International Journal of
Soft Computing And Software Engineering (JSCSE)
e-ISSN: 2251-7545
Vol.2,No.8, 2012
Published online: Aug 25, 2012
DOI: 10.7321/jscse.v2.n8.3

Long Term Energy Demand Forecasting based on Hybrid, Optimization: Comparative Study

[1]Wahab Musa, [2]Ku Ruhana Ku-Mahamud, [3]Azman Yasin
[1]Electrical Engineering Dept. Universitas Negeri Gorontalo, Indonesia
[2,3] School of Computing, College of Arts and Sciences, Universiti Utara Malaysia, 06010 UUM Sintok, Kedah, Malaysia
Email: [1]wmusa2001@yahoo.com, [2]ruhana@uum.edu.my, [3]yazman@uum.edu.my

Abstract. **The objective of this research is to develop a long term energy demand forecasting model that used hybrid optimization. To accomplish this goal, a hybrid algorithm that combined a genetic algorithm and a local search algorithm method has been developed to overcome premature convergence. Model performances of hybrid algorithm were compared with former single algorithm model in estimating parameter values of an objective function to measure the goodness-of-fit between the observed data and simulated results. Averages error between two models was adopt to select the proper model for future projection of energy demand.**

Keywords: *energy demand forecasting, hybrid algorithm, optimization*

**Corresponding address:*
Wahab Musa,
Electrical Engineering Dept. Universitas Negeri Gorontalo, Indonesia
Email: wmusa2001@yahoo.com

1. Introduction

Long-term energy demand forecasting used many approach to estimate model parameters. These approach including classic and modern approach [1]. Genetic Algorithm (GA) as an artificial intelligence (AI) modern approach received much attention as robust stochastic search algorithms for various problems. This class of methods is based on the mechanism of natural selection and natural genetics, which combines the notion of survival of the fittest, random and yet structured, search and parallel evaluation of the points in various areas. GA is one of approximate (heuristic) algorithms that used to tackle the hard optimization problems that have great importance in research and development [2].

The approach using GA for long-term demand forecasting is done by [3]; [4] and [5]. GA is used as optimization tools for complex problems that involve numerous variables or involve combinations of linear and non-linear equations. As an optimization tool, the GA attempts to improve performance leading to an optimal solution.

There are many examples of long-term energy demand forecasting models based on GA. Genetic Algorithm Electricity Demand (GAED), exponential for total electricity demand and quadratic for forecasting industrial sector electricity demand are three examples models in forecasting the electricity demand for Turkey [3]. These models used original genetic algorithm as optimization tool. However, the performances of these models are far from being ideal and need some improvement in term of estimation errors.

Several long-term demand forecasting models using the modern approaches to decrease the problems in estimation error (EE), local optimality (LO), large iteration (LI) and computational time (CT). More efforts are need to be taken in order to develop long-term demand forecasting model and

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this study is an effort to reflect the characteristics problem in long-term demand forecasting. These problems affect model performance.

Previous models related to GA have several strengths. GA is easy to use, quick in finding global optimization area and quick in producing best solution if the number of variables is low. However, if the number of variables increased, the performance will decrease. Efforts to improve previous model performance can be done on reducing the number of variables, transform model from non linear form to linear form by using logarithmic mathematical representation, and to pre-processing the input data. This research is one of the efforts needed to solve these problems.

Estimation errors can rapidly increases in the single genetic algorithm when the number of variables increases. Typically, genetic algorithm is coupled with a local search mechanism to find the optimal chromosome in the region. GA with some additional heuristics which improves the convergence rate of the algorithm as well as finds better solution is commonly known as hybrid genetic algorithm (HGA). Although a GA can rapidly locate the region in which the global optimum exists, they take a relatively long time to locate the exact local optimum in the region of convergence. Therefore a combination of a GA and a local search method can speed up the search to locate the global optimum.

Using the hybrid function can improve the accuracy of the solution efficiently [6]. Hence, the HGA seems to be the appropriate approach to improve the performances of long-term energy demand models because it offers good opportunity to find global optimal solution. Based on these features, this research is considering the use of hybrid algorithm (such as HGA) with some new organizing techniques.

However, the scope of this study is focus on the comparison between long-term energy demand forecasting model using original genetic algorithm approach and long-term energy demand forecasting model using hybrid algorithm approach. The estimation errors are taken as an indicator of chosen model selection. The future work is the projection of energy demand by selected model and forecasting variables using scenario analyses.

The organization of this paper is as follows. Section 1 introduced the general description in which the research has been developed. First, overview of the approaches in long-term energy demand forecasting is presented, followed by the explanation of the problem in conventional approach, features using hybrid approach to solve the local optimality problem. Section 2 presents the overview related to energy demand forecasting, characteristics of demand pattern, and the relation between energy and economic. Hybrid optimization approach and detail procedure for the proposed method used in this study are illustrated in Section 3. First, overview of hybrid, optimization followed by the explanation of HGA methods and proposed hybrid methodology. Section 4 discussed the experimental results. The comparison results between two HGA model are illustrated. Section 5 presented the conclusion and future work of this study.

2. Energy demand forecasting

Energy demand forecasting is always a key instrument for the effective operation and planning of power systems. For a power system with large geographical area, a single model for load forecasting of the entire area sometimes cannot guarantee satisfactory forecasting accuracy because of the load diversity [7]. Therefore, they considered to develop a multi-region load forecasting model which can find the optimal region partition under diverse weather and load conditions and finally achieve more accurate forecasts for aggregated system demand.

Demand for electric utility is one of energy demand that have a set of input variables uncertainty. As an important energy industry, electricity section is the infrastructure of national economy, balancing the electricity supply and demand could provide a reliable energy supply for the nation economic development [8]. One of the primary tasks of an electric utility is accurately predicts load demand requirements at all times, especially for long-term. Based on the outcome of such forecasts, utilities coordinate their resources to meet the forecasted demand using a least-cost plan [9].

Peak load demand in a given season is subject to a range of uncertainties, including population and economic growth, changing technology, and weather condition. It is also subject to calendar effects due to the time of day, day of week, time of year, and public holidays. Long-term demand forecasting presents the first step in planning and developing future generation, transmission and distribution facilities. Resource planning is performed subject to numerous uncertainties.

Accurate long-term demand forecasting is helpful to improve the stability and economy of power network operation. While, for the factors affecting long term demand are complicate and random, to forecast accurately seems a difficult job [10].

3. Research methodology

3.1 Hybrid optimization

There are three methods to find optimal solution; exact, approximate and meta-heuristic [2]. Exact algorithms are guaranteed to find optimal solution to any instance within an instance-dependent run time. Approximate methods (also called heuristic methods) are search methods that find (near-) optimal solution to an optimization problem in a short time. There is no guarantee of finding the optimal solution or a solution within certain range of the optimal one.

Meta-heuristics methods are general algorithmic frameworks that can be used to solve different hard optimization problems with few modifications by adding problem-dependent heuristics. The goal of meta-heuristic algorithms is to efficiently explore the search space in order to find optimal or near-optimal solution and to avoid local optimality [2].

3.2 HGA methods

As mentioned in previous section, the HGA is an appropriate algorithm and considered as a proposed algorithm to tackle the optimization problem in long-term energy demand forecasting model. The proposed method consists of two algorithms, GA as global search and unconstrained function minimization search algorithm as local search. HGA is an extension of the GA in which a local search addition work together to solve some combinatorial optimization problem.

Optimization algorithms can be divided into local and global search methods. Local methods usually converge at local optima. In term of the requirement of derivative information of the function to be optimized, local methods can be further classified into two categories as non-gradient based and gradient-based methods. The gradient-based methods use the derivative information of the objective function to compute and update the values of decision variables. However, the gradient-based methods are subject to two major limitations. *First*, objective functions are often difficult to achieve convergence with gradient-based methods. *Second*, the gradient based methods are liable to converge at a local minimum rather than finding a global optimal solution.

The non-gradient based method require only the evaluations of the objective function values but not the partial derivatives of the function and hence are also called the direct search methods. The gradient based methods (also called indirect search methods) require not only the calculation of the function values, but also the first and in some cases the second derivatives of the objective function or gradient vectors. The error is measured by the objective function which is dependent on the parameters values. Although the objective function is generally continuous and differentiable with respect to the parameters, it is usually difficult to calculate the derivatives of the objective function analytically except for very simple model. While using genetic algorithm to solve constrained optimization problems, some of its shortcomings appear such as difficulty in obtaining feasible individuals in many strong constraint conditions and poor local search ability [11].

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3.3 Proposed methodology

Based on the available historical data that are affected random demand, a new methodology to forecast long-term random demand up to twenty years ahead is proposed. The proposed methodological technique is illustrated in Figure 1 and can be summarized in three stages, these are pre-processing and modeling, simulating and forecasting, and evaluating. In long-term energy demand forecasting, the role of historical information is very important. Success of a demand forecasting method largely depends on the availability of data.

Energy demand of a power system is heavily influenced by several factors like the weather, socio-economic and demographic variables. Other data of considerable significance are gross national product (GNP), population of the franchise area, number of consumers connected, number of new housing and industry permits allotted, number of new infrastructural projects etc. [3]. However, the numbers of such variables are too many and they should be carefully selected. The selection criterion would have to be finally validated by their correlation and contribution analyses for a long-term forecast.

The first step in develop the forecasting model is to clearly understand the problem in order to establish the forecast range and objectives. Once the problem is fully assessed, the planners should focus their attention on preparing the data for developing the forecasting model.

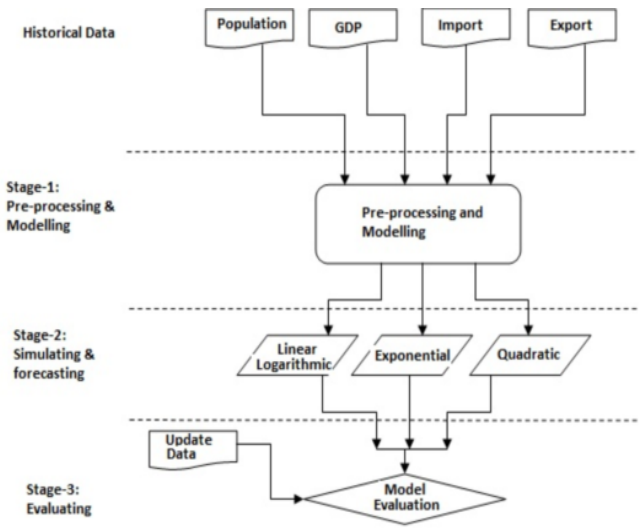

Figure 1. Block diagram of methodology

Data preparation for modeling can be broadly classified into three distinct areas. Firstly is data specification, in which variables of interest are identified and collected. Secondly is data inspection, in which data is examined and analyzed, and thirdly is data pre-processing, in which some data may be restructured or transformed to make it more useful.

In the second stage, the forecast distributions of energy demand were obtained by simulating and processing each model with the available data. Any method of long-term energy demand forecasting is then based on a special way of relating the above variables to demand. With all candidate variables being correct, complete and normally distributed, the planner must select an appropriate forecasting model(s) to use. Selection among these techniques will depend on the forecast time horizon selected, available data, available time, and on the cost of operating with a poor or inadequate forecast. The proper forecasts models were obtained from the estimated model that has a minimum error using simulations, and future assumed economic scenarios.

Finally, the third stage is to evaluate the forecasting performance of the model, the actual demand

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and estimation results of each model were compared. A good forecasting model at predicting the distributions of long-term energy demand is selected by measure of the effectiveness of the model for forecasting (taking out the effect of the forecasting errors in the input variables).

Once forecast results are obtained from the selected model(s), they need to be validated for accuracy. Some of the common indices that are used to determine forecast accuracy are mean square error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2). These indices are extremely useful in comparing forecast accuracy. When evaluating the different forecasting techniques, we should always remember that the objective of any forecasting activity is to provide a forecast with a sufficient degree of accuracy at the least possible cost.

4. Experimental and results

4.1 Model description

This paper used the historical information for long term energy demand forecasting based on data in [5] for the years 1980-2003 as followings:

- Yearly Electricity Domestic Consumption (TWh), year 1980-2003 (23 years)
- Population (Million Person), Gross National Product (Billions U.S. dollars), Import (Billions U.S dollars), and Export (Billions U.S dollars), year 1980-2003 (23 years)

The forecasting model is given by (1-3) as the following:

Exponential model:

$$\text{Exp } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} \quad (1)$$

Quadratic Model:

$$\text{Quad } Y = \beta_1 + \beta_2 X_1^{\beta_3} + \beta_4 X_2^{\beta_5} + \beta_6 X_3^{\beta_7} + \beta_8 X_4^{\beta_9} + \beta_{10} X_1X_2 + \beta_{11} X_1X_3 + \beta_{12} X_1X_4 + \beta_{13} X_2X_3 + \beta_{14} X_2X_4 + \beta_{15} X_3X_4 \quad (2)$$

In (1) and (2), X_1 is the Gross National 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. The fitness value is calculated for minimum least square error using fitness evaluation function as in (3).

$$S = [y - f(X,\beta)]' \, [y - f(X,\beta)] \quad (3)$$

Where S is the square errors, y is the actual of energy demand, and f is the forecasting values as the function of variables and weighting parameters.

4.2 Simulation results

Table 1 shows the comparison between exponential model in term of error found by former (GAED) method by [3] and proposed method.

Table 1. Results comparation for exponential model

Years	Total Actual (TWh)	GAED_Exp (Twh)	Relative errors (%)	Proposed Exp (TWh)	Relative errors (%)
1997	105.52	106.06	0.51	100.5399	4.71
1998	114.02	111.25	2.43	106.1839	6.87
1999	118.48	111.54	5.86	111.7817	5.65
2000	128.28	117.57	8.35	120.7550	5.83
2001	126.87	130.23	2.64	125.2162	1.30
2002	132.55	154.64	16.66	136.3701	2.88
2003	140.86	219.73	55.99	148.3939	5.34
	Average		**13.207**		**4.654**

Table 1 analyses demonstrate that proposed Exponential model with HGA estimation approach for Total net energy demand presents better forecasting accuracy than former (GAED exp) model. The simulated results for quadratic model are shown in Table 2. Table 2 analyses

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shows the average error found by proposed Quadratic model for Industrial energy demand is less than GAED Quad_in model.

Table 2. Results comparation for quadratic model

Years	Industrial Actual (TWh)	GAED_quad _in (Twh)	Relative errors (%)	Proposed Exp (TWh)	Relative errors (%)
1995	38.01	54.59	43.63	38.4321	1.11
1996	40.64	73.96	82.00	40.6186	0.05
1997	43.49	102.05	134.63	43.3224	0.38
1998	46.14	106.43	130.67	45.4234	1.55
1999	43.77	84.03	91.99	46.5808	6.42
2000	48.37	102.55	112.04	48.9272	1.15
2001	48.70	76.96	58.03	49.9258	2.51
	Average		**93.283**		**1.88**

4.3 Model comparison

To evaluate model performance, the actual energy demand of the twenty three years of data (1980-2003) has been compared with two different types of forecasting models as in Figure 2-3.

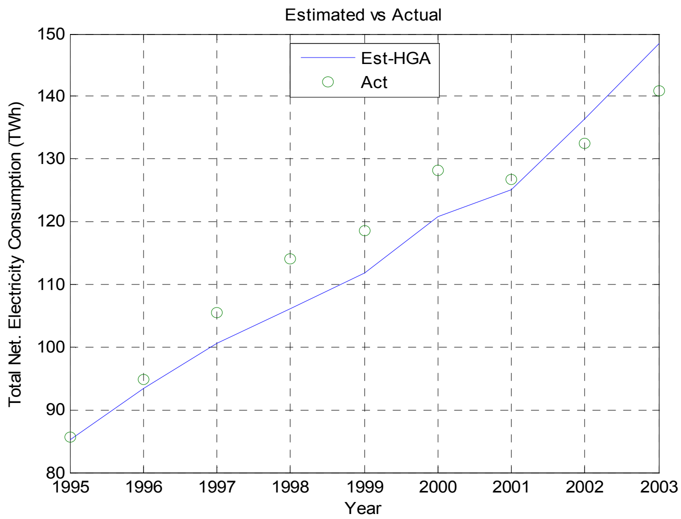

Figure 2. Comparison between actual and simulation result by proposed exponential model.

The simulation was compared the actual data and simulation results for exponential forecasting energy demand model and quadratic forecasting energy demand model using HGA estimation.

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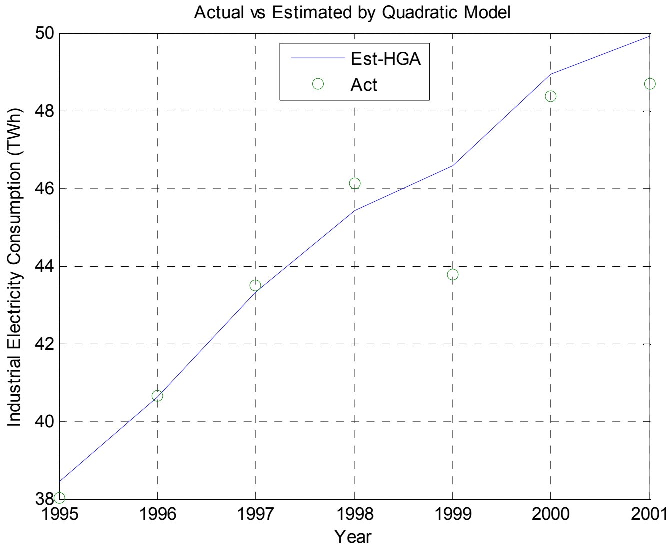

Figure 3.Comparison between actual and simulation result for proposed quadratic model

Optimum parameters values using hybrid optimization approach for exponential and quadratic model are illustrated in Table 3.

Table 3. Optimum Model Parameters

Parameter	Model	
	Exponential	**Quadratic**
β_1	1.0156	0.9126
β_2	1.5415	4.7097
β_3	-0.0210	-2.9006
β_4	2.0374	-2.1227
β_5	3.7811	-0.9927
β_6	1.0482	-0.8707
β_7	0.1680	-3.0073
β_8	0.8192	0.5152
β_9	-0.0978	-2.8064
β_{10}		1.5747
β_{11}		-2.7192
β_{12}		-1.5083
β_{13}		-2.9475
β_{14}		-3.8909
β_{15}		0.8052
S	**0.0075**	**0.0161**

From equation (1) and (2) when used HGA estimation for energy demand forecasting by exponential and quadratic models, mathematical models can be expressed as:

$$\text{Tot.net Electricity Consumption} = 1.0156 + 1.5415\, X_1^{-0.0210} + 2.0374\, X_2^{3.7811} + 1.0482\, X_3^{0.1680} + 0.8192\, X_4^{-0.0978} \quad (4)$$

and

$$\text{Industrial Electricity Consumption} = 0.9126 + 4.7097\, X_1^{-2.9006} - 2.1227 X_2^{-0.9927} - 0.8707 X_3^{-3.0073} + 0.5152 X_4^{-2.8064} + 1.5747\, X_1X_2 - 2.7192\, X_1X_3 - 1.5083\, X_1X_4 - 2.9475\, X_2X_3 - 3.8909\, X_2X_4 + 0.8052\, X_3X_4 \quad (5)$$

4.4 Future Projection

Figure 4 presents the pattern of Total net of Turkeys 'native demand' period from 1995 to 2003 and prediction by exponential model with data pre-processing and two scenarios of economic growth (low and high) period from 2004 to 2020. Average error is 4.654 % estimated by HGA.

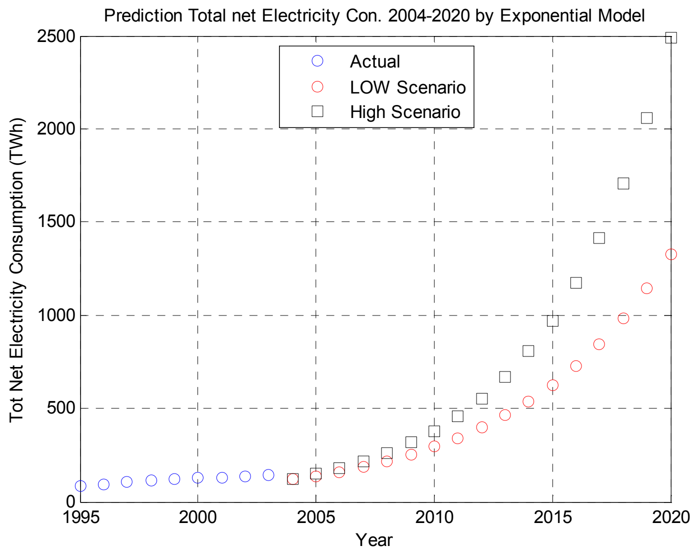

Figure 4. Pattern of Total net of Turkeys 'native demand' period from 1995 to 2003 and future projection 2004-2020

5. Conclusion and future work

Long-term energy demand forecasting using single genetic algorithm and hybrid genetic algorithm have been applied to estimate and prediction future projection for total energy demand. Experiment results shows that hybrid algorithm outperform the single algorithm. The approach is used to estimates yearly energy demand from 1980 to 2003. GAED energy demand models are investigated as a basic for comparison. Results of experiment show that hybrid approach can achieves better performance than single algorithm optimization. For future work, the hybrid approach can be adopted to estimate the demand patterns that have the same characteristics problems such as Non-deterministic Polynomial (NP) hard optimization problems and evolutionary computations. These problems exist in many research and development [12, 13].

6. Acknowledgment

The authors would like to thank the Indonesian Directorate General of Higher Education for financial supporting of this research. Authors also like to thank referees for their helpful.

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