Scientific Research and Essays Vol. 6(8), pp. 1817-1830, 18 April, 2011
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE10.884
ISSN 1992-2248 ©2011 Academic Journals

Full Length Research Paper

Modelling and forecasting electricity consumption of Malaysian large steel mills

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Accepted 1 April, 2011

This paper describes a model to forecast the daily maximum demand of Malaysian large steel mills and the annual maximum demand contributed by these steel mills. This study attempts to combine both the top-down and bottom-up approaches to forecast the daily and annual maximum demand of the steel mills. The top-down approach uses regression analysis to forecast the annual amount of electricity consumption of the steel mills. The bottom-up approach uses the Model for Analysis of Electric Demand_Electric Load (MAED_EL) to convert the annual steel mills electricity consumption (which was earlier obtained from the regression model) into hourly load of the steel mills. The proposed method shows good forecasting accuracy, with weekly Mean Absolute Percentage Error (MAPE) of 2.3%.

Keywords: Load forecasting, regression analysis, top-down, bottom-up, steel mills.

INTRODUCTION

The iron and steel industry in Malaysia comprises of the manufacturing of iron ore and raw materials into primary iron and steel products and their subsequent products through the process of iron making, steel making, casting and rolling. The iron and steel industry is acknowledged as one of the most energy intensive industrial subsectors. Industrial electricity consumption accounts for approximately 50% (42,000 GWh) of the total electricity consumed in Peninsular Malaysia (Tenaga Nasional Berhad, 2008). The iron and steel industry alone represents approximately 20% (8,400 GWh) of the total industrial electricity consumption. This percentage is expected to increase as demand for iron and steel products continue to rise.

In Peninsular Malaysia, there are 42 plants with a total installed capacity of 24.3 million tonnes that are involved in manufacturing primary and finished (rolling) products (Economic Planning Unit, 2006). Primary products include scrap substitutes such as Hot Briquetted Iron (HBI) and Direct-Reduced Iron (DRI), as well as semi-finished products such as billets, blooms and slabs. Finished products consist of longs and flats. Longs include bars, wire rods and sections while flats consist of hot-rolled plates and sheets as well as cold-rolled coils.

Out of these 42 plants which manufacture primary and finished products, 8 plants were selected as the sample of this study. Although this sample size is small (19%), its percentage contribution of electricity consumption is significant. The total installed capacity of this sample is 15.2 million tonnes, which is three-quarter of the total installed capacity of plants involved in manufacturing primary products (Malaysian Iron and Steel Industry Federation, 2008). This sample also contributes approximately 85% (7,000 GWh) of the total iron and steel industry electricity consumption, and 13% (6,300 GWh) of the total industrial load in Peninsular Malaysia. These large steel mills are located in the northern and central parts of Peninsular Malaysia, and each of them are connected directly to the national power grid.

In the national load dispatch centre in Peninsular Malaysia, load profile of the eight large steel mills is constantly monitored at an hourly basis. These steel mills, which manufacture the bulk of Malaysian steel using Electric Arc Furnace (EAF) technology consume a large amount of electricity in a highly varying pattern. The daily maximum demand of steel mills utilising EAF represents a significant portion of the country's total peak demand. During the peak hours for instance, consumption from these steel mills alone account for

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around approximately 500 to 700 MW out of the average 13,000 MW of the total system maximum demand. This is almost equivalent to the capacity of one coal-fired power plant.

Due to this significant amount of load from the steel mills, Tenaga Nasional Berhad (TNB) which is Peninsular Malaysia's sole electricity utility, forecasts the daily maximum demand of these steel mills and incorporates them in the daily system load forecast. Due to unavailability of data in terms of historical and projected steel mills daily production, the current practice is to forecast the daily peak maximum demand of the steel mills using the moving average method (based on the previous two days observations). Although this method is simple and takes into consideration the most recent observations, it is unable to handle trend and seasonality (Hanke and Wichern, 2005). The most evident drawback is the high inaccuracy of forecast on Mondays as the weekend maximum demand is commonly higher as compared to other days.

The main objective of this study therefore, is to model and forecast the daily maximum demand of Malaysian large steel mills and the annual maximum demand contributed by these steel mills. To achieve this, the first task is to develop the top-down model to forecast the annual electricity consumption of these steel mills. This is done using regression analysis, which attempts to capture the relationship between electricity consumption and various external variables. The second task is to develop the bottom-up model to forecast the hourly load profile of the steel mills. This is done using MAED_EL, which attempts to define the load behaviour of steel mills based on its seasonality, day type and hourly variation. Based on these definitions, the model calculates and converts the annual steel mills' electricity consumption (obtained earlier from the regression model) into hourly load of the steel mills.

Data for the top-down model is limited to 17 observations for each variable. This limitation is mainly due to the limited amount of data available in Malaysia. It is acknowledged that a large sample size is preferable as it improves the probability of detecting difference and association, and determines the reliability and preciseness of the estimates (VanVoorhis and Morgan, 2001). However, there are several rules of thumb in determining the number of observations required in conducting a multiple regression analysis (Green, 1991; Tabachnick and Fidell, 1996). One is that there should be 10 observations for each independent variable that is included in the model. But, in most situations, this is not always possible. According to Tabachnick and Fidell (1996), 'a bare minimum requirement is to have at least 5 times more cases than the independent variables – at least 25 cases if 5 independent variables are used'. Therefore the sample of 17 observations for 4 independent variables is deemed acceptable in an unpermissing situation.

Greening et al. (2007) in their survey on industrial energy modelling have listed out the categories of techniques in modelling and forecasting industrial energy consumption, namely the energy trend decomposition method, the top-down model (exponential smoothing, regression, input-output) and bottom-up model (ARIMA, regression, neural network). Each of these methods has their own strength and weaknesses, and the selection of method depends on the issue to be analysed and the purpose of the investigation.

In Malaysia, the bottom-up engineering approach to study the end-uses of energy in the industrial sector has recently been conducted by Saidur et al. (2009). The study which is based on data collected from energy audit, managed to capture parameters such as end-use power rating, operation time, peak and off-peak tariff usage behaviour and power factor. The strength of this method is the ability to model specific processes and technological options. However, the most evident drawback of this method is that it frequently includes theoretical considerations (assumptions, estimations and calibrations), rather than observed consumer behaviour (Parti and Parti, 1980; Sanchez et al., 1998).

Direct metering data provides the best description of consumers' demand characteristics and behaviour (Saidur et al., 2009). Since TNB has a wide range of information regarding industrial electricity consumption, consumers' billing data and hourly metered data, it is best to utilise this wealth of information for this study. With load profile data, the better technique will be to use the bottom-up statistical method (such as regression or neural network) to construct the relative load shape based on exogenous variables such as weather and industrial production (Chen et al., 2000). However, this is not possible due to the following reasons: industrial load is not weather sensitive, and daily production data is unavailable (due to refusal of manufacturers to disclose production data). Recent works by Zhou et al. (2004), Świątek et al. (2005), Zhou et al. (2006) and Klempka and Świątek (2009) have successfully attempted to forecast steel mill load using regression and neural network methods; however these studies are only focused on a single steel mill plant. Klempka and Świątek (2009) proposed a forecasting model using neural network for each transformer station in a Polish steel mill. In this study, the neural network finds the relationship between electricity consumption of a particular transformer station and the operation sets of the plant. In the work conducted by Zhou et al. (2006), total electrical load of a Chinese steel mill is decomposed into two components, which are the basic load and the EAF load. The basic load is projected using the Moving Average method, while the EAF load is forecasted using neural network and support vector regression techniques, with temperature and production plan as the influencing factors.

In order to overcome the limitation of not having the

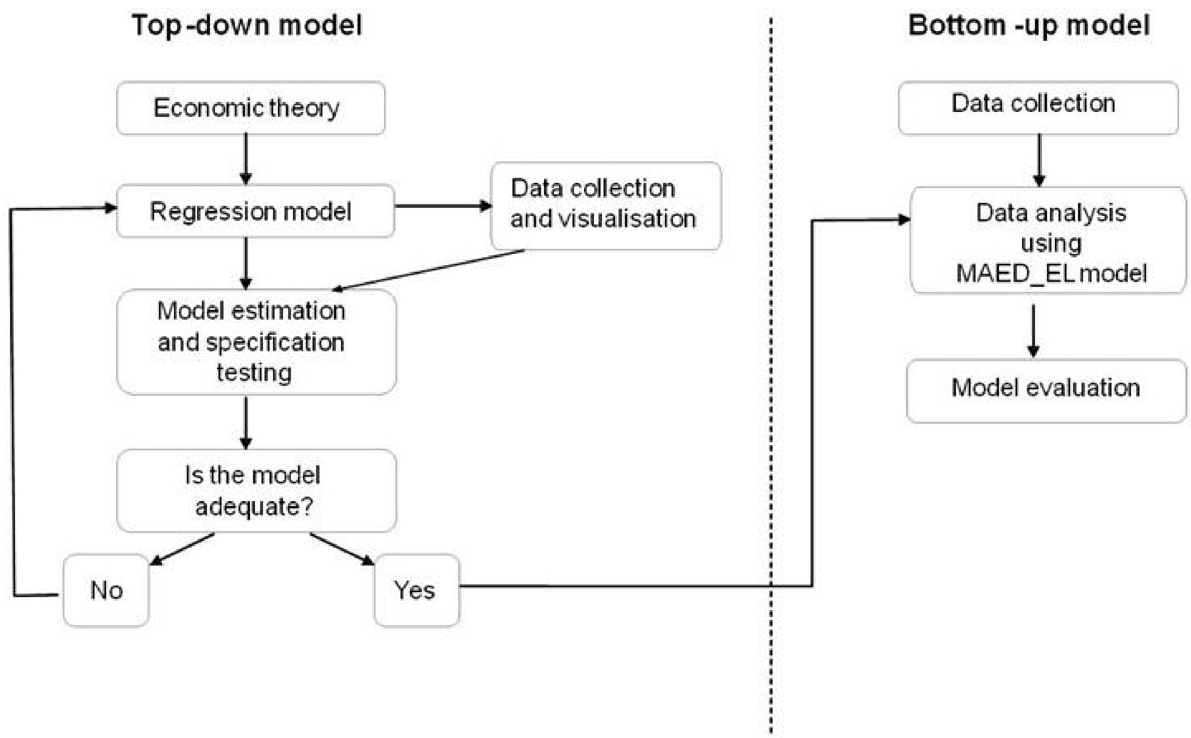

Figure 1. Research methodology.

production data, this study will attempt to make use of existing available macro and micro level data in Peninsular Malaysia. This study will therefore, try to combine both the bottom-up and top-down approaches to forecast the maximum demand of the steel mills. Böhringer and Rutherford (2005) and Kahn (1998) have supported the idea of integrating the top-down and bottom-up models in a single framework and have presented successful outcomes. Hybrid modelling efforts have also been proposed in load modelling (Hofman and Jorgesen, 1976; Broehl, 1981; Hogan and Weyant, 1982; Jacobsen, 1998; Hainoun, 2009).

The proposed method will integrate both economic and behavioural factors in a single framework. The top-down approach will utilise the regression method which captures the various macro factors that influence steel mills' annual electricity consumption, such as GDP, steel production, steel consumption and electricity price. The bottom-up approach will involve modelling using MAED_EL which captures the load behaviour of the steel mills based on its seasonal, daily and hourly variation. The output of the top-down model will be integrated into the bottom-up model to construct the forecasted hourly load of the steel mills. The daily and annual maximum will then be derived from the constructed hourly load. The research methodology is as shown in Figure 1.

This study produces several important outcomes. The large amount of consumption and highly varying pattern of these steel mill loads have been a challenge in the planning and operation of the national grid. To ease this problem, it is therefore necessary to provide accurate forecasts of the steel mills load, which will be incorporated in the overall system load forecast. Accurate forecasts will help to reduce both investment and operation costs of the utility. The ability to forecast steel mills' load profile will also facilitate the utility in determining load management strategies that can help alleviate peak demand. This in return will provide a better means for the utility in designing the best tariff structure for its customers.

MATERIALS AND METHODS

Top-down model

Regression analysis

The top-down approach is used to forecast the annual amount of electricity consumption of the steel mills. To achieve this, the multiple regression method has been applied. Regression is chosen instead of other methods because this method has the ability to capture the various factors that influence electricity consumption. Although the time series method is easy to implement, it does not take into account explanatory variables and only depends on historical trends, which may not re-occur in the future. Regression analysis has also proven to be an effective tool in providing information about energy analysis and future demands (Al-Ghandoor et al., 2008). It has in fact been cited as one of the most popular techniques in predicting electricity consumption (Tso and Yau, 2007).

Several variables that determine the annual amount of electricity consumption will be examined. This is based on economic theories and previous reported studies (Broehl, 1981; Fung and Tummala, 1993; Mohamed and Bodger, 2003). Equation (1) presents the proposed multivariate linear regression model to forecast electricity consumption:

$$Y=\alpha+\beta_1X_1+\beta_2X_2+\beta_3X_3+\beta_4X_4 \quad (1)$$

Where
Y = Electricity consumption
α = constant
$\beta_1....\beta_4$ = regression coefficients
X_1 = steel production
X_2 = steel consumption
X_3 = Gross Domestic Product (GDP)
X_4 = electricity price

The software applied to develop the regression model is ForecastX. This forecasting tool is developed by John Galt Solutions Incorporated, and is an add-in within Microsoft Excel. This software is chosen because of its capability of performing various forecast methods and various statistical analyses. It has advanced data analysis features and includes over 20 types of accuracy measurements (John Galt Solutions, 2008).

Data collection

The variables selected to test for their relationship with electricity consumption are as follows:

Electricity consumption: The annual electricity consumption data from the eight steel mills are extracted from the TNB Enhanced Customer Information Billing System (ECIBS). For this purpose, the customer account number for each steel mill must first be identified. The total unit kWh consumed by each steel mill during the peak and off-peak period is then extracted from the system on a monthly basis. These data are then aggregated to obtain the annual electricity consumption that represents the whole sample.

Steel production: It is important to note that all industry indicators such as steel production and steel consumption in this study only involve primary and rolling (finished) products. This is because the eight large steel mills involved in this study only produces steel products which fall in these categories. Products that fall under the primary category are HBI and DRI. Finished products include longs (billets, bars, wire rods, sections) and flats (hot-rolled plates and sheets, cold-rolled sheets and coils). These data are obtained from the Malaysian Iron and Steel Industry Federation (2008).

Steel production is known to be the most important factor that affects electricity consumption patterns (Zhou and Guan, 2004; Ashok, 2005; Zhou et al., 2006; Al-Ghandoor et al., 2008). Production is directly affected by market conditions and demand in steel products, which in turn is influenced by local and global economic situations. The coefficient sign of this variable is expected to be positive.

Steel consumption: Consumption of steel products in Malaysia is largely influenced by economic conditions, the nation’s industrial progress as well as domestic demand (Malaysian Iron and Steel Industry Federation, 2008). The coefficient sign of this variable is expected to be positive.

Real electricity price: When electricity price increases, the industry is expected to respond by employing more efficient processes and changing their production trend. Correspondingly, the amount of electricity consumption is expected to be reduced. Therefore the coefficient sign of this variable is expected to be negative. This price removes the inflation effects of the country, as proposed in previous studies (Liu et al., 1991; Harris and Liu, 1993). The price data from 1992 to 2008 is obtained from TNB.

Gross domestic product (GDP): GDP is an important indicator of the nation’s economic prosperity. Economic progress of the country will contribute towards a construction boom and thus rise in demand of steel products. The coefficient sign of this variable is therefore expected to be positive. The GDP data from 1992-2008 is obtained from Department of Statistics Malaysia (Department of Statistics Malaysia, 2009).

The full data set used in this study is summarised in Table 1.

Bottom-up model

MAED_EL model

In this study, the bottom-up model is developed using MAED_EL. MAED_EL is a model developed by the International Atomic Energy Agency (IAEA). The methodology is based upon a well established methodology created by the Electricité de France (EDF) and the program DURAT which was originally developed for the UN Economic Commission for Latin America (ECLA) (International Atomic Energy Agency, 2006).

The original purpose of MAED_EL is to analyse the national hourly electric load by several sectors, namely the industrial, transportation, domestic and commercial sectors to construct the load duration curve of the whole power system. This model is originally used in conjunction with the MAED_D model to project the future annual energy demand. The general approach of MAED_D relies upon the end-use methodology that evaluates future energy demand based on socio-economic, technology and demographic development of each economic sector (Hainoun, 2009). However, for the purpose of this study, the regression model developed earlier in the top-down analysis is used in conjunction with MAED_EL instead. Several specifications have been made to the model to focus solely on the steel mills load, while maintaining the basic principles of the model.

The most prominent feature of this model is its flexibility in representing the structure of electricity consumption according to specific needs and data availability. This powerful model has been used by energy planners and analysts in energy ministries, electric utilities and research institutions in 115 member states of IAEA, for instance China, India, Republic of Korea, Russia, Brazil, Mexico, Syria and Thailand (International Atomic Energy Agency, 2009). The World Bank, the Latin American Energy Organisation (OLADE) and the European Commission also use this model as part of their research studies and energy projects in developing countries (International Atomic Energy Agency, 2009).

Data collection

Information source for the data required in MAED_EL consist of the hourly load data of the eight steel mills. This data was extracted online from the TNB metering system. The one-hour metered interval data is gathered from each steel mill for a period of one year, that is between 1 January 2007 and 31 December 2007. The data is then aggregated to obtain the cumulative load profile. Data from year 2007 is selected as the base year as it is the most recent year that is able to represent stable conditions of electricity consumption.

Table 1. Data set.

Year	Electricity consumption (GWh)	Production ('000 mt)	Consumption ('000 mt)	GDP (RM million)	Real electricity price (sen/kWh)
1992	1,074	3,811	5,294	213,964	9.49
1993	1,203	4,521	6,476	235,137	10.20
1994	1,602	5,749	8,089	256,796	9.73
1995	2,281	6,929	9,872	282,039	10.23
1996	3,044	8,313	11,655	310,248	10.75
1997	3,089	8,707	12,109	332,967	11.16
1998	1,652	5,281	6,393	308,463	11.22
1999	2,037	6,301	8,230	327,397	11.06
2000	3,140	8,141	9,706	356,401	10.82
2001	3,202	8,518	9,498	358,246	10.57
2002	3,225	9,096	10,459	377,559	10.33
2003	3,916	10,513	10,612	399,419	10.13
2004	4,448	11,817	12,110	426,508	10.13
2005	4,278	10,513	11,120	449,250	9.57
2006	4,540	11,630	12,096	475,192	9.62
2007	5,414	13,136	13,136	505,353	10.22
2008	5,343	12,850	10,188	528,804	10.02

Prior to analysis, missing data points are first identified and replaced. This is important to cater for problems in data collection due to faulty meters and communication network failure. Overall, the quality of data collected was excellent, in which only 29 out of 8760 data points (0.3%) were missing due to communication network failure. The missing values detected within the daily load profile are estimated using historical data based on the same type of day, month and hour (Yu et al., 2005; Amakali, 2008).

Data analysis in MAED_EL

Based on the definition of behaviour of the steel mills, MAED_EL converts annual steel mills electricity consumption obtained from the results of the regression model into hourly load of the steel mills. Calculation of hourly load of the steel mills is performed using various modulation coefficients, which characterise or correlate changes in electricity consumption of each particular hour with respect to the average consumption.

The load curve of a particular sector at a given hour, day and week of a year is dependent on the following factors (International Atomic Energy Agency, 2006):

i. Trend of average growth rate of electricity over the year
ii. Seasonal variations in consumption (this variation may be reflected on a monthly or weekly basis, depending on available information)
iii. The changes in electricity consumption owing to the type of day being considered (that is working days, weekends and special holidays)
iv. The hourly variation in electricity consumption during the given type of day considered.

This analysis takes into account the following coefficients based on Equation 2 below. The load at a particular hour *h*, in day *j* of week number *i* for the year *n* is therefore calculated as follows (International Atomic Energy Agency, 2006):

$$P_{h,i,j,n} = \frac{W_n}{N_n} * T_{i,n} * K_{i,n} * P_{j,i,n} * \frac{1}{24} \Pi_{h,i,j,n} \qquad (2)$$

where:

W_n is the annual electricity consumption (obtained from regression model)

N_n is the number of days

$T_{i,n}$ is the growth trend coefficient

$K_{i,n}$ is the seasonal coefficient

$P_{i,j,n}$ is the daily weight coefficient

$\Pi_{h,i,j,n}$ is the hourly coefficient

RESULTS

Top-down model

Data visualisation

A time series plot of the dependent and independent variables, as shown in Figure 2 shows that there is a linear trend with no seasonal or cyclical components. The correlation matrix shown in Table 2 suggests a positive relationship between electricity consumption and steel production, steel consumption and GDP.

However, electricity price appear to have a weak relationship with electricity consumption. This is because

Figure 2. Time series plot of the independent and dependent variables.

Table 2. Correlation matrix.

Variable	Electricity consumption	Production	Consumption	GDP	Real electricity price
Electricity consumption	1.00	0.99	0.84	0.97	-0.20
Production		1.00	0.86	0.96	-0.20
Consumption			1.00	0.73	0.00
GDP				1.00	-0.18
Real electricity price					1.00

the electricity supply industry in Malaysia is regulated and electricity price (tariff) is determined by the government. In this situation there is no price elasticity of demand, that is demand of electricity is insensitive to price changes. The variable electricity price is therefore omitted from the proposed model in Equation 1. The model is thus reduced to Equation 3.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (3)$$

Table 3. Model estimation.

Variable	Coefficient	T-test	P-value
Electricity consumption	-1,156.22	-3.71	0.00
Steel production	0.39	5.41	0.00
GDP	0.00	1.66	0.12
Steel consumption	-0.01	-0.19	0.85

R^2 = 99.20%, Adjusted R^2 = 99.02%, F-value = 540.55, MAPE=4.23%, Durbin-Watson=2.06

Table 4. Model estimation.

Variable	Coefficient	T-test	P-value
Electricity consumption	-1,206.99	-7.76	0.00
Steel production	0.38	9.90	0.00
GDP	0.00	2.47	0.03

R^2 = 99.20%, Adjusted R^2 = 99.09%, F-value = 870.75, MAPE = 4.27%, Durbin-Watson = 2.05.

Where
Y = Electricity consumption
α = constant
$\beta_1 .... \beta_3$ = regression coefficients
X_1 = steel production
X_2 = steel consumption
X_3 = GDP

Model estimation and specification testing

The regression coefficients based on the proposed model in Equation 3 are estimated.

Several statistical tests are used to validate the model. These include the adjusted R^2 test, the t-test, the F-test and the Durbin-Watson test. The estimated output from the proposed model as described in Equation 3 is as shown in Table 3.

In evaluating the significance of the variables in the proposed model, the desired level of confidence is 95%. The variables steel production and GDP prove to be significant and the signs of coefficients follow common economic theories. However the variable steel consumption is found to have an incorrect sign and is insignificant at the 95% confidence level. This may be due to multicollinearity between consumption and production since both variables are generally measuring the same thing. As shown in Table 2, the correlation between consumption and production is 0.86, which is quite high. The variable consumption is therefore removed and the model is reduced to follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 \tag{4}$$

Where
Y = Electricity consumption
α = constant
$\beta_1 .... \beta_2$ = regression coefficients
X_1 = steel production
X_2 = GDP

Table 4 shows the final outputs for the modified model, as described in Equation 4.

As seen from Table 4, the regression model is significant and all coefficients have their expected sign. The calculated values of *t* for each variable are higher than the critical *t* values. Therefore there is sufficient evidence to suggest that both production and GDP have significant, positive impacts on electricity consumption. Similarly, the calculated value of *F* is much higher than the critical value of F, thus suggesting that the overall model is significant. The adjusted R^2 value of this model is 99.09%, implying that 99.09% of the variations in electricity consumption can be explained by the variations in steel production and GDP. Durbin-Watson statistic which lies between 1.5 and 2.5 suggests that serial correlation is not present.

Since the suggested model fulfils all validity requirements and demonstrates a high measure of goodness-of-fit, the complete equation of the model proposed in Equation 4 is therefore written as follows:

$$Y = -1206.99 + 0.383 X_1 + 0.003 X_2 \tag{5}$$

Where
Y = Electricity consumption

Table 5. Actual versus forecast.

Year	Electricity consumption		Error (%)
	Actual (GWh)	Forecast (GWh)	
2006	4,540	4,615	-1.6
2007	5,414	5,275	2.6
2008	5,343	5,228	2.1
MAPE			2.1

X_1 = steel production

X_2 = GDP

Model evaluation

The accuracy of the model will be evaluated by calculating the Mean Absolute Percentage Error (MAPE). MAPE is used as an indication of how large the forecast errors are in comparison to the actual values of the series. MAPE is calculated by finding the absolute error in each period, dividing this by the actual observed value for that period, and then averaging these absolute percentage errors. This is as shown in Equation 6 (Gujarati and Porter, 2010):

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|Y_t - \hat{Y}_t\right|}{Y_t} \quad (6)$$

Where

Y_t = actual value in time period *t*

$\hat{Y}_t$ = forecast value for time period *t*

n = number of observations

The model represented in Equation 5 shows good performance with MAPE of 4.3%. Another approach to model testing is to use a 'holdout' period for evaluation, in which a part of data is set aside to assess the performance of the model on the holdout data. For this purpose, data between 2006 and 2008 are excluded from the estimation and is used for checking the forecast performance. As seen in Table 5, the model performs well in forecasting electricity consumption. Forecast error recorded for each year between 2006 and 2008 were all less than 3%. The overall MAPE for the hold-out period is 2.1%.

Bottom-up model

Growth trend coefficient, $T_{i,n}$

Since MAED_EL models load for a standard day, the first correction to be made corresponds to the general trend of growth of electricity consumption. The growth trend coefficient, $T_{i,n}$ which takes into account the increase of consumption during the year, is therefore calculated as follows (International Atomic Energy Agency, 2006):

$$T_i = \left(1 + \frac{Growth}{100}\right)^{\frac{i-26}{52}} \quad (7)$$

where *i* =1, 2…..52

$T_{i,n}$ is calculated based on the steel mills' average annual growth rate of electricity consumption for the past 5 years (2003 to 2007) which is 6.8%.

Seasonal coefficient, $K_{i,n}$

Seasonal coefficient, $K_{i,n}$ is ratio of weekly consumption to average weekly consumption. The weekly coefficient is obtained by ratio of the weekly load to the average weekly load. The trend effect is then removed by dividing the weekly coefficient with the corresponding trend coefficient (International Atomic Energy Agency, 2006):

$$K_{i,n} = \frac{E'_{i,n}}{AWC} \quad (8)$$

Where

Average weekly coefficient,

$$AWC = \frac{1}{53}.\sum_{1}^{53} E'_i \quad (9)$$

and Weekly consumption,

$$E'_{i,n} = \frac{E_i}{T_i} \quad (10)$$

Figure 3 gives the summary of weekly load for Peninsular Malaysia as calculated from hourly readings from 1

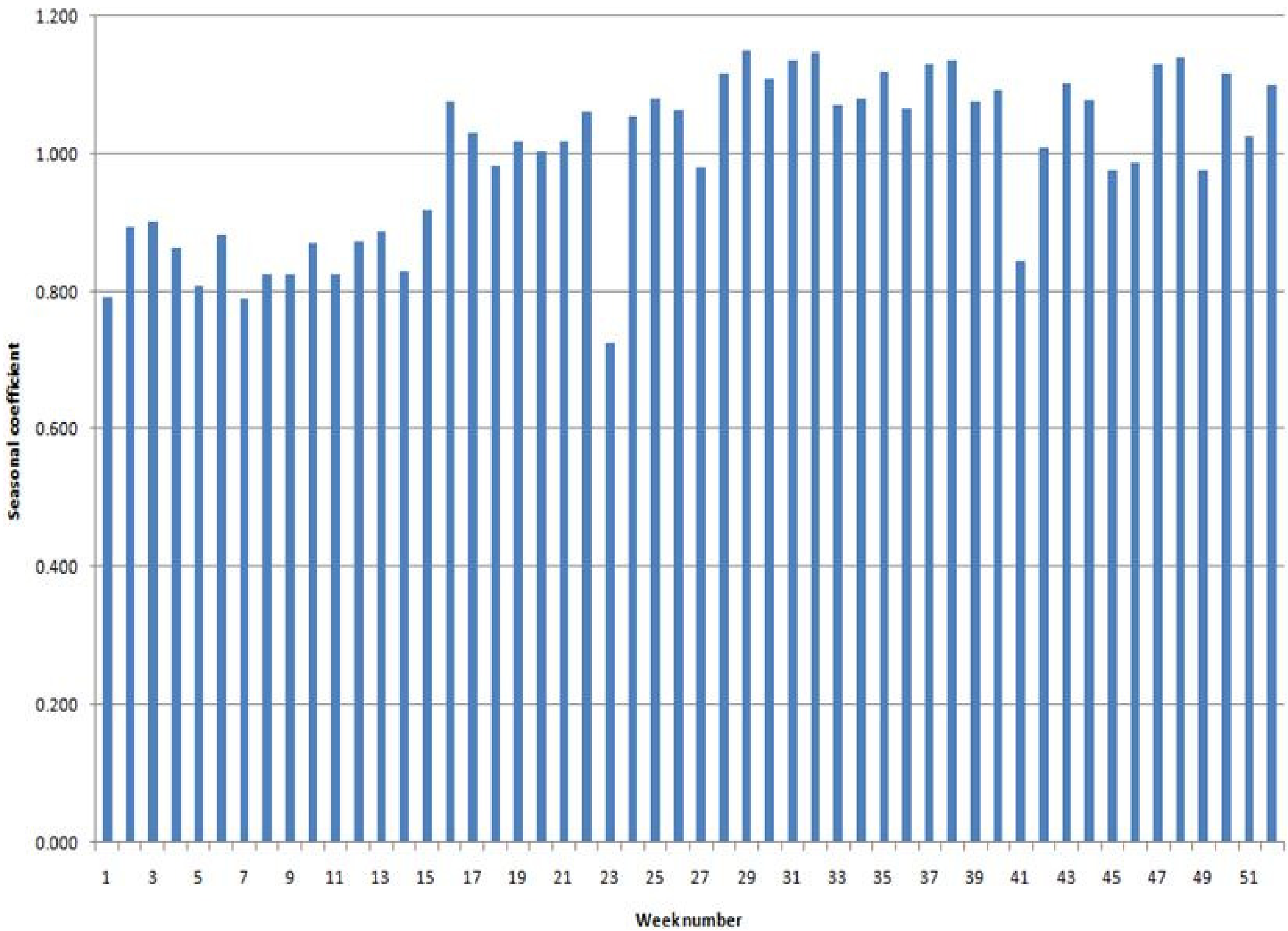

Figure 3. Seasonal coefficient.

January 2007 to 31 December 2007. Results show that there are no pronounced seasonal variation in demand with the exception of two weeks in the year, which are during week 23 (plant shutdown for maintenance) and during week 41 (Eid: Eid is a major festive occasion in Malaysia.). Since Eid is a major festive occasion that largely affects weekly load, this particular holiday is defined in the model to accommodate for the changes in electricity consumption.

Daily weight coefficient, $P_{j,i,n}$

Daily weight coefficient, $P_{j,i,n}$ is the consumption of each day relative to the average daily consumption in a week. In other words, this type of coefficient reflects fluctuations of electricity consumption due to the type of day being considered, that is working day and weekend. In general, these coefficients fluctuate during the year according to the time period considered. However since Malaysia is a country with no seasonality such as spring, summer, autumn and winter, the values are relatively the same throughout the year.

Based on Figure 4, it is observed that the daily weight coefficient is almost similar during working days (Monday to Friday), and evidently higher during weekends. Electricity consumption is noticeably higher during weekends because these eight steel mills (which are categorised as high voltage industrial consumers) are eligible for a scheme known as Sunday Tariff Rider, which waives the maximum demand charge on Sundays (Tenaga Nasional Berhad, 2006). According to the general observed behaviour, days were therefore distributed into two types, that is working day (Monday-Friday) and weekend (Saturday and Sunday).

The daily weight coefficient is calculated as follows (International Atomic Energy Agency, 2006):

$$P_{j,i,n} = \frac{P_j}{P_{average}} \tag{11}$$

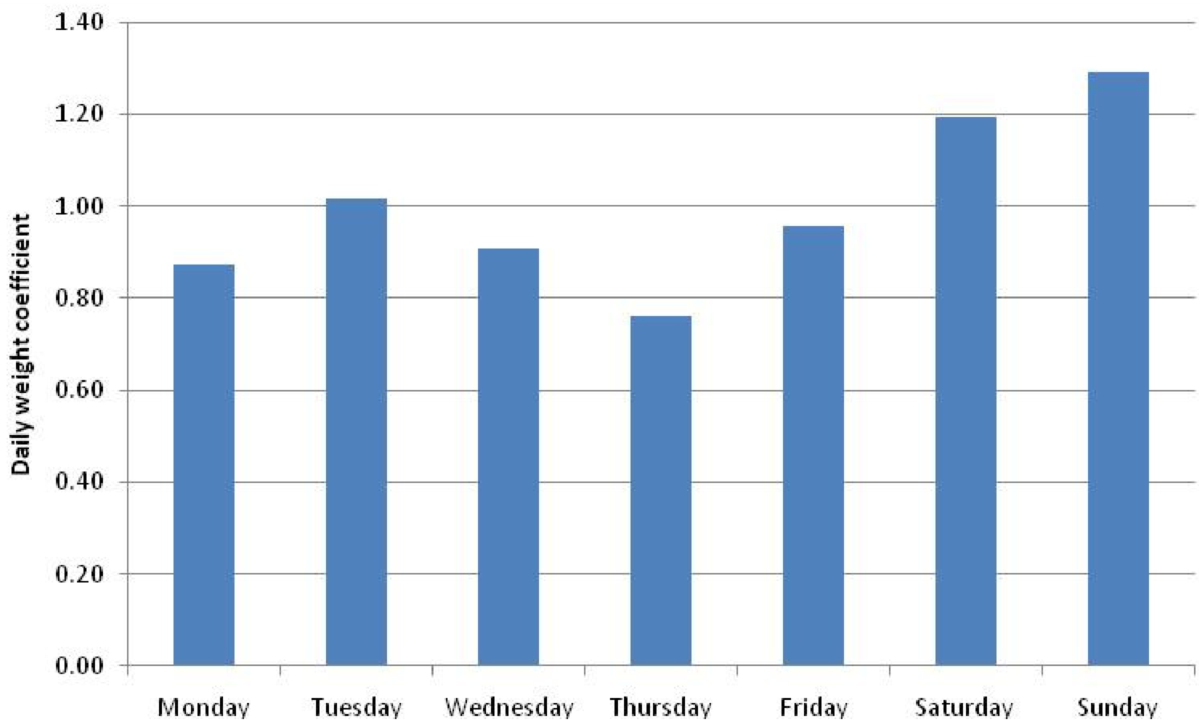

Figure 4. Daily weight coefficient.

where

$$P_{average} = \frac{Weekly\ consumption}{7} \quad (12)$$

Hourly coefficient, $\Pi_{h,i,j,n}$

Hourly coefficient, $\Pi_{h,i,j,n}$ is the relative consumption of each hour within a day, relative to the average hourly consumption in a day. The objective of hourly coefficient is to weight electricity consumption over 24 h of the day. In general, these coefficients are dependent on the time period of the year. They are also different for each day type within the week being considered. In this study, the hourly load coefficient is determined based on the base to peak ratio.

In Peninsular Malaysia, industrial consumers are entitled to peak and off-peak energy rates. Peak period is daily from 8 am to 10 pm while off-peak period is daily after 10 pm up till 8 am. The peak period tariff rate is 20.3 sen/kWh while the off-peak tariff is 11.2 sen/kWh (Tenaga Nasional Berhad, 2006). This tariff scheme heavily influences the steel mills' operation, in which higher electricity usage is observed daily between 10 pm and 8 am to utilise the cheaper tariff rate. Typical pattern shows that electricity consumption gradually decreases beginning 6 am, which is towards the end of the off-peak period. Consumption maintains low during the peak period and gradually builds up again beginning 4 pm.

It is assumed that the hourly load coefficient curves of the steel mills constructed from the base year data will be valid for future years, as it is expected that consumption behaviour does not change significantly since the tariff scheme remains the same. In Malaysia, the tariff rate is determined by the government and tariff is rarely reviewed.

The hourly load coefficients of the various sectors considered in MAED_EL are as shown in Figure 5.

DISCUSSION

All the calculated coefficients that have been analysed and described previously are input to the MAED_EL software. These coefficients, together with the forecasted steel mills' annual electricity consumption (that was earlier projected using the regression equation), are used to construct the annual hourly load curves by employing Equation 2. From the calculated hourly load curves, the daily maximum demand and consequently the annual maximum demand of these steel mills are derived.

Results of the model developed in MAED_EL from the base year are shown in Figures 6(a) and 6(b). Figure 6(a) shows the comparison between the actual hourly load and the hourly load calculated by MAED_EL for the base year. It is observed that the model has the ability to generate the envelope of the load curve, which represents the estimated highest demand of each hour.

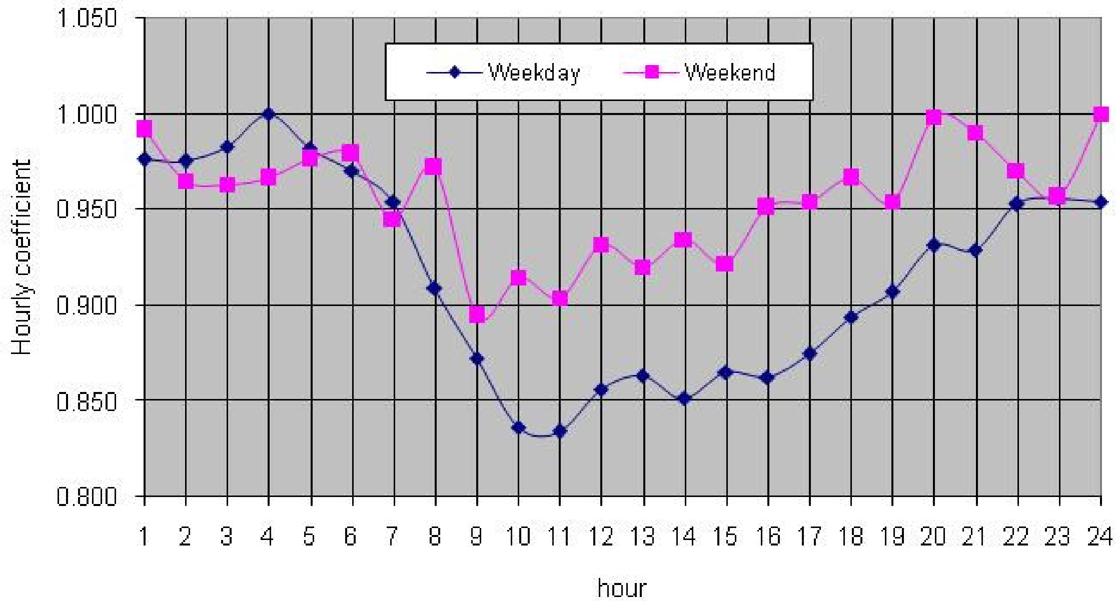

Figure 5. Hourly coefficient.

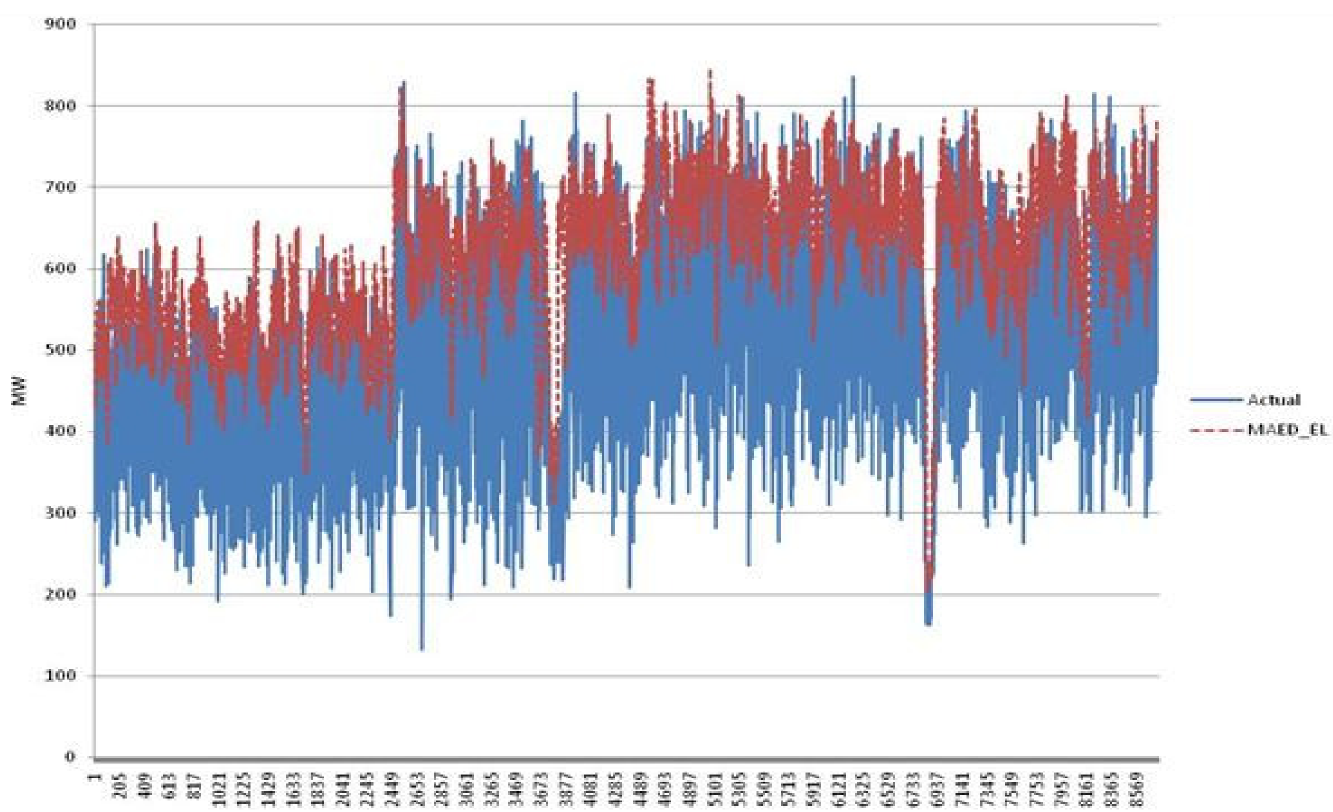

Figure 6(a). Hourly load for 2007 - actual versus forecasted (MAED_EL).

The maximum demand of the day is then derived based on the hourly load of each day.

Figure 6(b) which portrays the hourly load curve taken between 4 April 2007 and 22 May 2007 gives a clearer picture of this. To illustrate the level of performance of this model, results of this model is compared with forecast results using the current practice of moving average method, which is based on two days' past

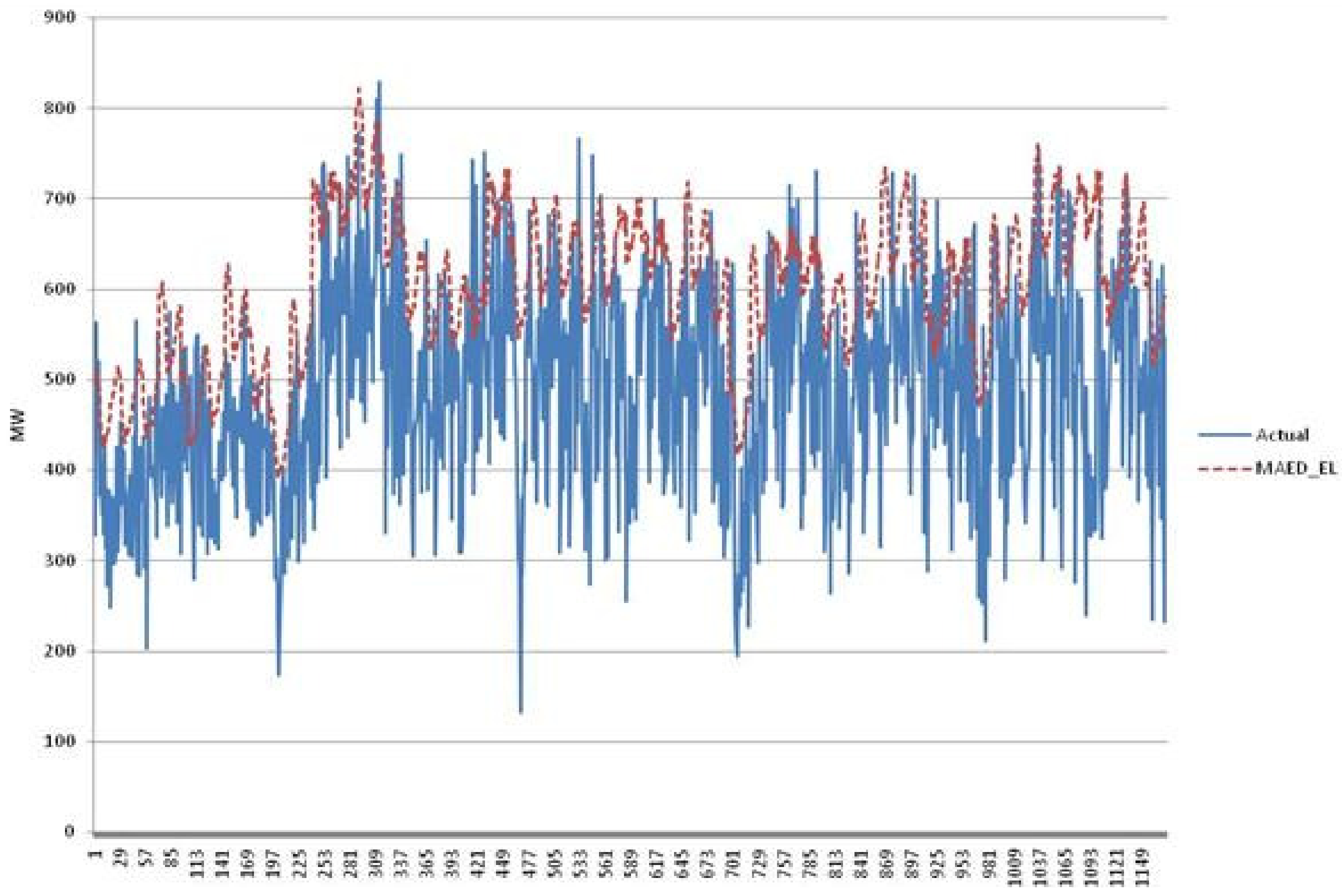

Figure 6(b). Hourly load between 4 April 2007 and 22 May 2007 - actual versus forecasted (MAED_EL).

Table 6. Comparison of results.

Date	Day	Forecasted daily maximum demand (MW)	
		MAED_EL error (%)	Moving average (2) error (%)
16 May 2007	Wednesday	-0.9	1.0
17 May 2007	Thursday	-0.6	10.7
18 May 2007	Friday	0.4	2.5
19 May 2007	Saturday	-6.3	-8.3
20 May 2007	Sunday	5.7	-7.1
21 May 2007	Monday	-0.1	7.0
22 May 2007	Tuesday	2.0	-10.2
Weekly MAPE		2.3	6.7

observation (Moving Average (2)). Results of the comparison are shown in Table 6. The proposed method gives much better forecasting accuracy with weekly MAPE of 2.3%, which reduces the error tremendously to more than half. Improvement can also be seen in the forecasting result for Monday, in which error is reduced to -0.1% as opposed to the 7.0% using the moving average method.

Comparison between the actual annual maximum demand recorded by the steel mills and the annual maximum demand calculated by MAED_EL shows a very small deviation (Table 7). The error in year 2007 is -1.3%.

Conclusion

In this paper, we propose a combination of the top-down and bottom-up methods to forecast the daily maximum demand of Malaysian large steel mills and the annual maximum demand contributed by these steel mills. The

Table 7. Annual maximum demand – actual versus forecasted.

Year	Annual maximum demand (MW)		Error (%)
	Actual	MAED_EL	
2007	836	847	-1.3

top-down approach uses regression analysis to forecast the annual electricity consumption of these large steel mills, based on its relationship with annual steel production and GDP. The projected annual electricity consumption from regression analysis was then integrated into the bottom-up model using MAED_EL to construct the hourly load curves. From the hourly load curves, the daily and annual maximum demands of the steel mill are determined. This model has the ability to forecast accurately the daily maximum of the large steel mills, with MAPE of less than 3%.

The proposed method however, is purely based on the assumption that the future trend of daily consumption follows the base year. Although this is a slight drawback, nevertheless the proposed method has provided the utility with a better means to forecast steel mills' load, despite the unavailability of daily production data which is vital in forecasting.

The outcome of this study will benefit the utility in ensuring reliable and economic operation of the national grid, and is also useful for analysis pertaining development of future optimal generation and transmission expansion plans. Findings of this study also give a valuable contribution to the utility in determining load management strategies and designing of tariff structures.

A possible approach to improve the forecast performance is by combining the model with a time series method such as ARIMA. This will enable the model to take into account the most recent behaviour of steel mills load, and thus increase the accuracy of the forecast.

The best approach however, would still be the one that is able to take into account the daily production data of the steel mills. With the availability of this particular data, many other complex and more effective methods can be explored such as Artificial Neural Network (ANN) and fuzzy linear regression. These methods will have the ability to capture the factors that highly influence steel mills daily load such as daily production plan and maintenance schedule, and hence improve the accuracy of the forecast.

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