LONG TERM ANNUAL ELECTRICITY DEMAND FORECASTING BY ARTIFICIAL NEURAL NETWORKS INCLUDING SOCIO-ECONOMIC INDICATORS AND CLIMATIC CONDITIONS

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Degree of Master of Science

Department of Electrical Engineering

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DECLARATION

I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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D.C. Hapuarachchi

The above candidate has carried out research for the Masters Dissertation under our supervision.

Signatures of the supervisors:

_________________________ Date: ______________

Dr. K.T.M.U. Hemapala

_________________________ Date: ______________

Dr. A.G.B.P. Jayasekara

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ABSTRACT

Electricity has become a major form of end use energy in present complex society. The influence of electricity is tremendous and has been recognized as a basic human need. It is an important element of infrastructure on which the socio economic development of the country heavily depends.

Electricity demand forecasting is very important and crucial for a utility, in order to make right decisions regarding future power plant and network development. Accurate electricity demand forecasting is one of the challenges and several techniques are used in forecasting demand based on the availability of data in each country.

CEB in their long term generation expansion planning studies use three long term demand forecasting methodologies namely econometric approach, time trend approach and end user approach.

New application for long term demand forecasting based on Artificial Intelligence has identified as important due to its ability in mapping complex non-linear relationships. Therefore under this study, the use AI method based on Artificial Neural Networks for long term annual electricity demand forecasting in Sri Lanka is discussed and modeled including Socio-Economic Indicators and Climatic Conditions.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBRIVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
CBSL	-	Central Bank of Sri Lanka
CCPI	-	Colombo Consumer Price Index
CEB	-	Ceylon Electricity Board
EI	-	Energy Intensity
GDP	-	Gross Domestic Product
GDPPC	-	Gross Domestic Product Per Capita
LTGEP	-	Long Term Generation Expansion Plan
MLR	-	Multiple Linear Regressions
MSE	-	Mean Squared Error

LIST OF APPENDICES

1.0 INTRODUCTION

1.1 BACKGROUND

The world electricity demand has increased rapidly in the recent years as the world become more advance in technology, economic and social aspects. With the urbanization, electricity consuming devices and appliances have become more common in the daily lives of people by enhancing living pattern.

Sri Lanka also has been facing a continuously increasing electricity demand every year, mainly due to the socio-economic development of the country, increase in electrification level, population growth and climatic conditions.

Table 1.1 shows the annual demand variation for electricity in the country during the last fifteen years [2].

Table 1.1 – Electricity Demand in Sri Lanka, 2002-2016

Year	Demand (GWh)	Avg. Growth (%)	Total energy Losses[+] (%)	Generation (GWh)	Avg. Growth (%)	Load Factor (%)	Peak (MW)	Avg. Growth (%)
2002	5638*	5.6	19.2	6810	4.4	54.7	1422	-1.6
2003	6209	10.1	18.4	7612	11.8	57.3	1516	6.6
2004	6782*	9.2	17.1	8043	5.7	58.7	1563	3.1
2005	7255	7.0	17.3	8769	9.0	57.3	1748	11.8
2006	7832	8.0	16.6	9389	7.1	56.6	1893	8.3
2007	8276	5.7	15.7	9814	4.5	60.8	1842	-2.7
2008	8417	1.7	15.0	9901	0.9	58.6	1922	4.3
2009	8441	0.3	14.6	9882	-0.2	60.4	1868	-2.8
2010	9268	9.8	13.5	10714	8.4	62.6	1955	4.7
2011	10026*	8.2	13.1	11528	7.6	60.8	2163	10.6
2012	10475*	4.5	11.2	11801	2.4	62.8	2146	-0.8
2013	10624	1.4	11.2	11962	1.4	63.1	2164	0.8
2014	11063	4.1	10.9	12418	3.8	65.9	2152	-0.6
2015	11786	6.5	10.4	13154	5.9	65.8**	2283	6.1
2016	12785	8.5	10.3	14250	8.3	66.3**	2453	7.4
Last 5 year		5.1%			4.8%			3.4%
Last 10 year		5.0%			4.2%			3.2%
Last 15 year		6.0%			5.4%			4.0%

*Include Self-Generation
**Load Factor includes Other RE
[+]Includes generation auxiliary consumption

By end of year 2016, 6.5 million consumers have been served by the Sri Lankan power utility and the total electricity demand of the country has grown to 12,785 GWh which had been only 8,276 GWh ten years ago [1][2]. The average demand growth rate is about 5% per annum. The recorded maximum demand within the year 2016 was 2,453 MW, which was 1,842 MW 10 years ago with growth rate is about 3.2% per annum.

The total electricity demand/sales of about 12,785 GWh have been contributed by the Domestic, Industrial, General Purpose, Hotel, Government, Religious and Street Lighting with the share of 38%, 33%, 24%, 2%, 1.5%, 0.5% and 1% respectively.

1.2 MOTIVATION

Electricity is a commodity that cannot be stored in the grid where demand and supply have to be continuously balanced. Therefore, it is vital for a country to be able to supply the electricity exactly equal to the demand. If the electricity generation capacity is lower than the gross demand, all the consumers will affect negatively by resulting huge economic burden to the country. Further, a higher electricity generation capacity than the demand leads for the power plants to work with idle capacity, which is again a waste in economic resources. Hence, accurate prediction of the electricity demand for the future is very important to correctly plan and develop new electricity generation investments for maintaining the electricity demand and supply balance.

Present long term electricity demand forecasting studies in CEB are carried out by considering most possible explanatory variables with econometric approach based on multiple linear regression.

However, it is important to develop AI based nonlinear forecasting approach with explanatory variables including climatic condition which will justify and compare the performance of the official predictions.

1.3 OBJECTIVE OF THE STUDY

The main objectives of this study are,

- To develop an AI based model for the Long Term Electricity Demand Forecast (20 years)
- To compare and analyze the performance of electricity demand forecast developed based on AI model and present long term national electricity demand forecast (official predictions by CEB based on regression technique)

1.4 SCOPE OF WORK

The electricity demand used in this study is the total end use consumption of electricity in GWh by all tariff categories. Explanatory variables are identified through literature surveys done in other countries and also considered variables by CEB in their econometric approach.

In this work, all the computational models were created in MATLAB 9.0 (R2016a) environment.

In this research study, past electricity demand and factors affecting to the electricity demand including climatic conditions are analyzed and identified the most significant factors out of them.

Two ANN models are developed by evaluating different ANN architectures, one for the prediction of significant variables and the other for the electricity demand forecast.

To complete the study, the work flow was arranged as shown in schematic diagram with Figure 1.1.

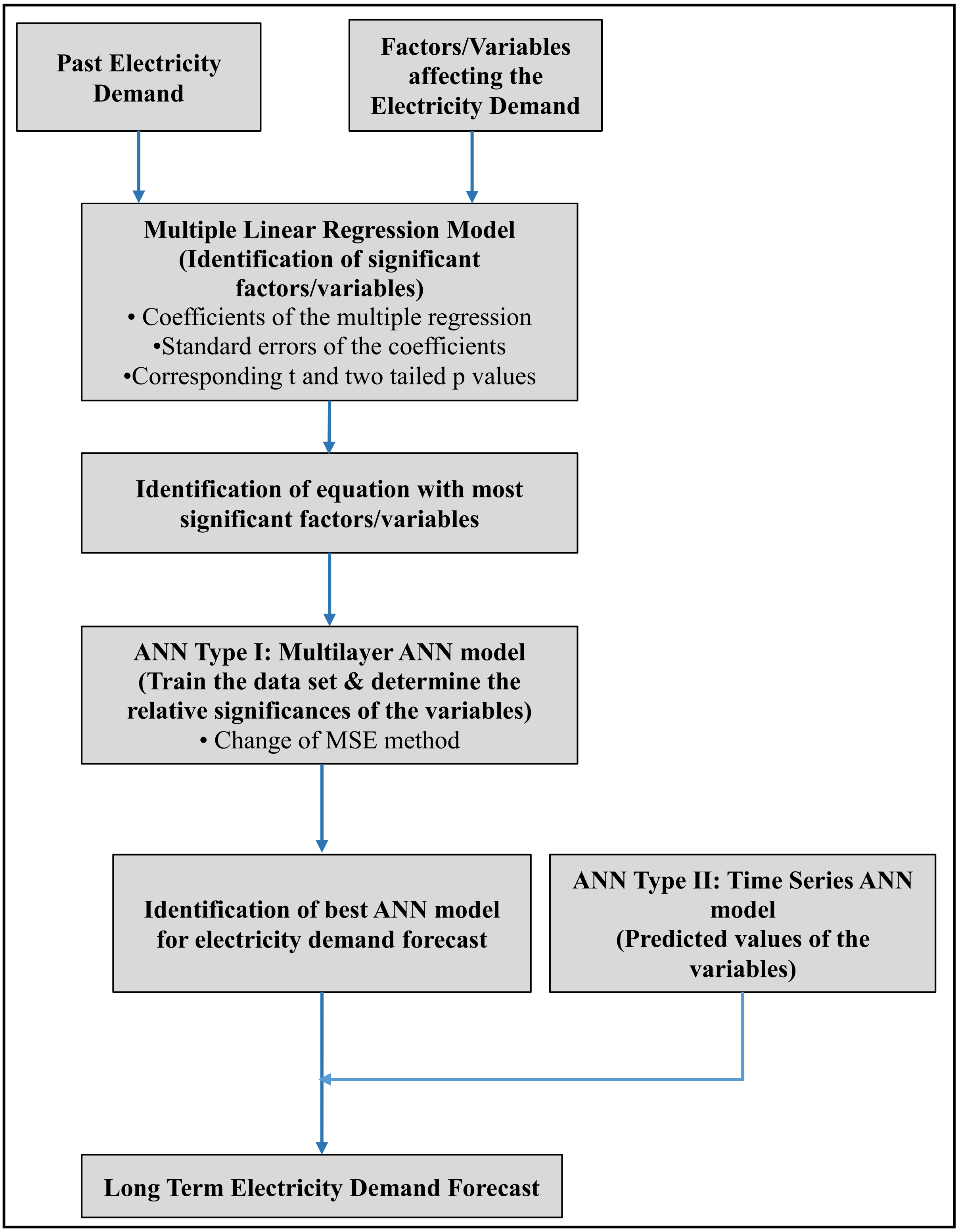

Figure 1.1 – Study Methodology

2.0 LITERATURE REVIEW

2.1 FACTORS INFLUENCE THE ELECTRICITY DEMAND

In order to forecast the electricity demand with a good precision, correct determination of the variables which influence the electricity demand in the country is very much crucial.

The growth in electricity consumption is linked with the growth in economy. Therefore, it is quiet common to consider main economic indicators in correlation with the electricity demand such as Gross Domestic Product (GDP) and Gross Domestic Product Per Capita (GDPPC) [3]. GDP refers to the total national income of the country while GDPPC refers to the wealth of the people living in a country.

Population is another key factor which is highly correlate with the electricity demand. More people with higher living standards will directly impact for more electricity consumption.

Another factor that has a possible effect on electricity consumption is the average electricity price [4]. If there are available alternatives to the electricity consumed in a country, the electricity demand is expected to be price elastic (an increase in price causes significant decline in the demand);otherwise, the demand is expected to be price inelastic(an increase in price causes only minor decline in the demand) [5].

The impact of electrical energy efficiency on electricity demand is worth studying due to the fact that various energy efficiency measures and energy efficient electrical equipments have been introduced in present context of Sri Lanka [6]. Energy Intensity is an indicator of the energy efficiency and is calculated as the total energy divided by GDP.

Electrification level of a country is the representation of percentage household electrified. Growth of electrification level will increase the total no. of electrified households and impact for the electricity demand variation [6].

Total no. of consumer accounts in tariff categories and its variation will directly impact for the electricity demand. Growth in no. of consumer accounts means the increase of no. of consumers/end users. More consumers with higher living standards and industrialized nature will directly impact for more electricity consumption.

The consumption of electricity may also depend on climatic conditions such as the average summer and winter temperatures [5]. For a tropical country like Sri Lanka, majority days of the year are hotter and more electricity will consume for cooling and refrigeration applications. Therefore, consideration of avg. temperature is important factor for electricity demand variation in Sri Lanka.

Addition to the above, in this study considered the average annual rainfall and annual relative humidity under the climatic conditions for analysis of electricity demand variation.

2.2 DETERMINING THE STATISTICALLY SIGNIFICANT VARIABLES FOR ELECTRICITY DEMAND

Selection of most significant variables out of identified factors is done based on the statistical approaches. In this research study, below mentioned statistical approaches are considered and the selection of statistically significant variables for electricity demand was done based on them [5].

2.2.1 Pearson Correlation Coefficient (r)

Correlation is a technique for investigating the relationship between two quantitative variables. Pearson correlation coefficient (r) is a measure of the strength of the association between the two variables. Correlation coefficient can take on any value in the range -1 to 1. The sign of the correlation coefficient indicates the direction of the relationship between two variables while the magnitude of the correlation indicates the strength of the relationship [7].

- Values of r close to 1 indicate variables that are positively correlated. As the value of x increases, the value of y tends to increase as well.

- Values of r close to -1 indicate variables that are negatively correlated. An increase in the x variable is associated with a decrease in the y variable. As the value of x increases, the value of y tends to decrease.
- Other values of r indicate variables that are uncorrelated. As the value of x increases, the value of y tends to remain unaffected.

If magnitude of the correlation coefficient r is:

- Greater than $|0.7|$, the variables are strongly correlated.
- Between $|0.33|$ and $|0.7|$, the variables are mildly/moderately correlated.
- Less than $|0.33|$, the variables are not correlated.

Pearson correlation coefficients (r) were analyzed to determine the degree of relationship between the identified variables and the electricity demand and will be discussed the results at a later section of the report.

2.2.2 Multiple Linear Regression (MLR)

Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation. The sample regression equation can be expressed as follows [8],

$$y = b0 + b1x1 + \cdots + bkxk$$

In this study, a multiple linear regression model applied on the entire data set was used to determine whether a particular descriptor variable was significant or not. The coefficients of the multiple regression model, standard errors, the corresponding t and two tailed p values were calculated using the “regstats” function of MATLAB and based on P-Value approach for significance testing, the variables with a two tailed value smaller than 0.05 were considered as statistically significant with a 95% confidence interval [7, 8]. The result of the multiple linear regression model is given in latter section of the report.

2.3 DETERMINING ARTIFICIAL NEURAL NETWORK (ANN) MODELS

An ANN is an information processing paradigm that is inspired by the way that biological nervous systems, such as the brain, process information [9]. It has great ability to approximate any nonlinear relationship that exists between a set of input variables and an output variable [4]. Further, ANNs are also proven to be very successful for time series modeling in which the future values of a variable is determined using its past values [9].

Major elements of ANNs consist of;

- Layers : Mainly three layers including Input layer (with input variables), Hidden layers and Output layer (with output variables)
- Neuron : Each neuron within the network is usually a simple processing unit which takes one or more inputs and produces an output
- Weight: At each neuron, every input has an associated weight which modifies the strength of each input
- Activation function and Learning Algorithm

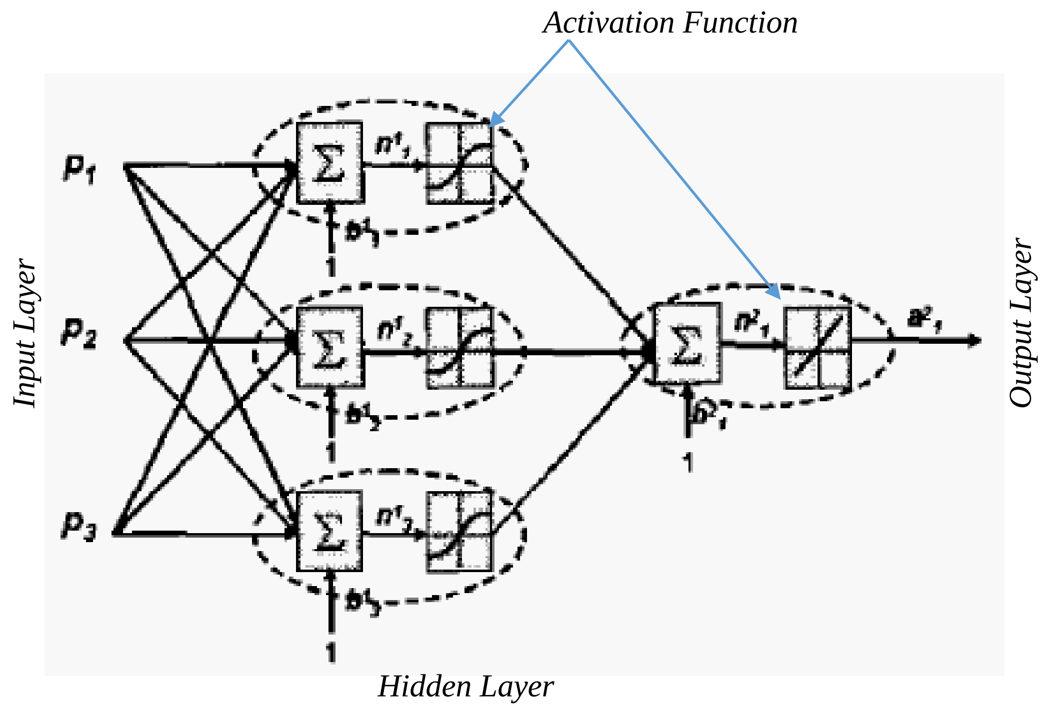

Figure 2.1 – Schematic Diagram of a Neural Network

In this study, ANN models are used for two different purposes;

- ANN Type I: The electricity demand is modeled as a function of the most significant descriptor variables (only the statistically significant variables are used as input variables in the final model)
  Different types of ANNs have evolved based on the neuron arrangement, their connections, and training paradigm used. Among the various types of ANNs, the multi-layer perceptron (MLP) has been proved to be most useful in engineering applications [10].
- ANN Type II: The future values of the statistically significant descriptor variables is determined by using time series ANN models , in which one particular variable in the year "t" was modeled as a function of its values in the past years [5].

ANN type I is trained by the "trainbr" function of MATLAB, which is a network training function that updates weight and bias values according to Levenberg–Marquardt optimization based on gradient descent and Gauss Newton iteration [11]. This training function uses Bayesian regularization and it was considered to be very suitable for obtaining a high generalization accuracy (extrapolating the results for the uncertain conditions) [12].

Further, ANN type II is trained by the "narnet" function of MATLAB which trained to predict a time series from the series past values.

In both ANN types, the Mean Squared Error (MSE) and R^2 were employed as the network performance parameter to determine the most accurate model and architecture.

Architecture selection of the two ANN models including input and output variables, number of hidden layers, hidden and output activation functions are discussed in respective sections of this report.

2.4 ADVANTAGES AND DISADVANTAGES OF ANN METHOD OVER THE CONVENTIONAL APPROACHES

ANN model the technique based on Artificial Intelligence for long term demand forecasting has advantages and disadvantages over the conventional demand forecasting approaches [13, 14]. Table 2.1 shows the summary of the comparison.

Table 2.1 – Advantages and Disadvantages of ANN Model and Conventional Approaches

Method	Advantage	Disadvantage
Conventional approaches	The relationships between input and output variables are easy to comprehend	Use of linear representation cannot provide adequate justification
	Provides detailed information on future levels of electricity demand, why future electricity demand increases and how electricity demand is affected by all the various factors	
Techniques based on AI	More accurate forecast	Training usually takes a lot of time
	Maintained accuracy for prolonged horizons	
	Ability to accommodate non-linear data	
	Ability of pattern recognition	
	One trained on initial set of patterns, recognition of similar pattern is accomplished very quickly	

3.0 ANALYSIS OF FACTORS AFFECTING TO THE LONG TERM ELECTRICITY DEMAND

As explained in the previous chapter, factors affecting to the electricity demand is important for the forecasting. Historical data of identified factors were analyzed with past electricity demand for the years between 1984 and 2015.

3.1 PAST DATA ANALYSIS

It has been noticed that the demand for electricity in Sri Lanka grows steadily and continuously over last 32 years. By end of year 2015, the total electricity demand of the country has grown to 11,786 GWh as shown in Figure 3.1.

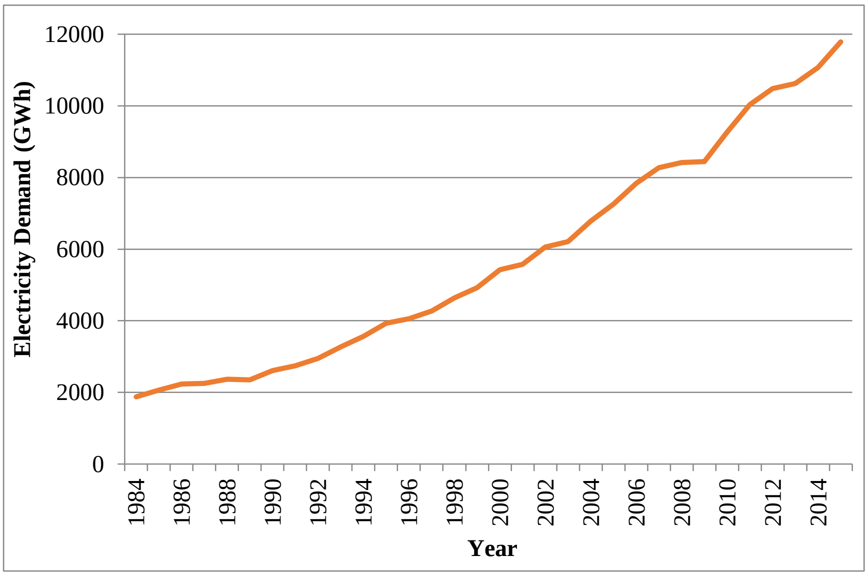

Figure 3.1 – Past Electricity Demand (GWh) 1984 – 2015

Source: Historical Data Book 1969-2009, Statistical Unit, Ceylon Electricity Board
Statistical Digests 2010-2015, Ceylon Electricity Board

For this study, estimated power cuts were considered in the past electricity data to determine the actual electricity demand. Scheduled rolling power cuts due to lack of generation has considered and the estimated power cut at the generation level for major power cut years are shown in Table 3.1 [20]. The generation level estimated power cuts were transferred to the demand side, by taking into account of total energy losses. After that, it has added to the total electricity demand of the respective years.

Table 3.1 – Estimated Power Cuts at Generation Level

Year	Power Cut (GWh)
1992	46.00
1996	381.00
2001	289.00
2002	525.00
2010	1.03
2011	6.42
2012	5.67
2013	2.01
2014	5.05

Main economic indicators, GDP and GDPPC are at 2010 constant factor prices for the period of 1984 to 2015 is shown in Figure 3.2 and 3.3. CBSL Annual Report 2015 indicates 2010 constant factor prices for the years starting from 2010. Past GDP values were available in constant 1982, 1996 and 2002 factor cost prices. Respective values based on 1982, 1996 and 2002 constant factor prices were updated to 2010 base considering their yearly growth rates in order to have a uniform base for the GDP values. Accordingly, it can be notice that the both indicators show exponential growth over the last 32 years.

Population values used in this study were the total end year population of Sri Lanka for each year during the period of 1984 to 2015 and an abrupt drop was observed in years 2001 and 2011, where an actual census has been carried out. The data was linearized using the average annual growth rate of 0.83% from 1991 to 2001 and 0.67% from 2002 to 2012. As shown in Figure 3.4, linear growth can be observed with approximately 0.9% average growth rate over the period of analysis.

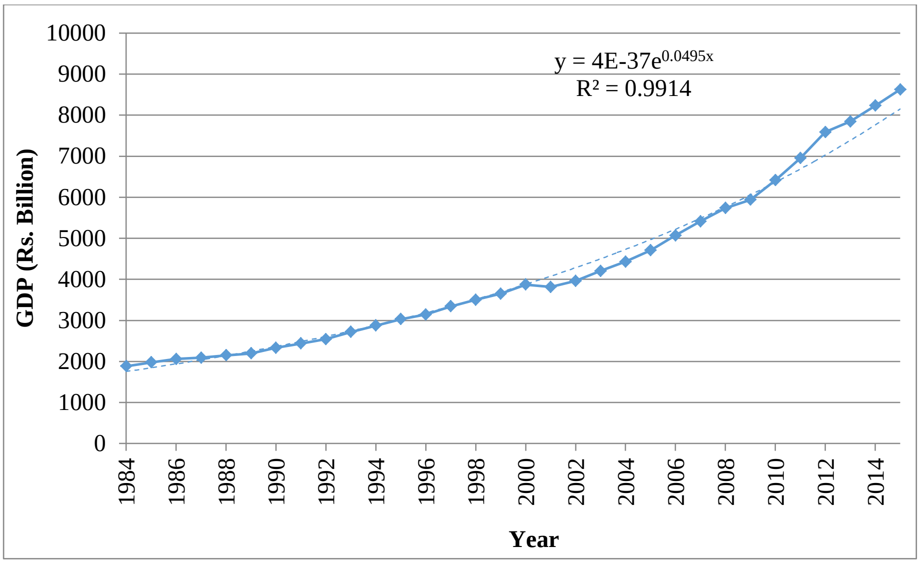

Figure 3.2 – GDP at 2010 FCP 1984 – 2015
Source: Annual Reports 1984-2015, Central Bank of Sri Lanka (CBSL)

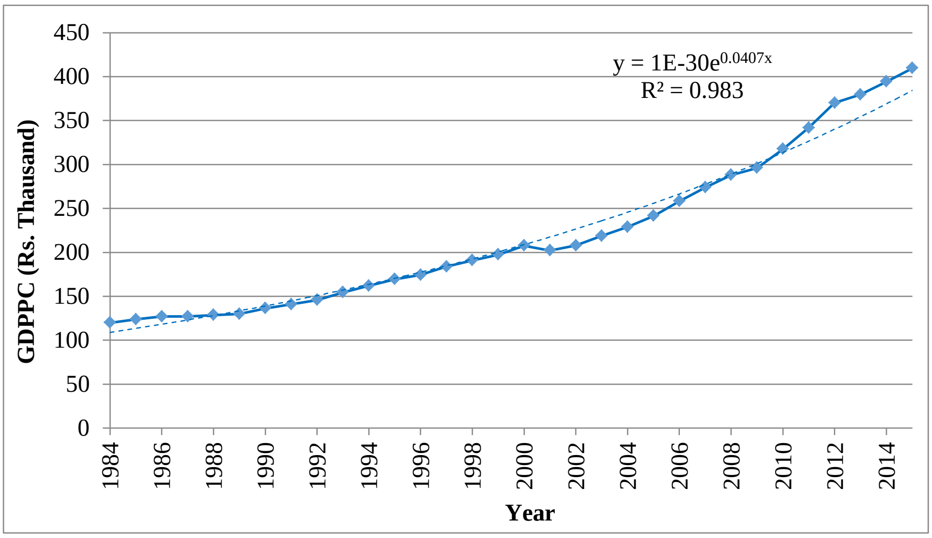

Figure 3.3 – GDPPC at 2010 FCP 1984 – 2015
Source: Annual Reports 1984-2015, Central Bank of Sri Lanka (CBSL)

Yearly average electricity prices for the period of 1984 to 2015 are in current terms converted in to real terms based on CCPI price index 2002 base. Accordingly, electricity price with current terms shows exponential growth but real prices with the currency inflation adjustments shows decreasing trend over the past 32 years as shown in Figure 3.5.

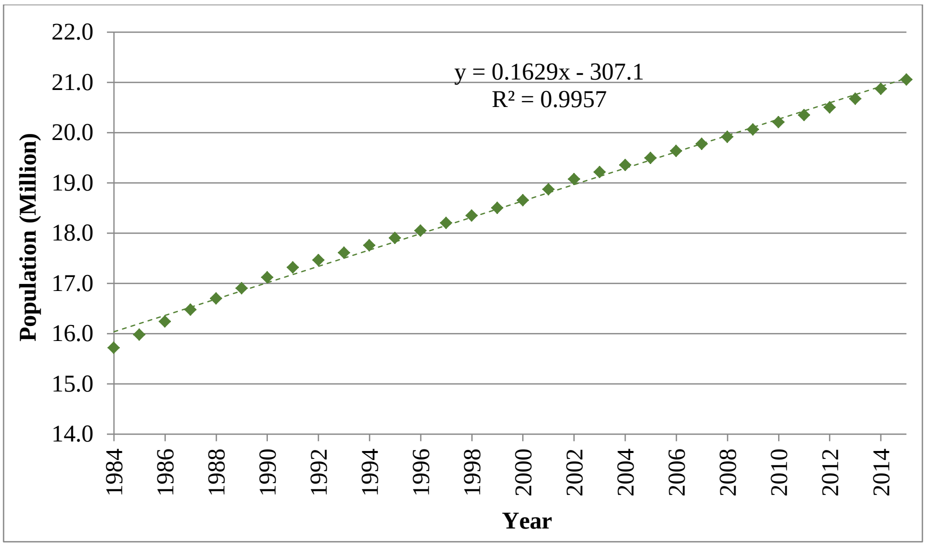

Figure 3.4 – Population 1984 – 2015

Source: Annual Reports 1984-2015, Central Bank of Sri Lanka (CBSL)

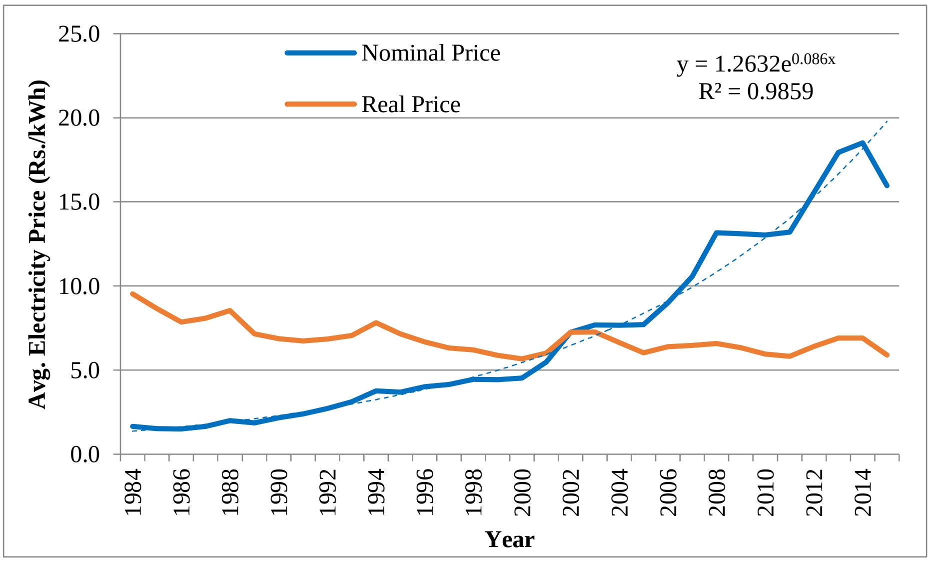

Figure 3.5 – Average Electricity Price (Nominal and Real) 1984 – 2015

Source: Statistic Reports 1984-2015, Ceylon Electricity Board

Electrification level of the country shows increasing trend over the last 32 years with the accelerated implementation of rural electrification projects. By the end of December, 2016, approximately 99% of the total population had access to electricity from the national electricity grid [2]. When the planned electrification schemes are implemented it is expected that this will increase further. Electrification Level shows 99% correlation and higher impact with no. of domestic consumer account variation. Therefore, it has considered the no. of consumer account as a factor in further analysis. Figure 3.6 and 3.7 shows the past data variation of electrification level, no. of domestic consumer account and total no. of consumer account.

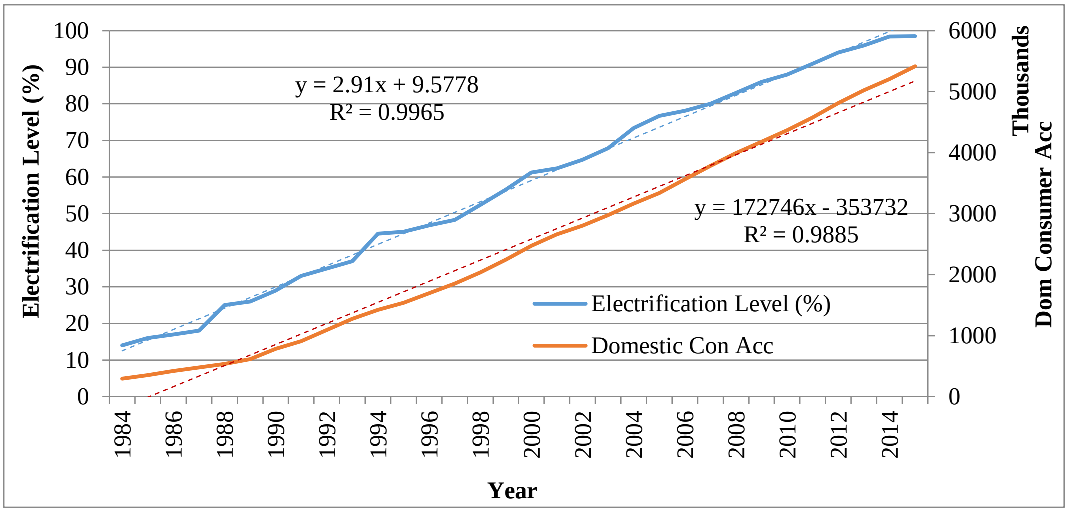

Figure 3.6 – Electrification Level and No. of Domestic Consumer Accounts1984 – 2015

Source: Historical Data Book 1969-2009, Statistical Unit, Ceylon Electricity Board

Statistical Digests 2010-2015, Ceylon Electricity Board

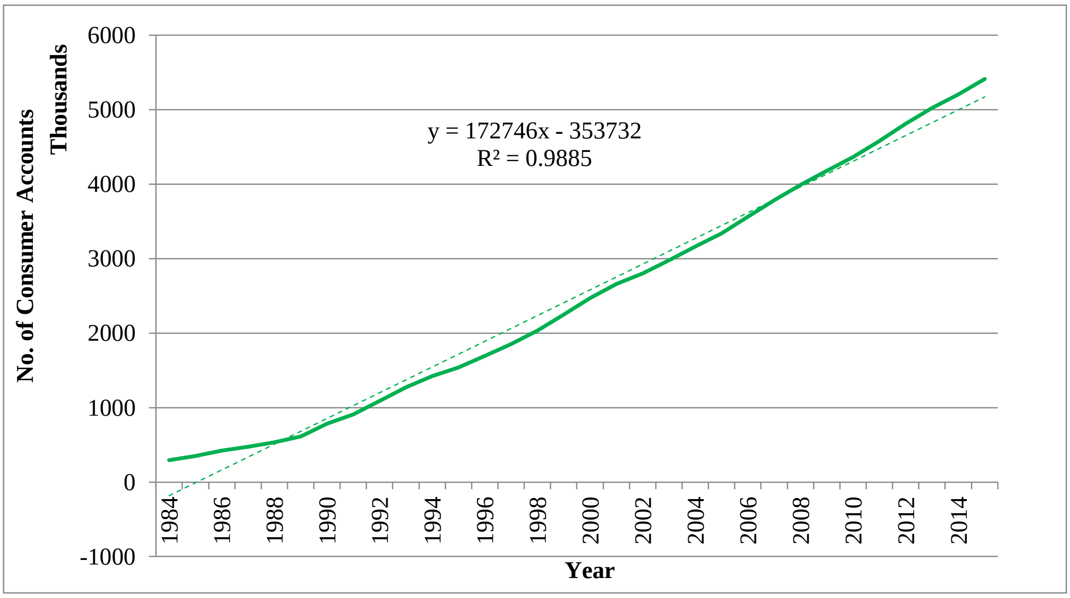

Figure 3.7 – Total No. of Consumer Accounts1984 – 2015

Source: Historical Data Book 1969-2009, Statistical Unit, Ceylon Electricity Board

Statistical Digests 2010-2015, Ceylon Electricity Board

For the temperature variation, average temperature at Colombo observation station is considered for the study. This has decided based on the analysis done considering Colombo daily electricity demand variation with daily maximum temperature and it is given in Appendix A. Figure 3.8 shows the annual average air temperature at Colombo observation station over last 32 year and increasing trend can be observed.

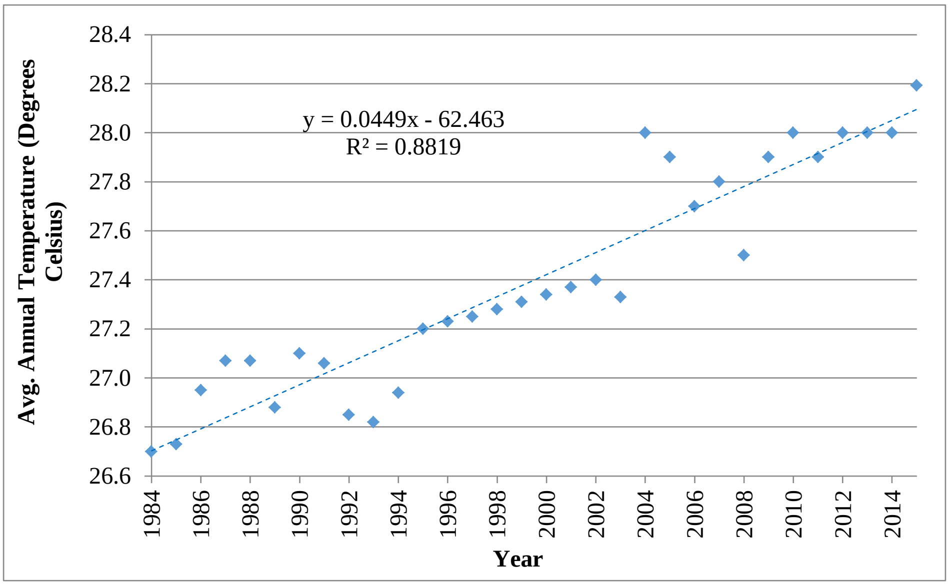

Figure 3.8 – Annual Average Temperature 1984 – 2015

Source:http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_download&menu=historical

Average annual rainfall variation of Sri Lanka over last 32 years is shown in Figure 3.9. Accordingly, throughout the period it lies within the range of 100mm – 180mm and doesn't show the considerable trend.

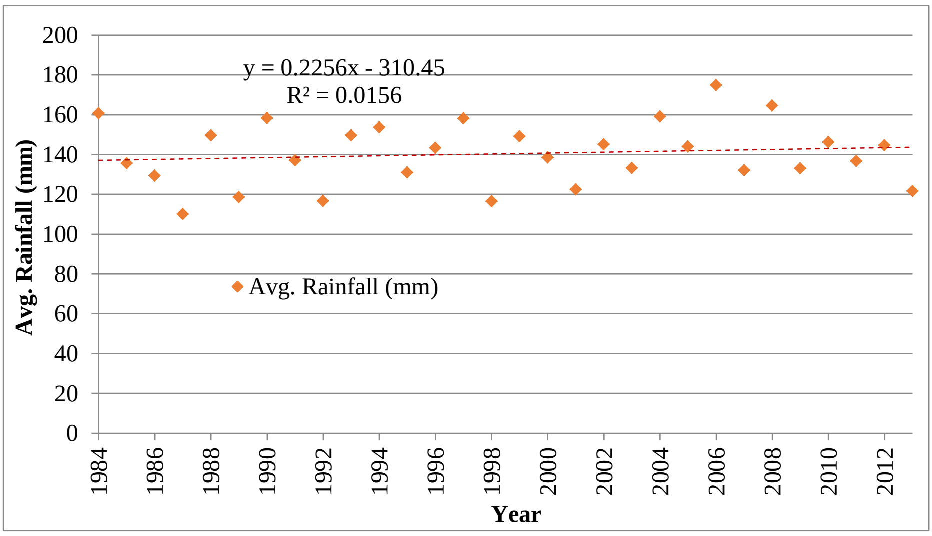

Figure 3.9 – Annual Average Rainfall 1984 – 2015

Source:http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_download&menu=historical

Annual relative humidity variation of Sri Lanka is shown in Figure 3.10 for the period of 2004 – 2013 according to the data availability. Accordingly, throughout the period it lies within the range of 85% – 90% and no particular trend was observed for this variable in this time period.

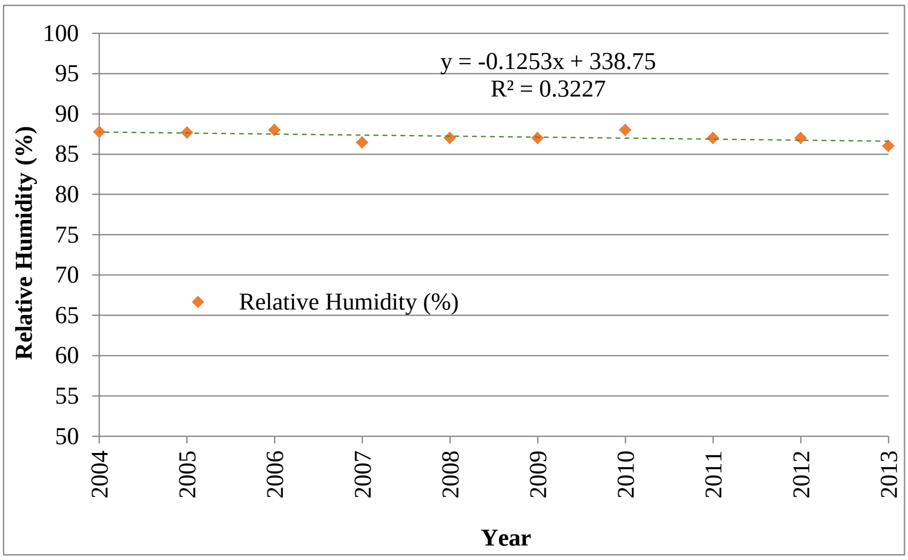

Figure 3.10 – Annual Relative Humidity 2004 – 2013

Source: Annual and monthly average relative humidity, 2004 – 2013, Department of Meteorology

Based on the past data analysis, correlation of these factors with past electricity demand was analyzed as shown in next section.

3.2 ELECTRICITY DEMAND CORRELATION WITH FACTORS

Pearson correlation coefficients were analyzed to determine the degree of relationship between past 32 years annual data of electricity energy demand & factors. Table 3.2 shows the analysis results with respective coefficients.

It was found that GDP, Population, GDP per capita, Avg. Annual Temperature, No. of Consumer Accounts and Previous Year Demand (Lag Demand) are strongly positively correlated with the electricity demand while Energy Intensity is moderately positively correlated with the electricity demand.

Further, the Avg. Electricity Price and Relative Humidity (%) are moderately negatively correlated while Avg. Rainfall is not correlated with electricity demand.

Table 3.2 – Correlation coefficients for the variables

Dependent Variable	Factors/Variables	Pearson Correlation Coefficient [r]	Result
Electricity Demand	GDP	0.990	Strong Positive Correlation
Electricity Demand	Population	0.968	Strong Positive Correlation
Electricity Demand	GDPPC	0.990	Strong Positive Correlation
Electricity Demand	Avg. Electricity Price	-0.609	Moderately Negative Correlation
Electricity Demand	Avg. Annual Temperature	0.926	Strong Positive Correlation
Electricity Demand	Energy Intensity (EI)	0.409	Moderately Positive Correlation
Electricity Demand	Avg. Rainfall	0.259	No Correlation
Electricity Demand	No. of Consumer Accounts	0.997	Strong Positive Correlation
Electricity Demand	Relative Humidity (%)	-0.559	Moderately Negative Correlation
Electricity Demand	Previous Year Demand (Lag Demand)	0.998	Strong Positive Correlation

Note: Electricity prices normally strongly correlated with electricity demand. But in Sri Lankan case the electricity tariff is highly controlled price and therefore doesn't show strong correlation. However, when consider about the electricity generation cost, it shows increasing trend over the years.

3.3 IDENTIFICATION OF MOST SIGNIFICANT FACTORS FOR ELECTRICITY DEMAND

It is recommended to determine the statistically significant factors affecting the electricity demand of a particular country before performing future predictions.

The data between the years 1984 and 2015 was used to construct the Multiple Linear Regression (MLR) model in the form as shown in equation below, where electricity demand is the dependent variable (with an estimated value of Y) while GDP (X_1), Population (X_2), GDP per capita (X_3), Avg. Annual Temperature (X_4), No. of

Consumer Accounts (X_5), Lag Demand (X_6), Energy Intensity (X_7), Avg. Electricity Price (X_8), Relative Humidity (X_9) and Avg. Rainfall (X_{10}) were the independent (descriptor) variables.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10}$$

The final equation for the MLR model is given in equation below while the regression coefficient (β) of each variable, the standard errors, the t values and the two tailed p values of the coefficients are summarized in Table 3.3. The statistical significance of each variable was determined by inspecting on their p values (P-Value approach); those variables with a two tailed p value lower than 0.05 was accepted as statistically significant (with a 95% confidence interval) as discussed in Chapter 2.

It was found that GDP per capita (X_3), No. of Consumer Accounts (X_5), Energy Intensity (X_7), Avg. Electricity Price (X_8), Relative Humidity (X_9) and Avg. Rainfall (X_{10}) were not statistically significant according to this criterion.

Table 3.3 – Parameters of initial MLR model for Estimating Annual Electricity Demand

Variables	β	SE (β)	t Value	p Value
Constant	-13.28	5.40	-2.46	0.021
GDP	0.26	0.15	2.70	0.045
Population	0.17	0.09	2.85	0.046
Avg. Annual Temperature	0.40	0.21	2.91	0.048
Lag Demand	0.72	0.13	5.68	0.000
GDPPC	0.65	0.39	1.72	0.098
Avg. Electricity Price	-0.07	1.76	-1.18	0.250
No. of Consumer Accounts	0.01	0.00	0.41	0.687
Avg. Rainfall	0.08	0.05	1.05	0.605
Relative Humidity	0.07	0.04	1.25	0.801
Energy Intensity	0.03	0.07	1.15	0.785

The final equation for the full MLR model is as follows.

$$Y = -13.28 + 0.26X_1 + 0.17X_2 + 0.65X_3 + 0.40X_4 + 0.01X_5 + 0.72X_6 + 0.03X_7 - 0.07X_8 + 0.07X_9 + 0.08X_{10}$$

Then, a reduced model excluding the insignificant variables was constructed, using GDP in trillion rupees (X_1), Population in million (X_2), Avg. Annual Temperature in Celsius (X_4) and Lag Demand in TWh (X_6) as the independent variables. The final equation for the reduced MLR model is as follows and the regression coefficient (β) of each variable, the standard errors, the t values and the two tailed p values of the coefficients are summarized in Table 3.4.

$$Y = -13.28 + 0.26X_1 + 0.17X_2 + 0.40X_4 + 0.72X_6$$

Table 3.4 – Parameters of final MLR model for Estimating Annual Electricity Demand

Variables	β	SE (β)	t Value	p Value
Constant	-13.28	5.40	-2.46	0.021
GDP	0.26	0.15	2.70	0.045
Population	0.17	0.09	2.85	0.046
Avg. Annual Temperature	0.40	0.21	2.91	0.048
Lag Demand	0.72	0.13	5.68	0.000

As it is shown in Table 3.3, the two tailed p values of all the variables were found to be lower than 0.05 meaning that all of them were statistically significant for electricity demand. After that, the coefficients of MLR model were examined and the results were found to be consistent with what was expected; such that, GDP, Population, Avg. Annual Temperature and Lag Demand were directly proportional with the electricity demand (positive coefficients).

4.0 ARTIFICIAL NEURAL NETWORK (ANN) MODEL DEVELOPMENT FOR ELECTRICITY DEMAND FORECAST

4.1 INTRODUCTION

As discussed in the chapter 2, first ANN model is developed for electricity demand forecasting by statistically significant descriptor variables which were selected based on MLR model as described in previous chapter.

ANN network type and learning algorithm was selected based on literature review which are popular for the predictions. Then ANN architecture was selected with number of hidden layers, number of hidden neurons and hidden and output activation functions.

4.2 DETERMINATION OF BEST ANN STRUCTURE

In order to determine best ANN architecture, the testing of several possible architectures with the best generalizing ability is required. First ANN is trained with inputs and output and then it is verified. In this study ANN is trained with 25 years (1984 – 2008) past data and verified with next 7 years (2009 – 2015) actual data. From the training it is expected to find the best ANN architecture weight values and bias values. Then with the identical ANN architecture, weight & bias values electricity demand is forecast for the verifying years.

Main factors of ANN development;

- Network Model : Multilayer Feed Forward Neural Network
  Figure 4.1 shows the Multilayer Feed Forward Neural Network with an input layer of source neurons, one or more middle or hidden layer of computational neurons, and an output layer of computational neurons. The input layer accepts input signals from the outside world and redistributes these signals to all neurons in the hidden layer. The hidden layer detects the feature. The weights of the neurons in the hidden layers represent the features in the input

patterns. The output layer establishes the output pattern of the entire network [16].

The function of the network shown in Figure 4.1 can be described as follows:

$$Yj \ = f \ (\sum_i wijXij + b)$$

Where Yj is the output of node j, f (.) is the transfer function, wij the connection weight between node j and node i in the lower layer, Xij is the input signal from the node i in the lower layer to node j and b is the bias value.

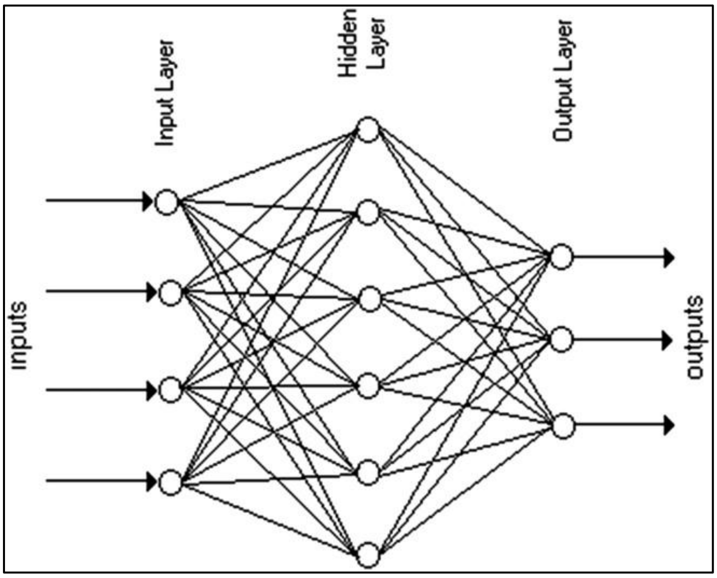

Figure 4.1 – Multilayer Feed Forward Artificial Neural Network

Source: Ekonomou, L. "Greek long-term energy consumption prediction using artificial neural networks." Energy 35.2 (2010): 512-517

- Leaning Algorithm : Levenberg–Marquardt Back Propagation Algorithm

  More than a hundred different learning algorithms are available, but the most popular one is the back propagation. In a back propagation neural network, the learning algorithm has two phases. First a training input data set is presented to the network input layer. The network then propagates the input data set from layer to layer until the output data set is generated by the output layer. If this data set is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated.

This is very important since;

- Faster & advanced training algorithm [17]
- High generalization accuracy
- Good for small and medium size networks

- Network Training Function

  "Trainbr" is the network training function that updates the weight and bias values according to Levenberg–Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization.

Based on the above factors, input variables (GDP, Population, Avg. Annual Temperature and Lag Demand), output variable (Electricity Demand) and activation functions, several ANN models have developed and summary of the results are shown in Table 4.1.

Table 4.1 – Summary of ANN model structures and results

Model No.	Network Structure	R^2	Mean Squared Error (Validation Part)
1	4–10–1	0.999	0.045
2	4–13–1	0.999	0.013
3	4–15–1	0.999	0.029
4	4–20–1	0.999	0.073
5	4–30–1	0.999	0.014
6	4–50–1	0.999	0.053
7	4–100–1	0.999	0.045
8	4-125-1	0.967	0.080
9	4–13-10-1	0.999	0.045
10	4–15–15–1	0.998	0.055

As discussed in the Chapter 2, Mean Squared Error (MSE) and R^2 were employed as the network performance parameter to determine the most accurate ANN model and architecture.

Accordingly after trying different neural network structures, the optimal neural network structure was found as 4-13-1 (4 inputs, 13 neurons in the hidden layer and 1 output) with the activation functions of “Tangent Sigmoid” function for the hidden layer and “Pure Linear” function for the output layer.

Figure 4.2 shows the ANN model schematic diagram in MATLAB with four inputs, thirteen neurons with one hidden layer and one output.

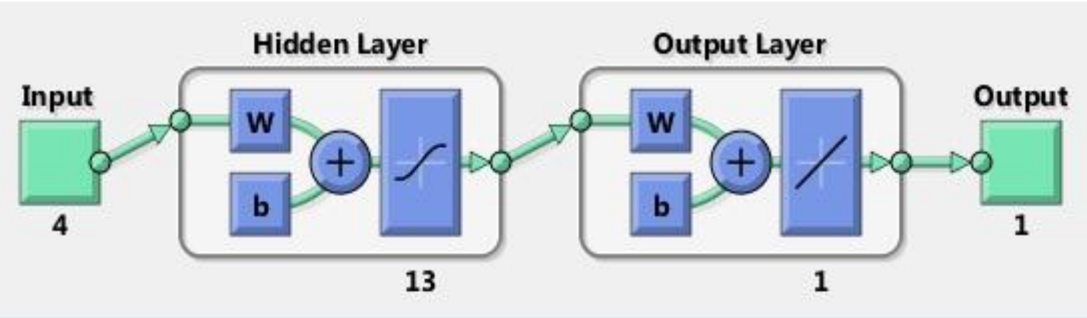

Figure 4.2 – Final ANN Model Structure in MATLAB

Table 4.2 and Figure 4.3 show the finalized ANN structure for electricity demand forecasting.

Table 4.2 – Final ANN Model Structure for Electricity Demand Forecasting

Description	ANN Structure
Total no. of Inputs	4
No. of hidden layers	1
No. of hidden neurons	13
Activation function of hidden layer	Tan-Sigmoid
Activation function of output layer	Pure linear
Training function	trainbr

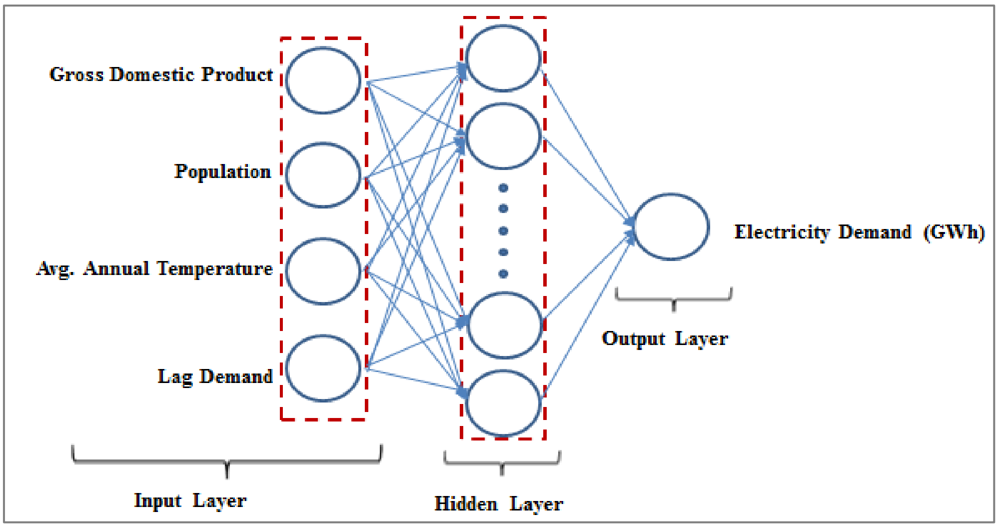

Figure 4.3 – Final ANN Model Structure

4.3 TRAINING AND VALIDATION OF ANN STRUCTURE

As discussed in Section 4.2, ANN is trained with 25 years past data of input variables (GDP, Population, Avg. Annual Temperature and Lag Demand) and the output variable (Electricity Demand). Figure 4.4 shows the comparison of ANN model training output (which is the electricity demand) and actual electricity demand for the period of 1984 – 2008.

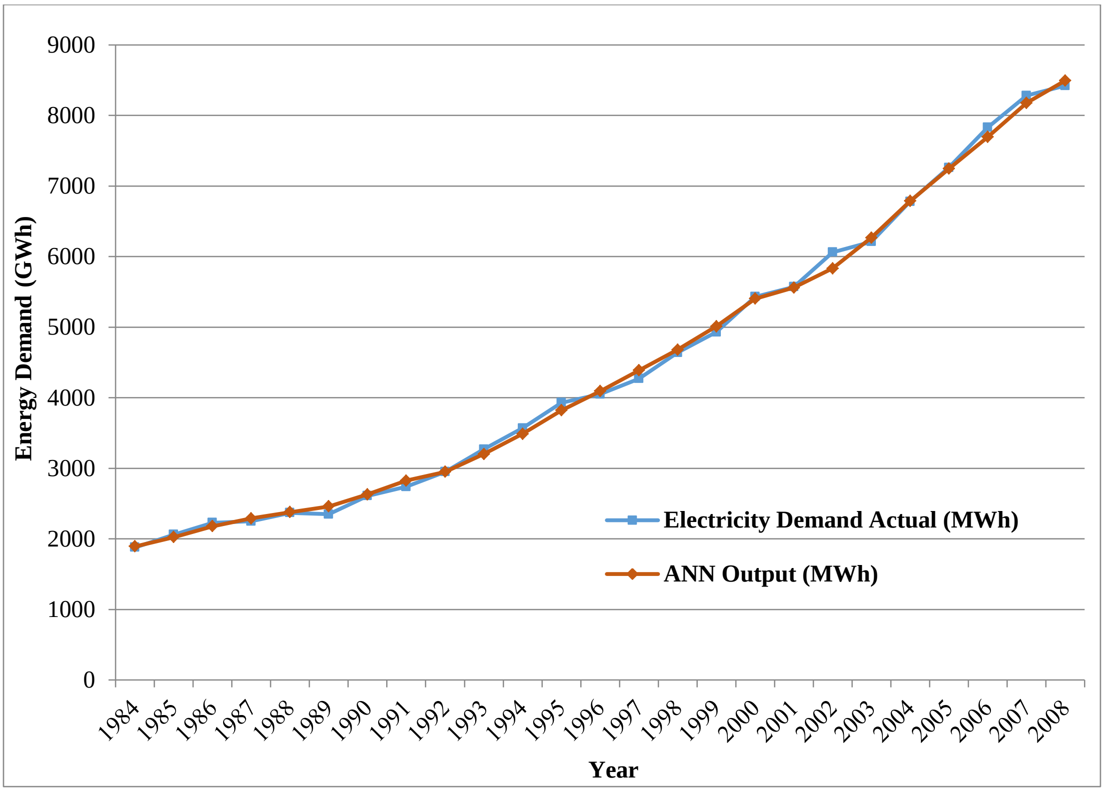

Figure 4.4 – Comparison of ANN Demand Output and Actual Demand

The percentage error between actual electricity demand and ANN computed final electricity demand for the period of 1984-2008 given by below equation is approximately 0.03% which also clearly implies that the proposed ANN model is well working and has an acceptable accuracy. Then ANN model has validated for the period of 2009 – 2015 and compared the ANN model electricity demand output with the actual electricity demand.

$$\mathrm{PE}(\%) = \frac{\mathrm{ED_{actual}} - \mathrm{ED_{ANN\ output}}}{\mathrm{ED_{actual}}} \, .100\%$$

Here the PE is the percentage error, $\mathrm{ED_{actual}}$ is the actual electricity demand and $\mathrm{ED_{ANN\ output}}$ is the computed electricity demand from ANN model.

As per the Figure 4.5, developed ANN model structure is validated by forecasting the electricity demand from 2009 to 2015 and compared it with the actual electricity demand for the same period. The percentage error between actual electricity demand

and ANN model output is approximately 0.09% which also shows an acceptable accuracy.

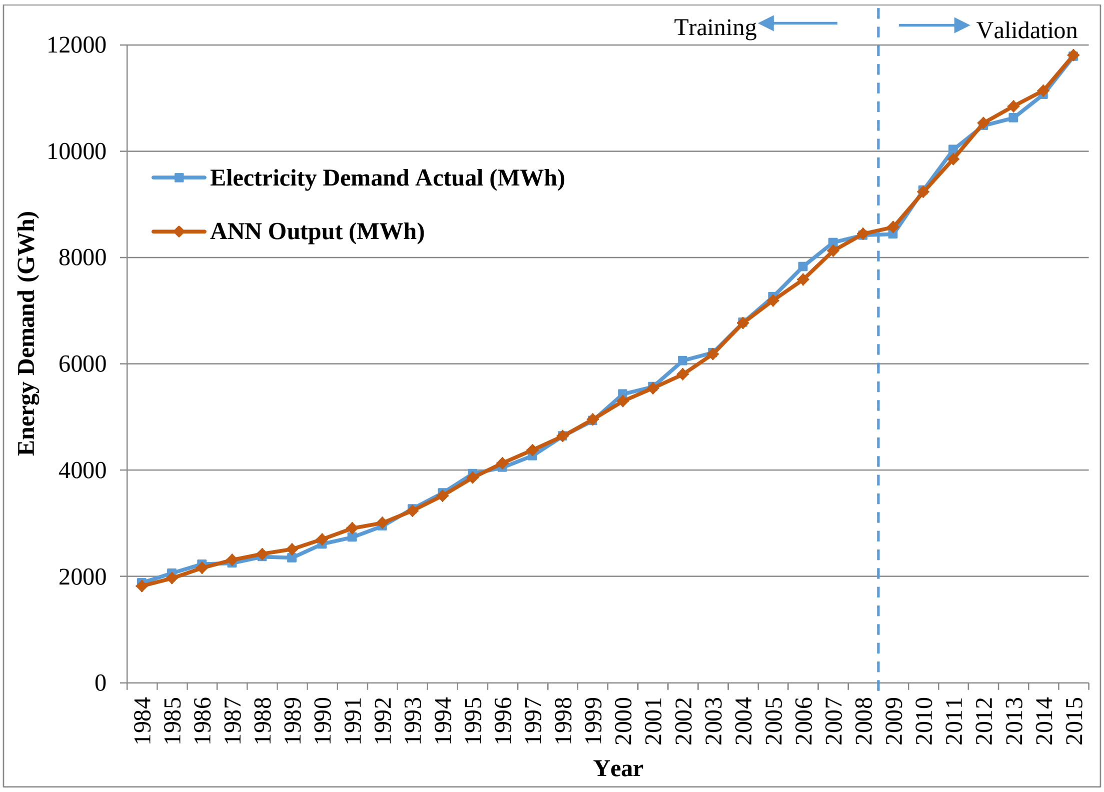

Figure 4.5 – Validation of ANN Demand Output and Actual Demand

Accordingly, developed ANN model structure is considered for the electricity demand forecasting and long term demand forecast results based on this is discussed latter part of the report.

5.0 TIME SERIES ARTIFICIAL NEURAL NETWORK (ANN) MODEL DEVELOPMENT FOR THE PREDICTIONS OF SIGNIFICANT FACTORS

5.1 INTRODUCTION

In this study, second ANN model is developed to determine the future values of statistically significant descriptor variables in which one particular variable in the year "t" was modeled as a function of its values in the past years. ANN models separately developed for the input variables and ANN architecture was selected with number of hidden layers, number of hidden neurons and hidden and output activation functions.

5.2 DETERMINATION OF BEST ANN STRUCTURES

Time series ANN model is consist of input layer, one or more hidden layers and the output layer. Nonlinear autoregressive neural network with "narnet" function of MATLAB is used to train and predict the time series data from the series of past values. This has main two steps;

- Open loop mode - Value of a particular variable in the year model as a function of its literature values in the past years
- Closed loop mode - Value of a particular variable in the next year determine as a function of feedback and past values

Accordingly, the networks were trained in open loop mode, where the value of a particular variable in the year "t" was modeled as a function of its literature values in the past years. Then, for determining the forecasting ability of the networks, a closed loop simulation was implemented; such that, the first value of the variable in the year "t" was determined as a function of its past values, then, the predicted value was fed back to the network to determine another value corresponding to one step in the future [5]. Repeating this procedure year by year, it was possible to get into the future years, where no literature data was available; hence, the corresponding future values of the variable could be determined by its past predicted values.

Figure 5.1 and 5.2 indicates the open loop and closed loop neural network schematic diagrams in MATLAB with one input layer, one hidden layer with 15 nos. of neurons and one output layer.

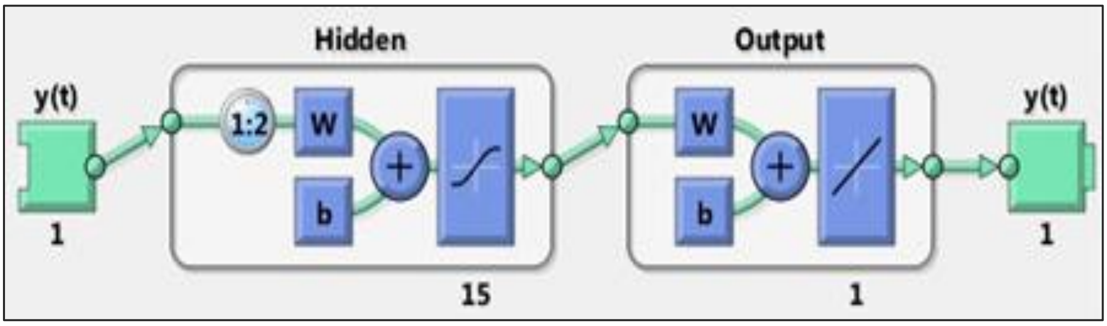

Figure 5.1 – Open Loop ANN Model

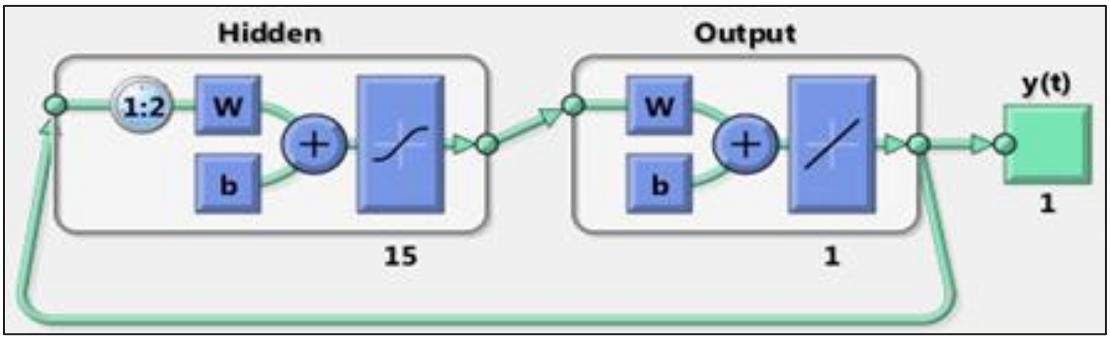

Figure 5.2 – Closed Loop ANN Model

Time Series ANN is trained based on above and then forecast is verified with the actuals. In this study ANN is trained with 25 years (1984 – 2008) past data of each variable and verified with next 7 years (2009 – 2015) actual data. As discussed in the Chapter 2, Mean Squared Error (MSE) and R^2 were employed as the network performance parameter to determine the most accurate ANN model and architecture.

In this study, time series ANN models are developed only for three variables GDP, Population and Avg. Annual Temperature. Future values of lag demand is taken as the previous year total electricity demand which is the output of electricity demand forecast ANN model.

Figure 5.3 and 5.4 show the open loop and closed loop mode neural networks schematic diagrams which considered determining the GDP in the future from its past values.

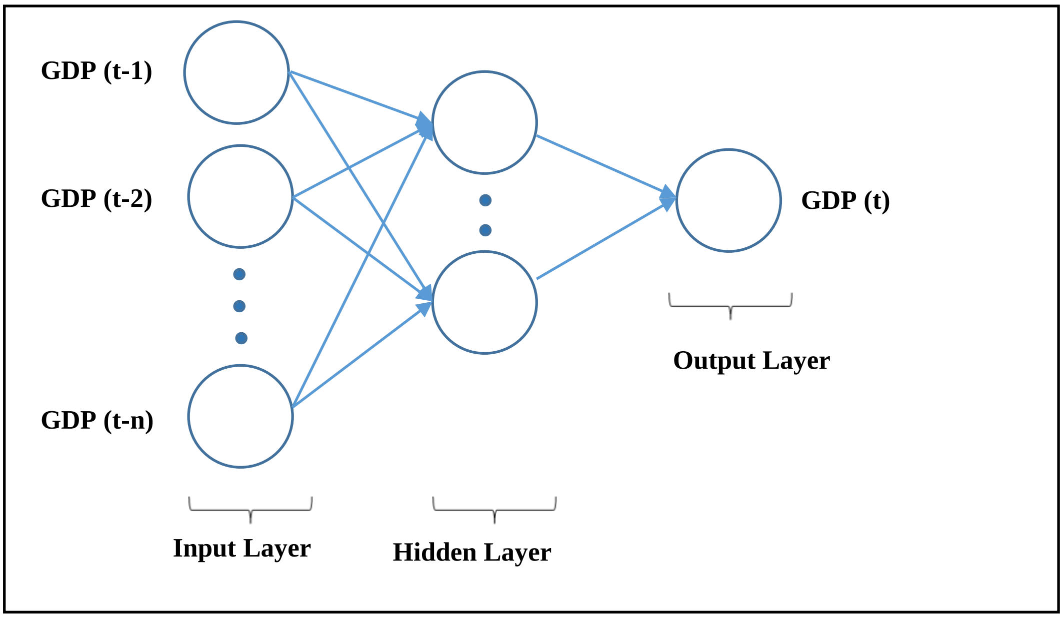

Figure 5.3 - Time Series ANN to determine the GDP in the future from its past values (in open loop mode)

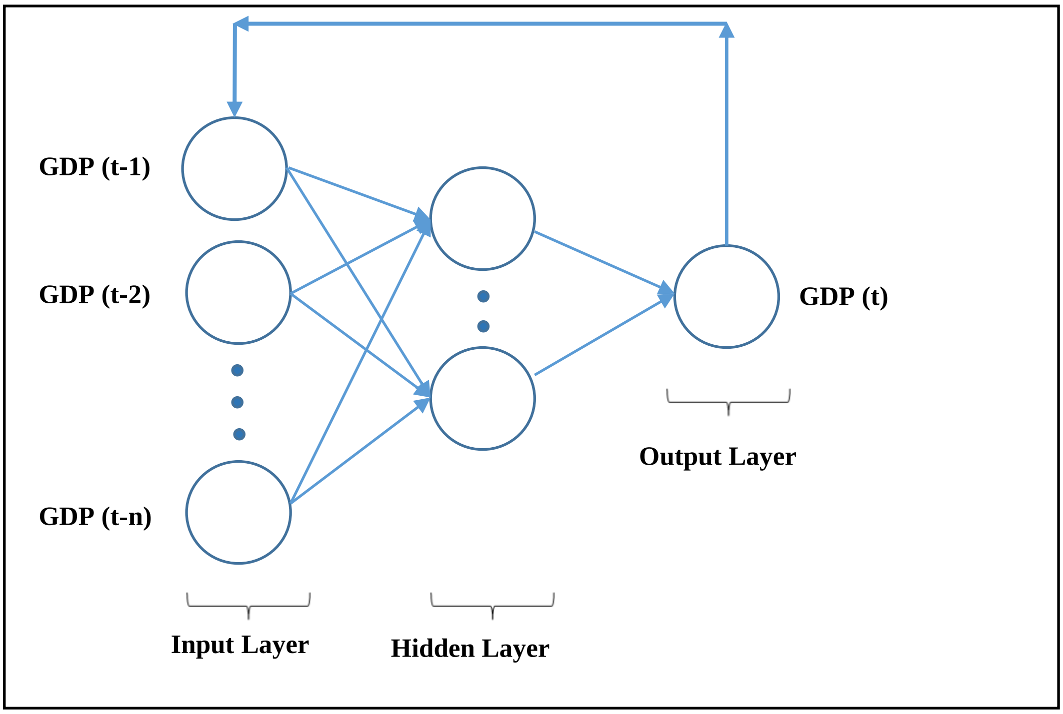

Figure 5.4 - Time Series ANN to determine the GDP in the future from its past values (in closed loop mode)

Developed time series ANN models for GDP, Population and Avg. Annual Temperature and summary of the results are shown in Table 5.1.

Table 5.1 – Summary of ANN model structures and results

Variable	No.of Hidden Layers	No. of Neurons	R^2	Mean Squared Error (Validation Part)
GDP	1	10	0.999	0.035
Population	1	15	0.999	0.023
Avg. Annual Temperature	1	17	0.999	0.018

5.3 TRAINING AND VALIDATION OF ANN STRUCTURES

Data corresponding to the years between 2009 and 2015 were excluded from the dataset, and the statistically significant descriptor variables (GDP, Population and Avg. Annual Temperature) were predicted for the years 2009 – 2015 from their past data by using time series ANN models. It should be noted that time series modeling of all three variables were modeled as a function of the last 25 years to get the successful trends.

Figure 5.5, 5.6 and 5.7 show the closed loop performance of the time series ANN models for forecasting the GDP, Population and Avg. Annual Temperature. The ANN model successfully estimated the values corresponding to the past (1984 – 2008) and predicted the values of the future (2009 – 2015) for three variables as indicated by the high coefficient of determination (R^2) values.

The percentage error between actual GDP and time series ANN model future prediction is 0.96% which shows an acceptable accuracy. Actual population and time series ANN model population future prediction shows 0.004% variation with higher accuracy. Also, actual average temperature and forecast from ANN model shows 0.003% error with higher accuracy.

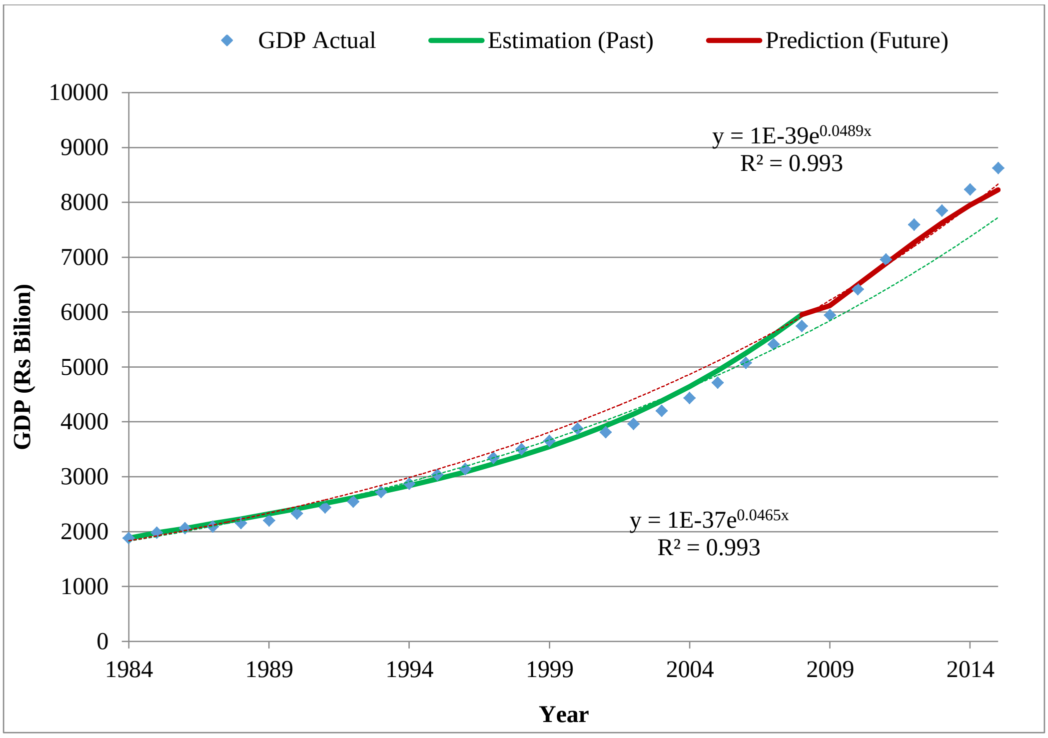

Figure 5.5 – GDP: Past Estimation and Future Prediction using time series ANN model

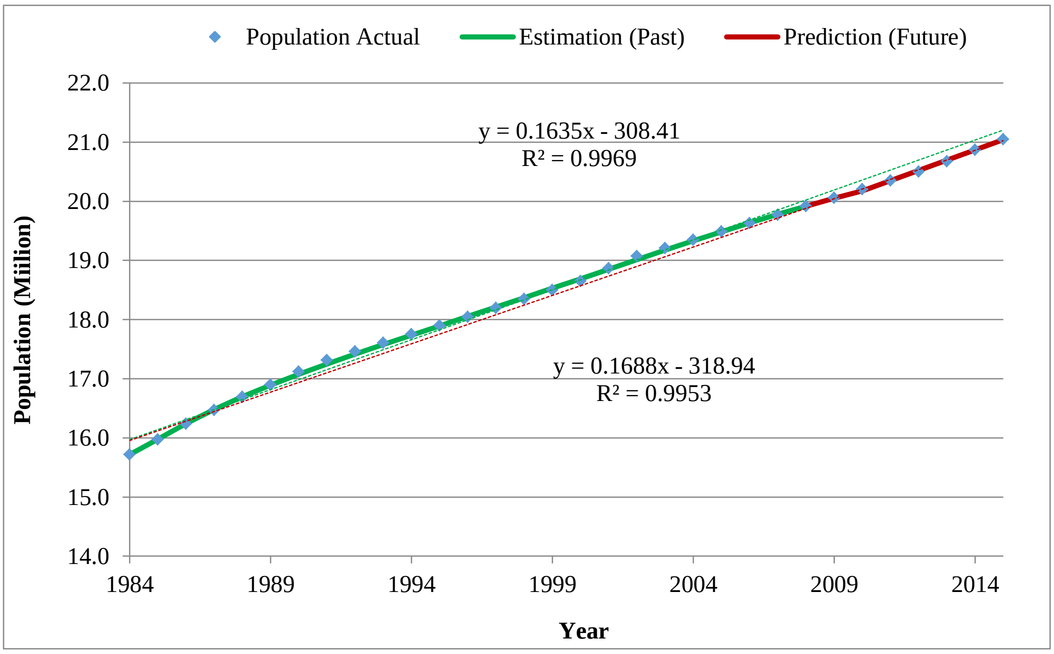

Figure 5.6 – Population: Past Estimation and Future Prediction using time series ANN model

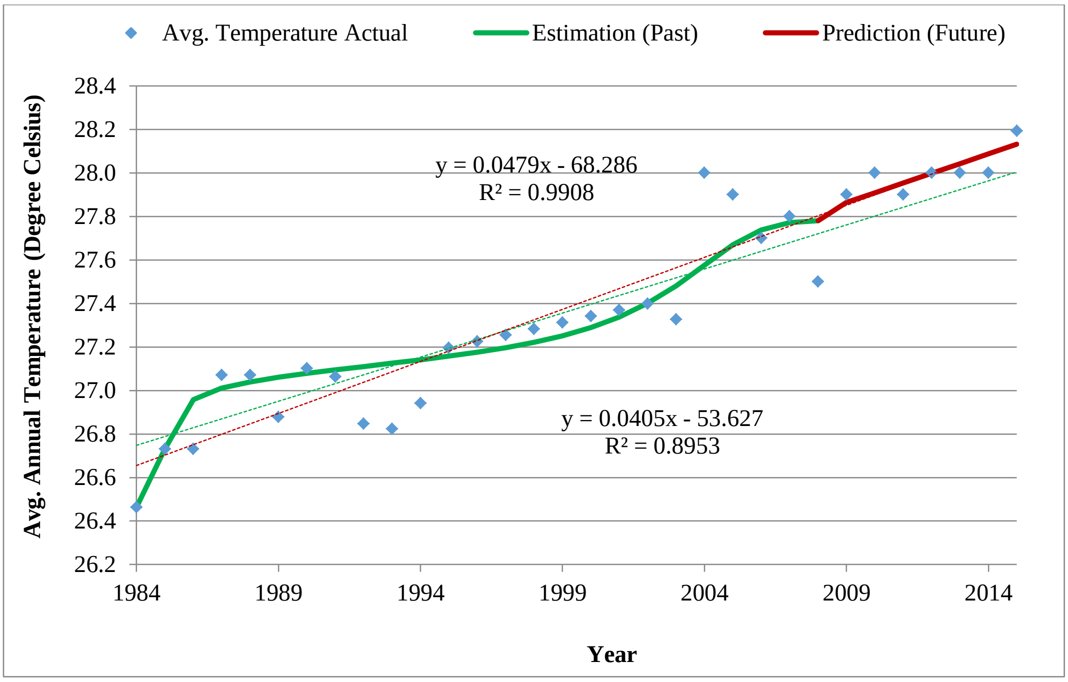

Figure 5.7 – Avg. Annual Temperature: Past Estimation and Future Prediction using time series ANN model

Accordingly, developed time series ANN model structures for GDP, Population and Avg. Annual Temperature are considered for the future predictions of these factors and long term demand forecast results based on this is discussed latter part of the report.

6.0 RESULTS

Use of ANN for long term electricity demand forecasting and the results for immediate past with validation and long term electricity demand forecast is discussed in this section.

6.1 ACTUAL AND FORECAST OF ELECTRICITY DEMAND 2009-2015 COMPARISON

To determine the accuracy of demand forecast by use of time series ANN model outcomes and multilayer ANN model, it has compared the actual and forecast of electricity demand for the 2009-2015 period.

Accordingly, the predicted values of the GDP, population and average annual temperature for the years 2009-2015 from time series ANN model were used and simulated by multilayer ANN model to forecast the electricity demand for these years. The demand prediction of the ANN model is compared with the actual values as shown in Figure 6.1, which indicates the 0.06% error with actual and good accuracy for the forecast.

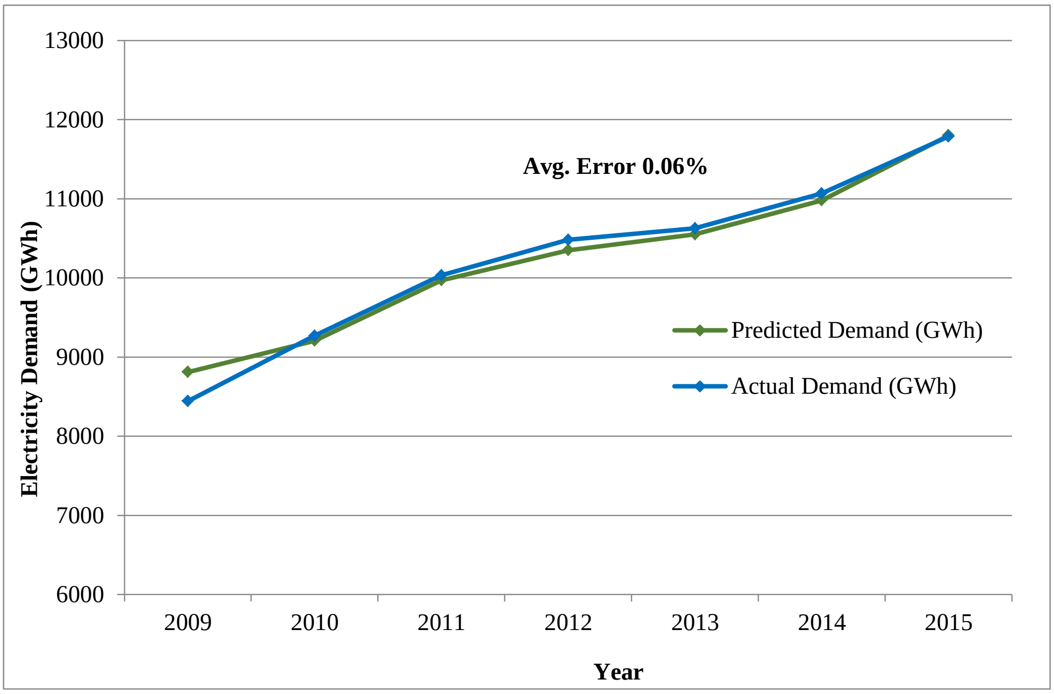

Figure 6.1 – Comparison of Actual and Prediction 2009-2015

6.2 SIGNIFICANT VARIABLE FORECAST 2017-2037

In this part of the work, future values of GDP, population and average annual temperature in the years between 2017 and 2037 were predicted by time series ANN models with the same neural network parameters that were used in Chapter 5. The variation of three variables through years is shown in Figure 6.2, 6.3 and 6.4.

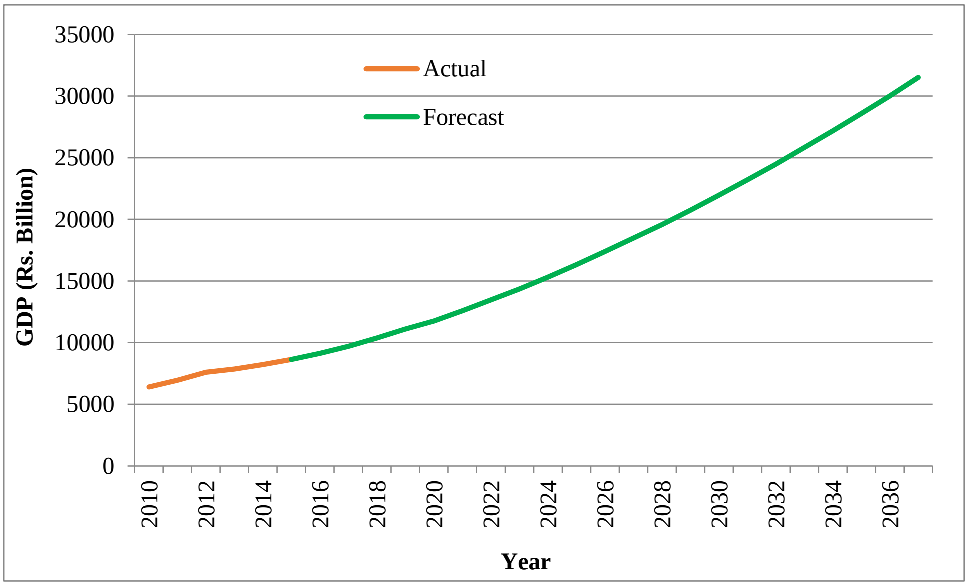

Figure 6.2 – GDP Forecast 2017-2037 using Time Series ANN Model

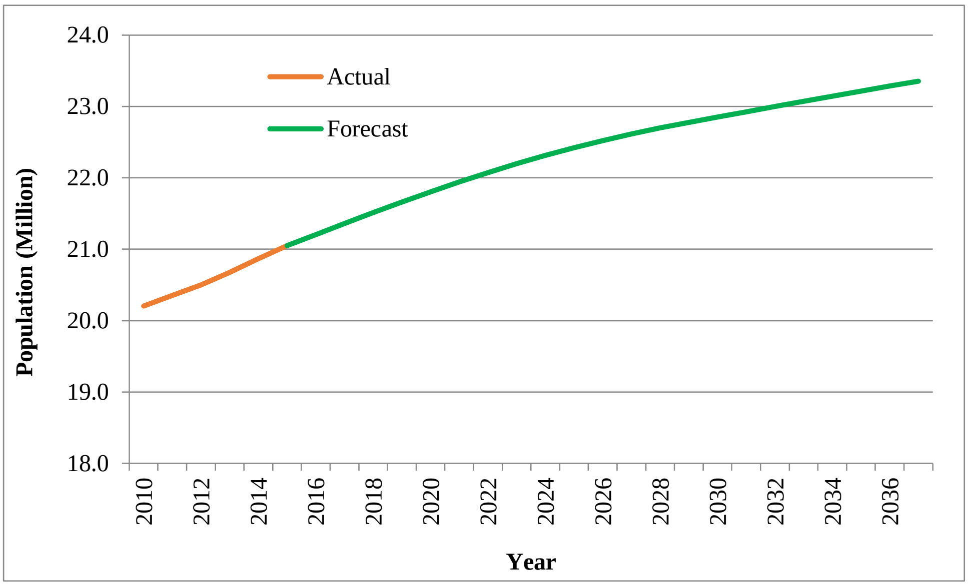

Figure 6.3 – Population Forecast 2017-2037 using Time Series ANN Model

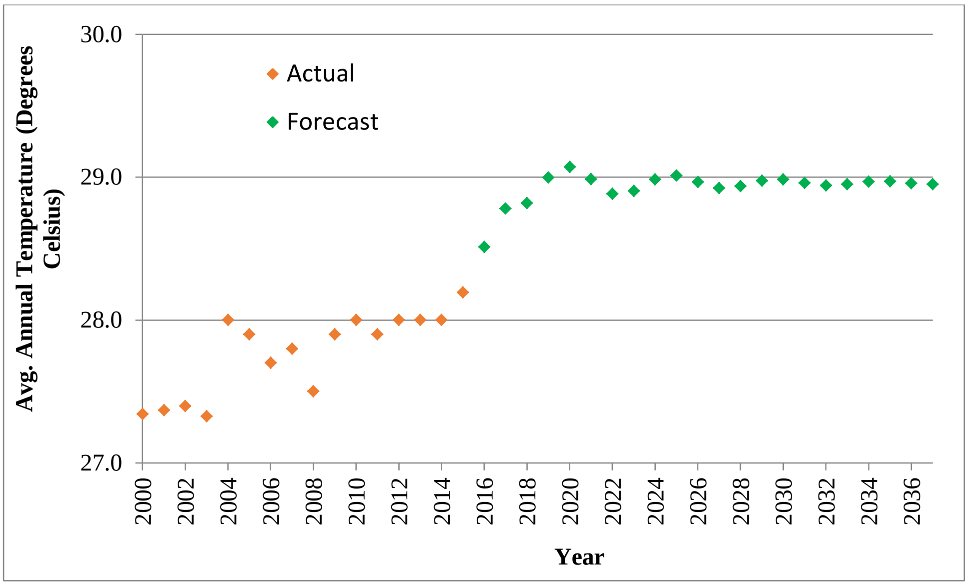

Figure 6.4 – Avg. Annual Temperature Forecast 2017-2037 using Time Series ANN Model

For initial years up to 2019, CBSL published GDP growth rates were considered and calculated accordingly. Beyond 2019, GDP forecast is based on time series ANN model and the Figure 6.2 indicates that the GDP is expected to reach over Rs. 30,000 billion in the year 2037.

Figure 6.3 shows the Population prediction and it is expected to reach over 23 million in the year 2037, while the population forecast available in the Department of Census and Statistics (DCS) shows 24 million in 2037.

Average annual temperature is predicted to increase by about 0.9°C in this 20 year period as shown in Figure 6.4. Fourth variable which is the Lag Demand (Past Year Demand) doesn’t required separate future prediction and immediate last year demand data is taken for the current year.

6.3 LONG TERM ELECTRICITY DEMAND FORECAST 2017-2037

As discussed in Chapter 4, the data from the year 1984 to 2015 were used to train and validation of multilayer ANN model and the predicted values of GDP, Population and average annual temperature with lag demand in the years between 2017 and 2037 were used to simulate the ANN model to forecast the electricity demand.

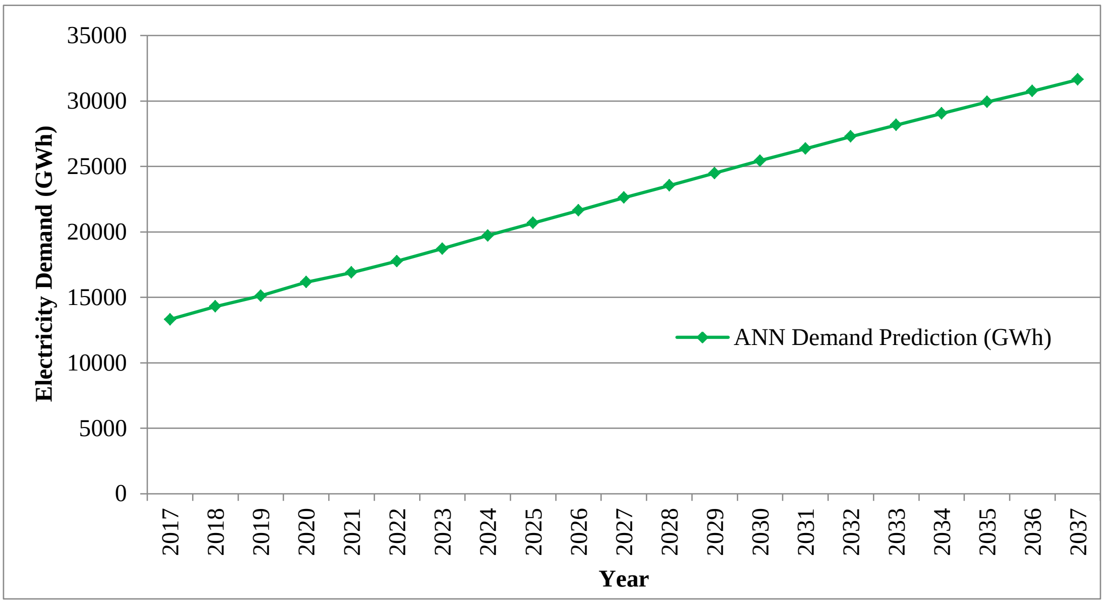

Figure 6.5 – Electricity Demand Forecast 2017-2037 using ANN Model

Figure 6.5 shows the electricity demand forecast 2017-2037 based on multilayer ANN model and shows continuous increasing trend. Accordingly, the electricity demand will reach over 31,000 GWh in the year 2037. Average growth rate over next 20 years will be 4.4%.

The forecast results of the annual electricity demand obtained by the ANN model employed in this work was compared with the CEB official predictions based on MLR and Time Trend for the 2017-2037 time period [2, 18]. For the LTGEP 2015-2034 electricity demand forecast, it has used purely the econometric approach with MLR while for the draft LTGEP 2018-2037, it has used the combination of time trend and econometric approach with MLR.

Table 6.1 and Figure 6.6 shows the comparison of demand forecasts of ANN model, LTGEP 2015-2034 and Draft LTGEP 2018-2037.

Table 6.1 – Demand Forecasts Comparison 2017-2037

Year	ANN Model Output (GWh)	LTGEP 2015-2034 Demand Forecast (GWh) [18]	% Variation	LTGEP 2018-2037 (Draft) Demand Forecast (GWh) [2]	% Variation
2017	13,313	12,842	3.67%	-	-
2018	14,298	13,726	4.17%	14,588	-1.99%
2019	15,116	14,671	3.04%	15,583	-2.99%
2020	16,154	15,681	3.02%	16,646	-2.96%
2021	16,888	16,465	2.57%	17,478	-3.37%
2022	17,760	17,288	2.73%	18,353	-3.23%
2023	18,715	18,155	3.09%	19,273	-2.90%
2024	19,709	19,069	3.35%	20,242	-2.63%
2025	20,680	20,033	3.23%	21,260	-2.73%
2026	21,628	21,050	2.75%	22,332	-3.15%
2027	22,608	22,125	2.18%	23,459	-3.63%
2028	23,537	23,243	1.26%	24,639	-4.47%
2029	24,485	24,402	0.34%	25,867	-5.34%
2030	25,436	25,598	-0.63%	27,164	-6.36%
2031	26,351	26,827	-1.77%	28,388	-7.17%
2032	27,285	28,087	-2.86%	29,637	-7.94%
2033	28,157	29,395	-4.21%	30,926	-8.95%
2034	29,040	30,759	-5.59%	32,251	-9.96%
2035	29,924	32,184	-7.02%	33,642	-11.05%
2036	30,750	33,673	-8.68%	35,090	-12.37%
2037	31,639	35,231	-10.20%	36,613	-13.59%

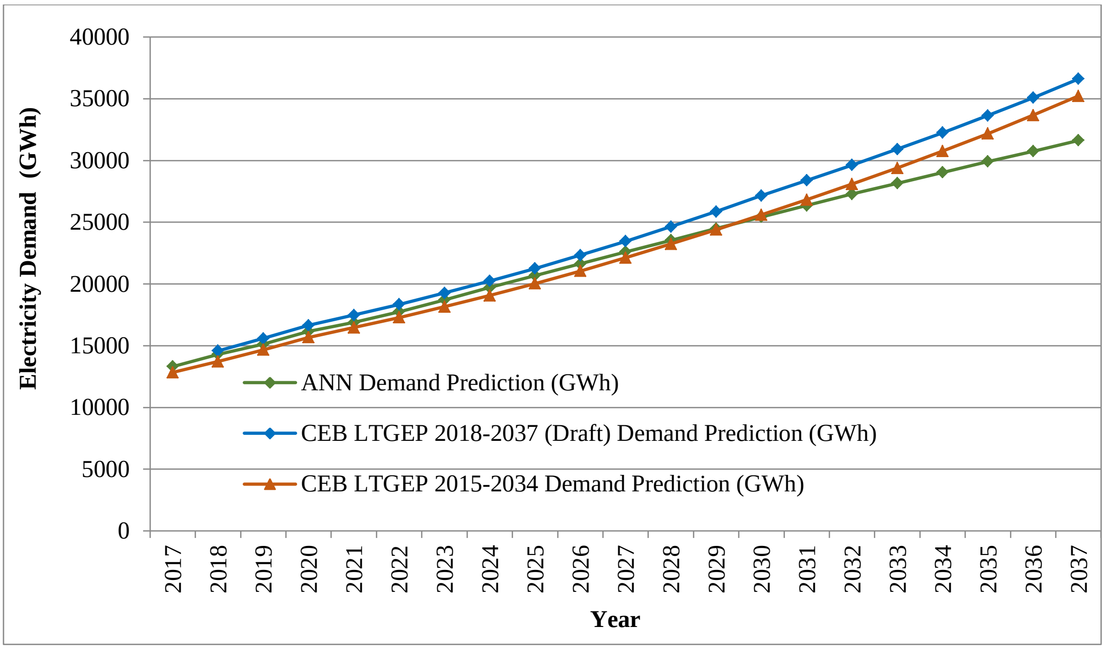

Figure 6.6 – Comparison of electricity demand predictions by ANN model with official predictions 2017-2037

Accordingly, up to year 2030 ANN demand prediction is in between the demand predictions of LTGEP 2015-2034 and draft LTGEP 2018-2037. Beyond 2030, the official predictions were found to be higher variation than the predictions of the ANN model as indicated by Figure 6.6.

7.0 CONCLUSION

In this work, gross annual electricity demand (without categorizing for different sectors based on tariff categories) of Sri Lanka was modeled by ANN model by the use of most significant factors which affect to the electricity demand. Initially the correlation coefficient for each factors were calculated to visualize the degree of relationship with electricity demand based on the historical data from 1984 to 2015. Most significant factors were determined based on MLR with p value approach and GDP, Population, Avg. Annual Temperature and Lag Demand were found to be the major factors affecting to the demand.

A multilayer ANN model for electricity demand forecast was trained with data between 1984 and 2008 period and verified with 2009 and 2015 actual data. The values of the statistically significant descriptor variables in 2009-2015 period was predicted by time series ANN models trained by the data between 1984 and 2008. Then, the constructed multilayer ANN model was simulated with the predicted values of significant variables to forecast the demand between 2009 and 2015. It was found that the ANN model forecast the electricity demand with 0.06% variation compared to actual, and the results were superior to the past official predictions for the same period. This way, the ANN modeling approach applied in this work was validated successfully.

Then, a similar procedure was applied for forecasting the electricity demand for the years between 2017 and 2037 using the predicted values of the statistically significant descriptor variables. Finally, the predicted values of the variables in these years were used to simulate a multilayer ANN model to forecast the electricity demand for the future years.

After observing the results in chapter 6, below conclusions could be made regarding the use of Artificial Neural Networks for the Long Term Electricity Demand Forecasting in Sri Lanka.

- ANN model shows higher accuracy for the past validation data (0.03% error compared to actual) and will show the better performance when it comes to the future predictions. Accordingly, ANN model future predictions shows continues increasing trend in electricity demand with an average growth rate at nearly 4.4%. Further, electricity demand annual growth rates show the slight decrement.

- Electricity demand forecast based on ANN model lies in intermediate state by showing the higher figures than demand forecast of LTGEP 2015-2034 and lower figures compared to demand forecast of draft LTGEP 2018-2037 up to year 2030. Beyond that, electricity demand forecast based on ANN model shows lower figures than both LTGEP forecasts by signifying the saturation of the longer term future electricity demand of Sri Lanka.
- After determining the statistically significant descriptor variables influencing the electricity demand, the approach applied in this work can be appropriately apply and implemented in Sri Lanka to make long term electricity demand predictions for the future.

REFERENCES

[1] Ceylon Electricity Board, Statistical Digest 2016.

[2] Ceylon Electricity Board, Long Term Generation Expansion Plan 2018-2037 (Draft), April 2017.

[3] Askarzadeh, A., 2014.Comparison of particle swarm optimization and other metaheuristics on Electricity demand estimation: a case study of Iran.Energy72, 484–491.

[4] Kialashaki, A., Reisel, J.R., 2014.Development and validation of artificial neural network models of the energy demand in the industrial sector of the United States.Energy76, 749–760.

[5] Günay, M. Erdem. "Forecasting annual gross electricity demand by artificial neural networks using predicted values of socio-economic indicators and climatic conditions: Case of Turkey." *Energy Policy* 90 (2016): 92-101.

[6] Kumarasinghe, P.J., "Energy Demand and Dilemma of Forecasting: A study on Ceylon Electricity Board." Sri Lanka Energy Empowered Nation- Research Findings Vol. 1. No 01 (2015).

[7] Larose, D.T., 2006. Data Mining Methods and Models. Wiley, New Jersey.

[8] Walpole,R.E.,Myers,R.H.,Myers,S.L.,Ye,K.,2012.Probability & Statistics for Engineers &Scientists,9ed.Pearson,Boston.

[9] Kheirkhah, A.,Azadeh,A.,Saberi,M.,Azaron,A.,Shakouri,H.,2013.Improved estimation of electricity demand function by using of artificial neural network, principal component analysis and data envelopment analysis. Comput.Ind. Eng. 64,425–441.

[10] Kankal, M.,Akpınar, A.,Kömürcü,M.İ., Özşahin, T.Ş., 2011.Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables. Appl.Energy88, 1927–1939.

[11] Wilamowski, B.M., Chen, Y., 1999.Efficient algorithm for training neural networks with one hidden layer. In: Proceedings of International Joint

Conference on NeuralNetworks3, pp.1725–1728.

[12] Pan, X., Brian, L., Zhang, C.A., 2013.A Comparison of Neural Network Back propagation Algorithms for Electricity Load Forecasting. In: Proceedings of IEEE International Workshop on Intelligent Energy Systems, pp.22–27.

[13] Ghods, Ladan, and Mohsen Kalantar. "Different methods of long-term electric load demand forecasting; a comprehensive review." Iranian Journal of Electrical & Electronic Engineering 7.4 (2011): 249-259.

[14] Sugianto, Ly Fie, and Xue-Bing Lu. "Demand forecasting in the deregulated market: a bibliography survey." Australasian Universities Power Engineering Conference. 2002.

[15] Ekonomou, L. "Greek long-term energy consumption prediction using artificial neural networks." *Energy* 35.2 (2010): 512-517.

[16] Negnevitsky M. Artificial intelligence: a guide to intelligent systems. 2nd ed. Addison-Wesley; 2005.

[17] Anil K. Jain, Jianchang Mao and K.M. Mohinddin. "Artificial Neural Network: A Tutorial."

[18] Ceylon Electricity Board, Long Term Generation Expansion Plan 2015-2034, September 2016.

[19] Central Bank of Sri Lanka, Annual Reports 1984-2015.

[20] Ceylon Electricity Board, Historical Data Book 1969-2015.

APPENDIX A: Analysis of Average Annual Temperature

Western province electricity demand (GWh) and total electricity demand (GWh) for 2014 and 2015 is shown in Table 1.

Table 1 – Western Province and Total Electricity Demand in GWh 2014 & 2015

Year	2014	2015
Western Province (GWh)	5,916	6,224
Total (GWh)	11,063	11,786

Accordingly, Western Province contribution for total energy demand is 50% - 55% and total peak demand is 40% - 45% (approximately). Since the province is the most densely populated province in the country with rapid development of the largest infrastructure development projects, it has contributed for half of the electricity demand of the country.

Figure 1, 2 and 3 shows the Colombo daily electricity demand variation and daily maximum temperature variation of year 2014, 2015 and 2016.

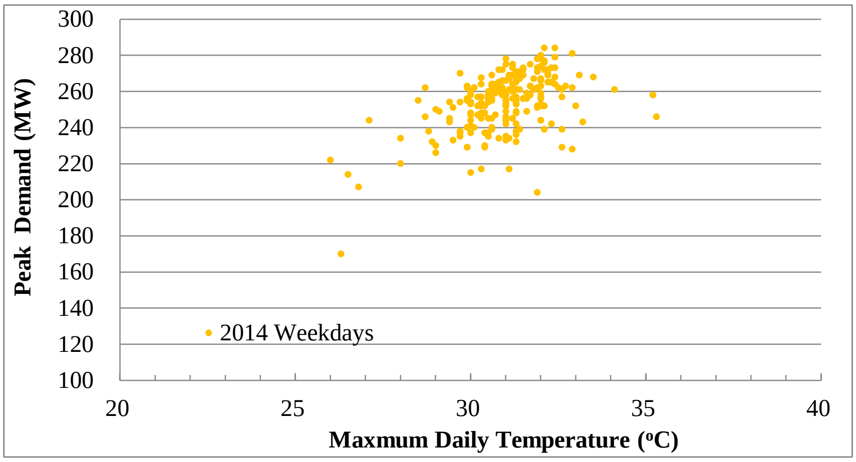

Figure 1 – Peak Demand Vs Maximum Daily Temperature 2014

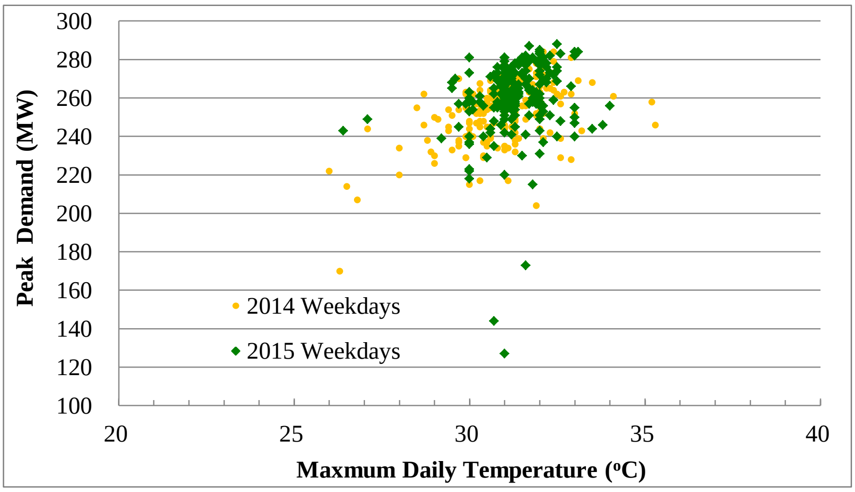

Figure 2 – Peak Demand Vs Maximum Daily Temperature 2014& 2015

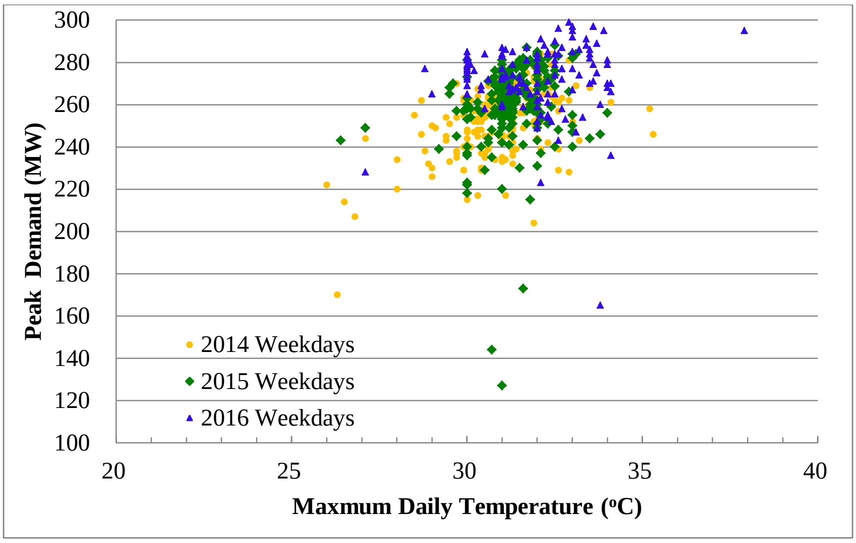

Figure 3 – Peak Demand Vs Maximum Daily Temperature 2014, 2015 & 2016

According to the above, it can be seen that the yearly peak demand is increasing while maximum daily temperature also increasing. Figure 4 shows the average maximum demand and average daily temperature variation of Colombo over last 3 years.

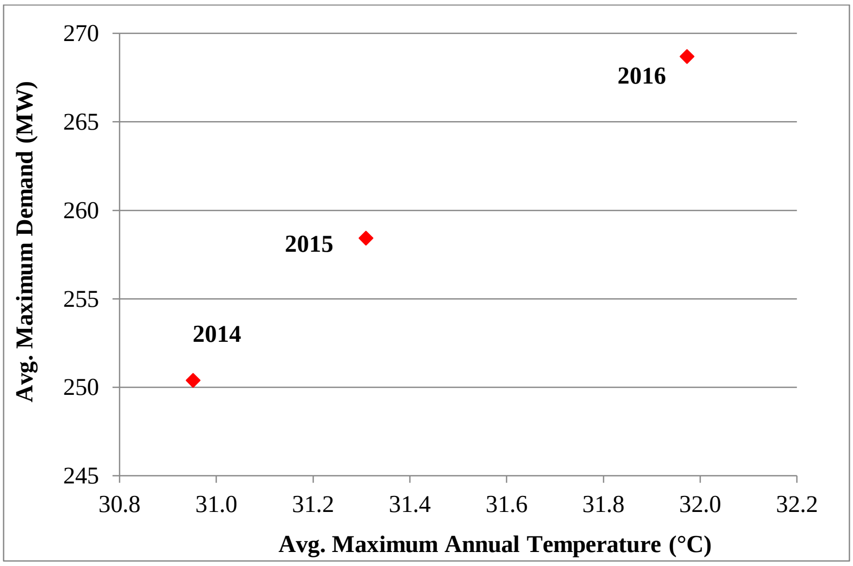

Figure 4 – Avg. Peak Demand Vs Avg. Maximum Daily Temperature

Accordingly both figures show increasing trend and indication of impact from temperature over the electricity demand variation is significant. Therefore, average annual temperature of Colombo meteorological station is considered for the analysis in this study.