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Lacir Jorge Soares, Leonardo Rocha Souza

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Lacir Jorge Soares
Leonardo Rocha Souza

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Lacir Jorge Soares
Department of Electrical Engineering
Catholic University of Rio de Janeiro

Leonardo Rocha Souza
Graduate School of Economics
Fundação Getúlio Vargas

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Abstract. This paper studies the electricity hourly load demand in the area covered by a utility situated in the southeast of Brazil. We propose a stochastic model which employs generalized long memory (by means of Gegenbauer processes) to model the seasonal behavior of the load. The model is proposed for sectional data, that is, each hour's load is studied separately as a single series. This approach avoids modeling the intricate intra-day pattern (load profile) displayed by the load, which varies throughout days of the week and seasons. The forecasting performance of the model is compared with a SARIMA benchmark using the years of 1999 and 2000 as the out-of-sample. The model clearly outperforms the benchmark. We conclude for general long memory in the series.

Keywords. Long Memory, Generalized Long Memory, Load Forecasting.

1 – Introduction

Managing electricity supply is a complex task. The system operator is responsible for the hourly scheduling of the generators and aims foremost at balancing power production and demand. After this requirement is satisfied, it aims at minimizing production costs, including those of starting and stopping power generating devices, taking into account technical restrictions of electricity centrals. Finally, there must always be a production surplus, so that local failures do not affect dramatically the whole system. It is relevant for electric systems optimization, thus, to develop a scheduling algorithm for the hourly generation and transmission of electricity. Amongst the main inputs to this algorithm are hourly load forecasts for different time horizons. Electricity load forecasting is thus an important topic, since accurate forecasts can avoid wasting energy and prevent system failure. The former when there is no need to generate power above a certain level and the latter when normal operation is unable to withstand a heavy load. The importance of good forecasts for the operation of electric systems is exemplified by many works in Bunn and Farmer (1985) with the figure that a 1% increase in the forecasting error would cause an increase of £10 M in the operating costs per year in the UK.

There is also a utility-level reason for producing good load forecasts. Nowadays they are able to buy and sell energy in the specific market whether there is shortfalls or excess of energy, respectively. Accurately forecasting the electricity load demand can lead to better contracts. Among the most important time horizons for forecasting hourly loads we can cite: one to 168 hours ahead. This paper deals with forecasts of load demand one to seven days (24 – 168 hours) ahead for a Brazilian utility situated in the southeast of the country.

The data in study cover the years from 1990 to 2000 and consist of hourly load demands. We work with sectional data, treating each hour as different time series, so that 24 different models are estimated, one for each hour of the day. All models, however, have the same structure. Ramanathan et al. (1997) won a load forecasting competition at Puget Sound Power and Light Company using models individually tailored for each hour. They also cite the use of hour-by-hour models at the Virginia Electric Power Company. However, our approach differs from theirs in various ways, including that we use only sectional data in each model. Using hour-by-hour models avoids modeling the daily load profile, which varies for different days of the week and different parts of the year, increasing model complexity much more intensely than

allowing improvements in the forecast accuracy. Although temperature is an influential variable to hourly loads, temperature records for the region in study are very hard to obtain and we focus our work on univariate modeling.

Long memory in stationary processes has traditionally two alternative definitions, one in the frequency-domain and the other in the time-domain. In the frequency-domain, this feature implies that the spectrum is proportional to $|\lambda|^{-2d}$ as the frequency λ approaches zero. In the time-domain, the autocorrelations decay hyperbolically, instead of geometrically as in ARMA processes ($\rho_k \sim C|k|^{1-2d}$ as $k \to \infty$, where k is the lag and C is a constant). In both cases, d is the long memory parameter and the above relationships characterize long memory and stationarity if $d \in (0, 0.5)$. Good reviews of long memory literature are found in Beran (1994) and Baillie (1996). Hosking (1981) and Granger and Joyeux (1980) proposed at the same time the fractional integration, which has no physical but only mathematical sense. It is represented by a noninteger power of $(1 - B)$, where B is the backward-shift operator such that $BX_t = X_{t-1}$, and can generate long memory while still keeping the process stationary. Generalized (seasonal) long memory can be generated by a noninteger power of the filter $(1 - 2\gamma B + B^2)$ and the periodicity is implicit in the choice of the parameter γ. Gray, Zhang and Woodward (1989) call such processes as Gegenbauer process, because they admit Gegenbauer polynomials in the MA(∞) representation. They explore the properties of Gegenbauer and related processes, which present the generalized long memory feature. The noninteger power of a finite polynomial filter is equivalent to an infinite polynomial filter, which can be obtained by a Binomial expansion.

The time series modeling includes a stochastic trend, seasonal dummies to model the weekly pattern and the influence of holydays. After filtering these features from the log-transformed data, there remains a clear seasonal (annual) pattern. Analyzing the autocorrelogram, a damped sinusoid is observed, consistent with a general long memory (Gegenbauer) process. The forecasting performance 24 to 168 hours ahead for the years 1999 and 2000 (each year separately) is compared with that of a benchmark, namely a SARIMA model, and the results are highly favorable to our modeling. For one day (24 hours) ahead, the model yields mean absolute percentage error (MAPE) going from 2.2% (21th hour, 1999) to 4.4% (2nd hour, 2000), and for seven days (168 hours) ahead it goes from 3.1% (20th hour, 1999) to 8.4% (3nd hour, 2000). Given the characteristics observed in the data and the results obtained in

forecasting, we conclude for the presence of generalized long memory in the data studied.

The plan of the paper is as follows. The next Section briefly explains ordinary and generalized long memory, both used in the modeling process. Section 3 describes the data and the model proposed to fit the load demand, while Section 4 shows the forecasting results of this modeling. Section 5 offers some concluding remarks.

2 – (Generalized) Long Memory

2.1 – Ordinary Long Memory

Stationary long memory processes are defined by the behavior of the spectral density function near the frequency zero, as follows. Let f(λ) be the spectral density function of the stationary process X_t. If there exists a positive function $c_f(\lambda)$, $\lambda \in (-\pi, \pi]$, which varies slowly as λ tends to zero, such that d ∈ (0, 0.5) and

$$f(\lambda) \sim c_f(\lambda)|\lambda|^{-2d} \text{ as } \lambda \to 0, \qquad (1)$$

then X_t is a stationary process with long memory with (long-)memory parameter d. Alternatively, let $\rho(k)$ be the *k*-th order autocorrelation of the series X_t. If there exists a real number $d \in (0, 0.5)$ and a positive function $c_\rho(k)$ slowly varying as k tends to infinity, such that:

$$\rho(k) \sim c_\rho(k) k^{2d-1} \text{ as } k \to \infty \qquad (2)$$

then X_t is said to have long memory or long range dependence.

X_t is said to follow an ARFIMA(p,d,q) model if $\Phi(B)(1-B)^d X_t = \Theta(B)\varepsilon_t$, where ε_t is a mean-zero, constant variance white noise process, B is the backward shift operator such that $BX_t = X_{t-1}$, d is not restricted to integer values as in the ARIMA specification, and $\Phi(B)= 1-\phi_1 B-\ldots-\phi_p B^p$ and $\Theta(B)=1+\theta_1 B+\ldots+\theta_q B^q$ are the autoregressive and moving-average polynomials, respectively. ARFIMA processes are stationary and display long memory if the roots of Φ(B) are outside the unit circle and d ∈ (0, 0.5). If d < 0 the process is short memory and said to be "antipersistent" (Mandelbrot, 1977, p.232), and Equation (1) holds so that the spectrum has a zero at the zero frequency. Note that in this case the process does not fit into the definition of long memory, since the parameter d is outside the range imposed by this definition. If d = 0 the ARFIMA process reduces itself to an ARMA. If the roots of Φ(B) are outside the unit circle and d < 0.5, the process is stationary and if the roots of Θ(B) are outside the

unity circle and d > -0.5, the process is invertible. The autocorrelations of an ARFIMA process follow $\rho(k) \sim Ck^{2d-1}$ as the lag k tends to infinity and its spectral function behaves as $f(\lambda) \sim C|\lambda|^{-2d}$ as λ tends to zero, satisfying thus (1) and (2). A non-integer difference can be expanded into an infinite autoregressive or moving average polynomial using the binomial theorem:

$$(1-B)^d = \sum_{k=0}^{\infty} \binom{d}{k} (-B)^k , \qquad (3)$$

where $\binom{d}{k} = \frac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)}$ and $\Gamma(.)$ is the gamma function.

2.2 – Generalized Long Memory

Seasonal long memory is usually not defined in the literature, as different spectral behaviors bear analogies with the definition in (1) within a seasonal context. Rather, processes with these analogous properties are defined and their spectral and autocovariance behaviors explored. We in this paper work with Gegenbauer processes as in Gray, Zhang and Woodward (1989) and Chung (1996), but alternative models have been used by Porter-Hudak (1990), Ray (1993) and Arteche (2002), for example. The Gegenbauer processes were suggested by Hosking (1981) and later formalized by Gray, Zhang and Woodward (1989) and are defined as follows. Consider the following process

$$\left(1 - 2\gamma B + B^2\right)^d X_t = \varepsilon_t , \qquad (4)$$

where $|\gamma| \leq 1$ and ε_t is a white noise. This process is called a Gegenbauer process, because the Wold representation of (4) admits the important class of orthogonal polynomials called Gegenbauer polynomials as the coefficients (Gray et al., 1989). This Wold representation is achieved by using the binomial theorem as in (3), expanding the representation to an MA(∞). If $|\gamma| < 1$ and $0 < d < ½$, the autocorrelations of the process defined in (4) can be approximated by

$$\rho(k) = C\cos(k\nu)k^{2d-1} \quad \text{as } k \to \infty \qquad (5)$$

where C is a constant not depending on k (but depends on d and ν) and $\nu = \cos^{-1}(\gamma)$. That means that the autocorrelations behave as a damped sinusoid of frequency ν and that γ determines the period of the cycle (or seasonality). Moreover, the spectral density function obeys

$$f(\lambda) = \frac{\sigma^2}{2\pi}\left\{2\left|\cos\lambda - \cos\nu\right|\right\}^{-2d} \qquad (6)$$

behaving as $\lambda \to \nu$ like

$$f(\lambda) \sim \left|\lambda^2 - \nu^2\right|^{-2d} \qquad (7)$$

for $0 \le \lambda \le \pi$. Note that if $\gamma = 1$ then (4) is an FI(2d), or ARFIMA(0,2d,0), and that is why we can call these processes as having the "generalized" long memory property. Moreover, the (long memory) analogy of Gegenbauer processes with FI processes comes from the fact that the latter have a pole or zero at the zero frequency while the former have a pole or zero at the frequency ν, depending on whether d is respectively positive or negative. Note that the Gegenbauer processes can be generalized into k-factor Gegenbauer processes as in Gray et al. (1989) and Ferrara and Guégan (2001), by allowing that different Gegenbauer filters $(1 - 2\gamma_i B + B^2)^{di}$; i = 1, …, k; apply to X_t. We work in this paper with a mix of Gegenbauer and ARFIMA process to model the detrended load after the calendar effect is removed.

3 – Data and model

3.1 - Data

The data comprise hourly electricity load demands from the area covered by the utility in study, ranging from the first day of 1990 to the last of 2000. The data set is then separated into 24 subsets, each containing the load for a specific hour of the day ("sectional" data). Each subset is treated as a single series, all of them modeled following a same overall specification, although estimated independently of the others (univariate modeling). We use an estimation window of four years, believing it sufficient for a good estimation. Some experiments with longer and shorter estimation windows yielded results not much different from the ones obtained here. As the focus is in multiples of 24 hours ahead forecasts, the influence of lags up to 23 may be unconsidered without affecting predictability. Furthermore, using these "sectional" data avoids modeling complicated intra-day patterns in the hourly load, commonly called load profile, and enables each hour to have a distinct weekly pattern. This last feature is desirable, since it is expected that the day of the week will affect more the middle hours, when the commerce may or not be open, compared to the first and last hours of the day, when most people are expected to sleep. Hippert, Pedreira and Souza (2001, p. 49), in

their review of load forecasting papers, report that difficulties in modeling the load profile are common to (almost) all of them.

The hour-by-hour approach has been also tried by Ramanathan et al. (1997), who win a load forecast competition, but their modeling follows a diverse approach than ours. Unlike them, we use neither deterministic components to model the load nor external variables such as those related to temperature. This is a point to draw attention to, as some temperature measures (maximums, averages and others) could improve substantially the prediction if used, particularly in the summer period when the air conditioning appliances constitute great part of the load. The forecasting errors are in general higher in this period and we do not use this kind of data because it is unavailable to us. However, the temperature effect on load is commonly nonlinear as attested by a number of papers (see Hippert, Pedreira and Souza, 2001, p. 50), and including it in our linear model would probably add a nonlinear relationship to it.

3.2 – Model

A wide variety of models and methods have been tried out to forecast energy demand, and a great deal of effort is dedicated to artificial intelligence techniques, in particular to neural network modeling[1]. Against this tidal wave of neural applications in load forecasting, we prefer to adopt statistical linear methods, as they seem to explain the data to a reasonable level, in addition to give an insight into what is being modeled. The forecasting performance makes us believe the choice is correct for the data in study. A contemporaneous work of Soares and Medeiros (2003) analyses the same data set, adopting instead a deterministic components approach, modeling as stochastic only the residuals left after fitting these deterministic components. Their results are fairly comparable to ours (slightly better), but the deterministic components approach should not adapt well to the case where a structural break is present in the data, like during the 2001 Brazilian energetic crisis, when the electricity consumption was reduced by about 20%. On the other hand, our methodology is shown to yield good forecast results in this period (details in Souza and Soares, 2003).

The model for a specific hour is presented below, omitting subscripts for the hour as the specification is the same. Let the load be represented by X_t and $Y_t = \log(X_t)$. Then,

[1] Hippert, Pedreira and Souza (2001) provide a review of works that used varied techniques in predicting load demand, paying especial attention to evaluate the use of neural networks.

$$Y_t = L_t + WD_t + \alpha H_t + Z_t \qquad (8)$$

where L_t is a stochastic level (following some trend, possibly driven by macroeconomic and demographic factors), WD_t is the effect of the day of the week, H_t is a dummy variable to account for the effect of holidays (magnified by the parameter α) and Z_t is a stochastic process following:

$$\left(1 - 2\gamma B + B^2\right)^{d1}(1 - B)^{d2}(1 - \phi_t B)Z_t = \varepsilon_t, \qquad (9)$$

where ε_t is a white noise. The first multiplicative term on the left hand side of (9) takes the annual (long memory) seasonality into account, where γ is such that the period is 365 days and d1 is the degree of integration. The second refers to the pure long memory, where d2 is the degree of integration. The third refers to an autoregressive term, with seven different and static values of ϕ_t, one for each day of the week (rather than ϕ_t being a stochastic parameter).

No assumptions were made up on the trend driving the stochastic level, but it is reasonable to think it is related to macroeconomic and demographic conditions. L_t is estimated simply averaging the series from half a year before to half a year after the date t, so that the annual seasonality does not interfere with the level estimation. It is forecasted by extrapolating a linear trend estimated by local regression on the estimated L_t. The calendar effect, in turn, is modeled by WD_t and αH_t, where the former is constituted by dummy seasonals, H_t is a dummy variable which takes value 1 for holidays, 0.5 for "half-holidays" and 0 otherwise, and α is its associated parameter. The days modeled as "half holidays" are part-time holidays, holidays only in a subset of the area in study or even for a subset of the human activities in the whole region, in such a way that the holiday effect is smooth. For two examples of "half-holidays", one can cite the Ash Wednesday after Carnival, where the trading time begins in the afternoon; and San Sebastian's day, feast in honor of the patron saint of one of the cities within the region in study (holiday only in this city). H_t could allow values in a finer scale (e.g., measuring out the "holiday intensity" of different holiday types), but there is a trade-off between the fit improvement and the measurement error in so doing. As it is, the huge forecast errors present when no account of the holiday effect is taken disappear. WD_t and α are estimated using dummy variables by OLS techniques. Seasonal and ordinary long memory are estimated using the Whittle (1951) approach, details of which[2] are

[2] Such as consistency and asymptotic normality.

found in Fox and Taqqu (1986) and in Ferrara and Guégan (1999) respectively for ordinary and generalized long memory. Chung (1996, p. 245) notes that when the parameter γ is known, as in the present case, the estimation of seasonal long memory is virtually identical to that of ordinary long memory. However, there are varied long memory estimators in the literature and we chose this one for its comparatively high efficiency. The weekly autoregressive terms are estimated with the remaining residuals, using for it OLS techniques.

Figure 1 shows the autocorrelation function (ACF) of the series from December 26, 1990 to December 25, 1998 (eight years), for selected hours, after the trend and the calendar effects (weekdays and holidays) are removed. The form of the ACF, which resembles a damped sinusoid as in (5), with annual period, highly justifies using Gegenbauer processes to model Z_t. The exception is hour 20, in which either there is a sinusoidal component of semiannual period or there are two sinusoidal components, one with annual period and the other with semiannual period. This behavior does not occur with any other hour, being specific of hour 20. However, our modeling does not use a k-factor (k would equal to 2 in this case) Gegenbauer process as proposed by Gray et al. (1989) and studied by Ferrara and Guégan (2000, 2001) to model hour 20, obtaining good results though. In fact, hour 20 obtains the lowest errors, the exception being one and sometimes two steps ahead, where it is beaten by hour 21. Figure 2 shows the periodogram (raw and smoothed by a Parzen lag window with degree of smoothness 0.9, respectively represented by dots and a solid line) for the same series in log-log scale. Note the resemblance with the behavior described by (7). The eighth Fourier frequency, corresponding to an annual period as we use eight years of data, shows a sharp peak in the raw periodogram, whereas its vicinity shows a smooth decrease (in log-log scale) going farther to either side. The subfigure corresponding to hour 20 in Figure 2 is consistent with the ACF shown in Figure 1, since there are peaks at the eighth and the sixteenth Fourier frequencies, meaning that there may be one (semiannual) or two (annual and semiannual) Gegenbauer factors.

We chose working with logarithms as the weekly seasonality and the holiday effect can be modeled additively while they are multiplicative in the original series X_t. These effects are believed to be multiplicative while relating to consuming habits, varying proportionally when the number of consumers expands. However, we experimented applying the same modeling as in (8)-(9) to X_t, instead of Y_t, yielding

very similar results. The choice of the logarithm transformation is thus only to be coherent to our beliefs and not result-oriented.

4 – Results

We run a forecasting exercise with the data specified in the previous section, comparing the results of model (8)-(9) to a benchmark. The benchmark used is a SARIMA, like the works of Darbellay and Slama (2000) and Soares and Medeiros (2003), for example. It is modeled and estimated using EViews™ software package. The "seasonal" period considered for the SARIMA is one week, since there must be in general small variation between one week and the next within the context of annual seasonality. In fact the SARIMA performs quite well in the early hours, when the load is smoother. A different SARIMA is estimated for each hour of the day, as is done with model (8)-(9).

The period used to estimate the models begins four years before December 25, 1998, and ends on this date (in sample). That is, the model is estimated once using a four-year estimation window, as it seems to be enough. The estimated parameters for each hour are presented in Table 1. The degrees of fractional integration, both seasonal and ordinary, vary throughout the hours, though d1 is always positive (long memory) and d2 always negative (short memory). The (seasonal) long memory is stronger for the hours in the beginning and in the end of the day, coinciding with the hours where the load is smoother. The calendar effect, modeled by WD_t and αH_t, is also not the same for all the hours, as it is apparent that business days affect more the load in the middle hours (trading hours) than in the first or last ones. The use of one autoregressive parameter for each day is fully justified as one sees in Table 1 the difference in estimated values there can be (for instance, ϕ_t estimated for the hour 19 varies from –0.125 to 0.472; respectively ϕ_{we} and ϕ_{tu}). Note that ϕ_{tu} corresponds to the effect of the residual (of the remaining model) of Monday on that of Tuesday, and so on. We experimented varying the estimation window from three to eight years but the results were practically the same. The out-of-sample, i.e., the period used to test the forecasting accuracy of the models ranges from the first day of 1999 to the last of 2000, split in two sets of one year. Note that the model is not re-estimated during this period. The reason why the out-of-sample is split in two is that the trend is estimated at once (from 1998) for 1999 and 2000 by a linear extrapolation. By visual inspection, there is an apparent break in the trend, as if this was piecewise linear, seeming to have occurred in 2000, so that results

for this year are likely to be worse than those for 1999. Indeed they are, as one can inspect by comparing Tables 2.1 and 3.1. The reason for this apparent break may relate to macroeconomic factors, being beyond the scope of this paper. In a practical application, it would be wise to frequently re-estimate the model, but in this illustration, not re-estimating the model allows one to observe that the model does not suffer from misspecification (remember the trend is forecasted as linear, but not modeled so).

The favorite measure of forecasting accuracy in the load forecasting literature (c.f. Darbellay and Slama, 2000, Park et al., 1991, and Peng et al., 1992) is the Mean Absolute Percentage Error (MAPE), which is defined below, as it measures the proportionality between error and load.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\hat{X}_{T+i} - X_{T+i}\right|}{X_{T+i}}, \qquad (10)$$

where X_t is the load at time t, $\hat{X}_t$ its estimate, T is the end of the in-sample and n is the size of the out-of-sample. Other measures could be used, as some works suggest that these measures should penalize large errors and others suggest that the measure should be easy to understand and related to the needs of the decision makers. For an example of the former, Armstrong and Collopy (1992) suggest the Root Mean Square Error (RMSE), while for an example of the latter, Bakirtzis et al. (1996) use Mean Absolute Errors (MAE). However, both measures lack comparability among different data sets, and, maybe because of that, the MAPE still remains as the standard measure. Some authors (c.f., Park et al., 1991, and Peng et al., 1992) achieve MAPEs as low as 2% when predicting the total daily load, but results of different methods cannot be compared on different data sets as some data are noisier than others. If different data sets are used, the same method(s) must be used, and the comparison be made among data sets and not methods. As to the present data, Table 2 shows the MAPE one to seven days ahead for the year of 1999 both for the model proposed in this paper and the SARIMA benchmark. The best method for each hour and number of steps ahead is shown in bold. The proposed model outperforms the benchmark for all hours at one step ahead. The benchmark is better mainly for the first five hours and more than one step ahead. The middle hours see a huge difference in the forecast ability, with our model performing well, attaining MAPEs of around 3% for one step ahead going to 4% for seven steps ahead. In contrast, the benchmark attains two-digit MAPEs for steps ahead higher than one. The peak hours (19-21) see the best MAPEs, in part because the load is

the highest in the day (but the proportional predictability is more accurate for both methods). Table 3 presents the same as Table 2, but for the year 2000. The results are slightly worse, mainly because the linear trend is not re-estimated but seems to suffer a break in 2000, as explained before. Even so, the results are good and are qualitatively equal to the year of 1999, the difference being that the SARIMA fares better also in the sixth hour for steps ahead higher than one. The worst MAPEs from the model (8)-(9), namely those for the first hours seven steps ahead, rise from below 7% in 1999 to above 8% in 2000. As to one step ahead results, the best MAPE rises from 2,23% in 1999 to 2,63% in 2000 (hour 21) and the worst from 3,76% (hour 1) to 4,43% (hour 2). The hour 20 is the best predictable hour for seven steps ahead using the MAPE as the criterion, yielding MAPEs of 3,12% in 1999 and 3,93% in 2000. It is important to note that when we speak of h steps ahead, we consider the sectional data and hence refer to days. As the primary data are hourly, one must interpret as $24h$ steps ahead, so that (1, 2, …, 7) daily steps ahead actually correspond to (7, 14, …, 168) hourly steps ahead. In practice, it would be interesting to use the model proposed here and the benchmark, each one for the hours and time horizons in which each one fares better, or even in a combined way. The combination is out of the scope of this paper.

Figure 3 illustrates with a typical week the one step ahead forecasting performance of the proposed model and the benchmark. This week goes from May 9, 1999 to May 15, 1999. One can notice that the forecasts from the proposed model fit more closely to the observed loads than those from the benchmark do, reflecting the smaller error obtained by (8)-(9) as presented in Table 2. However, both fits are reasonably good, and the benchmark is not a bad predictor for this horizon (24 hours ahead). Figure 4 illustrates the seven steps ahead forecasting performance of the proposed model and the benchmark, using the same week as Figure 3. The fits are looser than those for one step ahead, as expected, but the proposed model forecasts still track the realized loads. The benchmark forecasts, on the other hand, miss out the real loads too often for this horizon (168 hours ahead), corroborating the superiority of the proposed model.

5 – Final remarks

This paper proposes a stochastic model for the hourly electricity load demand from the area covered by a specific Brazilian utility. This model applies to sectional data, that is, the load for each hour of the day is treated separately as a series. This model can be

applied to other utilities presenting similar seasonal patterns, such as many in Brazil. The model explains the seasonality by generalized (seasonal) long memory using Gegenbauer processes, having in addition a stochastic level (driven by some trend), and a calendar effects component (consisting of dummy variables for the days of the week and for holidays). The Gegenbauer processes fit in well the form of the autocorrelations observed after the estimated level and calendar effects are removed.

A forecasting exercise against a SARIMA model (the benchmark) is highly favorable to our modeling. This exercise included the entire years of 1999 and 2000, forecasting one to seven days ahead (24, 48, …, 168 hours ahead), using models estimated up to the end of 1998. We conclude for the presence of seasonal long memory in the data in study and suggest that it may be present in the load demand of other utilities with similar seasonal behavior as well.

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Table 1: Parameter estimates of model (8)-(9) for each hour.

hour	d1	d2	WD_{su}	WD_{mo}	WD_{tu}	WD_{we}	WD_{th}	WD_{fr}	WD_{sa}	α	ϕ_{su}	ϕ_{mo}	ϕ_{tu}	ϕ_{we}	ϕ_{th}	ϕ_{fr}	ϕ_{sa}
1	0.361	-0.370	-0.013	-0.047	0.001	0.006	0.010	0.013	0.031	0.006	0.407	0.695	0.495	0.552	0.289	0.574	0.541
2	0.374	-0.395	-0.013	-0.044	-0.001	0.007	0.010	0.013	0.030	0.015	0.434	0.687	0.513	0.560	0.301	0.558	0.550
3	0.385	-0.407	-0.019	-0.041	0.001	0.010	0.011	0.013	0.025	0.016	0.473	0.665	0.485	0.525	0.335	0.607	0.606
4	0.394	-0.411	-0.026	-0.039	0.003	0.012	0.012	0.015	0.022	0.010	0.450	0.646	0.480	0.582	0.316	0.624	0.639
5	0.398	-0.408	-0.036	-0.034	0.006	0.015	0.015	0.018	0.017	-0.004	0.471	0.617	0.485	0.559	0.331	0.679	0.604
6	0.396	-0.410	-0.063	-0.020	0.015	0.024	0.022	0.023	-0.002	-0.042	0.493	0.537	0.439	0.538	0.338	0.713	0.673
7	0.350	-0.340	-0.121	0.006	0.035	0.042	0.038	0.039	-0.039	-0.126	0.537	0.291	0.400	0.406	0.363	0.700	0.751
8	0.315	-0.280	-0.175	0.028	0.048	0.057	0.052	0.055	-0.066	-0.194	0.613	0.295	0.305	0.340	0.244	0.714	0.620
9	0.280	-0.192	-0.220	0.046	0.059	0.068	0.065	0.068	-0.084	-0.252	0.494	0.309	0.286	0.304	0.096	0.789	0.401
10	0.251	-0.112	-0.246	0.057	0.065	0.072	0.070	0.073	-0.091	-0.285	0.367	0.163	0.278	0.345	-0.002	0.739	0.171
11	0.230	-0.072	-0.257	0.064	0.069	0.076	0.073	0.074	-0.099	-0.300	0.298	0.158	0.389	0.378	0.040	0.527	-0.109
12	0.238	-0.126	-0.257	0.066	0.070	0.078	0.074	0.073	-0.105	-0.306	0.398	0.151	0.379	0.383	0.109	0.631	0.088
13	0.239	-0.140	-0.249	0.066	0.069	0.076	0.072	0.073	-0.105	-0.297	0.439	0.183	0.379	0.354	0.125	0.599	0.089
14	0.244	-0.160	-0.255	0.068	0.072	0.079	0.075	0.075	-0.115	-0.303	0.473	0.338	0.468	0.414	0.116	0.543	0.113
15	0.248	-0.177	-0.261	0.072	0.077	0.085	0.078	0.076	-0.126	-0.311	0.481	0.409	0.511	0.289	0.126	0.547	0.147
16	0.253	-0.201	-0.263	0.073	0.078	0.086	0.080	0.074	-0.128	-0.308	0.508	0.462	0.600	0.212	0.156	0.597	0.208
17	0.219	-0.128	-0.253	0.072	0.075	0.086	0.079	0.066	-0.126	-0.297	0.321	0.336	0.648	-0.029	0.127	0.537	0.128
18	0.198	-0.149	-0.192	0.053	0.054	0.066	0.061	0.048	-0.090	-0.257	0.441	0.165	0.567	-0.024	0.114	0.523	0.203
19	0.271	-0.062	-0.131	0.032	0.039	0.044	0.041	0.030	-0.055	-0.207	0.409	0.086	0.472	-0.125	-0.040	0.296	0.112
20	0.292	-0.121	-0.096	0.021	0.026	0.032	0.028	0.018	-0.029	-0.156	0.526	0.238	0.449	0.127	0.068	0.374	0.203
21	0.279	-0.273	-0.081	0.019	0.023	0.029	0.025	0.015	-0.030	-0.114	0.755	0.457	0.695	0.329	0.439	0.508	0.312
22	0.311	-0.355	-0.072	0.017	0.025	0.030	0.025	0.014	-0.039	-0.097	0.909	0.462	0.608	0.360	0.484	0.523	0.422
23	0.330	-0.346	-0.058	0.010	0.020	0.025	0.023	0.017	-0.038	-0.063	0.776	0.481	0.639	0.350	0.468	0.493	0.461
24	0.343	-0.349	-0.050	0.006	0.010	0.018	0.017	0.024	-0.024	-0.040	0.772	0.477	0.618	0.336	0.509	0.523	0.400

Table 2: MAPE for the entire year of 1999 (the best model in bold).

	model (8)-(9) steps ahead							SARIMA steps ahead						
hour	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	**3.76%**	5.14%	5.82%	6.08%	6.30%	6.49%	6.71%	3.93%	**4.93%**	**5.63%**	**5.84%**	**5.83%**	**5.63%**	**4.72%**
2	**3.68%**	5.09%	5.84%	6.12%	6.33%	6.59%	6.81%	3.85%	**4.79%**	**5.37%**	**5.51%**	**5.46%**	**5.40%**	**4.67%**
3	**3.54%**	4.97%	5.75%	6.00%	6.18%	6.47%	6.70%	3.67%	**4.55%**	**5.21%**	**5.36%**	**5.26%**	**5.14%**	**4.40%**
4	**3.35%**	4.67%	5.54%	5.73%	5.92%	6.18%	6.40%	3.46%	**4.39%**	**5.07%**	**5.24%**	**5.20%**	**5.02%**	**4.17%**
5	**3.21%**	4.39%	5.20%	5.39%	5.56%	5.83%	6.04%	3.37%	**4.16%**	**4.95%**	**5.18%**	**5.16%**	**4.90%**	**4.01%**
6	**2.91%**	**4.09%**	**4.70%**	**4.93%**	**5.07%**	**5.35%**	5.54%	3.26%	4.31%	5.29%	5.90%	5.95%	5.43%	**4.30%**
7	**2.85%**	**3.69%**	**4.16%**	**4.30%**	**4.43%**	**4.63%**	**4.72%**	3.62%	6.21%	8.24%	9.08%	9.16%	8.42%	6.27%
8	**2.74%**	**3.37%**	**3.75%**	**3.88%**	**4.04%**	**4.22%**	**4.31%**	4.09%	8.43%	11.04%	11.80%	11.99%	11.38%	8.38%
9	**2.75%**	**3.45%**	**3.76%**	**3.86%**	**3.98%**	**4.12%**	**4.21%**	4.63%	10.33%	13.18%	13.76%	13.98%	13.62%	10.05%
10	**2.82%**	**3.46%**	**3.78%**	**3.86%**	**3.93%**	**4.00%**	**4.07%**	4.91%	11.38%	14.42%	14.89%	15.07%	14.84%	11.05%
11	**2.92%**	**3.59%**	**3.86%**	**3.97%**	**4.01%**	**4.04%**	**4.05%**	4.95%	11.81%	15.19%	15.48%	15.67%	15.57%	11.40%
12	**2.89%**	**3.61%**	**3.88%**	**3.96%**	**3.97%**	**3.98%**	**4.00%**	5.02%	12.06%	15.61%	15.81%	15.93%	15.96%	11.58%
13	**2.99%**	**3.79%**	**4.07%**	**4.17%**	**4.19%**	**4.19%**	**4.24%**	5.04%	11.69%	15.32%	15.64%	15.72%	15.50%	11.19%
14	**3.15%**	**4.06%**	**4.40%**	**4.51%**	**4.49%**	**4.49%**	**4.52%**	5.10%	12.01%	15.91%	16.14%	16.20%	16.04%	11.45%
15	**3.22%**	**4.16%**	**4.52%**	**4.63%**	**4.67%**	**4.67%**	**4.73%**	5.16%	12.45%	16.78%	17.08%	17.16%	16.89%	11.79%
16	**3.21%**	**4.11%**	**4.48%**	**4.60%**	**4.70%**	**4.74%**	**4.77%**	5.11%	12.40%	16.92%	17.33%	17.34%	16.93%	11.70%
17	**3.26%**	**3.84%**	**4.17%**	**4.27%**	**4.35%**	**4.40%**	**4.43%**	4.82%	11.57%	16.16%	16.57%	16.64%	16.11%	10.97%
18	**2.95%**	**3.49%**	**3.71%**	**3.79%**	**3.81%**	**3.85%**	**3.90%**	4.27%	8.97%	11.95%	12.46%	12.56%	12.19%	8.65%
19	**2.82%**	**3.38%**	**3.57%**	**3.73%**	**3.87%**	**3.94%**	**3.99%**	3.54%	6.04%	7.55%	8.02%	8.01%	7.89%	6.12%
20	**2.35%**	**2.87%**	**2.93%**	**3.04%**	**3.05%**	**3.07%**	**3.12%**	3.07%	4.90%	5.63%	5.98%	5.94%	5.77%	4.88%
21	**2.23%**	**2.83%**	**3.10%**	**3.21%**	**3.27%**	**3.35%**	**3.47%**	2.85%	4.47%	5.44%	5.84%	5.82%	5.44%	4.42%
22	**2.56%**	**3.39%**	**3.75%**	**3.88%**	**3.93%**	**4.02%**	**4.13%**	3.08%	4.85%	6.21%	6.73%	6.70%	6.09%	4.76%
23	**3.04%**	**3.99%**	**4.45%**	**4.66%**	**4.72%**	**4.87%**	5.01%	3.35%	4.83%	6.18%	6.67%	6.55%	6.07%	**4.63%**
24	**3.54%**	**4.75%**	**5.33%**	**5.60%**	**5.72%**	**5.92%**	6.10%	3.76%	4.97%	6.00%	6.38%	6.34%	5.93%	**4.76%**

Table 3: MAPE for the entire year of 2000 (the best model in bold).

	model (8)-(9) steps ahead							SARIMA steps ahead						
hour	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	**4.37%**	6.42%	7.38%	7.92%	8.18%	8.20%	8.16%	4.53%	**5.77%**	**6.55%**	**6.71%**	**6.73%**	**6.65%**	**5.70%**
2	**4.43%**	6.54%	7.62%	8.15%	8.43%	8.45%	8.42%	4.53%	**5.73%**	**6.42%**	**6.55%**	**6.54%**	**6.50%**	**5.65%**
3	**4.37%**	6.45%	7.61%	8.15%	8.46%	8.44%	8.45%	4.44%	**5.58%**	**6.27%**	**6.36%**	**6.35%**	**6.33%**	**5.48%**
4	**4.23%**	6.24%	7.40%	7.93%	8.26%	8.28%	8.26%	4.35%	**5.30%**	**6.05%**	**6.15%**	**6.15%**	**6.06%**	**5.24%**
5	**4.03%**	5.99%	7.12%	7.69%	8.01%	8.06%	8.09%	4.24%	**5.07%**	**5.82%**	**5.92%**	**5.97%**	**5.87%**	**5.11%**
6	**3.81%**	5.60%	6.58%	7.05%	7.32%	7.40%	7.46%	4.14%	**5.10%**	**6.21%**	**6.48%**	**6.46%**	**6.16%**	**5.14%**
7	**3.60%**	**5.08%**	**5.88%**	**6.21%**	**6.43%**	**6.53%**	6.59%	4.47%	6.93%	8.68%	9.12%	9.16%	8.72%	**6.57%**
8	**3.22%**	**4.61%**	**5.26%**	**5.54%**	**5.73%**	**5.81%**	**5.88%**	4.70%	9.08%	11.41%	12.08%	12.13%	11.58%	8.61%
9	**3.03%**	**4.28%**	**4.75%**	**5.03%**	**5.22%**	**5.30%**	**5.35%**	4.92%	10.69%	13.48%	14.28%	14.33%	13.86%	10.25%
10	**2.97%**	**4.06%**	**4.49%**	**4.67%**	**4.80%**	**4.86%**	**4.92%**	5.24%	12.01%	15.02%	15.80%	15.85%	15.52%	11.48%
11	**3.00%**	**3.97%**	**4.39%**	**4.56%**	**4.69%**	**4.76%**	**4.81%**	5.39%	12.69%	16.11%	16.81%	16.79%	16.53%	11.99%
12	**3.05%**	**3.99%**	**4.41%**	**4.56%**	**4.68%**	**4.73%**	**4.75%**	5.60%	12.78%	16.47%	17.14%	17.12%	16.84%	12.10%
13	**3.00%**	**4.00%**	**4.44%**	**4.59%**	**4.71%**	**4.76%**	**4.78%**	5.40%	12.56%	16.27%	16.94%	16.93%	16.49%	11.71%
14	**3.17%**	**4.29%**	**4.72%**	**4.93%**	**5.05%**	**5.10%**	**5.10%**	5.55%	12.85%	16.80%	17.65%	17.60%	17.09%	12.11%
15	**3.38%**	**4.51%**	**4.98%**	**5.19%**	**5.31%**	**5.35%**	**5.36%**	5.74%	13.29%	17.70%	18.40%	18.45%	17.89%	12.41%
16	**3.43%**	**4.55%**	**4.98%**	**5.23%**	**5.33%**	**5.41%**	**5.43%**	5.77%	13.17%	17.77%	18.47%	18.57%	17.90%	12.29%
17	**3.60%**	**4.43%**	**4.77%**	**4.89%**	**4.98%**	**5.04%**	**5.02%**	5.39%	12.19%	16.65%	17.26%	17.39%	16.63%	11.25%
18	**3.44%**	**4.19%**	**4.43%**	**4.52%**	**4.58%**	**4.58%**	**4.59%**	4.79%	9.24%	12.18%	12.66%	12.68%	12.09%	8.67%
19	**3.21%**	**3.77%**	**4.07%**	**4.30%**	**4.44%**	**4.50%**	**4.53%**	4.03%	6.43%	7.81%	8.13%	8.14%	7.80%	6.18%
20	**2.71%**	**3.30%**	**3.60%**	**3.74%**	**3.87%**	**3.93%**	**3.93%**	3.47%	5.15%	5.74%	5.95%	6.05%	5.80%	4.99%
21	**2.63%**	**3.45%**	**3.85%**	**4.11%**	**4.16%**	**4.23%**	**4.22%**	3.17%	4.89%	5.67%	5.84%	5.95%	5.69%	4.56%
22	**2.98%**	**4.12%**	**4.62%**	**4.94%**	**5.11%**	**5.17%**	5.16%	3.36%	5.30%	6.61%	6.92%	6.90%	6.56%	**4.92%**
23	**3.58%**	**5.15%**	**5.82%**	**6.22%**	**6.41%**	**6.43%**	6.41%	3.99%	5.64%	6.95%	7.28%	7.24%	6.79%	**5.30%**
24	**4.14%**	5.96%	6.81%	7.34%	7.56%	7.60%	7.56%	4.50%	**5.79%**	**6.78%**	**7.09%**	**6.98%**	**6.70%**	**5.59%**

Figure 1: Autocorrelation function of the series from January 1, 1990 to December 31, 1998, for hours 1, 8, 14 and 20, after removal of the trend and the calendar effects (weekdays and holydays), up to lag 1000. Note the resemblance to a damped sinusoid.

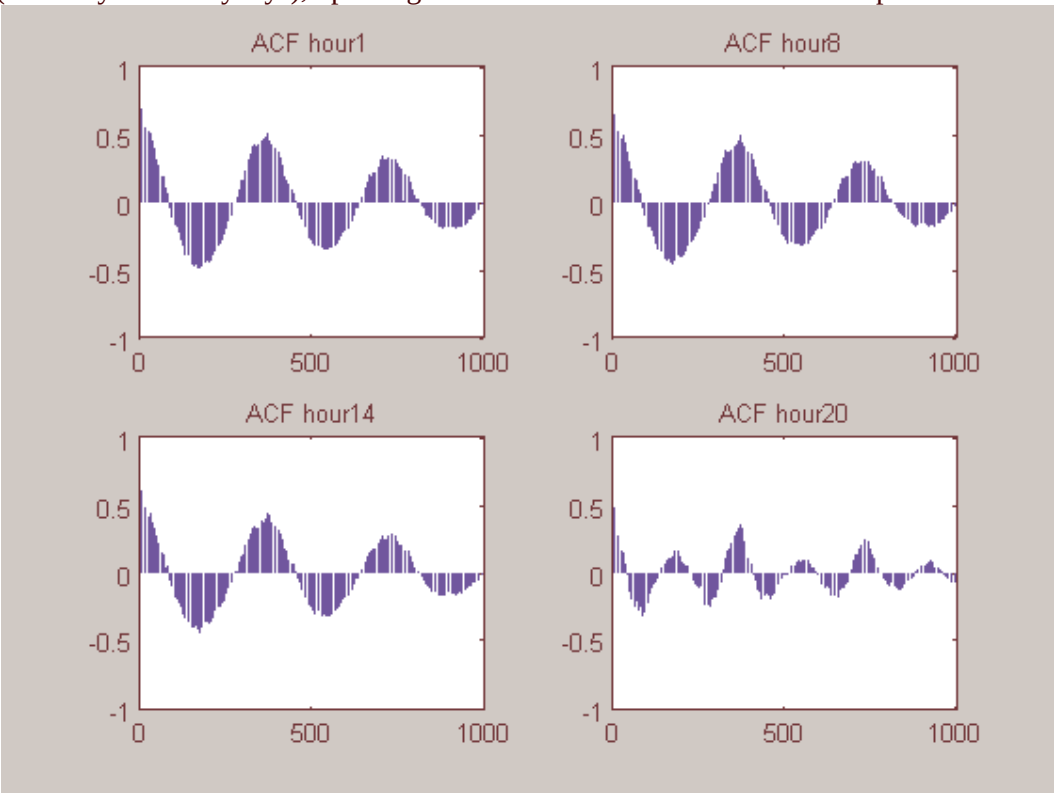


Figure 2: Raw and smoothed periodogram of the series from January 1, 1990 to December 31, 1998, for hours 1, 8, 14 and 20, after removal of the trend and the calendar effects.

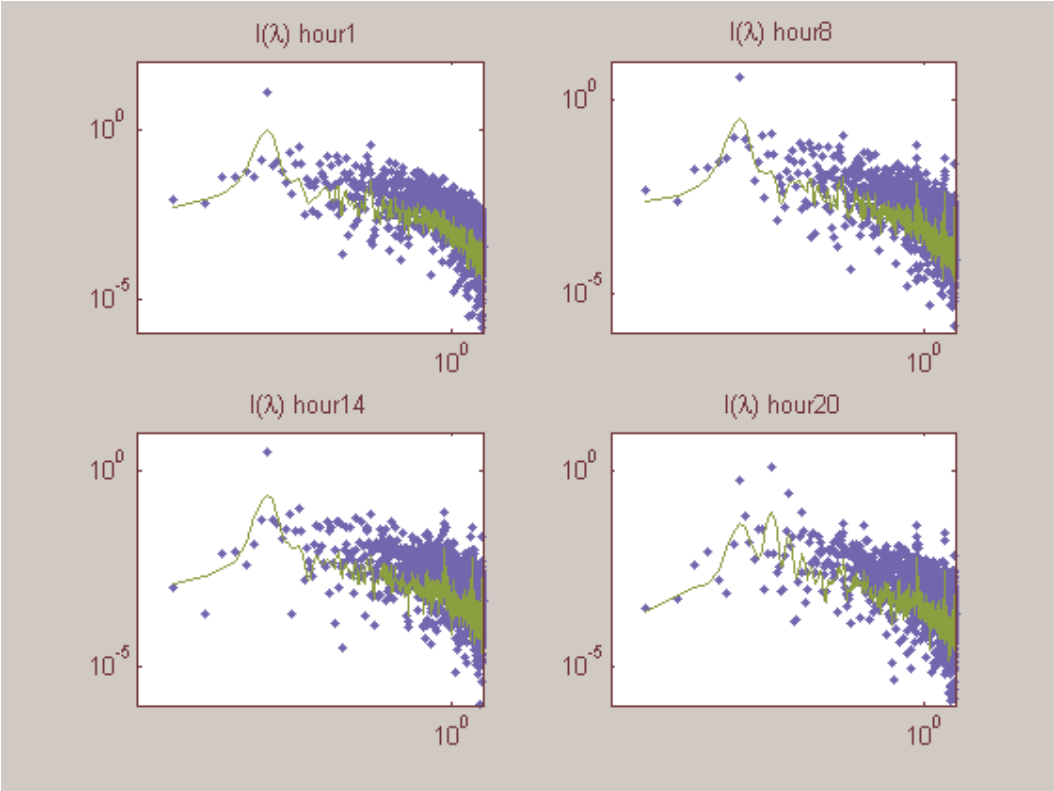


Figure 3: Real versus predicted load (MWh), for both the model proposed here and the SARIMA benchmark, one step ahead, from May 9, 1999 to May 15, 1999 (one week, from Sunday to Saturday).

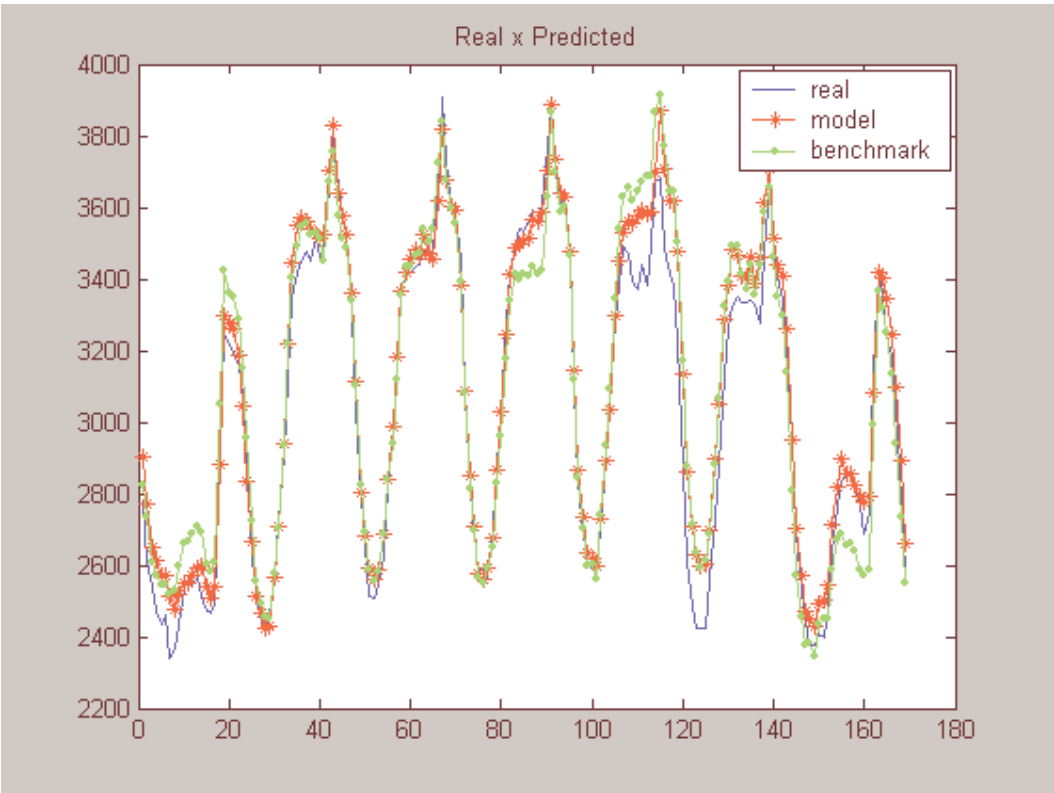
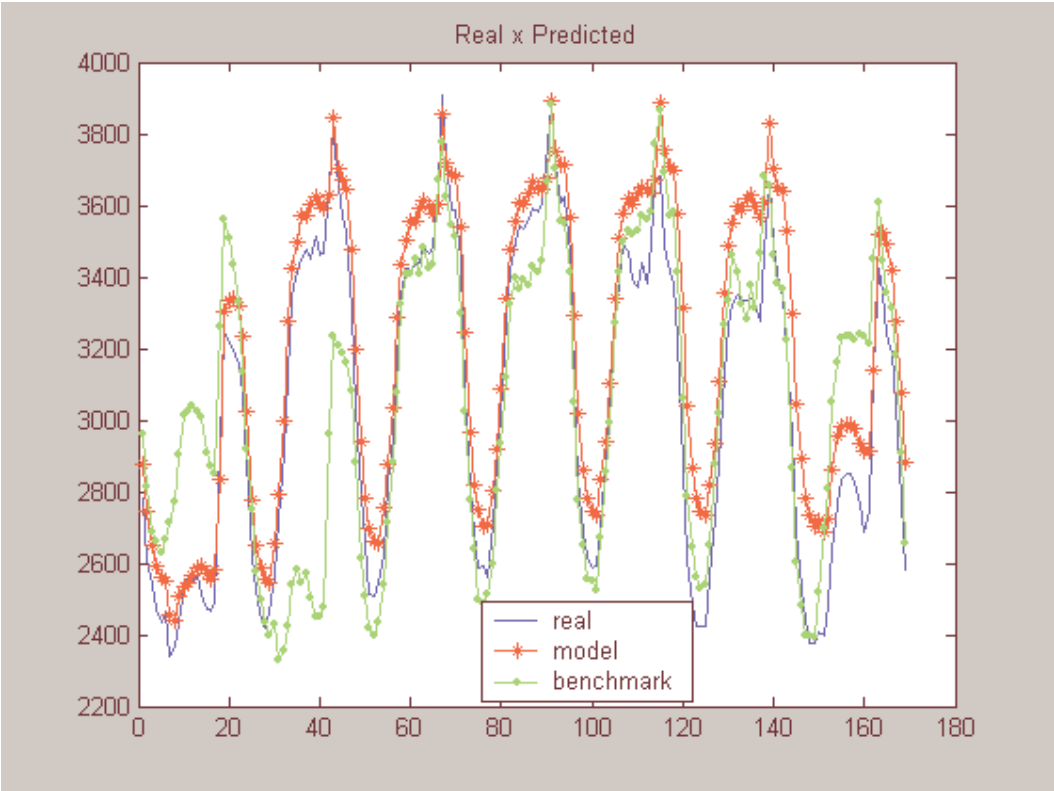


Figure 4: Real versus predicted load (MWh), for both the model proposed here and the SARIMA benchmark, seven steps ahead, from May 9, 1999 to May 15, 1999 (one week, from Sunday to Saturday).



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