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ONE WEEK AHEAD SHORT TERM LOAD FORECASTING

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ABSTRACT
Short-term load forecasting plays an important role in planning and operation of power system. The accuracy of this forecasted value is necessary for economically efficient operation and also for effective control. This paper describes a method of autoregressive Burg in solving one week ahead of short term load forecasting. The proposed method is tested based from historical load data of National Grid of Malaysia and load demand in New South Wales, Australia. The accuracy of proposed method, i.e., the forecast error, which is the difference between the forecast value and actual value of the load, is obtained and reported.

KEY WORDS
Short term load forecasting (STLF), autoregressive (AR), Autoregressive moving average (ARMA), Burg, Durbin, MAPE

1. Introduction

Prediction of future events and conditions is called forecasts**,** and the act of making such predictions is called forecasting**.** It is essential to have accurate models to forecast the future load demand. Load demand forecasting is significant for efficient network operation, network planning, economic scheduling of generation units and also maintenance activities.

Load demand forecasting is typically categorized into long term and short term prediction. Long term forecast usually covers from one to ten years ahead (monthly and yearly values), which is used for applications in capacity expansion of generation and transmission. While short term load forecast (STLF) is normally carried out for an interval ranging from possibly half an hour or one hour to one week ahead. To supply the load demand over this particular duration of time involves the start up and shutdown of entire generating units, which will be determined by a number of generation control functions such as hydro scheduling, hydro thermal coordination, unit commitment and interchange evaluation [1,2]. These load information is obtained from the STLF system and it is vital to the operational of dispatch centre in order to dispatch load economically. It is a main goal for any utilities company to operate as low as possible of operating cost. One way to achieve this is to minimize the forecast error. It was estimated that an increase of operating cost associated with a 1% increase of forecast error was 10 million pounds per year [3].

The numbers of references in the literature that have been presented are quite large. However it is very tough to justify from the available references whether there is a model or method that can solve for all load forecast problem. The reason is that utility service areas vary in differing mixtures of industrial, commercial and residential customers. They also vary in geographic, climatologic, economic and social characteristics.

A large variety of time series [4], statistical, expert system and artificial intelligence techniques have been developed to solve load forecast problem. Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. The advent of artificial intelligence technique increases a tool of solving load forecast problem. Techniques like artificial neural network (ANN) and fuzzy logic are the most common used for load forecast [5]. The most popular artificial neural network architecture for electric load forecast is back propagation [6, 7]. The approach technique of ANN for load forecast is also discussed in details in [8-10]. The technique proven reliable in prediction error, however very large historical data is needed. This is contrast with the fuzzy logic technique. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. A simple linear prediction of fuzzy model in [11, 12] proves that it could provide a very satisfying prediction error. Other fuzzy logic techniques are discussed in [13-15]. Unlike ANN, fuzzy logic doesn't needs large historical data in doing prediction, however the technique could predict for some short period of time only, though revised model has to justify.

2. Objectives and Scope

Short term load forecast (STLF) plays an important role in economic operation and also for the reliability of power systems. The main objective of the STLF is to advise dispatcher in making a decision for economic dispatching. Therefore with an accurate prediction model, it is also could benefit dispatch systems to:

- supply load with stability aspect and consistence,
- estimate fuel allocation,
- determine operational constraints, and
- determine equipment limitations.

The second objectives of the STLF are for security assessment and updating the system. STLF system requires offline historical data to do predictions. The data helps to run the model in advance, therefore allows dispatcher to provide any corrective counter measure to the system.

This paper proposed a technique for STLF by using the approach of signal modeling to predict one week ahead of the future load. The proposed technique introduced a signal modeling by using Burg's method [16] in solving load forecast for Malaysia grid system and NSW load demand system. The method is essentially one of the digital signal processing approach, where a signal (historical data) $P_S(n)$ is known over a given interval of time and the goal is to predict $P_L(n)$ over some other interval. The predicted value is hourly to a maximum of 168 hours (one week ahead). In this paper AR model is proven that it can provide in the most of power systems better mean absolute percentage error (MAPE) values for the STLF. The Burg's algorithm is chosen of the linear algorithms to produce AR model. The AR model then is compared with Durbin's ARMA [17, 18] for STLF relative error in two power systems. One is the Malaysia national grid, representing tropical countries, and secondly the New South Wales grid, representing seasonal countries.

3. Stochastic Models

In some applications it is necessary to develop models for random processes. Examples includes signals whose time evolution is affected or driven by random or unknown factors, as is the case for power load forecasting. Models for random processes differ from those for deterministic signals in the characteristics of the signal that is used as input to the system. Whereas for deterministic signals the input signal is usually a unit sample, for random process the input signal must be a random process. Typically, this input will be taken to be unit variance white noise.

3.1 The Autoregressive Moving Average (ARMA) and Autoregressive (AR) Model

A time-series model that approximate many discrete-time stochastic processes encountered in practice is presented by the filter linear difference equation of complex coefficients

$$x(n) = -\sum_{k=1}^{p} a_p(k)x(n-k) + \sum_{k=0}^{q} b_q(k)u(n-k) = \sum_{k=0}^{\infty} h(k)u(n-k) \tag{1}$$

in which $x(n)$ is the output sequence of a causal filter ($h(k) = 0$ for $k < 0$) that models the observed data and $u(n)$ is an input driving white noise sequence. Eq. (1) determines the autoregressive-moving average (ARMA) model for the time series $x(n)$. The $a_p(k)$ parameters form the autoregressive portion of the ARMA model. The $b_p(k)$ parameters form the moving average portion of the ARMA model. Thus, a wide sense stationary ARMA(p,q) process may be generated by filtering unit variance white noise $u(n)$ with a causal linear shift-invariant filter having p poles and q zeros.

$$H(z) = \frac{B_q(z)}{A_p(z)} = \frac{\sum_{k=0}^{q} b_q(k)z^{-k}}{1+\sum_{k=1}^{p} a_p(k)z^{-k}} \tag{2}$$

Therefore, a random process $x(n)$ may be modeled as an ARMA(p,q) process using the model shown in Figure 1, where $u(n)$ is unit variance white noise.

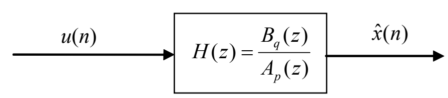

Figure 1: Modeling a random process x(n) as the response of a linear shift-invariant filter to unit variance white noise.

The Burg's method is developed of the spectrum estimation known as maximum entropy method [18]. As part of this method, which involves finding an all-pole model for the data, the method proposed that the reflection coefficients be computed sequentially by minimizing the mean-square of the forward and backward prediction error [19].

$$\varepsilon_j^{fb} = \varepsilon_j^{f} + \varepsilon_j^{b} = E\left\{\sum_{n=j}^{N}\left|e_j^f(n)\right|^2 + \sum_{n=j}^{N}\left|e_j^b(n)\right|^2\right\} \tag{3}$$

Now, we may find the value of the reflection coefficients Γ_j^{fb}, that minimizes ε_j^{fb} by setting the derivates of ε_j^{fb} with respect to $(\Gamma_j^{fb})^*$ equal to zero as follows.

$$\begin{aligned}\frac{\partial}{\partial\left(\Gamma_j^{fb}\right)^*}\varepsilon_j^{fb} &= \frac{\partial}{\partial\left(\Gamma_j^{fb}\right)^*} E\left[\sum_{n=j}^{N}\left\{\left|e_j^f(n)\right|^2 + \left|e_j^b(n)\right|^2\right\}\right] \\ &= E\left[\sum_{n=j}^{N}\left\{e_j^f(n)\left[e_{j-1}^b(n-1)\right]^* + \left[e_j^b(n)\right]^* e_{j-1}^f(n)\right\}\right] = 0\end{aligned} \tag{4}$$

Substituting the error update equations for $e_j^f(n)$ and $\left[e_j^b(n)\right]^*$, which are similar to those given for $e_{j+1}^f(n)$ and $\left[e_{j+1}^b(n)\right]^*$ in Eq. (3), and solving for Γ_j^{fb} we find that the value of Γ_j^{fb} that minimizes ε_j^{fb} is

$$\Gamma_j^{fb} = -\frac{2\sum_{n=j}^{N} e_{j-1}^f(n)\left[e_{j-1}^b(n-1)\right]^*}{\sum_{n=j}^{N}\left\{\left|e_{j-1}^f(n)\right|^2 + \left|e_{j-1}^b(n-1)\right|^2\right\}} \tag{5}$$

From computational point of view, Burg's method works as given in Table 3

Table 3: The Burg Recursion

1. Initialize the recursion
   a. $e_0^f(n) = e_0^b(n) = x(n)$
   b. $D_1 = 2\sum_{n=1}^{n}\left\{\left|x(n)\right|^2 - \left|x(n-1)\right|^2\right\}$
2. For $j = 1$ to p
   a. $\Gamma_j^{fb} = -\frac{2}{D_j}\sum_{n=j}^{N} e_{j-1}^f(n)\left[e_{j-1}^b(n-1\right]^*$
   b. For $n = 1$ to N
      $e_j^f(n) = e_{j-1}^f(n) + \Gamma_j^{fb} e_{j-1}^b(n-1)$
      $e_j^b(n) = e_{j-1}^b(n-1) + \left(\Gamma_j^{fb}\right)^* e_{j-1}^f(n)$
   c. $D_{j+1} = D_j\left(1 - \left|\Gamma_j^{fb}\right|^2\right) - \left|e_j^f(j)\right|^2 - \left|e_j^b(N)\right|^2$
   d. $\varepsilon_j^{fb} = D_j\left[1 - \left|\Gamma_j^{fb}\right|^2\right]$

It is important to indicate that sequentially minimizing ε_p^{fb} by Burg guarantee that the reflection coefficients are bounded by one in magnitude and thus, the AR model is stable.

4. Numerical Study

The comparisons of performance of the discussed ARMA and AR methods for short term load forecasting, data from the Malaysian national grid [1] as well as from New South Wales (NSW), Australia grid [20] is collected. In this study, the Malaysian grid is selected to represent power load variations in tropical countries, where temperature change over the day is the main factor in load fluctuation. On the other hand, the New South Wales grid is chosen to represent power load in seasonal countries, where seasonal changes of great impact on load variations.

Figure 2 shows an example of hourly load curves of almost six month data of the Malaysian grid extends over a period from 1 March 2005 to14 August 2005. In the figure, the load behavior is relatively the same over the days of the year. This is mainly because of the tropical weather where seasonal changes are absent. On the other hand, Figure 3 shows the variations in power load of Malaysian grid over the days of the week. In the figure, the load behavior of weekdays (Tuesday through Friday) is seen mutually similar, while for the Monday load is somewhat similar to weekdays curve, but shows slightly different curves during early and morning time. Mean while that of Saturday and Sunday load behavior are significantly different. It is clear in Figure 3 that Saturdays load is approximately two-third of the average weekdays load and Sundays load is approximately half the average weekdays load. The reason for this pattern difference is that in year of 2005 in Malaysia, based on Government regulations, Saturdays are half day work and Sundays are days off; therefore, it caused the difference of load pattern between Saturdays and Sundays. In other words, the load patterns of the Malaysian grid can be categorized into three groups: weekdays, Saturdays, and Sundays.

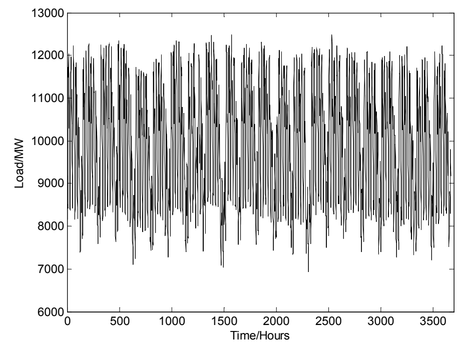

Figure 2: Historical data for the Malaysian grid from 01 March 2005 to14 August 2005.

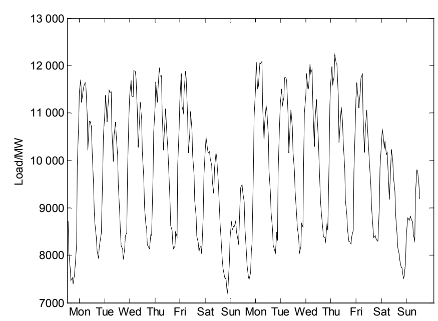

Figure 3: Hourly load curve for the Malaysian grid for two weeks.

In the contrary to the Malaysian grid where seasonal effects are marginal, their significant impact on New South Wales (NSW) power load is shown in Figure 4. In the figure, power load variation in New South Wales grid over approximately one year data record is depicted.

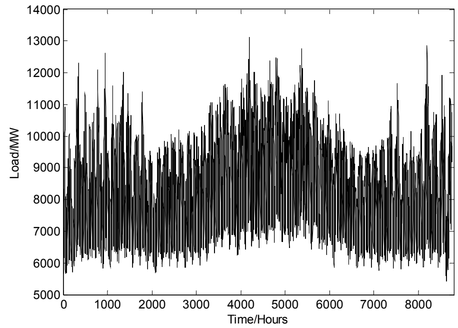

Figure 4: Historical data for the NSW grid between 01 January 2005 and 31 December 2005

The hourly load curve of two weeks of NSW grid is depicted in Figure 5. In the figure the load behavior of weekdays (Monday through Friday) is relatively similar, while that of Saturday and Sunday are somehow different.

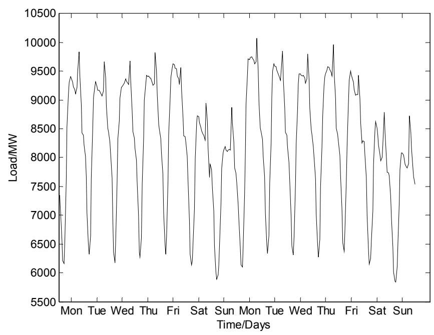

Figure 5: Hourly load curve for NSW grid for two weeks.

In this study, we investigate the performance of the different parametric techniques on one week ahead forecast among different load types. Since, the intention is to test the capability of ARMA-Durbin and AR-Burg models in modeling power load data, no attempt has been initially made to reduce its degree of fluctuation by sorting data into different patterns; weekdays, weekends or even into seasonal patterns in case of NSW grid. In describing the performance of the different models, the Mean Absolute Percentage Errors (MAPE), calculated from 24 forecasts over the day is used. MAPE is given as

$$MAPE = \frac{1}{24}\sum_{i=1}^{24}\frac{|\hat{x}_i - x_i|}{x_i} \tag{6}$$

where x_i is the hourly data and $\hat{x}_i$ is the predicted value.

With the Malaysian grid the tested ARMA and AR models use an hourly daily data over 14 weeks (2×98 historical data for each half an hour forecast). Table 5 tabulates the recorded period and the predicted period for the Malaysian grid.

Table 5: Record and Forecast Period

Grid	Recorder period	Forecast period
Malaysian	07 March 2005-12 June 2005	13-19 June 2005

To show the performance of the studied techniques, Figure 6 exhibits their accuracy in forecasting the load at 4 pm over the seven days of the considered one week forecasts.

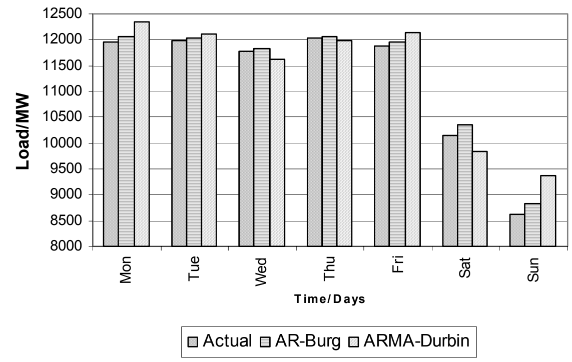

Figure 6: Load forecasts at 4 pm over the period 13-19 June 2005 for the Malaysian grid.

To show the performance of the considered parametric models in statistical form, MAPE based on 24 forecasted samples is calculated for each day and tabulated in Table 6.

Table 6: MAPE values of one week ahead forecasts of the Malaysian grid

	MAPE (%)	
	ARMA	AR
Day	**Durbin**	**Burg**
Mon	2.33	1.21
Tue	1.67	1.17
Wed	1.29	1.06
Thu	0.96	0.59
Fri	1.52	0.88
Sat	3.21	1.22
Sun	3.67	1.31
Average	**2.09**	**1.06**

Figure 6 and Table 6 show clearly the better performance of the different AR models to Durbin-ARMA. From Table 6 it is clearly that the three considered AR methods develop less MAPE values than Durbin's ARMA especially during the Saturday, Sunday and Monday, where most of load variations exist. Table 6 also indicates that the average value of MAPE over seven days is nearly 54% less for AR models than Durbin's ARMA. It is evident that the AR-Burg performs better results than ARMA-Durbin.

It is worth mentioning that sorting out the data record into weekdays and weekends will reduce the average value of MAPE for the Malaysian scenario by nearly half making it close to 1% for AR methods and a little bit higher than

1.7% for Durbin's ARMA. With NSW grid, Durbin's ARMA and the AR method are tested using hourly data over 14 weeks (2×98 historical data for each hourly forecast). Table 7 tabulates the recorded period and the predicted period for the NSW grid.

Table 7: Record and Forecast Period

Grid	Recorder period	Forecast period
NSW	01 January 2005 - 03 April 2005	4 - 10 April 2005

Figure 7 shows the accuracy of the studied ARMA and AR method in forecasting the power load at 7 pm over the considered one week period of prediction. The performances of ARMA and AR method in forecasting the power load of NSW grid are tabulated in Table 8. It is apparent from Figure 7 and Table 8 that the considered AR model is showing better load forecast than Durbin's ARMA. From Table 8 it is evident that AR model develop less MAPE values than Durbin's ARMA for almost all days, where at this point, Durbin's ARMA reaches its worst prediction limit because of the high load variations. Table 8 also indicates that the average value of MAPE over seven days is nearly 64% less for AR model than Durbin's ARMA. On the other hand and in the contrary to the Malaysian grid, with NSW grid there is no differences in the performance of the considered AR method. It is also worth mentioning here that, sorting data record of NSW scenario into seasons, weekdays, weekends, will reduce the average value of MAPE by approximately 40% for AR and 50% for ARMA.

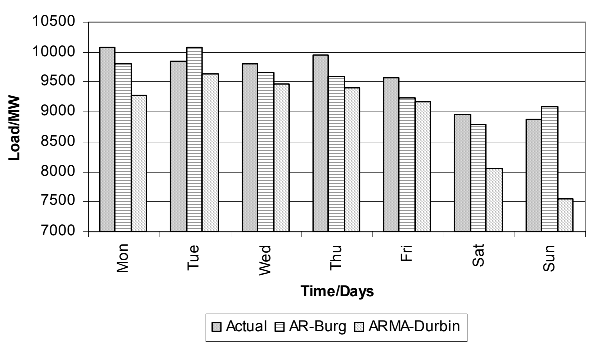

Figure 7: Load forecasts at 7 pm over the period 04 -10 April 2005 for NSW grid.

Table 8: MAPE values of one-week ahead forecasts of the NSW grid.

	MAPE (%)	
	ARMA	AR
Day	**Durbin**	**Burg**
Mon	6.59	2.75
Tue	2.92	1.83
Wed	2.45	1.35
Thu	7.76	1.65
Fri	5.15	2.23
Sat	5.53	1.63
Sun	4.98	1.77
Average	**5.05**	**1.89**

5. Conclusion

In this paper we prove the better performance of AR based methods to ARMA in short term power load forecast. The AR model Burg is tested and compared with Durbin's ARMA model. Only fourteenth weeks of data records from both Malaysian and New South Wales grid are used for one-week ahead forecast. With the Malaysian grid the results indicate better performance by the considered AR model to Durbin's ARMA by nearly 54%. In the contrary to ARMA, AR model managed to cope with the high variation in power load over Sundays and Mondays and show a relatively consistent MAPE values over the days of the week. With New South Wales grid where fluctuation in power load is much higher than it with the Malaysian grid, AR model show better MAPE values to Durbin's ARMA by nearly 64%. The results indicate poor performance by ARMA for almost all days where most of load variations exist. It is important to note that sorting out the Saturdays and Sundays from the rest of the load data record improves ARMA by nearly 50% and AR by 40%.

Acknowledgments

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