FORECASTING ELECTRICAL ENERGY DEMAND OF SRI LANKA: GENETIC ALGORITHMS BASED APPROACH

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Department of Electrical Engineering, University of Moratuwa
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by
D. Y. T. BAMBARAVANAGE

Supervised by: Dr. Lanka Udawatta

Department of Electrical Engineering
University of Moratuwa, Sri Lanka

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Abstract

A novel approach for electrical energy demand forecasting (Short term projection) using genetic algorithms is presented. This model is based on genetic algorithms. Possible factors that affect the electrical energy demand of a system have been counted as variables for the model. By subjecting real time past data for 18 years, on each factor, to natural evolution the forecasting model was obtained. Validation of the model has been carried out and results show the effectiveness of the proposed technique.

Forecasting is both a science and an art. The need and relevance of forecasting demand for an electric utility has become a much discussed issue in the recent past. This has led to the development of various new tools and methods for forecasting in the last two decades.

In the past, straight line extrapolations of historical energy consumption trends served well. However, with the onset of inflation and rapidly rising energy prices, emergence of alternative fuels and technologies (in energy supply and end use), changes in lifestyles, institutional changes etc., it has become very important to use modeling techniques which capture the effect of factors such as price, income, population, technology and other economic, demographic, policy and technological variables.

There is an array of methods that are available today for forecasting demand. An appropriate method is chosen based on the nature of the data available and the desired nature and level of detail or forecasting. The proposed methodology is based on Genetic Algorithms, where all possible factors that affect the electrical energy demand of a system are considered.

The forecasted electricity demand with this model for the last two years was with more accuracy compared to the Ceylon Electricity Board forecasted demand; i.e. the

modal forecasted demand in each year (year 2002 and 2003) was very much closer to the actual data.

DECLARATION

The work submitted in this dissertation is the result of my own investigation, except where otherwise stated.

It has not already been accepted for any degree, and is also not being concurrently submitted for any other degree.

DYTBambaravanage
D. Y. T. Bambaravanage

25/11/2005
Date

I endorse the declaration by the candidate.

UOM Verified Signature

Dr. Lanka Udawatta

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CHAPTER 1

Introduction

1.1 Concept of GA and evolutionary programming

Our lives are essentially dominated by genes. They govern our physical features, our behavior, our personalities, our health, and indeed our longevity [1]. The recent greater understanding of genetics has proved to be a vital tool for genetic engineering applications in many disciplines, in addition to medicine and agriculture. It is well known that genes can be manipulated, controlled and even turned on and off in order to achieve desirable amino acid sequences of a polypeptide chain. This significance discovery has led to the use of genetic algorithms (GA) for computational engineering [1].

Genetic algorithms have been developed by John Holland, his colleagues, and his students at the University of Michigan. The goal of their research has been two fold:

1. To abstract and rigorously explain the adaptive process of natural systems
2. To design artificial systems software that retains the important mechanisms of natural systems

This approach has led to important discoveries in both natural and artificial systems science [2], [3].

GA presumes that the potential solution of any problem is an individual and can be represented by a set of parameters. These parameters are regarded as the genes of a chromosome and can be structured by a string of values in binary form. A positive value, generally known as a fitness value, is used to reflect the degree of "goodness" of the problem that would be highly related with its objective value.

GAs are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of human search. In every generation, a new set of artificial creatures (strings) is created using bits and pieces of the fittest of the old; an occasional new part is tried for good measure. While randomized, genetic algorithms are no simple random walk. They efficiently exploit historical information to speculate on new search points with expected improved performance.

Throughout a genetic evolution, the fitter chromosome has a tendency to yield good quality offspring that means a better solution to any problem. In a practical GA application, a population pool of chromosomes has to be installed and these can be randomly set initially. The size of this population varies from one problem to another although some guidelines are given in. In each cycle of genetic operation, termed as an evolving process, a subsequent generation is created from the chromosomes in the current population. This can only succeed if a group of these chromosomes, generally called "parents" or a collection term "mating pool" is selected via a specific selection routine. The genes of the parents are mixed and recombined for the production of offspring in the next generation. It is expected that from this process of evolution (manipulation of genes), the "better" chromosome will create a larger number of offspring, and thus has a higher chance of surviving in the subsequent generation, emulating the survival-of-the-fittest mechanism in nature.

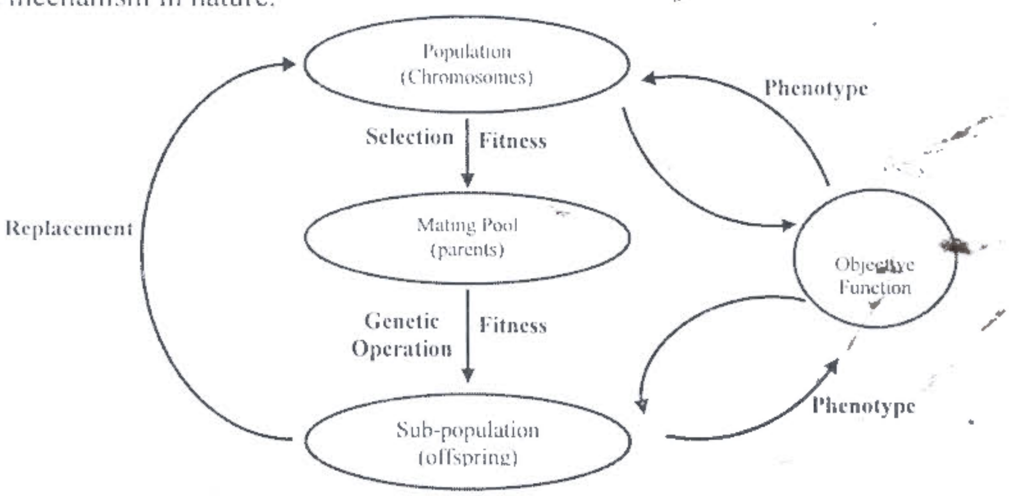


Figure 1.1: A Genetic Algorithm cycle

1.1.1 What are Genes?

In 1859 Charles Darwin (1809-82) published an extremely controversial book whose full title is "*On the origin of species by means of natural selection, or the preservation of favored races in the struggle for life*", which is now popularly known as *The origin of species.* He suggested that a species is continually developing, his controversial thesis implying that man himself came from ape-like stock. During his explorations, Darwin was impressed by the variations between species. He noticed that in almost all organisms there is a huge potential for the production of offspring as, for example, eggs and spores, but that only a small percentage survive to adulthood. He also observed that within a population there is a great deal of variation. This led him to deduce that those variants which survived the struggle to adulthood were, presumably, the ones most fit to do so. Supposing that individual variation could be inherited by offspring, Darwin saw evolution as the natural selection of inheritable variations.

Around the same time, Gregor Mendel (1822-84) investigated the inheritance of characteristics, or traits, in his experiments with pea plants. By examining hybrids from different strains of plant he obtained some notion of the interactions of characters. For example, when crossing tall plants with short ones, all the resulting hybrids were tall regardless of which plant donated the pollen. Mendel declared that the characters or genes as they later came to be known, for the tall plant was dominant and that the gene for shortness was recessive. Although Mendel's experiments laid the foundations for the study of genetics, it was not until 30 years after his death that Walter Sutton (1877-1916) discovered that genes were part of chromosomes in the nucleus.

However, Darwin's theory emphasized the role of continuous variation within species. In contrast, distinct differences between species are not uncommon in nature, i.e. discontinuous variation. Hugo de Varis (1848-1935) observed that in a population of cultivated plants, strikingly different variants would occasionally appear. To explain this discontinuous variation, de Varis developed a theory of mutation. Superficially, the new science of genetics seemed to support the mutation theory of evolution against orthodox Darwinism. With greater understanding of the structure of genes, genetics came to realize how subtle the effect of mutation could be. If a characteristic is determined by a single gene, mutation may have a dramatic effect; but if a battery of genes combines to control that characteristic, mutation is one of them may only have a negligible effect. It is clear, therefore, that there is not a sharp distinction between mutation and Darwinian theory of evolution as they overlap. The principle of selection does, however, remain sound.

The fundamental unit of information in living system is the gene. In general, a gene is defined as a portion of a chromosome that determines or affects a single character or pheno type (visible property), for example, eye colour. It comprises a segment of deoxyribonucleic acid (DNA), commonly packaged into structures called chromosomes. This genetic information is capable of producing a functional biological product that is most often a protein.

1.1.2 Evolutionary Computation

Evolutionary Algorithms can be divided into three main areas of research [4]: Genetic Algorithms (GA) (from which both Genetic Programming (which some researchers argue is a fourth main area) and Learning Classifier Systems are based), Evolution Strategies (ES) and Evolutionary Programming. Genetic Programming began as a general model for adaptive process but has become effective at optimization while Evolution Strategies was designed from the beginning for variable optimization.

The origins of Evolution Computing can be traced to early work by Computer Scientists in the 1950s and 1960s with the idea that evolutionary processes could be applied to engineering problems of optimization. This led to three major independent implementations of Evolutionary Computing of which two are Evolution Strategies and Genetic Algorithms.

Genetic Algorithms were initially developed by Bremermann in 1958 but popularized by Holland who applied GA to formally study adaptation in nature for the purpose of applying the mechanisms into computer science.

However, while Holland popularized the GA, Bremermann made significant advances in the development of GA with the idea that in the future computers would be capable of implementing his more advanced methods. Bremermann was the first [4] to implement real-coded Genetic Algorithms as well as providing a mathematical model of GA known as the one-max function.

In contrast to Genetic Algorithms, Evolution Strategies were initially developed for the purpose of Parameter Optimization. According to Rechenberg [4], the first Evolution Strategies were developed in 1964 at the Technical University of Berlin (TUB). The idea was to imitate the principles of organic evolution in experimental parameter optimization for applications such as pipe bending or PID control for a nonlinear system.

Evolutionary computing is a family of stochastic search techniques that mimic the natural evolution [5] proposed by Charles Darwin in 1858. In the realm of search techniques the following classification indicates the position of evolutionary algorithms:

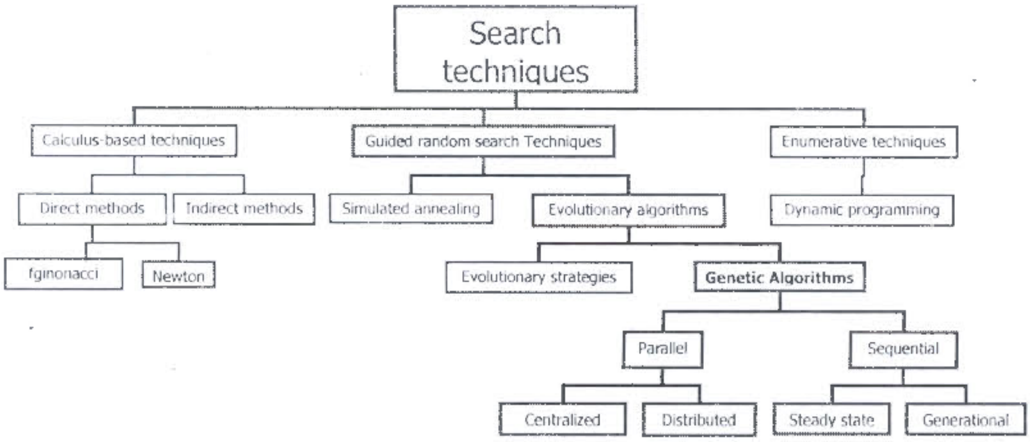


Figure 1.2: Search techniques

If we consider intelligence as a kind of capability of an entity to adapt itself to ever changing environment, we could consider evolutionary algorithms as a subdivision of soft computing:

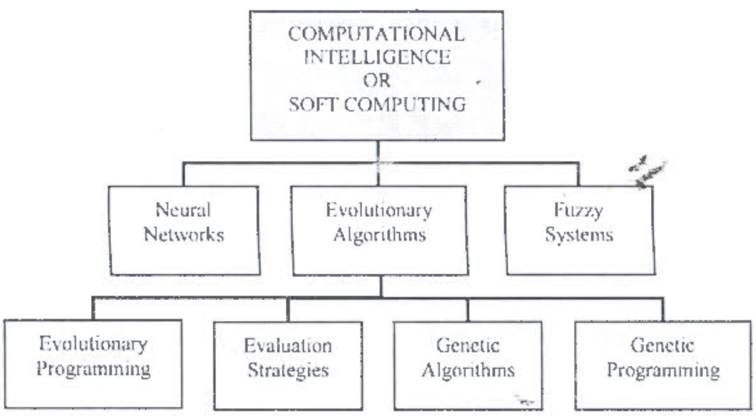


Figure 1.3: Artificial Intelligence techniques

These algorithms are made of several iterations of the basic Evolution Cycle:

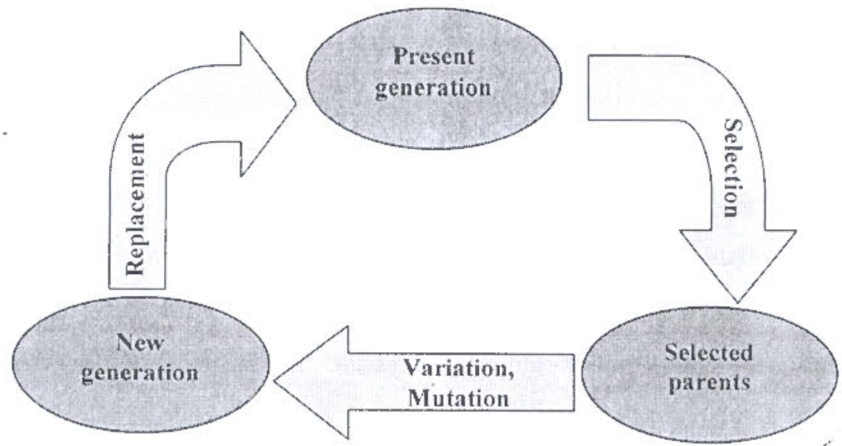


Figure 1.4: Basic Evolution Cycle

Different variations of Evolutionary Computing incorporate the same basic cycle with different presentations' model or specific combinations of Variation, Mutation, Selection, and Replacement methods. The interesting point in implementation is the balance between two opposite operations. In one hand the Selection operation intends to reduce diversity of population (set of possible solutions) and on the other hand the Variation and Mutation operators try to increase diversity of population. This fact leads to the convergence rate and quality of solution.

1.1.3 Genetic Algorithms

The GA is a stochastic global search method that mimics the metaphor of natural biological evolution. GAs operate on a population of potential solutions applying the principle of survival of the fittest to produce (hopefully) better and better approximation to a solution. At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural genetics. This process leads to the evolution of populations of individuals that are better suited to their environment than the individuals that they were created from.

Individuals or current approximations are encoded as strings, chromosomes, composed over some alphabet(s), so that the genotypes (chromosome values) are uniquely mapped onto the decision variable (phenotypic) domain. The most commonly used representation in Gas is the binary alphabet {0,1} although other representations can be used, e.g. ternary, integer, real-valued etc. For example, a problem with two variables, x_1 and x_2, may be mapped onto the chromosome structure in the following way:

1 0 0 1 0 1 1 0 1 1 | 0 1 0 0 1 0 1 1 1 0 1 1 0 1 1

$\longleftarrow x_1 \longrightarrow$ $\longleftarrow x_2 \longrightarrow$

Where, x_1 is encoded with ten bits and x_2 with 15 bits, possibly reflecting the level of accuracy or range of the individual decision variables.

Examining the chromosome string in isolation yields no information about the problem, which we are trying to solve. It is only with the decoding of the chromosome into its phenotypic values that any meaning can be applied o the representation. However as described below, the search process will operate on this encoding of the decision variables, rather than the decision variables themselves, except, of course, where real-valued genes are used.

Having decoded the chromosome representation into the decision variable domain, it is possible to assess the performance, or fitness, of individual members of a population. This is done through an objective function that characterizes an individual's performance in the problem domain. In the natural world, this would be an individual's ability to survive in its present environment. Thus, the objective function establishes the basis for selection of pairs of individuals, which will be mated together during reproduction.

During the reproduction phase, each individual is assigned a fitness value derived from its raw performance measure given by the objective function. This value is used in the selection process to bias it towards fitter individuals. Highly fit individuals, relative to the whole population, have a high probability of being selected for mating whereas less fit individuals have a correspondingly low probability of being selected.

Once the individuals have been assigned a fitness value, they can be chosen from the population, with a probability according to their relative fitness, and recombined to produce the next generation. Genetic operators manipulate the characters (genes) of the chromosomes directly, using the assumption that certain individual's gene codes, on average, produce fitter individuals.

A scheme called Roulette Wheel selection is one of the most common techniques being used for such proportionate selection mechanism. To illustrate this further, the selection procedure is listed in table 1.1.

Table 1.1

Roulette wheel selection procedure

- Sum the fitness of all the population members; named as total fitness (F_{sum}).
- Generate a random number (n) between 0 and total fitness F_{sum}.
- Return the first population member whose fitness, added to the fitness of the preceding population members, is greater than or equal to n.

For example, in figure 1.5, the circumference of the Roulette wheel is F_{sum} for all five chromosomes. Chromoseme 4 is the fittest chromosome and occupies the largest interval, whereas chromosome 1 is the least fit that corresponds to a smaller interval within the Roulette wheel. To select a chromosome, a random number is generated in the interval $[0, F_{sum}]$ and the individual whose segment spans the random number is selected.

The cycle of evolution is repeated until a desired termination criterion is reached. This criterion can also be set by the number of evolution cycles (computational runs), or the amount of variation of individuals between different generations, or a pre-defined value of fitness.

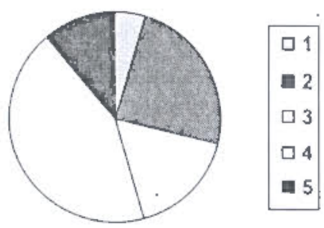


Figure 1.5: Roulette wheel selection

In order to facilitate the GA evolution cycle, two fundamental operators: Crossover and mutation are required, although the selection routine can be termed as the other operator. To further illustrate the operational procedure, a one-point crossover mechanism is depicted on figure 1.6. A crossover point is randomly set. The portions of the two chromosomes beyond this cut-off point to the right are to be exchanged to form the offspring. An operation rate (p_c) with a typical value between 0.6 and 1.0 is normally used as the probability of crossover.

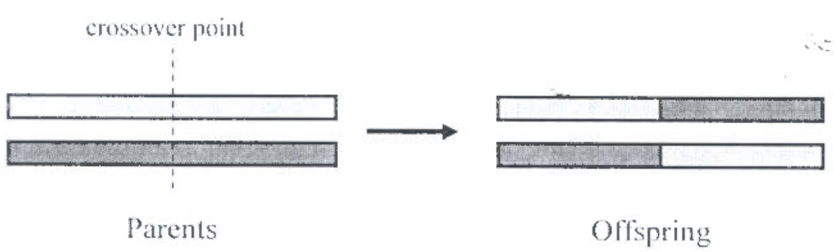


Figure 1.6: Example of one point crossover

However, for mutation (figure 1.7), this applied to each offspring individually after the crossover exercise. It alters each bit randomly with a small probability (p_m) with a typical value of less than 0.1.

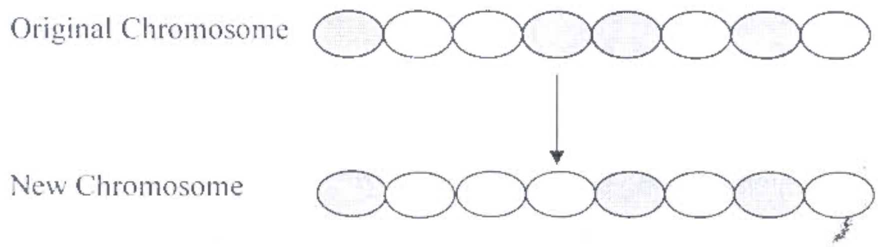


Figure 1.7: Process of mutation

The chose of p_m and p_c as the control parameters can be a complex nonlinear optimization problem to solve. Furthermore, their settings are critically dependent upon the nature of the objective function. This selection issue still remains open to suggestion although some guidelines have been introduced.

- For large population size (100)
  Crossover rate: 0.6
  Mutation rate: 0.001

- For small population size (30)
  Crossover rate: 0.9
  Mutation rate: 0.01

1.2 Electrical energy demand forecasting

Forecasting demand is both a science and an art. The need and relevance of forecasting demand for an electric utility has become a much-discussed issue in the recent past. This has led to the development of various new tools and methods for forecasting in the last two decades. In the past, straight-line extrapolations of historical energy consumption trends served well. However, with the onset of inflation and rapidly rising energy prices, emergence of alternative fuels and technologies (in energy supply and end-use), changes in lifestyles, institutional changes etc, it has become very important to use modeling techniques which capture the effect of factors such as prices, income, population, technology and other economic, demographic, policy and technological variables [6].

There is an urgent need for precision in the demand forecasts. In the past, the world over, an underestimate was usually attended by setting up turbine generator plants fired by cheap oil or gas, since they could be set up in a short period of time with relatively small investment. On the other hand, overestimates were corrected by demand growth. The underlying notion here was that in the worst case, there would be an excess capacity, which would be absorbed soon.

Today an underestimate could lead to under capacity, which would result in poor quality of service including localized brownouts, or even blackouts. An overestimate could lead to the authorization of a plant that may not be needed for several years. Many utilities do not earn enough to be able to cover such a cost with out offsetting revenues. Moreover, in view of the ongoing reform process, with associated unbundling of electricity supply services, tariff reforms and rising role of the private sector, a realistic assessment of demand assumes ever-greater importance. These are required not merely for ensuring optimal phasing of investments, a long-term consideration, but also rationalizing pricing structures and designing demand side management programs, which are in the nature of short- or medium-term needs.

The construction period for power plants, which are set up to meet consumer demand, typically varies between 5 to 7 years in the case of thermal and hydro plants and 3 to 4 years for gas-based plants. As a result, utilities must forecast demand for the long run (10 to 20 years), make plans to construct facilities and begin development well before the indices of forecast growth reverse or slowdown. Since electric utilities are basically dedicated to the objective of serving consumer demands, in general the consumer can place a reasonable demand on the system in terms of quality of power. With some built-in reserve capacity, the utilities may have to configure a system to respond to these to the extent possible.

In the process of making predictions, forecaster bears in mind the feedback effects of pricing and other policy changes, and therefore, participates in the process of designing ways and means to meet consumer demands.

1.3 Proposed methodology of electrical energy demand forecasting

There is an array of methods that are available today for forecasting demand:

i. Time trend method

ii. End-use method

iii. Econometric approach

An appropriate method is chosen based on the nature of the data available and the desired nature and level of detail of the forecasts.

The proposed methodology is based on Genetic Algorithms. The all-possible factors that affect the electrical energy demand are considered in designing the forecasting model. By giving a particular weight to each factor & subjecting to natural evolution a more accurate electrical energy demand-forecasting model could be obtained.

CHAPTER 2

Survey of Available Electrical Energy Demand Forecasting Methodologies

2.1 Time Trend Method

This method falls under the category of the non-causal models of the demand forecasting that do not explain how the values of the variable being projected are determined [6]. Here the variables to be predicted are expressed as a function of time, rather than by relating it to other economic, demographic, policy & technological variables. This function of time is obtained as the function that explains the available data, and is observed to be most suitable for short-term projections.

The time trend method has the advantage of its simplicity and ease of use. However, the main disadvantage of this approach lies in the fact that it ignores possible interaction of the variable under study with other economic factors. For example, the role of incomes, prices, population growth and urbanization, policy changes etc., are all ignored by the method. The underlying notion of trend analysis is that, time is the factor determining the value of the variable under study, or in other words, the pattern of the variable in the past will continue into the future.

Hence, it does not offer any scope to internalize the changes in factors such as the effects of government policy (pricing or others), demographic trends, percapita income etc. However this method is important as it provides a preliminary estimate of the forecasted value of the variable. It may well serve as a useful cross check in the case of short-term forecasts.

The table 2.1 is a forecast of electricity demand for system planning requirements [7]. This is a short term projection done based on the Time trend methodology.

Figure 2.1: Electrical Energy demand forecasted by The CEB in year 2001: Short-term projections (done by the system planning branch of the CEB)

Table 2.1

CEB forecasts in year 2000 - Short Term

Year	Forecasted Electricity Demand (TWh)
2002	7.381
2003	8.106
2004	8.889
2005	9.748

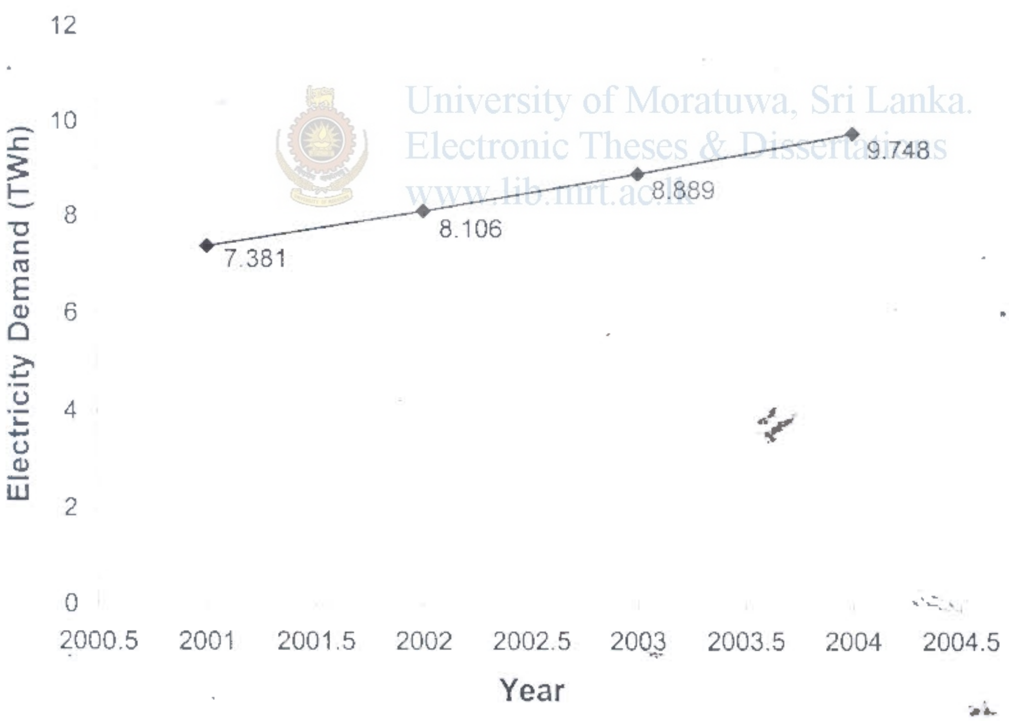


Figure 2.1: Electricity demand forecasted by The CEB in yr. 2001: Short-term projections

2.2 End-use method

The end-use approach attempts to capture the impact of energy usage patterns of various devices and systems. The end-use models for electricity demand focus on its various uses in the residential, commercial, agriculture and industrial sectors of the economy [6]. For example, in the residential sector electricity is used for cooking, air conditioning, refrigeration, lighting, and agriculture for lift irrigation. The end use method is based on the idea that energy is required for the service that it delivers and not as a final good. The following relation defines the end use methodology for a sector:

$$E = S \times N \times P \times H$$

E = Energy consumption of an appliance in kWh

S = penetration level (n terms of number of such appliances per customer)

N = number of customers

P = power required by the appliance in kW

H = hours of appliance use.

This, when summed over different end-uses in a sector, gives the aggregate energy demand. This method takes into account improvements in efficiency of energy use, utilization rates etc., in a sector as these are captured in the power required by an appliance, P. In the process the approach completely captures the price, income and other economic and policy effects as well.

The end use method is most effective when new technologies and fuels have to be introduced and when there is lack of adequate time-series data on trends in consumption and other variables. However, the approach demands a high level of detail on each of the end-uses. One criticism raised against the method is that it may lead to mechanical forecasting of demands, with out adequate regard for behavioral responses of consumers. Also, it does not give regard to the variations in the consumption pattern due to demographic, socio-economic, or cultural factors. A feature of this method is that the data is collected with a picture of the end result in mind. For example, a study of the agriculture sector may require look at the area under each of the major crops, cultivation practices and water requirement per unit area irrigated (including percentage rain-fall) for these crops, etc. However, if one were to look at the agricultural sector as a whole, the degree of detail required might not be as intensive. Therefore, the degree of detail required in the data depends on the desired nature of the forecasts.

2.3 Econometric approach

This approach combines economic theory with statistical methods to produce a system of equations for forecasting energy demand [6]. Taking time-series (detailed data over the last, some 20 to 25 years) or cross-sectional/pooled data (detailed data pooled over different regions/states/individuals and time as well), causal relationships (functional forms where a cause-and-effect relationship is established between variables. Eg., changes in income cause a change in consumption and/or vice versa)could be established between electricity demand and other economic variables. The dependant variable, in this case, demand for electricity, is expressed as a function of various economic factors. These variables could be population, income per capita, price of power etc. Thus one would have:

$$DE = f(Y, Pi, POP)$$

Where,

ED = electricity demand

Y = income per capita

Pi = price of power

POP = population

Several functional forms and combinations of these and other variables may have to be tried till basic assumptions of the model are met and the relationship is found statistically significant.

For example, the demand for energy in specific sectors could be explained as a function of the variables indicated in the right hand side of the following equations:

Residential ED = f (Y of per capita, POP, Pi)

Industrial ED = g (Y of power intensive industries, index of T, index of GP)

Where,

T = technology

GP = government policy

Inserting forecasts of the independent variables into the equation would yield the projections of electricity demand. The sign and the coefficients of each variable, thus estimated, would indicate the direction and strength of each of the right-hand-side variable in explaining the demand in a sector.

The econometric method requires a consistent set of information over a reasonably long duration. This requirement forms a pre-requisite for establishing both short-term and long-term relationships between the variables involved. Thus, for instance, if one were interested in knowing the price elasticity of demand, it is hard to arrive at any meaningful estimates, given the long period of administered tariffs and supply bottlenecks. However, the price effect will have an important role to play in the years to come. In such a case, one may have to broaden the set of explanatory variables apart from relying more rigorous econometric techniques to get around the problem. Another criticism of this method is that during the process of forecasting it is incorrect to assume a particular growth rate for the explanatory variable. Further, the approach fails to incorporate or capture, in any way, the role of certain policy measures/economic shocks that might otherwise result in a change in the behavior of the variable being explained. This would have to be built into the model, maybe in the form of structural changes.

2.4 Combining econometric and time series models

It is common to use a combination of econometric and time series model to achieve greater precision in the forecasts. This has the advantage of establishing casual relationships as an econometric model along with the dependency relationship [6]. Various functional forms such as linear, quadratic, long-linear, translog, etc. are used to capture the possible trends that may be evident in the data. The functional form of the model is derived at after a trial and error process. A model is built using the available data, truncating the last few observations. The procedure for testing the model entails making predictions for the last few time periods for which actual data are available and were truncated. The functional form where the forecasts have least deviations from the data available is chosen.

2.5. Load forecast for 2001 Generation Expansion planning Studies with Econometric Method

The general multiple linear regression model used in econometric analysis is of the form:

$$Y_i = b_1 + b_2 X_{2i} + b_3 X_{3i} + \Lambda + b_k X_{ki} + e_i$$

Where, Y is the dependant variable; the X's are the independent variables. e_i the error term and b_1 is the constant term or intercept of the equation. (X_{2i} represents for example, the i^{th} observation on explanatory variable X_2) [8].

In view of the above discussion, the following models were used to analyse the demand behavior of different sectors under investigation.

2.5.1 Domestic sector

$$D(t)_t = b_1 + b_2 NoDC(t-1)_t + b_3 D(t-1)_t + e_t$$

Where,

$D(t)_t$ - Demand for electricity in domestic consumer category

$NoDC(t-1)_t$ - Number of domestic consumers in previous year

$D(t-1)_i$ - Demand in domestic consumer category in previous year

2.5.2 Industrial and Commercial Sector

$$D(t)_i = b_1 + b_2 GDP +_i b_3 GDP(t-1)_i + b_4 D(t-1)_i + e_i$$

Where,

$D(t)_i$ - Demand for electricity in Ind. And Commercial consumer categories

GDP - Gross Domestic Product

$GDP(t-1)_i$ - Gross Domestic Product in previous year

$D(t-1)_i$ - Demand in previous year

2.5.3 Other sector

The other two consumer categories which do not fall into any of the above two categories are considered in the 'other sector' which includes sales to religious purpose consumers and that consumed in street lighting. Because of the diverse nature of the consumers included in this category, it is better to analyze this category with out any links to other social or demographic variables. Hence, a time- trend analysis was used to predict the demand in this sector.

For the time trend analysis, the following linear regression equation (1) was derived starting from the relationship:

$SALES_t = b_1 (1+g)t$

Where g - the average annual growth rate

b_1 - constant

B - constant

$$ln(SALES)_t = B + ln(1+g)t \qquad \text{-----------------(1)}$$

The table 2.2 gives the forecasted electricity demand for the use of generation planning branch in the CEB in year 2000, based on the Econometric approach. The 2[nd] column shows the expected electricity demand (for consumption) as Low, Medium and High values till year 2020. The expected system losses are given in the next column, as a percentage. The required generation to meet the total demand is presented next. Considering a Load Factor of 54.2%, the possible peak demand of the year is calculated and given (as Low, Medium and High values) in the final column.

Table 2.2

CEB forecasts in year 2000 - Long Term

Year	Demand (GWh)			System Losses (%)	Generation (GWh)			Load Factor (%)	Peak (MW)		
	Low	Medium	High		Low	Medium	High		Low	Medium	High
2000	5416	5416	5416	21.40%	6886	6886	6886	54.20%	1450	1450	1450
2001	5748	5748	5748	19.30%	7119	7119	7119	54.20%	1491	1491	1491
2002	6191	6234	6278	18.50%	7594	7647	7701	54.20%	1591	1602	1613
2003	6642	6759	6875	17.80%	8080	8222	8363	54.20%	1692	1722	1752
2004	7106	7301	7496	16.80%	8541	8775	9009	54.20%	1789	1838	1887
2005	7585	7865	8145	16.10%	9042	9376	9710	54.20%	1894	1964	2034
2006	8083	8450	8816	15.40%	9549	9982	10415	54.20%	2000	2091	2181
2007	8581	9036	9492	14.90%	10080	10615	11151	54.20%	2111	2223	2336
2008	9083	9632	10181	14.80%	10660	11304	11948	54.20%	2233	2368	2503
2009	9591	10240	10889	14.60%	11232	11993	12753	54.20%	2353	2512	2671
2010	10109	10865	11622	14.60%	11837	12722	13608	54.20%	2479	2665	2850
2011	10639	11511	12384	13.80%	12342	13354	14366	54.20%	2585	2797	3009
2012	11195	12194	13193	13.50%	12949	14105	15260	54.20%	2712	2954	3196
2013	11768	12903	14039	13.30%	13573	14882	16193	54.20%	2843	3117	3392
2014	12357	13641	14925	13.10%	14213	15690	17167	54.20%	2977	3286	3596
2015	12964	14409	15855	12.80%	14870	16527	18186	54.20%	3115	3462	3809
2016	13591	15211	16831	12.60%	15547	17400	19253	54.20%	3256	3645	4033
2017	14237	16047	17857	12.30%	16242	18307	20372	54.20%	3402	3835	4267
2018	14904	16921	18937	12.10%	16959	19254	21548	54.20%	3552	4033	4513
2019	15594	17835	20075	11.90%	17698	20241	22783	54.20%	3707	4240	4772
2020	16307	18791	21275	11.70%	18459	21271	24083	54.20%	3866	4455	5044

Figure 2.2 shows the electrical energy demand of Sri Lanka from year 1985 till year 2000 [9], [10].

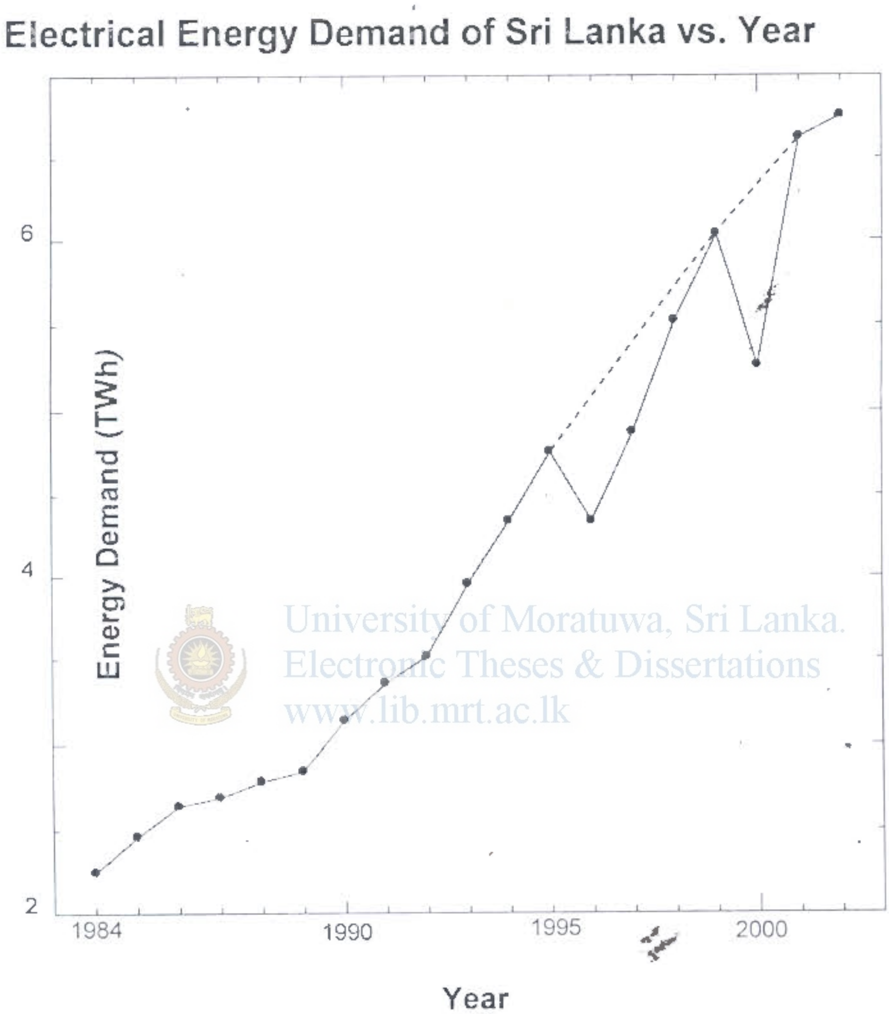


Figure 2.2: The electrical energy demand of Sri Lanka from year 1985 till year 2002

In the above figure (Figure 2.2) during the years 1996, 1997, 1998 and 2000 a significant demand reduction could be observed. This may be because of the power-cuts imposed by the CEB during those years.

In 90's Sri Lanka was a country mainly depended on hydro-power. As the only electric utility available in the country this should never happen. The demand forecasting, planning, implementation, as well as decision making, at correct time in an efficient way is a must. Otherwise the outcome would be very pathetic.

Long and heavy droughts experienced in above mentioned years limited the hydropower generation. The capacity of thermal power plants connected to the system could not meet the demand. So the result was power cuts on public consumption. In certain years this led to blackouts even. As the authority that caters electricity to the country it is their duty (as well as a responsibility) to maintain the quality and reliability of power. That should never be limited to a couple of words. As consumers, people pay for electricity not only for their consumption; but also expecting a high quality of service from the utility. If the utility was up to its plans this would never happen. It is a well known fact that inefficiency and poor decision making of top management of the CEB are the major reasons for this national crisis [11], [12], [13].

As a country, lack (or may be its scarcity) of availability of energy/electricity is a major factor for poverty. So the authorities and the personals of decision making in this sector are bound to act efficiently, effectively, and intelligently in the march towards its future goals.

Hence, there is an urgent need for precision in the demand forecasts. Today an under estimate could lead to under capacity, which would result in poor quality of service including localized brownouts, or even blackouts. An overestimate could lead to the authorization of a plant that may not be needed for several years.

Figure 2.3 shows the electricity demand forecasted by the Generation planning branch of the CEB in year 2001 [9], [10].

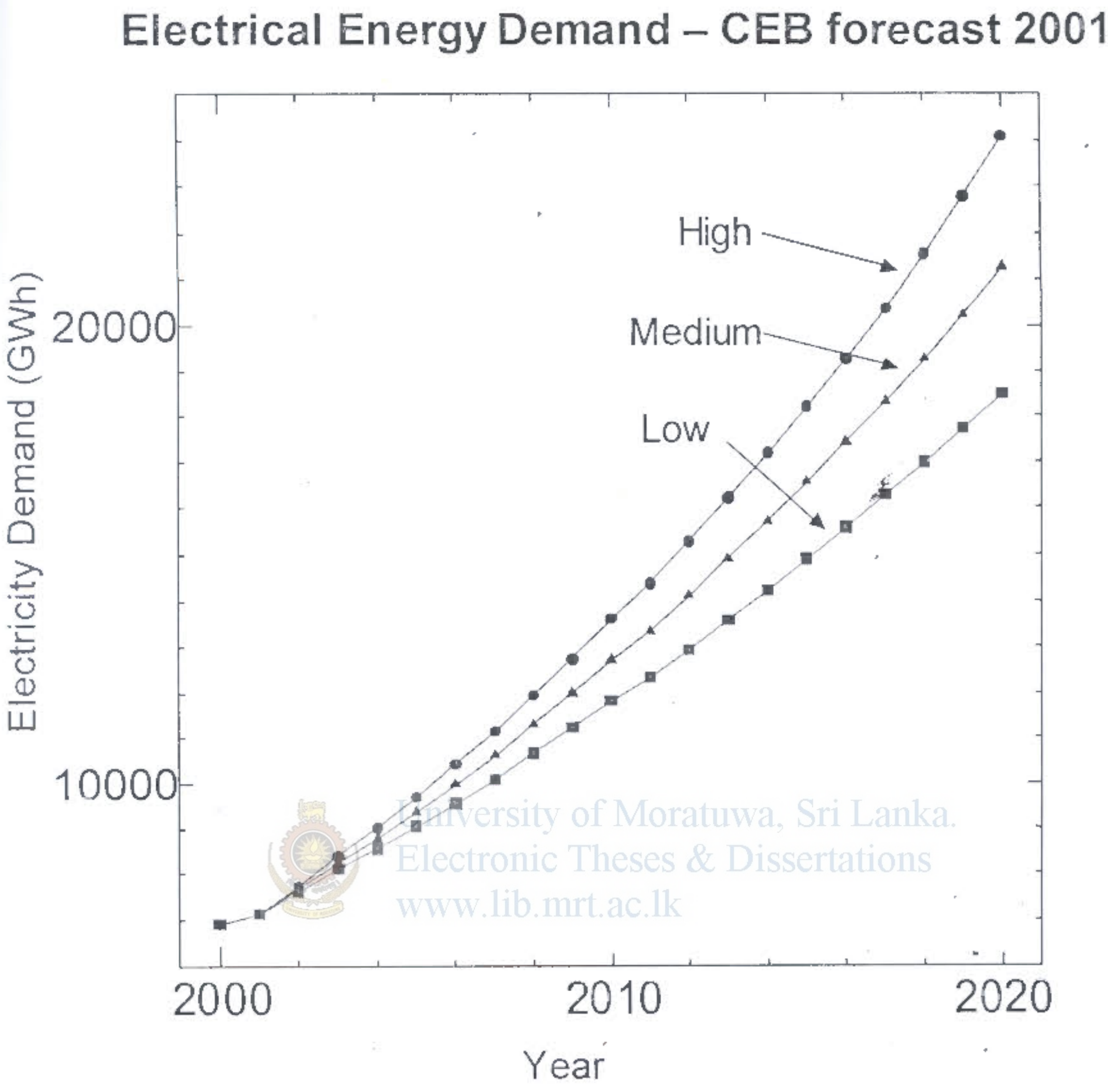


Figure 2.3: Electrical Energy demand forecasted by The CEB in year 2001: Long term

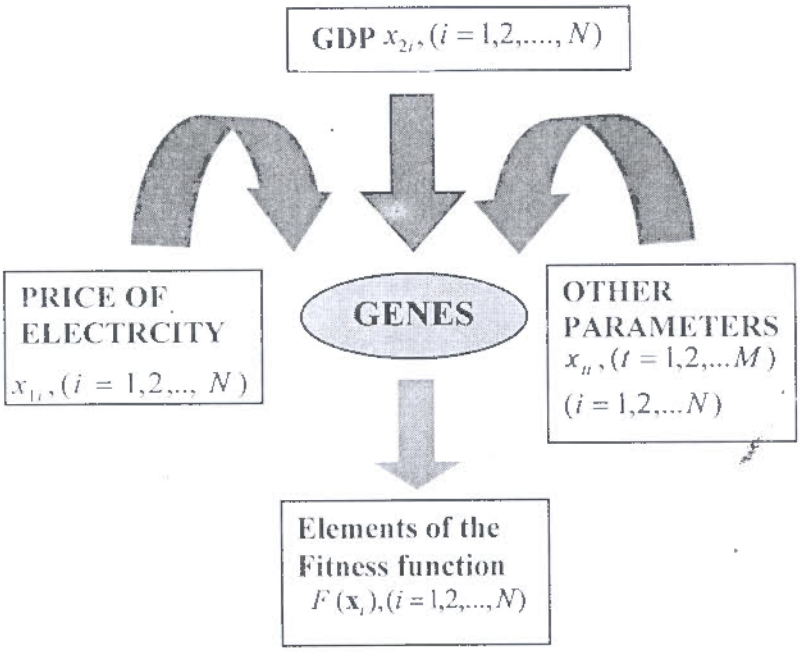
CHAPTER 3

Proposed Methodology of Forecasting Electrical Energy Demand based on Genetic Algorithms

3.1 Proposed Methodology

This is a new methodology with which the Electricity Demand of a particular system could be forecasted with a higher accuracy. In this method all possible factors that affect the electrical energy demand of the system such as time, population, population growth rate, GDP per capita, average US $ value (in Sri Lankan rupees), number of domestic consumers, average electricity price, rain fall, other institutional factors (policy & technological variable) etc. are considered.

Considering all possible factors, derive and represent genetically to a model for Electrical Energy Demand Forecasting. The Figure 3.1 demonstrates the representation of Genes in the Genetic Algorithm.



M – number of factors under consideration

N – number of parameters

Figure 3.1: Representation of genes

By giving a certain weight to each factor and subjecting to natural evolution, a more accurate forecasting model could be obtained, as briefed in Figure 3.2.

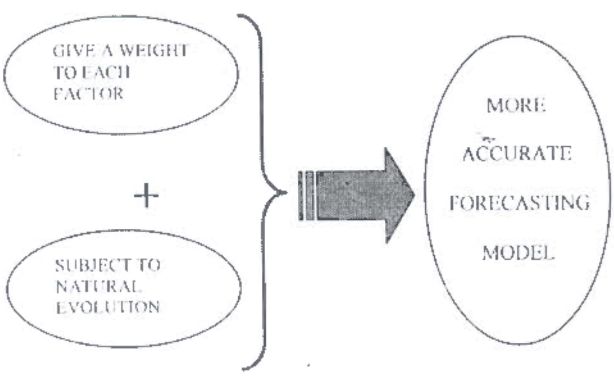


Figure 3.2: Way to obtain the forecasting model

Forecasted Electrical Energy Demand, f(x),

$$f(x)=(x_1, x_2, x_3, ...)$$

Where,

$x_1, x_2, x_3, \ldots x_M$=factors under consideration

Let $f(x)$ be,

$$f(x)=\left(a_1 x_1^{p_1}+a_2 x_2^{p_2}+......+a_M x_M^{p_M}.\right) \qquad \text{-----------} \quad (1)$$

Where,

a_M & p_M - Unknown parameters to be found

M - no. of factors under consideration

$$f_{ERROR} = f_{ACTUAL} - f_{FORECASTED}$$

When,

$$f_{ERROR} \rightarrow 0$$

$$f_{FORECASTED} \rightarrow f_{ACTUAL}$$

Where,

$$f_{FORECASTED} = f(x)$$

To avoid negative values,

$$f_{ERROR}^{\ 2}=\left(f_{ACTUAL}-f_{FORECASTED}\right)^2 \qquad \text{----------------} \quad (2)$$

When $f_{ERROR}^{\ 2}$ is plot against the number of generations, a graph as shown in Figure 3.3 would be received.

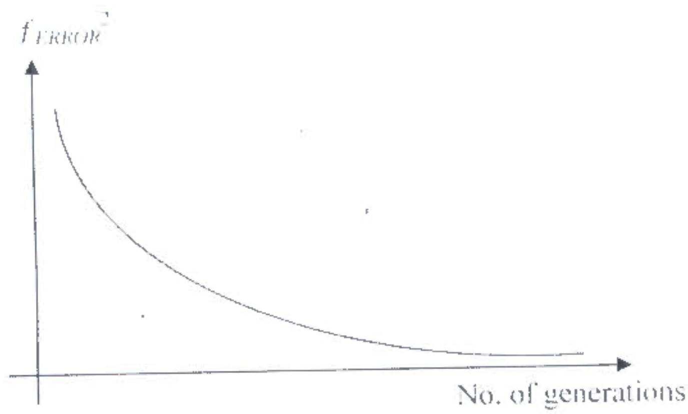


Figure 3.3: Distribution of f_{ERROR}^2 vs. Number of generations

In this analysis, actual data for each factor have been considered from year 1984 to year 2000.

(1) & (2) $\Rightarrow$

$$f_{ERROR}^2 = (f_{ACTUAL} - f_{FORECASTED})_{1984}^2 + (f_{ACTUAL} - f_{FORECASTED})_{1985}^2 + \ldots\ldots\ldots + (f_{ACTUAL} - f_{FORECASTED})_{2000}^2$$

Nine factors have been considered in this model. Hence the **Genes** of the Genetic Algorithm would be these factors.

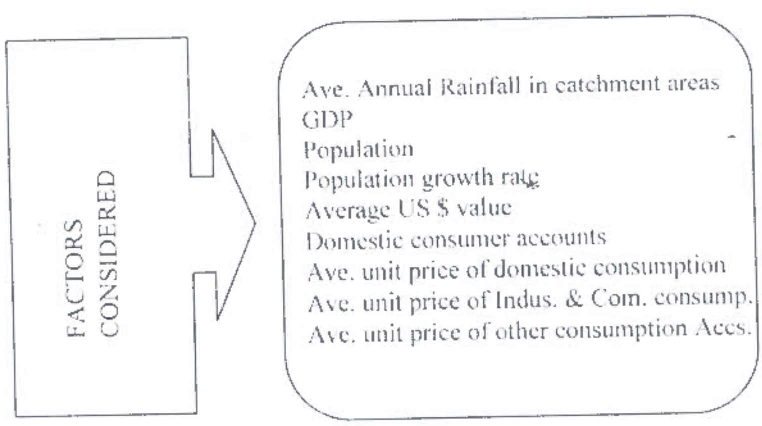


Figure 3.4: Factors considered in the forecasting model

3.5 Justification of selecting the considered factors

When referred to the Sri Lankan context, there are several factors that affect the electricity demand significantly. The Figure 3.5 and Figure 3.6 show the consumption of electricity by main consumer categories of Sri Lanka and that as a percentage of the total consumption of the year, referring to the year's 1990, 1995, 2002 and 2003 data.

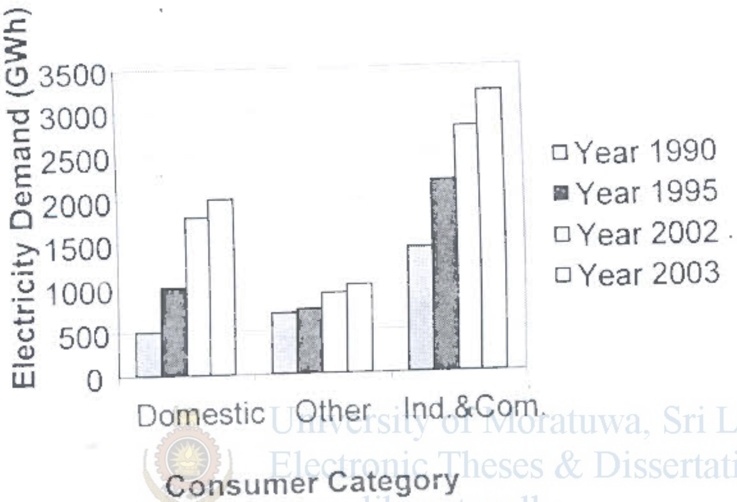


Figure 3.5: Consumption of electricity by main consumer categories of Sri Lanka

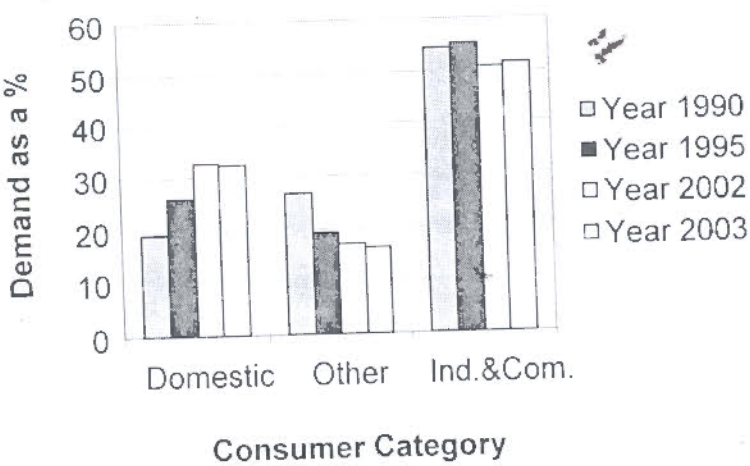


Figure 3.6: Consumption of electricity by main consumer categories of Sri Lanka as a percentage of the total consumers of that year

The above information clearly shows that the demand for electricity by the Industrial and commercial sector consumers, increases annually compared to that of other sectors. Our electricity supply is a system in transition. The fuel mix in the generating system is rapidly changing from a predominantly hydroelectric system to a predominantly thermal system, and Sri Lanka is unable to manage this transition [11], [12], [13].

The structure of electricity consumption is also changing from a consumption pattern dominated by the manufacturing industry, to one in which households and commercial buildings use more than 48% of electricity sold (Figure 3.7 - Year 2003 data).

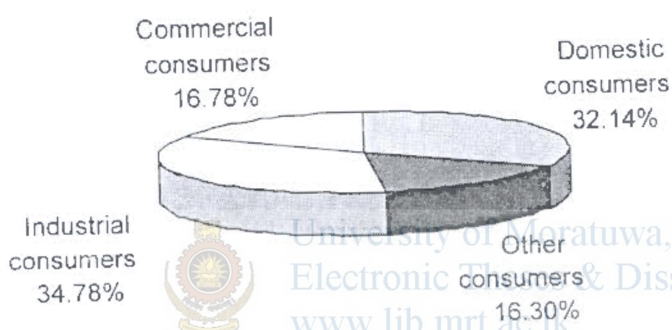


Figure 3.7: Consumption of electricity by Commercial, Domestic, Industrial and Other consumers in Sri Lanka in year 2003.

Sri Lanka electricity generation sector has been dominated by hydroelectricity for many years. With the saturation of economically exploitable hydropower capacity and in the absence of any other reliable indigenous primary energy sources that can be used for large scale electricity generation, Sri Lanka will have to rely heavily on thermal generation based on imported fossil fuels [14].

3.5.1 Rainfall data in catchments areas

When rainfall is considered as a factor which affects the electricity demand of Sri Lanka, one can look at it in several point-of-views such as,

- the direct impact on the consumption of electricity due to the rainfall itself,
- the cost of energy due to the variations in the usage of fuel in electricity generation.

Out of the above two, the second one is more out-smart. The more the rainfall we get higher the hydropower generation. Hence the cost of generation of an energy unit becomes less (e.g. Because of the heavy droughts occurred in year 1996 and year 2000, the Sri Lankan power utility was unable to meet the demand, with the available hydro and thermal power plants. This caused localized brown-outs and even black-outs.). Since there are limitations in collecting rainfall data all over the country, the average rainfall figures in catchments areas that have a considerable impact on the hydropower generation have been considered.

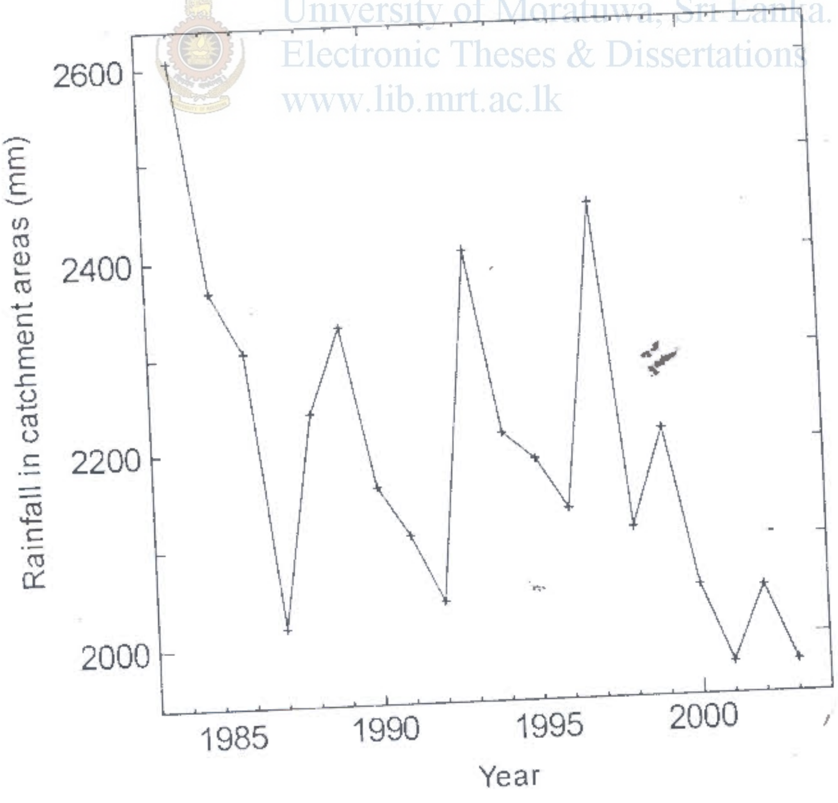


Figure 3.8: Rainfall in catchment areas

The past data shows that the rainfall in Sri Lanka gradually reduces [15], (Figure 3.14: Rainfall in catchment areas). So even though the installed hydro capacity is much higher, it may not cater the system fully due to lack of rainfall. Hence special attention was paid to analyze the effect of rainfall on supply/demand

3.5.2 Domestic consumer accounts

Although there are very large industrial consumers connected to the system, a considerable portion of the electricity demand in Sri Lanka is due to the domestic consumers (More or less the night peak is due to the electricity consumption in household.). So they could be considered as an element, which decides the energy demand of the country.

The Major component of the Number of Electricity Consumers in Sri Lanka falls in to the category of Domestic Consumers. In Sri Lankan power system, the peak demand occurs around 8.30 p.m. (Typical example - Figure 5.4: Load curve of Sri Lanka 1st June 2005). In fact the domestic consumption is the reason for the night peak. Hence it performs a major role in deciding the energy demand of Sri Lanka.

3.5.3 Average US $ value

With the onset of inflation, rapidly rising energy prices, development project done under foreign aids (loans), etc. the value of the rupee reduces day by day compared to that of the US $. This US $ value is more stable in the market.

Sri Lanka does not have its own oil wells to provide fuel for electricity generation. When dealing with foreign market in purchasing fuel, it is more convenient (even to do a comparison), when it is given in terms of US $ rather than in rupees.

The price of the fuel imported affects the electricity generation and hence the tariff system. This influences the energy usage and the energy usage patterns of the consumer.

Therefore the average US $ value in rupees could be considered as a major factor that affects the electricity demand of Sri Lanka.

3.5.4 Population, Population growth rate

With the increase of the population and population growth rate, the electricity demand increases. This is due to reasons such as

- the energy demand directly exerts on the system by the consumers during there house hold activities
- introduction of new industries and their developments to cater the population

Hence the population and population growth rate have been considered as factors which affect the electricity demand of Sri Lanka. The Figure 3.9 shows the Estimated mid year population against year for the past 22 years, [16].

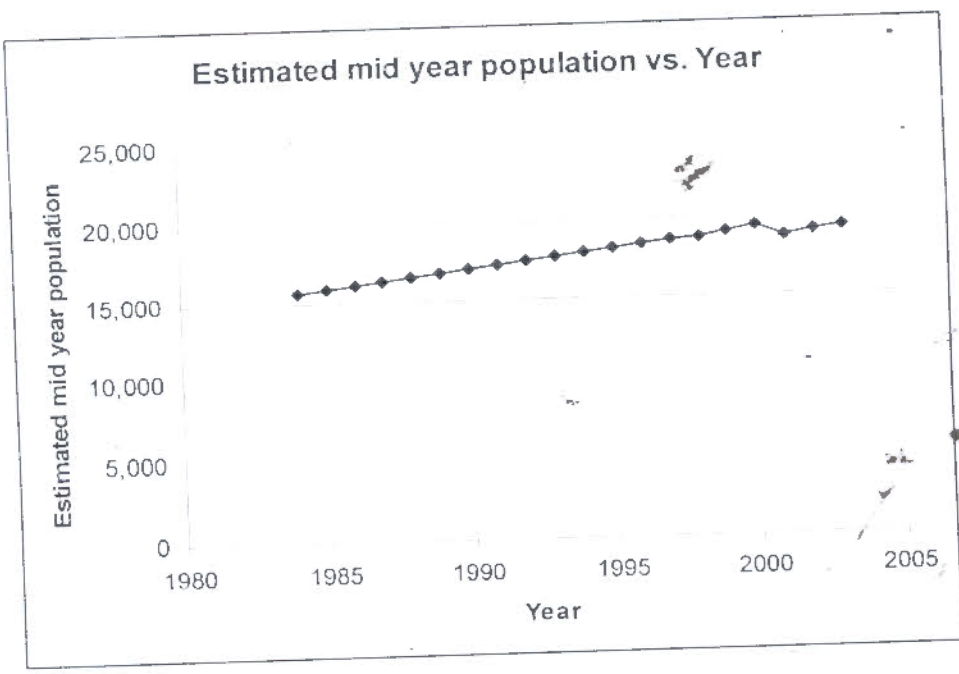


Figure 3.9: Estimated mid year population vs. Year

3.5.5 GDP

Gross Domestic Product (GDP) is the unduplicated value of all goods and services produced in a year within Sri Lanka's boarders at market prices. It is the standard of the overall size of the economy.

The market value of final goods and services produced over time including the income of foreign corporations and foreign residents working in Sri Lanka, but excluding the income of Sri Lankan residents and corporations overseas.

Increasing energy consumption / the development of the electricity sector is strongly coupled with the economic growth of Sri Lanka [14]. The Figure 3.10 and Figure 3.11 show "the variation of Economic Growth and Demand for Energy in Sri Lanka" and "the variation of the GDP in US $ against year" during the past 22 years.

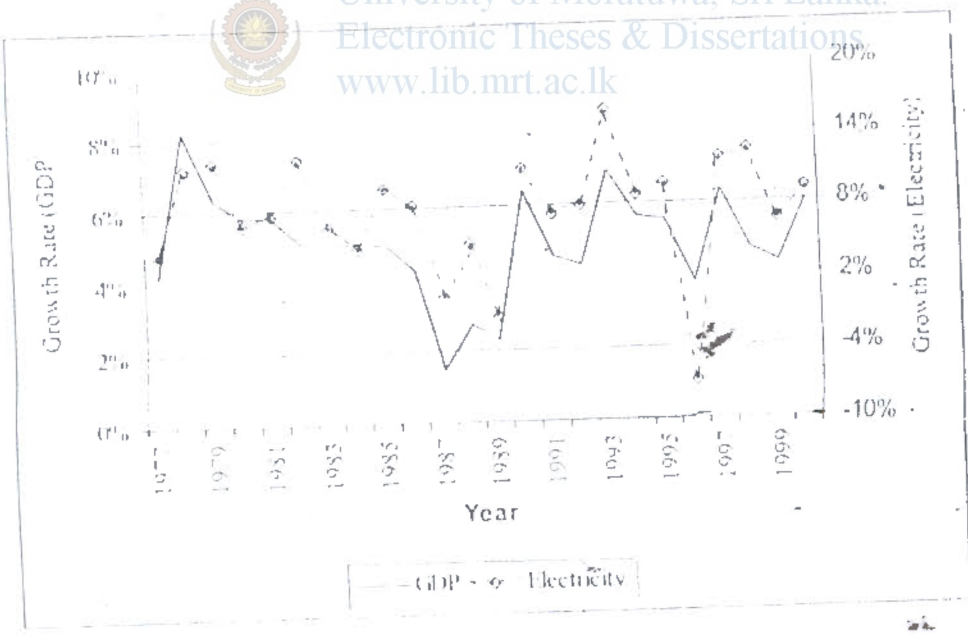


Figure 3.10: The variation of Economic Growth and Demand for Energy in Sri Lanka.

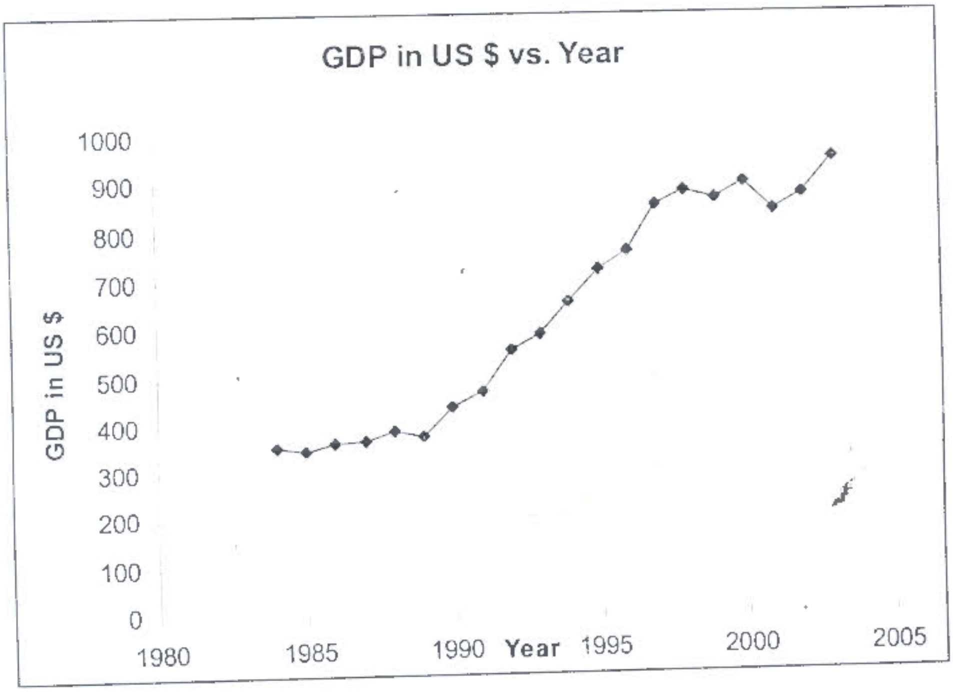


Figure 3.11: The variation of the GDP in US $ against year

3.5.6 Price of Electricity (Domestic)

The increasing electricity consumption is also strongly coupled with the price of electricity [14]. It is a well known fact that people purchase commodities when ever that commodity is more valuable to them than its price. Today to get our work done energy is essential. As the most convenient way of receiving energy is electricity, it has a very high demand. The inability to meet the demand is the reason for the power crisis we are experiencing today in Sri Lanka.

The unit price of electricity is a main factor that decides the demand of electricity. When consider the power system of Sri Lanka basically the electricity consumers could be divided in to three major categories as

- Domestic consumers
- Industrial and commercial consumers
- Religious and other purpose consumer.

As discussed before, the demand by the Domestic Consumers is a main reason for the night peak. As a whole these consumers do not consume bulk power. Their consumption is just to satisfy their day to day requirements. Hence the number of domestic consumers as well as the average price of such a domestic consumer could be considered as the factors that affect the electricity demand of Sri Lanka.

When refer to the Industrial and commercial sector consumers, although they are much less in quantity, the demand they exert on the system is very high. Since the number of units they consume varies with in a large range, number of Industrial and Commercial consumers could not be counted as a factor that affects the electricity demand, but the average unit price of electricity they consume.

Religious purposes and Street lighting categories have different tariff systems compared to above two. Their consumption pattern is also much different to the other two consumer types. When consider the CEB as the main supplier, LECO (Lanka Electricity Company) purchase power from them. In this analysis the LECO is considered as a consumer that purchases power at lower rates as religious purposes and street lighting categories. Hence, the third category "other purposes" would compose with above all three units. The average unit price is considered as a component on which the demand of electricity depends on.

3.6 Parametric Study

A parametric study was conducted to enhance the GA's performance when using transformation. There, three parameters were subjected to changes:

- Number of individuals per subpopulation.
- Maximum Number of Generations.
- Precision of binary representation.
- Upper and lower limits (range) of a and p.

The results showed that the choice of these parameters influenced the results. In fact, using an appropriate parameter setting the GA achieved much better solutions than the ones obtained with the first set of parameters. All the parameters had great influence in the obtained results [17]. The table 3.2 shows the Fitness values obtained with different parameter settings.

Detailed output results of the table 3.2 are appeared in the Appendix I.

Table 3.2

Fitness values obtained with different parameter settings (based on data from year 1984 till year 2000)

Row Number	Fitness	Mutation	No. of individuals per sub population	Max^{m} no. of generations	Gen. Gap-how many new individuals are created	No. of variables	Precision of binary representation	Field descriptor
1	1.02990	0.7x250	100	1000	0.9	18	20	between -2 & 2
2	1.26670	0.7x250	100	5000	0.9	18	20	between -2 & 2
3	0.96224	0.7x250	100	10000	0.9	18	20	between -2 & 2
4	0.98872	0.7x250	100	10000	0.9	18	20	between -3 & 3
5	0.66140	0.7x250	200	20000	0.9	18	20	between -2 & 2
6	0.94470	0.7x400	100	10000	0.9	18	20	between -2 & 2
7	0.69783	0.7x500	100	10000	0.9	18	20	between -2 & 2
8	0.88647	0.7x1000	100	10000	0.9	18	20	between -2 & 2
9	0.69783	0.7x500	100	10000	0.9	18	20	between -2 & 2
10	0.68424	0.7x500	100	10000	0.9	18	20	between -2 & 2
11	0.87006	0.7x500	100	10000	0.9	18	40	between -2 & 2
12	0.70225	0.7x500	100	20000	0.9	18	20	between -2 & 2
13	0.67783	0.7x500	400	20000	0.9	18	20	between -2 & 2
14	0.64937	0.7x500	400	20000	0.9	18	20	between -2 & 2
16	0.80135	0.7x500	500	5000	0.9	12	20	between -2 & 2
17	0.79787	0.7x500	500	20000	0.9	12	20	between -2 & 2

Comment on Row no. 13 and 14:

Even though the same number of generations has been considered, the fitness values received are considerably different. The corresponding parameter values are also different at each case.

⇨ The parameter values have not been converged to a steady state condition at 20, 000 no. of generations.

3.7 Limitations in considering all the possible factors

Even the number of factors considered in the process had a great influence on the fitness value, due to various limitations the number of factors considered in this modal happened to set to six.

Although in the beginning of this report it has been mentioned there is a large number of factors that affect the electricity demand of Sri Lanka, practical problems are there in collecting data for the past twenty years duration under each factor.

E.g.

- Rain fall, humidity, temperature data:

  Due to the terrorist problems in North & East region of Sri Lanka the weather records available in such areas are with less information; the accuracy with the available data in these areas may be less; the records are not continuous. Hence an island wide consideration of above factors was not done.

- Number of televisions, refrigerators available (in Sri Lanka):

  The television & the refrigerator are the most common and considerable amount of power drawing equipment utilized in Sri Lankan household. Three surveys have been conducted in Sri Lanka [18], [19] to find out the living status of the people in Sri Lanka within the past 17 years' period (from year 1984 to 2000); there in determining that, the number of televisions available with them was one, out of several such factors. North and East provinces were excluded in the surveys, due to the terrorist problems existing. So the figures available do not cover the whole country. Further more the surveys were not conducted annually. Hence the above factor was not considered in designing the model.

- Special Programs:

Special programs such as cricket matches for which Sri Lanka team participate etc. too affect the electricity demand. Although the previous records on which days these matches were held are available, the future schedules of matches are not known. Even if it is known (short term), once again have to see, out of them which days are week ends (demand increases during week ends). So consideration of this factor in designing the GA for electricity demand forecast is practically difficult.

CHAPTER 4

Results

4.1 Parameters set in the Genetic Algorithm

Having trained the GA with the available past data for 18 years (from 1984 till 2001) with an appropriate parameter set for the GA, a set of 'a' and 'p' values were obtained.

By using a set of appropriate parameters in the Genetic Algorithm, more accurate forecasted data could be obtained.

When the following parameters were set with the corresponding values in the GA, the forecasted figures received were with a high accuracy.

Number of individuals per subpopulations	= 500
Maximum Number of generations	= 20, 000
Generation gap (that decides how many new individuals are created)	= 0.9
Number of variables	= 18
Precision of binary representation	= 20
Upper and lower limits (range) of a and p (Field descriptor)	= between -2 and +2

After 20, 000 no. of generations,

$f_{ERROR}^2 = 0.6775375$

Within the first 5000 generations the variation of the best fitness was significant, (Figure: 4.1).

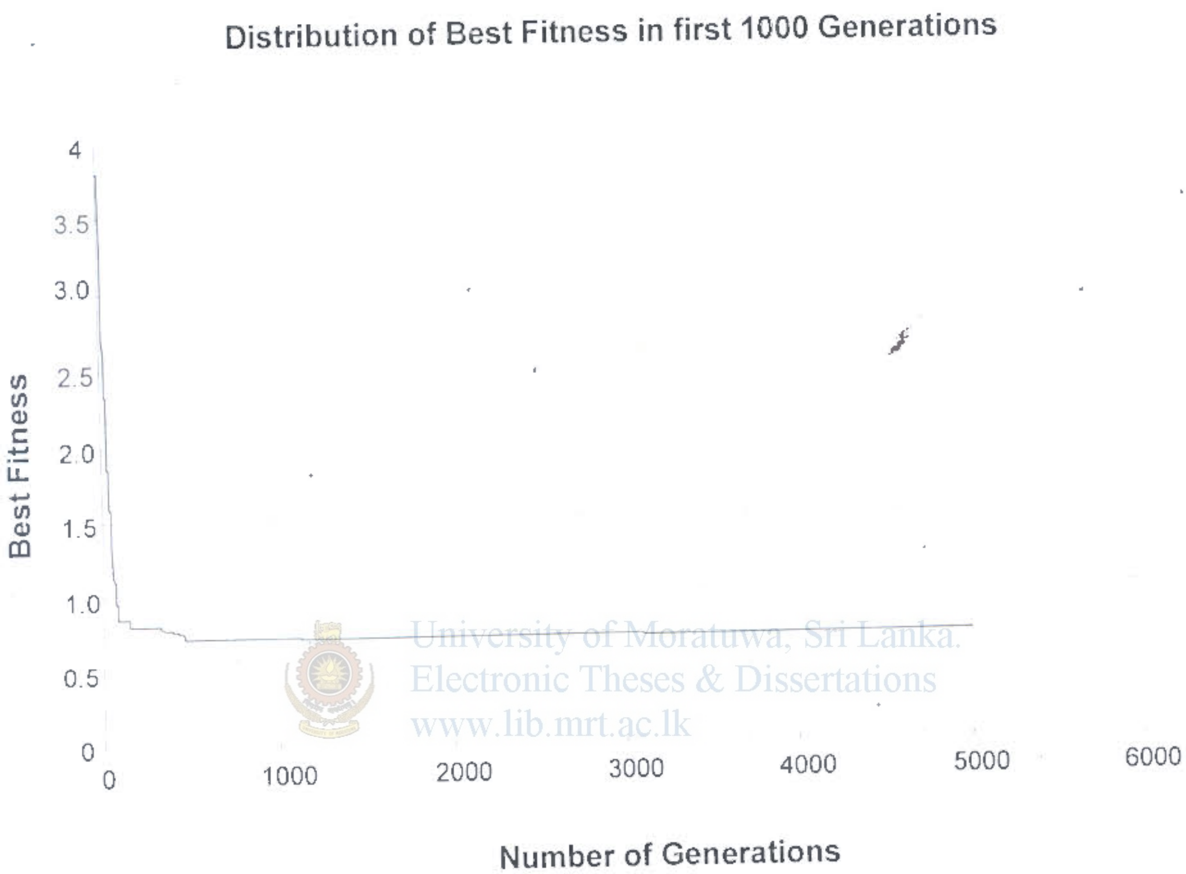


Figure 4.1: Sample f_{ERROR}^2 vs. No. of generations-distribution with 1000 generations

4.2 Results used in the forecasting Model

The graph in Figure 4.2 gives the Distribution of Best Fitness value vs. number of generations. After 20, 000 generations 0.6775375 was received as the best fit value.

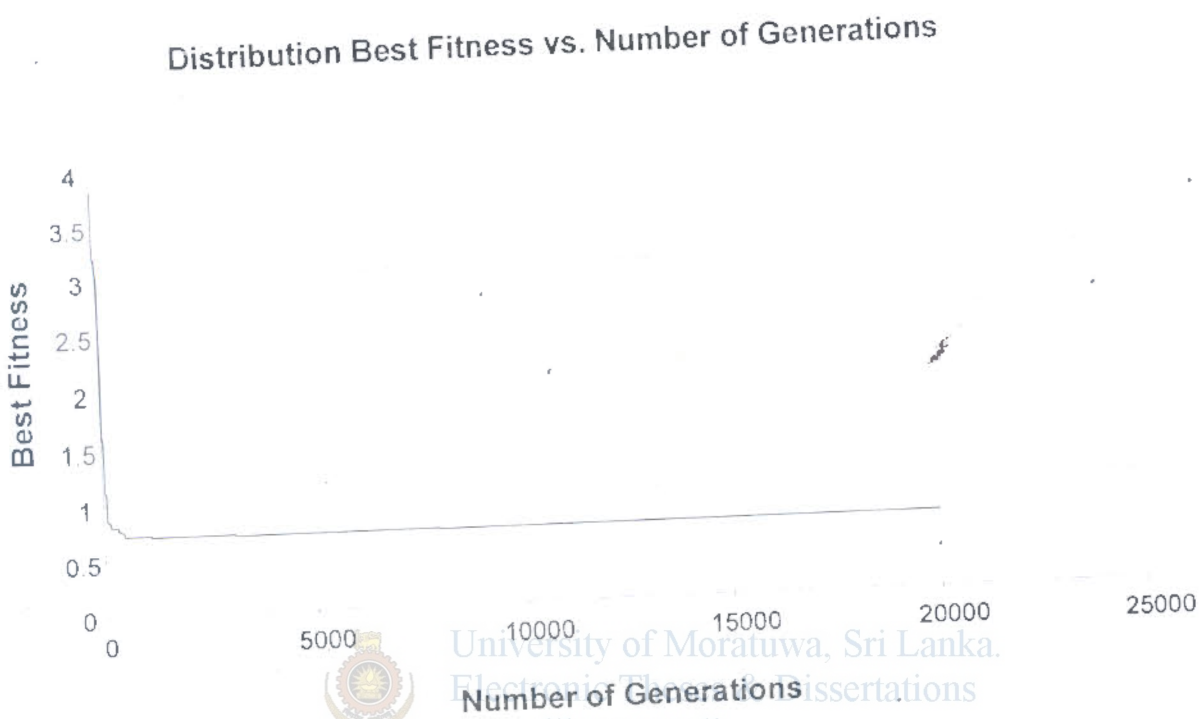


Figure 4.2: Distribution of best fitness vs. no. of generations

Considering the Best Fit value = 0.6775375,

a_i and p_i in (1), where $i = 1, \ldots\ldots\ldots, 6$

were set to the following values that were received at the best fit condition after 20,000 generations in order to obtain the Model for Forecasting Electrical Energy Demand of Sri Lanka.

a_1	-1.18024
a_2	0.742877
a_3	0.128874
a_4	-0.92489
a_5	1.033729
a_6	1.98654
a_7	1.557174
a_8	-0.44033
a_9	-1.64072
p_1	-1.31335
p_2	0.048903
p_3	-1.5704
p_4	-1.51104
p_5	-.37124
p_6	-1.77698
p_7	0.452536
p_8	0.080473
p_9	-1.4893

Figure 4.3: Parameters obtained at the best-fit value

4.3 Graphical Representation of evolution of the parameters

The following graphs (from Figure 4.4 up to Figure 4.21) give the evolution of these parameters, and some of them clearly show their convergence (either a_i or p_i values) to a steady state condition.

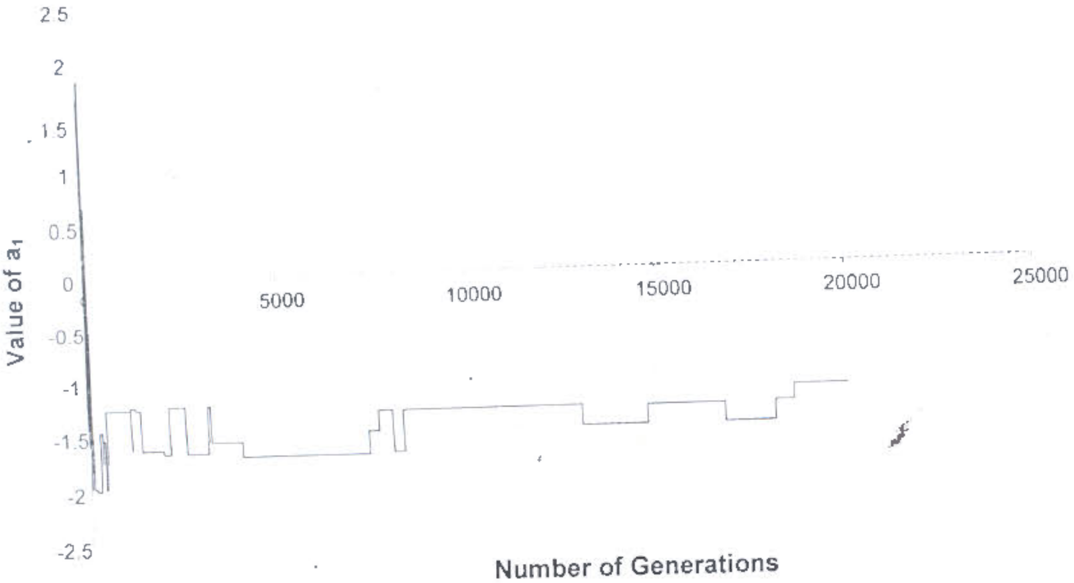


Figure 4.4: Distribution of Variable 1 (a_1) vs. Number of Generations

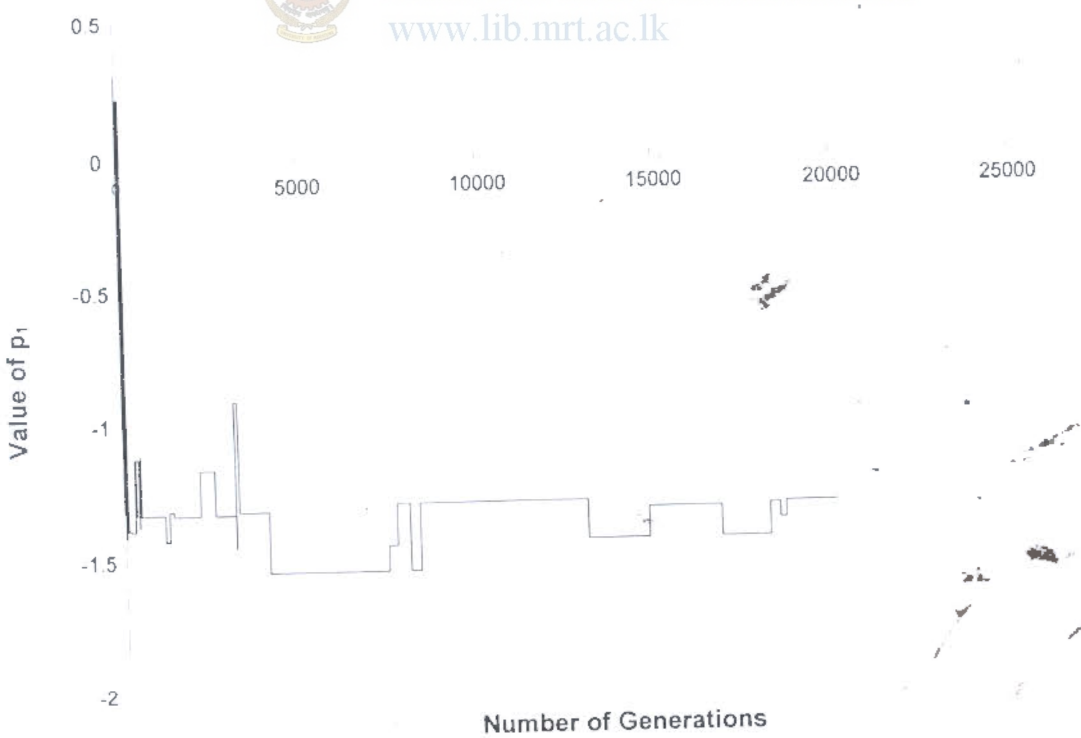


Figure 4.5: Distribution of Variable 2 (p_1) vs. Number of generations

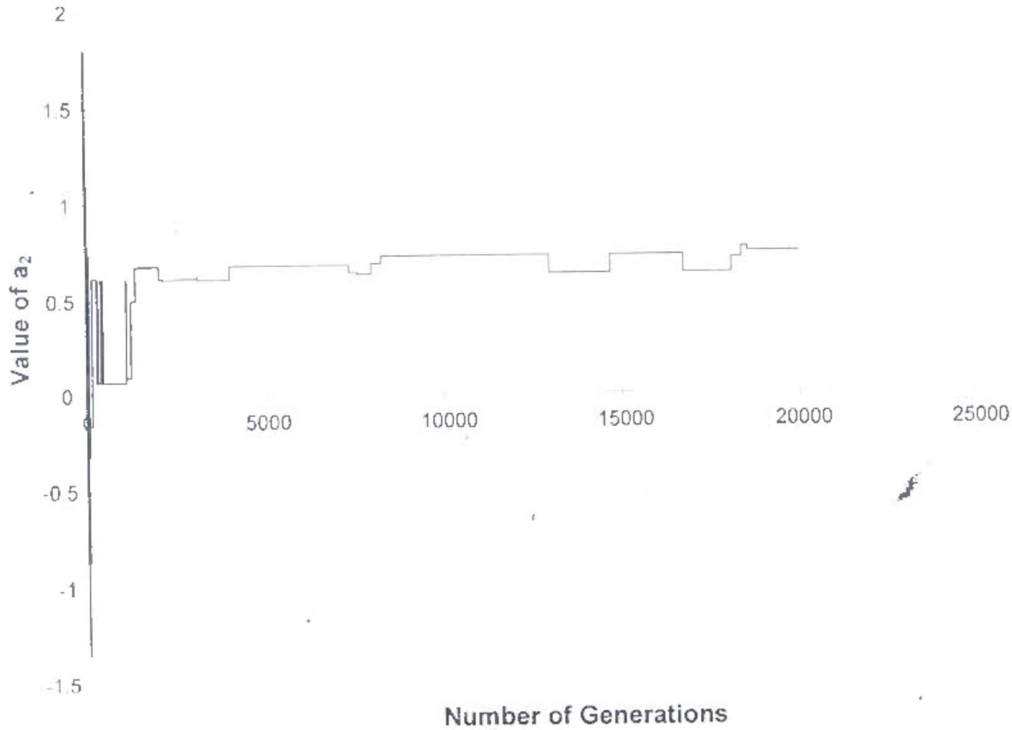


Figure 4.6: Distribution of Variable 3 (a_2) vs. Number of generations

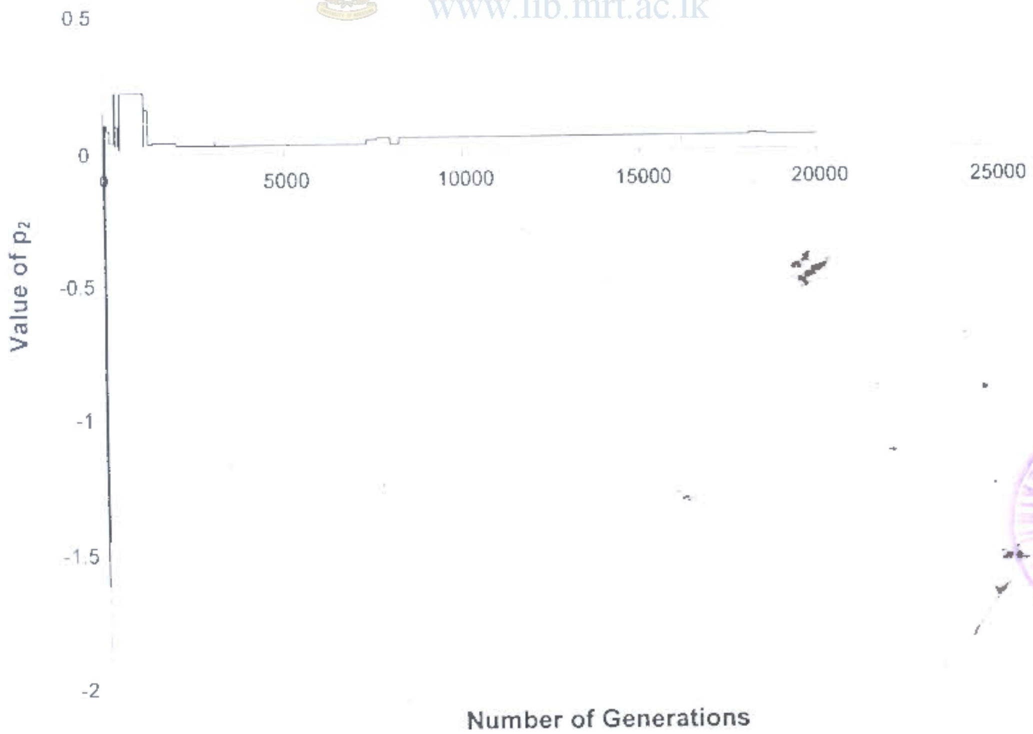


Figure 4.7: Distribution of Variable 4 (p_2) vs. Number of generations

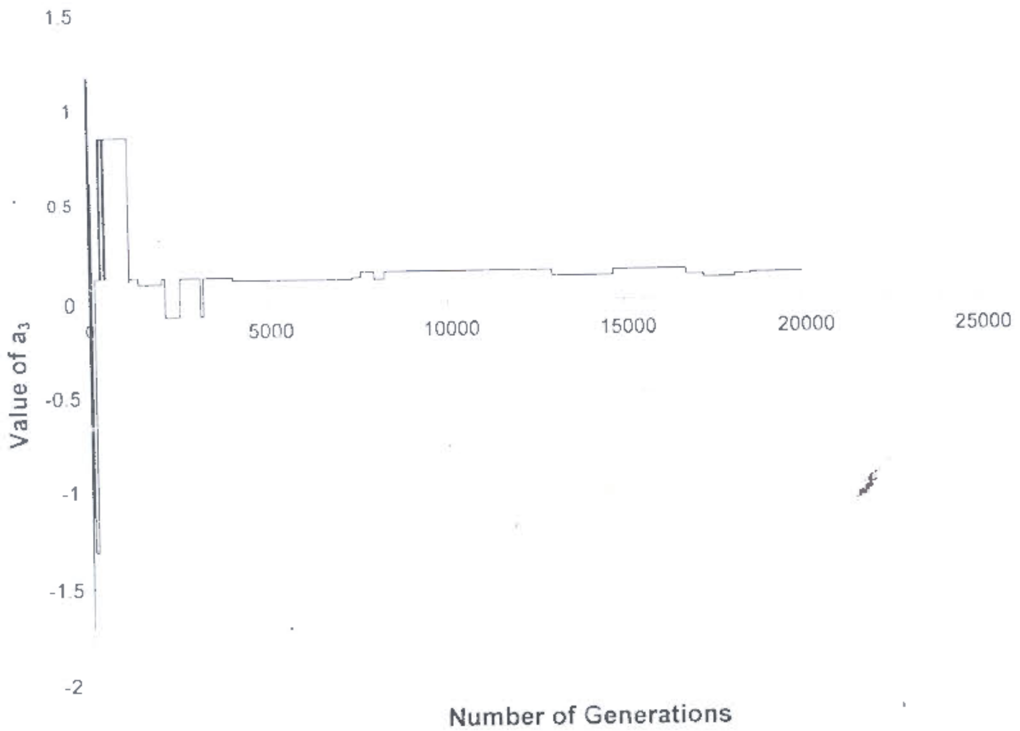


Figure 4.8: Distribution of Variable 5 (a_3) vs. Number of generations

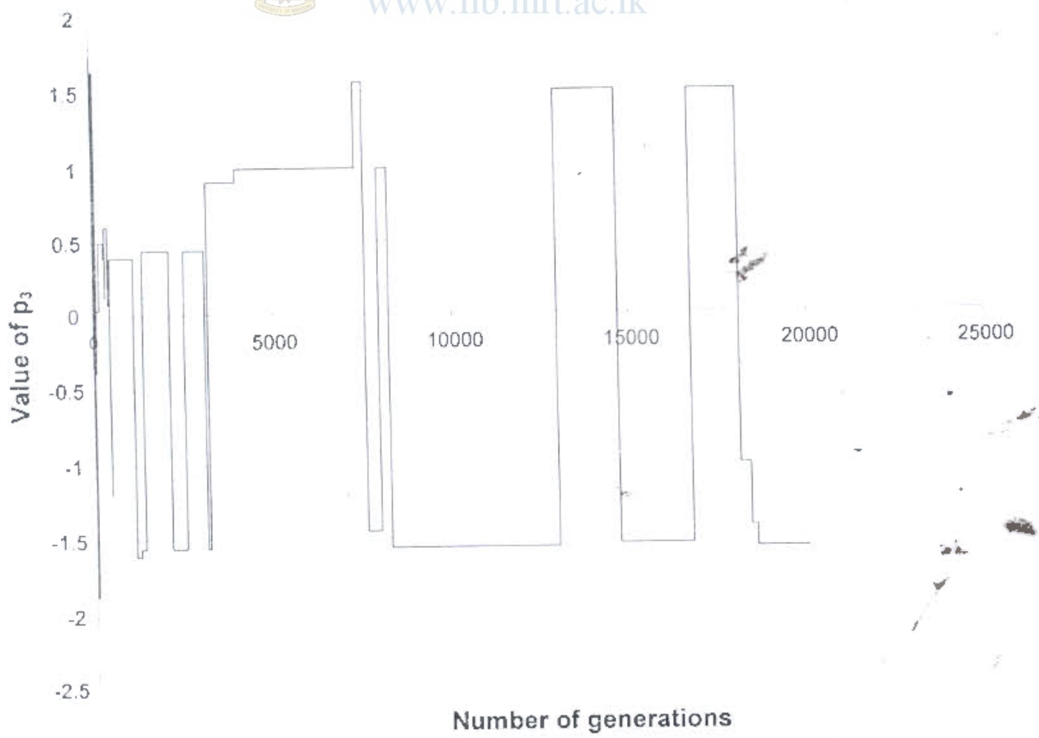


Figure 4.9: Distribution of Variable 6 (p_3) vs. Number of generations

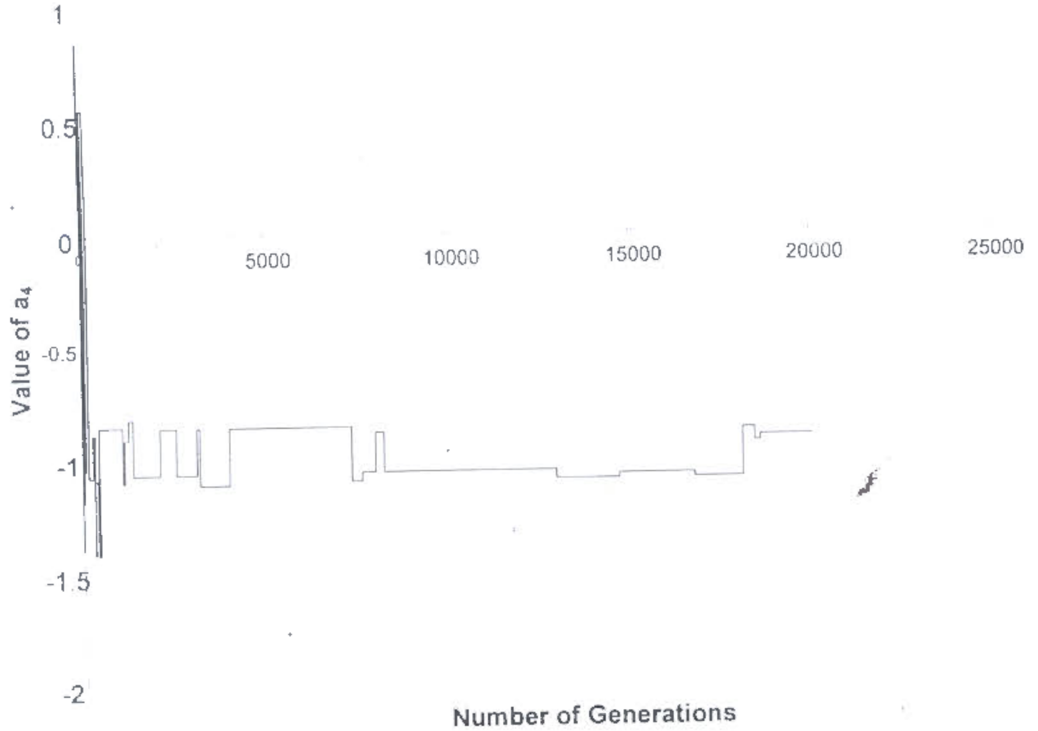


Figure 4.10 Distribution of Variable 7 (a_4) vs. Number of generations

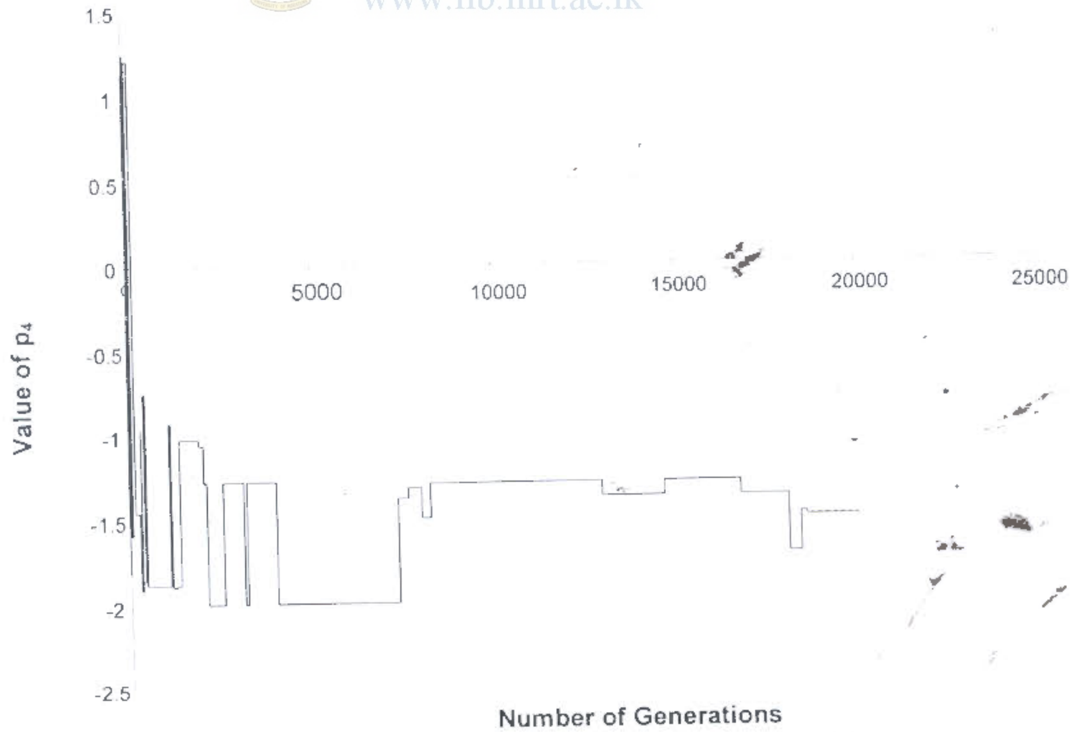


Figure 4.11 Distribution of Variable 8 (p_4) vs. Number of generations

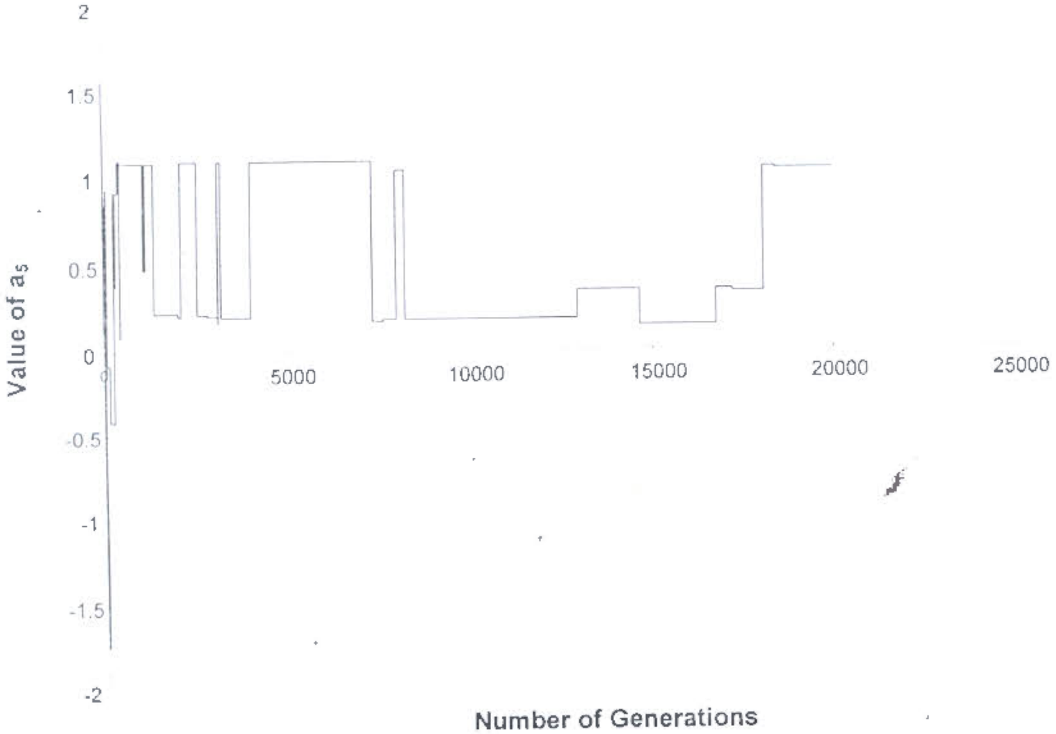


Figure 4.12: Distribution of Variable 9 (a_5) vs. Number of generations

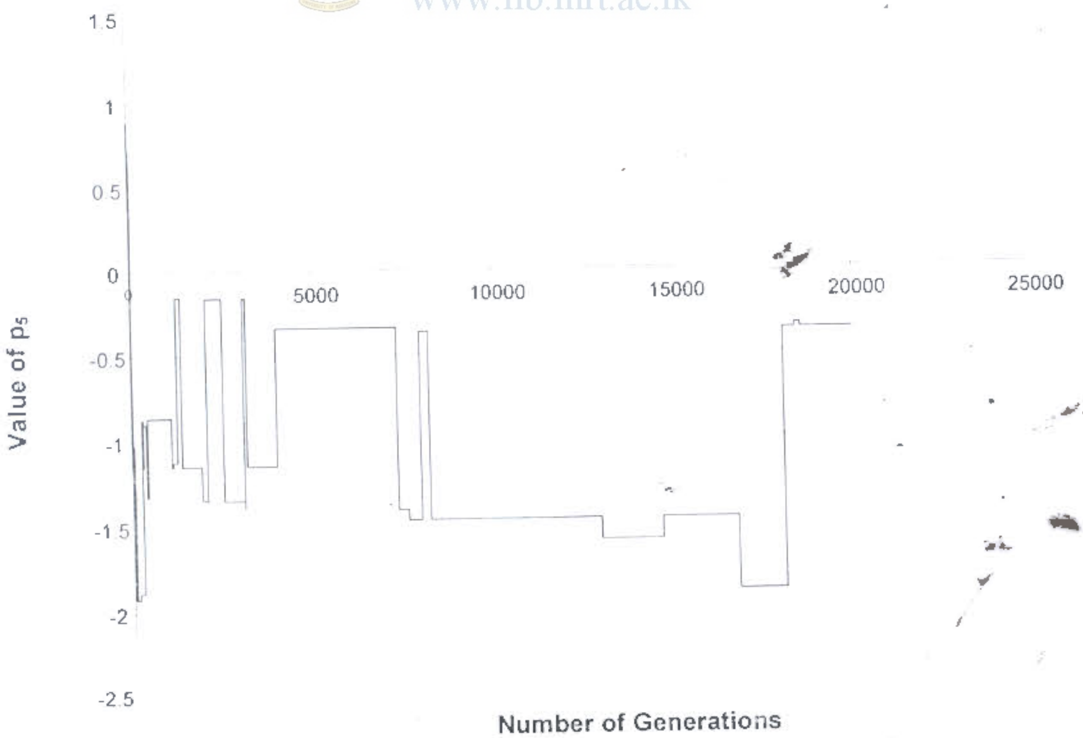


Figure 4.13: Distribution of Variable 10 (p_5) vs. Number of generations

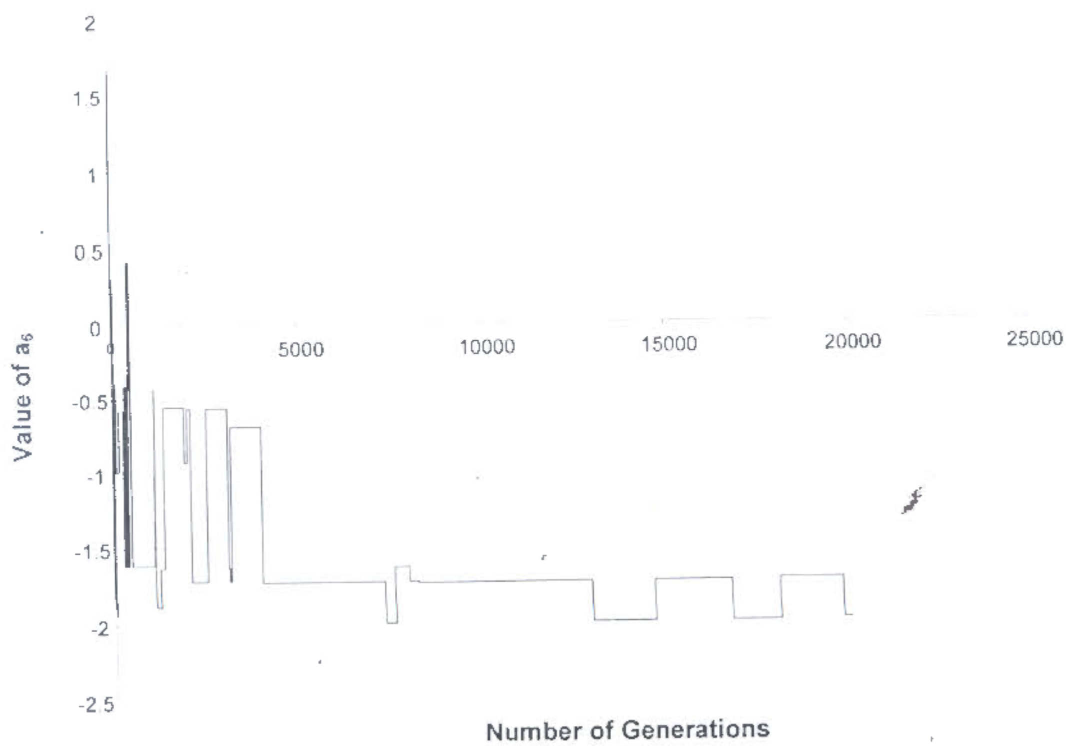


Figure 4.14: Distribution of Variable 11 (a_6) vs. Number of generations

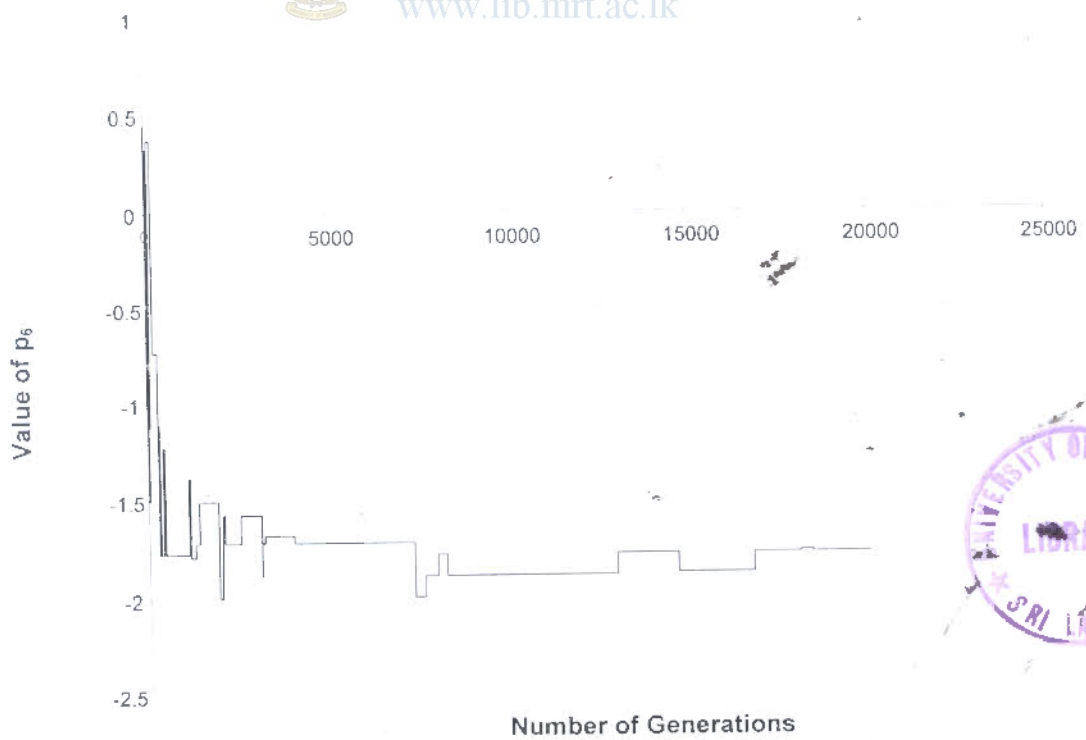


Figure 4.15: Distribution of Variable 12 (p_6) vs. Number of generations

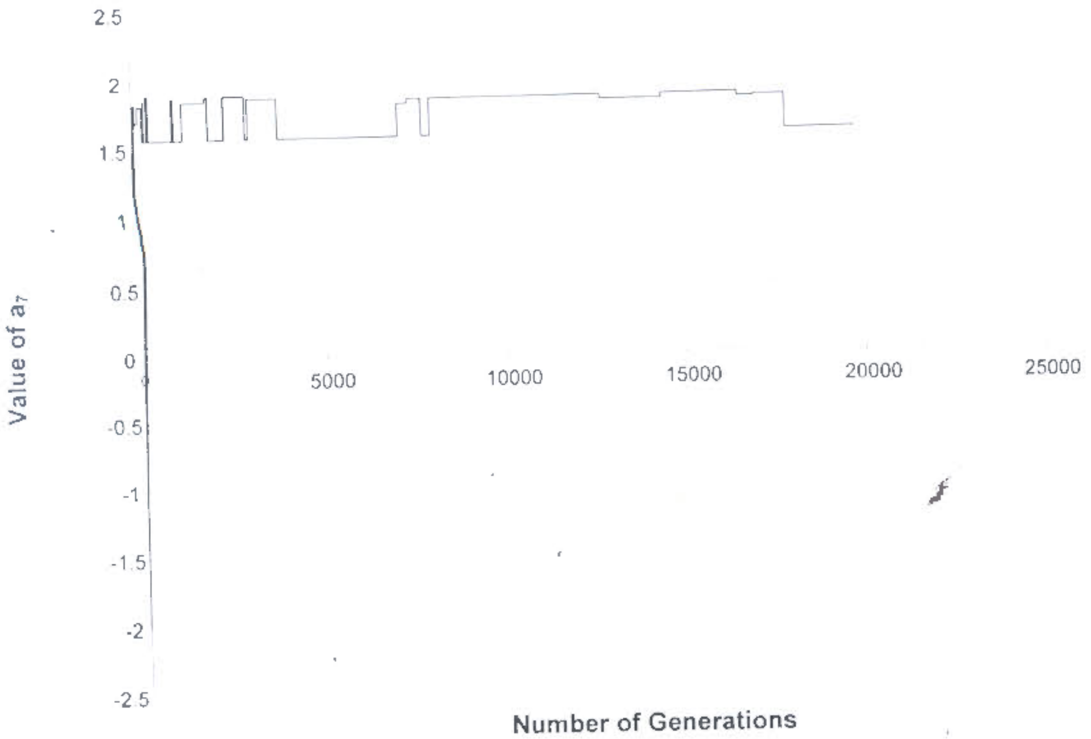


Figure 4.16: Distribution of Variable 13 (a_7) vs. Number of generations

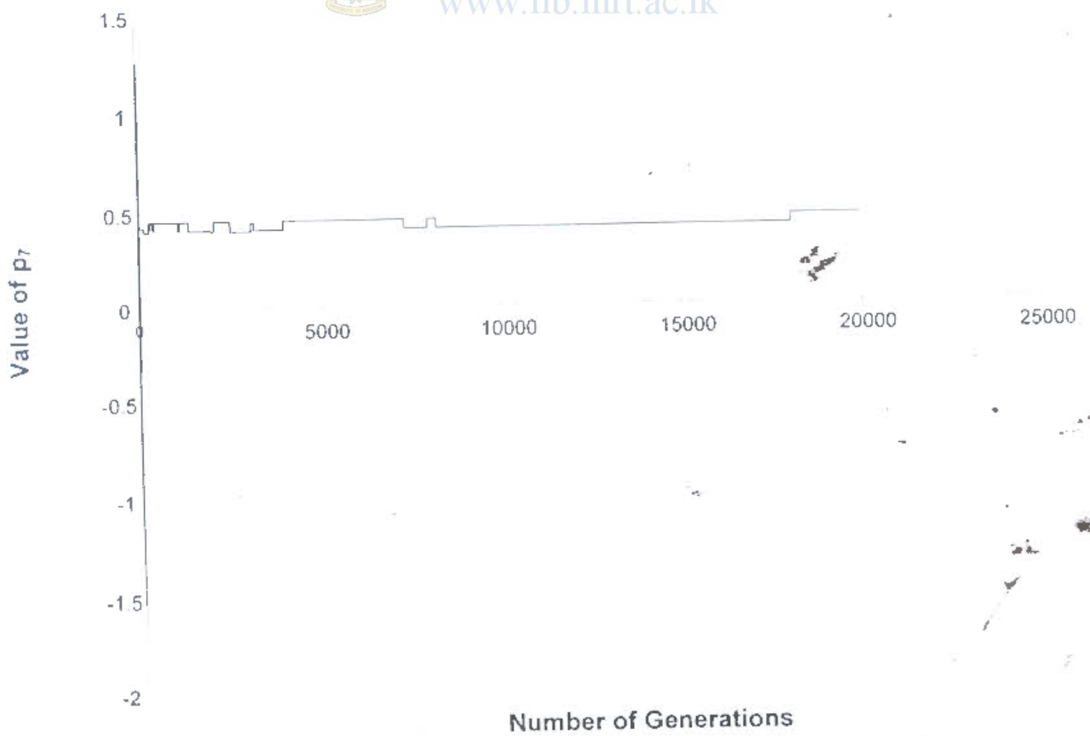


Figure 4.17: Distribution of Variable 14 (p_7) vs. Number of generations

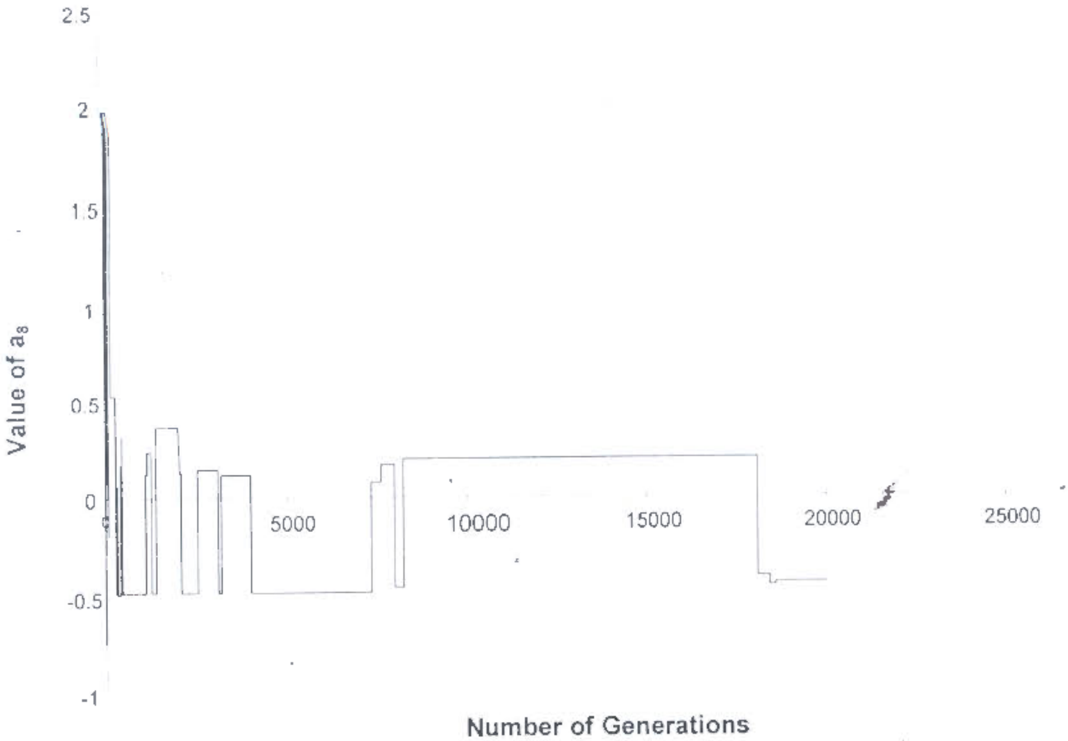


Figure 4.18: Distribution of Variable 15 (a_8) vs. Number of generations

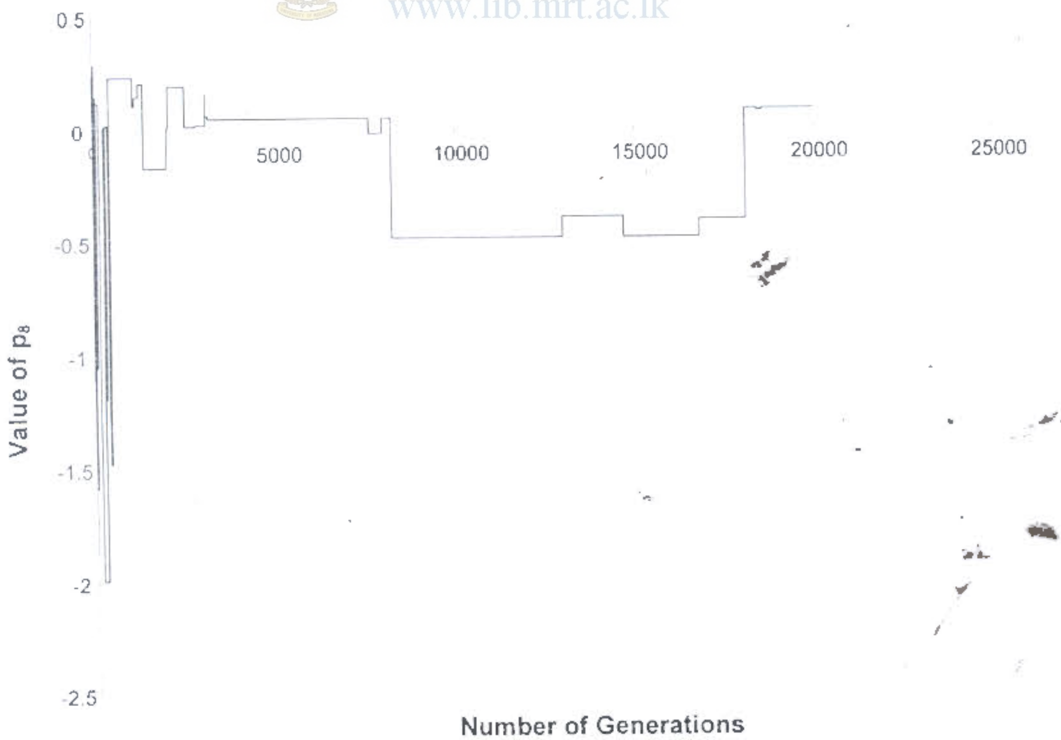


Figure 4.19: Distribution of Variable 16 (p_8) vs. Number of generations

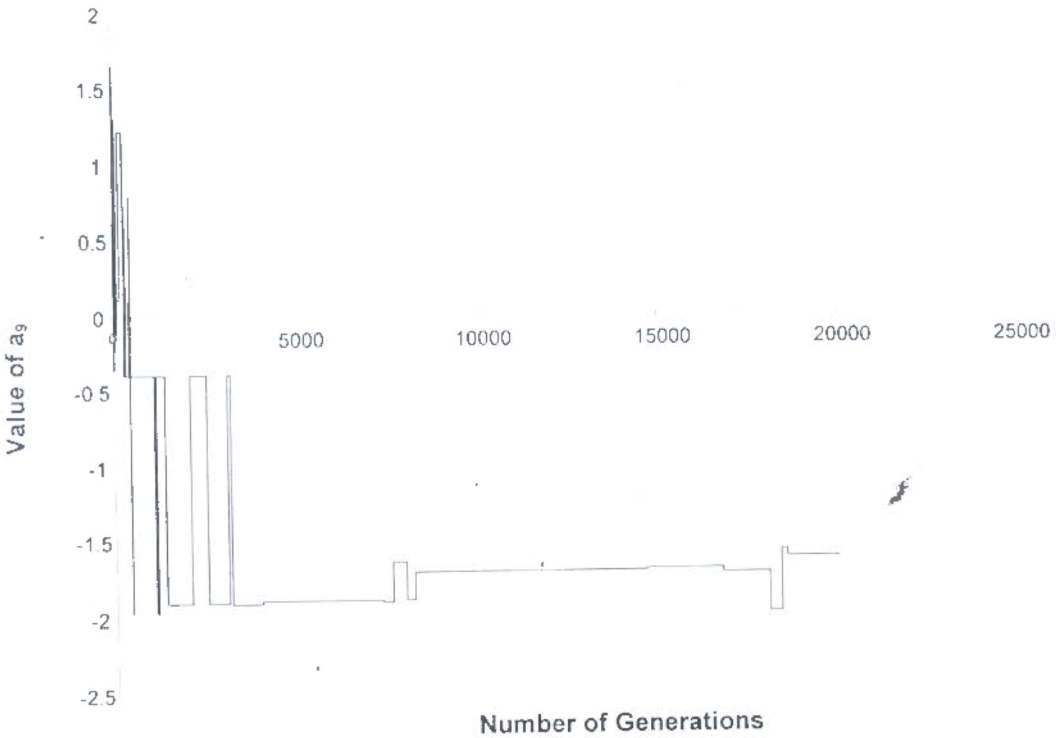


Figure 4.20: Distribution of Variable 17 (a_9) vs. Number of generations

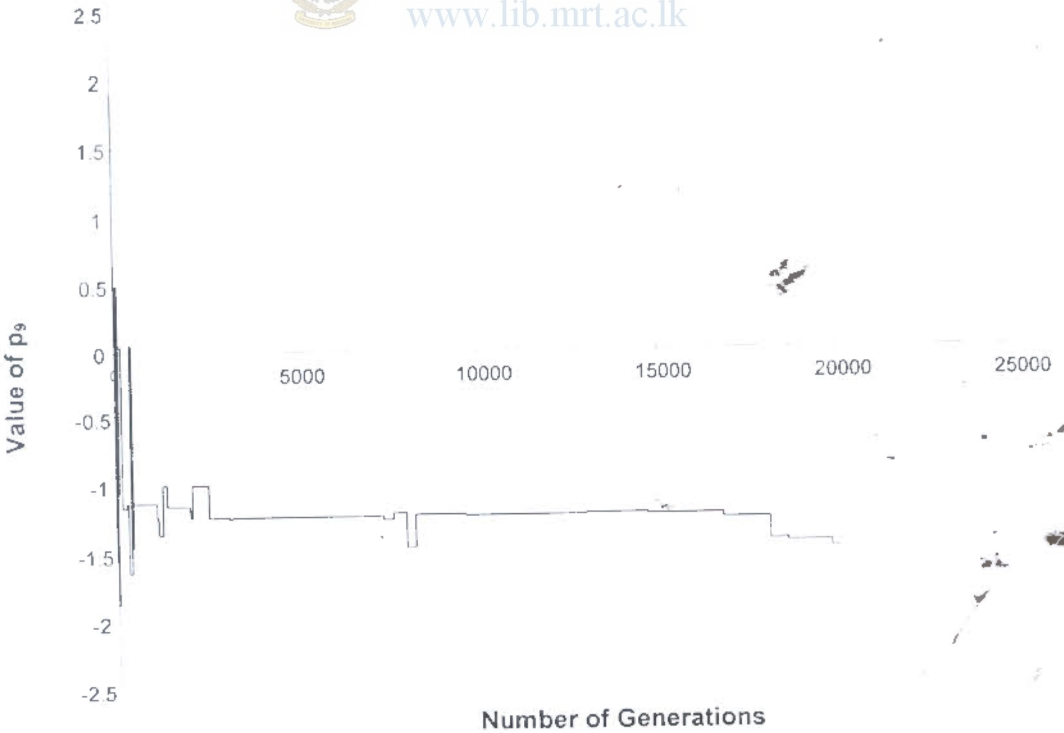


Figure 4.21: Distribution of Variable 18 (p_9) vs. Number of generations

According to the Figures 4.7 and 4.17, it could be considered that the parameters p_2 & p_7 have come to a steady state condition after 20, 000 number of generations. But when refer to figures such as Figure 4.9, parameter p_3 has not been converged to a steady state condition and it does not show even an indication of its convergence. The evolution of the parameters p_1 (Figure 4.5), a_3 (Figure 4.8) and p_6 (Figure 4.15) show they would converge to some steady state level with the increase of the number of generations.

Suggestions:

From (1) and (2),

$$F(x) = f_{ERROR}^{0.5} + \left(a_1 x_1^{p_1} + a_2 x_2^{p_2} + \ldots\ldots + a_M x_M^{p_M}.\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

Sensitivity of equation (3):

$$F(x) = f_{ERROR}^{0.5} + \left(a_1 x_1^{p_1} + a_2 x_2^{p_2} + \ldots\ldots + a_M x_M^{p_M}.\right)$$

$$\frac{\partial F(x)}{\partial x_1} = a_1 p_1 x_1^{(p_1 - 1)} = S_1$$

$$\frac{\partial F(x)}{\partial x_2} = a_2 p_2 x_2^{(p_2 - 1)} = S_2$$

$$\vdots$$

$$\frac{\partial F(x)}{\partial x_M} = a_M p_M x_M^{(p_M - 1)} = S_M$$

It may be assumed equal sensitivity for all variables-since we do not know the influence of each factor on the forecasting model.

i.e.

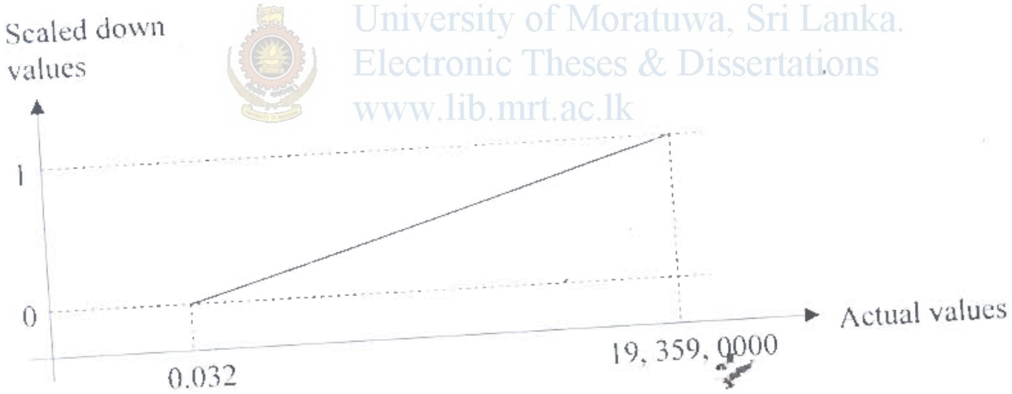
$$S_1 = S_2 = \ldots\ldots\ldots\ldots\ldots\ldots = S_M$$

$$a_1 p_1 x_1^{(p_1 - 1)} = a_2 p_2 x_2^{(p_2 - 1)} = \ldots\ldots\ldots\ldots\ldots\ldots = a_M p_M x_M^{(p_M - 1)}$$

CONTINUED....

- The figures of the factors considered vary with in a very wide range. For an example, the mid year population of year 2000 was 19, 359, 000 and the population growth rate was 1.4 as a percentage. Compared to the value of population, the latter value is negligible. But, since it is considered that each and every factor (variables of the fitness function) has equal sensitivity, any of those figures can not be neglected.

  The methodology "Input-scaling" could be practiced at the stage of GA training. When consider the whole set of data from yr. 1984 till yr. 2001, the smallest value is 0.032 (unit price of electricity – Indus. and comm. in US $ in yr. 1986) and the largest value is 19, 359, 000 (population in yr 2000). All the other figures vary with in this range. So, input scaling is done by mapping 0.032 to 0 and 19, 359, 000 to 1 as shown in the following figure.



- If the number of generations could have been increased to a higher value (e.g. 60, 000), more clear idea about the convergence.

CHAPTER 5

Forecasting Model for Electrical Energy Demand of Sri Lanka

5.1 Preparing the forecasting Model

When consider the Genetic Algorithm, it has been trained for a particular set of data. So the accuracy of the output is high with in the state-space of the input data. When the input data moves beyond the stat-space considered, gradually the accuracy of the output reduces.

As discussed in chapter 4, with the values obtained at the Best Fit condition after 20,000 number of generations was used in preparing the model for Electrical Energy Demand Forecasting.

From (2),

$$\begin{aligned} F(x) = {} & \left(0.79787^{0.5}\right) + \left(-1.18024 \times x_1^{-1.31335}\right) + \left(0.742877 \times x_2^{0.048903}\right) + \left(0.128874 \times x_3^{-1.5704}\right) + \\ & \left(-0.92489 \times x_4^{-1.51104}\right) + \left(1.033729 \times x_5^{-0.37124}\right) + \left(-1.98654 \times x_6^{-1.77698}\right) + \left(1.557174 \times x_3^{0.452536}\right) + \\ & \left(-0.44033 \times x_3^{0..080473}\right) + \left(-1.64072 \times x_3^{-1.4893}\right) \end{aligned} \qquad \text{.................(3)}$$

The description of the variables in equation (4) is given in the Figure 5.1.

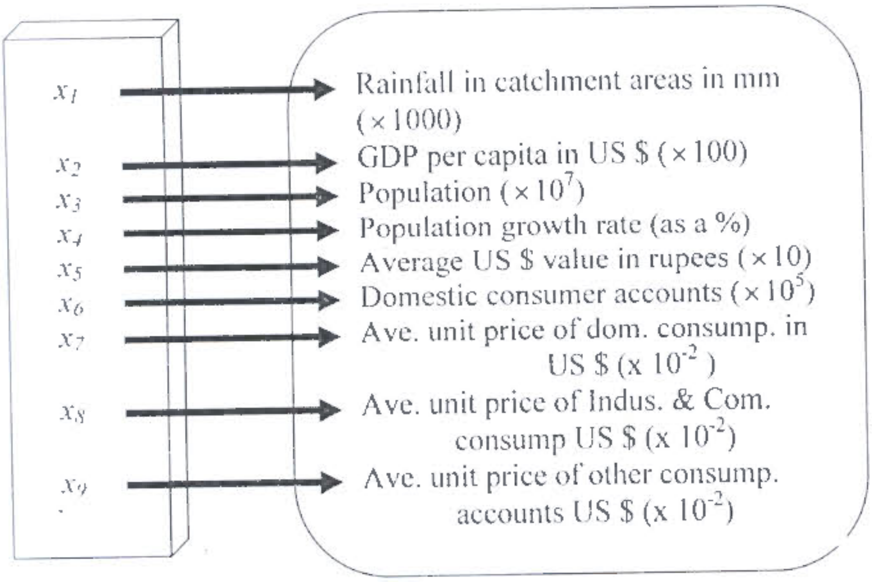


Figure 5.1: Details of the factors considered in the model

Hence,

With the available real time data for the above factors in year 2002 & 2003, the forecasted electricity demand for corresponding years using (4):

Electrical energy demand for year 2002 = 7.11091 TWh

Electrical energy demand for year 2003 = 7.17532 TWh

5.2 Error with the forecasted data

Error with the forecasted demand with respect to the actual demand could be defined as,

$$\% \text{ error} = \frac{\text{actual dem. - forecasted dem.}}{\text{actual demand}} \times 100\%$$

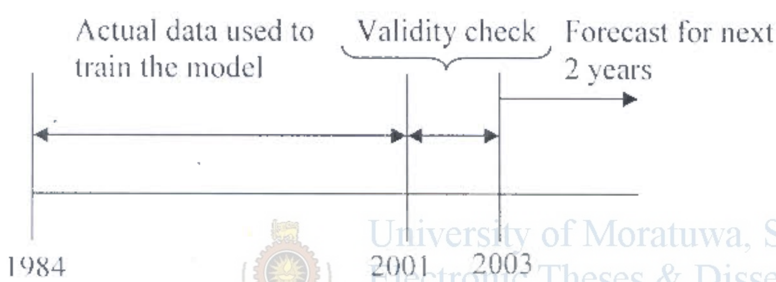
For year 2002:

$$\left(\frac{6.75559-7.11091}{6.75559}\right)\times 100\% = 5.736731\%$$

For year 2003:

$$\left(\frac{7.612-7.17532}{7.612}\right)\times 100\% = \text{-}5.25964\%$$

5.4 Validity of the forecasting Model



The model has been trained with 18 years (from year 1984 till year 2001) of actual data. Then the validity of the results was checked for the next 2 years. The table shown in Table 5.1 presents a comparison between the accuracy of the GA model forecast and the Time trend forecast (done by the CEB) for these two years.

Table 5.1

Comparison of the GA model forecast and the Time trend forecast (done by the CEB) for these two years.

Year	Forecasted Demand	error %	Actual Demand (TWh)	Time Trend Forecasted demnad by the CEB	error %
2002	7.110906	-5.25319	6.756	7.381	-9.251036
2003	7.175318	5.73675	7.612	8.106	-6.489753
2004	7.668869	4.65164	8.043	8.889	-10.518463
2005	7.836188			8.889	
2006	8.069451			9.748	

Electricity Demand of Sri Lanka with the model forecasted data is appeared in figure 5.2.

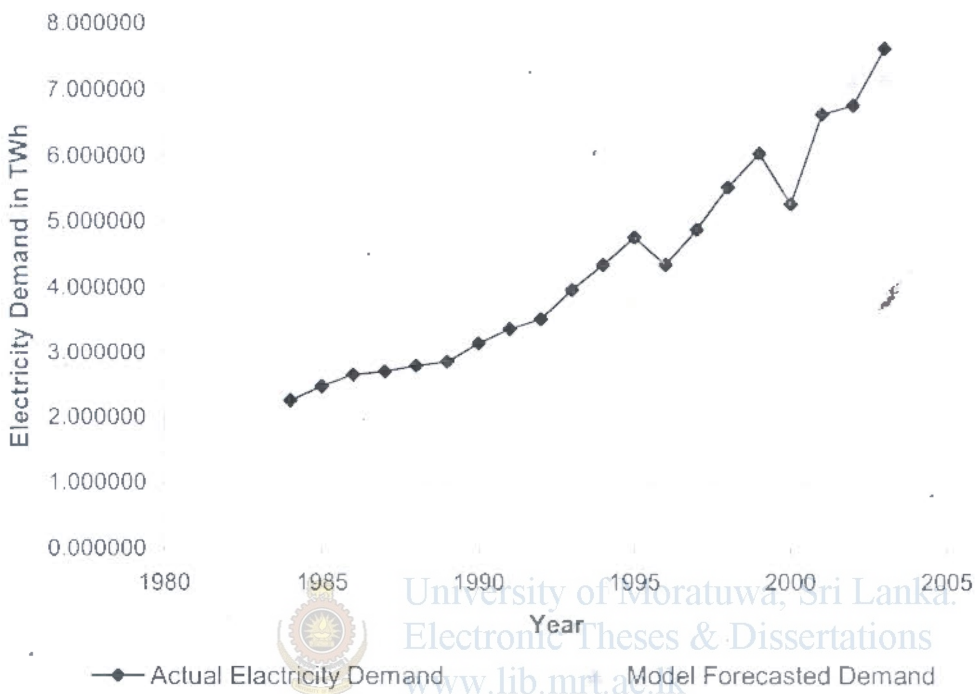


Figure 5.2: Energy demand vs. Year (actual data and the model forecasted data)

5.5 Electricity Demand forecast

In the process of forecasting Electrical Energy Demand of Sri Lanka, forecasted data of each factor under consideration (the factors that are been considered in designing the forecasting model) are needed.

Sources of forecasted data:

- CEB – domestic consumer accounts
- By doing a time trend analysis to obtain the rest of the data by myself.

Appendix II shows the forecasted data under each factor.

The forecasted electrical energy demand with the above data is shown in Figure 5.3.

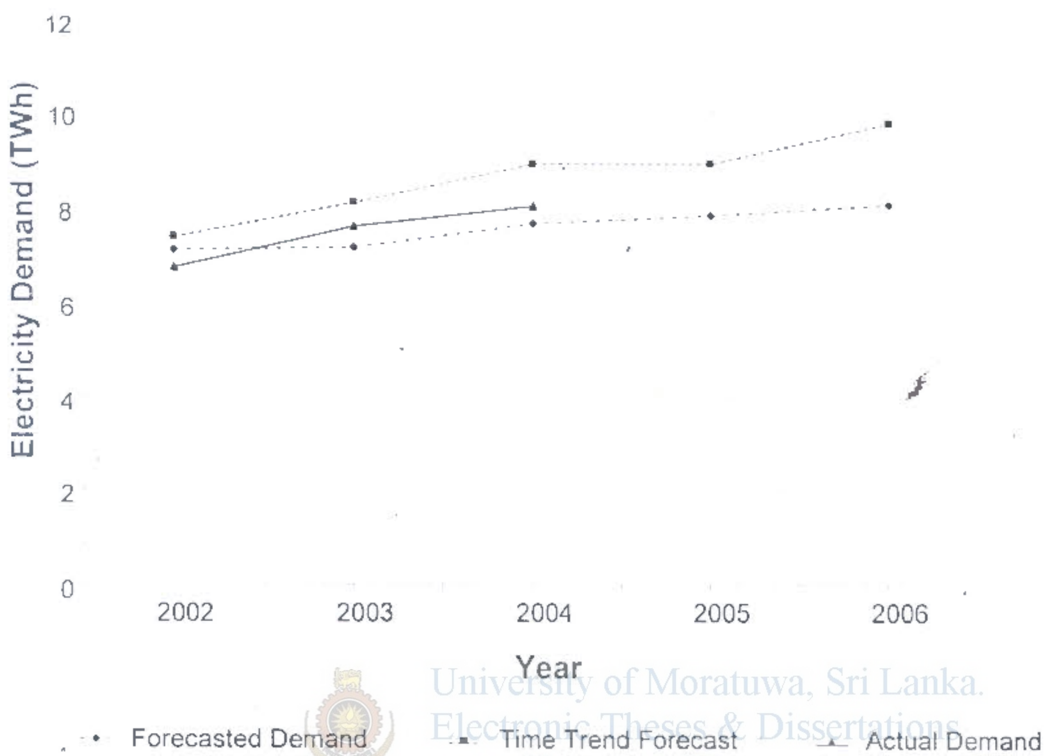


Figure 5.3: Electrical Energy Demand forecast done with the model – Short Term

Considering a 55% Load Factor, The possible Peak Electricity Demand could be presented as shown in Table 5.2.

Table 5.2

The possible Peak Electricity Demand considering a 55% Load Factor

Year	Forecasted Demand (TWh)	Load Factor	Maximum possible peak demand (MW)
2004	7.668869	55%	1591.712121
2005	7.836188	55%	1626.440017
2006	8.069451	55%	1674.854919

The Figure 5.1 shows the load curve of an average day of the Sri Lankan Power system. The Peak demand occurred around 20 00 hours and it was 1604 MW. This demand could be met with the forecast done with the GA based model; i.e. 1626.44 MW.

Figure 5.4: Load curve of Sri Lanka on 1st June 2005

Comment on Section 5.4 and 5.5:

According to the above validity check as well as the forecast, it is shown there is a higher accuracy with the forecasted data when compared with the actual available data.

⇨ **If the GA could have been trained with actual data up to the year we know, with a larger number of generations (e.g. 60, 000), more accurate short term demand forecasting could be obtained.**

5.6 Conclusion

This thesis has described a novel concept of forecasting electrical energy demand of Sri Lanka. The effectiveness of the proposed methodology based on Genetic Algorithms (GA) optimization was demonstrated by the results.

This GA based electricity demand forecasting model has several advantages. It was modeled considering 9 major factors that could affect the electricity demand of Sri Lanka. They are GDP, Population, Population growth rate, Average annual rain-fall in catchment areas, Average US $ value, Domestic consumer accounts, Average unit price of domestic electricity consumption (in US $), Average unit price of industrial and commercial elect. consumption (in US $), Average unit price of other elect. consumption accounts (in US $). In this model **TIME has not been considered as a factor**, since the electricity demand of the country is dominated by the several other components (Discussed in Chapter 3) but not time.

The applicability of GA for the problem and the validity for the electricity demand of the Forecasting Model have been verified experimentally. **This GA based model would support the short term electricity demand forecasting of a given system.**

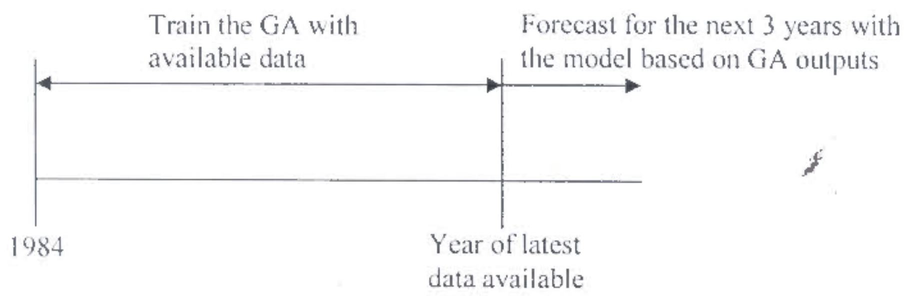
More accurately forecasted data for each factor would predict the Electrical Energy Demand with a larger accuracy. In the prediction of figures of each factor, support of the Genetic Algorithms is highly recommended.

To improve the accuracy of the results,

- **Input Scaling could be practiced at the stage of GA training.**
- **Number of generations could be increased to a range such as 60,000 or more.**
- **Use of more improved programs (GAs) with less processing time etc.**

CONTINUED ....

- **Use of computers with higher memory capacity**
- **Use of more speedy computers**
- **In order to run such programs specially committed computers for the work concerned are essential.**



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APPENDIX I

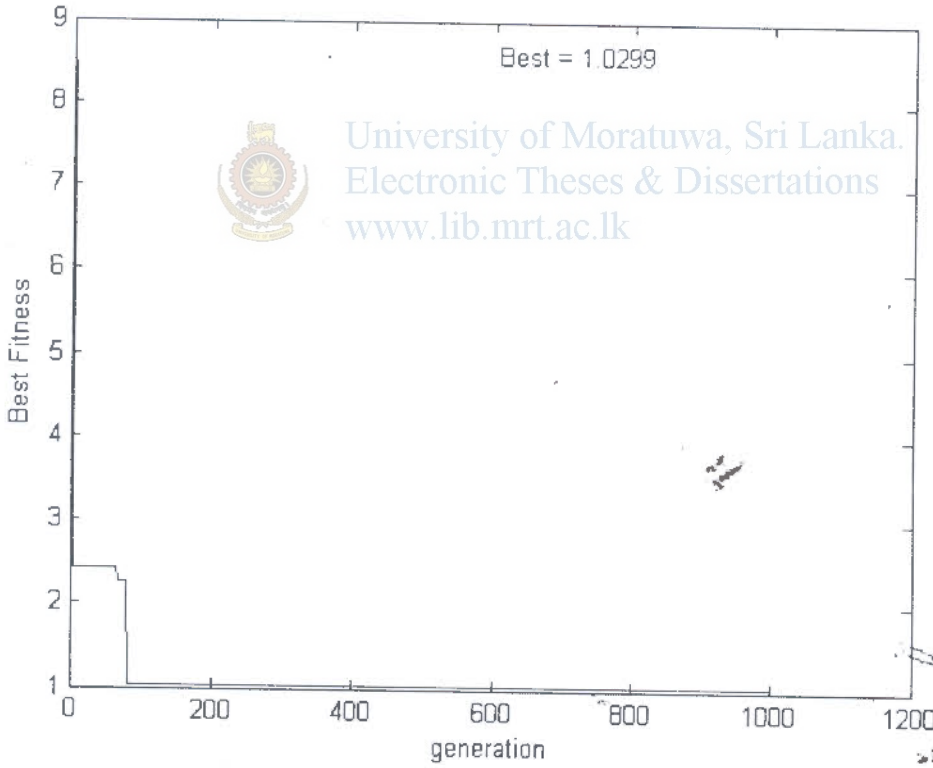
Fitness values obtained with different parameter settings
(Based on data from year 1984 till year 2000)

Results when Mutation Probability, Pm = 0.7*250/Lind

NIND = 100;	- Number of individuals per subpopulations
MAXGEN = 1000;	- Maximum Number of generations
GGAP = 0.9;	- Generation gap, how many new individuals are created
NVAR = 18;	- Generation gap, how many new individuals are created
PRECI = 20;	- Precision of binary representation
FieldD	- Build field descriptor [16]

FieldD = [rep ([PRECI], [1, NVAR]);...
-2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 ;...
rep ([1; 0; 1 ;1], [1, NVAR])];

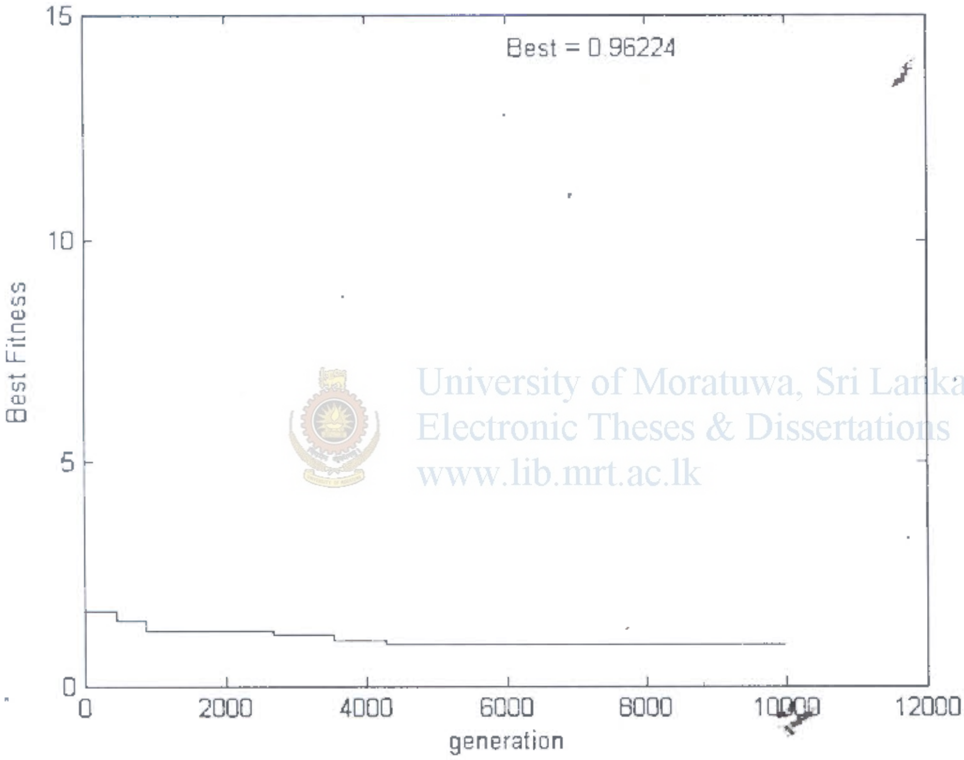
Upper and lower limits (range) of a_M and p_M.



Results = Columns 1 through 6
-1.5251 -1.2937 0.9246 0.7158 -0.0089 -0.8835
Columns 7 through 12
1.8537 0.2487 -1.5434 -1.0076 0.4868 0.3781
Columns 13 through 18
-1.7182 -1.8608 -1.1003 -0.8356 -0.4940 0.437

```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep ([PRECI], [1, NVAR]);...
        -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
         2  2 2 2  2 2 2  2 2 2  2 2 2  2 2 2  2 2 ;...
         rep ([1; 0; 1 ;1], [1, NVAR])];
```

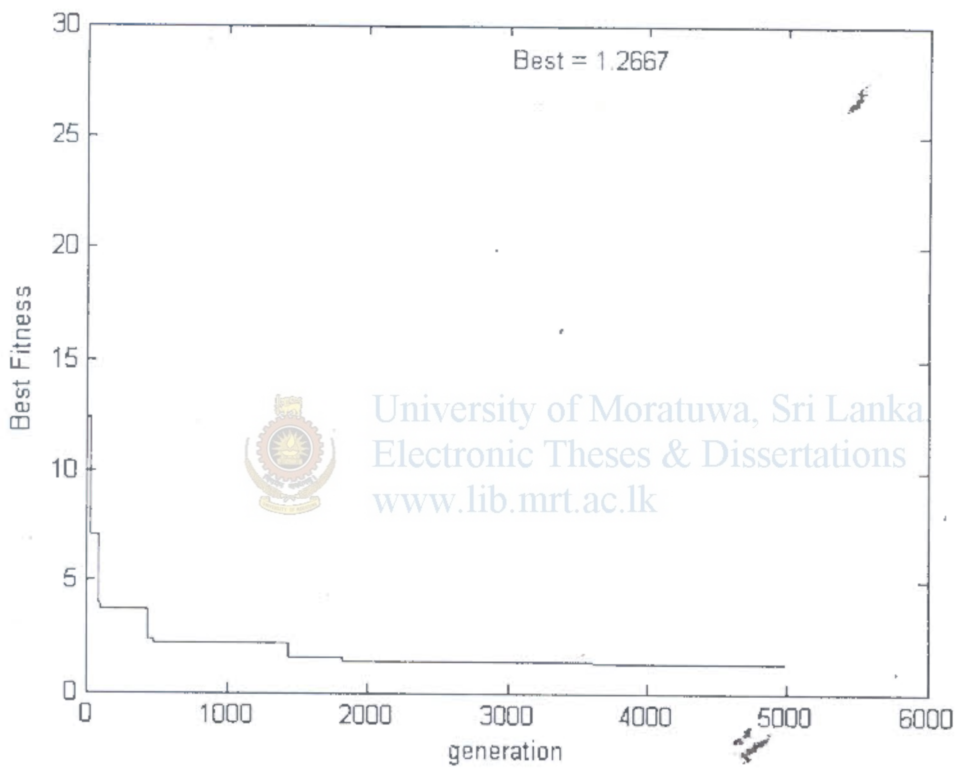
Upper and lower limits (range) of a_M and p_M.




```
Results =
  Columns 1 through 6
   1.0076    0.5993   -1.4192   -1.7846   -0.5897   -0.2624
  Columns 7 through 12
   0.3174    0.5689   -1.7132   -1.5359    0.9429   -0.9363
  Columns 13 through 18
   0.4754    0.6944   -0.0940   -1.6930    0.1108    0.1660
```

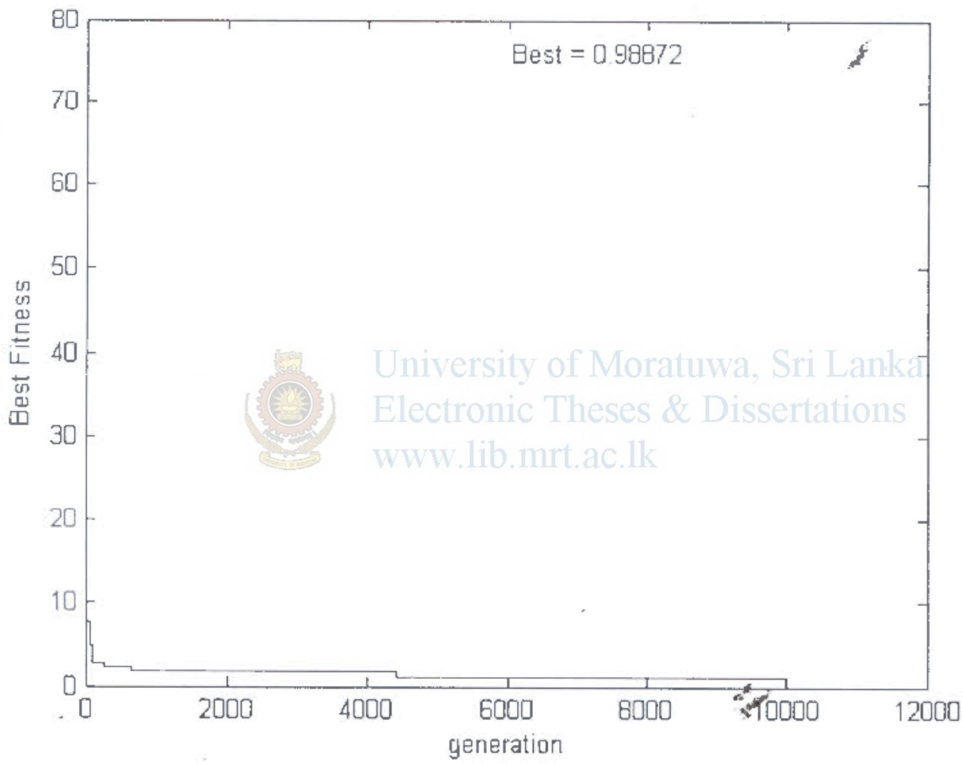
```
NIND = 100;
MAXGEN = 5000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep ([PRECI], [1, NVAR]);...
        -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 ;...
         3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3 ;...
         rep ([1; 0; 1 ;1], [1, NVAR])];
```

Upper and lower limits (range) of a_M and p_M.




```
Results =
  Columns 1 through 6
   2.4247   -2.4113   -2.8759   -2.4226    2.0302   -1.2192
  Columns 7 through 12
  -0.4386   -0.9009    0.8850    0.8931    0.7326   -0.7946
  Columns 13 through 18
  -0.7488   -2.2293   -1.8770   -0.1972    0.0252    1.7023
```

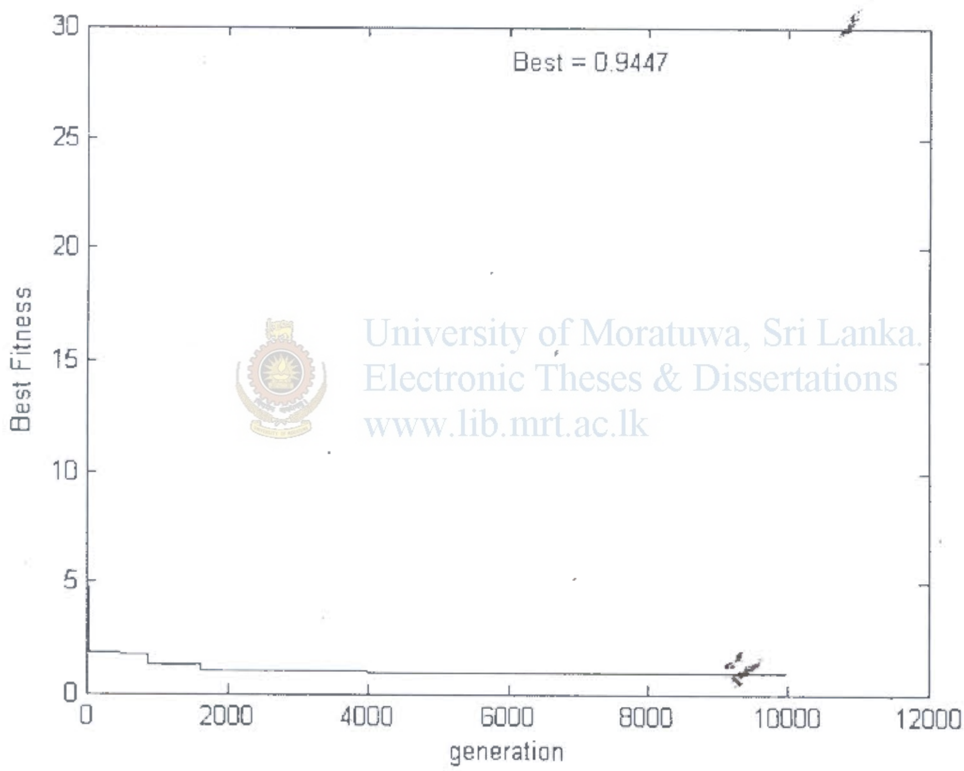
```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep ([PRECI], [1, NVAR]); ...
         -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 -3 ; ...
          3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3  3 ; ...
          rep ([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
  Columns 1 through 6
    0.6812    0.9254    0.9343    0.6422   -2.4843   -0.3081
  Columns 7 through 12
    0.2420    2.1772    1.8777    0.5213   -2.7037   -0.2658
  Columns 13 through 18
   -0.0831    0.8562   -2.9682   -1.4105   -2.6174   -2.1406
```

Results when Mutation Probability, Pm = 0.7*400/Lind

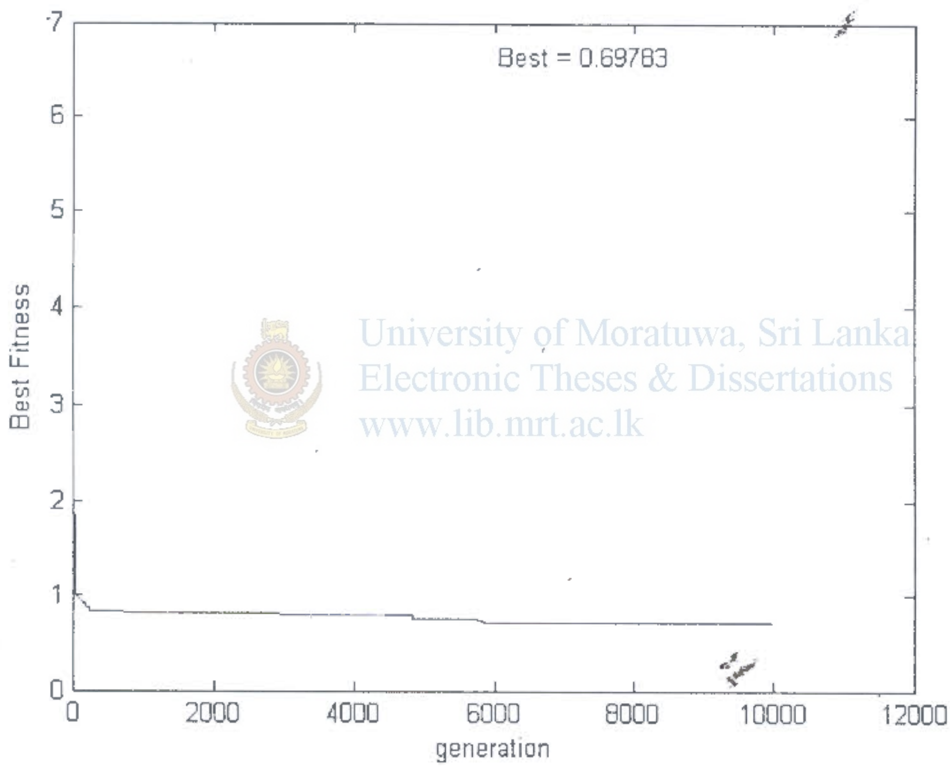
```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep ([PRECI], [1, NVAR]); ...
        -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ; ...
         2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
         rep ([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
  Columns 1 through 6
   0.8439  -1.3774   1.1086   0.7406   0.0182   1.1819
  Columns 7 through 12
  -1.1449  -0.3957   0.3422   0.3424  -0.7233  -0.8952
  Columns 13 through 18
  -0.1905  -1.9047   0.4735  -0.7872  -0.1141  -1.5473
```

Results when Mutation Probability, Pm = 0.7*500/Lind

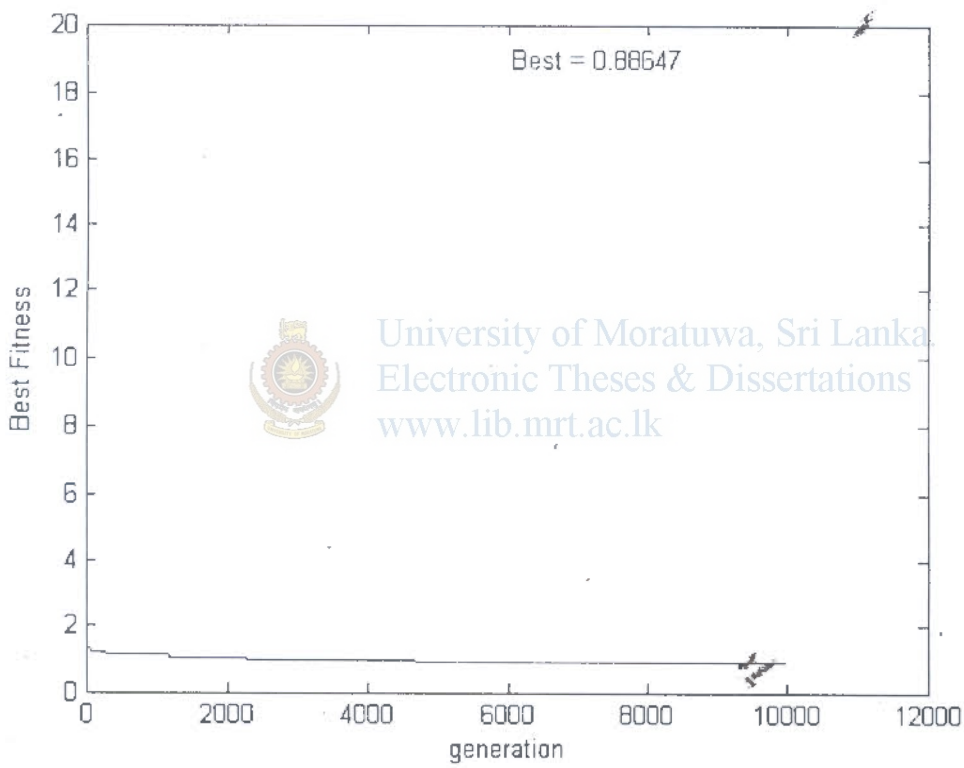
```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep ([PRECI], [1, NVAR]);...
          -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
           2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
           rep ([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
 Columns 1 through 6
  -1.6527    0.3665    1.9263    0.3314   -1.0139    0.7109
 Columns 7 through 12
  -1.2844   -0.8623    0.9255    0.6094   -0.1223   -1.5298
 Columns 13 through 18
   0.5933    0.3651    1.8038    0.0138   -1.9523   -1.0373
```

Results when Mutation Probability, Pm = 0.7*1000/Lind

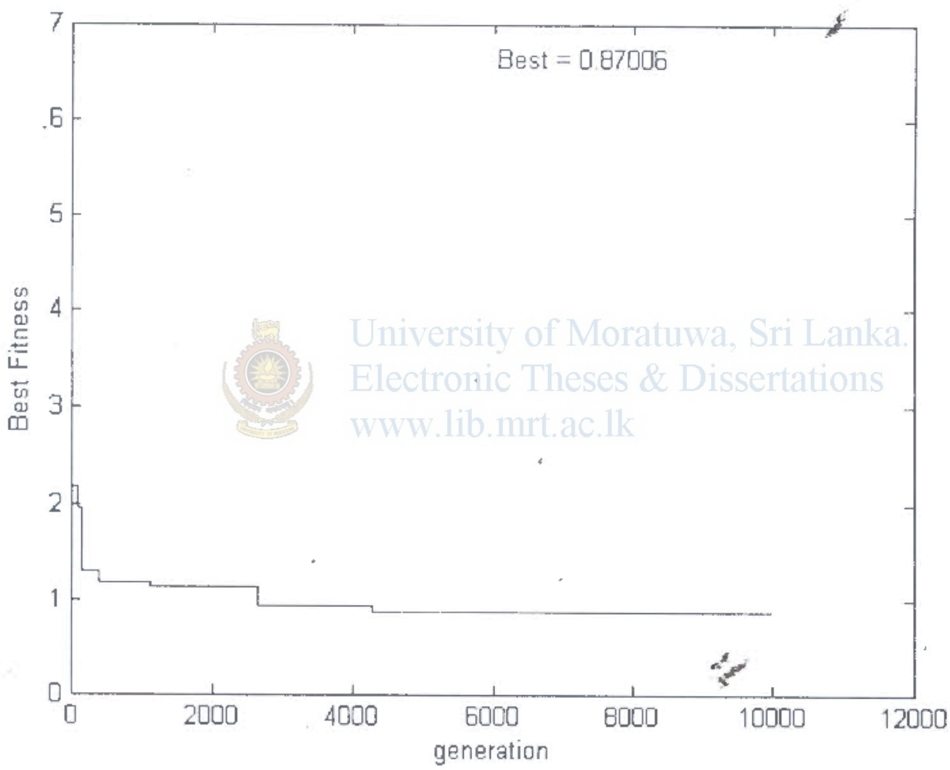
```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep ([PRECI], [1, NVAR]);...
          -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
           2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
           rep ([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
 Columns 1 through 6
  -1.8395   -0.4219    1.7896    0.0257   -0.4341   -0.5839
 Columns 7 through 12
  -1.9218   -0.3233    1.0436    0.3747    1.0628   -1.5312
 Columns 13 through 18
   0.8008    0.5234   -0.3124   -1.0164    1.0561   -0.1016
```

Results when Mutation Probability, Pm = 0.7*500/Lind

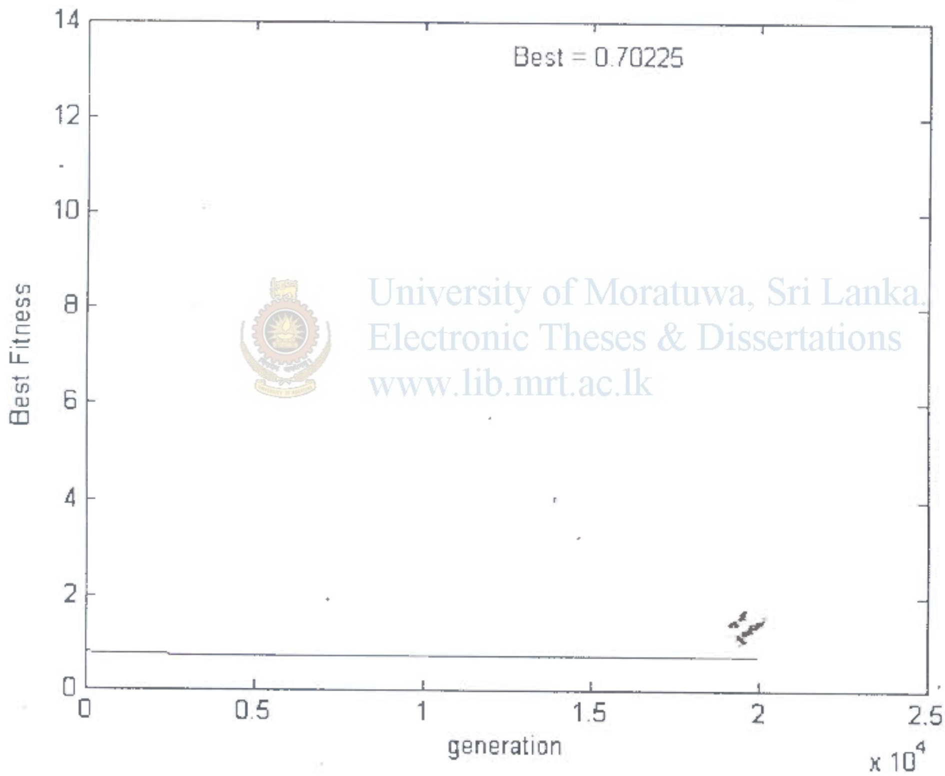
```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 40;
FieldD = [rep ([PRECI], [1, NVAR]);...
          -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
           2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
           rep ([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
 Columns 1 through 6
  -0.7057    0.1503   -0.3770   -1.6977   -1.6695    1.6845
 Columns 7 through 12
   1.2519    0.6184    1.8636   -0.1017    0.3175   -0.5775
 Columns 13 through 18
   1.5402    0.5034   -0.1287   -1.5052    0.4004    0.5004
```

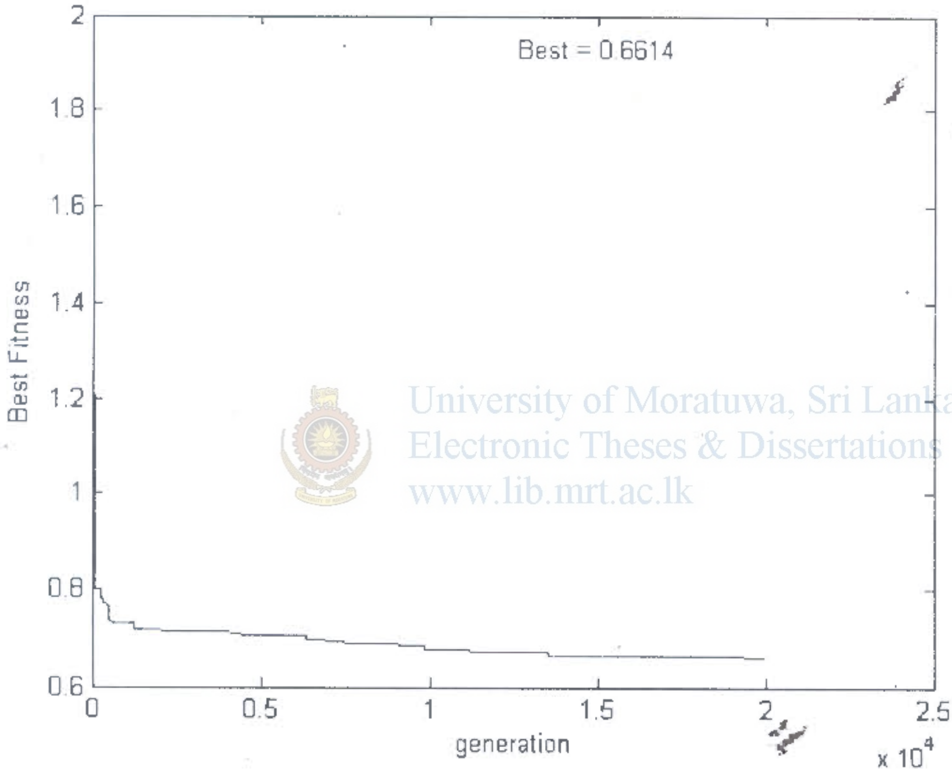
Results when Mutation Probability, Pm = 0.7*500/Lind

```
NIND = 100;
MAXGEN = 20000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep([PRECI],[1, NVAR]);...
         -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
          2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
          rep ([1; 0; 1 ;1], [1, NVAR])];
```



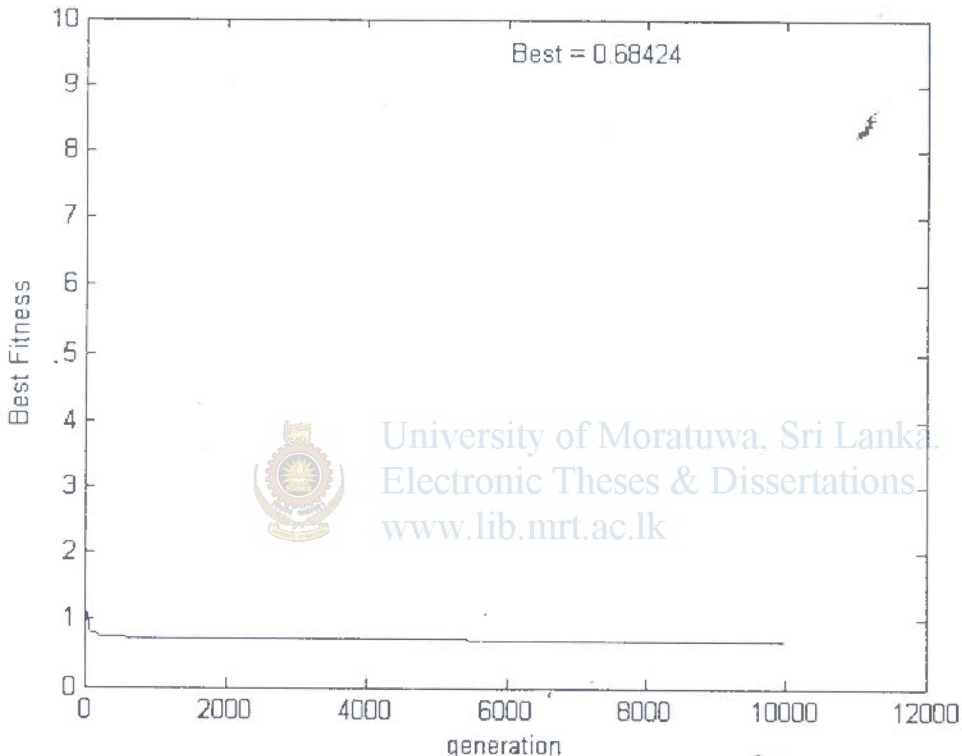

```
Results =
 Columns 1 through 6
  -0.4052    1.7932    1.4570    0.3500    1.9972   -1.5002
 Columns 7 through 12
  -1.0014   -1.3785   -1.2461   -0.4979    0.7342   -1.6090
 Columns 13 through 18
   1.2301    0.4015   -0.6925   -1.9561   -1.0947   -1.8497
```

```
NIND = 200;
MAXGEN = 20000; .
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep([PRECI],[1, NVAR]);...
          -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
           2  2  2  2  2  2  2  2  2  2  2  2  2  2  2· 2  2  2 ;...
           rep([1; 0; 1 ;1], [1, NVAR])];
```



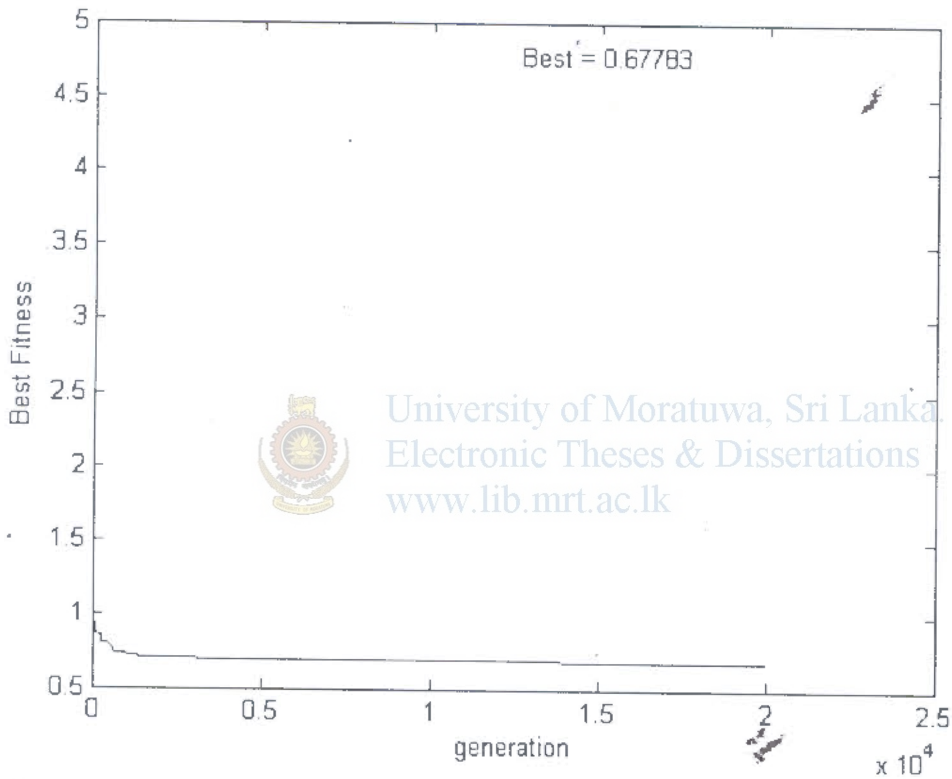

```
Results =
 Columns 1 through 6
  1.8031   0.0592   0.3374   0.8585  -0.8947      1.8110
 Columns 7 through 12
  -0.9129  -1.3025  -1.8756  -1.2351              -0.4553  -1.9585
 Columns 13 through 18
  1.8921   0.3113  -0.0097   0.2202   0.0593   0.3691
```

```
NIND = 100;
MAXGEN = 10000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep([PRECI],[1, NVAR]);...
        -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
         2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
         rep([1; 0; 1 ;1], [1, NVAR])];
```



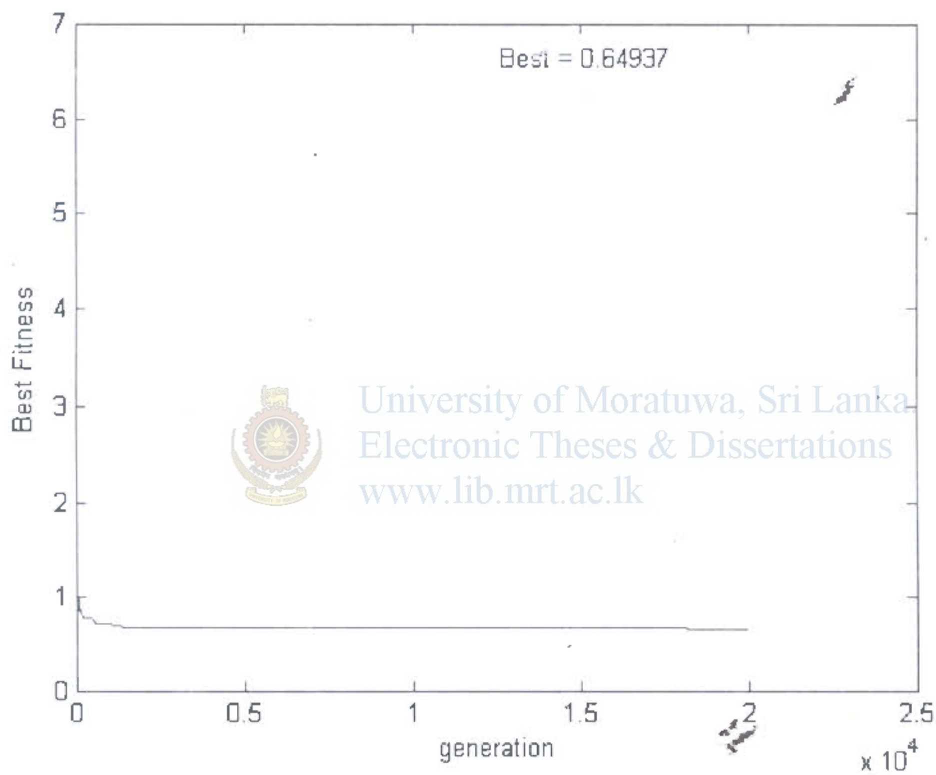

```
Results =
 Columns 1 through 6
  -0.0807   -0.1618    0.5893    0.7643   -0.9611    0.9286
 Columns 7 through 12
   0.7930    1.0060   -1.8088   -1.2625   -0.2940   -1.8920
 Columns 13 through 18
   1.2794    0.3009   -1.4847   -1.9957    0.6170   -1.4907
```

```
NIND = 400;
MAXGEN = 20000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep([PRECI],[1, NVAR]);...
        -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
         2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
         rep([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
  Columns 1 through 6
   1.3363   -0.1313    1.0611    0.5355   -0.3078    1.9737
  Columns 7 through 12
  -1.5057   -0.7148   -1.9642   -1.5308    1.1888   -0.7728
  Columns 13 through 18
   0.7418    0.4505   -1.4299   -1.8278   -0.4736   -1.6152
```

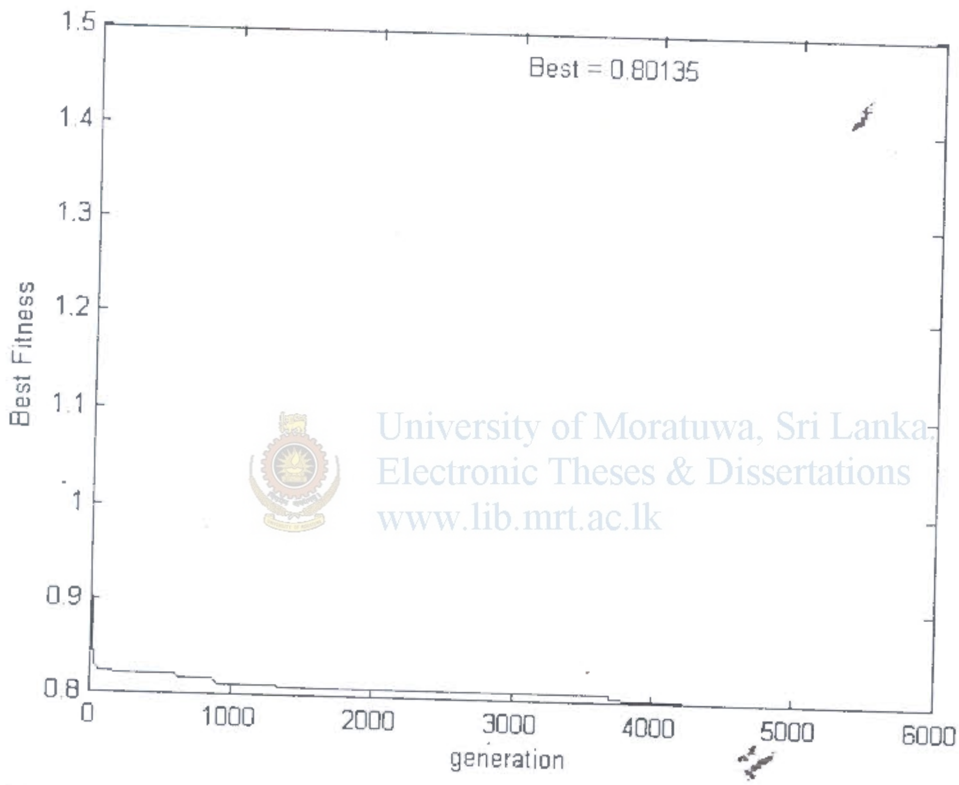
```
NIND = 400;
MAXGEN = 20000;
GGAP = 0.9;
NVAR = 18;
PRECI = 20;
FieldD = [rep([PRECI],[1, NVAR]);...
        -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 ;...
         2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2  2 ;...
         rep([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
 Columns 1 through 6
 -0.8728  -0.0338   0.3219   0.5761  -1.7686   1.1190
 Columns 7 through 12
  0.4882   1.3843   1.1971   0.3303  -0.3677  -1.4959
 Columns 13 through 18
   1.7387   0.3654  -1.1338  -1.9822   0.1605   0.8406
```

Results when Mutation Probability, Pm = 0.7*500/Lind

```
NIND = 500;
MAXGEN = 5000;
GGAP = 0.9;
NVAR = 12;
PRECI = 20;
FieldD = [rep([PRECI],[1, NVAR]);...
        -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2 -2  ;...
         2  2  2  2  2  2  2  2  2  2  2  2  ;...
         rep([1; 0; 1 ;1], [1, NVAR])];
```




```
Results =
 Columns 1 through 7
  1.2837  -1.9859  -1.0000  -1.7500   0.4458   0.3750  -1.2656
 Columns 8 through 12
   -0.7500   0.1602   0.5845   1.3820   0.4375
```

APPENDIX II

Data used for the forecast

Figure 2.2: The electrical energy demand of Sri Lanka from year 1985 till year 2003.

Year	Electricity Demand (TWh)
1984	2.250083
1985	2.462867
1986	2.642101
1987	2.692351
1988	2.784288
1989	2.843976
1990	3.133769
1991	3.354094
1992	3.509674
1993	3.952684
1994	4.338150
1995	4.756927
1996	4.338189
1997	4.872005
1998	5.517904
1999	6.027877
2000	5.258206
2001	6.626548
2002	6.755590
2003	7.612

The [shaded] coloured figures – figures used in designing the forecasting model.
The [shaded] coloured figures – figures used in forecasting the Electricity demand.

The figures used in forecasting the Electrical energy demand of Sri Lanka

Year	Ave. Rainfall in catchment area X_1	GDP per capita (in US $) X_2	Popu. (x 1000) X_3	Popu. growth rate (%) X_4	Ave. US $ value X_5	Unit price of elect. (US$./kWh) Dome. X_7	Dome. Consu. accounts. X_6	Unit price of elect. (US$./kWh) Indus. & Com. X_8	Unit price of elect. (US$./kWh) Other X_9
1984	2606.5	352	15,603	1.2	25.48	0.046	295, 854	0.078	0.046
1985	2368.6	344	15,841	1.5	27.21	0.041	329, 965	0.068	0.042
1986	2304.6	362	16,127	1.8	28.07	0.037	370, 048	0.032	0.04
1987	2019.4	368	16,373	1.5	29.55	0.037	404, 962	0.034	0.042
1988	2240.1	385	16,599	1.4	31.90	0.049	450, 431	0.074	0.047
1989	2329.4	374	16,825	1.3	36.33	0.042	495, 932	0.061	0.039
1990	2160.5	437	17,017	1.1	40.09	0.047	628, 741	0.066	0.037
1991	2110.3	469	17,267	1.5	41.45	0.051	751, 614	0.07	0.036
1992	2041.7	557	17,426	1.0	44.18	0.049	917, 319	0.076	0.04
1993	2404.0	588	17,646	1.2	51.61	0.045	1, 089, 287	0.075	0.037
1994	2213.7	656	17,891	1.4	51.87	0.049	1, 222, 124	0.096	0.047
1995	2185.7	719	18,136	1.4	49.92	0.045	1, 322, 087	0.093	0.046
1996	2132.4	759	18,336	1.1	57.58	0.046	1, 466, 815	0.090	0.045
1997	2447.7	853	18,567	1.2	59.85	0.047	1, 611, 102	0.091	0.044
1998	2111.5	879	18,774	1.3	70.39	0.044	1, 781, 388	0.088	0.044
1999	2213.0	863	19,043	1.5	75.78	0.040	1, 981, 691	0.082	0.040
2000	2050.5	899	19,359	1.4	89.36	0.034	2, 191, 301	0.082	0.038
2001	1972.4	841	18,732	1.4	95.66	0.041	2, 364, 853	0.079	0.042
2002	[illegible]	[illegible]	[illegible]	1.5	[illegible]	0.054	[illegible]	[illegible]	[illegible]
2003	[illegible]	947	[illegible]	[illegible]	[illegible]	0.057	[illegible]	[illegible]	[illegible]
2004	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.046	[illegible]	[illegible]	0.059
2005	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.047	[illegible]	0.107	0.062
2006	[illegible]	1275	19,800	1.02	[illegible]	0.047	[illegible]	0.111	0.066
2007	[illegible]	1365	20,000	1.01	140	0.048	[illegible]	0.114	0.070
2008	[illegible]	[illegible]	[illegible]	1.01	[illegible]	0.049	[illegible]	0.118	0.074

Figure 5.2: Energy demand vs. Year (actual data and the model forecasted data)

Actual Data

Year	Electricity Demand
1984	2.250083
1985	2.462867
1986	2.642101
1987	2.692351
1988	2.784288
1989	2.843976
1990	3.133769
1991	3.354094
1992	3.509674
1993	3.952684
1994	4.338150
1995	4.756927
1996	4.338189
1997	4.872005
1998	5.517904
1999	6.027877
2000	5.258206
2001	6.626548
2002	**6.755590**
2003	**8.043**

Model Forecasted Data

Year	Electricity Demand
2002	7.110906
2003	7.175318

Figure 6.5: Load curve of Sri Lankan Power System on 01st June 2005.
(Readings taken by the System Control Division, at 30 minute intervals)

Time	Generation(MW)
0.30	775
1.00	738
1.30	718
2.00	706
2.30	701
3.00	694
3.30	693
4.00	700
4.30	723
5.00	770
5.30	894
6.00	1013
6.30	1082
7.00	957
7.30	885
8.00	914
8.30	979
9.00	1045
9.30	1073
10.00	1097
10.30	1118
11.00	1131
11.30	1141
12.00	1135

Time	Generation(MW)
12.30	1082
13.00	1069
13.30	1081
14.00	1097
14.30	1120
15.00	1114
15.30	1115
16.00	1130
16.30	981
17.00	1027
17.30	1003
18.00	982
18.30	1025
19.00	1229
19.30	1575
20.00	1604
20.30	1575
21.00	1510
21.30	1423
22.00	1252
22.30	1087
23.00	969
23.30	883
24.00	794