www.ijlemr.com || Volume 02 - Issue 04 || April 2017 || PP. 65-68

Electricity Demand Forecasting for Malaysia Using Artificial Neural Network

Jebaraj S.

Department of Mechanical & Manufacturing Engineering Technology, Jubail Industrial College, Al-Jubail, Kingdom of Saudi Arabia.

Abstract: Energy is a vital input for the growth of any nation. Since electricity supply becomes a vital factor for future developments of the country, a system of models has to be developed to provide forecasts of the electricity demand. This analysis utilizes regression techniques, double moving average, double exponential smoothing, triple exponential smoothing, Auto Regressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) for the electricity demand forecasting in Malaysia. The model validation is done to select the best forecasting model. It is found that the ANN model gives better results. Hence, the ANN model is used for the electricity demand forecasting in Malaysia. It is also predicted that the total electricity demand for the year 2020 and 2030 is 172,665 and 245,037 GWh respectively.

Keywords: Electricity consumption, demand forecasting, forecasting models, Artificial Neural Network.

Introduction

Over the many years, forecasting has gained a widespread acceptance as an integral part of business planning and decision-making. Recent survey on literature in energy demand forecasting offers a broad range of forecasting tools. The electricity consumption is characterized by its large variations over time period. It varies widely from year to year and exhibits seasonal variations. Development of an energy planning model that can accurately forecast the electricity consumption is of prime importance. This paper aims in formulating the forecasting models by different techniques for the electricity demand for Malaysia for the years 2020 and 2030.

A detailed literature review has been carried out in the areas of various energy models such as energy planning models, energy supply-demand models, forecasting models and energy models by Artificial Neural Network. The potential of demand-side management in energy-intensive industries for electricity markets in Germany has been developed by Paulus and Borggrefe (2011) [1]. Kamyar et al. (2011) have formulated a prediction model to determine the differences between different commercial oil prices in the Persian Gulf region [2]. Electricity load prediction is performed by Wei-Chiang (2011) using seasonal recurrent support vector regression with chaotic artificial bee colony algorithm [3]. The future oil requirement of Iran has been determined by Behrang et al. (2011) using gravitational search algorithm [4]. Chi-hsiang (2012) formulated a regional electricity demand prediction model using decomposition and statistical analysis [5]. A short-term electric load modelling has been done by Ali and Hemen (2012) by means of echo state networks [6]. Barton et al. (2013) have studied the evolution of electricity requirement and the role for demand side participation, in buildings and transport [7]. Ning et al. (2013) developed an electricity demand prediction model by using multioutput feed-forward neural network with empirical mode decomposition based signal filtering method [8]. An energy prediction model has been formulated by Christopher et al. (2014) to find the low voltage distribution network consumption profiles by using a pattern recognition expert system [9]. Chunlei et al. (2014) has determined the energy demand of multiproduct pipeline using artificial neural networks [10].

It has been found that the Artificial Neural Network (ANN) can be implemented in the electricity demand forecasting in the country. In the present ANN forecasting model, the input variables such as past electricity consumption data, GNP, population, energy generation capacity have been used in the ANN multivariate model. In other models, only the past electricity consumption data is used as the input variable.

Methodology

In the present work, forecasting models to determine the electricity demand in Malaysia have been developed. This work utilizes time series regression techniques, double moving average model, double exponential smoothing model, triple exponential smoothing model, Auto Regressive Integrated Moving Average (ARIMA) model and Artificial Neural Network (ANN) (Univariate and Multivariate) model. Time series regression is a statistical approach of fitting a curve by data to obtain minimizes squared error. The objective of the regression is to determine the equation of a line through a set of data that minimizes the sum of the squared differences between the actual value and the line. The time series models namely linear, exponential, power and quadratic models are used in the development of forecasting model. In the linear model, the relationship that is

www.ijlemr.com || Volume 02 - Issue 04 || April 2017 || PP. 65-68

used to fit the 'n' number of data is a linear form with one input variable. Exponential models are suitable for long-term prediction when growth trend are consistent over time. The power model is also one of the time series regression approach used for the prediction with one input variable. If the data appear to follow a quadratic pattern, then the quadratic model is selected. The double moving averages are suitable to time series approach and in various cases they are more suitable to use than regression models. The term "moving average" is used because, as each new data in the series becomes inserted in the queue, the oldest data is removed and a new average is computed. To evaluate the double moving average, the simple moving average is used as an individual data and a moving average of these averages is calculated. The term α (alpha) is called smoothing constant normally ranges between 0.01 to 0.3 in the exponential smoothing models. The single exponential smoothing cannot deal with non-stationary data. The linear exponential smoothing is an attempt to deal with linear non-stationary data. Its only difference from single exponential smoothing is that it introduces extra formulas that can estimate the trend and subsequently use it for forecasting. To develop an equation that takes account of a linear trend in data, double exponentially smoothed statistics $S_t^{[2]}$ was calculated. The value of α is generated by trial and error method, starting with a certain value of α and then increasing or decreasing it to find the value that reduces the error. The triple exponential smoothing is also called as quadratic exponential smoothing. It is an extension of linear exponential smoothing. It aims at dealing with trend of a higher order than linear trend. This is achieved by introducing triple exponential smoothing which, in addition to the double exponential smoothing, is used to remove quadratic trends. If the data used for the analysis exhibits curvature in nature, then double exponential smoothing is inadequate. In such cases, triple exponential smoothing is used. Triple exponential smoothed data are sufficient for almost all practical applications. The double exponential smoothing method and triple exponential smoothing method were used in the analysis. Another common method to the forecasting is the Box-Jenkins time series technique, which is used here for the forecasting of electricity demand. The objective here is to formulate an Auto Regressive Integrated Moving Average (ARIMA) model, which represents the data generating stages. The Box-Jenkins method has four-stage iterative steps namely, model identification, model estimation, diagnostic checking and forecasting by the final model.

In general ANN's are computational paradigms that implements simplified models of their biological counterpart, biological neural structures. ANN's are characterized by local processing in artificial neuron, which is implemented by the rich connection pattern between processing elements. The first and last layers of Feed Forward Neural Network (FFNN) are called the input and output layers and those in between are called as hidden layers. In the total data available, 80 % is used for training and remaining data for validation of the model. Once the network is trained, it is used for forecasting the future electricity demand. The Artificial Neural Network uses Back Propogation Network (BPN) algorithm. Figure 1 illustrates the general processing element of artificial neural network model.

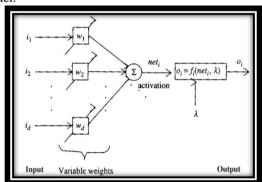


Figure 1. General processing element of Artificial Neural Network.

In the present electricity demand forecasting, the network has four input neurons, six hidden neurons and one output neuron. So, twenty four weights are present between input to hidden layer and six weights between the hidden to output layer. Input to the neural network should always be in the range 0.0 and 1.0. So, all the actual input data should undergo a transformation process termed as normalization. Here 0.1 was made equivalent to year 1978 data and 0.9 to year 2030 data. Since the data for the year 2030 is not available, some arbitrary value is selected from regression analysis. During the training phase, weights are changed continuously until the optimization of the weights is attained.

Model validation

All Model validation is required in order to determine its accuracy. A comparison of the Artificial Neural Network (ANN) model with the other models is made for the validation purposes. The predicted

electricity demand is compared with the actual electricity consumption data and the percentage error and correlation coefficient is arrived. The results indicate that the forecasting of the electricity predicted by the Artificial Neural Network (ANN) model is closer to the actual data than that predicted by the other models. From the Table 1, it is clear that the Artificial Neural Network (Univariate) gives the least Mean Percentage Error (MPE). After validating the various models, it iss concluded that the Artificial Neural Network (ANN) (Univariate) based forecasting model can be used for prediction of electricity demand in Malaysia.

Table 1. Electricity demand forecasting models.

No.	Forecasting Models	Mean Percentage Error , MPE (%)	Correlation Coefficient, R ²
1	Power Model $y = 2490.1x^{0.977}$	-6.80	0.972
2	Linear Model y = 3310.6x -13110	9.21	0.974
3	Quadratic Model $y = 77.852x2 + 507.89x + 4172.8$	-79.22	0.840
4	Exponential Model	-1.11	0.975
5	Double Exponential Smoothing Model y = 3046.6x - 17797	-26.38	0.995
6	Triple Exponential Smoothing Model $y = 93.034x^2 - 712.16x + 7689.6$	-42.43	0.990
7	ARIMA Model (0,2,0)	-2.70	0.995
8	ANN (Univariate) Model	-0.16	0.999
9	ANN (Multivariate) Model	-24.63	0.997

Electricity demand prediction

The past electricity consumption, GNP (Gross National Product), population and electricity generation capacity are used for electricity demand forecasting. The above discussed forecasting techniques are used for the forecasting of electricity demand in Malaysia. All the forecasting models are validated using Mean Percentage Error (MPE) and correlation coefficient and whichever model gives less error, is used for electricity demand prediction. The data used in the study represents the year wise consumption of electricity in Malaysia. The various forecasting models namely linear, exponential, power, quadratic, double moving average, double exponential smoothing, triple exponential smoothing, ARIMA and Artificial Neural Network (ANN)(Univariate and Multivariate) models are listed in Table1. Figure 2 shows the forecast of electricity demand for the years 2020 and 2030 in Malaysia. It was found that the consumption of electricity is increasing every year. The forecast of electricity demand for Malaysia for the years 2020 and 2030 is 172,665 and 245,037 GWh respectively.



Figure 2. Forecast of electricity demand in Malaysia.

ISSN: 2455-4847

www.ijlemr.com || Volume 02 - Issue 04 || April 2017 || PP. 65-68

Conclusion

The different prediction models are formulated for the prediction of electricity demand in Malaysia. After the formulation of prediction models, model validation is performed to select the optimum forecasting model. It is observed that the Artificial Neural Network (ANN) (Univariate) model gives the less Mean Percentage Error (MPE). Then based on the optimum forecasting model, electricity demand is predicted for the year 2020 and 2030 for Malaysia. It is found that the electricity demand is increasing every year. The forecast of electricity demand in Malaysia for the years 2020 and 2030 would be 172,665 and 245,037 GWh respectively. This study would be very useful to the policy makers and energy planners for energy planning in Malaysia.

References

- Paulus, M., and Borggrefe, F., 2011, "The potential of demand-side management in energy-intensive [1]. industries for electricity markets in Germany," Applied Energy, 88, pp.432–441.
- [2]. KamyarMovagharnejad, BahmanMehdizadeh, MortezaBanihashemi, and MasoudSheikhiKordkheili, 2011, "Forecasting the differences between various commercial oil prices in the Persian Gulf region by neural network," Energy, 36(7), pp.3979-3984.
- Wei-Chiang Hong, 2011, "Electric load forecasting by seasonal recurrent SVR (support vector [3]. regression) with chaotic artificial bee colony algorithm," Energy, 36(9), pp.5568-5578.
- Behrang, M.A., Assareh, E., Ghalambaz, M., Assari, M.R., and Noghrehabadi, A.R., 2011, [4]. "Forecasting future oil demand in Iran using GSA (Gravitational Search Algorithm)," Energy, 36(9), pp. 5649-5654.
- [5]. Chi-hsiang Wang, George Grozev, and SeongwonSeo, 2012, "Decomposition and statistical analysis for regional electricity demand forecasting," Energy, 41(1), pp.313-325. Ali Deihimi, and HemenShowkati, 2012, "Application of echo state networks in short-term electric
- [6]. load forecasting," Energy, 39(1), pp. 327-340.
- Barton, J., Huang, S., Infield, D., Leach, M., Ogunkunle, D., and Torriti, J., 2013, "The evolution of [7]. electricity demand and the role for demand side participation, in buildings and transport," Energy Policy, 52, pp. 85–102.
- Ning An, Weigang Zhao, Jianzhou Wang, Duo Shang, and Erdong Zhao, 2013, "Using multi-output [8]. feedforward neural network with empirical mode decomposition based signal filtering for electricity demand forecasting," Energy, 49, pp.279-288.
- [9]. Christopher, J. Bennett, Rodney, A. Stewart, and Jun Wei Lu. 2014, "Forecasting low voltage distribution network demand profiles using pattern recognition based expert system," Energy, 67, pp.200-212.
- Chunlei Zeng, Changchun Wu, LiliZuo, Bin Zhang, and Xingqiao Hu, 2014, "Predicting energy [10]. consumption of multiproduct pipeline using artificial neural networks," Energy, 66, pp.791-798.