w_{kj}{}^{o}(t) + \eta.\partial_{Pk}{}^{0}.\ i_{Pj} \qquad \dots \quad \dots \quad \dots. \quad (5.13)$$

So far, only the weights of the output layer have been modified. The weights of the hidden layers need modification as error signal propagates downwards. Going back to Eq. (5.6) :

$$E_P = 0.5.\sum_k (y_{Pk} - O_{Pk})^2 \quad \dots\dots \quad \dots \qquad \dots\dots \qquad (5.6)$$

$$\text{or,} \qquad = 0.5.\sum_k (y_{Pk} - f_k^o(net_{Pk}^o))^2$$

$$\text{or,} \qquad = 0.5.\sum_k (y_{Pk} - f_k^o(\sum_j w_{kj}^o.i_{Pj}))^2 \quad \dots\dots \quad \dots\dots \qquad (5.14)$$

Again, i_{pj} depends on the weights on the hidden layer through Eqs. (5.1) and (5.2). Exploiting this fact, to calculate the gradient of $\mathbf{E_P}$ with respect to the hidden layer weights :

$$\frac{\partial E_P}{\partial w_{ji}^h} = 0.5.\sum_k \frac{\partial}{\partial w_{ji}^h}(y_{Pk} - O_{Pk})^2$$

$$\text{or,} \qquad = -\sum_k (y_{Pk} - O_{Pk}).\frac{\partial O_{Pk}}{\partial(net_{Pk}^o)}.\frac{\partial(net_{Pk}^o)}{\partial i_{Pj}}.\frac{\partial i_{Pj}}{\partial(net_{Pj}^h)}.\frac{\partial(net_{Pj}^h)}{\partial w_{ji}^h} \quad \dots \qquad (5.15)$$

or, $$= \sum_k (y_{Pk} - O_{Pk}).f_k^{o\prime}(net_{Pk}^o).w_{kj}^o.f_j^{h\prime}(net_{Pj}^h).x_{Pi} \quad \ldots \qquad (5.16)$$

With the help of Eq. (5.16) the weights of the hidden layer are updated,

$$\Delta_P.w_{ji}^h = \eta.f_j^{h\prime}(net_{Pj}^h).x_{Pi}.\sum_k (y_{Pk} - O_{Pk}).f_k^{o\prime}(net_{Pk}^o).w_{kj}^o \quad \ldots \quad .. \qquad (5.17)$$

where η is once again the learning rate.

The weight updating Eq. (5.17) for the hidden layer can be rearranged with the help of δ_{Pk}^o from Eq. (5.12).

$$\Delta_P.w_{ji}^h = \eta.f_j^{h\prime}(net_{Pj}^h).x_{Pi}.\sum_k \partial_{Pk}^o.w_{kj}^o \quad \ldots \quad \ldots \quad \ldots\ldots\ldots \qquad (5.18)$$

A hidden layer error term similar to δ_{Pk}^o can be defined,

$$\delta_{Pj}^h = f_j^{h\prime}(net_{Pj}^h).\ \sum_k \partial_{Pk}^o.w_{kj}^o \quad \ldots\ldots\ldots \quad \ldots \quad \ldots \quad \ldots\ldots \qquad (5.19)$$

Finally, weight update equation for the hidden layer is reduced to the following form :

$$w_{ji}^h(t+1) = w_{ji}^h(t) + \eta.\delta_{Pj}^h.x_{Pi} \quad \ldots \quad \ldots\ldots\ldots \quad \ldots\ldots\ldots \quad \ldots\ldots \qquad (5.20)$$

The formulation of the above learning algorithm requires that the activation function of the nodes, defined by Eqs. (5.2) and (5.4), be differentiable. The simplest of all that can be thought of is surely the straight line function. But for a nonlinear mapping the activation function may be nonlinear. The most utilized function prescribed by Hopfield is the **sigmoid function**. The mathematical equation of sigmoid function is given below:

$$f_k^0(net_{jk}^o) = 1/(1+ e^{-(net)}) \quad \ldots \quad \ldots \quad (5.21)$$

The derivative of the sigmoid function can be arranged in the following way,

$$f_k^{0\prime}(net_{jk}^o) = f_k^o(1-f_k^o) = O_{Pk}(1-O_{Pk}) \quad \ldots \quad \ldots \quad (5.22)$$

5.2.3 BPN Features

In the previous section, the relevant mathematical equations required for BPN programming are presented. A computer program has been developed based on those equations. This program will calculate the weights of different layers for network convergence within acceptable error limit. A part from the mathematical analysis of BPN, certain practical features of its algorithm require special attention which are discussed in the following sub-section.

5.2.3.1 Training Data

There are no hard and fast rule of selecting the training patterns for BPN learning. Experience is often the best teacher. Yet, it should be kept in mind that BPN is very good in generalization but equally bad in extrapolation. If a BPN is inadequately and insufficiently trained on a particular class of input vectors subsequent identification of members of that class may be unreliable. So, training vectors should be selected in such way that they will cover the total range of variation, the network might experience in practical field.

5.2.3.2 Network sizing

The sizes of the input and output layers are determined by the input and the target set to be learned. Determining the number of units to be used in the hidden layer is not so straight forward. The main idea is, to use as few hidden layer units, as possible. Because this makes the learning process fast and implementation of the network easy. But in case of too much complex mapping, size of the hidden layer may be large for network convergence. Usually networks are initially designed big in size. After learning, the network is pruned by examining the weight values.

5.2.3.3 Initial weights

The initial weights are generally selected at random. Values within ±0.5 are chosen frequently. But there is always a possibility that the network may stuck to a **local minimum** in weight space. Once a network settles on a minimum, whether local or global, learning ceases. If a local minimum is reached, the error of the network may still be unacceptably high. In such a case, the initial weights need to be changed. Sometime the increase in number of hidden layer or learning rate can fix the problem. But if the error keeps within acceptable limit, whether the network has stuck into local or global, a minimum does no effect.

5.2.3.4 Learning rate parameter

Selection of the value of the learning rate parameter, η, has a significant effect on learning speed. Usually, η should be kept low (below 1.0) to ensure that the network will settle to a solution. A small value of η makes the iteration process slow. Too large value of η makes too much oscillations in the learning process. It is often suggested that η initially kept high and then varied dynamically during training.

CHAPTER - 6

FORECASTING OF LOAD BY NEURAL NETWORK

6.1 INTRODUCTION

The forecasting of load for an isolated area is an uncertain problem and the mathematical analysis cannot be implemented properly. As discussed earlier, neural network method is suitable and being used for this kind of problem. In the present study, a neural network is used to forecast the load of an isolated area. In this chapter, the forecasting of load of the proposed isolated area, Sandwip, with neural network is discussed in brief.

6.2 SELECTION OF PBSs FOR FORECASTING THE LOAD OF AN ISOLATED ISLAND

In Bangladesh, there are 45 PBSs (energized upto 1995-96) distributed over the country. A varity of characteristics exist for different PBSs. For forecasting the load, for a certain area it is very difficult to co-relate different variables of all the 45 PBSs areas. It is more convenient, if a number of groups are formed signifying a common characteristics. For predicting load of an isolated island like Sandwip, it is proposed that PBSs of similar geographical characteristics be chosen in a group. But unfortunately, there is none such isolated PBS in Bangladesh. Therefore, it is decided to choose the PBSs which are closer in climatic condition, may be grouped together.

It is obvious that the PBSs nearer to the Bay of Bengal would have climate similar to Sandwip. On this assumption, seven PBSs are chosen. Five out of the seven are used to train the neural network and the rest are used to varify the training. If the verification is found to be correct, the trained network may be used to predict the load for Sandiwp.

6.3 TRAINING OF THE NETWORK

6.3.1 Selection of Input and Output

The input and output of the network has been chosen as follow and shown in fig.6.1

X_1 = Population (1000) X_2 = Adult Literacy Rate (%)

X_3 = Per capita Income (Taka) X_4 = Agricultural Land (% of Total Area)

X_5 = Road Length ($Km/(Km)^2$) X_6 = Distance from Local Town (Km)

Y_1 = Maximum Demand (MW) Y_2 = Average Demand (MW)

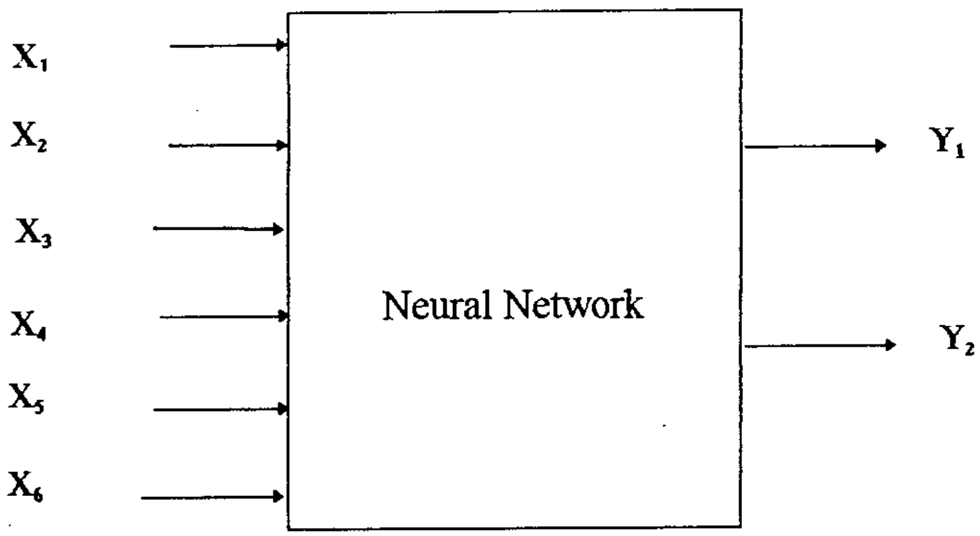

Figure : 6.1 Network Input and Output Vector

6.3.2 Training of Data.

Data of the training set for neural network has been collected from REB, Bangladesh Bureau of Statistics, etc. To give input to neural network the, data are normalized to fit within 0 ~ 1.0. Initially, 45 set of data have been collected from different sources. But finally only a set of five data are selected for training. Because these are very similar with the data of isolated area, Sandwip which is a big island of Bangladesh. Data for training set is shown in Table 6.1. The computer program for back-propagation is shown in Annexure 3.

Table 6.1 : Data for Training Set :

Sl. No.	Name of PBSs	POP (1000)	LR (%)	PI (TK.)	AL (%)	RL (Km/Km^2)	DT (Km)
01.	Perojpur	1660	49.02	4842	69.51	0.22	20
02.	Barisal	1089	39.92	4842	72.33	0.07	20
03.	Patuakhali	1277	40.21	5010	70.03	0.07	22
04.	Satkhira	1268	31.72	5627	67.93	0.28	16
05.	Cox's Bazar	1324	2056	7689	40.38	0.15	26

Table 6.2: Results Obtained After Training :

Sl. No.	Name of PBSs	Maximum Demand (Actual,MW)	Maximum Demand by NNM (MW)	Average Demand (Actual,MW)	Average Demand by NNM(MW)
01.	Perojpur	1.22	1.2200	1.11	1.1100
02.	Barisal	2.14	2.1489	1.89	1.8830
03.	Patuakhali	2.91	2.9100	2.56	2.5669
04.	Satkhira	8.13	8.1300	6.53	6.5300
05.	Cox's Bazar	7.13	7.1300	6.68	6.6800

NNM = Neural Network Method

6.3.3 Network Size and Learning Parameters

The network has 6 input units to represent the six input variables and 2 output units for two output variables. The network has been trained with 10 units in a single hidden layer. All the weights and biases are initialized by uniformly generated random values between +0.5 to -0.5. The learning parameters are shown below and are kept unchanged during learning.

The back-propagation algorithm is used for training of the network which already described in chapter-5. The training parameters are selected as follows:

No of hidden layers = 10
Learning Rate = 0.1
Momentum factor = 0.2

The weights and bias have been initiated randomly within -0.5 to +0.5.

After 10,00,000 training cycles, the sum-squared error has come down below 0.000001 and the training has been stopped. The output of this network in response to training set is shown in Table 6.3 The outputs of the network are matched very closely with the desired outputs used in training set Table 6.4.

Table 6.3: Data for Testing

Sl. No.	Name of PBSs	POP (1000)	LR (%)	PI (TK.)	AL (%)	RL (Km/Km^2)	DT (Km)
01.	Bagerhat	1335	52.42	5627	68.01	0.27	20
02.	Laxmipur	1977	39.13	3953	66.47	0.18	12

Table 6.4: Results Obtained After Testing

Sl. No.	Name of PBSs	Maximim Demand (Actual,MW)	Maximum Demand by NNM(MW)	Average Demand (Actual,MW)	Average Demand by NNM(MW)
01.	Bagerhat	3.45	3.41	2.89	2.97
02.	Laxmipur	5.82	5.85	4.19	4.11

NNM = Neural Network Method

6.4 WEIGHTS OF THE NETWORK

The evaluated weights of the network that have been considered for the forecast model are given below:

Table 6.5: Weights between Input and Hidden Layer

-1.482334	2.714815	0.571011	-1.353646	-0.000940	0.290160	0.444004	-3.750835	0.074576	2.097418
2.868662	-2.735266	2.032222	-6.078344	3.240567	-0.233418	0.908936	1.403118	-1.240543	2.393337
-1.143714	-0.541650	-0.691011	0.069590	0.334148	-1.298666	-0.461536	0.855139	0.639366	-.882208
-0.469526	0.189603	0.988414	-2.680755	-0.264575	0.645096	-1.211492	3.619145	-1.548108	.568901
-0.182740	-1.033192	0.865313	-3.352861	2.013975	0.159983	0.297390	0.582700	0.286816	-0.657977
-0.568761	1.480443	·0.159151	-0.029832	0.097546	-1.231407	-0.545021	0.753415	0.424940	-0.326250

Table 6.6: Bias of the Hidden Layer

-0.149945	0.320972	1.053034	0.196895	-0.449914	0.233373	-0.460465	0.537691	- 0.475173	-0.079020

Table 6.7: Weights between Hidden and Output

-2.851071	3.071329
4.580915	-1.841501
1.251093	-3.448686
-3.204332	1.197662
1.255695	0.735494
-2.861343	3.678356
3.259452	-2.945467
0.653822	-0.389982
-2.891772	2.730824
-0.182715	0.578016

Table 6.8: Bias of the Output

-2.053604
-1.055736

6.5 FORECASTED RESULTS

The above trained network is then used for forecasting average and maximum loads for an isolated area, Sandwip. The input variables are normalized by the same factor as used earlier for other data. The forecasted results are shown in Table 6.10.

6.9: Load Dependent Factors of An Isolated Area, Sandwip

Sl. No.	Name of Isolated Area	POP (1000)	LR (%)	PI. (TK.)	AL (%)	RL (Km/Km^2)	DIT (Km)
01	Sandwip	272	35	7689	60.1	.22	50

Table 6.10 : Forecasted Loads of An Isolated Area, Sandwip .

Sl. No.	Name of an Isolated Area	Maximum Demand (Forecasted) (MW)	Average Demand (Forecasted) (MW)	Load Factor
01	Sandwip	4.47603	2.47572	55.31 %

6.6 DISCUSSION ON FORECASTED RESULTS

Forecasting with neural network, the training data has very important role. Because the model is developed by the training data. If the training data are not accurate then the model will not be perfect. In Bangladesh, the source of data is not as perfect as required for research purpose. For this reason, there may be some errors in the training set. The errors of the developed model considered are within the range assumed for this research work. So this model can be implemented for forecasting the average and peak demands for the isolated island of Sandwip.

Load factor of the proposed isolated area is 55.31%, which seems to be very poor. When there is a new electric supply system in a certain rural/isolated area the industrial as well as the commercial load consumption will not rise very rapidly. So, during day time, consumption of electricity is very small than peak hour and thus load factor is poor. So, the forecasted maximum demand and average demand considered to be correct.

The forecasted results that are shown in Table 6.10 are evaluated on the basis of the data for the year 1995-96. So, the above forecasted results are valid only for the year 1995-96.

6.7 COMPARISION WITH LINEAR REGRESSION ANALYSIS :

The results obtained by Neural Network (NN) method and those of obtained by Linear Regression Analysis (LRA) have been presented earlier. For comparision, a separate Table is presented here. Table 6.11 shows a large differences in forecasted values. It is not surprising, because the coefficients obtained from the LRA have no physical meanings. Some of the coefficients are found to be negative. Unexpected sign of the coefficient made the LRA inappropriate to apply in forecasting. Moreover, the coefficients even considering their negative sign, when applied to predict other demands of known values produced inaccurate results (Table 4.5). On the other hand, the trained NN when applied to predict the demands of an area of similar climate has given a close agreement with the actual values (Table 6.4). Therefore, the LRA can not be applied for predicting demands of an isolated area. Rather the NN method should be applied for predicting loads of an isolated area like Sandwip.

Table 6.11 : Forecasted Load of Isolated Area with NNM and LRA

Sl. No.	Name of an Isolated Area	Maximum Demand (Forecasted) (MW)	Average Demand (Forecasted) (MW)	Load Factor
01	Sandwip	4.47603	2.47572	55.31 %
02	Sandwip	9.64	8.97	93.05%

01 forcasted Load of An Isolated Area, Calculated by NN Method

02 Forecasted Load of An Isolated Area, Calculated by LRA

CHAPTER - 7

CONCLUSION AND RECOMENDATIONS

7.1 OBSERVATION AND DISCUSSION

The weighting factors that have been evaluated according to, equation 3.8 of the isolated area load forecasting technique is shown in Table 4.3. For this evaluation data of 6 PBSs of almost similar adult literacy rate has been considered. From Table 4.3 it is observed that the weighting factors relating to adult literacy rate is the highest while that relating to percapiita income is the lowest which has been mentioned earlier. But from the same Table 4.3 it is also seen that weighting factors relating to population, road length i.e. communication have negative effects which are not desirable. For this reason we have decided to forecast the load of the typical island by using neural network method.

7.2 CONCLUSION

Electrical energy and the economic development of a society are interlinked and the quality of life achieved in a community or country can be assessed from the amount of energy it consumes.

In a modern society, uninterrupted electric power supply is desirable. To ensure the uninterrupted power supply, usually the electric networks are interconnected to form a grid. However, there are areas, which may not be incorporated within a grid due to technical or economic reasons. This makes the generation plan of an isolated area different from that of an area which is a part of a grid and in a generation plan, the appropriate models of load and generating sources are the basic requirements.

Therefore, the objective of this research has been to develop 'a load forecasting technique appropriate for an isolated area.'

The main objective of this research has been achieved by presenting a load forecasting technique of an isolated area where either the electric power supply as a source of energy has not started yet or the history of load development is not available. The technique is based on the concept,

a. identification of the load dependent variables;

b. evaluation of the weighting factor for each load deciding variable from the data of different known electrified areas;

c. selection of a suitable area in which the load deciding variables are similar to those of the typical isolated area;

evaluation of the maximum and average demands of the selected area and the typical isolated area to forecast the load.

7.3 RECOMMENDATIONS FOR FURTHER RESEARCH

a) The proposed load forecasting technique may be performed by incorporating additional prospective load growth deciding variables.

b) The proposed load forecasting technique may be compared with the conventional technique.

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ANNEXURE -1

OBJECTIVES AND PRIORITY SELECTION CRITERIA OF RURAL ELECTRIFICATION PROGRAM

A1.1 OBJECTIVE

The importance and necessity of Rural Electrification (RE) in Bangladesh was thus felt by the power planners as early as the beginning of the sixties. On an experimental basis, a few rural electrification pilot projects were taken up by the Power Development Board (PDB) in 1964-65.

The primary objective of Rural Electrification Pilot Projects were to provide electricity in certain selected rural areas for the development and improvement of irrigation system and small scale industries as well as for domestic uses. These projects yielded highly encouraging results in the said fields.

Since its independence in 1971, Bangladesh Government attached priority to accelerate the RE Program and made it a constitutional obligation to provide electricity in the rural areas as early as possible. It was decided that approximately 88000 miles of power distribution lines with necessary numbers of sub-stations and other bare minimum auxiliary facilities to construct an infra-structure of Rural Electrification System (RES) covering the major populated landmass of the country. **This excluded areas of Chittagong Hill Tracts (CHT), Sunderban Forest Areas, Coastal islands and north eastern low land areas (haor areas).**

A.1.2 PRIORITY SELECTION CRITERIA

In order to ensure that final feasibility study on area selection would be made in an objective manner, the consults developed criteria for priority basis selection and a weight factor was assigned to each criterion. The following Table A.1.1 reflects the percentage of influence each criterion exerted the final selection.

Table A.1.1 Reflects of Percent Influence for Various Types of Consumers:

Criteria	Weight Factor	Percent Influence
Power Supply	0.70	8.3%
Roads	0.75	8.9%
Residential	0.80	9.5%
Cottage Industry	0.30	3.6%
Institutions	0.80	7.1%
Pump Irrigation	1.00	11.9%
Industrial	0.90	10.7%
Flooding	0.30	3.6%
Potential Economic Benefit	0.90	10.7%
Probability of Residential Connection	0.80	9.5%

ANNEXURE -2

COMPUTER PRINT OUTS OF LRA

ANNEXURE-2

A2.1 DATA OF PBSs OF ALMOST SIMILAR ADULT LITERACY RATE

Name of PBSs	POP	LR	PI	AL	RL	DT	MD	AD
jessore-2	1455	34.67	4949	77.68	0.13	25	11.50	9.77
comilla-2	2027	34.85	4567	76.77	0.08	32	6.97	4.46
sylhet	1621	37.28	5045	57.67	0.19	30	8.13	5.63
chittgong-1	1810	34.81	7689	41.21	0.28	20	8.63	7.13
chandpur	2032	36.90	4567	77.98	0.04	24	10.52	8.80
noakhali	2135	36.11	3935	69.69	0.14	17	7.05	6.69
SANDWIP	272	35.00	7689	60.10	0.22	50	F	F
JESSORE-1	1476	33.62	4949	75.97	0.22	20	17.17	12.78

Note:- The symbol 'F' denotes the data which should be forecasted.

A2.2 INVERSE MATRIX FOR LOAD DEPENDENT VARIABLES FOR MAXIMUM DEMAND

-0.00101541	0.001338253	-0.000727624	0.000307619	-0.000619898	0.000771481
-0.03850498	-0.163217437	0.12963138	-0.036313907	0.139678679	-0.019374652
0.000123986	2.29206E-05	-0.00028352	0.000261009	0.000174028	-0.000277905
0.042273738	0.018157307	-0.034957494	-0.003107203	-0.030712246	0.012357972
3.531136873	3.746104501	-0.777531889	0.125664811	-12.04905585	5.986602062
-0.02176332	0.06801771	0.031363614	-0.010211465	-0.033994723	-0.032546446

A2.3 WEIGHTING FACTORS OF LOAD GROWTH DECIDING VARIABLES FOR MAXIMUM DEMAND

X1	X2	X3	X4	X5	X6
-0.00669287	0.492909703	0.001404639	0.065715698	-23.05500756	-0.196410394

A2.4 FORECASTED LOAD (MAXIMUM DEMAND) OF JESSORE-1 PBSs AND SANDWIP

JESSORE-1	9.636622024
SANDWIP	15.28854236

A2.5 INVERSE MATRIX FOR LOAD DEPENDENT VARIABLES FOR AVERAGE DEMAND

-0.00101541	0.001338253	-0.000727624	0.000307619	-0.000619898	0.000771481
-0.03850498	-0.163217437	0.12963138	-0.036313907	0.139678679	-0.019374652
0.000123986	2.29206E-05	-0.00028352	0.000261009	0.000174028	-0.000277905
0.042273738	0.018157307	-0.034957494	-0.003107203	-0.030712246	0.012357972
3.531136873	3.746104501	-0.777531889	0.125664811	-12.04905585	5.986602062
-0.02176332	0.06801771	0.031363614	-0.010211465	-0.033994723	-0.032546446

A2.6 WEIGHTING FACTORS OF LOAD GROWTH DECIDING VARIABLES FOR MAXIMUM DEMAND

X1	X2	X3	X4	X5	X6
-0.0061491	0.466319042	0.001250615	0.087438024	-18.24708481	-0.322388503

A2.7 FORECASTED LOAD (AVERAGE DEMAND) OF JESSORE-1 PBSs AND SANDWIP

JESSORE-1	8.971409632
SANDWIP	9.385835147

ANNEXURE -3

PROGRAMME FOR BACKPROPAGATION

ANNEXURE-3

```
/*programme backpropagation learning algorithm*/
#include  <stdio.h>
#include  <math.h>
#include  <stdlib.h>
#include  <string.h>
#include  <time.h>

#define IN  6
#define ON  2
#define MPN 10
#define MHN 20

#define f2(x,u)      x/u
#define f1(x,u)      (1.0/(1.0+exp(-(x/u))))
#define rnd()        (((double)rand()/0x7fff)*(Wmax-Wmin)+Wmin)

float   o1[MPN][IN];
float   o2[MPN][MHN];
float   o3[MPN][ON];
float   t[MPN][ON];
float   w21[MHN][IN];
float   dw21[MHN][IN];
float   w32[ON][MHN];
float   dw32[ON][MHN];
float   bias2[MHN];
float   dbias2[MHN];
float   bias3[ON];
float   dbias3[ON];
float   b2[MPN][MHN];
float   b3[MPN][ON];
float   d2[MHN];


float   alpha, Eta, Wmax, Wmin, u;
int     HN, lp_no, tp_no, ran_sd;

#define  WEIGHT_SAVE_FILE   "amin.wt"
static char *wb=WEIGHT_SAVE_FILE;


main (argc, argv)
int argc;
char *argv[];
```

```
{
     FILE *fps;
     int   i, j, k, read, p;
     long  iteration,tm;
     char  file[30], sbmax[80], sbmin[80], sread[80], setah[80],
swmin[80], oslope[80],hslope[80];
     char  ss[80], save[80], sr[80], seta[80], sw[80], sloop[80],
shn[80], salpha[80];
     char  filesig[80];
     float ef;


     void propagation();
     void back_propagation();
     void state();
     void read_file();
     void savewb();
     void readwb();
     void initialize();


     if( argc <= 1) {

      printf("Learning file: ");
      gets(ss);
      sscanf(ss, "%s",file);

      printf("save file: ");
      gets(ss);
      sscanf(ss, "%s", save);
     }

     else

      strcpy(file, argv[1]);

      printf("random: ");
      gets(sr);
      printf("Eta: ");
      gets(seta);
      printf("Wmax: ");
      gets(sw);
      printf("Wmin: ");
      gets(swmin);
      printf("iteration_no: ");
      gets(sloop);
      printf("HN: ");
      gets(shn);
```

```
    printf("Alpha: ");
    gets(salpha);
    printf("read: ");
    gets(sread);
    printf("u=");
    gets(hslope);


   if((fps=fopen (save,"w"))==NULL) printf("Can't open file");

    u=atof(hslope);
    HN=atoi(shn);
    Eta=atof(seta);
    iteration= atol(sloop);
    Wmax=atof(sw);
    Wmin=atof(swmin);
    alpha=atof(salpha);
    read=atoi(sread);
    ran_sd=atoi(sr);


    read_file(file);

    fprintf(fps,"\n\n\n\n");
    fprintf(fps,"u=%.4f   Eta=%.4f    HN=%3d   Alpha=%.4f
random_seed=%4d  Wmax=%.4f \n\n",u,Eta,HN,alpha,ran_sd,Wmax);
    srand(ran_sd);

    if(read==0)     initialize();
    else            readwb();

 /* ----------------- Before Learning  --------------------- */

   for( ef=0.0, j=0; j < lp_no; j++) {
        state(j);
         for( k=0; k < ON; k++ )
        ef += (t[j][k]-o3[j][k])*(t[j][k]-o3[j][k]);
   }
   ef/=2.0;
   tm=0;
   fprintf(fps, "%.5f  %d\n", ef, tm);
   printf("%.2f %d\n", ef, tm);


 /* -------------- Start to learn -------------------------- */
```

```
for( tm=1; ef >=0.000001 && tm <= iteration; tm++)
  {

     for(j=0; j < lp_no; j++)
      {
      propagation(j);
      back_propagation(j);
       }
     for( ef=0.0, j=0; j < lp_no; j++)
      {
      state(j);
      for(k=0; k < ON; k++) ef+= (t[j][k]-o3[j][k])*(t[j][k]-
o3[j][k]);
       }
      ef/=2.0;
    if((tm%100)==0)
     {
      printf("%.9f    %ld\n", ef, tm);
      fprintf(fps, "%.9f  %ld  \n", ef,tm);
      }
     }


/* ------- learning over-saving weights & printing output -------*/

     savewb();

   fprintf(fps, "\n ****** After Learning  ****** \n");

     for(i=0; i < lp_no; i++)
       {
                fprintf(fps, "\tpat[%2d]-> ", i);
            for(j=0; j < ON; j++)
                fprintf(fps, "\t%5.3f \t%5.3f", (o3[i][j]),
(t[i][j]) );

                fprintf(fps,"\n");
         }
       fprintf(fps, "\n\n");

    for(i=0; i < lp_no; i++)   {
                fprintf(fps, "\tpat[%2d]-> ", i);
            for(j=0; j < HN; j++)
                fprintf(fps, "\t%5.3f", o2[i][j]);
                fprintf(fps,"\n");
    }

       fprintf(fps, "\n\n");
```

```
        for(i=lp_no; i < lp_no+tp_no; i++)   {
                    state(i);
                    fprintf(fps, "\ttestpat[%2d]-> ", i-lp_no);
                for(j=0; j < ON; j++)
                    fprintf(fps, "\t%5.3f", o3[i][j]*8.13);
                    fprintf(fps,"\n");
        }
           fclose(fps);

  return 0;
 }

 /* -------------  close main   ------------------- */


 void propagation(p)
 int p;
 {
  int i,j;
  float net;

  for(i=0; i < HN; i++) {
        for(net=0.0, j=0; j < IN; j++)
        net += w21[i][j] * o1[p][j];
        b2[p][i] = net + bias2[i];
        o2[p][i] = f1(b2[p][i], u);
  }


  for(i=0; i < ON; i++) {
        for(net=0.0, j=0; j < HN; j++)
        net += w32[i][j] * o2[p][j];
        b3[p][i] = net + bias3[i];
        o3[p][i] = f1(b3[p][i], u);
  }

}



void back_propagation(int p)

{
 int i,j;
 float d3[ON];
 float sum;
```

```
    for(i=0; i < ON; i++)
        d3[i] = (t[p][i]-o3[p][i])*o3[p][i]*(1.0-
o3[p][i])*(1.0/u);

    for(i=0; i < HN; i++) {
        for(sum=0.0, j=0; j < ON; j++) {
        dw32[j][i] = Eta * d3[j] * o2[p][i] + alpha * dw32[j][i];
        sum += d3[j] * w32[j][i];
        w32[j][i] +=dw32[j][i];
        }
        d2[i] = (1.0/u) * o2[p][i] * (1.0 - o2[p][i]) * sum;
    }


    for(i=0; i < ON; i++) {
        dbias3[i] = Eta * d3[i] + alpha * dbias3[i];

        bias3[i] += dbias3[i];
    }

    for(i=0; i < IN; i++) {
        for(j=0; j < HN; j++) {
        dw21[j][i] = Eta * d2[j] * o1[p][i] + alpha * dw21[j][i];
        w21[j][i] += dw21[j][i];

        }
    }

    for(i=0; i < HN; i++) {
        dbias2[i] = Eta * d2[i] + alpha * dbias2[i];
        bias2[i] += dbias2[i];
    }
  }


 void state(p)
 int p;
 {
  int i;
  /*   print("\t%d->", p); */
  propagation(p);
  /* for(i=0; i < HN; i++)   */
  /*   print("\t%5.3f", o3[p][i]);  */
  /* fputc("\n", stdout);           */
 }
```

```
void read_file(name)
char *name;
{
 int   i,j;
 FILE  *fp;

 if(( fp=fopen(name, "r"))==NULL)
  {
     fprintf(stderr,"%s : File open error !!\n", name);
     exit(-1);
  }

 fscanf(fp, "%d", &lp_no);
 for(i=0; i < lp_no; i++)
  {
      for(j=0; j < IN; j++)  fscanf(fp, "%f", &o1[i][j]);
      for(j=0; j < ON; j++)  fscanf(fp, "%f", &t[i][j]);
  }


/* fscanf(fp, "%d", &tp_no);
 for(i=lp_no; i < lp_no+tp_no; i++) {
      for(j=0; j < IN; j++)
     fscanf(fp, "%f", &o1[i][j]); }
   */

     fclose(fp);

}

void    savewb()
{
 FILE  *fpwb;
 int   i,j;

 if((fpwb=fopen(wb,"w"))==NULL) printf("Can't open weight save
file !!");

/* -------  weight between input and hidden layer ---------- */

     for(i=0; i < HN; i++) {
      for(j=0; j < IN; j++)
     fprintf(fpwb, "%.6f\n", w21[i][j]);
 }

 for(i=0; i < HN; i++)
      fprintf(fpwb, "%.6f\n", bias2[i]);
```

```
/* -------  weight between hidden and output layer ---------- */

    fprintf(fpwb,"\n\n");

    for(i=0; i < ON; i++) {
          for(j=0; j < HN; j++)
         fprintf(fpwb, "%.6f\n", w32[i][j]);
    }

    for(i=0; i < ON; i++)
         fprintf(fpwb, "%.6f\n", bias3[i]);

    fprintf(fpwb,"\n\n\n");
    fprintf(fpwb, "u=%.4f   Eta=%.4f   HN=%3d  alpha=%.4f
random_seed=%4d\n\n", u,Eta,HN,alpha,ran_sd);

         fclose(fpwb);

    }


   void    readwb()
   {
    FILE  *fpwb;
    int   i,j;

    if((fpwb=fopen(wb,"r"))==NULL) printf("Can't open weight save
file !!");

    for(i=0; i < HN; i++) {
          for(j=0; j < IN; j++)
         fscanf(fpwb, "%f\n", &w21[i][j]);
    }

    for(i=0; i < HN; i++)
        fscanf(fpwb, "%f\n", &bias2[i]);


    for(i=0; i < ON; i++) {
          for(j=0; j < HN; j++)
         fscanf(fpwb, "%f\n", &w32[i][j]);
    }

    for(i=0; i < ON; i++)
         fscanf(fpwb, "%f\n", &bias3[i]);
```

```
        fclose(fpwb);

}


void initialize()
{
    int i,j;

   for(i=0; i < HN; i++) {
         for(j=0; j < IN; j++){
       w21[i][j] = rnd();
       dw21[i][j] = 0.0;   }
   }

   for(i=0; i < ON; i++) {
         for(j=0; j < HN; j++){
       w32[i][j] = rnd();
       dw32[i][j] = 0.0;   }
   }

   for(i=0; i < ON; i++)   {
       bias3[i] = rnd();
       dbias3[i] = 0.0;
   }

   for(i=0; i < HN; i++)   {
       bias2[i] = rnd();
       dbias2[i] = 0.0;
   }

}
```