Paper Title:

Forecasting Electricity Consumption: A Comparison of Models for New Zealand

Authors:

Zaid Mohamed[1] and Pat Bodger[2,*]

Affiliations:

1. Mohamed, Z., B.E (Hons), is a Ph.D. student in the Department of Electrical and Computer Engineering at the University of Canterbury, Christchurch, New Zealand.
   e-mail: zmo10@student.canterbury.ac.nz

2. Bodger, P.S, B.E (Hons), Ph.D., is Professor of Electric Power Engineering, Department of Electrical and Computer Engineering
   University of Canterbury, P.O Box 4800, Christchurch,
   New Zealand,
   Phone: (64)3642070, Fax: (64)3642761
   e-mail: p.bodger@elec.canterbury.ac.nz

Presenter:

Zaid Mohamed

[*] Corresponding author

Forecasting Electricity Consumption

A comparison of models for New Zealand

Zaid Mohamed and Pat Bodger[†]
Department of Electrical and Computer Engineering
University of Canterbury
Christchurch, New Zealand

ABSTRACT

Forecasting electricity consumption is of national interest to any country. Future electricity forecasts are not only required for short and long term power planning activities but also in the structure of the national economy. This paper proposes six forecasting models developed for electricity consumption in New Zealand. Three of these models (Logistic, Harvey Logistic and Harvey) are based on growth curves. A further model uses economic and demographic variables in multiple linear regression to forecast electricity consumption while another uses these factors to estimate future saturation values of the New Zealand electricity consumptions and combine the results with a growth curve model. The sixth model makes use of the Box-Jenkins ARIMA modeling technique. The developed models are compared using goodness of fit, forecasting accuracy and future consumption values. The future consumptions are also compared with the available national forecasts. The comparisons revealed that the best overall forecasts are given by the Harvey model for both the Domestic and the Total electricity consumption of New Zealand while a specific form of the Harvey model, the Harvey Logistic model, is the best in forecasting Non-Domestic electricity consumption.

1. Introduction

Forecasting electricity consumption has been applied using many theoretical methods including growth curves [1-6], multiple linear regression methods that use economic, social, geographic and demographic factors [7-13], and Box-Jenkins autoregressive integrated moving average (ARIMA) techniques [14-20].

This paper investigates the effectiveness of six forecasting models developed for electricity consumption in New Zealand. Firstly, a Logistic model [1, 2] based on the growth curve is developed. The fitting of logistic curves to the historical data employs a Fibonacci search technique to establish optimum asymptotes [1, 2]. In a second model, the influence of selected economic and demographic variables on the annual electricity consumption in New Zealand has been investigated [21]. The study uses population, price of electricity and Gross Domestic Product (GDP) of New Zealand. The resulting Combined Models [21] are developed using

[†] Corresponding author

multiple linear regression analysis. The third models [22] use an ARIMA technique in developing electricity forecasting models. Fourthly, two other growth curve models, Harvey models and Harvey Logistic models, based on growth curves are developed [23].

Finally, the paper discusses a Variable Asymptote Logistic (VAL) model for electricity consumption in New Zealand [24]. The saturation levels of the logistic curve are estimated using the Fibonacci search technique. Correlation of the estimated saturation level with population, price of electricity and gross domestic product (GDP) is determined. The VAL model for forecasting electricity consumption in New Zealand is proposed using one or more of the above explaining variables. Multiple linear regression is used in studying the correlation between the explaining variables and electricity consumption. Since ARIMA techniques are well known for predicting economic variables, they are used in predicting future values of population, price of electricity and GDP.

The developed models are compared for goodness of fit to the historical data and forecasting accuracy in the short, medium and long term. The future forecasts of these models are also compared with the available national forecasts in New Zealand [25, 26].

2. Models Theory

2.1. Logistic Model

The proposed Logistic model is [1, 2] of the form:

$$Y = \frac{F}{1 + \exp(C_0 + C_1 t)} \tag{1}$$

where;

Y is the annual consumption data in GWh,
F is the asymptotic value obtained by the Fibonacci search technique in GWh,
t is time in years,
C_0 and C_1 are constants.

2.2. Combined Model

The proposed Combined model using multiple linear regression is of the form [21]:

$$Y = a + b_1 X_1 + b_2 X_2 + b_3 X_3 + u \tag{2}$$

where,

Y is the electricity consumption (GWh),
X_1 is GDP ($NZ millions),
X_2 is electricity price (cents/ kWh),
X_3 is population,
u is the error (*disturbance term* or *white noise*).

Each of the independent variables X_1, X_2 and X_3 are themselves obtained from simple linear regression applied to data sets of these variables over time (t).

$$\begin{aligned} X_1 &= c_{01} + c_{11} t \\ X_2 &= c_{02} + c_{12} t \\ X_3 &= c_{03} + c_{13} t \end{aligned} \tag{3}$$

where, c_{01}, c_{11}, c_{02}, c_{12}, c_{03} and c_{13} are the constants of the respective simple linear regressions.

2.3. ARIMA models

ARIMA models are generally written as ARIMA(p,d,q), where p represents the order of the autoregressive (AR) part, d denotes the degree of first differencing (I) involved and q denotes the order of the moving average (MA) part. The autoregressive (AR) part of the model with order p is of the form:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots\dots\dots + \phi_p Y_{t-p} + e_t \tag{4}$$

The moving average (MA) part of the model consists of the past errors as the explanatory variable. A moving average model of order q is of the form:

$$Y_t = c + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots\dots\dots + \theta_p e_{t-q} + e_t \tag{5}$$

where

Y is the electricity consumption

e_t are the error series.

The Box-Jenkins methodology for modeling time series consists of identification, estimation, testing and forecasting. The resulting ARIMA models for New Zealand are discussed in detail in [22].

2.4. Harvey Logistic and Harvey Models

The Harvey Logistic model is based on the Logistic model. The proposed Harvey Logistic Model is [23]:

$$\ln y_t = 2 \ln Y_{t-1} + \delta + \gamma t + \varepsilon_t, \quad t = 2\dots T \tag{6}$$

where,

Y_t is the electricity consumption at year t,

$y_t = Y_t - Y_{t-1}$, $\qquad t = 2\dots T$

ε_t is a disturbance term with zero mean and constant variance,

δ and γ are constants to be found by regression.

The Harvey model is based on general modified exponentials. The proposed Harvey model is [23]:

$$\ln y_t = \rho \ln Y_{t-1} + \delta + \gamma t + \varepsilon_t \tag{7}$$

where,

$\rho = \dfrac{k-1}{k}$,

$\delta = \ln\left(k\beta\alpha^{1/k}\gamma\right)$,

ρ, β and γ are parameters to be estimated.

The value of k determines the form of the modified exponential function. When k = -1, it is Logistic and when k = 1 it is a simple modified exponential [23]. The only difference between the two models is that the parameter ρ in the Harvey model is significantly different from 2 in the Harvey Logistic model.

2.5. VAL model

In the VAL model, the saturation level F of the Logistic model (Eq. 1) is estimated using economic and demographic variables ($X_1 \ldots X_n$) and used as a variable asymptote $F(X)$ in Eq. 1. The proposed VAL model takes the form [24]:

$$Y = \frac{F(X_i)}{1 + \exp(a_0 + a_1 t)} \tag{8}$$

$$F(X_i) = c_0 + \sum_{i=1}^{n} (c_i . X_i) \tag{9}$$

where,

$F(X_i)$ is the saturation level expressed as a function of n variables,

c_0 and c_i are the parameters obtained from the explaining variables.

2.6. Statistical Measures

Mean squared error (MSE) is used to measure the goodness of the fit of each of the fitted model to the historical data. It is defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{10}$$

Mean absolute percentage error (MAPE) is used to compare the forecasting accuracy of the models. It is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(\frac{Y_i - \hat{Y}_i}{Y_i}\times 100\right)\right| \tag{11}$$

where,

Y_i is the actual consumption data at time i

$\hat{Y}_i$ is the forecasted consumption data at time i

n is the number of data points considered.

In addition, the developed models are tested against various statistical measures including autocorrelation analysis, Durbin-Watson (DW) statistic, *F*-test, *t*-test, residual plots and autocorrelation (ACF) and partial autocorrelation (PACF) plots of the data and residuals [1, 21-24].

3. Application to Electricity Consumption

The developed models are applied to the Domestic, the Non-Domestic and the Total electricity consumption data in New Zealand [27, 28]. Population and GDP data for New Zealand are obtained from Statistics New Zealand [29, 30]. Electricity price data are obtained from the Ministry of Economic Development, New Zealand [28, 31]. Electricity consumption for New Zealand from 1943-1999 is shown in Fig. 1. There is an increase in trend in the consumption data for all the sectors. However, the rate of consumption growth is generally very slow in the Domestic sector especially from 1975 onwards. The restrictions on electricity brought by the low lake inflows between late 1991 to mid 1992 can be clearly seen in all the three data sets with a sudden decrease in consumption in 1992.

Details of the developed models for electricity consumption are discussed in [1] for the Logistic models and [21-24] for the Combined models, ARIMA models, Harvey models and VAL models respectively. In the Logistic models, a Fibonacci search technique is applied to each of the data sets and the resulting models are proposed [1, 2]. The Combined models are proposed using the explaining variables population, price of electricity and GDP. In the ARIMA modeling, each data set is treated independently for stationarity, identification, estimation and diagnostic checking of residuals. The Domestic and the Total electricity consumption data required first order differencing while the Non-Domestic data required second order differencing to achieve stationarity. The proposed models are ARIMA(0,1,0) for the Domestic sector, ARIMA(0,2,1) for the Non-Domestic sector and ARIMA(1,1,0) for the Total consumption [22]. The Harvey and Harvey Logistic models showed acceptable degrees of statistical validity to the New Zealand electricity consumption data [23]. In the VAL models, the electricity consumption saturation levels are best explained by the population and price of electricity [24]. The addition of the extra variable GDP degraded the model. This indicates that GDP may not be a useful describing variable in forecasting electricity consumption, an observation that is contrary to many forecasting practices using econometrics including the proposed Combined model. The VAL model was not suitable to describe the Non-Domestic electricity consumption due to the inconsistencies in the saturation levels obtained due to possible immaturity in the sector [24].

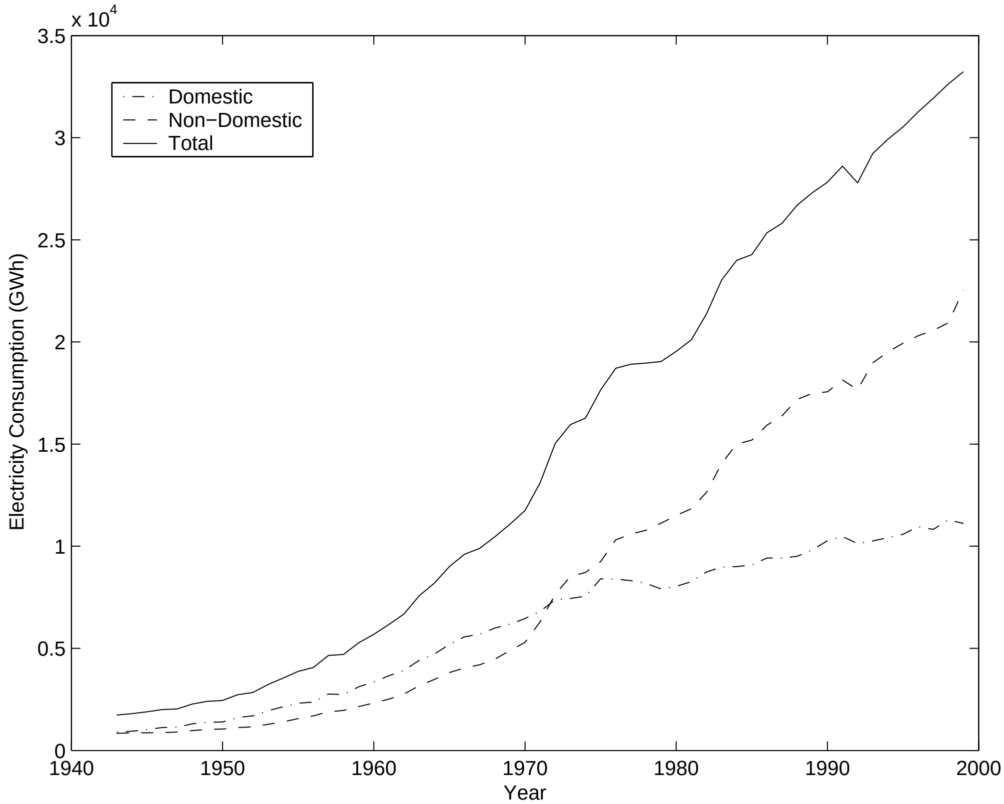

Fig. 1. Electricity consumption for New Zealand

The combined models are applied to the data sets from 1970-1999 while all other models are applied from 1943-1999. The combined models are not acceptable when applied to the whole data sets. The nature of electricity consumption growth in New Zealand was not suitable to apply a multiple linear regression model across the whole data sets, but this was adequately satisfied for the data sets from 1970-1999. In the development of the VAL models, saturation levels are obtained using the whole data sets for the years 1984-1999 and the model is fitted to the historical data from 1984-1999. That is, to obtain the saturation level for 1984, all data from 1943-1984 is used, similarly for the saturation level of 1999, all data from 1943-1999 is used. More details are available in [24].

4. Model Fit and Forecasting Accuracy

Forecasting accuracy of the six models is compared using MAPE. Forecasting accuracy is measured from one year ahead through to nine years ahead. To calculate the MAPE of the 1 year ahead forecast, the actual electricity consumption data for 1999 is held out while developing these models. The forecasts obtained by the models are then used in Eq. (11) along with the actual consumption data held out. In this case $n = 1$. Similarly, for 9 years ahead MAPE, actual data from 1991-1999 is held out in developing the models and $n = 9$. The MAPE plots of the six models from one year ahead through to nine years ahead are shown in Fig. 2, Fig. 3 and Fig. 4 for the Domestic, the Non-Domestic and the Total electricity consumption respectively.

The models are ranked according to their ability of model fit, short (1 to 3 years), medium (4 to 6 years) and long (7 to 9 years) term forecasting accuracy. Models are ranked from 1 (best) to 6 (worst) for the Domestic and the Total consumption, while 1 (best) to 5 (worst) for the Non-Domestic consumption as the VAL model is not applicable (n/a) for this sector. In ranking, the average of the MAPE values over the short, medium and long term is calculated and ranked from the lowest MAPE (best model) to the highest MAPE (worst model). The overall rankings for the Domestic, the Non-Domestic and the Total consumption are calculated by taking the average of the short, medium and long term rankings. Table 1 summarizes the results.

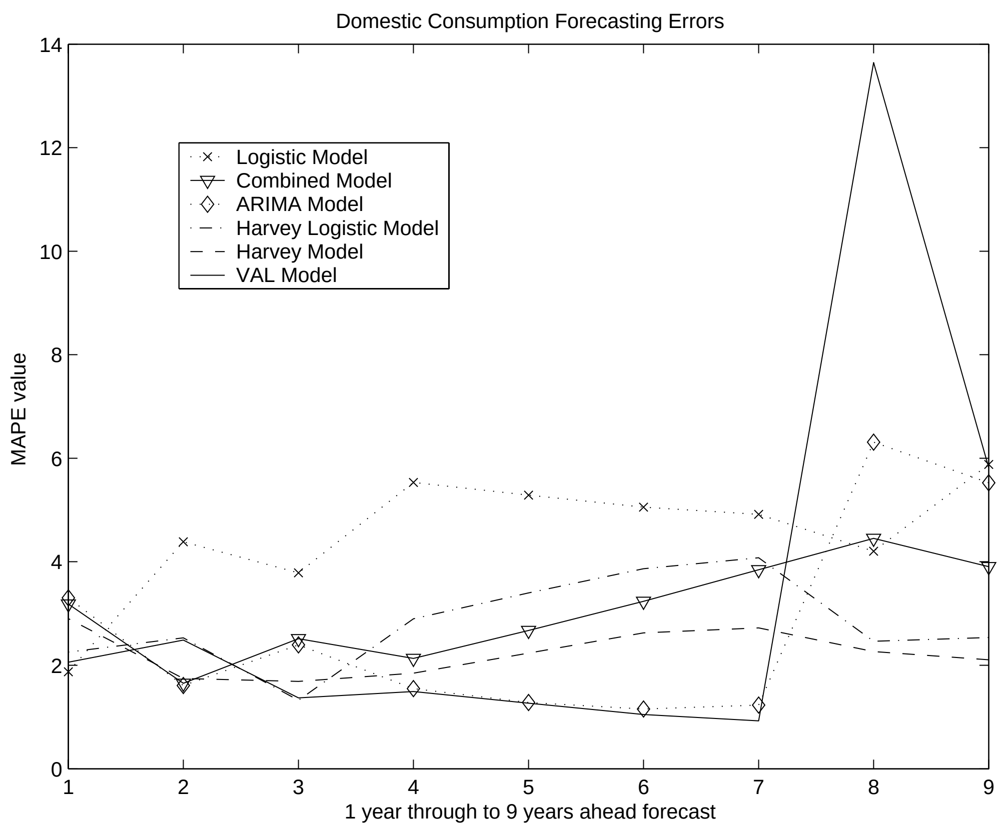

Fig. 2. Domestic electricity consumption forecasting accuracy of the six models

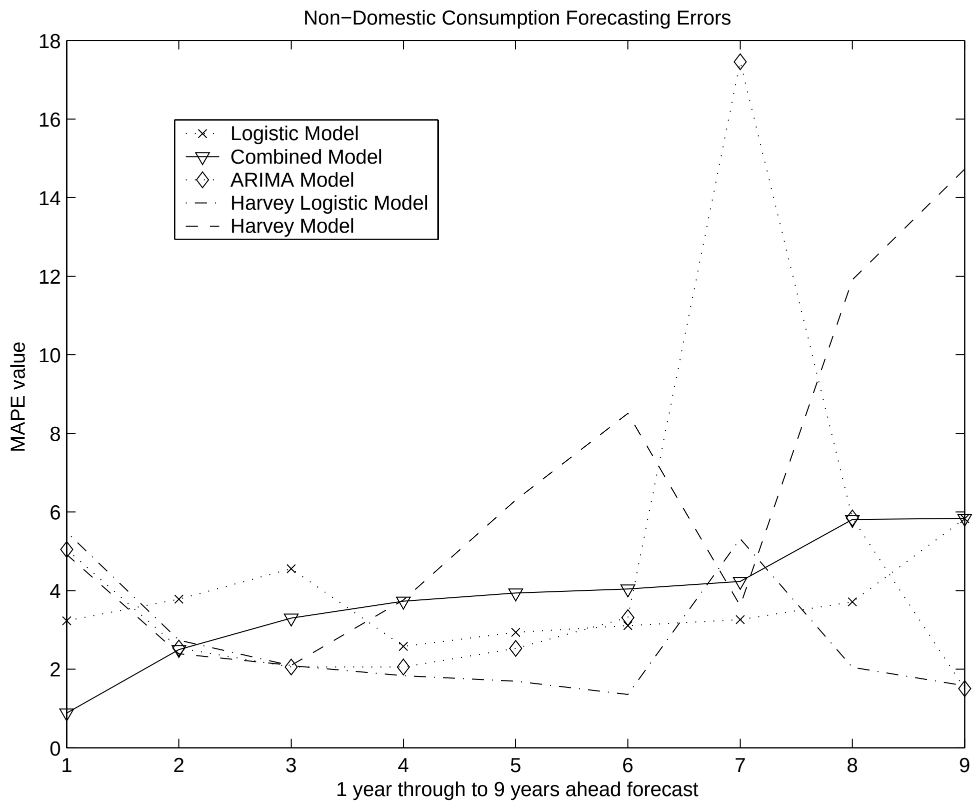

Fig. 3. Non-Domestic electricity consumption forecasting accuracy of the six models

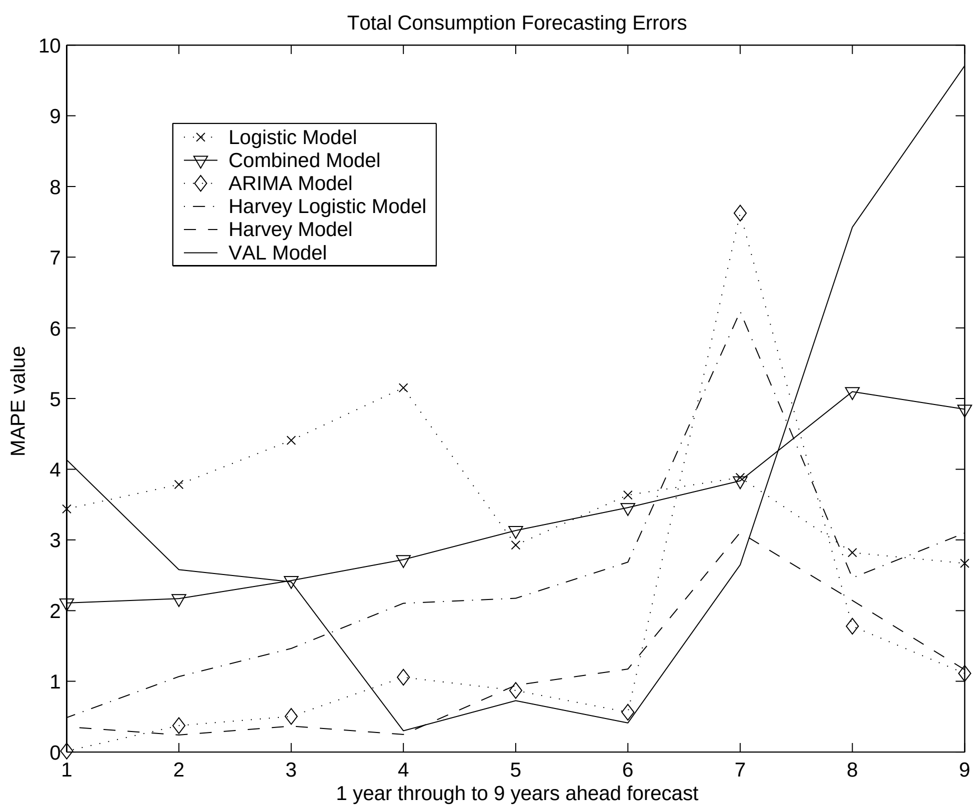

Fig. 4. Total electricity consumption forecasting accuracy of the six models

Table 1
Ranking of models in terms of model fit and short, medium and long term forecasting accuracy (1 = best, 6 = worst).

Model	Domestic					Non-Domestic					Total				
	fit	Forecast accuracy			**Overall MAPE**	**fit**	Forecast accuracy			**Overall MAPE**	**fit**	Forecast accuracy			**Overall MAPE**
		Short	medium	long			Short	medium	long			Short	medium	long	
Logistic	6	6	6	5	**6**	4	5	3	2	**4**	4	6	6	2	**5**
Combined	1	5	4	3	**5**	5	1	4	3	**2**	5	4	5	5	**5**
ARIMA	4	4	2	4	**4**	3	3	2	4	**3**	3	1	3	3	**2**
Harvey Logistic	2	2	5	2	**3**	2	4	1	1	**1**	2	3	4	4	**3**
Harvey	3	3	3	1	**1**	1	2	5	5	**5**	1	2	2	1	**1**
VAL	5	1	1	6	**2**	n/a	n/a	n/a	n/a	n/a	6	5	1	6	**4**

4.1. Domestic Sector

The best model in terms of fit is the Combined model while the Logistic is the worst. The short term forecasts given by all the models except the Logistic are very comparable. The VAL model is the best to forecast short and medium term Domestic electricity, while it is ranked the worst to forecast the long term. The best model to forecast long term Domestic electricity is the Harvey model. The worst forecasts for the short and medium term are given by the Logistic model. Overall, Harvey is the best model to forecast the Domestic electricity followed by the VAL model. The Harvey Logistic and the ARIMA are ranked in the middle. There is a sudden jump in MAPE of the VAL model at year 8. There are two possible reasons for this. Firstly, in the VAL method, the asymptotes are estimated for the years from 1984. Thus, in the 8 steps ahead forecast the saturation levels are initially calculated from 1984 to 1991. This means that as the number of step ahead forecast increases, the number of saturation values calculated decreases. The decrease in the number of data points generally increases the error in the estimate of the coefficients in the regression analysis. This will lead to an increase in forecasting errors. Secondly, for both the Domestic and Total consumption data, the decrease in the year 1992 due to the electricity restrictions brought by drought in that year resulted in an overall increase in the forecasting error.

4.2. Non-Domestic Sector

The best model fit is given by the Harvey model. The forecasts given by the ARIMA, Harvey Logistic and Harvey models are very similar for the short term. The Combined model gave the best short term forecast while the Harvey Logistic gave the best medium and long term forecasts. The worst forecasts are given by the Logistic model for short term and by the Harvey model for the medium and long term forecasts. Overall, Harvey Logistic is the best model to forecast Non-Domestic electricity. The ARIMA model continued to give the second lowest MAPE values up to year 6 with an overall ranking of 2. There is a large increase in error at the year 7 for the ARIMA. This corresponds to the forecasts made from the year 1992. The consumption is significantly low. The ARIMA forecasts are very dependent on the later values of the actual consumption. Thus, the overall forecast made for 7 years ahead is much lower. This resulted in a significant increase in error that is reflected in the MAPE plot. The Combined and the Logistic model gave similar and consistent MAPE errors throughout the compared period with an overall ranking of 2 and 4 respectively. As discussed before, the VAL model is not applied to the Non-Domestic electricity consumption data.

4.3. Total consumption

The best fit is again given by the Harvey model. The Harvey and ARIMA model gave very low MAPE values from year 1 to year 6. Thus, the ARIMA model was ranked the best for short term forecasting. The sudden decrease in MAPE by the VAL model at year 4 to 6 resulted in that model being the best to forecast the medium term. The Harvey model gave the best long term forecast. The Logistic and Combined models are ranked overall the worst forecasting models for Total electricity consumption. The consistently low forecasting errors by the ARIMA model except at year 7 resulted in that model being the second best to forecast the Total electricity consumption. Overall, the Harvey is the best model to forecast the Total electricity consumption.

5. Comparison of Future Forecasts

The forecasts obtained by the six developed models are compared with each other as well as with the national forecasts available in New Zealand. These are the CAE models [30] and the MED models [31]. The CAE forecasts are modelled using an annual load growth of 1.8%. Their study has used 1.8% as the baseline estimate, with 1.3% and 2.3 % growth used for sensitivity analysis. This paper uses the 1.8% baseline estimate for comparison purposes. The MED forecasts are made by the Ministry of Economic Development, New Zealand, using its SADEM energy supply and demand model. The SADEM model is a descriptive market equilibrium model focusing on the entire energy sector. The model determines equilibrium in the energy market by projecting demands for a given set of prices and comparing this with the modelled cost of supplying this level of demand [24]. These demands are re-estimated if the prices implied by modelling the level of supply are not consistent with the prices used to determine the initial demand. The process of re-estimation is continued until equilibrium is achieved with demand and supply in balance at market clearing prices. An interpolation technique is used for updates of the prices. Thus, the forecasts are also interpolated between these years.

The forecasts obtained by all the models from the year 2000 to 2015 for the Domestic and the Non-Domestic sectors and the Total consumption are shown in Fig. 5, Fig. 6 and Fig. 7 respectively. For the Domestic sector, the highest forecasts are given by the MED model followed by the CAE model. The forecasts by the Combined model and ARIMA models are very similar especially at the long term forecasts. The Harvey model forecasts approximately an average of all the other models. For the Non-Domestic sector, the ARIMA model predicted the highest consumption values followed by the Harvey model. CAE and MED forecasts are very similar at the early years while CAE and Harvey Logistic model forecasts are very similar at the latter years. The forecasts of the Combined model are more similar to but less than the Harvey model forecasts. For the Total electricity consumption, the forecasts are generally more comparable. Forecasts by the CAE, the MED and the Harvey models are very similar over the entire forecasted period. The forecasts by the Combined model are little higher on average than these three models. Forecasts by the ARIMA models are also very similar to the three models especially at the early years. In all cases the Logistic model has predicted the lowest consumption values followed by the Harvey Logistic model except for the Non-Domestic sector. The VAL model initially started with lower predictions than the Logistic model, but ultimately predicted higher consumptions values than the Logistic and Harvey Logistic model for the Domestic sector and Total consumption to which it is applied.

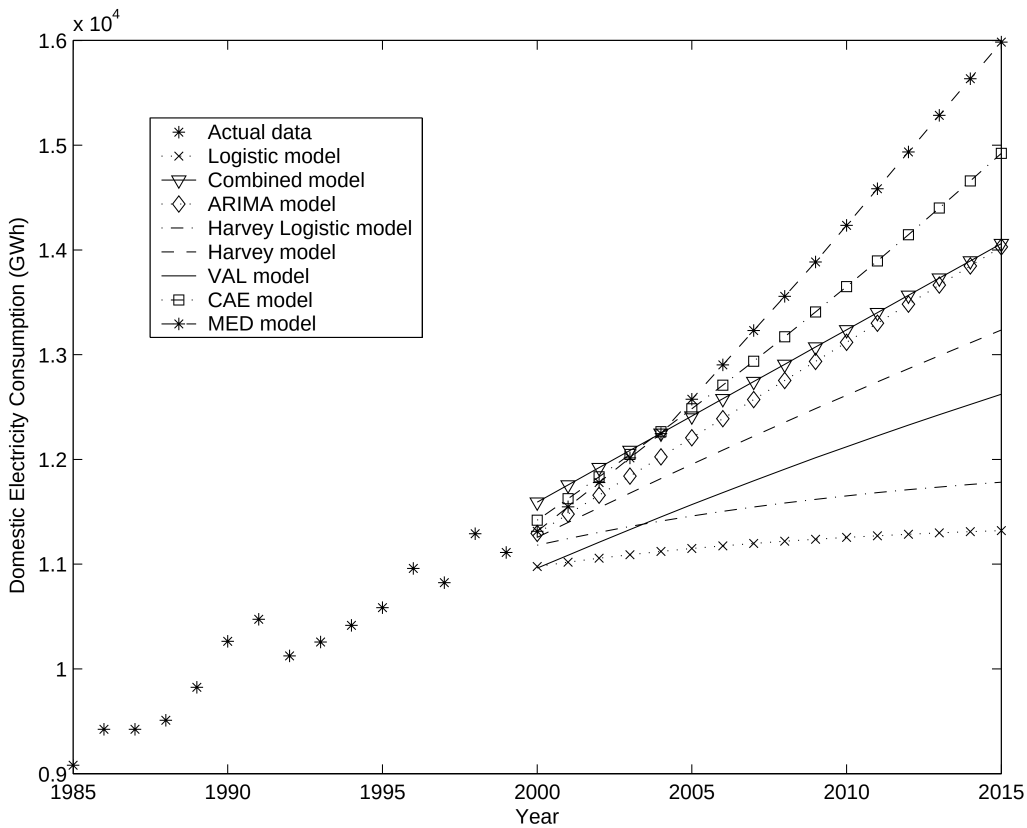

Fig. 5. Comparison of the Domestic Electricity Consumption Forecasts

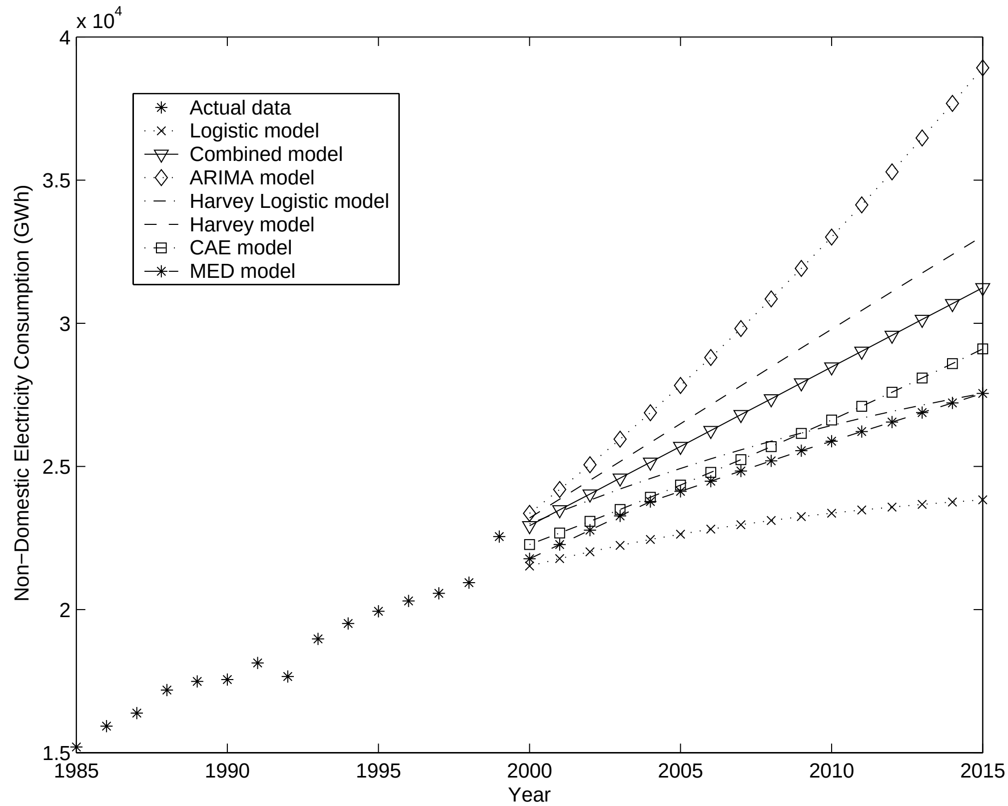

Fig. 6. Comparison of the Non-Domestic Electricity Consumption Forecasts

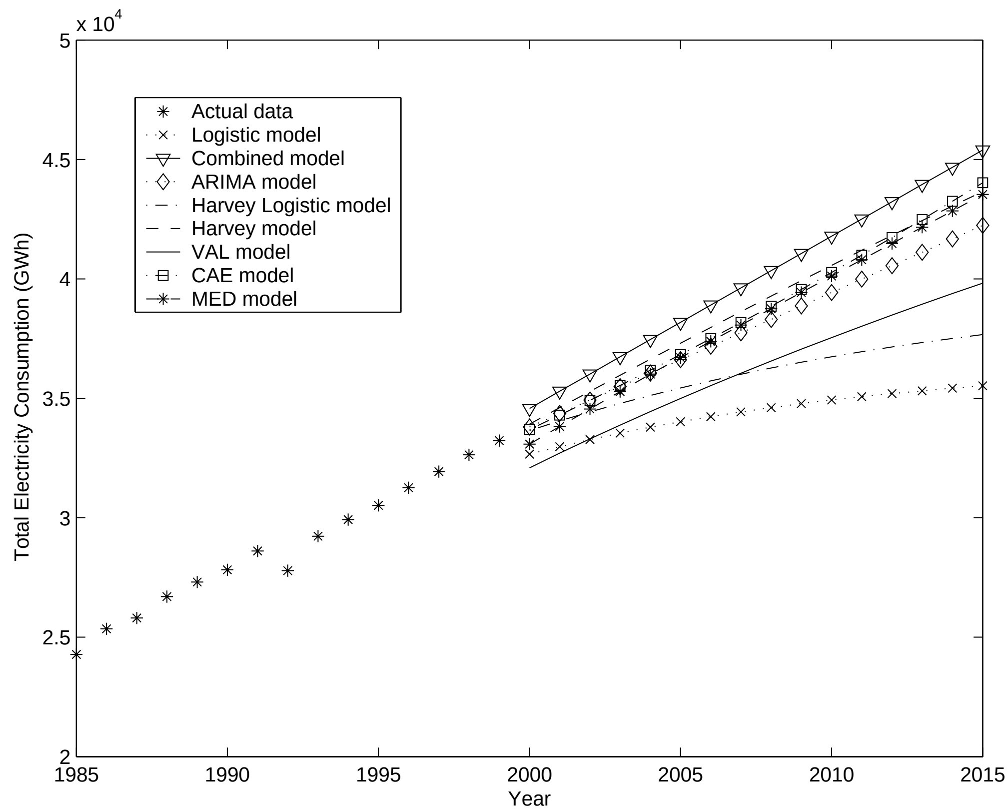

Fig. 7. Comparison of the Total Electricity Consumption Forecasts

6. Summary

This paper has compared six forecasting models developed for electricity consumption in New Zealand. They are the Logistic, Combined, ARIMA, Harvey Logistic, Harvey and the VAL model. One of each model was developed for each of the Domestic and the Non-Domestic sectors and the Total electricity consumption. The models were compared for goodness of fit to the historical data and forecasting accuracy. Forecasting accuracy is measured for short (1-3 years), medium (4-6 years) and long (7-9 years) term forecasts. The VAL model is the best in the short and medium term Domestic consumption forecasting while the Harvey model is the best for long term Domestic consumption forecasting. The Combined model is the best for short term Non-Domestic consumption forecasting while the Harvey Logistic model is the best for both the medium and long term Non-Domestic consumption forecasting. For the Total consumption forecasts, the best short term forecast is given by the ARIMA model, medium term by the VAL model and long term by the Harvey model. Overall, the best forecasts are given by the Harvey models for both the Domestic and the Total consumption and the Harvey Logistic model for the Non-Domestic consumption. In addition, the Harvey models gave the best model fit to the Non-Domestic and the Total electricity consumption.

References

[1] Mohamed, Z. and Bodger, P.S., "Analysis of the Logistic model for Predicting New Zealand Electricity Consumption," presented at the Electricity Engineer's Association (EEA) New Zealand 2003 Conference, Christchurch, New Zealand, Published in CD-ROM, 20-21 June 2003.

[2] Bodger, P.S. and Tay, H.S., "Logistic and Energy Substitution Models for Electricity Forecasting: A Comparison Using New Zealand Consumption Data," *Technological Forecasting and Social Change*, vol. 31, pp. 27-48, 1987

[3] Skiadas, C.H., Papayannakis L.L., and Mourelatos, A.G, An Attempt to Improve Forecasting Ability of Growth Functions: The Greek Electric System, *Technological Forecasting and Social Change* 44, 391– 404, 1993

[4] Sharp, J.A., and Price, H.R., Experience Curve Models in the Electricity Supply Industry, *International Journal of Forecasting* 6, 531–540, 1990.

[5] Young, P., Technological Growth Curves: A Competition of Forecasting Models, *Technological Forecasting and Social Change* 44, 375–389, 1993.

[6] Tingyan, X., A Combined Growth Model for Trend Forecasts, *Technological Forecasting and Social Change* 38, 175–186, 1990.

[7] Egelioglu F, Mohamad AA and Guven H., Economic variables and electricity consumption in Northern Cyprus. *Energy* 26, 355-362, 2001

[8] Harris, J.L. and Liu L., Dynamic structural analysis and forecasting of residential electricity consumption. *International Journal of Forecasting* 9,437-455, 1993

[9] Yan Y.Y., Climate and residential electricity consumption in Hong Kong. *Energy* 23(1),17-20, 1998

[10] Rajan, M. and Jain V.K., Modelling of electrical energy consumption in Delhi, *Energy* 24, 351-361, 1999

[11] Fung Y.H. and Tummala V.M.R., Forecasting of Electricity Consumption: A Comparative Analysis of Regression and Artificial Neural Network Models. *IEE 2nd International Conference on Advances in Power System Control. Operation and Management*, Hong Kong, 782-787, 1993

[12] Liu, X.Q., Ang, B.W. and Goh, T.N., Forecasting of Electricity Consumption: A Comparison Between an Econometric Model and a Neural Network Model, *IEEE International Conference on Neural Networks*, 2, 1254–1259, November 1991
[13] Lakhani, H.G. and Bumb B., Forecasting Demand for Electricity in Maryland: An Econometric Approach, *Technological Forecasting and Social Change* 11, 237-261, 1978
[14] Abdel-Aal, R.E. and Al-Garni, A.Z., Forecasting monthly electric energy consumption in Eastern Saudi Arabia using univariate time-series analysis, *Energy*, vol. 22(11), 1059-1069, Nov. 1997
[15] Chavez, S.G., Bernat, J.X. and Coalla, H.L., Forecasting of energy production and consumption in Austrias (northern Spain), *Energy,* vol. 24(3), 183–198, Mar. 1999
[16] Saab, S., Badr, E. and Nasr, G., Univariate modeling and forecasting of energy consumption: the case of electricity in Lebanon, *Energy*, vol. 26(1), 1 -14, Jan. 2001
[17] Wong Y.K. and Rad, A.B., Gauss-Markov models for forecasting and risk evaluation, in *Proc. EMPD'98 IEEE International Energy Management and Delivery Conf.*, vol. 1, 3-5 March 1998
[18] Gross, G. and Galiana, F.D., Short-Term load forecasting, *Proc. IEEE*, vol. 75(12), 1558-1573, Dec. 1987
[19] Hagan, M.T. and Behr, S.M., The time series approach to short term load forecasting, *IEEE Trans. Power Systems*, vol. 2, 785-791, Aug. 1987
[20] Komprej, I. and Zunko, P., Short term load forecasting, in *Proc. 1991 IEEE Electrotechnical Conf.*, 6th Mediterranean , 1470 -1473, vol. 2, 22-24 May 1991
[21] Mohamed, Z. and Bodger, P.S., Forecasting electricity consumption in New Zealand using economic and demographic variables, submitted for publication in the journal *Energy.*
[22] Mohamed, Z. and Bodger, P.S., "ARIMA Models to Forecast Electricity Consumption," being submitted for publication in the journal *Energy.*
[23] Mohamed, Z. and Bodger, P.S., "A Comparison of Logistic and Harvey Models for Electricity Consumption in New Zealand," submitted for publication in the journal *Technological Forecasting and Social Change.*
[24] Mohamed, Z. and Bodger, P.S., "A variable asymptote logistic (VAL) model to forecast electricity consumption," being submitted for publication in the journal *International Journal of Computer Applications in Technology.*
[25] Sinclair Knight Merz and CAE (Centre for Advanced Engineering, University of Canterbury, NZ), *Electricity Supply and Demand to 2015*. Fifth Edition, April 2000
[26] Ministry of Economic Development, Modelling and Statistics Unit., *New Zealand Energy Outlook to 2020*, February 2000
[27] Ministry of Energy, Electricity Forecasting and Planning: A Background Report to the 1984 Energy Plan, issues of 1982. –1984
[28] Ministry of Economic Development, *New Zealand Energy Data File*, July 2002
[29] Department of Statistics, New Zealand, *The New Zealand Official Year Book*, Wellington, N.Z. Govt. Printer, 2000 and 2002
[30] Statistics New Zealand, New Zealand. Web page: http://www.stats.govt.nz.
[31] Annual Statistics in Relation to Electric Power Development and Operation year ended .... condensed statistics for the combined developments + operations of the NZ Electricity Department + Distributing Electrical Supply Authorities. Wellington, A.R. Shearer. Government Printer. 1958 – 1974.