ELECTRICITY DEMAND FORECASTING IN TURKEY AND INDONESIA USING LINEAR AND NONLINEAR MODELS BASED ON REAL-VALUE GENETIC ALGORITHM AND EXTENDED NELDER-MEAD LOCAL SEARCH

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Abstract

Electricity demand patterns have many variables related to uncertainty behaviour such as gross domestic product, population, import and export. The characteristics of these variables lead to two problems in forecasting the electricity demand. The first problem is the fitness evaluation in the electricity demand forecasting model in which more than one variable are included which leads to increase the sum of squared deviations. The second problem is the use of a single algorithm that failed to solve local optima. These problems resulted in estimation errors and high computational cost. Hybrid genetic algorithm (GA) and Nelder-Mead local search model has been used to minimize demand estimation errors. However, hybrid GA and Nelder-Mead local search failed to reach the global optimum solution and involve high number of iteration. Hence, an electricity demand forecasting model that reflects the characteristics of electricity demand has been developed in this research. The model is known as the hybrid Real-Value GA and Extended Nelder-Mead (RVGA-ENM). The GA has been enhanced to accept real value while the Nelder-Mead local search is extended to assist in overcoming the local optima problem. The actual electricity demand data of Turkey and Indonesia were used in the experiments to evaluate the performance of the proposed model. Results of the proposed model were compared to the hybrid GA and Nelder-Mead local search, Real Code Genetic Algorithm and Particle Swarm Optimisation. The findings indicate that the proposed model produced higher accuracy for electricity demand estimation. The proposed RVGA-ENM model can be used to assist decision-makers in forecasting electricity demand.

Keywords: Genetic algorithm, Electricity demand forecasting, Nelder-Mead local search, Local optimal.

Abstrak

Corak permintaan elektrik mempunyai banyak pembolehubah yang berkaitan dengan tingkah laku tidak menentu seperti keluaran dalam negara kasar, penduduk, import dan eksport. Ciri pembolehubah ini membawa kepada dua masalah dalam ramalan permintaan elektrik. Masalah pertama ialah penilaian kecergasan dalam model ramalan permintaan elektrik di mana lebih daripada satu pembolehubah yang dimasukkan yang membawa kepada peningkatan jumlah sisihan kuasa dua. Masalah kedua ialah penggunaan algoritma tunggal yang gagal menyelesaikan optima setempat. Masalah ini mengakibatkan kesilapan anggaran dan kos pengkomputeran tinggi. Model hibrid algoritma genetik (*GA*) dan pencarian setempat *Nelder-Mead* telah digunakan untuk mengurangkan kesilapan anggaran permintaan. Walau bagaimanapun, hibrid *GA* dan pencarian setempat *Nelder-Mead* gagal mencapai penyelesaian optimum global dan melibatkan jumlah lelaran yang tinggi. Oleh itu, satu model ramalan permintaan elektrik yang menggambarkan ciri permintaan elektrik telah dibangunkan dalam kajian ini. Model ini dikenali sebagai hibrid *GA* bernilai real dan *Nelder-Mead* yang diperluaskan (*RVGA-ENM*). *GA* telah dipertingkatkan untuk menerima nilai real manakala pencarian setempat *Nelder-Mead* telah diperluaskan untuk membantu dalam mengatasi masalah optima setempat. Data sebenar permintaan elektrik Turki dan Indonesia telah digunakan dalam eksperimen untuk menilai prestasi model yang dicadangkan. Keputusan model yang dicadangkan dibandingkan dengan keputusan model hibrid *GA* dan pencarian setempat *Nelder-Mead*, algoritma genetik kod real dan pengoptimuman zarah swarm. Dapatan kajian menunjukkan bahawa model yang dicadangkan menghasilkan ketepatan anggaran yang lebih tinggi untuk permintaan bekalan elektrik. Model *RVGA-ENM* yang dicadangkan boleh digunakan untuk membantu pembuat keputusan dalam ramalan permintaan bekalan elektrik.

Kata kunci: Algoritma genetik, Ramalan permintaan elektrik, Pencarian setempat *Nelder-Mead*, Optimal setempat.

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Table of Contents

List of Tables

List of Figures

List of Appendices

List of Abbreviations

ABE	Analogy based estimation
AI	Artificial intelligence
AIC	Akaike information criterion
ANN	Artificial neural network
ANFIS	Artificial neural network with fuzzy inference system
CHA	Continuous hybrid algorithm
DC	Distribution-centers
DD	Degree days
DE	Differential evolution
DNA	Deoxyribonucleic acid
DOA	Direction-of-arrival
EA	Evolutionary algorithm
EDA	Estimation of distribution algorithm
EDF	Electricity demand forecasting
EDP	Electricity demand pattern
EDPF	Electricity demand pattern forecasting
EE	Estimation error
EGA	Enhanced genetic algorithm
EKPF	Extended Kalman particle filter
EM	Expectation maximization
GAED	Genetic algorithm electricity demand
GA-EKPF	Genetic particle filter
GDP	Gross domestic product
GP	Genetic programming
HGA	Hybrid genetic algorithm
HGAED	Hybrid genetic algorithm electricity demand
ENM	Extended Nelder Mead
KF	Kalman filter
LO	Local optimality
LS	Least square

LTEDF	Long-term electricity demand forecasting
MAE	Mean absolute error
MAI	Multiple access interference
MAPE	Mean absolute percentage error
MC-CDMA	Multi-carrier code-division multiple access
ME	Mean error
MSE	Mean squared error
MTOE	Million ton oil equivalent
MTEDF	Medium-term electricity demand forecasting
NP	Non-deterministic polynomial
OLS	Ordinary least squares
PWM	Pulse width modulation
RBFNN	Radial basis function neural network
EDP	Electricity demand pattern
RNN	Recurrent neural nets
RSS	Residual sum of squares
RVGA	Real-value genetic algorithm
RVGA-ENM	Real-value genetic algorithm - extended Nelder Mead
SA	Simulated annealing
SAA	Sample average approximation
SC	Schwarz Criteria
SDE	Standard deviation of error
SDMA	Spatial division multiple access
SS	Simplex search
STLF	Short-term load forecasting
STEDF	Short-term electricity demand forecasting
SVM	Support vector machine
SVR	Support vector regression
TDE	Time delay estimation
TS	Tabu search
TSP	Traveling salesman problem

CHAPTER ONE
INTRODUCTION

Sound and realistic electricity demand forecasting (EDF) is essential to good planning in any industry. One of the most important things in the planning of electricity demand in the utility industry is electricity demand forecasting that is more realistic. This means that the development of the electricity demand forecasts is essential in the planning of new resources for the system to meet the future demand. The importance of electricity demand forecasting is becoming clear to best demand utilities as they must sustain the demand expectations. However, the impossibility of developing truly accurate demand forecasts must be recognised. Results obtained from the electricity demand forecasting process are used in areas such as planning and operation (EL-Naggar & AL-Rumaih, 2005; Ghods & Kalantar, 2008; Ghods & Kalantar, 2011).

The soundness of a method for electricity demand forecasting performances should not be assessed only in a single case over the short term but using its record of success or failure over the long term. The usefulness of an electricity demand forecasting method should focus on issues such as the relationship of demand and weather, demand characteristics, pressure demand, demand growth patterns, and socioeconomic data (Ali, 2012; Fan, Methaprayoon, & Lee, 2010).

Based on the time horizon, electricity demand forecasting can be categorised into three types: (i) short-term electricity demand forecasting (STEDF), (ii) medium-term electricity demand forecasting (MTEDF), and (iii) long-term electricity demand forecasting (LTEDF) (Singh et al., 2012).

STEDF plays an important role in everyday operations such as daily utility operations. MTEDFs are necessary in fuel procurement planning, energy trading, utility revenue assessments, and scheduling unit maintenance. LTEDF is important for decision making in transmission expansion and system generation of energy planning (Eghbal et al., 2011; Fan et al., 2010; Singh et al., 2012).

The demand model varies from one application to another. The applications include demand for food, housing, transport, and utilities. Some demand models depend on the population size and some depend on the economic state of the country. There are demands that are seasonal in nature, namely the demand for utilities (e.g. electricity). Higher demands can be observed during the hot season compared to the wet season and during a festival season compared to a non-festival season.

Historical data are an important aspect of electricity demand forecasting and data preparation. For example, in LTEDF, historical data from one to ten years is applied in expansion planning and tariff setting. It is also applied in parameter estimation and the capital investment return problem. In general, there is a need for historical data to obtain an accurate LTEDF. An accurate LTEDF performance should be validated using historical information; then it is applied to predict the future long-term electricity demand (EL-Naggar & AL-Rumaih, 2005; Dalvand, Azami, & Tarimoradi, 2008; Hyndman & Fan, 2010; Zhao & Niu, 2010).

The driven variables for an electricity demand pattern are data with various uncertainties (e.g. measurement, estimation of parameters, and in processing).

The uncertainty variables for an electricity demand include socioeconomic conditions, weather conditions, population growth, general randomness inherent in individual usage, and changing technologies (Babayan, Savic, & Walters, 2007). Based on the complex relationships between the uncertainty variables and an electricity demand, the researchers categorised the electricity demand in the nondeterministic-polynomial (NP) (Ozturk & Ceylan, 2005; Zhang & Ye, 2011).

The risk of the "natural uncertainty" in electricity demand problems can severely increase the estimation error and affect the reliability of mathematical modelling. In this case, if the electricity demand forecasting model recognises the natural uncertainties with good accuracy, the system can reduce estimation error, search region, and computational time. Therefore, taking into account the uncertainty is of great practical interest when developing the methodology in predicting the behaviour of the system (Babayan et al., 2007; Zhang & Ye, 2011).

The original objective function of the mathematical model of long-term electricity demand pattern was to minimise forecasting errors where the demand variables contain population and economic indicators. Two classic approaches of optimisation have been applied to LEDF to estimate model parameters. They are: (i) static and, (ii) dynamic state estimation techniques.

In static state estimation approaches such as the least square (LS) techniques, the entire set of data is needed to obtain the optimal estimation solution (Franco et al., 2006; Yang, Huang, & Ma, 2009; Hsu & Huang, 2010). In dynamic state estimation approaches such as Kalman filtering and least absolute value filtering algorithms, a new measurement is used to update the new estimation.

As a modern estimation approach including expert system and neural network, artificial intelligence (AI) methods have been proposed by this researcher. This modern approach has shown promising and encouraging results. However, there are disadvantages of this approach; for example, unless using a large number of data points, when the dataset is contaminated with a bad measurement, the accuracy of estimation may decrease (Mohammad & Masoumi, 2010).

One of the AI approaches using genetic algorithm (GA) for various optimisation problems has received much attention of the researcher because GA as a stochastic search has promising robust results. This method is based on parallel search mechanism in various areas such as load flow problems and combinatorial optimisation problems.

The difference between genetic algorithm and conventional optimisation and search procedures are: (i) most search algorithms work with solution directly, while GA works with coding of the solutions, (ii) most search algorithms start the search from single solution, while GA starts from population of solutions, (iii) most algorithms use deterministic transition techniques, while GA uses probabilistic techniques. That is why this study focuses on improving GA as an AI approach to solve the problem of electricity demand forecasting.

Genetic algorithms have great importance in research and development because it can tackle the hard optimisation problems (Aljanabi, 2010). These problems have only a finite number set of feasible solutions and the aim is to find the optimal solution.

However, genetic algorithm promises convergence but not optimally. Even though there is no guarantee of optimality in genetic algorithm, exponential convergence is assured. Genetic algorithm will converge at different optimal chromosomes if it runs several times (Mamta & Sushila, 2010). The drawback of GA as a single algorithm contributed to decrease the model performance of electricity demand forecasting in terms of errors.

The ability of single algorithm decreases when the search is close to the optimal solutions (Huan, 2009). The stagnation in the bad optimal solution in a single algorithm is contributed to decrease the prediction accuracy. Genetic algorithm alone or local search algorithm alone cannot guarantee to reach the best optimal solution (Mamta & Sushila, 2010). However, a combination of optimisation and heuristic approaches has become the current popular approach in solving electricity demand pattern forecasting problem.

The effort to tackle the single algorithm problem in previous models is by combining several algorithms into hybrid algorithms such as genetic algorithm and local search. For instance, genetic algorithm can be used to search the optimal (or near-optimal) solutions in a considerable search space based on the objective function, and operates the local search algorithm for unconstrained function minimisation that will start at the points where the genetic algorithm stops.

The solutions that have been found by genetic algorithm will be used as the initial points by local search algorithm to find global (or best) optimum solutions. This may lead to efficient algorithms in terms of computation time, which inspires the development of hybrid genetic algorithm (HGA).

Therefore, this study focuses on the hybrid genetic algorithm and local search for electricity demand pattern models because the hybrid genetic algorithm and local search seem to be the appropriate approach and offer a good opportunity to find global optimal solutions.

1.1 Problem Statement

For most electricity demand forecasting models that use evolutionary algorithms (e.g. genetic algorithm); the objective function cannot obtain a good result. In single genetic algorithm, convergence cannot be obtained because the solution is trapped in the near local optimum (El-Mihoub et al., 2006; Lian et al., 2009; Tan et al., 2010). This problem cannot be solved even though the single genetic algorithm operations are repeatedly applied. This is difficult to fit into other methods in order to produce a good solution.

The ability of previous methods decreases because they fail to overcome the early convergence and local optimality problems. These problems will produce estimation errors when forecasting is made for the electricity demand. The accuracy of previous electricity demand forecasting models that apply genetic algorithms to complex problems is greatly related to the high computational cost due to their slow convergence rate (Yen et al., 1995; Wu et al., 2010). These issues, if not properly addressed prior to the model's development, could lead to inaccurate and unreliable prediction.

Technically, the early convergence and local optimality problems can be addressed by other methods like hybridising several algorithms such as combining genetic algorithm and local search algorithm. A combination of a genetic algorithm and a local search algorithm can speed up the search to locate the global optimum (Tan et al., 2010; Mamta and Shusila, 2010). In the existing method of hybrid genetic algorithm and simplex local search, the simplex method converges really well with small scale problems of some variables (Pham, 2012). However, in large scale problems of multiple variables, it does not have much success. The existing method needs a high computational cost in term of iterations to reach the global optimum solution because the search is on the wrong direction. A new technique is introduced to improved hybrid algorithm in terms of convergence rate with guidance search on the true direction by improved local search.

Two solutions are introduced to answer the following questions:

1. How to construct the hybrid algorithm that can give the electricity demand forecasting solutions with precision?
2. How to confront the hybrid algorithm that can converge without too expensive computing cost and has the ability to converge a wide range of problems?

1.2 Research Objectives

The aim of this study is to propose electricity demand forecasting using linear and nonlinear models based on the hybrid genetic algorithm and improved local search. In order to achieve this, two specific objectives are listed below:

1. To propose an improved hybrid genetic algorithm that can minimise the errors of electricity demand pattern forecasting using linear and nonlinear models.
2. To propose a new technique that could overcome early convergence and local optimality problems via combination between genetic algorithms and improved local search.

1.3 Scope and Limitation

This study will focus on the hybrid genetic algorithm for optimisation. A new algorithm technique which consists of genetic algorithm and local search algorithm will be proposed to overcome early convergence problems occurred in the original genetic algorithm optimisation process. The concentration of activities is on improving the performance of electricity demand pattern forecasting model and reducing the errors by combining genetic algorithm and local search algorithm.

The scope of the application domain of this research is the static optimisation problem. The type of problem chosen is long-term electricity demand pattern forecasting and projected future electricity demand by scenarios analysis. Different models of these problems are considered with various independent variables and scenarios to overcome the uncertainties of demand.

There are many independent variables as economic indicators are used in forecasting electricity demand models. However, this research work is limited into the case of handling long-term electricity demand pattern forecasting model that is estimated based on data of population, growth of gross domestic product, and the growth of import and export as the independent variables.

This study focuses on comparison between Electricity Demand Pattern (EDP) forecasting model using original genetic algorithm approaches and EDP forecasting model using hybrid genetic algorithm approaches. The accuracy is taken as the main indicator for model selection.

1.4 Significance of the Research

The output of this research is a hybrid algorithm optimisation technique that can be considered as a new technique that offers the chance to enhance the performance of available electricity demand pattern forecasting models.

A good EDP forecasting has a substantial effect on operational cost of power systems that is quite sensitive to forecasting errors. Power utility can save millions of dollars even for a small reduction of average forecasting errors. Accurate electricity demand pattern forecasting holds a great saving potential when it is used to control operation and decision planning such as fuel allocation, dispatch, and off-line network analysis and unit commitment.

In supply and demand fluctuation and the changes of weather conditions during peak situations, the energy prices increase by a factor of ten or more. In this situation, EDP forecasting is vitally important for the utility companies in operational decision and good planning.

EDP forecasting can help to reduce the occurrences of equipment failures and blackouts because its estimate can prevent overloading on time. It is also more important in the deregulated economy when the energy pricing and rate increases because of the market demand.

1.5 Thesis Organisation

This thesis has been divided into six chapters:

Chapter one introduces the general framework in which the thesis has been developed. First, the overview of electricity demand forecasting is presented followed by an explanation of the problem statement, research objectives, scope and limitation and significance of the research.

Chapter two presents the literature reviews related to the background of forecasting methods, electricity demand forecasting, variables and types of electricity demand forecasts, the applications of HGA in electricity demand forecasts and the summary of the chapter.

Chapter three contains the methodological steps, data collection and preparation, mathematical model development for HGA and local search. The performance evaluation of the proposed hybrid algorithm and local search is also described, and finally the summary of the chapter.

Chapter four discusses the results obtained in the experiments. The comparison between the proposed hybrid genetic algorithm approach and that of conventional approach is offered. Several benchmarking are also discussed in this chapter.

Chapter five discusses the improved hybrid algorithm and the application of selected models into future prediction of electricity demand. Electricity and economic profile as the main consideration in a scenario is also discussed before the summary of this chapter is presented.

The ends of this thesis are the conclusion and future work suggestion that are presented in chapter six.

CHAPTER TWO
REVIEW OF RELATED LITERATURE

This chapter discusses the literature related to the research field considered in this thesis. Section 2.1 presents an overview of forecasting methods. Electricity demand forecasting is reviewed in section 2.2. Several types and variables of electricity demand forecasts are surveyed in section 2.3. Section 2.4 reviews the hybrid algorithm including the methods in hybridisation of several techniques that are used to solve the electricity demand forecasting problems; and the chapter summary is given in section 2.5.

2.1 Forecasting Methods

The review of forecasting methods start with the discussions on methods commonly used in forecasting which include: Time Series, Econometric, End Use, Statistical based approach, Neural Network based model, and Hybrid Algorithm based models.

2.1.1 Time Series

Time series is one of the most attractive and mysterious mathematical subjects. Weather, temperature, rainfall, water flow volume of a river and other similar cases in meteorology are known as predictable time series; amount of load peak, electricity price and other similar cases in electrical engineering are considerable time series

(Reyhani & Moghadam, 2011). Time series forecasting is highly taken into account in economy. Stock prices in stock exchange market, currency equivalent rate in such market, world price of petroleum, sugar, gas, gold and other key items are best known time series. The discovery of chaos in economic time series such as stock exchange is highly regarded by scholars of economics (Reyhani & Moghadam, 2011).

Time Series forecasting method is a significant aspect on the field of research, which includes energy demand, statistics, econometrics, and computer sciences. The traditional procedures include the combination of linear auto-regression (AR) and moving-average (MA) in Time Series forecasting method, which was made popular by Box and Jenkins in the 1970s (Ardalani-Farsa, 2006). However, the need for nonlinear forecasting procedures arises since data are nowadays abundantly available, and complex patterns that are frequently not linear can be extracted.

The future state of a complex system is not known to anyone; however, the attempt to approximately predict the future state is beneficial to decision makers. In the past several decades, some nonlinear techniques have been introduced in the literature to forecast the future state of chaotic systems (Ardalani-Farsa, 2006).

The traditional linear autoregressive moving average (ARMA) models were popular models in the area of forecasting. However, ARMA models are linear and are not capable of forecasting nonlinear, non-stationary and chaotic time series. Therefore, ARMA models are unpopular, inaccurate and unpractical methods to forecast nonlinear time series.

There are two main approaches to forecast chaotic time series: (i) local modelling, and (ii) global modelling. A combination of forecasting methods known as the ensemble method is also used for forecasting. Local models perform the forecasting by searching for the local regions of the time series which approximately present a region of the data immediately before the point to be forecasted. In local modelling, the overall prediction model consists of several local estimators where the local estimators define the various portions of the input space (Ardalani-Farsa, 2006).

In global models, only one fitting function is engaged to forecast the future of the system. Since the 1970s, numerous global methods are introduced in the literature, such as bilinear models, exponential autoregressive models, state-dependent models, threshold auto-regression (TAR), the threshold model, neural gas, adaptive memory-based regression (AMB), the long short-term memory (LSTM), Gaussian process (GP), echo-state networks (ESNs), the flexible neural tree (FNT), and the dynamic evolving computation system (DECS) (Soelaiman et al., 2009).

The nonlinear autoregressive model with exogenous input (NARX) has also been applied to chaotic time series forecasting. The ensemble method is introduced to improve the result of forecasting by merging individual predictors. An ensemble can be the combination of the same class of models such as ANN, SOM, SVR or different types. The example of ensemble models are combination of the nearest neighbours, artificial neural networks, and genetic algorithms (Soelaiman et al., 2009).

Adapting ensemble method on time series prediction is done by Soelaiman et al. (2009) using boosting algorithm. On boosting algorithm, recurrent neural networks (RNN) are generated, each for training on a different set of examples on time series data. The difference between new algorithm and the original algorithm is the introduction of a new parameter for tuning the boosting influence on given examples. The boosting result is then tested on real time series forecasting, using a natural dataset and function-generated time series.

The middle-term electric load forecasting is an existing difficult work and often has a large error. To address the problem, Yang et al. (2006) proposed a novel cloud theory based time series predictive method for middle-term electric load forecasting. In this method, the time series of daily maximum load is partitioned into two parts, historical dataset and current tendency dataset. Backward cloud algorithm is applied to the two datasets to form the historical cloud and the current cloud, and the corresponding rule sets are mined. Then the historical cloud and current cloud are integrated to create predictive clouds through synthesised clouds. Finally, via cloud reasoning, the forecast result can be obtained. This predictive method effectively integrates quasi-periodical regularity and current tendency of time series data, and has a simple computing model.

On the experiment result, Soelaiman et al. (2009) proved that ensemble method is better than standard method, back-propagation through time for one step ahead of time series prediction. Ensemble methods used for classification and regression have been shown that they are superior to other methods, theoretically and empirically. However, the drawback of the method is an ineffective method for nonlinear data series in short-term load forecasting.

Tanuwijaya and Chen (2009) presented a new method to forecast enrolments using fuzzy time series and clustering techniques. First, the authors presented an automatic clustering algorithm to partition the universe of discourse into different lengths of intervals. Then, the authors presented a new method for forecasting enrolments using fuzzy time series and the proposed clustering algorithm. The historical data are used to illustrate the forecasting process of their method. As the experimental results, the authors concluded that their method receives a higher average forecasting accuracy rate than the existing methods (Tanuwijaya & Chen, 2009). However, a huge historical data is needed in time series forecasting methods.

2.1.2 Econometric

Econometrics is a set of quantitative tools for analysing economic data. Economists need to use economic data for three reasons: 1) to decide between competing theories, 2) to predict the effect of policy changes, and 3) to forecast what may happen in the future (Contos et al., 2009). The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationships between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least-squares method or time series methods (Contos et al., 2009).

Economists deal with different kinds of data (Like & Zongyi, 2007): (1) Time series data. For instance GDP data are collected each quarter of a year. Macroeconomics and finance use such data. In macroeconomics, frequencies are annual, quarterly or monthly. (2) Cross-sectional data. For instance, in a labour survey, 1000 workers of the chemistry industry were interviewed on their wages, their labor conditions, etc. All these interviews took place at about the same date. Each question gave many answers. Cross-sectional data are mainly met in microeconomics (observations can bear on workers, households or firms). But, macroeconomics can use such data when it compares different countries (for instance their GDP per head) (Like & Zongyi, 2007).

Time series data and cross-sectional data differ on a very important point. Time is oriented where the past comes before the future. One can use the past to forecast the future, but cannot use the future to forecast the past. Of course, the past and the present depend on the expectations of the future by economic agents. However, the expected future is based on the experienced past, and not on the true future which is unknown. On the other hand, there is no natural way orienting cross-sectional data. Because of its specificity, the econometrics of time series data is a bit special (Like & Zongyi, 2007).

There is a special field of econometrics to deal with this kind of data. In most cases, one will have a large number of individual units, and a small number of time periods. Like and Zongyi (2007) in their study, applied the spatial econometric model to examine the relationship between power consumption and real GDP for China. The estimation results indicated that the regional economic development level is influenced not only by "home" power consumption and economy, but also the neighbouring energy consumption. In order to keep the remarkable growth of China economy, the government should speed up the nationwide interconnection of power networks and upgrade interregional distribution grids.

Econometric models can be very useful for estimating the marginal impacts of changes in policy. A study by Contos et al. (2009) used the context of modelling taxpayer compliance burden for small businesses to explore some extensions to standard econometric simulation techniques that provide more robust support of the distribution of the characteristics of interest. However, their broader application as a tool for micro-simulation analysis posed a number of challenges and limitations.

Liu, Ang, and Goh (1991) in their study, compared two forecasting models, an econometric model and a neural network model, through a case study on electricity consumption forecasting for Singapore. The results of the study showed that the two models that forecasted the historical consumption gave very different results. This anomaly arises partly from the differences in the structure of the two models, and the problem is examined using the concept of elasticity in econometric studies. The results also showed that a fully trained neural network model with a good fitting performance is a better method to forecast the past. However, it may not give a good forecasting performance for the future. The econometric and end-use methods require a large amount of information relevant to appliances, customers, economics, etc. Their application is complicated and requires human participation.

2.1.3 End-Use

A variety of methods have been developed for short-term forecasting, which include regression models, similar day approach, statistical learning algorithms, fuzzy logic, time series, neural networks and expert systems. Two of the methods, so-called End-use and Econometric approach are broadly used for medium and long-term forecasting (Feinberg et al., 2003).

End-use models focus on the various uses of electricity in the industrial, commercial, and residential sectors. These models are based on the principle that electricity demand is derived from customer's demand for heating, cooling, refrigeration, light, etc. In this method, the distribution of equipment age is important for particular types of appliances. End-use models explain energy demand as a function of the number of appliances in the market (Feinberg et al., 2003).

The improvements and investigation of the mathematical tools will lead to the development of more accurate and appropriate load forecasting techniques. However, the statistical and simulation models based on the End-use approach require the description of appliances used by customers, customer behaviour, the size of the houses, population dynamics, the age of equipments and technology changes.

Ideally, End-use is a very accurate approach (Feinberg et al., 2003). However, its forecast requires less historical data and more information about customers and their equipment. End-use is sensitive to the amount and quality of end-use data.

2.1.4 Statistical based approach

The statistical approach is developed in order to simplify the medium-term forecasts, making them more accurate, and to avoid the use of the unavailable information. A statistical model that learned the load model parameters from the historical data was developed in a study by Feinberg et al. (2003).

A mathematical model that represents load as function of different factors such as weather, time, and customer class are used in statistical approaches. Additive models and multiplicative models are two important categories of such mathematical models (Feinberg et al., 2003).

Regression is one of the most widely used statistical techniques. For electric load forecasting, regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type, and customer class. Regression models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather.

However, the complexity of the regression models prevents the specification of a very highly parameterised hierarchical structure. The regression methodology faces important limitations due to the presence of potential unmeasured time-varying confounders. Important methodological developments, among others, focus on the definition of effect of interest, occurrence of non-linear trends and lagged effects, and inclusion of control areas.

2.1.5 Neural Network Based Models

Artificial neural networks (ANN) have been widely used in order to solve the time series forecasting problems. One of its most promising approaches is the combination with other intelligence techniques such as genetic algorithms, evolutionary strategies, etc. The efficiency of these techniques, if used correctly, can be very high (Reyhani & Moghadam, 2011).

Artificial Neural networks have been a widely studied electric load forecasting technique, which are essentially nonlinear circuits that have the demonstrated capability to do nonlinear curve fitting. The inputs of an artificial neural network may be the outputs of other network elements as well as actual network inputs. The outputs are some linear or nonlinear mathematical functions of its inputs (Feinberg et al., 2003).

Artificial neural networks (ANNs) as part of global modelling were employed by researchers to forecast chaotic time series. In recent years, chaos is discovered in many economic time series such as stock changes. Moreover, it has been proven that the discovery of chaos will help to forecast time series by intelligent algorithms better than before. Reyhani & Moghadam (2011) proposed a new heuristic method inspired from chaotic characteristics of economic time series, with forecasting this time series by means of artificial neural networks. In this method, the output of chaotic function is used to help time series prediction well.

Redrigues et al. (2009) proposed other fitness functions (instead of conventional MSE based) and presented an experimental investigation of eight different fitness functions for time series prediction based on five well-known measures of statistical performance in the literature. Using a hybrid method for the tuning of the ANN structure and parameters (a modified genetic algorithm), an analysis of the final result effects are made according to four relevant time series. This work showed that the small changes of the fitness function evaluation can lead to a significantly improved performance (Rodrigues, et al., 2009).

Artificial neural networks are widely used as predictor systems for the pollutant time series. In recent years, the dynamic system theory has also been exploited to find the optimal sampling time interval and the minimum embedding dimension of environmental time series in order to get helpful information and to implement appropriately the forecasting networks. A novel approach have been presented by Marra et al. (2003) to predict the concentration level of air pollutants in the area of the Messina Strait, whose harbour represents the unique link to reach Sicily Island from Europe by cars and trucks. By coupling feed-forward neural networks with Cao's method, the authors predicted the level of carbon monoxide and hydrocarbons from one to ten hours ahead with an accuracy of more than 90% (Marra, Morabito, & Versaci, 2003).

However, in terms of fitness function, there are still a few shortage of experimental (and theoretical) results to help the practitioners to use these techniques in order to find better predictions. In applying a neural network to electricity demand forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally.

2.1.6 Hybrid Algorithm Based Models

One method that combines forecasting using adaptive coefficients is applied in the electricity demand forecasting system to effectively take advantage of the meteorological prediction. The forecasting that shares the strength of the different temperature forecasts demonstrates the superiority of the methodology (Fan et al., 2010). There are several optimisation approaches in electricity demand forecasting. They are categorised as: (i) the classic optimisation approach: the approach which uses classical methods in finding solutions, and (ii) the modern approach: the approach which uses artificial intelligence (AI) e.g. the hybrid algorithm methods in finding the best solutions.

Hybrid algorithm approaches such as the hybrid genetic algorithm and artificial neural network with other heuristics undertake the difficult problem in electricity demand forecasting. These approaches have taken more attention in the researches of electricity demand related to their capabilities in overcoming local optimality problems (Fan et al., 2010).

Several optimisation approaches to solve the problems in original algorithms such as slow convergence, local optimality, speeding up the computational time, early-convergence, large iteration and finding the global optimal solutions are reviewed here in the next description. Related studies by Mamta & Sushila (2010) explored the capability of local search. These local approximations do not require additional evaluations; they are only generated using information already collected by the algorithm during the evolutionary process. Thus, the local search can speed up the process of overall optimisation through the improvement of some individuals of the population.

Due to various types of local search, the combination of local search and genetic algorithm is therefore found to be the favorite of many researchers. Local search is frequently used for determining the local optimum within a well-defined feasible region. The hybridisation of local search and the genetic algorithm, for example, was proposed by Mamta & Sushila (2010), the local search for improving the performance of a genetic algorithm was proposed by Tutum & Fan (2011) and Mei et al. (2011).

Several studies about the use of local search have been proposed among others by Guimaraes et al. (2007) and Carrano et al. (2008) proposed the local search phase of memetic algorithms using local approximations for cost optimisation functions. Two basic approaches have been adopted in utilising local information, which are: (i) the Lamarckian approach, and (ii) the Baldwinian approach. The Lamarckian approach forces the genetic structure to reflect the result of local search based on the inheritance of acquired characteristics obtained through learning. The fitness and genetic structure of individuals are changed to match the solution found by a local search method (Mamta & Sushila, 2010).

The local search method used in the Lamarckian approach is a refinement operator that modifies the genetic structure of an individual and places it back. Lamarckian evolution can interrupt the schema processing. This can badly affect the exploring abilities of a genetic algorithm, which may lead to premature convergence. On the other hand, the advantage of Lamarckian evolution is that it can accelerate the search process of a genetic algorithm (Mamta & Sushila, 2010). The Lamarckian approach is used in most hybrid genetic algorithms to satisfy constraints. The technique that repairs chromosomes has been especially effective in solving the travelling salesmen problem (TSP). The Lamarckian approach only retains the fitness of the parents; it does not allow their acquired characteristics to be passed on.

The Baldwinian approach is usually used in a local search method as a part of an individual's evaluation process. The global genetic algorithm uses local search to improve the results by using local search knowledge to produce a new fitness score.
In the Baldwinian approach, by applying a local search, individual fitness is improved without changing the genotype. This approach follows the normal process

of evolution that allows an individual to propagate its structure to the next generation. It is in contrast to the Lamarckian approach.

Mamta and Sushila (2010) exemplified how the Baldwinian effect can transform the fitness landscape of a difficult optimisation into a less difficult problem and how genetic search is profited. The Baldwinian effect consists of two learning steps: (i) learning gives individuals the chance to change their phenotypes to improve performance, and (ii) learning can accelerate the genetic acquisition of learned traits in genetic assimilation.

In a genetic algorithm, only the objective function for fitness evaluation is required after undergoing genetic operations, not the domain knowledge. It deals with a coding of the problem instead of decision variables. To guide the search, unlike most conventional methods and some meta-heuristics, which are conducted of a single directional search, the genetic algorithm uses stochastic transition rules to perform multiple directional searches using a set of candidate solutions.

Thus, as an artificial intelligent optimisation technique, genetic algorithm is one of the most favoured and effective approaches that has proved to be versatile (Lian, Zhang, Li, & Gao, 2009). However, the simple genetic algorithm in many situations does not perform well.

An improvement mechanism to overcome the early convergence problem in a single genetic algorithm is necessary. Among them are: improved crossover operation, nonlinear ranking selection, combining nonuniform mutation operation and arithmetic crossover with differential computation (Lian, Zhang, Li, & Gao, 2009). Holland in 1975, assumed that the population size is infinite and the interactions between genes are very small, so the fitness function accurately reflected the suitability of a solution according to his assumptions. However, in practice, the population size is finite, which influenced the sampling ability of a single genetic algorithm and as a result affected single genetic algorithm performance.

A genetic algorithm, due to its limited population size, may also sample good representatives of bad search regions and bad representatives of good search regions (El-Mihoub et al., 2006; Tan et al., 2010). Integrating a local search method within a genetic algorithm can ensure fair representation of the different search areas and can reduce the possibility of early convergence. Therefore, it can help to overcome the growth of most of the obstacles resulting from finite population size.

The solution quality produced by local search methods may be higher compared with the solution quality produced by a genetic algorithm; this is caused by the limited population size. The best solution is difficult to obtain, even in the best region accounts for the genetic algorithm, because a genetic algorithm operator lacks the power to make small acts in the neighbourhood of current solutions.

Exploiting the ability improvement of the algorithm search without limiting its exploring ability can be achieved by applying a local search method within a genetic algorithm. The algorithm can easily produce high solution accuracy if the right balance between local exploitation and global exploration capabilities can be achieved (El-Mihoub et al., 2006; Huang, Huang, & Zhang, 2008; Tan, Huang, Hsu, & Wu, 2010).

Mamta and Shusila (2010) showed the effect of the selection of any form of learning in a hybrid genetic algorithm using performance on an optimisation problem. They compared pure genetic algorithms, Lamarckian and Baldwinian, in evolving the architecture that learns Boolean functions. The conclusion stated that any form of learning has a great effect on hybrid genetic algorithm performance, and it is better than a pure genetic algorithm.

The effect of individual learning of a local search in a hybrid optimisation algorithm was used to train a recurrent neural network (RNN) in a study by Delgado, Cuellar, and Pegalajar (2008). Each weight in RNN was encoded as a floating-point number to form a chromosome that contains a chain of numbers. The hybrid algorithms were used to train the RNN to solve a long-term dependency problem. Baldwinian and Lamarckian mechanisms were compared in the hybrid algorithm mechanism to train the RNN. The authors found that Baldwinian learning lacked the ability to assist the cellular genetic algorithm.

In contrast, the Lamarckian mechanism in most of the combinations showed an improvement for an optimum network in reducing the number of generations. However, only a few of the combinations can reduce the actual time taken. To make it the fastest method, it is necessary to embed the delta rule in the cellular genetic algorithm (Singh & Khandelwal, 2010). A genetic algorithm derives its behaviour from an evolutionary biology metaphor. As a population-based meta-heuristic, the genetic algorithm creates a population of individuals as solutions. Individuals as solutions are termed chromosomes, in essence, character strings loosely based on DNA 4 chromosomes.

The chromosomes as the solutions are usually termed solution strings that are randomly generated. These string solutions formed into a population represent a variety of solutions for a given problem. These strings are encoded in some defined alphabets in some manner. They are evaluated according to the objective function or fitness function after decoding (Singh & Khandelwal, 2010).

After the evaluation process, selected individuals undergo reproduction to produce the next generation of offspring. Those parents who have higher fitness are assigned to produce offspring. Based on the fitness function, they have a higher probability of being selected. The parent population is then replaced by a new offspring population.

Singh et al. (2008), in their study described a novel algorithm based on evolutionary techniques to obtain an optimised input bit pattern. This algorithm, such as a genetic algorithm and swarm intelligence, is utilised to optimise input bit patterns that can result in noise and in the worst-case channel jitter. In a few test cases, the optimised bit pattern can be used for a large range of topologies and are resilient to the channel topology changes have also been shown.

The evolutionary algorithm has also been considered in optimising beam-forming weights in a nonlinear array system. These multi-objective optimisations use several constraints of the nonlinear array antenna: (i) constrain two variables, the level of the side lobe and the width of the main lobe or (ii) constrain an additional variable, the energy of beam forming weights on the former system. The cost of beam-forming weights is computed in each generation of each case. The optimal solution set (Pareto frontier) can be obtained at the end of the generations (Singh et al., 2008).

A genetic algorithm is also used to obtain optimal pulse density modulation patterns. Pulse density modulation (PDM) is an alternative to pulse width modulation (PWM) and can be utilised to drive resonant power converters. The main advantage of PWM is its simplicity. This allows achieving zero voltage (or current) switching of a power device while performing load power regulation. Switching stress reduction hinders polluting power lines with electromagnetic noise (Pimentel et al., 2006; Zhang et al., 2010). This technique is appropriate for designing power converters that show low total harmonic distortion and a good overall power factor.

PDM is more useful to drive resonant power converters (parallel or series). These converters deliver a wide range of output power and are required to operate at high frequencies. They are frequently used in induction heating applications. In a convenient manner, the power factor produced by a PDM converter is near unity, and at high-output power, total harmonic distortion is low. In contrast, the power factor moves away from unity because total harmonic distortion increases at low-output powers.

A technique presented by Pimentel et al. (2006) and Zhang et al. (2010) using simulations makes obtaining an optimal PDM pattern possible. The simulation, using a genetic algorithm to show intelligent PDM pattern generation, allows for an improved power factor. It also reduced total harmonic distortion at low-output powers (Pimentel et al., 2006; Zhang et al., 2010). As a result, a PDM pattern, based on a genetic algorithm technique, showed much better performance compared to other techniques.

A genetic algorithm combined with the steepest descent algorithm has been proposed by Toyama (2006). A genetic algorithm is used to overcome the local optima problem in the steepest descent algorithm. Using the steepest descent algorithm is very attractive because, an optimum solution is given in a relatively short convergence time. However, they depend much on initial conditions. The combination of the steepest descent algorithm and a genetic algorithm yield the best solution that satisfied all of the requirements. By using binary codes to determine the initial positions, the steepest descent algorithm can find an optimum solution. A unique method involves using sub-array positions represented by binary codes.

A comparative study was done by Zuniga, Erdogan and Arslan (2010) in a linear antenna array to find an optimal radiation pattern. They compared the particle swarm optimisation (PSO) and a standard genetic algorithm. In order to steer the beam in the intended direction, a set of phase shift weights is generated. The calculations of the phase shift weights in optimisation are allowed using an objective function. The results showed that the PSO achieves a better solution than the genetic algorithm and the PSO obtains a more consistent radiation pattern.

A hybrid algorithm that combines fuzzy and neural networks and a genetic algorithm were used to optimise the operational pattern of a copper flash smelting process. Fuzzy and neural networks are applied for pattern decomposition after the optimal sample set is filtered. To search the optimal operational sub pattern, a chaotic genetic algorithm is applied. This operational pattern optimisation method was proposed by Peng et al. (2007). Their method can improve the processing of the copper flash smelting and can demonstrate instructions for production. Therefore, a number of experiments showed the capability of their methods on average in solving the problem using fewer objective function evaluations.

An objective function has a chromosome, which consists of individual variables or genes. A combination of evolution and genetics corresponds in function to the numerical optimisation in obtaining the best result within constraints on the variables. An objective function input is a chromosome; a population consists of a group of chromosomes. The individual in a population with high fitness means the low cost is selected as a new offspring (Haup & Werner, 2007).

The basic form of genetic algorithm is referred to as a canonical genetic algorithm. The basic building block of the canonical genetic algorithm is the genome that consists of a number of "*alleles*" (representing locations that store genetic information). The canonical genetic algorithm utilises a binary-valued representation, where the only allowable values in each allele location are either 0 or 1. A genome of length η can encode a total of 2^{η} different states. A simple binary genome in a canonical genetic algorithm is shown in Figure 2.1. One such class of canonical algorithms is compact genetic algorithm that dramatically reduces the number of bits required to store the population and has a faster convergence speed (Al-Dabbagh et al., 2012).

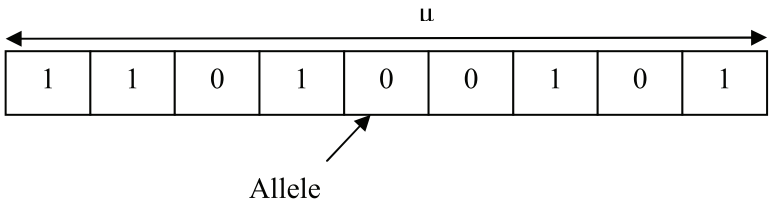


Figure 2.1 Binary genome used in a canonical genetic algorithm

The binary representation of the genome contains all of the genetic information that is manipulated by the genetic algorithm. The genetic representation is then mapped to a representation that is compatible with the problem domain. For example, the information encoded in the genome may be translated into one or more parameters of a constraint-optimisation problem. The Darwinian model requires that a measure of fitness be determined for each member of the population (Gallant, 2001; Wang, Li, Qi, & Li, 2008).

In optimisation, the fitness function is a carefully chosen function that measures the performance of the parameters. The fitness function is determined by the genetic algorithm and encoded into the genome for the particular problem under consideration. An individual is considered a collection of chromosomes each of which is constituted by genes. The characteristics of individuals depend on the composition of chromosomes (Wang, Li, Qi, & Li, 2008). However, the possible action of the operation by a genetic algorithm will be very low if the number of chromosomes is fewer than normal and it only searches in a small part of the search space.

The selection of individuals or solutions from a set of possible solutions is based on the quality of individuals (fitness values). There are three basic processes that control the evaluation of individuals in a genetic algorithm, namely reproduction, crossover and mutation (Zablotskiy et al., 2011). However, the size of the population (number of chromosomes) should be determined to find the best solutions.

The genetic algorithm does not require the allowable range of each parameter because it works with a set of populations of possible solutions (example, sets of parameter values). The population is some set of possible solutions, while the chromosome is a parameter of a component that affected the forecasting value (Zablotskiy et al., 2011).

A genetic algorithm is a famous algorithm that has been used in many fields to solve many problems because of its suitability to nearly any function. It simulates the mechanism and the process of evolution, as unique biological features. An algorithm generated from a genetic algorithm, namely the estimation of distribution algorithm (EDA), becomes a hot topic because it is superior.

The estimation of distribution algorithms replace some operations in a genetic algorithm, such as learning and sampling of the best individuals of the population, replacing the crossover and the mutation in each iteration of the algorithm (Qiu, Liu, Feng, & Huang, 2008). The application of a genetic algorithm is useful for estimations such among others has been proposed by Yang, Huang and Ma (2009) for target tracking and non-linear tracking problems.

A genetic algorithm has been used to optimise the tracking problem in an extended Kalman particle filter (EKPF). As a suboptimal filtering algorithm, it has good performance for nonlinear tracking and target tracking problems. In order to improve the estimation performances, EKPF used a resampling scheme to decrease the degeneracy phenomenon (Yang et al., 2009). A novel method is used to overcome the EKPF problem, namely the genetic particle filter (GA-EKPF). The GA-EKPF algorithm can enhance the filtering precision and overcome the deprivation of particles; experimental results show the superiority of this method. However, the precision of the target tracking mutation system is poorer.

Another approach in state estimation is based on the hybrid genetic algorithm (HGA). This approach combines HGA and simulated annealing to obtain optimal measurement placement for a power system. The optimal solution is obtained using the acceptance criterion of simulated annealing for chromosome selection. Results of this method indicated faster computational time and the best match at higher frequency, making it superior to other methods (Yang et al., 2009).

Parameter estimation using a genetic algorithm has attracted great attention from many researchers. A method for parameter pattern estimation using a hybrid genetic algorithm was proposed by Liu, Wu, & Zhang (2012). The hybrid algorithm is applied to characterise molecular biological systems and analyse the system dynamics.

An approach for cost estimation has been proposed by Li, Xie and Goh (2007); Alaei and Alaei (2011). The previous approach is analogy-based estimation (ABE), which is essentially a case-based reasoning approach. The previous study proposed effective methods to optimise the weights of the features to estimate the cost with a current project by referring to data collected from past projects. The results of the study by Li et al. (2007); Alaei and Alaei (2011) indicated that their methods were more effective for software cost estimation than other methods.

Therefore, to prevent early convergence in the genetic algorithm, the mutation probability and crossover are changed according to the fitness values of the population in each generation. These methods are successful in solving the problem of parameter estimation. This approach applied a genetic algorithm to alleviate the drawback of the previous study in terms of low prediction accuracy.

2.2 Electricity Demand Forecasting

The electricity demand model has an important input variable. It is the annual growth pattern of demand. The electricity demand is driven by data variable with various uncertainties. The uncertainties exist in data measurement, estimation of parameters, data processing, etc.

The risk of the "natural uncertainty" in electricity demand pattern problems can severely increase the estimation error and affect the reliability of mathematical modelling (Babayan et al., 2007). In this case, if the electricity demand forecasting model recognises the natural uncertainties with good accuracy, a system can reduce estimation rate, search region, and accelerate convergence speed. Therefore, taking into account the uncertainty is of a great practical interest when developing the methodology in predicting the behaviour of the system (Babayan et al., 2007).

The demand for a utility such as the demand for electricity, has a set of input variable uncertainties. Electricity, as an important energy industry, is the infrastructure of the national economy. To provide a reliable energy supply for national economic development, balancing electricity supply and demand is necessary (Jian-Chao et al., 2008). The characteristics of electricity sectioning are that it is unable to be stored on a large scale and needs a long construction period. The government may decide to cancel power resource projects in the following years if electricity supply exceeds demand. This is caused by the incorrect results of electricity forecasting, so it affects the fluctuation of electricity investment over the years (Jian-Chao et al., 2008).

Based on the analysis above, the rising trend of electricity demand can effectively be restricted by the economic structure adjustment. Alternatively, to solve the energy problem under the current energy situation by lowering the percentage of heavy industry in the economic structure is a reasonable solution (Jian-Chao et al., 2008).

In a recent work on short-term demand forecasting for an electric utility, Fan, Methaprayoon, and Lee (2010) focused on short-term operation and market. Several alternative forecasts are available for meteorological and different commercial weather services as their target is to cover a large geographical area of the power system.

The load diversity on the entire area sometimes caused issues; satisfactory forecasting accuracy cannot be guaranteed by a single model for electricity demand forecasting. Therefore, for a power system occupying a large geographical area, Fan et al. (2010) developed a multi-region electricity demand forecasting model, which can obtain the optimal region partition under diverse load and weather conditions, and achieved more accurate forecasts for aggregated system demand.

The role of long-term electricity demand forecasting is significant in planning facilities, such as for future generation facilities and transmission augmentation. It presents the first step in planning and developing facilities in transmission, distribution and future generation (Sing et al., 2012).

The main task of demand utilities is accurately predicting the electricity demand requirements during long periods. The outcome of accurate electricity demand forecasting is applied to coordinate the resources of a utility company with the lowest cost plan to meet the forecasted demand (Ghods & Kalantar, 2008; Ghods & Kalantar, 2011).

The decision maker in a demand utility company in a long-term context must take into account the probabilistic view of potential peak demand levels. The full probability distributions of the possible values of demand in the future are more helpful and necessary to hedge and evaluate the financial risk accrued by uncertainty of forecasting and variability of demand (Hyndman & Fan, 2010).

In a given season, peak electricity demand is driven by a range of randomness, including economic conditions, weather conditions, changing technology, underlying population growth, and the timing of those conditions as well as the natural uncertainty inherent in individual usage. The peak electricity demand also refers to calendar effects due to time and holidays.

A study by Hyndman and Fan (2010) proposed a comprehensive methodology of electricity demand forecasting. This new method is used to forecast the density of peak demand in long term. The relationships between the driver variables and electricity demand including economic variables, calendar effect, demographics and temperatures are estimated by semi-parametric additive models in the first step.

The next step forecasts the distributions of electricity demand using simulation of a variety of temperature, residual bootstrapping and scenarios of economic assumptions. The implementation of temperature simulation is done using a new seasonal bootstrapping method with variable blocks. To test the performance of this methodology, forecasting results are evaluated using the probability distribution of annual peak electricity demand and comparing it with the actual electricity demand (Hyndman & Fan, 2010).

Depending on time horizon, electricity demand forecasting is categorised as short-term forecasting, medium-term forecasting and long-term forecasting (Singh et al., 2012). Electricity demand forecast is concerned with the prediction of hourly, daily, weekly and annual values of the electricity demand system and electricity demand peak. Long-term electricity demand forecasting is an integral process in scheduling the development of transmission and distribution systems and the construction of new generation facilities. It usually corresponds to the forecast horizon from several months to several years ahead.

Long-term electricity demand forecasting has not received much attention, despite its value for system planning and budget allocation. Underestimated electricity demand forecasts will result in unmet electricity demand and insufficient generation, while an overestimate of long-term electricity demand forecasts will result in significant wasted investment in the construction of excess power facilities (Hyndman & Fan, 2010).

Figure 2.2 demonstrates an example of electricity demand pattern. It is a non-stationary demand pattern because the pattern trends according to time scale. This pattern can categorise as time series and forecasting methods using linear and nonlinear models are required in order for the model to fit the pattern correctly.

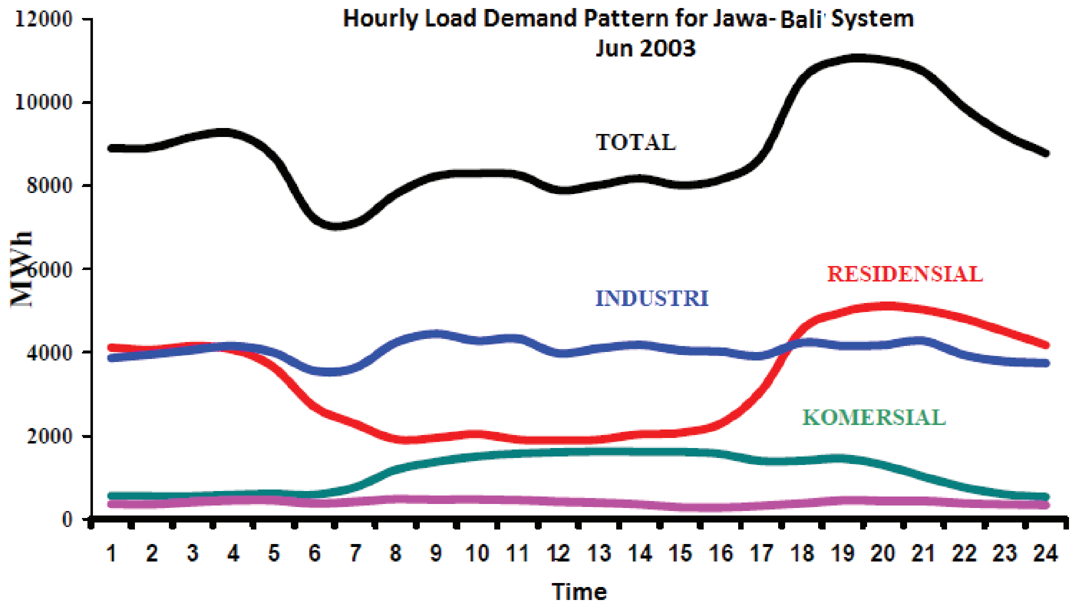


Figure 2.2 Electricity Demand Pattern for the Jawa-Bali System (Abimanyu, 2004)

Modelling and optimisation of production systems have received substantial attention by the research community in the last decades. In the literature, it was reported that production nodes modelling, among the works in the field, is categorised into two streams; continuous-time models and discrete-event models (Giglio, Minciardi, Sacone, & Siri, 2009).

Discrete-event models, in which the whole system dynamic is driven by the occurrence of asynchronous events, are generally studied with simulative approaches. In this approach, the results are suitable for representing real cases with a high level of detail. It is also suitable for comparing different scenarios when it is not possible to determine feedback solutions (Giglio et al., 2009).

2.3 Variables and Types of Electricity Demand Forecasts

Electricity demand has several characteristics, depending on weather conditions, work days, weekends, etc.; the growth of electricity demand depends on economic boom times and periods of recession.

2.3.1 Variables of Electricity Demand Forecasts

When economic growth increases, more needs are created to accompany the higher standard of living, more energy is needed to satisfy energy consumption. The absence of electricity has a negative effect on economic development. During the economic boom, a large number of projects for power resources should be constructed. This places heavy pressure on natural resources, the environment and the economy because it is beyond the allowable extent of the national economy (Ozturk & Ceylan, 2005; Jian-Chao et al., 2008).

A vital problem in economic development is a study on how to harmonise the fluctuation relationships between electricity construction and economic national development. It also requires scientific demand forecasts for future projections (Jian-Chao et al., 2008). Such a relationship is a difficult task and some specialists argue that it requires too many inputs and is circular.

Causal factors of energy consumption include gross domestic product, oil prices and population growth rate (Ozturk & Ceylan, 2005; Dalvand, Azami, & Tarimoradi, 2008). This study proposed a methodology that used population growth, gross domestic product, import, and export as the input variables to determined electricity energy demand as the output of the proposed model. Thus, in the proposed model, electricity demand is the function of population, gross domestic product, import and export. The relationship between electricity demand and independent variables is measured by using historical data over a long term period (Zhao & Niu, 2010).

In electrical load forecasting, electrical load is affected by various factors such as meteorological and economic conditions, and it has a time-varying nature (Ozturk & Ceylan, 2005; Dalvand, Azami, & Tarimoradi, 2008). Since the time horizon is relatively small in short-term load forecasting, the social and economic conditions have no influence in generating the forecast.

On the other hand, weather has a major role in forecasting load in the short term. The load patterns during the weekdays differ from those during the weekends and load patterns during the holidays and festive days differ from those of normal days.

The daily peak load normally occurs around the extreme maximum or minimum temperature, depending on weather energy is required for space cooling or heating, respectively. The daily load curve normally follows the daily temperature profile.

2.3.2 Types of Electricity Demand Forecasts

Based on time horizon, electricity demand forecasting can be categorised in three types: (i) short-term forecasts, (ii) medium-term forecasts, and (iii) long-term forecasts (Fan, Chen, & Lee, 2009). Short-term forecasts are required by utility planners for tactical operational planning and day-to-day decision-making. These forecasts are aimed at predicting the load on a system during an interval of hours or days, and they play a substantial role in determining unit commitment, spinning reserve, economic power interchange, load management, etc.

Short-term electricity demand forecasts as a famous topic in the electricity utility industry are basic for system operation and energy planning. They are important because their role is to increase prediction accuracy. The effect of a few percentage points in prediction accuracy can save millions of dollars (Fan, Chen, & Lee, 2009).

Medium-term electricity demand and energy forecasting is necessary in scheduling unit maintenance, fuel procurement and diversity interchanges. The forecast horizon is in the range of 1 to 5 years. Since the time horizon in medium-term forecasting is longer than that for short range, both load and energy consumption is to be forecasted. The monthly peak load forecast is required for scheduling unit maintenance and diversity interchanges for interconnected utilities. On the other hand, the energy forecast is required for the fuel procurement purposes (Zhao & Niu, 2010).

Unlike short-range forecasting, medium-range forecasting is influenced by many more factors apart from the weather conditions. Socioeconomic variables also play an important role in developing monthly load and energy forecasts. Energy consumption pattern is more or less cyclic in nature but load peak is shifting increasingly due to growth. It is then the job of the forecaster to recognise the pattern and identify the underlying growth trend (Dalvand et al., 2008).

Long-term electricity demand forecasting (commonly known as annual peak load and energy consumption forecasting) is of extreme importance for generation and transmission expansion planning, feasibility studies for interconnecting utilities, long term fuel requirement and tariff planning. The forecast horizon is normally 5-25 years. The time interval between the decision making and the project completion for generating unit installation could be anything from 2-12 years. Therefore, planning ahead is of extreme importance (Zhao & Niu, 2010).

Long-term electricity demand forecasts have a significant role in system expansion planning. Interconnection between utilities has often become necessary for better reliability and economy. However, feasibility studies of such huge capital intensive projects require that the project is spread and justified over a longer period. Long-term load and energy forecast are integral to such studies. In addition to the variables used for medium-term forecasting, population and gross domestic product (GDP) were also considered to be candidate variables in building the long-term model (Li & Meng, 2008).

The forecasting accuracy of an electricity demand forecast has a potential effect on the company in terms of profit, safety inventory and competitive power. The power demand forecast is the basis for making a power development plan. Through analysing the factors that affect power demand, one model by Yang and Li (2006) for forecasting power demand has been established and its data are standardised.

Then by designing the structure of back propagation neural networks and applying the improved genetic algorithm, the network structure and weights of neural networks for power demand are optimised. Finally, through training the data, a nonlinear relation model between power demand and its influential factors is obtained (Shi, Yang, Ding, & Pang, 2008). The method avoids the shortcomings such as the slow speed of obtaining the optimal solution by genetic algorithm and easily trapping into a local optimal solution by the neural networks. The study showed that the method is accurate and feasible (Yang, & Li, 2006; Shi et al., 2008).

The role of historical data in electricity demand forecasts is of great significance; the availability of data is largely affected by the success of an electricity demand forecasting method. Several variables heavily influence electricity demand of a power system such as percentage relative humidity, global radiation, wind speed, temperature, vapor pressure, cloud coverage in a day and duration of bright sunshine, precipitation, etc. They are categorised as demographic and socioeconomic variables.

Some other useful variables are also obtained by synthesising these raw variables. Temperature-humidity index and comfort index are examples of such variables. Degree days (DD), measures the deviation of average daily temperature from the air-conditioning threshold level. If DD is positive, energy is required for cooling and if it is negative, energy is required for heating.

Other data of considerable significance, especially for medium and long-term forecasts, are socioeconomic variables like the number of new housing and industry permits allotted, the number of new infrastructural projects, population of the franchise area, number of consumers connected, gross domestic product of the nation, etc. (Ozturk & Ceylan, 2005; Azadeh, Ghaderi, Tarverdian, et al., 2006; Deng, 2010). The number of variables that should be selected refers to the nature and the range of the forecast. Human intuition can be used as the criterion of the selection and their contribution and their correlation should be validated and analysed for a medium-term forecast. In addition to the above variables, there are some causal variables, which seldom arise but have a definite impulse-like effect on load such as the lunar festivals, religious events, national holidays, etc.

An electricity demand forecasting model based on a genetic algorithm has been proposed by Xie and Lie (2010). The authors enhanced the traditional gray forecasting model using a genetic algorithm to optimise the gray modelling process. The authors used the advantages of a genetic algorithm and the characteristic of the gray forecasting model to find a global solution. This method found an effective tool that was more accurate for electricity demand forecasting.

The error of electricity demand forecasting occurs mainly due to the load deviation. It is caused by variation in temperature, which increases the cost of each thermal unit and affects unit commitment scheduling. A method for short-term generation scheduling has been presented in a study by Senjyu et al. (2008). The unexpected deviation on electricity demand was considered in this methodology for thermal units integrated with a wind energy system. At a particular hour, it tracks down the load deviation using this method and repredicts the next hour electricity demand using a neural network forecasting technique. In this way, the learning process of NN can assist in achieving an accurate forecasting that will reduce fuel costs. The inclusion of wind energy on the base thermal unit system can also minimise fuel cost. To solve the problem in the unit commitment, a genetic algorithm is used, and the results show the effectiveness of this method (Senjyu et al., 2008).

The adoption of AI techniques such as GA, ANFIS, ANN in the forecasting in the past few years, has taken more attention to solve the different problems in engineering. It is vital for managing demand and supply using accurate load forecasting in power systems (Zhao & Niu, 2010; Yu & Zhang, 2010).

A study by Ghanbari et al. (2010) investigated all AI technique effects on performance after they are equipped with the preprocessing concept in order to improve forecasting accuracy. The outcomes of the approaches (in term of errors) have finally been evaluated. The results of this approach are: (i) AI outcomes are more approximate to the actual loads than other methods, and (ii) data preprocessing can significantly improve performance of the AI techniques. So AI techniques can be considered ideal in solving short-term load forecasting (SLTF) problems (Ghanbari, Hadavandi, & Abbasian-Naghneh, 2010).

Proper selection of relevant factors that really influence the STLF is very important to improve the accuracy of forecasting. In electric power operation, robust and accurate STLF plays a substantial role. However, it is a difficult task to select the appropriate factor because it is also influenced by the uncertainties and randomness of the load demand (Zhang & Ye, 2011; Singh et al., 2012).

A novel method was developed by Wang et al. (2008) to enhance the robustness of load forecasting results and improve the accuracy of STLF. The method combines rough set (RS) theory and genetic programming (GP); it employs RS to process a large amount of data to find relevant factors and GP to establish a forecasting model. Forecasted results show the method is more accurate than the BP ANN method.

2.4 Application of HGA in Electricity Demand Forecasts

The early sections have discussed several statistical and artificial intelligence techniques that have been developed for short, medium, and long-term electricity demand forecasting. Several statistical models and algorithms that have been developed, though, are operating ad hoc. The accuracy of the forecasts could be improved, if one would study these statistical models and develop a mathematical theory that explains the convergence of these algorithms (Zhao & Niu, 2010; Yu & Zhang, 2010).

Researchers should also investigate the boundaries of applicability of the developed models and algorithms. So far, there is no single model or algorithm that is superior for all utilities. The reason is that utility service areas vary in differing mixtures of industrial, commercial, and residential customers. They also vary in geographic, climatologic, economic, and social characteristics.

As a hard optimisation problem, the electricity demand problem needs the capability of local search to overcome the convergence problem in the pure genetic algorithm to find a global solution. Selecting the most suitable algorithm by a utility can be done by testing the algorithms on real data. In fact, some utility companies use several electricity demand forecasting methods in parallel (Zhao & Niu, 2010; Yu & Zhang, 2010).

Local search based on their exploration capability for finding a solution from the neighbourhood of solutions is used as the general approach for hard optimisation problems. They try to determine a high quality solution by local changes to improve the current solution.

Neighbourhood structures are used to determine the quality of a solution obtained and the type of local changes to be applied. Larger neighbourhood size increases the quality of the solution obtained (Ali, Pant, & Nagar, 2010).

Local search starts the search from the initial solution. Because it is based on the neighbourhood concept, it then searches the neighbourhood of the initial solution that was randomly selected. A target of the search process is to determine one of the best solutions with the lowest cost (global optimum solution). The capability of local search to find the local optimum is obvious but there is no guarantee for a global optimum solution (Ali, Pant, & Nagar, 2010).

Local search might be used as a stand-alone algorithm as described above or in conjunction with some other algorithms (like GA and ACO) that have the ability to find a good starting solution and this solution is then improved using local search to reach its local optimum solution. The latter approach has recently been used in solving many problems such as neighbourhood improvement for the classic travelling salesmen problem (Ali, Pant, & Nagar, 2010), optimisation of the input manufacturing allocation problem (Mamta & Sushila, 2010).

Typically, neighbourhood sizes are exponential and in the worst case, searching to improve solutions from the neighbourhood may take exponential time. Practically speaking, each step of a local search can be done in the polynomial time required. Therefore, this technique is not guaranteed for determining solutions to hard optimisation problems based on the solution quality of local optima (Ali, Pant, & Nagar, 2010).

In exact neighbourhoods, every local minimum is also a global minimum, so a guarantee can be given, but it is infeasible for searching because exact neighbourhoods are of exponential size. Alternatively, the number of steps needed for iterative improvement cannot be bounded by a polynomial for some problems. To speed up the overall process of optimisation, some individuals of the populations must be improved by local search (Guimaraes et al., 2007).

Applying a genetic algorithm to guide a local search to find the most promising region of the global optimum solution can reduce the time needed. Such a hybrid method can speed up the search to reach the exact global optimum. However, a genetic algorithm can take a relatively long time to locate the exact global optimum in the region of convergence, even though it can rapidly locate the region in which the global optimum exists (Mamta & Sushila, 2010).

In the next section, the applications of hybrid genetic algorithms are reviewed through presenting the different ways in which the roles of a local search method and a genetic algorithm can be integrated.

2.4.1 Application of HGA for Electricity Demand Optimisation Models

The optimality is the inherent nature of humans such as electric utility company wants to produce its products with the lowest cost. This is the typical example which optimisation theories can be applied to give optimal solutions. The goal of the optimisation theories is the creation of a reliable method to optimised models by an intelligent process. Applications of these theories play more important roles for modern engineering and planning. Many engineering problems can be defined as optimisation problems (Pham, 2012).

Electricity demand problem as a combinatorial optimisation problem needs a specific method to obtain optimal solutions. There are three methods to find optimal solution in combinatorial optimisation problems (Aljanabi, 2010). They are exact methods, approximate methods, and meta-heuristic methods. Exact algorithms are guaranteed to find an optimal solution to any instance within an instance-dependent run time.

Clausen and Woeginger, in their attempt to obtain an optimal solution for a given problem (as cited in Aljanabi, 2010), found the search is maintained as a reference point to the best solution found so far. The partial solution is discarded if it proves to be worse than the present best solution, and another potential solution is computed as the alternative solution. Then, a recursive search is continued until the optimal solution is obtained. The application of exact algorithms for many combinatorial problems remains limited to relatively small instances.

In contrast, in combinatorial optimisation problems, the number of candidate solutions is finite. Therefore, to solve the problem, one way is to enumerate all candidates by comparing the solutions against each other. However, this approach proves to be impractical in most combinatorial optimisation problems as the number of candidate solutions is simply too large. In 2003, Blum and Roli (as cited in Aljanabi, 2010) applied the heuristic search to tackle this problem but there is no guarantee of finding the optimum solution using that heuristic.

Practically, using a meta-heuristic and an approximate algorithm is one choice to tackle these problems. Approximate (heuristic) methods are methods that search an optimal solution in a short time for an optimisation problem (Aljanabi, 2010). In the certain range, there is no guarantee of finding the optimal solution. However, these methods have great practical importance to solve combinatorial optimisation problems since they are able to find a solution of high quality in a short time.

In practice, optimisation algorithms are able to solve these problems but to find the best solution for these problems is often not very easy and straightforward because they include large search spaces. It will be more challenging particularly in real live systems, which require optimal solutions in an acceptable amount of time.

With a few modifications to the heuristics, a meta-heuristic method formed by adding problem-dependent heuristics can be used to tackle a hard optimisation problem. They are general algorithmic frameworks that can efficiently avoid the local optimality problem and find the optimal solution as the objective of this algorithm (Aljanabi, 2010).

The hybrid genetic algorithm is an appropriate algorithm to tackle the optimisation problem in electricity demand forecasting model. The combination method consists of two algorithms, a genetic algorithm as a global search and a local search addition, that work together to solve a combinatorial optimisation problem (Aljanabi, 2010).

The local search method is a part of the optimisation algorithms, divided into two types: the gradient-based methods and the non-gradient-based methods. Gradient-based methods require the derivative information to update and compute the decision variable values of the objective function, while non-gradient based methods do not require the derivative information. These methods are the most widely used in nonlinear optimisation methods. However, the disadvantages of gradient-based methods are liable to converge at a local minimum, and it is often difficult to achieve convergence in a global optimal solution (Huang, 2009).

Non-gradient methods generally start with one or more initial guesses to the model parameters. Although they are not as fast as the gradient-based methods, these methods only evaluate the objective function values without involving the calculation of derivatives and can generally explore a larger search space than gradient-based methods.

The goal of local search in electricity demand forecasting model is to find a set of parameter values to minimise the error between actual demand and model predictions. It is difficult to measure the error using the derivative of the objective function because it dependent on the parameter values except for a very simple model (Huang, 2009). Therefore, gradient-based methods may not be used for an electricity demand forecasting model and thus, the non-gradient-based methods are the only choice.

However, hybridisation of genetic algorithms with other appropriate local search methods would also increase the performance of genetic algorithms in solving global optimisation of continuous multimodal functions (Asyikin, 2011).

Local search in optimisation to overcome early convergence has been implemented in many studies. Some of them used the simplex method, local gradient-based algorithms, and iterative hill climbing combined with global meta-heuristics such as genetic algorithm, simulated annealing, particle swarm optimisation, etc. These studies reported that the new hybrid algorithms have significantly reduced the speed of convergence of the algorithm compared with a single algorithm.

The local search method is applied on the first half of the sorted population while the mutation of differential evolution (DE) is applied on the other half after crossover. This mechanism can accelerate the speed of convergence and is implemented and tested to optimise crucial characteristics with practical constraints. The results indicated that the new algorithm is effective and efficient, compared with conventional GA (Lo, Yiming, & Li, 2010).

2.4.2 Application of HGA and Nelder-Mead Simplex Method

The main obstacle in applying genetic algorithm to combinatorial optimisation problems has been the high computational cost due to their slow convergence rate. One attempt to encounter this problem for estimating parameters of electricity demand model, developing a hybrid algorithm that combines genetic algorithm with a stochastic simplex method is needed. The Nelder Mead's simplex method is one of the most popular derivative-free optimisation algorithms in the fields of engineering, science, and statistics. NM simplex algorithm is widely used because of its simplicity and fast convergence. This method converges really well with small scale problems of some variables. However, for large scale problems with multiple variables, it does not have much success (Pham, 2012). As a solution to this problem, the quasi-gradient method was introduced by Pham (2012) in the study to improve NM simplex algorithm in terms of the convergence rate and the convergence speed. The author has succeeded to obtain the significant improvement of the method compared to the original simplex method.

In non-gradient-based methods, solutions are tried and progressively improved based on a set of rules. Examples of these methods are the random search method, the grid search method, the pattern search method, Rosenbrock's method, and the Nelder-Mead downhill simplex method. Among others, the simplex method and the downhill simplex method are widely used (Hai, Ashida, Thawonmas, & Rinaldo, 2012). They have some common features and do not require the calculation of the gradients of the objective function.

The Nelder-Mead downhill simplex method is an iterative algorithm using only function values to minimise a scalar-valued nonlinear function of real variables. This method is intended to move the simplex until it surrounds the minimum, and contract the simplex around the minimum until finding an acceptable error.

The minimisation of an objective function is started from a polyhedron simplex in N-dimensional space with N+1vertices. In three dimensions, the simplex is a tetrahedron, and in two dimensions, it is a triangle. This method evaluates the objective function in each iteration at trial points. The location of a trial point is dependent on the function values of the vertices and the earlier trial points. In order to find a new point to improve the worst vertex, the simplex is altered using reflection, reflection and expansion, contraction, and multiple contractions (Huang, 2009). The Nelder-Mead`s simplex method contributed towards stronger exploitation capabilities to achieve a global optimum solution in an effective way. However, the capabilities of existing Nelder-Mead's simplex method needs a high computational cost in term of iterations on the processes of reflection, expansion, contraction and multiple contractions or shrinking. In order to minimised the computational cost, the author proposed the improved Nelder-Mead simplex.

2.4.3 Application of HGA with Other Methods

There are various applications of hybrid genetic algorithms in solving optimisation problems and NP-hard problems. The application of hybrid genetic algorithms can be categorised into three types of hybridisation; application of hybrid genetic algorithms with other methods, application of hybrid genetic algorithms with local search and application of hybridisation genetic algorithms with parameter adaptation (Asyikin, 2011).

A hybrid genetic algorithm with other methods from various application domains has been widely published in recent years, for example, solving the global optimisation of continuous multimodal functions by hybrid genetic algorithms with a niche technique. The niche technique was claimed to assist the hybridisation genetic algorithm in maintaining population diversity.

Global algorithms such as the genetic algorithm are known for their drawbacks such as slower convergence to the true global optimum after the optimum region is found. By combining them with local gradient-based algorithms, the hybrid approaches can overcome that drawback. The faster convergence of a local gradient-based algorithm can improve the efficiency of the hybrid algorithm and avoid the need to specify a good initial point (Song & Xi, 2009).

Another source of the limitation of GA in solving real-world problems is improper choice of control parameters because it is a detrimental influence on the exploitation and the exploration capability of the algorithm. The algorithm can either succeed in finding a near optimum solution in an efficient way or fail depending on these parameters.

The selection of correct parameter values needs a long time. Alternatively, the evolutionary spirit of a genetic algorithm is in contrast with constant control parameters. Therefore, to set the values of these parameters whilst the search is progressing, other search techniques can be utilised.

Global search methods are able to find the highest or lowest function values. A number of global search methods have been used in model prediction. These methods are more robust than local search methods (Ali et al., 2010). However, they suffer from the limitation of intensive computation involved in the searching process, making it unrealistic to apply them directly in prediction models that are computationally demanding.

A number of global search methods such as GA, SA, ACO, the shuffled complex evolution algorithm and PSO, have been developed in the recent decades. Of the research, a genetic-based algorithm and particle swarm optimisation (Tang, Xu, & Lu, 2012) for load forecasting; genetic algorithm and extended Kalman particle filter (Yang, Huang, & Ma, 2009) for non-linear state estimation; ANN and GA (Azadeh, et al., 2006) for energy consumption estimation; genetic algorithm for grade estimation (Li, Wu, Zhang, Weng, & Qi, 2010); and genetic algorithm for state estimation (Yang, Huang, & Ma, 2009; Bahabadi, Mirzaei, & Moallem, 2011).

There were some attempts to improve the global search methods by modifying the algorithm itself or combining it with other algorithms. The improved global search methods include for job scheduling problems; improved genetic algorithm and its application in artificial neural network training; an improved genetic algorithm by combined algorithm for a time-varying system based on the damped least-squares estimation algorithm, etc. (Yan, 2010).

Hybrid genetic algorithm and particle swarm optimisation (GA + PSO) were proposed by Sheikhalishahi et al. (2013) for reliability optimisation in redundancy allocation problem. This approach is developed to identify the optimal solution and improve computation efficiency. Their approach found the improvement capabilities and effectiveness compared to the similar studies.

2.5 Summary

Based on literature, nothing is known on a priori condition that could detect which forecasting method is more suitable for a given load area. An important question is to investigate the sensitivity of the electricity demand forecasting algorithms and models to the number of customers, characteristics of the area, energy prices, and other factors.

The most common model trends are linear, exponential and quadratic. In some cases concerning to electricity demand, trend forecasting can be useful. In many cases, it can be hazardous such as they did not forecast well out of sample. A constructive alternative is to forecast growth rates, such as for the consumptions expenditure. Linear and nonlinear models can utilise to forecast the electricity demand. Modern approach using hybrid algorithms methods such as genetic algorithm coupled with simplex local search can improve the performance of electricity demand forecasting especially in term of error rates.

The performance of electricity demand forecasting model is naturally affected by the uncertainties of independent variables such as GDP. The relationship between electricity demand and the driven variables, however, is highly nonlinear in nature and a rather complex task that requires many inputs. This is typically estimated by a linear model after taking logs of the variable to be forecasted. In logarithms, the trend is approximately linear. Most economic series which are growing (aggregate output such as GDP, investment, consumption) are exponentially increasing. These series cannot be fit by a linear trend, but by their (natural) logarithm linear trend.

An accurate load forecasting is very important for electric utilities in a competitive environment created by the electric industry deregulation. This chapter reviewed some statistical and artificial intelligence techniques that are used for electricity demand forecasting. It also discussed the factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic and end-use factors.

The heuristic search can be applied to handle linear and nonlinear trends in electricity demand variable problems but the heuristic delivers no guarantee of finding the optimum solution. Hybrid algorithm methods can be used to solve different hard optimisation problems with few modifications by adding local search. The goal of hybrid algorithms is to efficiently explore the search space in order to find an optimal or near-optimal solution and to avoid local optimality.

CHAPTER THREE
RESEARCH METHODOLOGY

This chapter presents the research methodology related to electricity demand forecasting model using a hybrid algorithm technique that has been adopted in this research. Section 3.1 introduces the proposed research methodological steps. Section 3.2 to section 3.6 present six steps of the methodology. The detailed explanations are included in subsections. Section 3.5 presents the objective function development including the objective function formulation. Section 3.7 presents the summary of the chapter.

3.1 Research Methodological Steps

In developing the electricity demand pattern forecasting model, these six steps are the forecaster's responsibility, which are: (i) select the best possible forecasting tools, (ii) collect data as required, (iii) data preparation, (iv) the objective function development, (v) the design of the improved GA-LS, and finally, (vi) model performance evaluation. The methodological steps are illustrated in Figure 3.1.

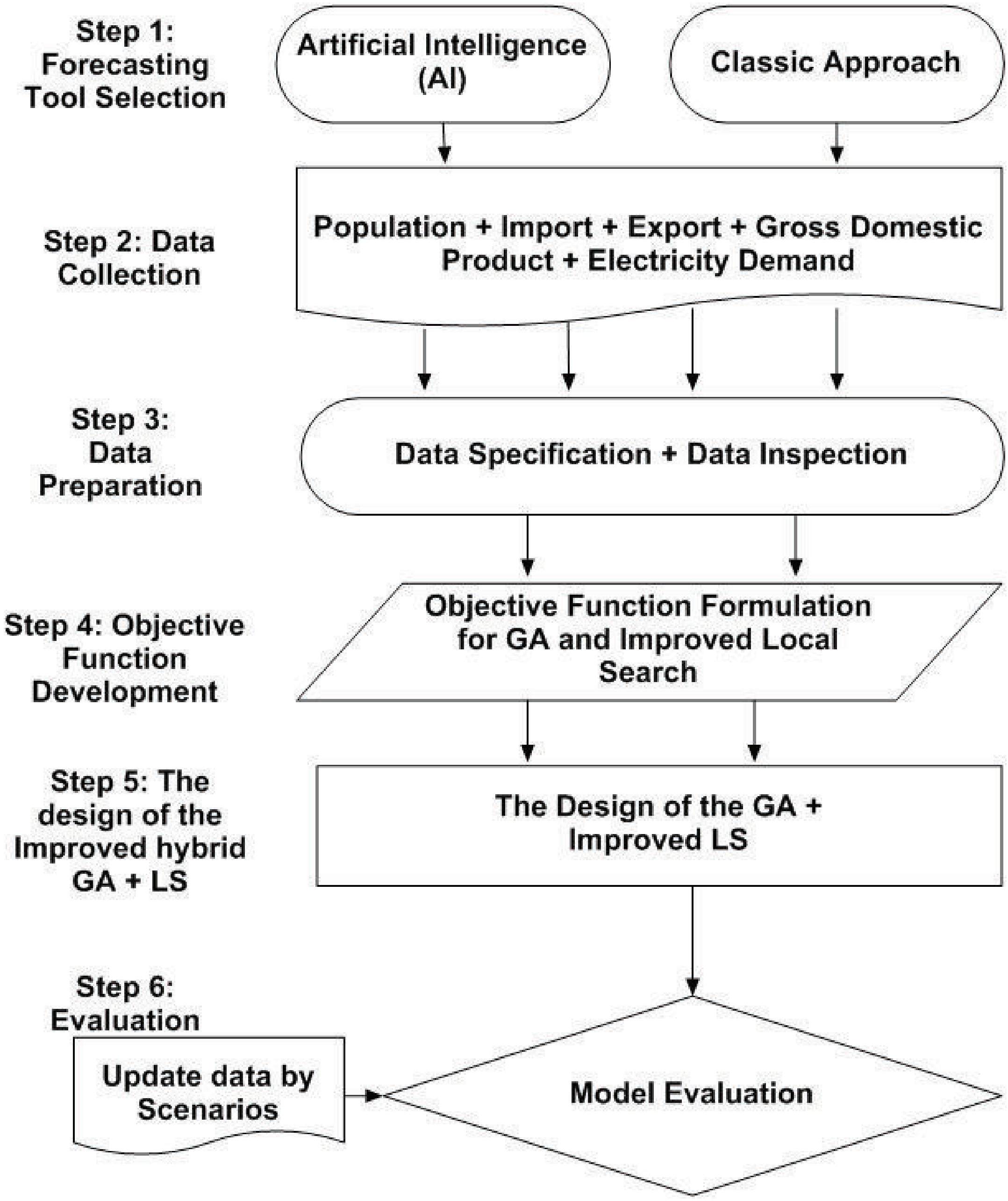


Figure 3.1 Methodological Steps

3.2 Forecasting Tool Selection

The first step in the proposed research methodology is to select an appropriate forecasting tool. Selection among these techniques will depend on the forecast time horizon selected, available data, available time, and the cost of operating with a poor or inadequate forecast. In this study, a long-term electricity demand forecasting was chosen because it appropriate to be applied in decision planning. The forecasting tool selected used the available data for electricity consumption gathering from Enerdata, and the data for model variables from National Statistic Office. In addition, benchmarking proposed forecasting tool used the available data from previous studies.

In general, there is seldom one single superior forecasting method. One organisation may find one approach to be effective, but another organisation may use several approaches. The approaches in forecasting tools can be categorised as: (i) classic approach, such as regression, and (ii) modern approach such as artificial intelligence (AI) in finding the best solutions. A modern approach using linear and nonlinear models based on genetic algorithm and simplex local search in the proposed forecasting tool was chosen to obtain a robust electricity demand forecasts.

In AI, approaches such as hybrid genetic algorithm and hybrid artificial neural network, along with other heuristics are used to tackle the problem in electricity demand forecasting. These approaches have gained more attention in researches of energy demand forecasting related to their capabilities in overcoming the local optimality problems.

The proposed methods chosen were the hybrid of GA and local search (LS) which are introduced as new AI approaches in the field of energy forecasting by exploring the capability of each approach to obtain a proper forecasting tool. The GA was chosen because of its capability in exploring the solutions in the range where the best solution exists, and LS was chosen because of its capability in finding the best solution through the exploitation of the solution on the neighbourhood solutions.

A robust forecasting tool that is obtained from simulations should have higher accuracy than other estimation models. The model that shows good forecasts in prediction would be the model selected for future projection of electricity demand using the economic scenarios.

In developing an electricity demand forecasting model, simulating and processing each model with the available data to obtain the forecast distributions of electricity demand is needed. Any method of electricity demand forecasting is then based on a special way of relating the above variables to demand. Zhang and Ye (2011) used the load forecast to predict future demand based on historical data.

3.3 Data Collection

In forecasting electricity demand, the role of historical information is very important. The success of an electricity demand forecasting method largely depends on the availabilty of data. Historical information of variables that are the gross domestic product, populations, import and export during the period from 1990 to 2009 were collected from various sources such as from the National Statistic Office. Historical information for electricity demand for Turkey and Indonesia were collected from

International Energy Agency (IEA) and Enerdata-Global Energy and CO2 (www.enerdata.net) for National electricity consumptions.

For more than two decades, Enerdata has been developing a full suite of energy information services, including databases, reports, forecasts, and business intelligence. The Enerdata online portal is the best single source of data and analysis for business developers, economists, strategists, analysts and researchers seeking the most comprehensive and up-to-date information, with the widest global coverage.

Enerdata Value proposition includes six points: (a) over 200 first-class statistical sources in a single interface, (b) exclusive government data, (c) harmonised data and units, (d) up to 184 countries covered, (e) outputs from the globally recognised POLES forecasting model, and (f) premium support from Enerdata's analysts.

Once data for a set of candidate variables are collected, data analysis should then be used to weed out the potential input variables from a wish list generated so that only the most relevant variables are used to develop the electricity demand forecasting model. Some of the more popular statistical techniques used are the coefficient of correlation R, the coefficient of determination R^2, and ordinary least squares (OLS) regression analysis.

Data collected for electricity demand and variables can be categorised as time series data and may be an integer sequence, so it will be normalised to zero at first observation. The normalised data using a simple method, for example dividing all historical data by a constant value. After the forecasting process, denormalised data is needed in order to obtain the original values.

3.4 Data Preparation

Data for electricity demand and economic indicators are collected from various sources. Electricity demand data for Turkey and Indonesian are gathered from the International Energy Agency (IEA), Enerdata-Global Energy and CO2. Economic indicator data for Turkey and Indonesia are gathered from the Turkish Statistical Institute (TSI) and Indonesian Statistical Yearbook (BPS).

The data figures of Turkey from 1980 to 2009 are collected from the International Energy Agency (IEA) and Turkish Statistical Institute (TSI) as the last update data for electricity until 2009. These data are available and divided into three sections. Two-thirds are used for model development or observations and one-third is used for testing or measuring accuracy.

Hence, the data for total electricity consumption from IEA and economic indicators from TSI (gross domestic product, population, import and export) from 1980 to 1998 (19 years) will be needed to be used as the main data for observations or developing experiments. The rest of the available data for total electricity consumption and economic indicators from 1999 to 2009 (11 years) are used to test model performance or prediction accuracy.

For example, Experiment 2 in Chapter Four using the historical information of Indonesian electricity demand and socioeconomic data were collected from different sources such as from the National Statistic Office of Indonesia (www.bps.org.id) for Indonesian gross domestic product, populations, import and export during 1990 to 2009 and Indonesian electricity consumption during 1990 to 2009 from Enerdata-Global Energy and CO2 (www.enerdata.net).

Indonesia is not a member of the International Energy Administration (IEA), but the IEA is one of the sources of data for Enerdata-Global energy and CO2. For more than two decades, Enerdata has been developing a full suite of energy information services, including databases, reports, forecasts, and business intelligence.

Experiment 2 is a long-term electricity demand forecasting model for Indonesian energy using historical data or historical information during the period of 1990-2009 for variables: (1) yearly electricity domestic consumption (TWh) from Enerdata-Global Energy and CO2 data, year 1990-2009 (20 years), (2) population (million person), (3) gross domestic product (billions U.S. dollars), (4) import (million U.S dollars), and (5) export (million U.S dollars) from the National Statistical Office of Indonesia for 1990-2009 (20 years).

The historical data of Indonesian electricity demand and socioeconomic indicators are presented in Table 3.1.

Table 3.1 Indonesian electricity demand and socioeconomic data

Year	Electricity Con.(TWh)	Population (10^6)	GDP (10^9)	Import (10^9)	Export (10^9)
1990	27.100	179.830	125.720	21.837	25.675
1991	30.700	182.940	140.820	25.869	29.142
1992	34.100	186.040	152.850	27.280	33.967
1993	38.000	189.140	174.600	28.328	36.823
1994	43.200	192.220	195.470	31.984	40.053
1995	49.800	195.290	223.360	40.629	45.418
1996	56.900	198.320	250.750	42.928	49.815
1997	64.500	201.350	238.410	41.680	53.444
1998	65.300	204.390	105.470	27.337	48.848
1999	71.300	207.440	154.710	23.995	48.652
2000	79.200	205.130	165.520	33.515	62.124
2001	84.500	207.930	160.660	31.010	56.454
2002	87.100	210.740	195.590	31.289	57.159
2003	90.400	213.550	234.830	32.551	61.058
2004	100.100	216.380	257.010	46.525	71.585
2005	107.000	219.850	285.860	57.701	85.660
2006	112.600	222.750	364.350	61.066	100.799
2007	121.200	225.640	432.230	74.473	114.101
2008	129.000	228.580	511.490	129.197	137.020
2009	136.100	240.300	539.380	96.829	116.510

The total ”native demand pattern” of Indonesian electricity demand from 1990 to 2009 as a dependent variable is shown in Figure 3.2 and Indonesian population and economic indicators as independent variables is shown in Figure 3.3.

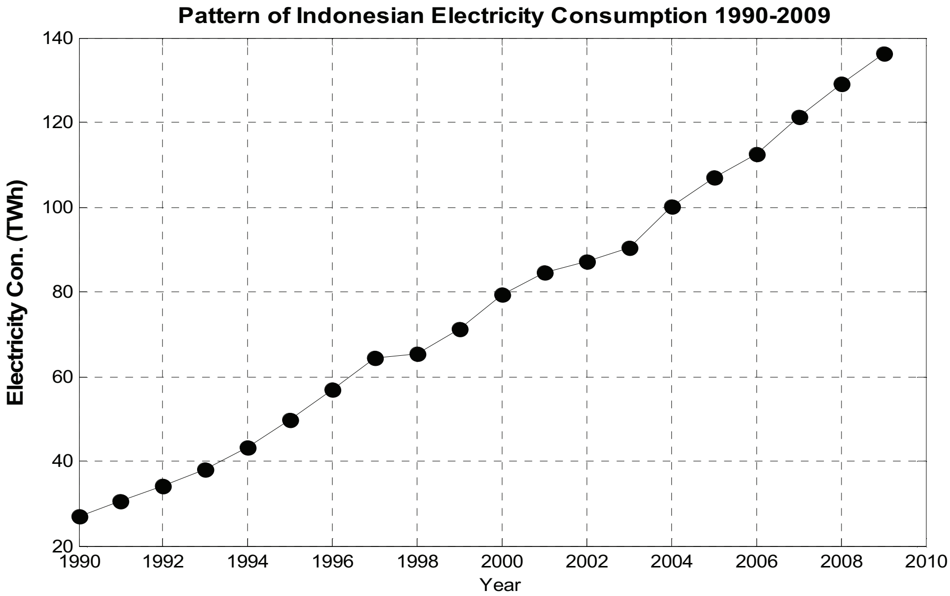


Figure 3.2 Demand pattern for Indonesian Electricity

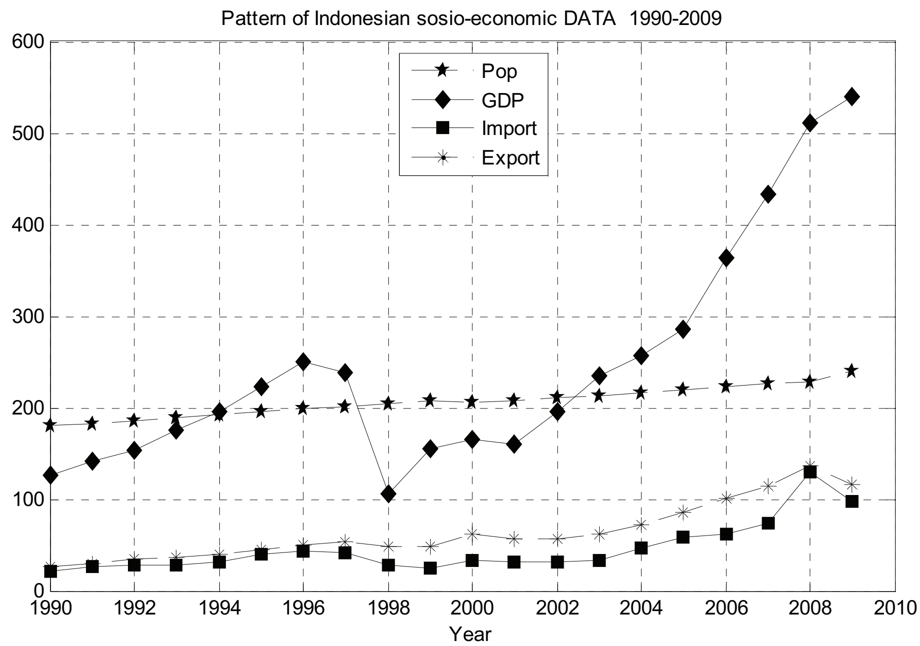


Figure 3.3 Population and socioeconomic variables data for Indonesian Electricity demand

The pattern of Indonesian electricity demand tends to rise as linearly as shown in Figure 3.2 and the gross domestic product rises as exponentially as shown in Figure 3.3.

3.5 Objective Function Development for Genetic Algorithm and Local Search

Objective Function representation of each model is the fitness functions that represent the relation between electricity-demand (ED) with independent variables. In this research, independent variables are population (X_1), gross domestic product (X_2), import (X_3) and export (X_4) in linear and nonlinear forms. In this method, the objective functions are the linear model, the logarithmic model, the exponential model, and the quadratic model. After a model has been developed, this model can be applied according to the range-term of time. Each model was tested using electricity demand data with and without preprocessing and local search.

The mathematical formulas are:

$$\text{Linear ED} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \qquad (3.1)$$

Nonlinear i.e. the exponential form

$$\text{Exponential ED} = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \qquad (3.2)$$

Where β_0, β_1, β_2, β_9 are the weighting parameters.

The objective function in this research is to minimise errors by measuring the least square error of the objective function values. The objective function is the difference between ED actual values and ED forecasting values using least square approach as stated in equation 3.3.

Objective Function:

$$S = \sum_{\mathrm{i=1}}^{\mathrm{n}} (\text{ED actual} - \text{ED forecasting})^2 \tag{3.3}$$

Where

$$\begin{cases} S = sum\ of\ the\ squared\ prediction\ errors \\ n = the\ number\ of\ data \\ ED\ actual = the\ existing\ recorded\ data \\ ED\ forecasting = approximation\ values \end{cases}$$

The evaluation of the objective function values and fitness is the process to calculate the objective function value's association with the chromosomes. A fitness value is calculated and assigned to each chromosome based on its objective function value through the proposed HGA operations. The process of the hybrid genetic algorithm and local search algorithm starts from the initial population of parameter values. Their objective function values are calculated using an objective function through a genetic algorithm process. Figure 3.4 shows the main phases of the existing hybrid genetic algorithm and the local search algorithm.

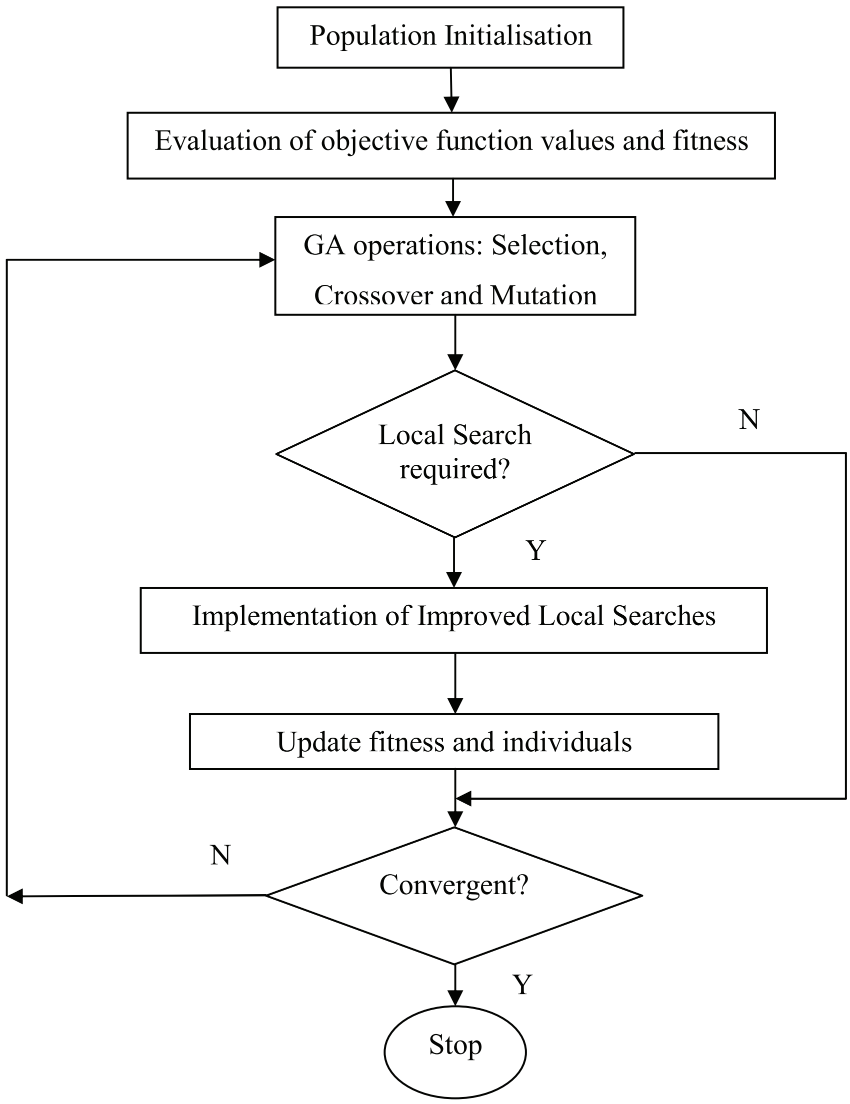


Figure 3.4 Hybrid algorithm of GA and Local Search (Huang, 2009)

The technical aspect combining an improved local search algorithm and a genetic algorithm is referred to as the HGA approach. The combining process starts by running GA with small iterations in order to be effective in computational time. During the process, the capability of GA to find a solution quickly in exploring the area of solutions and is the main consideration.

3.5.1 Population Initialisation

The population initialisation is the process of generating the initial population of *N-pop* chromosomes (*N-pop* sets of initial parameter values) where *N-pop* is the population size. Heuristic methods and random methods can be used to initiate the population. The commonly used random methods generated $N\text{-}_{Pop}$ x N parameter values between 0 and 1 and then all of these values are scaled to their feasible ranges by;

$$x = (x_{up} - x_{low}) \text{ x } x_{rand} + x_{low} \tag{3.4}$$

Where x = the actual value of the parameter; x_{low} = the lower bound of the parameter; x_{up} = the upper bound of the parameter; x_{rand} = a randomly generated value. However, the heuristic method requires some prior knowledge about the parameter set. One way is by taking default values as one chromosome and other chromosomes are generated randomly.

3.5.2 Evaluation of Objective Function Values and Fitness

The chromosomes after the initialisation in the previous step are inputted into the demand forecasting model, and the model is run to produce outputs. The model outputs associated with the chromosomes are passed to calculate the objective function value. If the objective function value is smaller than a predetermined value, then the process stops. Otherwise, a fitness value is calculated and assigned to each chromosome based on its objective function value.

In this study, the objective function formula is the mathematical models that are used to calculate demand as a function of socioeconomic variables. The formula consists of three models, which are linear logarithmic, exponential and quadratic models, as described in the mathematical representation in equations (3.5) until (3.7).

Linear logarithmic model:

$$\log Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 \qquad (3.5)$$

Exponential model:

$$\text{Exponential } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \qquad (3.6)$$

Quadratic Model:

$$\text{Quadratic } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} + \beta_{10} X_1X_2 + \beta_{11} X_1X_3 + \beta_{12} X_1X_4 + \beta_{13} X_2X_3 + \beta_{14} X_2X_4 + \beta_{15} X_3X_4 \qquad (3.7)$$

In equations (3.5) to (3.7); X_1 represents the GNP (10^9), X_2 represents the population (10^6) , X_3 represents the import (10^9) , X_4 represents the export (10^9) and $\beta_0, \beta_1, \beta_2, \ldots \beta_{15}$ are the weighting parameters.

In a genetic algorithm for a demand forecasting model, the parameters are represented by floating-point numbers. Assume there are N-parameters (an N-dimensional problem) to be optimised, given by $x_1, x_2, \ldots, x_N$, and then a chromosome can be written as an array with 1xN elements so that:

$$\text{chromosome} = [x_1, x_2, \ldots, x_N] \qquad (3.8)$$

In this way, the precision of the parameter values is no longer dependent on how many bits are used to represent the parameters as that binary genetic algorithm, but on the internal precision and round-of error of the computer. Figure 3.5 shows the example of the binary encoding for three parameters β_1, β_2, and β_3 as well as the related decimal number of each parameter. β is associated with the objective function such as $y = \beta_1 + \beta_2 \text{ Ln } X_1 + \beta_3 \text{ Ln } X_2$ where X_1 and X_2 are independent variables and y is the dependent variable.

Parameter	β_1				β_2				β_3			
Binary number	1	0	1	1	1	1	1	0	1	0	1	0
	g_1			g_4	g_5			g_8	g_9			g_{12}
Decimal number	11				14				3			

Figure 3.5 Binary encoding schemes

g_1 to g_4 are the group four bits for β_1, g_5 to g_8 are the group four bits for β_2, and g_9 to g_{12} are the group four bits for β_3. Each group bits represent the binary number values depend on binary positions. For example, the binary number for β_1 $(1 \text{ x } 2^3 + 0 \text{ x } 2^2 + 1 \text{ x } 2^1 + 1 \text{ x } 2^0) = 8 + 2 + 1 = 11$ in decimal form.

3.5.3 Minimised Objective Function by GA operations

The main operations of GA are selection, crossover and mutation. The GA terminates if conditions are satisfied. First, if the objective function value is less than the prescribed threshold, the GA terminates with an optimal solution. Second, if the maximum number of prescribed generations has been reached, the GA terminates without an optimal solution. Then the solution from the GA is used as the initial point for another optimisation solver that is faster and more efficient for local search.

The general pseudo-code of GA is illustrated in Figure 3.6.

```
GA Algorithm
Input: Size of random population (P), no. of generations/iterations, termination criterion
Output: Optimal value for GA parameters (β, fval) and classification of accuracy
BEGIN
        Initial Population Generation;
        Each individual fitness Computation;
                REPEAT  /*  create new generation /*
                        FOR size_of_population / 2 DO
                          Two parent's selection from old generation;
                           /* Favouring ones of the fitter */
                          Recombine parents for two offspring;
                          Offspring Fitness Computation;
                          Offspring insert in new generation;
                        END FOR
                UNTIL population has converged
                /* sort solutions and select the best one
END
```

Figure 3.6 Pseudo-code of GA

The ability of GA to find the feasible solution to a given problem is inspired by natural evolution. Evolution comprises the population of individual feasible solutions to a problem. The fitness function for each individual is used to select the individual to reproduce offspring for a new generation. The individual who has higher fitness has more chance to reproduce. Offspring that are reproduced from two parents have a combination of properties of those two parents. The population will converge to an optimal solution if well designed.

GA has an exploration capability that is quick to find the region in which the global optimum exists but it is difficult to find the global optimum. Generally, the main steps of operation of a genetic algorithm are selection, crossover and mutation. Each process is described in detail in the following subsections.

Step 1: Selection

The operator selections in a genetic algorithm mimic nature's survival of the fittest principle. This principle translates into discarding the chromosomes with the lowest fitness and ensuring that fitter chromosomes have high possibility to produce offspring, thereby gaining a higher chance of surviving in the new generations. This process consists of the following three steps.

The first step is to rank the N_{pop} chromosomes from the lowest to the highest in terms of their objective function values (for a minimisation problem). Then, only the best are kept; the rest are deleted to make room for new offspring. This process is called natural selection in some literature, such as in Chunyu & Xiaobo (2009) and Wang, Sun, & Ren (2009). The retained chromosomes form the mating pool. The number of chromosomes that are kept in each generation, N_{kept}, is calculated by:

$$N_{kept} = X_{rate} \times N_{pop} \tag{3.9}$$

Where X_{rate} is the natural selection rate, which is the fraction of N_{pop} that survive for mating. Determining the chromosome numbers to keep is still an open question and is usually determined by trial and error. Too many numbers of chromosomes allow bad chromosomes to contribute their traits to the offspring, while too few chromosomes limit the available genes to the next generation (Huang, 2009).

The second step is to assign fitness to each chromosome, which is used for the selection of individuals for mating. To select chromosomes from the retained chromosomes to generate new chromosomes to fill the discarded (N_{pop}-N_{kept}) chromosomes, each chromosome in the mating pool is assigned a fitness value in terms of its objective value.

To ensure that fitter chromosomes have high possibility to produce offspring, higher fitness should be assigned to them. The famous methods for fitness assignments are: (i) rank-based, and (ii) proportional. In the rank-based assignment, sorting the population according to their objective function values, the fitness is assigned to each chromosome dependent on its position in the individual rank. In contrast, in proportional fitness assignment, the fitness assigned to each individual depends on its actual value of objective function. However, one problem with the proportional fitness assignment is that selection pressure depends largely on the shape of the fitness function, which therefore needs to be carefully chosen to provide the right selection pressure.

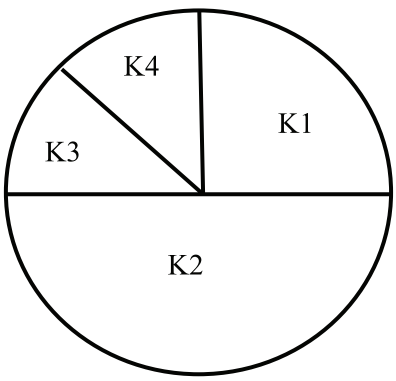
A selection pressure that is too high brings the optimisation to a premature convergence and conversely, a selection pressure that is too low does not direct the optimisation strongly enough and genetic drift will appear in the population (Goldberg, 1989 as cited in Huang, 2009).

Another problem comes from the fact that even with a good fitness function, the selection pressure will vary from one generation to another. In the beginning, the selection pressure will be quite high and with large improvements in the population, it will then weaken along the optimisation to finish very low towards the end when only small improvements are possible.

Rank-based fitness assignment is more robust than proportional assignment because it overcomes the problems of proportional fitness assignment; that is, it provides an effective and simple way of controlling selective pressure.

The third step is to select chromosomes for mating. This process chooses the chromosomes in the current generation to generate offspring to replace the discarded chromosomes. Several methods are available for selection operations. Among them, tournament selection and roulette wheel selection are widely used. Figure 3.7 shows an example of the roulette wheel selection method. Roulette wheel selection is performed based on the relative fitness f_r (p_i) of chromosome i, which is defined as follows:

$$fr(pi) = f(pi)/\sum_{j=1}^{Nkept} f(pj) \quad (3.10)$$



Chromosomes	Fitness Value
K1	1
K2	2
K3	0.5
K4	0.5
Total	4

Figure 3.7 Roulette wheel selections

The cumulative fitness $f_c(p_i)$ is calculated by:

$$f_c(p_i) = \sum_{j=1}^{i} fr(pj) \tag{3.11}$$

A random number r is generated within the range [0, 1] and selects chromosome pi whose cumulative fitness is greater or equal to the random number r as follows:

$$f_c(p_i) \geq r \tag{3.12}$$

Each chromosome has a space proportional to the fitness values. K1 has a cumulative interval [0:0.25]; K2 has a cumulative interval [0.25:0.75]; K3 has a cumulative interval [0.75:0.875]; and K4 has a cumulative interval [0.875:1]. A chromosome can be selected if the generated random number values are in the range interval of its chromosome. For example, if a generated random number value is 0.6, the chromosome K2 is selected as a parent, but if a generated random number is 0.9, chromosome K4 is selected as a parent (Sanjoyo, 2006).

As another method, tournament selection involves randomly picking a small subset of chromosomes from the mating pool; the chromosomes in this subset with the lowest value of objective function become parents.

Step 2: Crossover

One of the crossover methods used to implement the crossover operation is the simplest method. To mark the crossover point, it chooses one or more points in the chromosome. The genes on these points are then swapped between the two parents.

$$mother = [X_{m,1}, X_{m,2}, X_{m,3}, X_{m,4}, X_{m,5}, X_{m,6}, \ldots, X_{m,N}] \tag{3.13}$$

$$father = [X_{d,1}, X_{d,2}, X_{d,3}, X_{d,4}, X_{d,5}, X_{d,6}, \ldots, X_{d,N}] \tag{3.14}$$

Where the *d=father,* and *m* = mother.

Figure 3.8 shows the one-point crossover. The point is randomly selected, and then the first part of parent 1 (mother) is combined with the second part of parent 2 (father).

	β_1				β_2				β_3			
Mother	0	0	1	1	1	1	1	1	1	1	1	1
Father	1	1	0	0	0	0	0	0	0	0	0	0

	g_1			g_4				g_8				g_{12}
Offspr.1	0	0	0	0	0	0	0	0	0	0	0	0
Offspr.2	1	1	1	1	1	1	1	1	1	1	1	1

Figure 3.8 Example of crossover process

The gene or genes between crossover points are exchanged after they are randomly selected. Assume point 3 and 5 in equation (3.13) and (3.14) are selected and the two parents can be mated to produce the following offspring:

$$offspring\ 1 = [X_{m,1}, X_{m,2}, X_{d,3}, X_{d,4}, X_{d,5}, X_{m,6}, \ldots, X_{m,N}] \tag{3.15}$$

$$offspring\ 2 = [X_{d,1}, X_{d,2}, X_{m,3}, X_{m,4}, X_{m,5}, X_{d,6}, \ldots, X_{d,N}] \tag{3.16}$$

In the uniform crossover method, the two parents that would contribute genes at each position in the extreme case are selected and randomly chosen from N points. For example, assume genes 1, 3, 4 and 6 in the two parents in equation (3.13) and (3.14) are chosen to swap genes, the following offspring are generated:

$$offspring\ 1 = [X_{d,1}, X_{m,2}, X_{d,3}, X_{d,4}, X_{m,5}, X_{d,6}, \ldots, X_{m,N}] \quad (3.17)$$

$$offspring\ 2 = [X_{m,1}, X_{d,2}, X_{m,3}, X_{m,4}, X_{d,5}, X_{m,6}, \ldots, X_{d,N}] \quad (3.18)$$

However, no new information is introduced in this point crossover method. To introduce new genetic material, it is completely reliant on mutation. The genes are propagated from the parents to the next generation, only in different combinations.

The blending methods are finding ways to solve this problem by combining genes from parents into new genes in the offspring. A combination of the two genes from corresponding parents, produce a single offspring gene in the following way:

$$X_{offspring1,\, \mathrm{i}} = \beta X_{m,\, i} + (1-\beta)\, X_{\mathrm{d},\, i} \quad (3.19)$$

Where $\beta \in [0, 1]$ can be a variable or a constant value depending on the age of the population; $X_{\mathrm{d},\, i}$ = i^{th} gene in the father chromosome; and $X_{m,\, i}$ = i^{th} gene in the mother chromosome. The same gene of the second offspring is the complement of the first (i.e., β replacing by 1- β). That is:

$$X_{offspring2,\, \mathrm{i}} = (1-\beta)\, X_{m,\, i} + \beta X_{\mathrm{d},\, i} \quad (3.20)$$

If $\beta = 1$, then $X_{m,\, i}$ propagates in its entirety and $X_{\mathrm{d},\, i}$ dies. In contrast, if $\beta = 0$, then $X_{\mathrm{d},\, i}$ propagates in its entirety and $X_{m,\, i}$ dies. When $\beta = 0.5$, the result is an average of the genes of the two parents.

Step 3: Mutation

Genetic algorithms commonly use the nonuniform and uniform mutation method. The mutation operators introduce their variability by altering some of their genes to randomly selected chromosomes (Huang, 2009). The frequency of mutating the parameters to the next generation is different from one method to the next.

The number of genes to be mutated in uniform mutation is determined by mutation rate, while in nonuniform mutation, the mutation rate is reduced from one generation to another as the run progresses. The number of chromosomes to be mutated (N_m) in uniform mutation is determined by mutation rate (r_m) and the number of genes in a chromosome (N), i.e. $N_m = r_m$ x N. Given a chromosome as follows:

$$X = (X_1, X_2, X_k, X_N) \tag{3.21}$$

Then every randomly selected gene X_k ($k = 1, N$) has an equal opportunity of having the mutative process. The result of a single application of this operator is a chromosome

$$X = (X_1, X_2, X_{k,\ new}, X_N) \tag{3.22}$$

Where $X_{k,\ new}$ is a random value from the domain corresponding to the k^{th} gene. The process continues until N_m chromosomes have been mutated.

In the execution of a genetic algorithm, one generation is formed by the process of evaluation, selection, crossover and mutation. A new generation of chromosomes is produced after the process is complete. However, there is no guarantee that the best chromosome is carried through to the next generation, the new generation might not be better than the previous one.

The genetic algorithm terminates if conditions are satisfied. First, if the objective function value is below the prescribed threshold, the genetic algorithm terminates with an optimal solution. Second, if the maximum number of prescribed generations has been reached, the genetic algorithm terminates without an optimal solution.

The genetic algorithm is a population-based meta-heuristic; in many situations it does not perform well (Lian et al., 2009). A hybrid algorithm is used to solve this problem, by adding a local search algorithm. This method uses a hybrid optimisation scheme between local search and the genetic algorithm optimisation method for an objective function.

3.5.4 Minimised Objective Function by Improved Local Search Process

The local search phase usually improves the constructed solution generated by an original algorithm that is not necessarily optimal, even with respect to simple neighbourhoods. The local search process is required based on the objective function values. If the GA operation convergence and local search process are not required, then the process stops; otherwise, it returns to GA operations. If the local search process is required, it updates fitness and individuals until the processes converge. If the local search process is not convergent, it will continue with GA operations. This process is repeated until convergence is achieved.

A local search algorithm works in an iterative fashion by successively replacing the current solution with a better solution in the neighbourhood of the current solution. It terminates when no better solution is found in the neighbourhood. The pseudo-code of a basic local search algorithm starting from the solution constructed in the first phase and using a neighbourhood N is given in Figure 3.9.

```
Procedure Local-Search(V,dom,C)
    Inputs
        V: a set of variables
        dom: a function such that dom(X) is the domain of variable X
        C: set of constraints to be satisfied
    Output
        Complete assignment that satisfies the constraints
    Local
        A[V] an array of values indexed by V
    repeat
        for each variable X do
          A[X] ← a random value in dom(X)
    while (stopping criterion not met & A is not a satisfying assignment)
        Select a variable Y and a value V ∊ dom(Y)
        Set A[Y] ← V
    if (A is a satisfying assigment) then
        return A
    until termination
```

Figure 3.9 Pseudo-code of the local search phase

Local search has a capability that quickly exploits the solutions in the neighbourhood starting from the initial point. Setting the initial point is very important because local search is sensitive to the initial point (the worst of local search).

The mechanism to exploit the solutions, for example, is through the reflection, expansion, contraction, shrinkage process, such as in the Nelder-Mead downhill simplex method. To solve the unusage repetitions of iteration that take a great deal of computation time, setting the coefficients of reflection, contraction, expansion, and shrinking is very important. A simplex is the most elementary geometrical figure that can be formed in dimension N and has N + 1 side (e.g., a triangle in two-dimensional space) as shown in Figure 3.10.

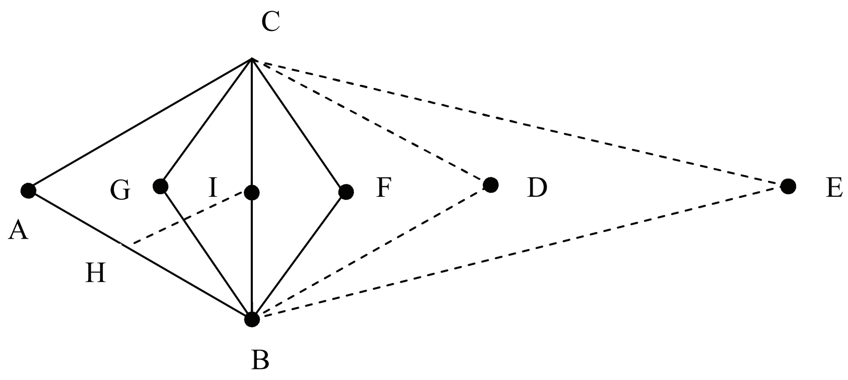


Figure 3.10 Nelder-Mead downhill simplex methods

Starting at the N + 1 point, this forms the initial simplex. Only one point of the simplex, P0, is specified by the user. The other N points are found by

$$Pn = P0 + cs\ en \tag{3.23}$$

Where *en* is N unit vectors and *cs* is a scaling constant. The steps used to trap the local minimum inside a small simplex are stated as follows:

(1) Creation of the initial triangle. Three vertices start the algorithm:

$$A = (x1, y1),\ B = (x2, y2),\ \text{and}\ C = (x3, y3) \tag{3.24}$$

(2) Reflection. A new point, $D = (x4,y4)$, is found as a reflection of the lowest minimum (in this case A) through the midpoint of the line connecting the other two points (B and C).

$$D = B + C - A \tag{3.25}$$

(3) Expansion. If the cost of *D* is smaller than that at A, then the move was in the right direction and another step is made in that same direction.

$$E = 3(B+C)/\ (2-2A) \quad (3.26)$$

(4) Contraction. If the new point, *D,* has the same cost as point *A,* then two new points are found.

$$F = (2A+B+C)/4, \qquad G = 3(B+C)/\ (2-2A) \quad (3.27)$$

The smaller cost between *F* and *G* is kept, thus contracting the simplex.

(5) Shrinkage. If neither *F* nor *G* has smaller costs than *A,* then the side connecting *A* and *C* must move toward *B* in order to shrink the simplex. The new vertices are given by:

$$H = (A+B)/2, \qquad I = (B+C)/2 \quad (3.28)$$

Each of iterations generates a new vertex for the simplex. If this new point is better than at least one of the existing vertices, it replaces the worst vertex. This way, the diameter of the simplex gets smaller and the algorithm stops when the diameter reaches a specified tolerance.

The local search process is required based on the objective function values after the genetic algorithm operations. Fitness value *fval* is evaluated based on the objective function. If the function is to minimise cost or find minimum values of the objective function, the deviation (usually known as ‘error’) between the result estimated by simulation and observation or the actual value must be calculated. The original simplex local search process for a minimisation problem with more than two decision variables is illustrated in the following steps as presented in Figure 3.11.

Step 1: Start with initial guess $X_0, X_1, ..., X_N$, where X_i (i=0,1,…,N) is a vertex of a simplex in N-dimensional space, and where $X_i = (x_1, x_2, \ldots, x_N)$. $X_0, X_1, ..., X_N$ are set to the top N+1 chromosomes (i.e. parameter set) that have the lowest objective function values and then go to Step 3.

Step 2: Evaluate the objective function at these N+1 points (including the original point X_0), i.e., $f(X_i)$, $i = 0, 1, N$.

Step 3: Sort the points in terms of their objective function values and select the point with the highest (X_h), second highest (X_s), and the least (X_l) function values.

Step 4: Judge the convergence. If the difference between the highest and lowest function values is below the prescribed tolerance, i.e., $f(X_h) - f(X_l) < \varepsilon$, then the process is terminated; otherwise, perform reflection as explained in the next step.

Step 5: Calculate the centroid (X_c) of all points except the highest, as given by

$$X_c = \frac{1}{N} \sum_{i=1}^{n} Xi \quad (3.29)$$

And generate a new point X_r by reflecting X_h about the centroid X_c and is given by the following expression

$$X_r = X_c + r\,(X_c - X_h) \quad (3.30)$$

Where r is the reflection coefficient ($r = 1$). A function evaluation is performing at the reflected point. If the reflection is successful, i.e., if $f(X_r) < f(X_l)$, the point is further expanded as explained in next step.

Step 6: A new expanded point, X_e is obtained using the following expression

$$X_e = X_c + e\,(X_c - X_r) \quad (3.31)$$

Where e is the expansion coefficient (e = 1). A function evaluation is performed at the expanded point. If the expansion is succeeds, i.e., if $f(X_e) < f(X_l)$, the point is further expanded. If the expansion fails, i.e., if $f(X_e) > f(X_r)$, the point is contracted.

The contracted point X_{ct} is obtain by

$$X_{ct} = X_c + c\,(X_c - X_h) \tag{3.32}$$

Where c is the contraction coefficient (c = 0.5).

Step 7: If all the operation including reflection, expansion, and contraction fail, multiple contraction is used to scale the simplex around the point with the least function value (X_l), which shrinks the simplex. The new scaled points XCi are given by

$$XC_i = X_l + s\,(X_i - X_l) \quad i = 0,\ldots, N, \;\; i \neq 1 \tag{3.33}$$

Where s is the multiple contraction coefficient, also call the shrinkage coefficient (s = 0.5).

If both the expansion and the contraction stages fail, then the previously reflected point X_r is accepted.

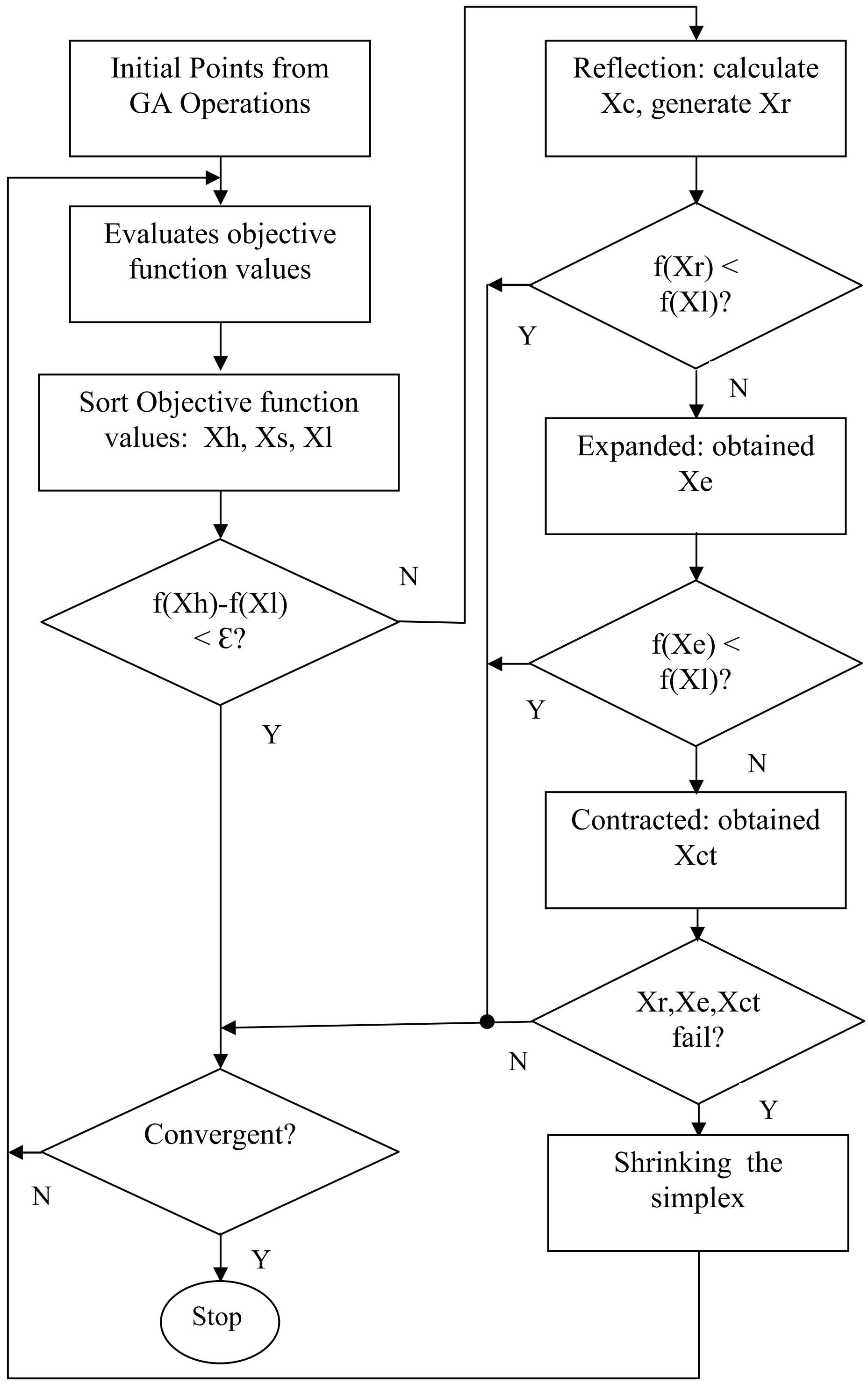


Figure 3.11 The Original Simplex Local Search flowchart (Huang, 2009)

Step 8: After performing the multiple contractions, go back to step 2 with the N+1 new simplex point.

Steps 2-8 are repeated until the local search convergence is achieved or the predetermined maximal number of iterations has been reached.

3.6 The Design of the Improved GA – LS

Hybridisation genetic algorithms with local search are commonly implemented in solving many complex problems where each new generated offspring follows local optimisation procedures to lead the solution towards a local optimum area before continuing to the next generation. In the improved version of binary genetic algorithm, the genetic algorithm involves binary genetic sequences that are converted from real valued variables before the crossover and mutation processes. After these processes, the binary genetic sequences are converted back to real-valued variables. It can handle real-valued variables while processing the crossover and mutation process. In this work, it is named the real-value genetic algorithm (RVGA). The improved local search performs local exploitation around individuals in the local neighbourhood, while genetic algorithms make global explorations in a population.

The proposed approach is known as hybrid real-value genetic algorithm and extended Nelder-Mead (RVGA-ENM). In order to take advantage of both, these hybrid algorithms basically use the way to hybridise the RVGA and ENM. The results solution from RVGA is returns as the initial solutions of the ENM. Individual solutions will experience both evolution from RVGA and the exploitation of local neighbourhood solutions from ENM in every iteration. To better exploit the ENM and real-value genetic algorithm, advance discussion of the hybrid mechanism is presented in Chapter Five.

3.7 Performance Evaluation of Proposed Hybrid Algorithm

Finally, to evaluate the performance of the electricity demand forecasting model based on the proposed hybrid algorithm, the actual demand and estimation results of each model were compared. Once forecast results are obtained from the selected model(s), they need to be validated for accuracy. Model selection for this study is based on several criteria.

Generally, the criteria are goodness of fit, information loss and the quality of being near the true value or accuracy. Some models for electricity energy demand were tested using available energy and socioeconomic data. Some of the common indices that are used to determine forecast accuracy are illustrated in (3.36) until (3.40). These indices are extremely useful in comparing forecast accuracy (Jing et al., 2011). To measure the fitness of the proper model, the fitness values of several candidate models can be used to rank the models after given a dataset:

a) the mean absolute error (MAE) = $1/n \sum_{t=1}^{n} |(yt - \hat{y}t)|$ (3.36)

Where, yt is the history value, and $\hat{y}t$ is the predictive value (the same as the followings).

b) the sum square error (SSE) = $\sum_{t=1}^{n} |(yt - \hat{y}t)|^2$ (3.37)

c) the mean square error (MSE) = $1/n\sqrt{\sum_{t=1}^{n}} |\left(yt - \hat{y}t\right)|^2$ (3.38)

d) the mean absolute percentage error (MAPE)

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{|yt-\hat{y}t|}{|\hat{y}t|} \tag{3.39}$$

e) the mean square percentage error (MSPE)

$$\text{MSPE} = \frac{1}{n}\sqrt{} \sum_{t=1}^{n} \left(\frac{|yt-\hat{y}t|}{|yt|}\right)^2 \tag{3.40}$$

When evaluating the different forecasting techniques, an essential consideration that the objective of any forecasting activity is to provide a forecast with a sufficient degree of accuracy at the least possible cost. In this methodology, a model with a sufficient degree of accuracy will be a candidate for the chosen model for forecasting future demand.

Data inputs for forecasting future demand are updated using scenarios. These scenarios are based on trends of annual growth of historical data. There are three scenarios that will be used in this research; the basic scenario, low scenario and high scenario. The actual annual growth of historical data is used as the basic for calculating the scenarios analysis.

In validating and evaluating the degree of accuracy, this work presents the genetic algorithm approach to find the optimum values that minimised the absolute summation of the forecasting errors. In order to emphasise the best string and speed up convergence of the iteration procedure, fitness is normalised between 0 and 1. The fitness function (ff) can be expressed as follows (Ghods & Kalantar, 2008):

$$\text{ff} = \frac{1}{1+k\ \sum_{k=1}^{m} |r(t)|} \tag{3.39}$$

The scaling constant is k and *r (t)* represents the forecasting errors. Like other stochastic methods, the GA has a number of parameters that must be selected: size of population, probability of crossover and probability of mutation. The associated error vector is r (t) and GA tries to keep the r (t) in the allowed limit. If r (t) is kept in the allowed limitation, the fitness function has the best values for demand forecasting. The values of demand forecasting can be calculated using the following equation:

$$y(t) = a_0 + \sum_{i=1}^{n} a_i t^i + r(t) \tag{3.40}$$

Where y (t) is the demand at time t, a_0, a_i are the regression coefficients relating the demand y (t) to time t, and r (t) is the residual demand at year (t).

3.8 Summary

Six methodological steps for electricity demand forecasting models using a hybrid genetic algorithm technique have been presented. Several models that will be used to forecast the relationship between electricity demand and its independent variables have been described in more detail.

The original objective function in the proposed method was to minimise errors by measuring the least square error of the objective function values. The objective function is the difference between electricity demand actual values and electricity demand forecasting values.

The evaluation of the objective function values and fitness is the process to calculate the objective function value's association with the chromosomes. A fitness value is calculated and assigned to each chromosome based on its objective function value through the GA operations. A local search is used to assist GA in overcoming uncertainty in demand and local optima problems. Genetic algorithms are efficient heuristics and stochastic global search methods that have the ability to handle complicated problems. Unfortunately, these results can only be achieved at the expense of intensive computational requirement. This ability decreases in searching the point that is close to the optimal solution. It can be increased by using an improved local search capability, which is good at converging at the local optima from nearby starting points.

In overcoming the limitation of a single meta-heuristic, the proper method is the hybridisation of a heuristic. In general, better results can be found in hybrid heuristics for classes of instances of the optimisation problem and a hybrid heuristic would outperform a standalone heuristics, although a priori there is no guarantee. One promising family of hybridisation algorithms is that of population-based heuristics with local search heuristics.

CHAPTER FOUR
EXPERIMENTS, ANALYSIS AND RESULTS VALIDATION

This chapter shows the experiments using a hybrid genetic algorithm with an original simplex local search algorithm for electricity demand (HGAED) to find the optimum solution. Section 4.1 presents the experimental design including dataset description and model description respectively in sub sections. Several experiments and analyses were done to evaluate the performance of a hybrid genetic algorithm and original simplex local search compared to other methods. Section 4.2 presents the evaluation of HGAED using electricity demand data. Firstly, comparison of HGAED and other methods using Turkish data is discussed. Next, the HGAED performance using Indonesian data is evaluated. In addition, the evaluation of the HGAED performance using the secondary data in Ozturk and Ceyland (2005) and Toksari (2007), and evaluate relativeness to some benchmarks using the original simplex local search is included. The results found in each experiment are also illustrated in subsections. Finally, section 4.3 presents the summary of the chapter.

4.1 Experimental Design

The first experiment is to evaluate the performance of HGAED in Turkey's data using the hybrid method as described in Chapter 3.

4.1.1 Models Description

There are five electricity demand models used in these experiments, namely: (1) the GAED-1 and GAED-2 models by Ozturk and Ceyland (2005), (2) the Linlog-ED model by Azadeh et al. (2006), (3) the Lin-ED model by Toksari (2007), (4) the DLin-ED model by Deng (2010), and (5) the HGAED1 and HGAED2 models.

The estimation of electricity demand based on economic indicators uses various forms of equations. These forms are linear, exponential and quadratic. In the GAED-1 and GAED-2 models by Ozturk and Ceyland (2005), electricity demand values are the function of gross national product, population, import and export in exponential and quadratic form, respectively. In the Linlog-ED by Azadeh et al. (2006), electricity demand values are the function of economic indicators in linear logarithmic form. While in the Lin-ED model by Toksari (2007) and DLin-ED model by Deng J. (2010), electricity demand values are the function of gross domestic product, population, import and export in linear form.

The forecasting model is given by equations (4.1) to (4.7) as the following:

GAED-1:

$$\text{Exp: } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \tag{4.1}$$

GAED-2:

$$\text{Quad: } Y = \begin{cases} \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} \\ + \beta_8 X_4^{\beta_9} + \beta_{10} X_1X_2 + \beta_{11} X_1X_3 + \beta_{12} X_1X_4 \\ + \beta_{13} X_2X_3 + \beta_{14} X_2X_4 + \beta_{15} X_3X_4 \end{cases} \tag{4.2}$$

LinLog-ED:

$$\text{Log: } Y = \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 \quad (4.3)$$

Lin-ED:

$$\text{Lin: } Y = \beta_1 + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_3 + \beta_5 X_4 \quad (4.4)$$

Dlin-ED:

$$\text{Lin: } Y = C_1 X_1 + C_2 X_2 + C_3 X_3 + C_4 X_4 + C_5 \quad (4.5)$$

HGAED Models Development

The estimation of functions in a linear form needs many simplifications particularly in electricity demand forecasting models with economic and social variables that include complex interaction. The HGAED models considered the interaction between variables. Suppose that electricity demand is the function of gross domestic product, population, import and export. The impact of population growth rate may have a complex relation with gross domestic product, and so as the other variables. Therefore, considering these interactions in forecasting, some nonlinear functions are used in the HGAED models. These are the derivation of exponential and quadratic models in the new logarithmic formulations.

HGAED1:

For example, consider the following exponential model:

$$\text{Exp: } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \quad (4.6a)$$

The formulation can be rewritten in logarithmic formula as shown in 4.6b.

$$\text{Log: } Y = Exp\begin{cases}\ln(\beta_1) + \beta_3\ln(\beta_2) + \beta_3X_1 + \beta_5\ln(\beta_4) + \beta_5X_2 \\ \quad + \beta_7\ln(\beta_6) + \beta_7X_3 + \beta_9\ln(\beta_8) + \beta_9X_4\end{cases} \qquad (4.6b)$$

Reformulation for quadratic model to linear logarithms form can also be done as shown in 4.7.

HGAED2:

$$\text{Quad: } Y = \begin{cases}\ln(\beta_1) + \beta_3\ln(\beta_2) + \beta_3X_1 + \beta_5\ln(\beta_4) + \beta_5X_2 \\ \quad + \beta_7\ln(\beta_6) + \beta_7X_3 + \beta_9\ln(\beta_8) + \beta_9X_4 \\ \quad + \ln\beta_{10} + 3X_1 + \ln\beta_{11} + 3X_2 + \ln\beta_{12} + 3X_3 \\ \quad + \ln\beta_{14} + 3X_4 + \ln\beta_{15}\end{cases} \qquad (4.7a)$$

$$\text{Mix: } Y = \beta_1 + \beta_2 * \exp(\beta_3 + \beta_4X_1 + \beta_5X_2 + \beta_6X_3 + \beta_7X_4) \qquad (4.7b)$$

In equations (4.1) to (4.7), X_1 is the gross domestic product (10^9), X_2 is the population (10^6), X_3 is the import (10^9), X_4 is the export (10^9) and $\beta_0, \beta_1, \beta_2, \ldots \beta_{15}$ are the weighting parameters, C1,..,C5 are the regression coefficients. The fitness value is calculated for minimum least square error using the fitness evaluation function in equation (3.3).

Equations 4.1 to 4.5 in this study have been implemented using single algorithms compared to equation 4.6 to 4.7 using a hybrid algorithm.

4.1.2 Dataset for Experiments

HGA Experiment 1 used the Turkish data for electricity demand and economic indicators as tabulated in Table 4.1. The Turkish data for electricity demand were obtained from IEA (International Energy Agency) as Turkey is a member of the IEA at www.eia.gov/countries/data.cfm, and the data for economic indicators was obtained from TSI.

Table 4.1 Electricity demand and socioeconomic data for Experiment 1

Years	Electric Consumption (Billion KWh)	GDP (10^9 U.S.$)	Population (10^6)	Import (10^9 $)	Export (10^9$)
1980	21.84	94.26	42.17	7.91	2.91
1981	22.49	95.5	43.12	8.93	4.70
1982	24.90	86.77	44.28	8.84	5.75
1983	26.15	82.91	46.97	9.24	5.73
1984	29.63	80.64	48.07	10.76	7.13
1985	32.57	90.38	49.17	11.34	7.96
1986	31.73	101.8	50.27	11.10	7.46
1987	35.02	117.18	51.37	14.16	10.19
1988	40.37	122.13	50.53	14.34	11.66
1989	40.19	144.03	51.25	15.79	11.62
1990	47.84	202.38	52.44	22.30	12.96
1991	50.46	202.72	53.52	21.05	13.59
1992	55.51	213.58	54.55	22.87	14.71
1993	60.45	242.14	55.59	29.43	15.35
1994	62.79	174.45	56.55	23.27	18.11
1995	68.39	227.51	57.51	35.71	21.64
1996	75.27	243.9	58.48	43.63	23.22
1997	82.73	255.07	58.1	48.56	26.26
1998	88.67	269.13	59.01	45.92	26.97
1999	91.63	249.82	59.91	40.67	26.59
2000	98.57	266.44	62.76	54.50	27.77
2001	97.39	195.55	63.82	41.40	31.33
2002	102.55	232.28	64.85	51.55	36.06
2003	110.43	303.26	65.89	69.34	47.25
2004	120.04	392.21	66.9	97.54	63.17
2005	129.01	482.69	67.9	116.77	73.48
2006	141.46	529.19	68.13	139.58	85.53
2007	153.66	649.13	68.89	170.06	107.27
2008	160.37	730.32	69.66	201.96	132.03
2009	155.19	614.47	70.54	140.93	102.14

Before algorithm processes can take place, the data must be processed in a form that is meaningful to the genetic algorithm. Each input variable should be preprocessed so that its values are close to zero. In this study, all input patterns have been normalised to the same ranges of values. Normalisation is simply dividing all values of a set by an arbitrary reference value, usually the maximum value. However, this process carries with it the potential for loss of information as it can distort the data if one or a few values are larger than the rest of the data.

The preprocessing normalises these original data in Table 4.1 to find usable data using the formula as described in section 3.4.3. The formula is selected based on trial and error until the normalised data are usable and the model obtains the goodness of fit results.

Figure 4.1 and 4.2 presents the pattern of original and normalised data of electricity demand and economic indicators, respectively. These patterns are nonlinear for gross domestic product and import and can be expressed as exponential and quadratic mathematical representations. The population growth rate may have a complex relation with gross domestic product and other variables. This interaction is considered in non linear models development for electricity demand forecasting.

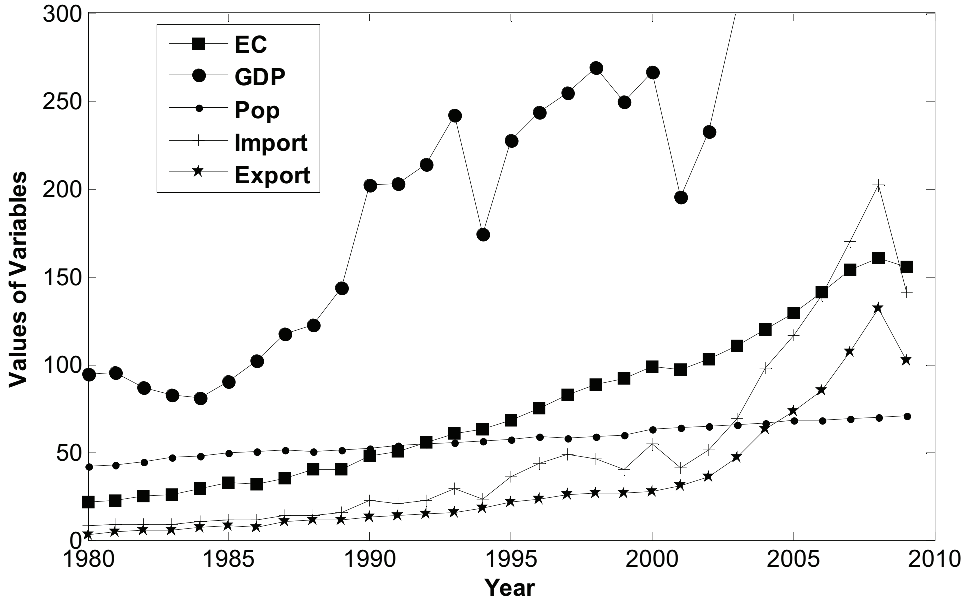


Figure 4.1 Pattern of original data for Experiment 1

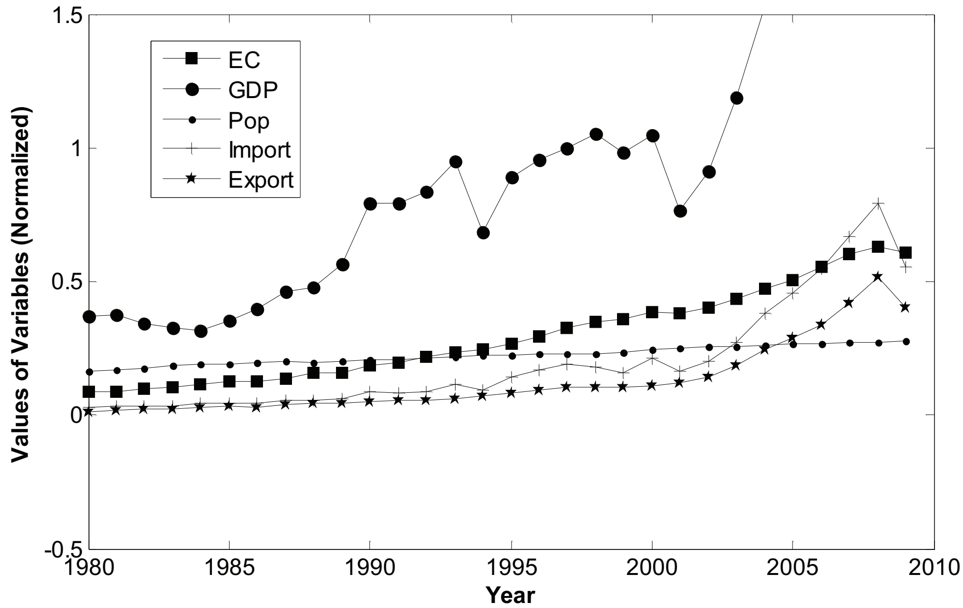


Figure 4.2 Pattern of normalised data for Experiment 1

HGA Experiment 2 uses a dataset for Indonesian electricity demand and economic indicators during the period from 1990 to 2009 as presented in Chapter 3.

The hybrid model for Indonesian data used the linear and exponential form as presented in equations 4.9 to 4.10.

HGAED-1:

$$\text{Lin: } Y = \beta_1 X_{1n} + \beta_2 X_{2n} + \beta_3 X_{3n} + \beta_4 X_{4n} + \beta_5 \tag{4.9}$$

HGAED-2:

$$\text{Logarithmic: } Y = \begin{cases} \ln(\beta_1) + \beta_3 \ln(\beta_2) + \beta_3 X_{1n} \\ \quad + \beta_5 \ln(\beta_4) + \beta_5 X_{2n} \\ \quad + \beta_7 \ln(\beta_6) + \beta_7 X_{3n} \\ \quad + \beta_9 \ln(\beta_8) + \beta_9 X_{4n} \end{cases} \tag{4.10}$$

Where Y is the normalised electricity demand, X_{1n} is normalised gross domestic product, X_{2n} is normalised population, X_{3n} is normalised import, X_{4n} is normalised export, and β_1 to β_9 are the weighting parameters.

In Experiment 3 and Experiment 4, the investigation is made for the single algorithm models (GAED-1 and GAED-2), and hybrid algorithm models (HGAED-1 and HGAED-2) using the secondary data in Ozturk and Ceyland (2005). The data for total electricity consumption and industrial electricity consumption for Experiment 3 are tabulated in Table-4.2.

Table 4.2 Electricity demand and socioeconomic data for Experiments 3 and 4

Years	Total net electricity con. (TWh)	Industrial sector electricity con. (TWh)	GNP (10^9)	Population (10 ^6)	Import (10^9)	Export (10^9)
1980	24.62	13.01	69.75	44.74	7.91	2.91
1981	26.29	14.21	72.78	45.86	8.93	4.70
1982	28.32	15.20	65.94	47.00	8.84	5.75
1983	29.57	15.58	62.19	48.18	9.24	5.73
1984	33.27	18.03	60.76	49.38	10.76	7.13
1985	36.36	19.61	68.20	50.66	11.34	7.96
1986	40.47	20.89	76.46	51.78	11.10	7.46
1987	44.93	23.87	87.73	52.92	14.16	10.19
1988	48.43	25.26	90.97	54.08	14.34	11.66
1989	52.60	27.60	108.68	55.27	15.79	11.62
1990	56.81	29.21	152.39	56.47	22.30	12.96
1991	60.50	28.51	152.35	57.50	21.05	13.59
1992	67.22	31.54	160.75	58.55	22.87	14.71
1993	73.43	34.25	181.99	59.61	29.43	15.35
1994	77.78	34.14	131.14	60.70	23.27	18.11
1995	85.55	38.01	171.98	61.81	35.71	21.64
1996	94.79	40.64	184.72	62.93	43.63	23.22
1997	105.52	43.49	194.36	64.08	48.56	26.26
1998	114.02	46.14	205.98	65.24	45.92	26.97
1999	118.48	43.77	187.66	66.43	40.69	26.59
2000	128.28	48.37	201.48	67.64	44.15	27.49
2001	126.87	48.70	144.00	68.59	41.40	31.30
2002	132.55		181.60	69.82	51.50	36.00
2003	140.86		238.00	71.08	68.70	46.90

Figure 4.2 and Figure 4.3 present the pattern of total electricity consumption and industrial electricity consumption for Experiment 3, respectively. The patterns are linear especially the industrial sector. The growth patterns of both total and industrial electricity demands are almost linear.

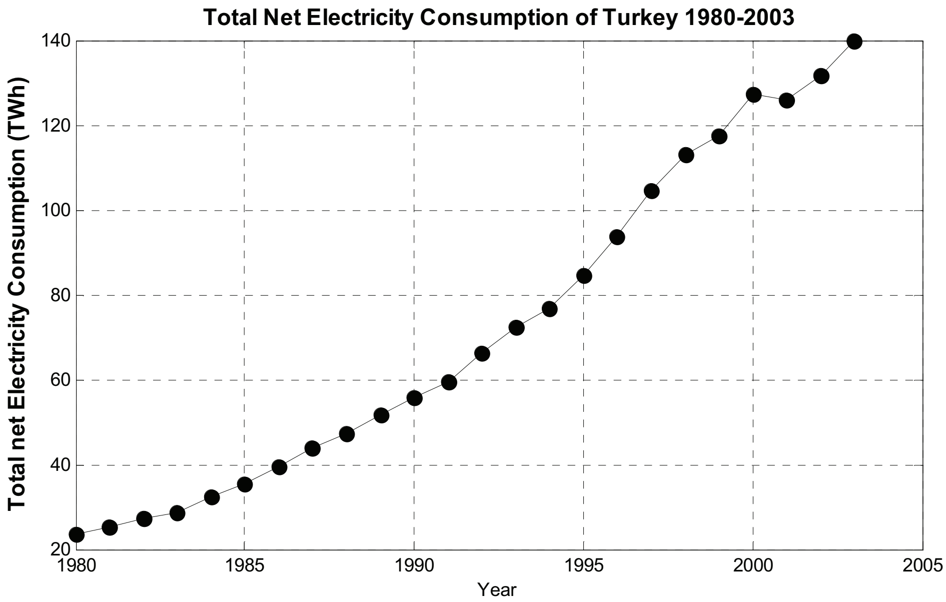


Figure 4.3 The total net electricity consumption for Experiment 3

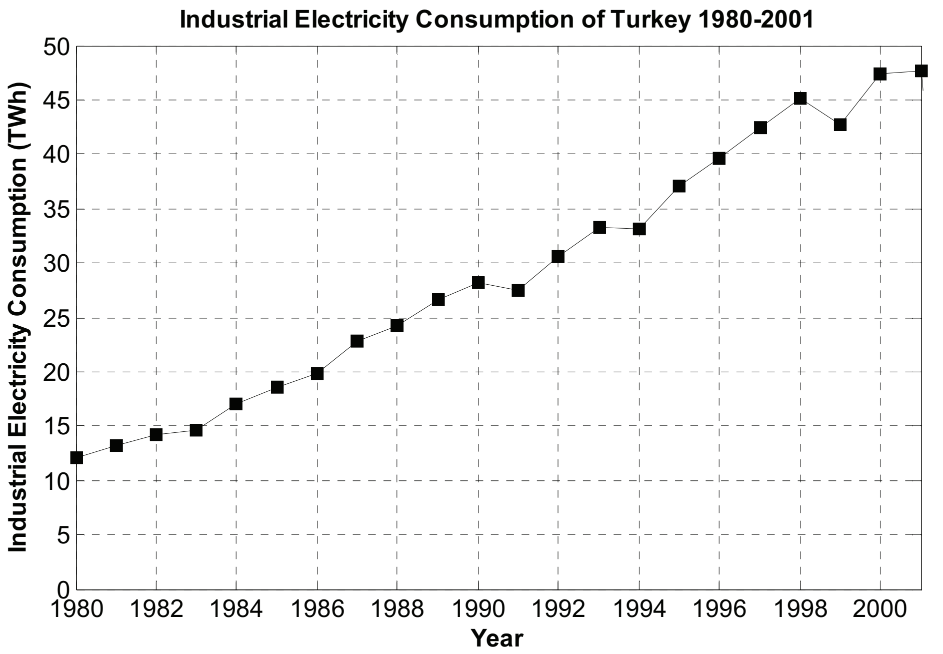


Figure 4.4 The industrial electricity consumption for Experiment 4

Experiment 5 used the secondary data in Toksari (2007). These data consist of the data for electricity demand that were collected from MENR and the data for economic indicators from TSI. The data are tabulated in Table 4.3.

Table 4.3 Electricity demand and economic indicators data for Experiment 5

Years	Energy Demand (MTOE)	GDP ($10^9)	Population (10^6)	Import ($10^9)	Export ($10^9)
1979	30.71	82	43.531	5.07	2.26
1980	31.97	68	44.439	7.91	2.91
1981	32.05	72	45.54	8.93	4.7
1982	34.39	64	46.688	8.84	5.75
1983	35.7	60	47.864	9.24	5.73
1984	37.43	59	49.07	10.76	7.13
1985	39.4	67	50.307	11.34	7.95
1986	42.47	75	51.433	11.1	7.46
1987	46.88	86	52.561	14.16	10.19
1988	47.91	90	53.715	14.34	11.66
1989	50.71	108	54.894	15.79	11.62
1990	52.98	151	56.098	22.3	12.96
1991	54.27	150	57.193	21.05	13.59
1992	56.68	158	58.248	22.87	14.72
1993	60.26	179	59.323	29.43	15.35
1994	59.12	132	60.417	23.27	18.11
1995	63.68	170	61.532	35.71	21.64
1996	69.86	184	62.667	43.63	23.22
1997	73.78	192	63.823	48.56	26.26
1998	74.71	207	65.001	45.92	26.97
1999	76.77	187	66.432	40.67	26.59
2000	80.5	200	67.421	54.5	27.78
2001	75.4	146	68.365	41.4	31.33
2002	78.33	181	69.302	51.55	36.06
2003	83.84	239	70.231	69.34	47.25
2004	87.82	299	71.152	97.54	63.17
2005	91.58	361	72.974	116.77	73.48

The data is divided into two parts, one part is for observation and the rest is for measurement of accuracy (compare actual and estimation results).

4.2 Experimental Results

Several experiments were done to obtain the appropriate method for solving the electricity demand pattern problem. These include experiments on a single algorithm for electricity demand pattern, application of preprocessing and the local search method, and comparison between the HGAED and other methods.

The experimental results in the first section are compared from the single genetic algorithm with and without preprocessing data, the genetic algorithm with local search, and the genetic algorithm with local search and preprocessing data for the electricity demand model as described in section 4.1.1 using the data as described in section 4.1.2. Next, the experiments compared the performance of the proposed model with other models. Therefore, the experiments in the second section will include: (i) Experiment 1 using data in Table 4.1, (ii) Experiment 2 using data in Table 3.1 in Chapter 3, (iii) Experiment 3 using data in Table 4.2 for Total, (iv) Experiment 4 using data in Table 4.2 for Industrial, and (v) Experiment 5 using data in Table 4.3.

4.2.1 Comparison of Single GA and Hybrid Algorithm

The literature reported that there are several disadvantages in the single algorithm performance in overcoming local optimality problems (Huan, 2009; Mamta & Sushila, 2010; Qiusheng, Hao, & Xiaoyao, 2011). This study is to investigate single genetic algorithm performance by measuring the average error using available data of electricity demand, testing the effect of using normalised data, testing the effect of using local search when combined with genetic algorithm and testing the preprocessing data in the hybrid genetic algorithm and local search algorithm. Table 4.4 and Figures 4.5, 4.6 and 4.7 present the findings from the experiments.

Table 4.4.Comparison of single GA and hybrid algorithm

Data	**Turkey-1**	**Indo-2**	**O&CTot-3**	**O&CInd-4**	**Toks-5**
			Average errors (%)		
GA	29.8392	13.369	8.4727	12.5832	8.6511
GA + Prep	25.5609	9.7307	7.2525	9.5239	8.3136
GA + LS + Prep	6.6571	4.389	3.3004	1.7370	3.464

Data: 1.Turkey's Electricity Demand; 2. Indonesia Electricity Demand; 3.Ozturk & Ceylan (2005) for Total Electricity Demand; 4. Ozturk & Ceylan (2005) for Industrial Electricity Demand; 5 Toksari (2007) Turkey Energy Demand.

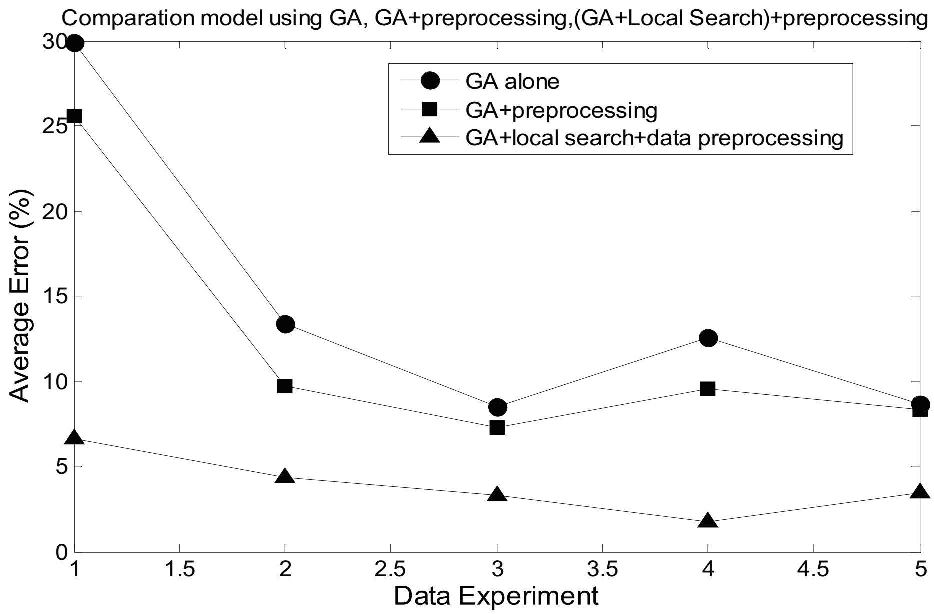


Figure 4.5 The average error of single GA and hybrid GA using normalised data

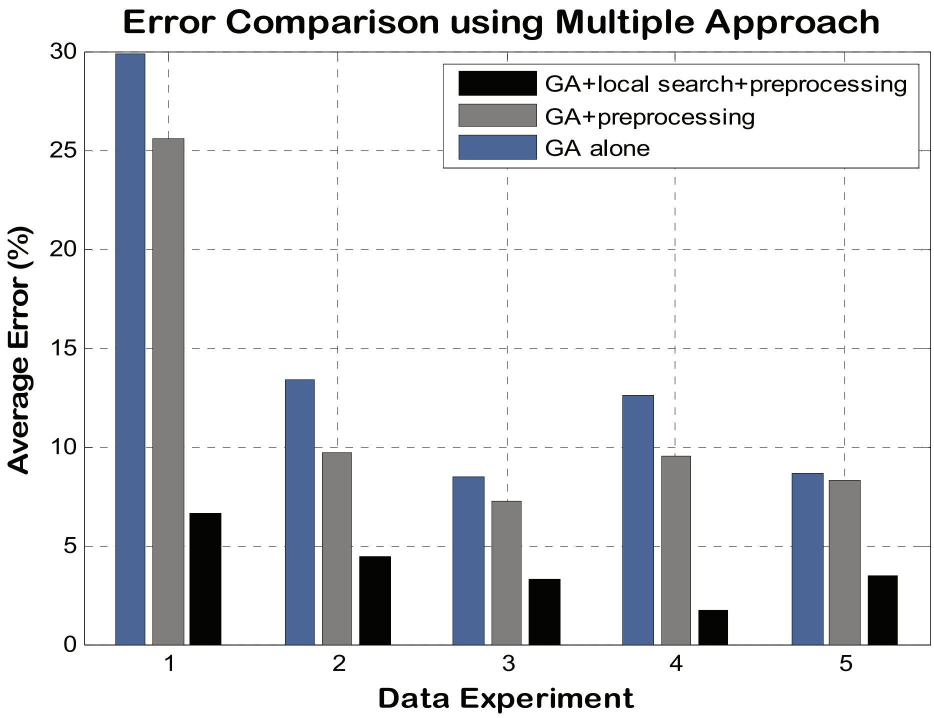


Figure 4.6 Performance of single GA and hybrid GA with preprocessing in terms of error

Through the experimental analysis, results indicated that the hybrid genetic algorithm and local search algorithm using preprocessing data obtained the best solutions. The application of local search combined with genetic algorithms resulted in good solution quality in solving the electricity demand pattern problem.

4.2.2 Experiment 1: Turkey's Data for Electricity Demand and Variables

Experiment 1 is compared between the HGAED model and other models using data in Table 4.1 in terms of relative errors. These models are taken as a basic comparison since they are long-term electricity demand forecasting models and used similar data variables. Experiment 1 results are presented in Table 4.5 and the visual results of simulation are illustrated in Figure 4.7.

Table 4.5 Results for Experiment 1

Years	Electricity demand Actual (Bil.KWh)	GAED-1 (Ozturk&Ceyland, 2005) (Bil.KWh)	GAED-2 (Ozturk&Ceyland, 2005) (Bil.KWh)	Linlog-ED (Azadeh et. al, 2006)(Bil.KWh)	Lin-ED (Toksari, 2007) (Bil.KWh)	DLin-ED (Deng, 2010) (Bil.KWh)	HGAED-2 (Bil.KWh)	HGAED-1 (Bil.KWh)
1999	91.63	79.241	63.710	77.943	73.994	75.578	84.440	72.585
2000	98.57	86.711	87.737	86.655	86.773	92.005	108.564	78.029
2001	97.39	69.074	106.364	81.695	67.320	88.615	105.623	86.430
2002	102.55	80.949	111.636	92.665	75.386	96.533	112.164	91.344
2003	110.43	103.637	117.941	113.209	86.465	108.169	115.907	100.836
2004	120.04	132.969	137.582	140.663	100.312	126.775	120.972	112.957
2005	129.01	160.441	135.409	159.147	116.261	138.183	125.458	121.137
2006	141.46	177.317	162.840	177.250	122.549	153.617	128.081	129.075
2007	153.66	215.789	174.261	206.422	136.809	171.288	125.938	145.420
2008	160.37	245.463	211.275	235.030	141.737	192.657	123.561	164.791
2009	155.19	203.809	138.538	193.474	127.027	154.149	122.6591	149.102
Average Err(%)		**20.238**	**11.2129**	**17.3587**	**12.792**	**6.728**	**8.811**	**6.657**

From the results above, the HGAED-1 found fit better than other models in the estimated electricity demand during the period of 1999 to 2009. The integrated ability between genetic algorithm and local search into hybrid genetic algorithm has shown better performance than either of them separately. Combining global search methods and local search methods which formed the hybrid algorithms have led to the best performance.

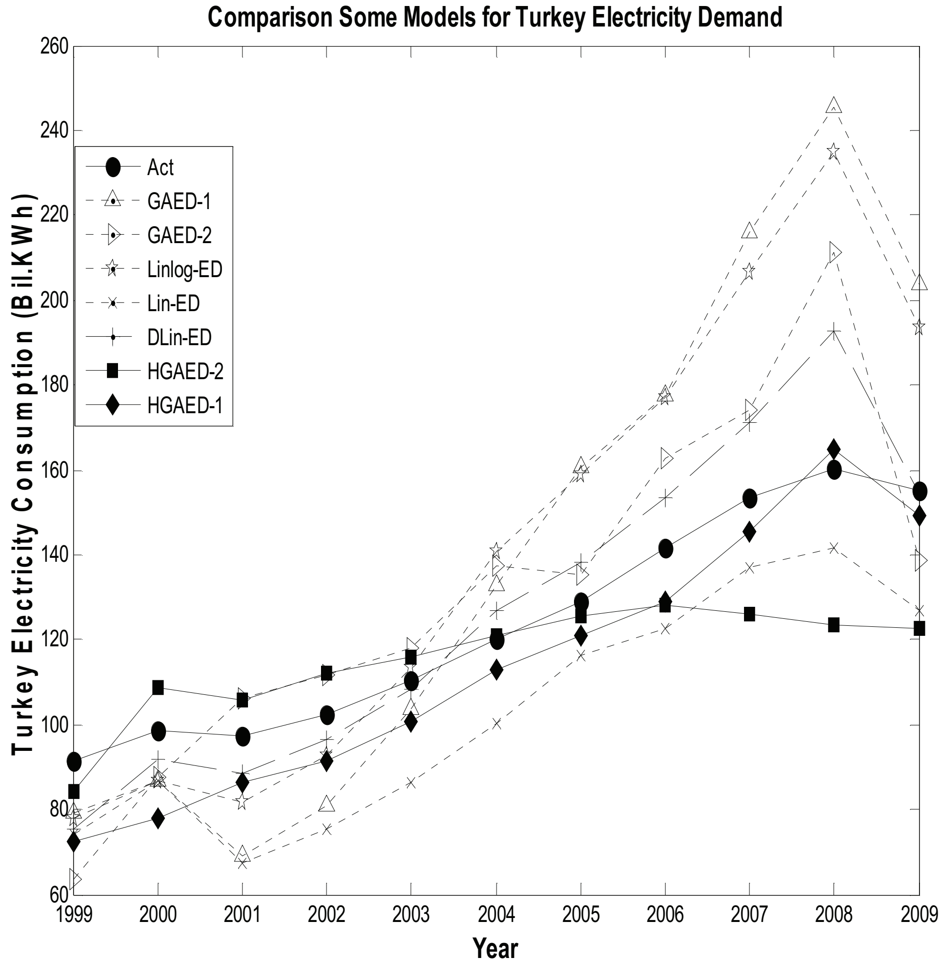


Figure 4.7 Visual results for Experiment 1

The performance of the electricity demand models which are measured by the goodness of fit between model outputs and the required target (actual electricity demand) are shown in Figure 4.7. It can be seen that the HGAED-1 using the hybrid genetic algorithm and local search approach has better performance. Although further investigation is required to compare the performances of the goodness of fit, the HGAED-1 model is considered to be used in further study. The goodness of fit is plotted in Figure 4.8.

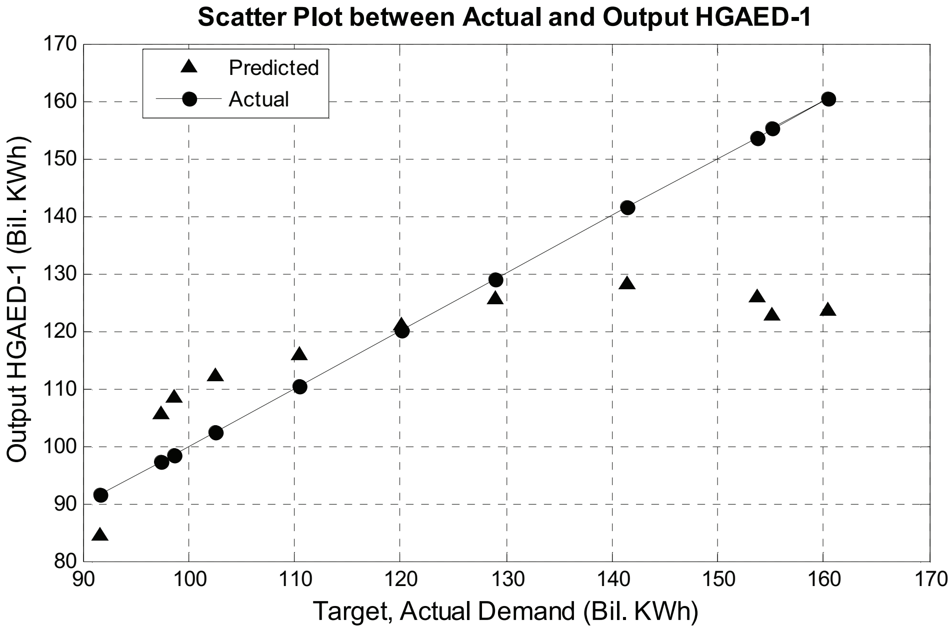


Figure 4.8 Scatter plot between target (actual) and predicted (output HGAED-1)

4.2.3 Experiment 2: Indonesian Data for Electricity Demand and Variables

Experiment 2 compared simulation results obtained from a model and the HGAED model for Indonesian data as presented in Table 3.1 in Chapter 3. Table 4.6 presents the comparison results, and the visual results of goodness of fit are shown in Figure 4.9 and Figure 4.10. The goodness of fit of the HGAED-1 for Indonesian data based on experiment 2 are illustrated in Figure 4.11

Table 4.6 Comparison results for Experiment 2

Years	Electricity demand Actual (TWh)	GAED-1 (Ozturk&Ceyland, 2005) (TWh)	GAED-2 (Ozturk&Ceyland, 2005) (TWh)	Linlog-ED (Azadeh et. al, 2006)(TWh)	Lin-ED (Toksari, 2007) (TWh)	DLin-ED (Deng, 2010) (TWh)	HGAED-2 (TWh)	HGAED-1 (TWh)
2001	**84.5**	79.521	131.419	81.022	82.280	91.222	75.908	75.9079
2002	**87.1**	82.566	118.636	76.879	79.893	85.991	78.7994	78.7989
2003	**90.4**	88.774	110.587	78.544	81.916	87.235	84.7542	84.7533
2004	**100.1**	103.651	165.166	86.676	100.360	102.466	92.3553	92.355
2005	**107.0**	122.129	213.404	102.063	122.678	126.762	105.566	105.5662
2006	**112.6**	138.873	200.979	116.901	136.123	145.911	123.0078	123.0078
2007	**121.2**	155.497	225.713	124.667	151.477	157.735	134.0133	134.0135
2008	**129.0**	187.313	389.613	131.086	191.912	169.584	137.4547	137.4572
2009	**136.1**	174.726	277.498	111.161	155.094	133.977	138.4148	138.4144
Average Err(%)		**15.293**	**70.619**	**6.426**	**13.842**	**9.731**	**5.364**	**<u>4.389</u>**

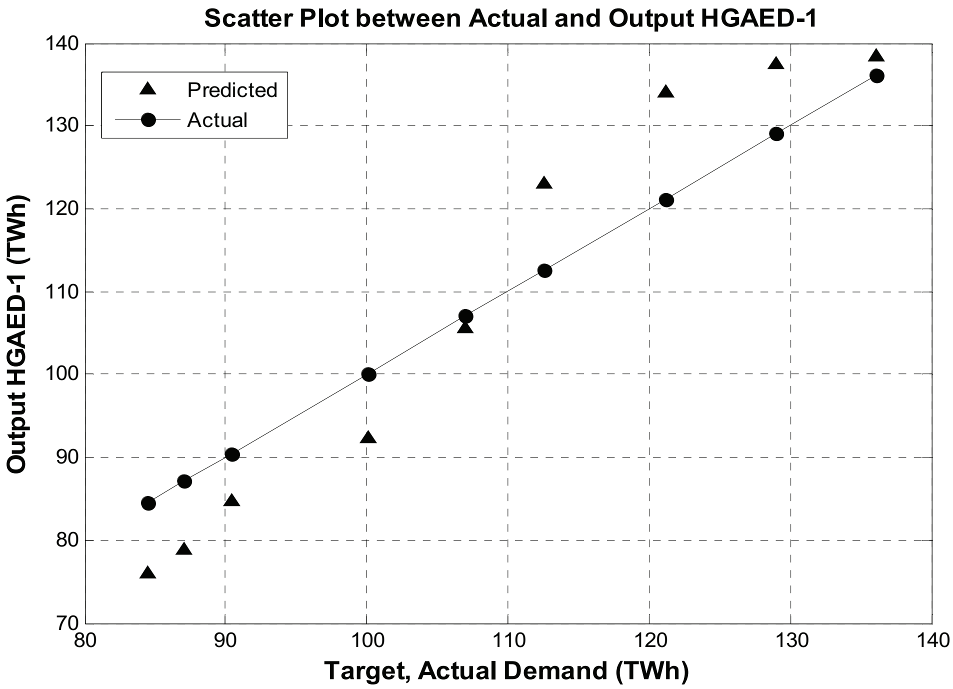


Figure 4.9 Scatter plot between target and predicted output HGAED-1

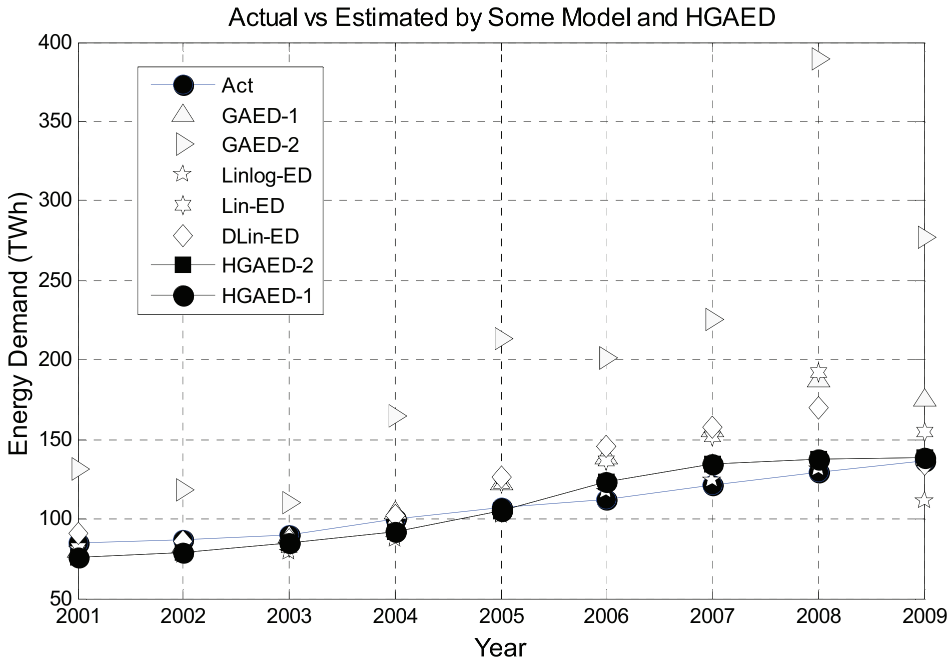


Figure 4.10 Visual results for Experiment 2

The visual results of Indonesian data estimated by the HGAED model and other electricity demand models for Experiment 2 are illustrated in Figure 4.10. From Table 4.6, Figure 4.9 and Figure 4.10, it is shown that the HGAED-1 model using a hybrid algorithm approach has performed more accurately and had a better fit than other models. Therefore, the HGAED-1 model is chosen as a robust model and is considered to be used in further study for the Indonesian electricity demand prediction.

4.2.4 Experiment 3: Ozturk and Ceylan (2005) Data for Total

Experiment 3 shows the comparison between the former models (GAED-1 model, GAED-2 model, GAED-3 model, MENR model) and the HGAED-1 and the HGAED-2 model using the data in Table 4.2 in terms of relative errors. These models used variables similar to the long-term electricity demand forecasting models and this is taken as a basic comparison. The simulation results are presented in Table 4.7, the visual results of comparison are illustrated in Figure 4.11 and the goodness-of-fit is illustrated in Figure 4.12.

Table 4.7 Simulation results of total electricity demand for Experiment 3

Years	Actual Energy Demand (TWh)*	GAED-1 (TWh)*	GAED-2 (TWh)*	GAED -3 (TWh)*	MENR** (TWh)*	HGAED-1 (TWh)*	HGAED-2 (TWh)*
1997	105.52	106.06	103.75	103.21	84.37	108.130	100.5399
1998	114.02	111.25	110.07	111.35	93.57	109.394	106.1839
1999	118.48	111.54	118.23	120.80	103.78	104.596	111.7817
2000	128.28	117.57	128.47	132.88	115.11	108.810	120.7550
2001	126.87	130.23	145.48	141.21	125.11	110.952	125.2162
2002	132.55	154.64	158.22	155.20	135.99	128.787	136.3701
2003	140.86	219.73	168.61	169.05	147.81	164.022	148.3939
Average Err(%)		**13.207**	**7.304**	**8.353**	**9.938**	**8.461**	**4.017**

*TWh = Tera Watt hour = Billion Kilo Watt hour
**MENR = Ministry of Energy and Natural Resources

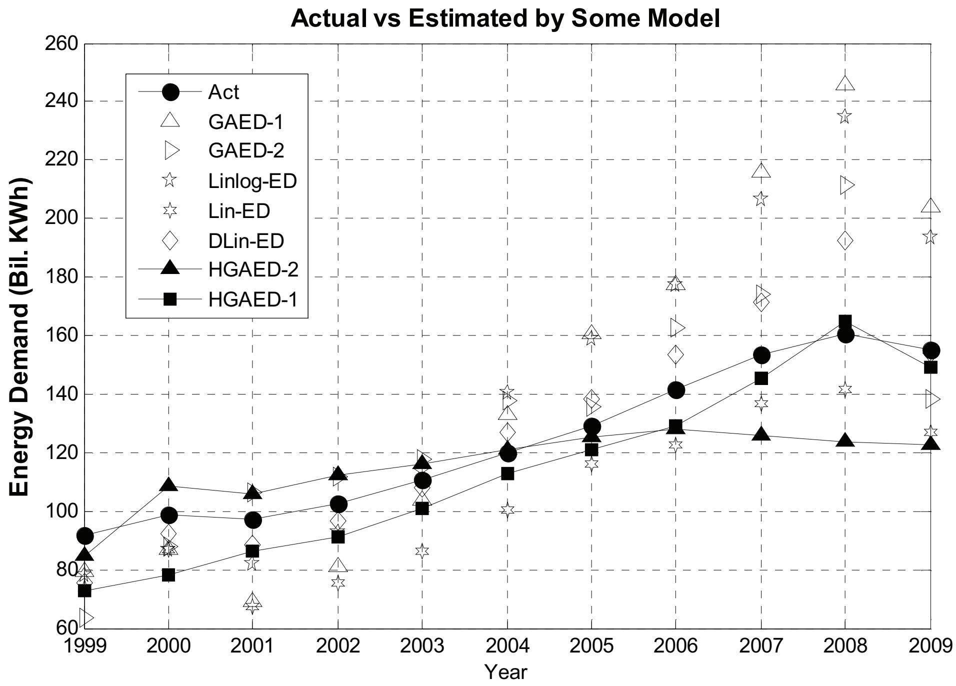


Figure 4.11 Visual results of total electricity consumption for Experiment 3

Table 4.7 analyses demonstrate that the HGAED-2 model with the HGA-estimation approach for total net electricity demand presents better forecasting accuracy than the former (GAED-1, GAED-2, GAED-3 and MENR) models. It can be seen from Table 4.7 that the previous method was a relative error that tends to rise as exponential especially in the last two years, whereas in the hybrid method (HGAED-2 with hybrid algorithm approach), it was found that the relative errors tend to be stable.

The average error in the GAED-1 model is 13.207% (larger than 10% of normal long-term electricity demand forecasting error), whereas in the HGAED-2 model with HGA estimation, the average error is 4.654% (less than the standard normal for long-term electricity demand forecasting error). Therefore, the HGAED-2 model is chosen as one of the best model and can be used for total electricity demand projection of Turkey.

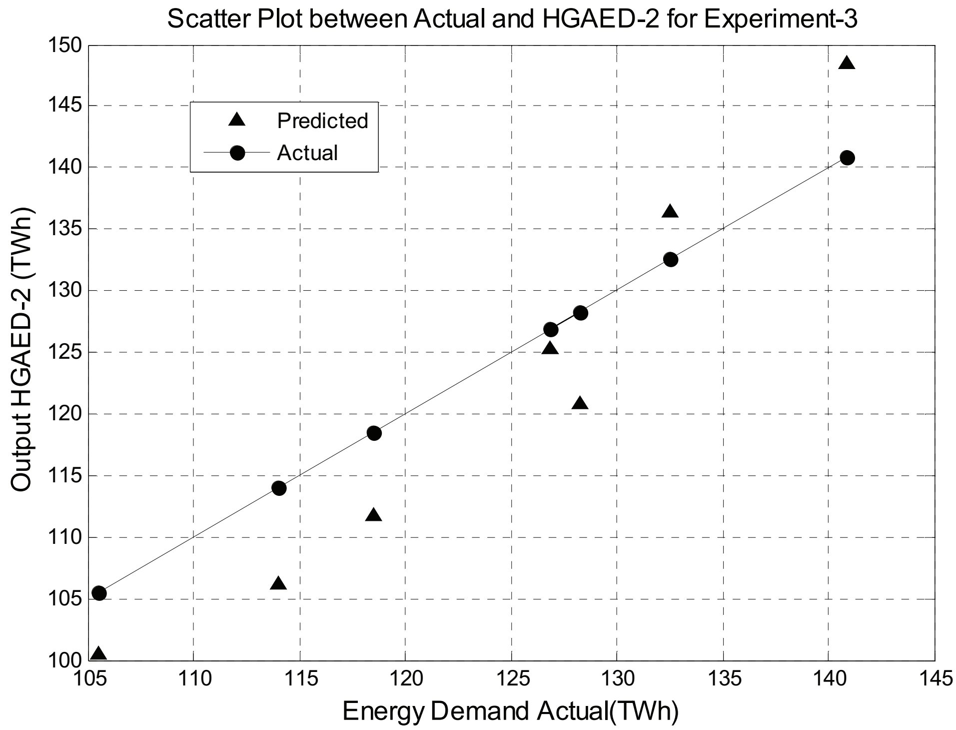


Figure 4.12 Scatter plot between actual vs. predicted electricity demand HGAED-2 for Experiment 3

4.2.5 Experiment 4: Ozturk and Ceylan (2005) Data for Industrial

The next experiment investigated the HGAED model and GAED model for industrial electricity consumption using the data in Table 4.2. The simulated results are presented in Table 4.8 and visual results in Figure 4.13.

Table 4.8 Simulation results of industrial electricity demand for Experiment 4

Years	**Actual Energy Demand (TWh)**	**GAED-2 (Twh)**	**GAED-3 (TWh)**	***MENR (TWh)**	**HGAED-1 (TWh)**	**HGAED-2 (TWh)**
1995	38.01	54.59	43.21	40	41.25	38.4321
1996	40.64	73.96	47.03	40	44.76	40.6186
1997	43.49	102.05	52.47	47.48	48.40	43.3224
1998	46.14	106.43	53.32	53.08	48.47	45.4234
1999	43.77	84.03	51.45	59.34	46.48	46.5808
2000	48.37	102.55	53.67	66.31	48.29	48.9272
2001	48.70	76.96	57.55	72.25	48.79	49.9258
Average Err (%)		**93.283**	**16.045**	**29.049**	**5.46**	**1.737**

***MENR = ministry of energy and natural resources**

Hybridisation of genetic algorithms with local search has proven to provide significant improvement, which was able to explore ability and enhance exploitation towards feasible and highly accurate solutions in solving combinatorial problems. Therefore, this study aims to apply a hybridisation approach in an electricity demand forecasting problem and combines local search with genetic algorithms to guide the search towards a feasible solution that minimises the forecasting error.

Experiment 4 compared the actual values of industrial electricity demand and results found by the GAED model (Ozturk & Ceylan, 2005) and the simulation results of the HGAED model using HGA estimation.

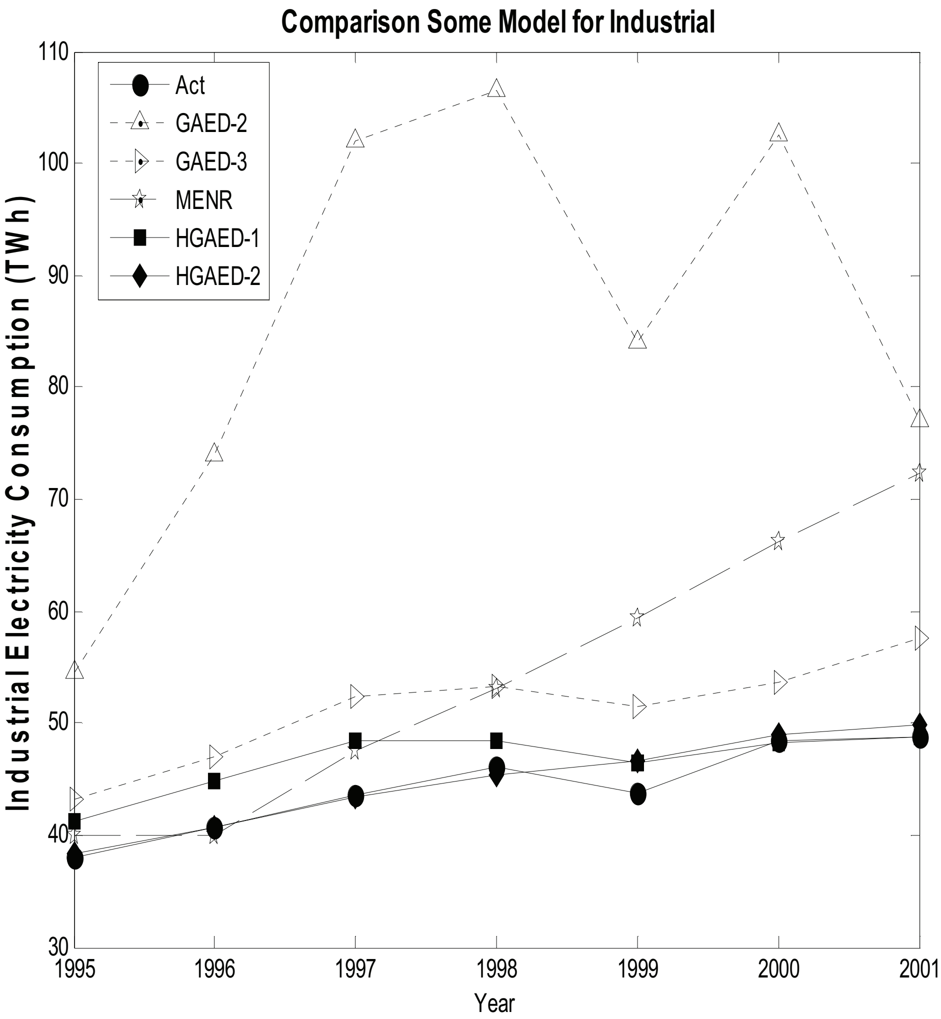


Figure 4.13 Visual result of industrial electricity demand for Experiment 4

It can be seen from Table 4.8 analyses that the HGAED-2 with the hybrid algorithm approach has the least average error (1.737%), leading so far than GAED model average error (93.283%) for industrial electricity demand. Therefore, the HGAED-2 model is more robust and is used in prediction of the industrial electricity demand projection of Turkey. It can be seen in a scatter plot as shown in Figure 4.14

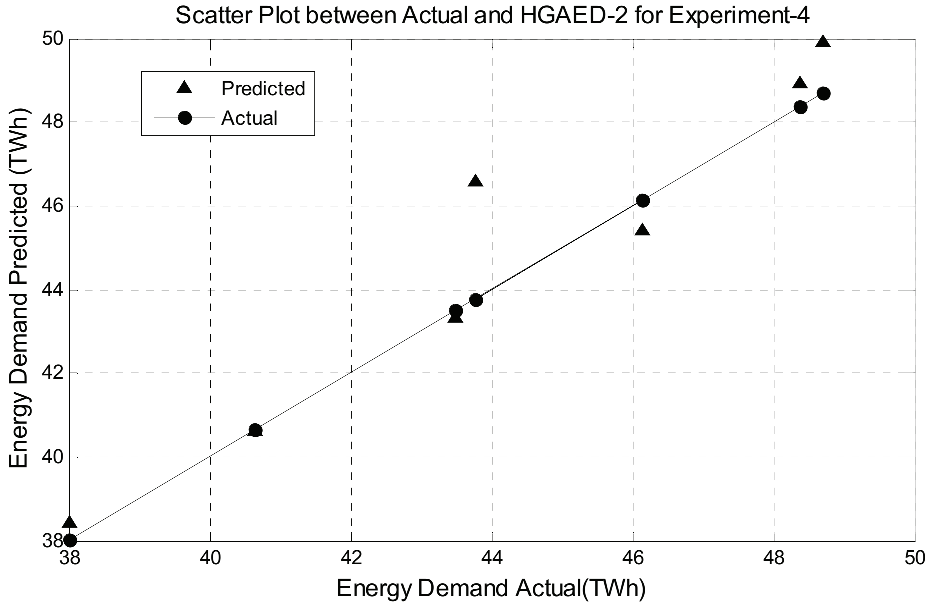


Figure 4.14 Scatter plot between actual and predicted electricity demand by HGAED2 for Experiment 4

4.2.6 Experiment 5: Toksari (2007) Data for Energy Demand

Experiment 5 investigated the performance of four models, which are Toksari-ED1 and Toksari-ED2, HGAED1 and HGAED2. The mathematical representations of the four models are presented in equations (4.12) to (4.15).

Toksari-ED1:

$$\text{Linear: } Y = w_1 + w_2X_1 + w_3X_2 + w_4X_3 + w_5X_4 \qquad (4.12)$$

Toksari-ED-2:

$$\text{Quadratic: } Y = \begin{cases} w_1 + w_2X_1 + w_3X_2 + w_4X_3 + w_5X_4 + w_6X_1X_2 \\ +w_7X_1X_3 + w_8X_1X_4 + w_9X_2X_3 + w_{10}X_2X_4 \\ + w_{11}X_3X_4 + w_{12}X_1^2 + w_{13}X_2^2 \\ + w_{14}X_3^2 + w_{15}X_4^2 \end{cases} \qquad (4.13)$$

HGAED1:

$$\text{Exp: } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \tag{4.14}$$

HGAED2:

$$\text{Quad: } Y = \begin{cases} \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \\ \beta_{10} X_1X_2 + \beta_{11} X_1X_3 + \beta_{12} X_1X_4 + \\ + \beta_{13} X_2X_3 + \beta_{14} X_2X_4 + \beta_{15} X_3X_4 \end{cases} \tag{4.15}$$

In the hybrid models (4.14 and 4.15), β_1, β_2, …, β_{15} are the weights parameters and these are obtained by simulation using the historical data of variables (X_1,X_2, X_3 and X_4) and estimate the electricity demand by comparing the actual values and forecasting values. The HGAED models are derived based on identified data in order to be easily implemented in Matlab code for simulation program.

The comparison results between Toksari models (T-ED1 and T-ED2) and the hybrid models (HGAED1 and HGAED2) are presented in Table 4.9 and the visual results of comparison are provided in Figure 4.15

Table 4.9 Result for Experiment 5

Years	Observed Energy Demand (MTOE)	Estimated Energy Demand (MTOE)			
		T-ED1	T-ED2	HGAED1	HGAED2
1996	69.86	69.48	70.52	65.86	68.77
1997	73.78	72.06	73.67	68.29	71.60
1998	74.71	73.14	75.67	70.85	74.26
1999	76.77	73.8	76.09	72.14	74.73
2000	80.5	80.1	81.47	74.21	76.53
2001	75.4	74.94	73.73	73.85	75.56
2002	78.33	78.55	80.55	77.28	80.52
2003	83.84	82.25	84.38	82.44	88.16
2004	87.82	87.54	88.1	88.15	95.78
2005	91.58	93.1	93.01	94.71	103.10
Average Error (%)		**1.231**	**1.0395**	**3.4647**	**3.9191**

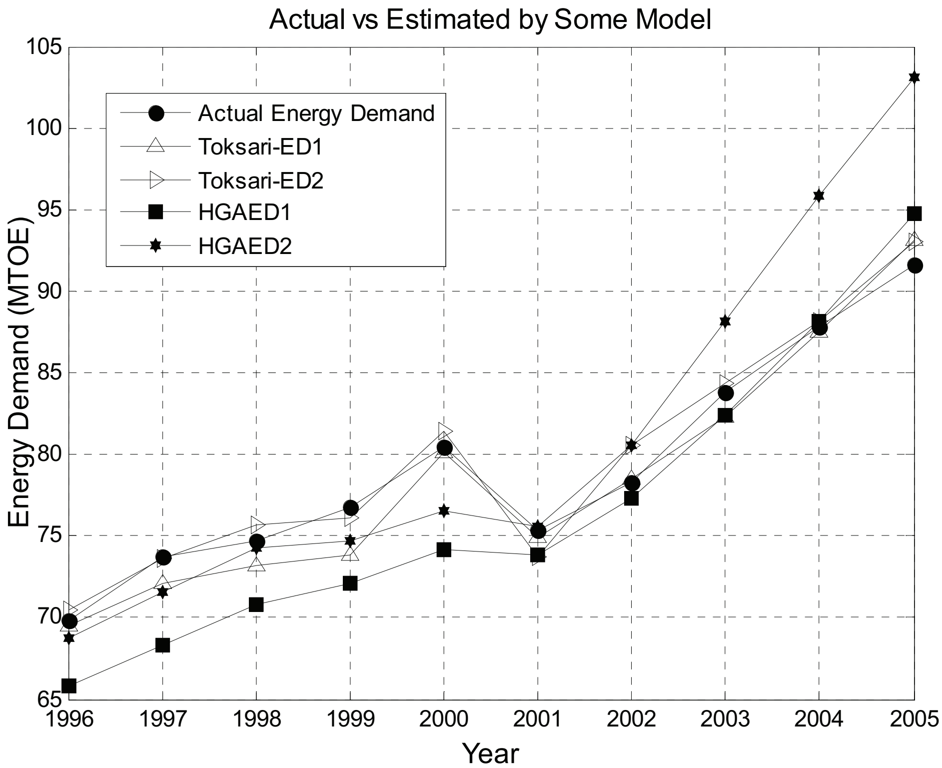


Figure 4.15 Visual results for Experiment 5

Figure 4.15 and Table 4.9 demonstrated that the HGAED models are comparable to the Toksari models in estimating electricity demand using different data. Although further investigations are required to increase the performance of the accuracy, the HGAED model is considered to be used in further study for electricity demand projection. The goodness of fit by the HGAED-1 to the actual electricity demand are illustrated in the scatter plot shown in Figure 4.16

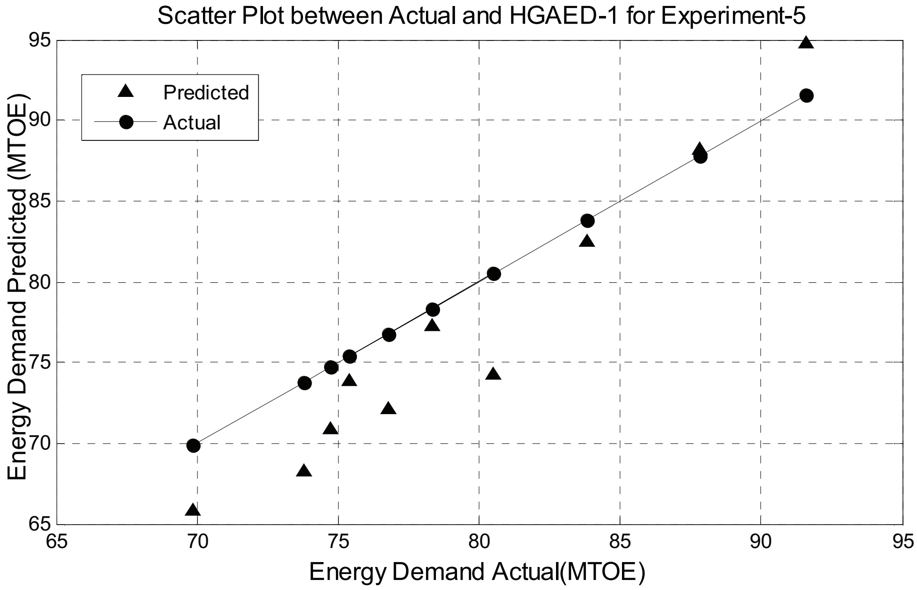


Figure 4.16 Scatter plot between actual and predicted electricity demand by HGAED-1 for Experiment 5

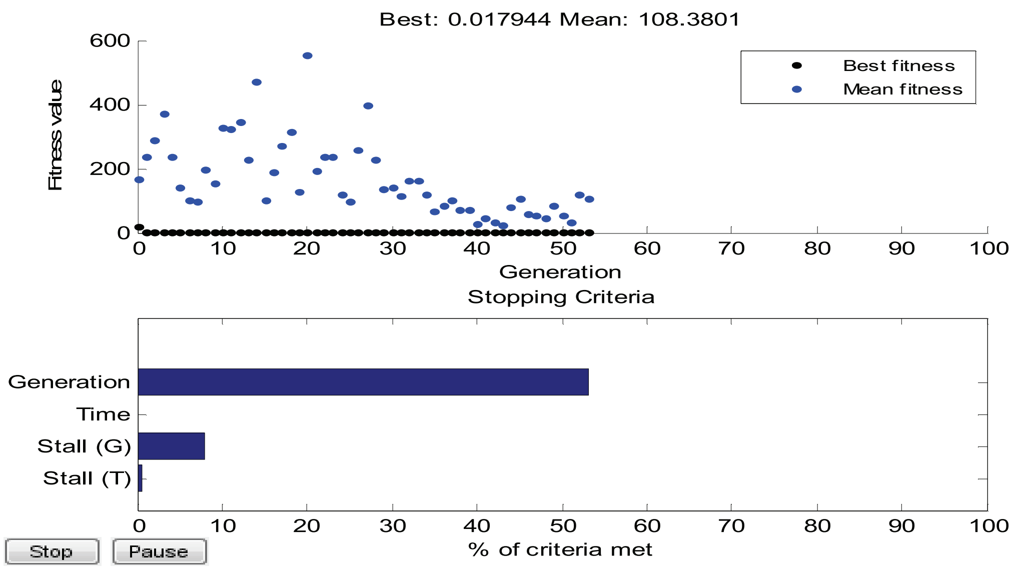
4.2.7 Optimum Parameter Values and Model Expression

The objective of the electricity demand model is to find parameter values with the lowest objective function value. Therefore, the lowest objective function value in each GA generation or iteration of a local search is the focus in the electricity demand model using HGAs. A greater decrease of the lowest objective function value from one GA generation or iteration of local search to the next implies a quicker convergence. The smaller the final objective function value, the better the HGAs perform. The parameter values with the best (i.e. lowest) objective function value are the final solution.

The two HGAED models were executed and the final parameter values found by the two HGAED in Experiment 1 to Experiment 5 are presented in Table 4.10.

Each experiment has obtained final parameter values that are used in estimation and in this section, only the best final parameter values are taken. In Experiment 1 to Experiment 4, the HGAED-1 and HGAED-2 models were used to obtain the lowest average errors. All parameters can be obtained in the estimation process and the next sections are illustration of the process of convergence for the HGAED in each experiment. Greater detail of each process is found in the appendices.

1) Run Program Experiment 1



Optimisation terminated: average change in the fitness value less than options.TolFun.

Iteration	Func-count	f(x)	Step-size	First-order optimality
0	10	0.0179443		1.25
1	50	0.0167471	0.00080079	0.245
2	60	0.0167052	1	0.153
3	70	0.0164706	1	0.312
4	80	0.0160544	1	0.556
63	860	0.00116647	0.690876	0.385
64	870	0.00116535	1	0.716

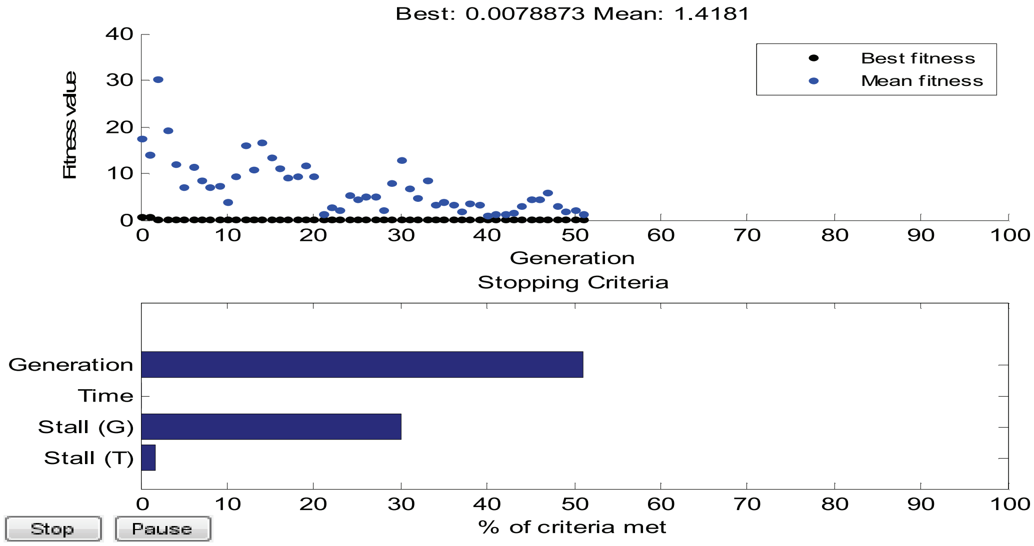
65	890	0.00116445	0.466705	0.255
66	900	0.00116323	1	0.278

```
Maximum number of function evaluations exceeded;
 increase options.MaxFunEvals
x =
   0.5751  -0.0081  -0.0100   0.7846   2.3112   0.5010  -0.1485   1.9193   0.9355
fval =
   0.0179
Av_err =
   6.6571
```

The HGAED-1 has convergence in 66 iterations for data Experiment 1, the convergence curve reaches a best fitness value (0.017944) and mean fitness value (108.301). It can be seen that the total number of iteration is reduced significantly, indicated by the small number of iterations to reach convergence. If the GA run time process is compared to HGA with local search run time process, the GA is very computationally time demanding. This computational time increased as the number of variables increased. In Experiment 1, the number of parameters is nine (x1 to x9), and the HGAED average error is 6.6751%.

2) Run Program Experiment 2:

In experiment 2, the HGAED reached convergence in 30 iterations and the best optimal fitness value is 5.7687e-004 (ideally, the best fitness is zero), average error is 4.3893% and x1 to x5 are the optimum parameter values.



Optimisation terminated: average change in the fitness value less than options.TolFun.

Iteration	Func-count	f(x)	Step-size	First-order optimality
0	6	0.00788734		0.124
1	24	0.00761296	0.0215401	0.0319
2	36	0.00735702	10	0.0281
28	222	0.000576885	1	7.81e-005
29	228	0.000576873	1	1.85e-005
30	234	0.000576872	1	1e-006

Optimisation terminated: relative infinity-norm of gradient less than options.TolFun.

x =

0.7769 0.0017 -0.4386 1.0918 -0.5512

fval =

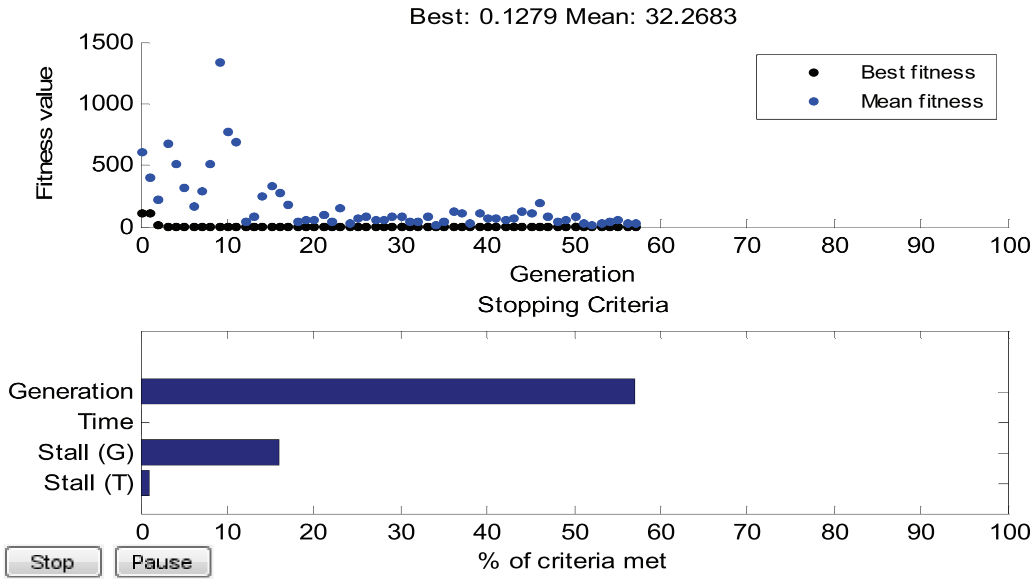
5.7687e-004

AVER_err_HGA =

4.3893

>>

3) Run Program Experiment 3



Optimisation terminated: average change in the fitness value less than options.TolFun.

Iteration	Func-count	f(x)	Step-size	First-order optimality
0	10	0.127903		0.573
1	50	0.127146	0.00192671	0.0559
2	80	0.126031	91	0.0477
3	90	0.12579	1	0.0823
65	820	0.0075309	1	7.35e-005
66	830	0.0075309	1	4.12e-006
67	840	0.0075309	1	6.01e-007

Optimisation terminated: relative infinity-norm of gradient less than options.TolFun.

```
x =
   1.0156   1.5415  -0.0210   2.0374   3.7811   1.0482   0.1680   0.8192  -0.0978
fval =
   0.0075
MAPE_HGA =
   3.3004
>>
```

The HGAED in experiment 3 reached convergence in 60 iterations with the best fitness value of 0.0075; error is 3.3004%. Optimum parameter values can be obtained. A similar process is applied to the run program in Experiment 4 and Experiment 5.

The values of parameters for both the HGAED-1 model and the HGAED-2 model in Experiment 1 to Experiment 4 are illustrated in Table 4.10 and the mathematical expressions are presented in equations 4.14 to 4.16.

Results in Table 4.10 demonstrate that in each experiment, several parameter values are more significant to others. This indicate that one variable or more are dominant to others which affect energy demand. Based on the data in Table 4.10, when the parameter values are substituted to the mathematical representation of each model as described in section 4.1, the equation form is as presented in equations 4.16 to 4.18 (no preprocessing data conducted for examples in Experiment 3 and Experiment 4).

Table 4.10 Optimum parameter values of Experiments

HGAED-1				HGAED-2
Exp.-1	**Exp.-2**	**Exp.-4**	**Exp.-5**	**Exp.-3**
β1=0.5751;	β1=0.7769;	β1=0.9126;	β1=39.4363;	β1=1.0156;
β2=-0.0081;	β2=0.0017;	β2=4.7097 ;	β2=0.0439;	β2=1.5415;
β3=0.0100;	β3=-0.4386;	β3=-2.9006;	β3=1.5125;	β3=-0.0210;
β4=0.7846;	β4=1.0918;	β4=-2.1227;	β4=-0.0108;	β4=2.0374;
β5=2.3112;	β5=-0.551;	β5=-0.9927;	β5 =0.1248;	β5 =3.7811;
β6=0.5010;		β6 = 0.8707;		β6 =1.0482;
β7=-0.1485;		β7=-3.0073 ;		β7=0.1680;
β8=1.9193;		β8=0.5152 ;		β8=0.8192;
β9=0.9355;		β9=-2.8064 ;		β9=-0.0978;
		β10=1.5747 ;		
		β11=-2.7192		
		β12=-1.5083 ;		
		β13=-2.9475 ;		
		β14=-3.8909 ;		
		β15 =0.8052		

Model: HGAED2

Tot.net Electricity Consumption = $1.0156 + 1.5415\, X_1^{-0.0210} + 2.0374\, X_2^{3.7811} +$

$1.0482\, X_3^{0.1680} + 0.8192\, X_4^{-0.0978}$ (4.16)

Or

Total electricity consumption (TWh) = 1.0156 + 1.5415* $[\text{GNP}(10\text{^}9 \text{ US } \$)]^{-0.0210}$ + 2.0374 *$[\text{Population}(10\text{^}6)]^{3.7811}$ + 1.0482* $[\text{Import}(10\text{^}9 \text{ US } \$)]^{0.1680}$ + 0.8192* $[\text{Export } (10\text{^}9 \text{ US } \$)]^{-0.0978}$ (4.17) and

Model: HGAED1

Industrial Electricity Consumption = $0.9126 + 4.7097\, X_1^{-2.9006} -$

$2.1227X_2^{-0.9927} - 0.8707X_3^{-3.0073} + 0.5152X_4^{-2.8064} + 1.5747\, X_1X_2 - 2.7192$

$X_1X_3 - 1.5083\, X_1X_4 - 2.9475\, X_2X_3 - 3.8909\, X_2X_4 + 0.8052\, X_3X_4$ (4.18)

Where

$X1$ = [GNP (10^9 US $)] $X2$ = [Population (10^6)]

$X3$ = [Import (10^9 US $)] $X4$ = [Export (10^9 US $)]

Industrial Electricity Consumption in Tera Watt hour [TWh]

If the preprocessing data have been conducted before estimation, all constants that are used in normalised data should be recalculated to obtain the original data.

4.2.8 Evaluate Relativeness to Some Benchmarks

In 2012, Piltan et al. proposed linear and nonlinear models based on evolutionary algorithms to estimate the electricity consumption function in Turkey. They used the four fitness functions (MSE, RMSE, MAD and MAPE) in the evolutionary algorithms and data from Ozturk and Ceylan (2005). The different linear and nonlinear models which were used for the estimation of electricity demand function of Turkey using evolutionary algorithms (PSO and RCGA) are Logarithmic model in addition to Exponential and Quadratic models and Mix models as the improvement of Ozturk and Ceylan (2005) results.

In the present study, the use of evolutionary algorithms (hybrid genetic algorithm and local search with simplex method) was developed to estimate the electricity demand of Turkey industrial sector using linear and nonlinear models as described in formulations 4.6(a, b) and 4.7(a, b) above using the data in Experiment 4. The best final results of the Hybrid GA+LS approach and also the best results of Piltan et al. (2012) are shown in Table 4.11.

Table 4.11 Compare of the best results (error in percentage) to Piltan et al. (2012)

	Methods	Models	Fitness Functions			
			MAPE	RMSE	MSE	MAD
Best results in Piltan et al.(2012)	PSO	Mix	91.33	33.70	34.76	59.48
		Quad	84.56	42.41	44.14	89.22
		Log	7.48	4.54	4.63	5.90
	RCGA	Mix	57.01	62.81	66.75	88.45
		Quad	209.24	148.17	166.47	118.48
		Log	8.31	4.71	4.46	6.43
Hybrid Models	GA + LS	Mix	8.5774	7.1298	50.8335	4.1772
		Quad	7.7615	5.0092	25.0925	3.7799
		Log	1.7370	1.0183	1.0369	0.8459

In the hybrid models, Logarithmic (Log), Quadratic (Quad) and Mix models were used for the estimation of electricity demand in Turkey as they were used in Piltan et al. (2012) and Ozturk et al. (2005). In this study, Turkey's industrial electricity consumption is the function of gross domestic product, import and export. The four fitness functions of error rate impact on the results can be seen in this experiment.

The best final results of hybrid genetic algorithm and local search approach can be compared to the RCGA and PSO approaches in Piltan et al. (2012). Their best result has 4.46% of error with Log model and MSE fitness function, whereas the hybrid genetic algorithm and local search has less error percentage of 0.8459 using Log model. The GA+LS algorithm are better than PSO and RCGA, whereas with the Quad model, the results of hybrid algorithm are better than other algorithms. The best forecasting model with optimum parameters can be expressed by substituting the optimum parameter values into Log and Quad models using MAD fitness function of error rate.

In further evaluation of the performance, the HGAED models (GA+LS) must be benchmarked with the state-of-the-arts models, which include PSO, RCGA, and hybrid (GA+PSO) models. The results of the two models as stated before is conducted and shown in Table 4.11. Table 4.12 presents the comparison of HGAED models with hybrid GA and PSO using data in Ozturk and Ceylan (2005) for industrial electricity consumption.

Table 4.12 Benchmarked HGAED models with other hybrid models

	Methods	Models	Fitness Functions			
			MAPE	RMSE	MSE	MAD
Other hybrid model	GA+PSO	Mix	63.6152	96.6473	9340.7	81.6056
		Quad	72.0496	108.882	11855.3	92.4253
		Log	4.9371	5.9957	35.9485	6.3333
HGAED Models	GA + LS	Mix	8.5774	7.1298	50.8335	4.1772
		Quad	7.7615	5.0092	25.0925	3.7799
		Log	1.7370	1.0183	1.0369	0.8459

One can see in Table 4.11 and Table 4.12 that using PSO, GA and RCGA as an optimiser for industrial electricity demand forecasting systems reduced the error rates on the average of 5-6%, which is the significant improvement on the existing previous models. But with the use of hybrid algorithms (GA and PSO; GA and the original simplex local search), the improvements reached the error rates on the averages of 1.7370 – 4.9371%. These improvements justified the use of the hybrid algorithm (GA and PSO; and GA and original simplex local search) as far as the error rates are concerned.

4.3 Summary

All experimental result findings in Experiment 1 to Experiment 5 are summarized in Table 4.13. It presents the comparison of average errors between other related models and the HGAED models.

Table 4.13 Summary of results in Experiment 1 to Experiment 5

Experiment	**1**	**2**	**3**	**4**	**5**
Model Average errors (%)					
GAED-1	20.328	15.293	13.207		
GAED-2	11.213	70.619	7.304	93.283	
GAED-3			8.353	16.045	
MENR			9.938	29.049	
LinLog-ED	17.359	6.426			
Lin-ED-1	12.792	13.842			1.231
Lin-ED-2					1.040
DLin-ED	6.728	9.731			
HGAED-2	8.811	5.364	4.017	5.46	3.919
HGAED-1	6.657	4.389	8.461	1.737	3.464

From Table 4.13, it can be seen that the HGAED models have good performance for all data used in the experiments, the average error of the HGAED models is less than 6%, even in benchmarking to PSO and RCGA models in Piltan et al. (2012), the hybrid version of the HGAED achieved less error percentage of 0.061 using MSE fitness function of error rate. It can be concluded that linear and nonlinear (exponential and quadratic) models using genetic algorithm and local search are more effective than other existing models for electricity demand.

These experimental results indicate that the hybrid genetic algorithm and local search approach generally have better performance, as measured by accuracy. The hybrid genetic algorithm and local search algorithm approach are promising for nonlinear model estimation.

CHAPTER FIVE
IMPROVED HYBRID ALGORITHM FOR ELECTRICITY DEMAND PREDICTION

From the results as presented in Chapter 4 using original hybrid genetic algorithm and local search, the study comes to propose the improved hybrid genetic algorithm for electricity demand predictions. Section 5.1 introduced the proposed improved hybrid algorithm for electricity demand prediction. Section 5.2 discusses the model application for Turkey electricity demand prediction. Section 5.3 discusses Indonesian electricity demand prediction, and the summary is given in section 5.4.

5.1 Introduction

In this section, the proposed improved hybrid algorithm for electricity demand prediction that has been mentioned in Chapter 3 as RVGA-ENM is discussed with the aims of understanding the steps and algorithms of solving electricity demand prediction problem for Turkey and Indonesia. Figure 5.1 presents the proposed improved hybrid algorithm.

5.1.1 Real-value Genetic Algorithm

In general, the steps in real-value genetic algorithm (RVGA) can be divided into seven steps which are: (1) initialization, (2) encode the individuals, (3) crossover and mutation, (4) decode the individuals, (5) evaluation of fitness, (6) check stopping criteria, and (7) ending the algorithm.

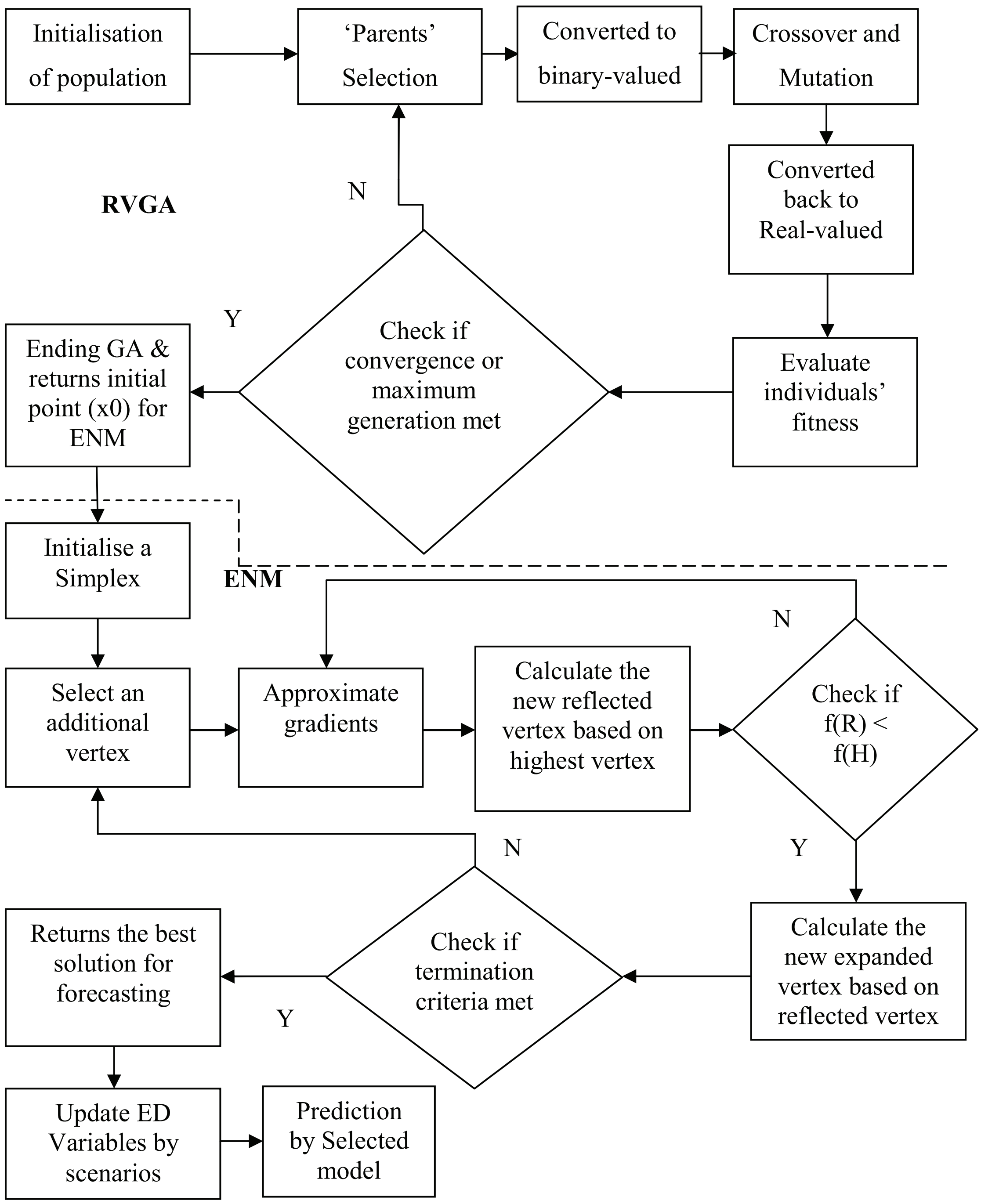


Figure 5.1 Proposed RVGA-ENM flowchart for electricity demand forecasting

The real-value genetic algorithm steps are presented as following:

Step 1: The initialisation step is to generate the first generation of individuals for starting the algorithm. To initialise the algorithm, every variable of an individual will be randomly generated within their defined range. In this study, the range is a two-element vector specifying to converted decimal number. The range of the initial population will have to cover the entire space of possible solutions. Depending on the nature of the problems, the population size can be from several to hundreds. In this study, the population is set to 50.

Step 2: Selection.

As one of the evolution progress steps, the proportion of the existing population is selected to breed a new generation during each succesive generation. Usually, individual solutions are selected through a fitness-based process, which means that fitter chromosomes have high possibility to be selected as 'parents' to produce offspring (solutions). There are different selection methods as have been described in Chapter 2, and in this work, roulette wheel selection is used.

Step 3: Converted to binary-valued. The 'parents' solutions will come from those individuals selected to survive from last generation. The 'children' solutions will be first generated by crossover process which all the variables of an individual solution will be clustered and converted into a binary form with ones and zeros. Its encode the individuals.

Step 4: Crossover and Mutation (Reproduction)

The reproduction step consists of crossover and mutation process. It will produce new born 'children' solutions which share the characteristics of their 'parents' solutions. One or more crossover point on both 'parents' organism string is randomly selected. All data beyond that point in either organism string is swapped between the two 'parents' organisms. The 'children' will be the resulting organisms. Different crossover methods such as one-point, two-point, and uniform crossover, have different rules on how the children solutions inherit the characteristics from their 'parents'. In this study, uniform crossover is used for 40 bits of each individual.

After crossover, the mutation process will prevent the premature convergence on poor solutions. In the classic genetic algorithm, the mutation operator involves an arbitrary bit in a genetic sequence having a probability to be changed from its original state. That is to flip some random part of the genetic sequence from '0' to '1' or from '1' to '0'.

Step 5: Converted back to real-valued. A parameter of mutation rate will be defined so that the higher the rate is, the more likely the 'children' will mutate. The newborn individual data will be evaluated by the fitness values after the reproduction process. After crossover and mutation, the individuals will be converted back to real form.

Step 6: Evaluation of fitness

This step focuses on the application demands. In this study, MSE, RMSE, MAD, and MAPE are used as the fitness evaluation functions to measure the least error between the actual electricity demand and the forecasting values.

Step 7: Termination

The reproduction process will repeat until one of the stopping conditions is met. Usually, the ending criteria will be one of the following:

1. A solution is found that satisfies the minimum criteria
2. A fixed number of generations is reached. The solution obtained from RVGA is returns as initial point (x0) for extended Nelder Mead (ENM) local search algorithm in step-8.

5.1.2 The proposed Extended Nelder Mead (ENM) Local Search

The proposed ENM simplex local search algorithm with additional vertex is similar to the original NM simplex local search method but with slight modifications in the reflection and expansion process that it has to approximate gradients to search for its reflected and expansion vertex. In other words, its convergence will rely on the true direction through the new reflected vertex *R*' and the new expansion vertex E' rather than the reflected vertex *R* calculated through the centroid vertex proposed by the original NM simplex local search algorithm. This method is effective for multidimensional unconstrained optimisation problems.

The original NM simplex local search algorithm (Huang, 2009) assumes that the direction to local minima can be found by the operations of reflection, contraction and expansion without caring about the gradient direction. However this assumption is not always true in reality. That is why the simplex algorithm fails easily with high dimensional optimization problems (Pham et al., 2011).

The proposed extended NM (ENM) simplex local search algorithm steps (Fig. 5.1) will follow the basic steps of improved NM version as described in Pham et al. (2011), but with slight modifications in the expansion processes (steps 13, 14,15,16,17). The proposed ENM local search steps as the following:

Step 8: Initialise a simplex with (n+1) random vertices x1, x2,…, xn

Step 9: Select an additional vertex XA with its coordinates composed from n vertices in the simplex. Coordinates of the selected vertex are a diagonal of the matrix X from n vertices in the simplex. XA = $[x_{1,1}, x_{2,2}, \ldots, x_{n,n}]$.

Step 10: Approximate gradients based on the additional vertex A with other n vertices in the selected simplex. To illustrated how this method works, a two dimensional case which has a triangular simplex ΔHSL, highest (xH), second highest (xS) and the least (xL) vertices is shown in Figure 5.2.

Step 11: Calculate the new reflected vertex R' based on the highest vertex H, where XR' = XH – σS. Parameter σ is the learning constant or step size. In this work, σ = 1.

Step 12: If the function value at R' is smaller than the function value at H, it means that HR' is on the right direction of the gradient.

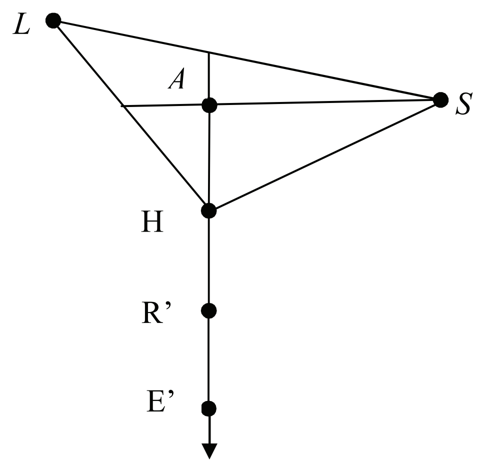
Step 13: Calculate the new expanded point E' based on the new reflected point R'. The R' can be expanded to E' using the formula XE' = (1 – γ) XH + γ XR'. γ is the expansion coefficient (in this work, γ=0.5). R' and E' are rely on the right direction towards global optimum point (Fig.5.2).

Step 14: Check if the termination criteria has been achieved. If convergence or termination criteria not met, go back to step 9 with (n+1) vertices.

Step 15: Returns the best function evaluation values and parameter values for forecasts the electricity demand.

Step 16: Update the electricity demand (ED) variables using scenarios based on the economic and the population growth

Step 17: Prediction for future electricity demand using selected model



Highest: $H(x_1,y_1)$

Second highest: $S(x_2,y_2)$

Least: $L(x_3,y_3)$

Additional: $A(x_1,y_2)$

R': new reflected point

E': new expansion point

Figure 5.2 The Simplex ΔHSL with Additional Vertex A

A is the additional vertex which has its coordinates formed from *H* and *S*. The approximate gradient of this dimensional plane will be:

$$g1 = \frac{\Delta f}{\Delta x} = \frac{f_{\mathrm{H}} - f_{\mathrm{A}}}{x_2 - x_1};\ g2 = \frac{\Delta f}{\Delta y} = \frac{f_{\mathrm{S}} - f_{\mathrm{A}}}{y_1 - y_2} \qquad (5.1)$$

In order to improve the convergence rate and speed, the algorithm needs to rely on the gradient (search in true direction). An improvement to the original NM simplex local search algorithm, one method is created as the guidance to the search direction. Its approximate gradients of a (n+1) dimensional plane created from a geometrical simplex. First, it selects an additional vertex compose from (*n*+*1*) vertices in a simplex and then combines this vertex with other n selected vertices in the same simplex. This method can estimate gradients more accurately, therefore, it converges faster.

5.1.3 Improved Hybrid Algorithm Benchmarking

The final evaluation of the performance, the proposed models based on hybrid GA and the extended NM simplex local search algorithm must be benchmarked with the hybrid model based on GA and the original simplex local search. Figure 5.3 shows the improved hybrid algorithm (RVGA+ENM) results for forecasting Turkey electricity demand using Mix (linear and nonlinear) models.

```
….      ….      …..     ….      ….      ….
Generation 99: f(0.0302 0.0503 0.0951 1.2635 1.8742 1.0955 1.8062)=0.060711
Generation 100: f(0.0302 0.0503 0.0951 1.2635 1.8742 1.0955 1.8062)=0.060711
x0 = 0.0303    0.0503    0.0951    1.2636    1.8743    1.0956    1.8063
Iteration = 1; Minimum value of f = 0.0024306
located at x = [-0.13143   0.21153   -0.56203    0.4248    2.4978    -1.4075    6.4775].
Iteration = 2; Minimum value of f = 0.000965;
located at x = [-0.0576    0.0221    0.2693    0.2669    7.7153    -0.2584    2.9479]
act_pred_err =
   56.8100       60.2221        3.4121
   60.5000       63.8661        3.3661
   67.2200       68.8178        1.5978
   73.4300       71.9428        1.4872
   77.7800   `   75.7123        2.0677
   85.5500       89.2974        3.7474
   94.7900       93.5093        1.2807
  105.5200      105.6721        0.1521
  114.0200      116.5410        2.5210
  118.4800      116.6038        1.8762
  128.2800      123.6716        4.6084
  126.8700      128.5275        1.6575
MAPE =1.0295; MAD =1.3206; MSE =0.4134; RMSE =0.6429
```

Figure 5.3 The proposed RVGA-ENM results for Turkey electricity demand forecasting

In five times of RVGA-ENM process, the best value of fitness have been reached by the hybrid algorithm (iteration=2, Minimum value of f = 0.00096588), it means that the ENM process have been reached 62.85 time less than optimisation value obtained by RVGA in 100 generations.

Figure 5.4 shows the fitness evaluation by proposed RVGA-ENM algorithm. Ideally, its converged fast at zero (minimum error) measured from the difference between forecasting values and actual values of electricity demand. But in this study, the minimum deviation required for termination was set initially to 0.0001.

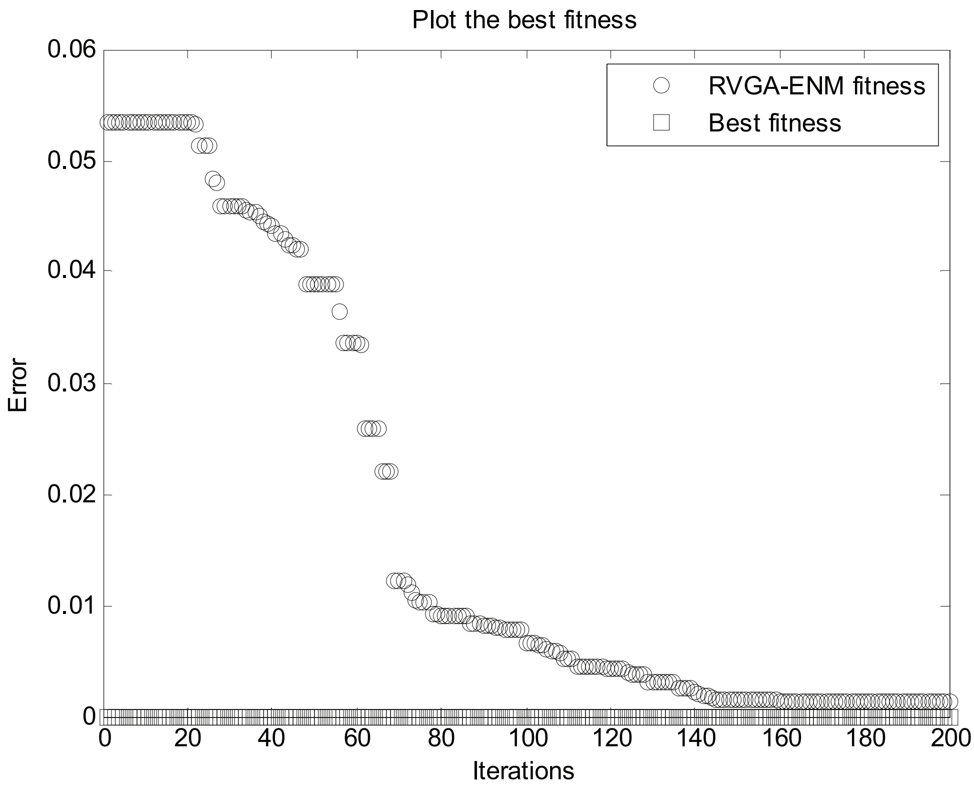


Figure 5.4 Fitness evaluation by proposed RVGA-ENM

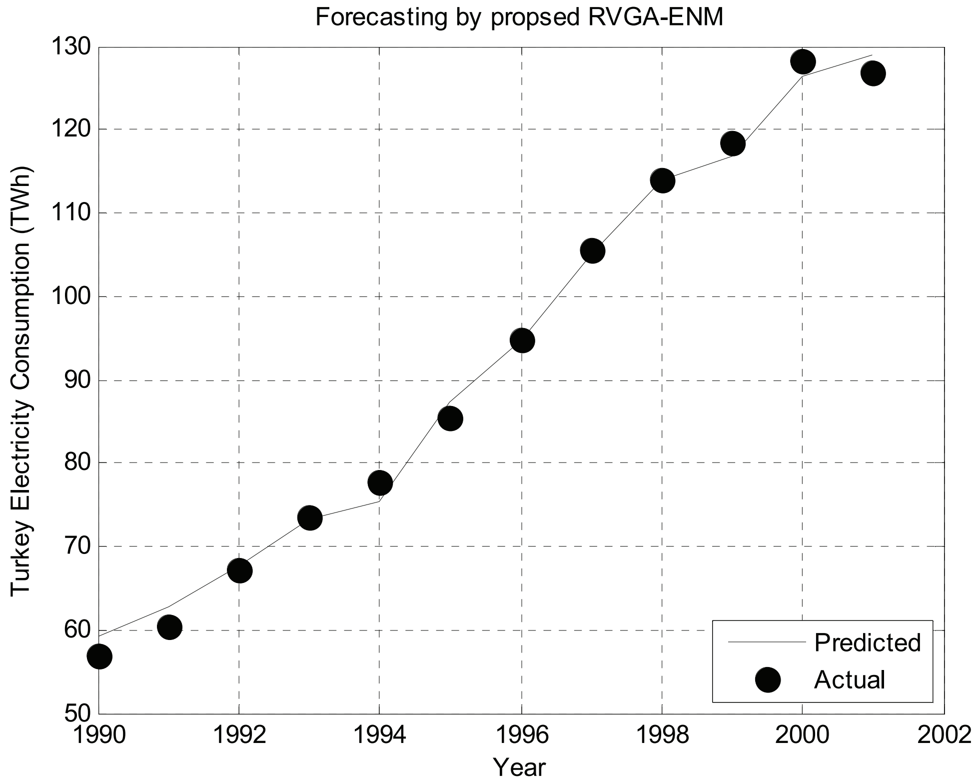


Figure 5.5 Turkey electricity demand forecasting by proposed RVGA-ENM

Table 5.1 presents the comparison of proposed models based on hybrid RVGA and the extended NM simplex (ENM) local search with hybrid GA and the original local search.

The comparison between the proposed RVGA-ENM models and the hybrid GA-original simplex local search are summarized below. From Table 5.1, a conclusion can be draw that the proposed hybrid RVGA-ENM algorithm shows its better performance than the original simplex method in terms of errors and convergence rate.

Table 5.1 The comparison of proposed RVGA-ENM models and GA-OLS models for Turkey electricity demand

	Methods	Models	Max Iter	Fitness Functions: MAPE	RMSE	MSE	MAD
Proposed Hybrid	RVGA+ENM	Mix	50	1.0295	0.6429	0.4134	1.3206
		Quad		3.6771	0.6685	0.4469	4.7170
		Log		1.768	0.248	0.061	2.268
		Exp		2.9458	1.8909	3.5755	3.7788
Original Hybrid	GA+OLS	Mix	2194	8.5774	7.1298	50.8335	4.1772
		Quad		7.7615	5.0092	25.0925	3.7799
		Log		3.4178	2.4365	5.9364	1.6645

The experimental result tell that the improved local search with gradients based on the additional vertex converge faster than the original simplex because the search is rely on the true directions.

5.2 Turkey Electricity Demand Prediction

The Turkish electricity demand prediction is calculated based on the two scenarios (low and high) for population, gross national product, import and export. The prediction of electricity demand to 2020 is made by using the proposed RVGA + ENM model. The data prediction is based on economic and population growth. The scenarios are similar to the scenarios applied in Ozturk and Ceyland (2005).

In the low scenario; gross national product, import and export average growth is 4% per year respectively, and population growth is 1.5% per year. While in the high scenarios; gross national product, import and export average growth is 5% per year respectively, and population growth is 1.8% per year. These data are used as the inputs of the proposed RVGA+ENM model. The prediction data for variables based on the scenarios until 2020 are presented in Table 5.2

Table 5.2 Variables data for Turkey electricity demand prediction until 2020

Low Scenario				High Scenario				
GNP (10^9$)	**Population** (10 ^6)	**Import** (10^9$)	**Export** (10^9$)	**GNP** (10^9$)	**Population** (10 ^6)	**Import** (10^9$)	**Export** (10^9$)	**Year**
238.00	71.08	68.70	46.90	238.00	71.08	68.70	46.90	2003
247.52	71.19	71.45	48.78	249.90	71.21	72.14	49.25	2004
257.42	71.29	74.31	50.73	262.40	71.34	75.74	51.71	2005
267.72	71.40	77.28	52.76	275.51	71.46	79.53	54.29	2006
278.43	71.51	80.37	54.87	289.29	71.59	83.51	57.01	2007
289.56	71.61	83.58	57.06	303.76	71.72	87.68	59.86	2008
301.15	71.72	86.93	59.34	318.94	71.85	92.06	62.85	2009
313.19	71.83	90.40	61.72	334.89	71.98	96.67	65.99	2010
325.72	71.94	94.02	64.19	351.63	72.11	101.50	69.29	2011
338.75	72.05	97.78	66.75	369.22	72.24	106.58	72.76	2012
352.30	72.15	101.69	69.42	387.68	72.37	111.91	76.40	2013
366.39	72.26	105.76	72.20	407.06	72.50	117.50	80.21	2014
381.05	72.37	109.99	75.09	427.41	72.63	123.38	84.23	2015
396.29	72.48	114.39	78.09	448.78	72.76	129.54	88.44	2016
412.14	72.59	118.97	81.22	471.22	72.89	136.02	92.86	2017
428.62	72.70	123.72	84.46	494.78	73.02	142.82	97.50	2018
445.77	72.81	128.67	87.84	519.52	73.15	149.96	102.38	2019
463.60	72.91	133.82	91.36	545.50	73.29	157.46	107.50	2020

Figure 5.6 illustrates the Turkey electricity demand prediction for the period of 2003-2020 using the proposed RVGA-ENM model with scenario analysis. The model is selected for future prediction because it has good performance with MAPE error is 1.0295%.

Table 5.3 Turkish Electricity Demand Prediction 2003 to 2020

Scenarios(Low_High) =		**Years**
199.5875	199.5875	2003
208.2377	210.3916	2004
217.4679	222.2531	2005
227.5417	235.2178	2006
238.4415	249.6897	2007
250.1438	265.7102	2008
262.9679	283.5005	2009
276.9601	303.3342	2010
292.1941	325.5281	2011
308.7985	350.4553	2012
326.8828	378.4958	2013
346.8682	410.1028	2014
368.8399	446.0594	2015
393.0160	486.9258	2016
419.7779	533.6223	2017
449.3167	587.2126	2018
482.1763	649.0743	2019
518.5802	720.9708	2020

Figure 5.6 is plotted based on the data for future prediction of total net electricity consumption in Turkey 2003 - 2020 as presented in Table 5.3. This future prediction is based on two scenarios calculated using economic growth, which has been adopted from the data in Ozturk and Ceylan (2005).

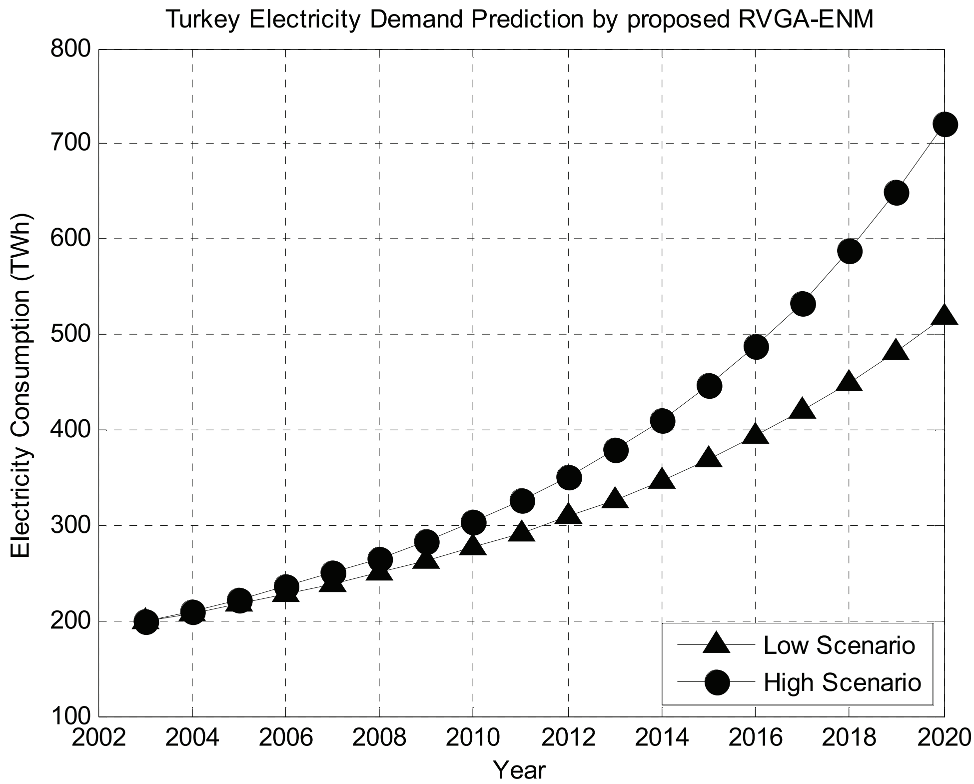


Figure 5.6 Prediction of Turkish electricity demand 2003 – 2020

From the data in Table 5.3, the proposed RVGA-ENM is applicable for the long-term electricity demand prediction up to 2020 using high economic growth of scenario and low economic growth of scenario. In high scenario, electricity demand has reached 720.9708 Billion Kilo Watt hour in 2020, while in low scenario, electricity demand has reached 518.5802 Billion Kilo Watt hour in 2020.

5.3 Indonesian Electricity Demand Prediction

The future prediction of Indonesian electricity demand is based on the latest data of economic indicators and electricity. The scenarios used the growth of electricity demand, economic indicators and populations in several years during the subject of study as the main consideration. The scenario is calculated based on the trends of the average growth of economic indicators in the period of 1990-2009.

Table 5.4 Indonesian electricity demand forecasting by proposed RVGA-ENM

actual_prediction_error =			**Years**	**%**
65.3000	75.1275	9.8275	1998	MAPE =
71.3000	76.3497	5.0497	1999	2.3063
79.2000	78.9180	0.2820	2000	
84.5000	80.7108	3.7892	2001	MAD =
87.1000	82.9010	4.1990	2002	
90.4000	86.6671	3.7329	2003	3.1388
100.1000	94.8039	5.2961	2004	
107.0000	106.5117	0.4883	2005	MSE =
112.6000	114.7307	2.1307	2006	17.2592
121.2000	121.5115	0.3115	2007	RMSE =
129.0000	128.9098	0.0902	2008	
136.1000	138.5688	2.4688	2009	4.1544

The data in Experiment 2 is the economic indicator and electricity demand data of Indonesia. The proposed RVGA-ENM is eligible to be used in the electricity demand prediction until 2030.

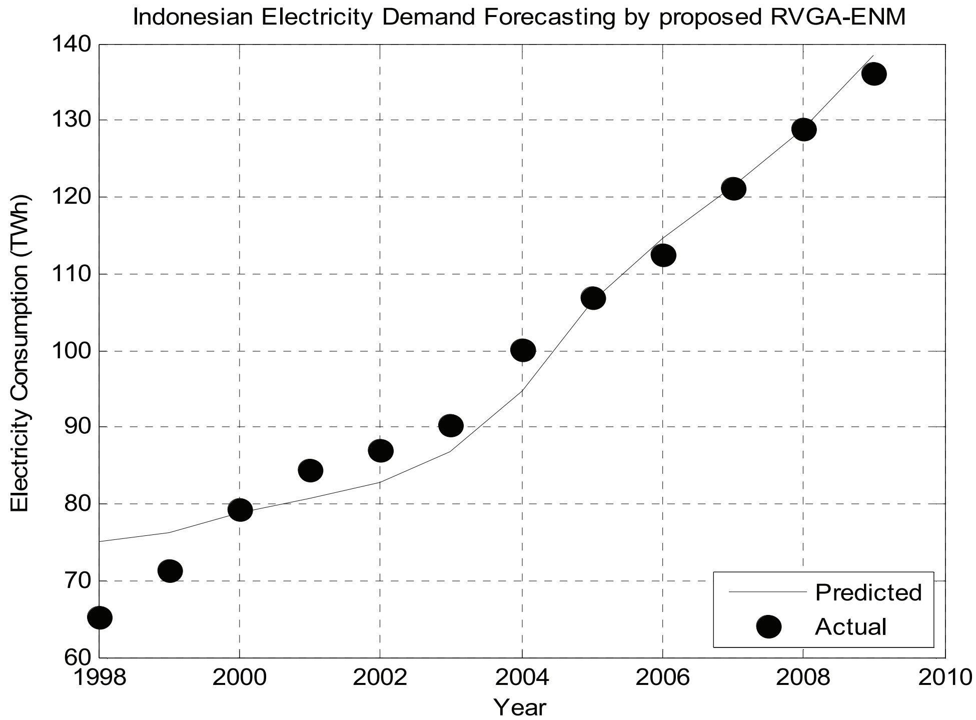


Figure 5.7 Indonesia electricity demand forecasting by proposed RVGA-ENM

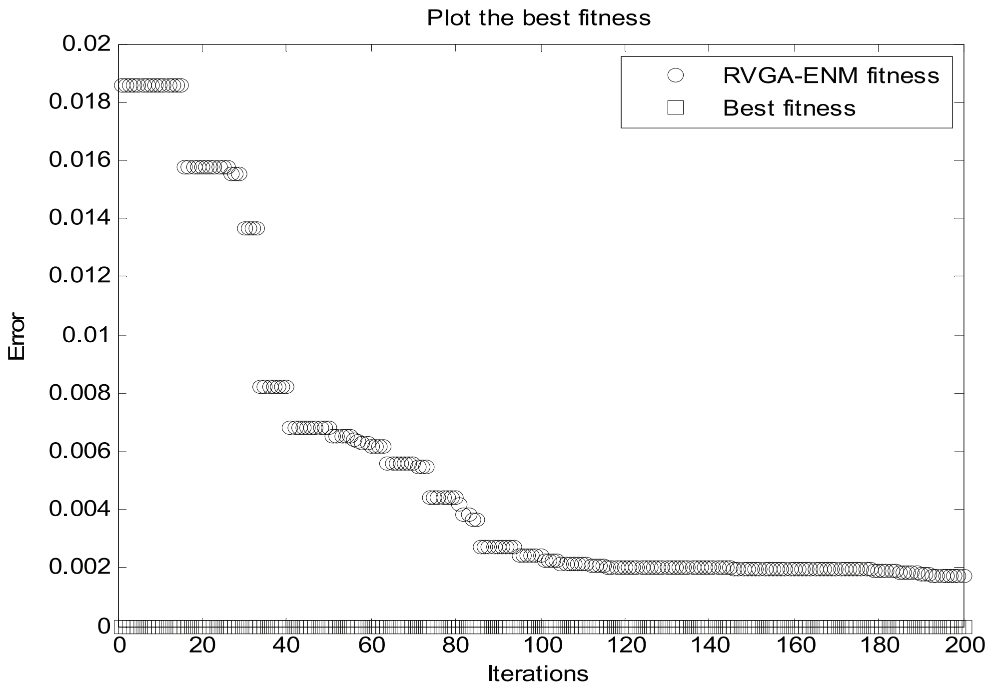


Figure 5.8 Fitness evaluation by proposed RVGA-ENM model for Indonesia electricity demand

Table 5.5 The comparison of proposed RVGA-ENM models for Indonesian electricity demand

Methods	**Models**	Fitness Functions				
		Max Iter	MAPE	RMSE	MSE	MAD
RVGA + ENM	Mix	50	2.3063	4.1544	17.2592	3.1388
	Quad		10.1145	16.7894	281.8854	13.7658
	Log		3.6293	5.5958	31.3127	4.9394
	Exp		2.4878	3.9694	15.7560	3.3859

Indonesian final energy consumption during the period of 1971 to 2009 had significant growth, i.e. approximately 14 times larger in 2009 than that of 1971 or increased with annual average growth of 7.3% (Ibrahim, 2010).

Table 5.6 Scenarios of prediction for Indonesian Variables

Parameters	Scenarios	
	High	Low
Pop	1.25%	1.20%
GDP	7.00%	5.00%
Import	7.00%	5.00%
Export	7.00%	5.00%

Table 5.6 shows the values of two scenarios for future prediction of population and economic indicators during the period of 2010 to 2030. The High and Low scenario data is tabulated in Table 5.7.

The prediction of Indonesian electricity consumption until 2030 using the proposed RVGA-ENM model is presented in Table 5.8 and the visual prediction is illustrated in Figure 5.9.

Table 5.7 High-Low scenario 2010 to 2030 for population and economic indicators

	High				Low			
Year	Population	GDP	Import	Export	Population	GDP	Import	Export
2010	260.223	257.121	103.607	124.666	260.094	252.315	101.670	122.336
2011	263.475	275.119	110.860	133.392	263.215	264.931	106.754	128.452
2012	266.769	294.378	118.620	142.730	266.374	278.177	112.092	134.875
2013	270.103	314.984	126.923	152.721	269.570	292.086	117.696	141.619
2014	273.480	337.033	135.808	163.411	272.805	306.690	123.581	148.700
2015	276.898	360.626	145.314	174.850	276.079	322.025	129.760	156.135
2016	280.359	385.869	155.486	187.090	279.392	338.126	136.248	163.941
2017	283.864	412.880	166.370	200.186	282.744	355.033	143.061	172.138
2018	287.412	441.782	178.016	214.199	286.137	372.784	150.214	180.745
2019	291.005	472.706	190.477	229.193	289.571	391.423	157.724	189.783
2020	294.642	505.796	203.811	245.236	293.046	410.995	165.610	199.272
2021	298.326	541.202	218.077	262.403	296.562	431.544	173.891	209.235
2022	302.055	579.086	233.343	280.771	300.121	453.121	182.586	219.697
2023	305.830	619.622	249.677	300.425	303.723	475.778	191.715	230.682
2024	309.653	662.995	267.154	321.455	307.367	499.566	201.301	242.216
2025	313.524	709.405	285.855	343.957	311.056	524.545	211.366	254.327
2026	317.443	759.063	305.865	368.034	314.788	550.772	221.934	267.043
2027	321.411	812.198	327.275	393.796	318.566	578.311	233.031	280.395
2028	325.429	869.052	350.185	421.362	322.389	607.226	244.682	294.415
2029	329.496	929.885	374.698	450.857	326.257	637.587	256.916	309.136
2030	333.615	994.977	400.927	482.417	330.172	669.467	269.762	324.593

During the period of 2010 to 2030, the electricity consumption of Indonesia has increased 2.895 times, from **220.0877** TWh (low scenario) in 2010 and in 2030 has reached **637.5702** TWh. The average growth of electricity consumption during those periods is 5% per year for low scenario.

Table 5.8 Indonesian Electricity Consumption (TWh) 2010-2030

Indonesian Electricity Demand Prediction 2010-2030 by proposed RVGA-ENM		
LOW_HIGH =		**YEARS**
220.0877	**221.6878**	2010
231.4672	**234.9271**	2011
243.4436	**249.0661**	2012
256.0545	**264.1848**	2013
269.3507	**280.3888**	2014
283.3822	**297.7840**	2015
298.2028	**316.5004**	2016
313.8734	**336.6810**	2017
330.4658	**358.4848**	2018
348.0526	**382.1019**	2019
366.7109	**407.7370**	2020
386.5290	**435.6449**	2021
407.6119	**466.0922**	2022
430.0658	**499.4043**	2023
454.0049	**535.9606**	2024
479.5729	**576.1917**	2025
506.9067	**620.6016**	2026
536.1823	**669.7847**	2027
567.5782	**724.4425**	2028
601.2954	**785.3882**	2029
637.5702	**853.6150**	2030

For the high scenario, the average growth is 7% per year. These annual growth are realistic compared to the average annual growth of electricity consumption is 6.2% during the period of 1970 to 2009. Final energy consumption for the period of 1971 to 2009 had significant growth; it increased with the annual average growth of 7.3% from 6.78 MTOE in 1971 to 97 MTOE in 2009 (MEMR, 2009).

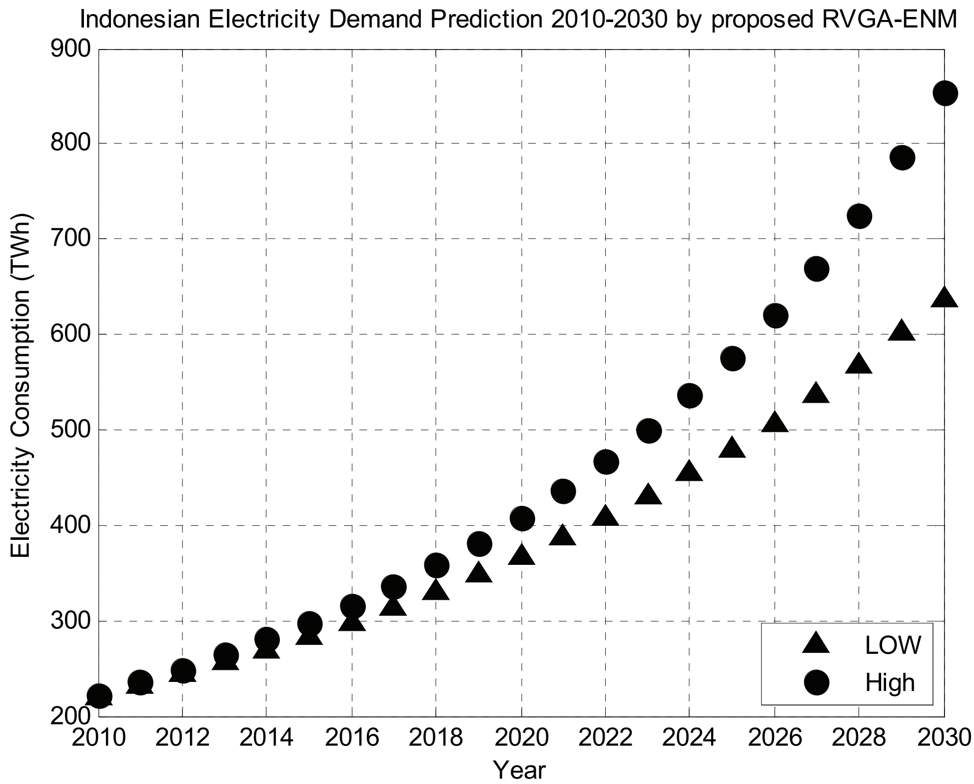


Figure 5.9 Prediction of Indonesian electricity consumption to 2030

5.4 Summary

Based on the above results, it has been shown that the integration of local search into a hybrid genetic algorithm method is applicable for the long-term electricity demand forecast with high approximation accuracy and fast convergence time capability to reach the global optimal solution. The model has been developed in such a way that outputs for different socioeconomic scenarios can be obtained. The solution obtained using the proposed RVGA-ENM indicated improved quality over that obtained by a single genetic algorithm or standard hybrid GA-local search. This enhanced the confidence of long-term electricity demand forecasts, especially under uncertain economic conditions.

CHAPTER SIX
CONCLUSION

This chapter presents the conclusion of the study discussed in the earlier sections. Section 6.1 discusses the introduction; the conclusion and contributions of the study are presented in section 6.2 and 6.3, and section 6.4 discusses the future work.

6.1 Introduction

The objective of the study is to solve electricity demand forecasting problems. The proposed technique to increase the performance of electricity demand forecasting is by using linear and nonlinear models based on genetic algorithm coupled with local search simplex method. Integrating exploration capability of genetic algorithm and exploitation capability of local search produces more improvements as compared to their ability alone. Upon the comparative study of hybrid genetic algorithm and local search used to forecast electricity demand, it seems like the hybrid method has more advantages than other algorithms based on evolutionary computations. The comparison were summarised in Tables 5.1 and 5.5. The technique used to solve the electricity demand forecasting problems is known as hybrid real-value genetic algorithm and extended Nelder-Mead (RVGA-ENM).

6.2 Research Conclusion

Linear and nonlinear models based on genetic algorithm and local search were utilised to forecast electricity demands in Turkey and Indonesia. These models were tested over several benchmark problems of electricity demand forecasting models, and show better performance than the original algorithm methods in terms of error rates and the number of iterations.

Based on the extensive experiments and obtained results, it appears that the proposed RVGA-ENM is more accurate than the conventional genetic algorithm approach. In the proposed RVGA-ENM, improved hybrid algorithms and preprocessing of available data and variables have more effect towards the forecasting process, therefore, the obtained results proved to have the best accuracy.

The performance of the proposed RVGA-ENM model was evaluated and it was also used to predict future electricity demand using a scenario analysis of economic growth. The predictions are useful for an energy planner as the significant input for national energy decision planning.

Based on the experimental analysis in Chapter 4, there are several advantages and disadvantages of the related model using conventional genetic algorithms. Among them are: (a) conventional GA is quick in exploring the area of the global optimum, and (b) conventional GA easily obtains the best solutions for a low number of independent variables, but if the number of variables is high, conventional GA needs a long time to obtain the global optimum; at times, it is does not converge.

The performance of electricity demand forecasting model can be improved by overcoming the trends of variables using the natural logarithmic process. In addition, preprocessing or normalising data are important tasks. In logarithms, the trend is approximately linear. Most economic series which are growing (aggregate output such as GDP, investment, consumption) are exponentially increasing. Percentage changes are stable in the long run. These series cannot be fit by a linear trend, but by their (natural) logarithm linear trend.

The experiments indicate that to overcome the early convergence problem in conventional GA, utilised local search have to improve their performance and obtain a robust result with good quality, which indicate the hybrid algorithm is a promising approach in solving the slow convergence and local optimality problems.

The genetic algorithm is one of the optimisation techniques that have been successfully applied in a few optimisation problems including function and parameter optimisation. However, unnecessary repetition such as if traps caused slow convergence, is the downside of a single algorithm.

One attempt to eliminate the slow convergence in GA is to introduce a small total number of iterations, but this does not guarantee better processing time and in the worst case, it is unable to achieve an optimal solution. A combination of the fitness functions and utilised extended NM (ENM) local search for the minimisation approach is used to exploit the faster convergence on the single genetic algorithm. A mixture of the RVGA exploration capability and ENM local search exploitation capabilities produced optimum global solutions. Therefore, it shows a great deal of large scale optimisation problems and has been successful in forecasting electricity demand.

6.3 Research Contribution

The most significant contribution of the study is a new approach for energy demand forecasting using linear and nonlinear models based on RVGA and ENM local search. Experimental results have revealed that the approach was capable of accelerating the convergence and subsequently improving the iteration rate. The main contributions of this study can be categorised into three parts: (i) the new objective function formulation to obtain a good solution. Therefore, the performance of electricity demand forecasting model can be improved by overcoming the trends of variables using the natural logarithmic process in its formula, (ii) extended NM local search to help real-value genetic algorithm in overcoming the slow convergence and local optimality problems, and (iii) the proposed RVGA-ENM algorithm discovered multidimensional vertices on the variables of electricity demand. Hence, the extended NM local search when combined with RVGA was able to improve prediction rates. It was a main contribution of the study towards theory. The impacts of the study were the significant contribution towards practitioners (energy demand utility planners) and governments.

6.3.1 Contribution of Study towards Theory

The objective function formulation has more effect towards the results of forecasting models in terms of accuracy. The new objective function formulation was derived to overcome exponential trend of electricity demand variables by using the natural logarithmic linear trend. This effort makes significant contributions towards the theory of evolutionary algorithm, specifically in hybrid genetic algorithm approaches. The combination of optimisation methods and a heuristic approach has contributed to solving nonlinear and linear trends that involve many variables and uncertainties of electricity demand.

This research offers a new technique of a hybrid between a real-value genetic algorithm and an extended Nelder-Mead local search algorithm to decrease the percentage of error rates and the number of iterations. The new objective function formula for proposed hybrid algorithm is also an effort to decrease the estimation error of the available electricity demand forecasting models.

The performance of linear and nonlinear models based on real-value genetic algorithm and extended Nelder-Mead local search were investigated using multiple fitness evaluation functions of error rate. They are: Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD). The previous linear and nonlinear models were used as the basic of comparisons.

The addition of an extended NM local search into a hybrid real-value genetic algorithm in the proposed RVGA-ENM and the new objective function formulation will have a great effect on the search process, and increase the performance of the algorithm. Thus, the research output is a new technique that offers the chance to enhance the performance of available electricity demand forecasting models.

6.3.2 Contributions of Study towards Governments

The proposed RVGA-ENM for electricity demand can help to assist the government and the utility company in developing countries with the least cost long-term electricity planning. Therefore, they can overcome the more dynamic electricity demand and manage their sustainable electricity supply. The sustainability of electricity supply is one of the indicators for developed countries. Electricity demand forecasting can provide benefits such as: (i) prevent overloading, (ii) help to estimate load flows, (iii) improve the reliability of the network, and (iv), to reduce the occurrences of blackouts and the equipment failures.

Another importance of the proposed RVGA-ENM for an electricity demand forecasting is the increase in the deregulated economy for contract evaluations and financial product evaluations. In this economic situation, rate increases could not be justified by capital expenditure projects but by the market.

The factors that affected the electricity demand in a nation in the long term are the economic indicators, population growth etc. For the utility corporation that deals with the demand for utility, sustainable supply and cost optimality are the importance tasks. They need hard efforts to control these variables. The proposed RVGA-ENM for electricity demand has taken into account these factors and estimated all the parameters. By this simulation, the planner can choose which variables that significantly affect the demand.

6.3.3 Contributions of Study towards Practitioner

This study has several advantages to electricity demand planning practice especially for those who are operating power generations, transmission and distribution. In the planning and operation of utilities of demand, electricity demand forecasts have a central and integral role in process. In control operation and decisions of a demand utility, accurate electricity demand forecasts hold a great savings potential in fuel allocation and off-line network analysis, and unit commitment and dispatch.

The power system operations may be quite sensitive to forecasting errors. Therefore, the accuracy of electricity demand forecasts has a substantial effect to control the economy of operations. For example, if the prediction accuracy increased for a few percentages, it can save millions of dollars of operation cost. It makes electricity demand forecasts become more important. The accuracy of electricity demand forecasts has substantial effect on operational cost of power systems that are quite sensitive to forecasting errors.

6.4 Future Work

The proposed long-term electricity demand forecasting using linear and nonlinear models based on genetic algorithm and local search has been applied to estimate and predict future prediction of electricity demand. The experimental results indicated that the proposed hybrid approach could achieve a higher quality performance than single algorithm optimisation. However, the local search algorithm presented in this study can be improved by using other techniques to estimate the demand parameters more accurately. The improved simplex method can converge at least ten times faster than the conventional simplex local search method. This type of improvement can be a good topic of future research.

The application of the proposed RVGA-ENM is not only for electricity demand forecasting models. These approaches can also be applied in solving more environmental system optimisation problems that are highly nonlinear and computationally intensive.

The hybrid approach can be adopted in other demand pattern forecasting processes that have similar characteristics to the electricity demand problems in study cases. In general, this proposed hybrid approach can be applied to solve problems such as evolutionary computations and optimisation problems.

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