5
Analysis with Real Load Data

5.1
Introduction

Much of the early literature on electricity load forecasting models is summarized in Bunn and Farmer (1985) and the references therein. More recent developments have typically focused on highly structured, larger scale, models whose fitting, calibration and forecasting procedures are computationally intensive, and have taken advantage of the exponential growth in computing power that has occurred over the last two decades. A key consideration in all these models is how best to capture the diverse time scales, from half-hourly through to years, present in the data.

Two broad classes of conceptual models have emerged which address these time scales issues in different ways. These are:

(i) univariate times series models with components such as trend, annual, weekly and daily periodicity, exogenous variables such as temperature and special treatment for holidays, among others, where these components are all defined on a half-hourly or hourly time scale depending on the series. Examples of univariate time series models are given in Harvey and Koopman (1993), Bruce et al (1994), Smith (2000), Lunney (2001), Amjady (2001), Nowicka-Zagrajek and Weron (2002), Huang (2003), Taylor (2003), Taylor and Buizza (2003), Hamadi and Soliman (2004), Huang et al (2005) and Taylor et al (2006).

(ii) vector or multivariate times series models that organize the data into daily (or weekly) vectors of half-hourly or hourly loads; the vector model operates over a daily or weekly times scale. For example, daily profiles of 48 half hourly loads can be regarded as a vector times series with a daily times scale. Here intra-day half hourly variation is accounted for implicitly by the cross-sectional model for each vector, and inter-day variation is modeled explicitly using the daily time scale. Of course it can also include deterministic variables, temperature variables, etc. Equally, the same data could be treated as a vector time series of weekly loads with a weekly times index, or a univariate time series with a half-hourly time index. Articles using this conceptual are Fiebig et al (1991), Peirson and Henley (1994), Ramanathan, Engle and Granger (1997), Cottet and Smith (2003), Soares and Medeiros (2005) and Soares and Souza (2006).

In principle, all vector models can be reformulated as univariate models and vice versa. However, the different conceptual frameworks discussed above have inevitably lead to different stochastic models being adopted for each of the various model formulations.

Because of the strong periodicity and systematic evolution present in electricity load time series, both univariate and vector models are highly dependent on accurate modeling of the trends (if present) and periodic components, using regressions or other techniques. If this is not done well, then the resulting residuals are likely to be dominated by lack of fit, rather than by any real dynamic error structure that may be present. Appropriate modeling of this error structure is important for accurate parameter estimation, short-term forecasting, and the generation of realistic sample paths for all time horizons. It is also important, at all time horizons, for the evaluation of risk using predictive distributions of aggregations, and other functions of future loads.

Artificial Neural Networks (ANN) models have proved popular as alternative load forecasting models and directly compete, in terms of accuracy, with the mainly univariate and vector models cited above. However, the ANN models are complex, difficult to understand, and are often over fitted to data. Indeed, their structure is sufficiently opaque that it is not clear why they should forecast so well and, as a result, the literature is still somewhat divided as to their utility in practice. Hippert et al (2005) discuss these issues, and compare the short-term forecasting performance of several load forecasting procedures, including ANN models as well as univariate and vector linear models of the type discussed above. One conclusion is that well-chosen linear models are competitive, and sometimes better than ANN models. This was also a conclusion of Darbellay and Slama (2000), who used formal nonlinear and linear measures of association to compare conventional linear models with ANN models. Other articles that deals with ANN are Khotanzad et al (1998), Alves da Silva and Moulin (2000), Metaxiotis, Kagiannas, Askounis and Psarras (2003), Reis and Alves da Silva (2005), Alves da Silva and Ferreira (2007).

This thesis will concentrate on a short-term load forecasting up to 7 days ahead or 336 half-hours ahead. The model considered is the nonlinear Smooth Transition Periodical Autoregressive (STPAR). However, other models will be estimated as benchmarks, they are: a simple autoregressive model, periodic autoregressive and the STAR model. Both classes of conceptual models (univariate and vector) are also tested. The chapter is organized as follows: section 5.2 presents the temperature and load data set used. Section 5.3 describes the model and the modeling strategy. Section 5.4 is divided in two: the first (5.4.1) part will report the results for specification, estimation and forecasting using the univariate conceptual and second (5.4.2) part presents the results for the vector conceptual.

5.2
The Data Set

In this thesis we consider a set of observations that is composed of half hourly measurements of load and temperature from July 1, 2001 to June 30, 2005, a total of 4 years of data or 70128 points. The observations from July 1, 2001 to June 30, 2004 will be used as the estimation sample (in-sample) and the last year (July 1, 2004 to June 30, 2005) will be used for forecast evaluation or out-of-sample analysis.

The data set of load is from the state of New South Wales (NSW) in Australia and it was kindly supplied by Integral Energy, a utility in NSW state. NSW concentrates a total population of around 10 million people and covers around 20% of the country. The energy consumption corresponds to 60% of the total consumption in Australia. The temperature data set was collect in the Bankstown Airport area in the suburbs of Sydney. Figures 23 and 24 show the demand and temperature observations in a univariate format and figures 25, 26, 27 and 28 illustrate the half hourly loads and temperature for each half hour of the day.

It is well known in the literature that load time series contains a trend component. By testing the null hypothesis of a stochastic trend (unit root) using the Phillips-Perron Test (Phillips and Perron (1988)), the hypothesis is not rejected with 95% level of confidence ($p_{value} = 0.13$). As pointed out in Soares and Medeiros (2005) the usual procedure is to take first-order differences of the load series and doing so, has a disadvantage: when it is assumed that the process follows a deterministic trend, it introduces a non invertible moving average component in the data generating process that leads to estimation problems. In addition, there won't exist any linear autoregressive model able to capture the dynamics of the data (for more detail see Chapter 4 of Enders (2004)). Hence, before any modeling commences, the state load data is de-trended. A linear trend is allowed for the load data by taking logarithms of the loads, and fitting a linear model to the logarithms by Ordinary Least Squares (OLS). The fitted trend is exponentiated and then subtracted from the raw load data to yield a detrended load series. When load is being forecasted, then it is necessary to add to the prediction the trend that was estimated and removed from the raw data series.

The last comment about the data set will consider the treatment of "special days" such as bank holidays. One of the main goals of this thesis is to compare methods in forecasting load series. Taylor et al (2006) argue that when comparison of methodologies is the objective, the treatment for those days is likely to be unhelpful because the pattern of load on these days is a lot different. Hence, univariate methods are likely to generate poor forecast for these days. Therefore, data from these days shouldn't be considered. From another point of view, if the purpose for which the model was developed is to assist in the hedging of electricity prices, "special days" are not likely to be a material issue in hedging electricity prices, as loads are invariably smaller on "special days" than on normal days. "Special days" do not drive hedging policy or practice. Thus the treatment for a holiday in this paper will be deleting the data from that day and include the simple mean of the data from the same day one week before and one week later.

By looking at figure 23 one concludes that there is a trend as a component of the process. And the observations are volatile. Temperature follows the same pattern as in other places of the world. The range of temperature is 0 degrees until peaks of more than 40 degrees. Analyzing figure 25 it is easy to see that between /0:00 and 5:00 the series is well behaved. After that it is much more volatile.

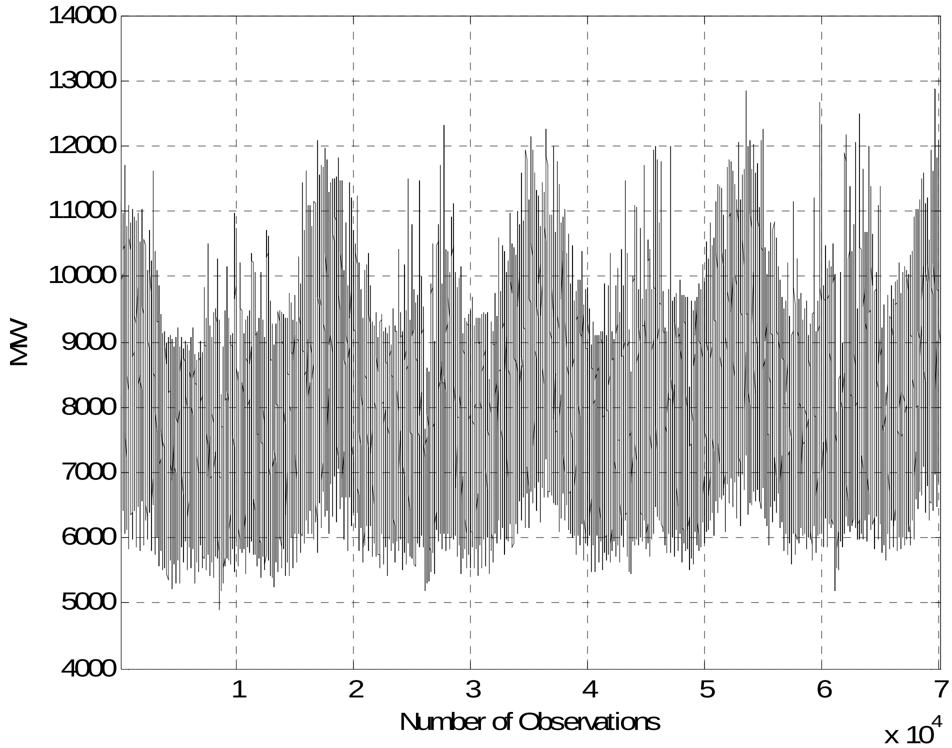

Figure 23 – Half-hourly demand from July 1, 2001 to June 30, 2005.

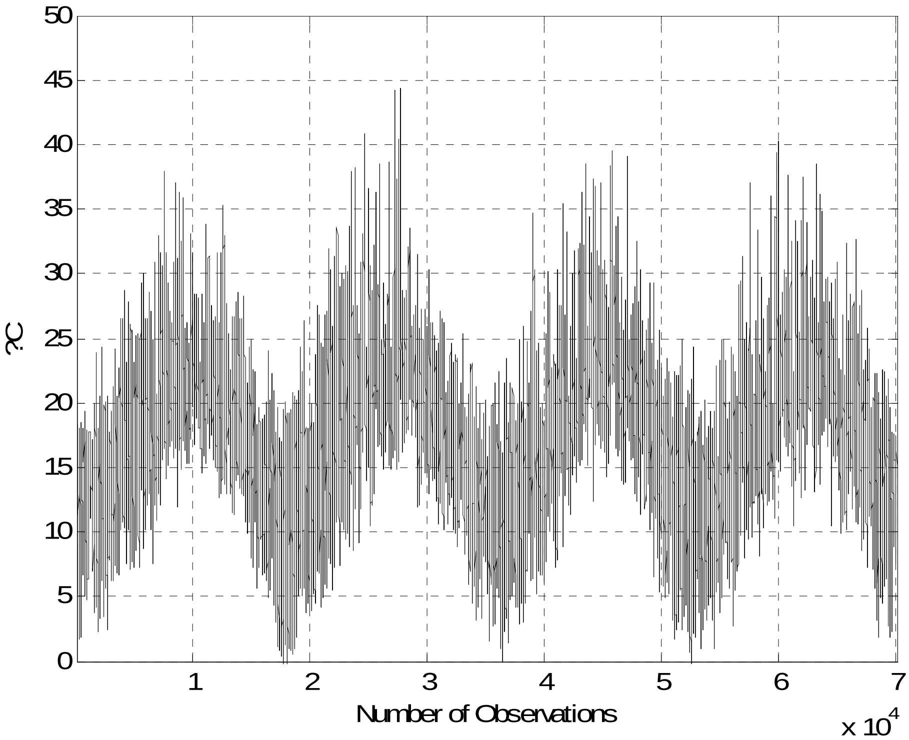

Figure 24 – Half-hourly temperature from July 1, 2001 to June 30, 2005.

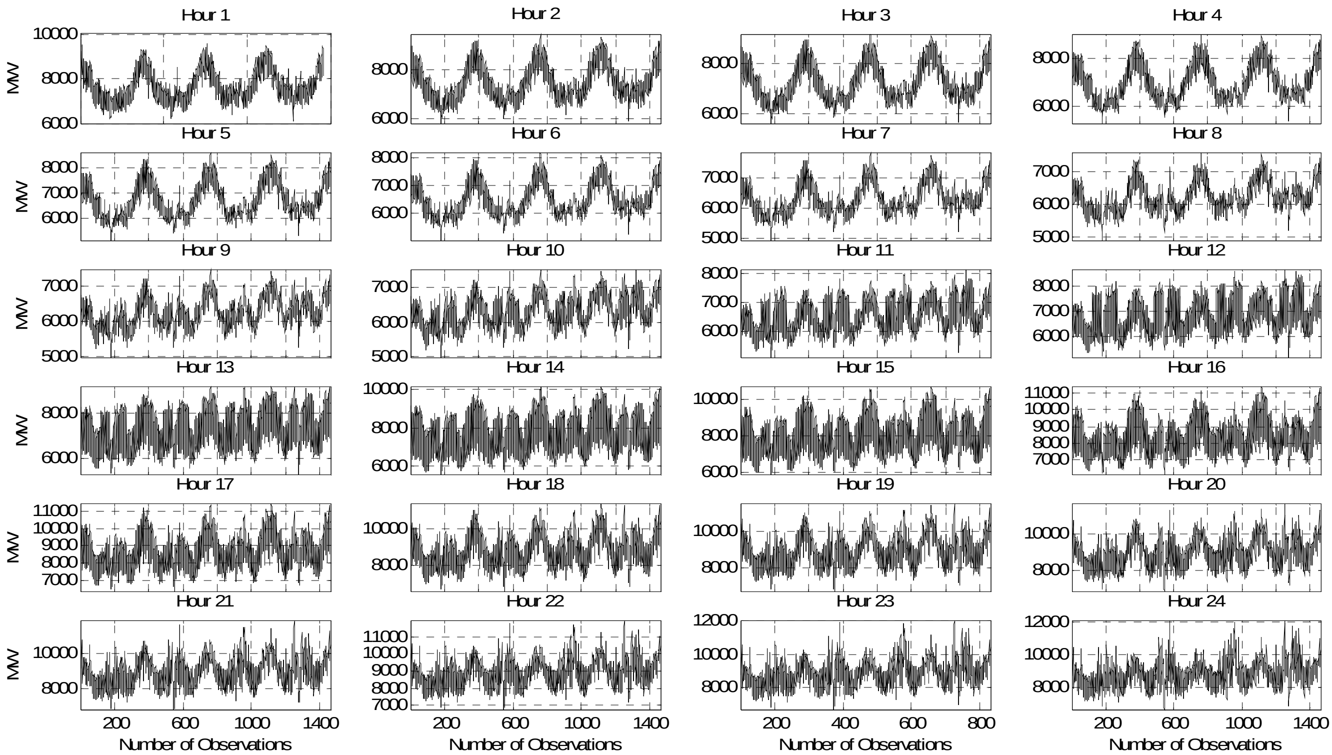

Figure 25 – Load of the first 24 half-hours from July 1, 2001 to June 30, 2005.

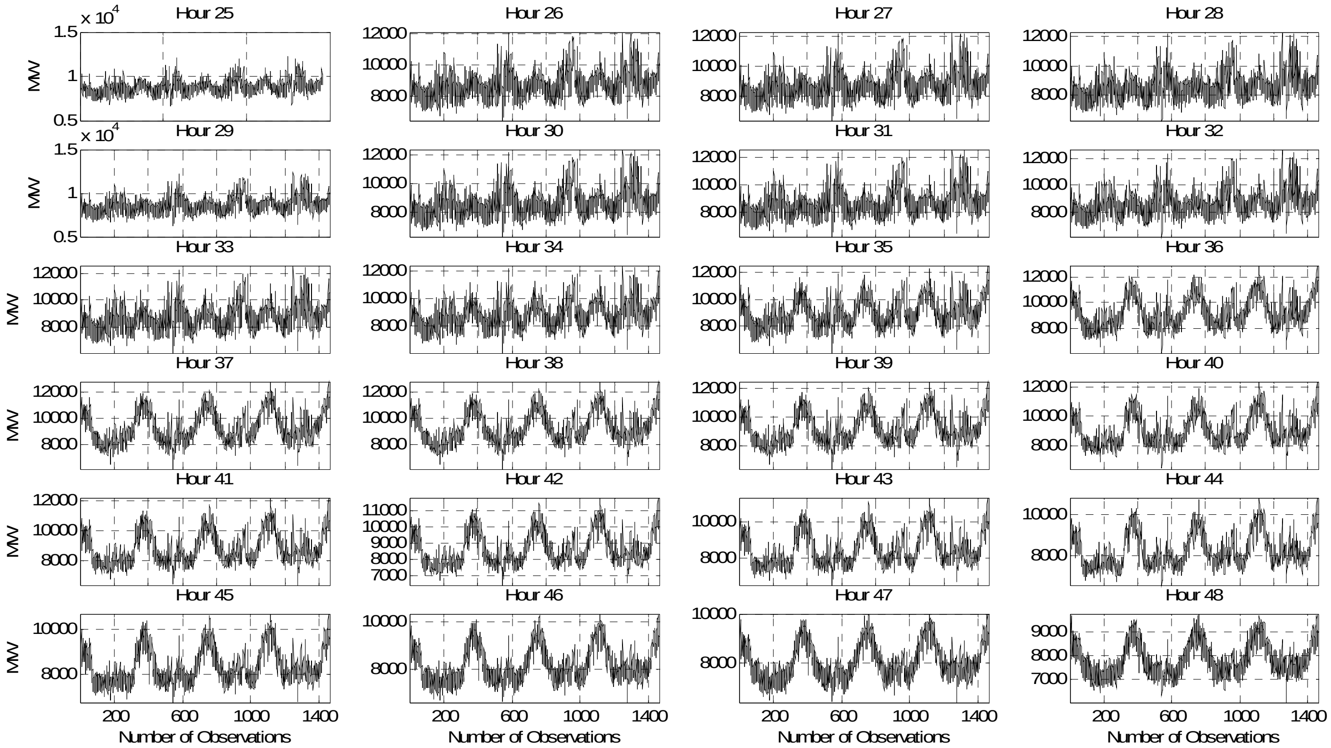

Figure 26 – Load of the last 24 half-hours from July 1, 2001 to June 30, 2005.

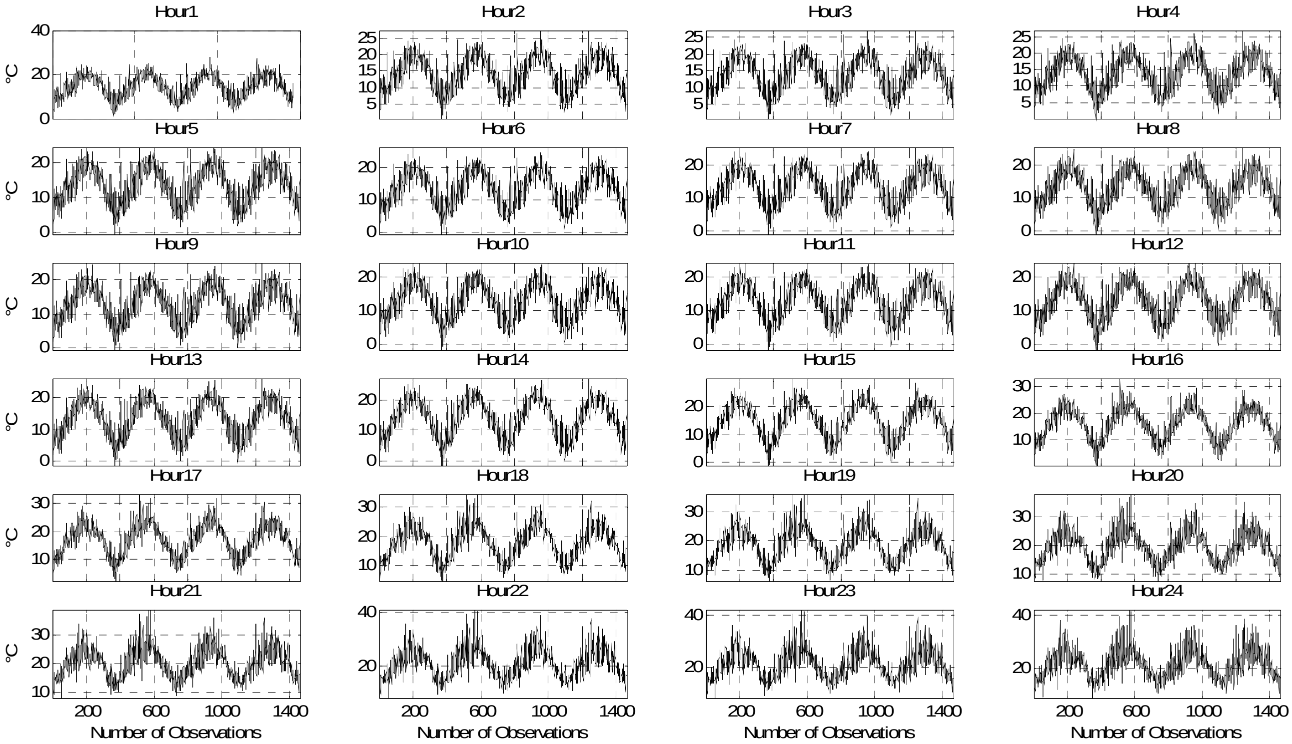

Figure 27 – Temperature of the first 24 half-hours, July 1, 2001 to June 30, 2005.

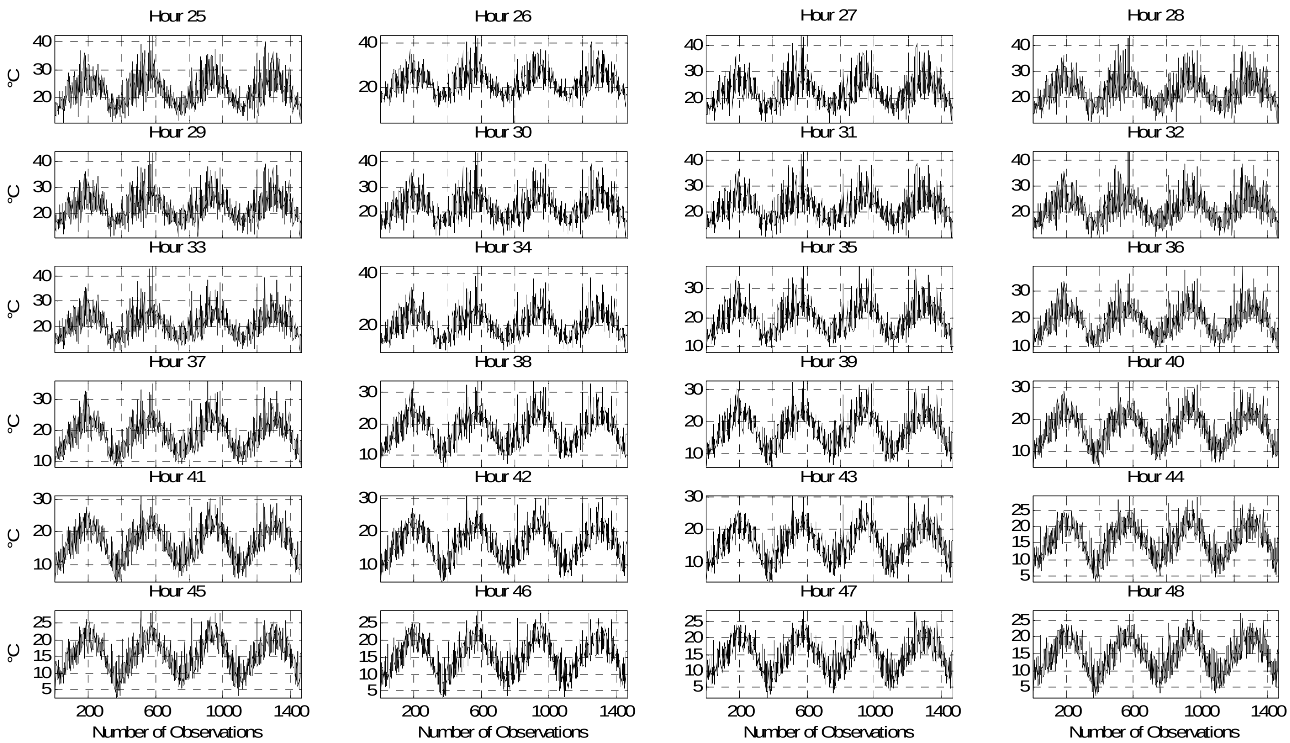

Figure 28 – Temperature of the last 24 half-hours, July 1, 2001 to June 30, 2005.

5.3
Models

As previously mentioned, the models tested are the simple linear autoregressive (AR) model, the periodic autoregressive (PAR), the smooth transition autoregressive (STAR) and the smooth transition periodic autoregressive (STPAR).

To find the best model for each class, we follow the common modeling cycle proposed in the literature, that is, in the AR context we analyze the autocorrelation function to discover the *p* order; for the PAR we analyze how the autocorrelation at lags found in the AR analysis varies for each half-hour of the day. Figures 29, 30 and 31 show the autocorrelation for lags equal to 1, 48 and 336.

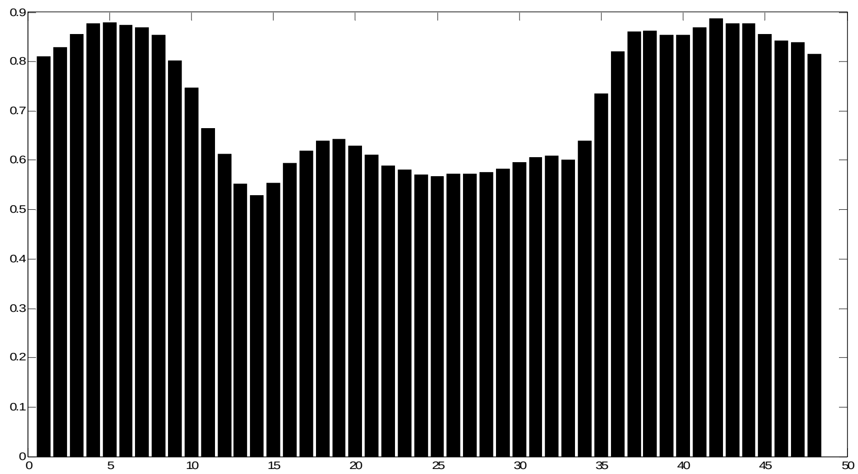

Figure 29 – Lag 1 autocorrelation at the 48 half-hours of the day

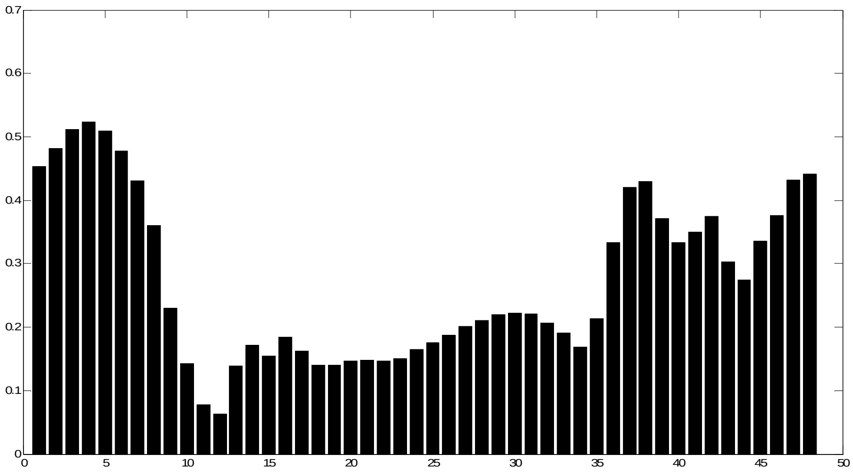

Figure 30 – Lag 48 autocorrelation at the 48 half-hours of the day

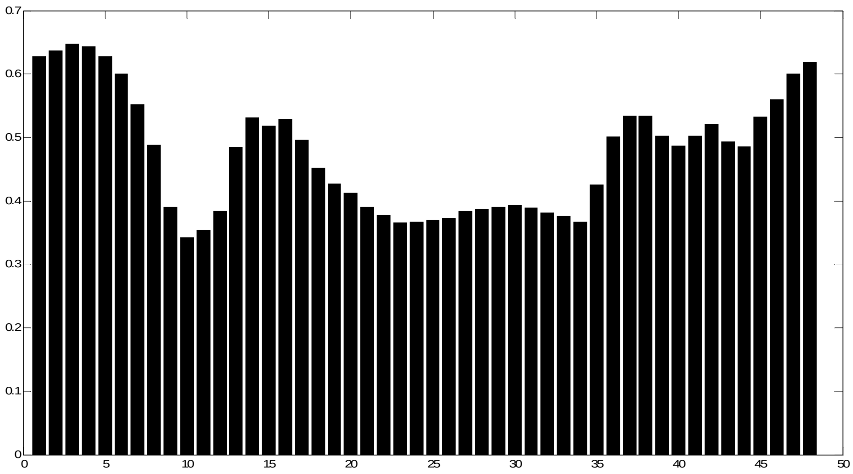

Figure 31 – Lag 336 autocorrelation at the 48 half-hours of the day

The graphs show that the appealing to use the periodic model is more evident in lags 48 and 336 because of the variation in the value of the autocorrelation during the day. In lag 1 it seems to be more stable. However, it will be considered periodicity in all AR terms and like in Taylor (2006) we also considered the possibility of periodicity in the constant term.

The STAR and the STPAR follows the procedure proposed in Terasvirta (1994) and here.

It is important to mention that temperature will be included in the analysis. When dealing with the AR or the PAR, temperature will be considered an explanatory variable. However, the use of temperature in the STAR and STPAR context will be considered as the transition variable in the logistic function. There is a strong appeal to do that. By looking at figure 32, the relation between load and temperature is clear. Therefore, we could say that temperature gives an indication if the consumption of energy will be high or low and that is exactly what the transition variable is capturing, i.e., the dynamics of changes from one regime to another.

The forecasting model for temperature will be the same as in the analysis of Svec and Stevenson (2006) relying heavily on the seasonal and cyclical nature of temperature. It is approximated by two periodic functions representing the seasonal and daily periodicity. Both are modeled as a low-order Fourier series with a repeating step function that cycle through each half hour. For details see Svec and Stevenson (2006).

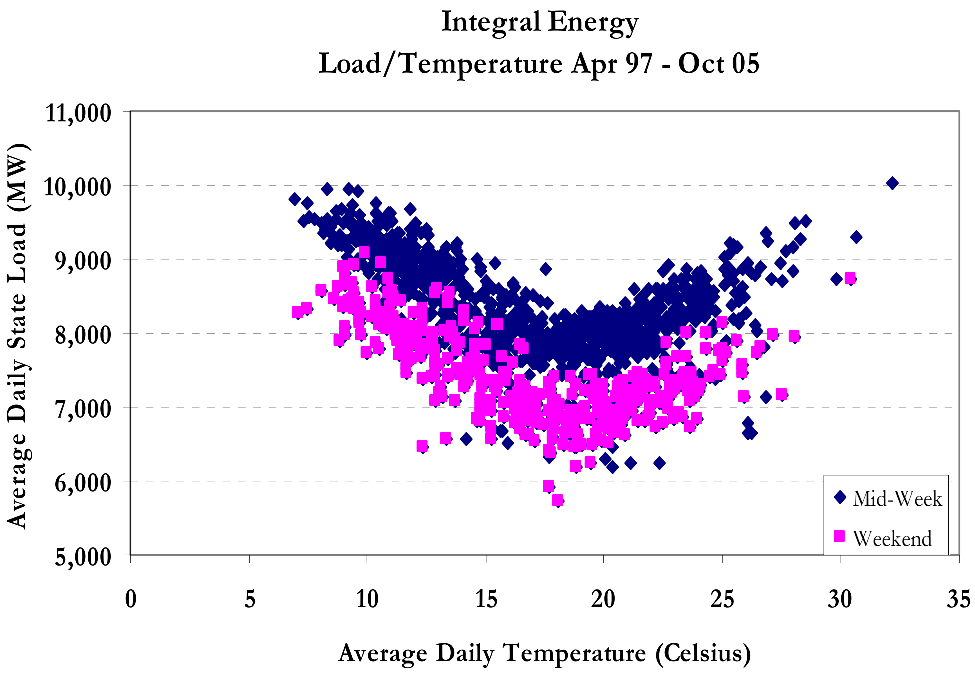

Figure 32 – Scatter plot between Load and Temperature

5.4
Results

5.4.1
Univariate

First when the order of the autoregressive model was determined, the autocorrelation function together with the AIC and BIC suggested the use of lags 1, 48 and 336. These lags were accepted to be the basis of the linearity test when judged by the Ljung-Box statistic.

Tables 3 and 4 report the results for the linearity test when the transition variables are load and temperature, respectively. The linearity test is rejected most strongly at the delay equal to 1 for load and 3 for temperature.

Table 3 – P values linearity test; Different values of the delay parameter for load

	Delay - Transition variable: Load					
	1	2	3	4	5	6
p-value	**0.000**	0.008	0.026	0.048	0.133	0.074

Table 4 – P values linearity test; Different values of the delay parameter for temperature

	Delay - Transition Variable: Temperature					
	1	2	3	4	5	6
p-value	0.032	0.009	**0.001**	0.051	0.016	0.102

The next step is to estimate the model and select the number of h in (30) by using an Information Criterion, preferably the BIC. We considered periodicity in the lags 1, 48 and 336 and in the constant term. In the analysis of both transition variables, the selected number of Fourier forms was two.

$$y_t = \phi_{01} + \phi_{11} y_{t-1} + \phi_{21} y_{t-48} + \phi_{31} y_{t-336} + \{(\phi_{02} + \phi_{12} y_{t-1} + \phi_{22} y_{t-48} + \phi_{32} y_{t-336}) \times F(\gamma(s_t - c))\} + \varepsilon_t$$

where (30)

$$\phi_{ij} = \varpi_i + \sum_{k=1}^{h} \lambda_{ik} \sin(2k\pi(D(s)/48)) + \kappa_{ik} \cos(2k\pi(D(s)/48)) + \tau_{ik} \sin(2k\pi(W(s)/336)) + \omega_{ik} \cos(2k\pi(W(s)/336))$$

Next, we show the results for the forecasting performance (out sample analysis) using the Mean Absolute Percentage Error (MAPE) when the transition variable is load and temperature. Table 5 presents the results for a month and for each day. Overall, the forecasting performance using temperature as the transition variable is better than when using load. Other conclusions are that January and December are the most difficult months to predict, where MAPES are higher!

Table 5 – Forecasting performance for the STPAR using MAPE – Transition variable: Load (d=1) and Temperature (d=3) – 2 Fourier Forms – Lags: 1, 48 and 336

	Transition Variable - LOAD							Transitioin variable - TEMPERATURE						
	Forecast Horizon - Days							Forecast Horizon - Days						
Month	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Jan	4.27	4.55	4.73	4.59	5.27	5.96	6.39	3.51	4.01	4.51	4.56	4.87	5.05	5.54
Feb	2.71	3.67	4.13	4.22	4.72	4.53	5.21	2.11	3.14	3.14	3.61	4.81	4.85	5.14
Mar	2.67	3.03	4.96	5.23	5.31	6.05	6.12	2.07	2.88	3.01	3.42	4.64	4.87	5.61
Apr	2.70	3.55	5.41	4.95	4.98	5.32	5.55	1.87	2.29	2.76	4.17	4.93	5.47	5.99
May	3.01	3.80	5.18	5.12	5.22	6.00	6.43	1.91	2.05	3.08	4.46	4.30	5.21	5.46
Jun	2.62	3.31	4.52	4.21	4.82	4.80	5.10	1.96	2.25	3.07	4.90	4.97	4.71	5.74
Jul	2.51	3.18	4.10	3.99	4.16	4.75	5.09	1.84	2.21	3.25	4.80	4.98	4.66	5.31
Aug	2.98	2.50	3.62	4.07	3.97	5.68	5.71	1.96	2.38	3.27	4.09	4.95	4.66	5.85
Sep	3.27	4.05	3.73	3.05	3.95	4.39	4.85	1.88	2.79	3.18	4.70	4.61	4.90	5.22
Oct	2.93	3.16	2.99	3.20	3.54	5.58	6.43	1.56	3.02	3.70	4.17	4.83	5.39	5.69
Nov	2.85	3.14	4.43	5.08	5.45	4.19	4.52	2.22	3.10	3.53	4.94	4.99	4.91	5.32
Dec	5.24	5.61	5.22	5.97	6.11	6.51	7.10	3.31	4.14	5.02	5.21	5.55	6.06	6.87
Minimum	2.51	2.50	2.99	3.05	3.54	4.19	4.52	1.56	2.05	2.76	3.42	4.30	4.66	5.14
Average	3.15	3.63	4.42	4.47	4.79	5.31	5.71	2.19	2.86	3.46	4.42	4.87	5.06	5.64
Maximum	5.24	5.61	5.41	5.97	6.11	6.51	7.10	3.51	4.14	5.02	5.21	5.55	6.06	6.87

Table 6 presents the results for the evaluation tests applied for the model where the transition variable is temperature. There is an indication that the model was correctly specified.

Table 6 – Results of evaluation tests of the estimated STPAR model

	Test for q-th order serial correlation								No remaining nonlinearity
q	1	2	4	12	24	48	96	336	
p-value	0.56	0.38	0.61	0.72	0.44	0.21	0.47	0.51	0.77

Finally, we compare the performance of the STPAR with other models. The AR and the PAR included temperature as an explanatory variable with a lag of order 3. And for the STAR we have used the temperature as the transition variable and with d = 3.

We conclude that the model seems to work better in the first, second and third day. For the rest of the forecast horizon, the model doesn’t perform better than the STAR although the results are not that different.

Table 7 – Forecasting performance for the STPAR, STAR, PAR and AR models – MAPE – Univariate (1 model)

	STPAR							STAR							PAR							AR						
	Forecast Horizon - Days							Forecast Horizon - Days							Forecast Horizon - Days							Forecast Horizon - Days						
Month	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7	1	2	3	4	5	6	7
Jan	**3.51**	**4.01**	**4.51**	**4.56**	4.87	5.05	5.54	4.06	4.16	4.55	4.87	**4.04**	**4.67**	**4.95**	3.83	4.41	4.77	4.94	4.79	5.11	5.78	4.98	5.71	6.93	6.53	7.33	7.78	7.95
Feb	**2.11**	**3.14**	**3.14**	**3.61**	4.81	4.85	5.14	2.90	3.19	3.62	3.98	**4.23**	**4.59**	**5.05**	2.24	3.17	3.17	3.98	4.91	5.43	5.47	5.00	5.79	6.44	6.40	6.33	6.58	7.45
Mar	**2.07**	**2.88**	**3.01**	**3.42**	4.64	4.87	5.61	2.82	3.22	3.56	4.19	**4.53**	**4.84**	**5.49**	2.28	3.18	3.50	3.82	4.69	5.26	5.73	4.79	5.49	6.06	6.86	6.04	7.45	7.40
Apr	**1.87**	**2.29**	**2.76**	4.17	4.93	5.47	5.99	2.13	3.37	3.35	**3.50**	**4.79**	**5.00**	**5.55**	2.07	3.20	3.23	4.13	4.96	5.38	5.75	4.87	5.03	6.29	6.04	6.25	6.94	7.18
May	**1.91**	**2.05**	**3.08**	4.46	4.30	5.21	5.46	2.27	3.59	3.12	**4.14**	**4.26**	**5.03**	**5.10**	2.10	3.39	3.11	4.23	4.90	5.17	5.54	4.06	5.12	6.36	6.95	6.14	6.70	7.00
Jun	**1.96**	**2.25**	**3.07**	4.90	4.97	4.71	5.74	2.41	3.88	3.64	**4.36**	**4.77**	**4.66**	**5.45**	1.99	3.34	3.11	4.94	4.84	4.99	5.51	4.05	5.53	6.07	6.66	6.11	6.67	7.93
Jul	**1.84**	**2.21**	**3.25**	4.80	4.98	4.66	5.31	2.61	3.61	3.76	**4.67**	**4.91**	**4.59**	**5.21**	2.13	3.52	3.42	4.92	4.83	4.96	5.55	4.10	5.57	6.22	6.80	6.94	6.48	7.89
Aug	**1.96**	**2.38**	**3.27**	4.09	4.95	4.66	5.85	2.63	2.77	3.46	**4.05**	**4.66**	**4.51**	**5.04**	2.28	3.57	3.42	4.07	4.70	4.89	5.88	4.03	5.51	6.11	6.00	6.16	6.88	7.37
Sep	**1.88**	**2.79**	**3.18**	4.70	4.61	4.90	5.22	2.27	3.89	3.77	**4.57**	**4.57**	**4.74**	**5.11**	2.39	3.84	3.59	4.66	4.60	5.09	5.31	4.83	4.98	6.03	6.91	6.94	6.66	6.99
Oct	**1.56**	**3.02**	**3.70**	4.17	4.83	5.39	5.69	2.24	3.79	4.11	**4.10**	**4.77**	**5.16**	**5.25**	2.91	3.30	3.83	4.80	4.89	5.78	5.88	4.68	5.57	6.96	6.81	6.51	6.25	6.69
Nov	**2.22**	**3.10**	**3.53**	**4.94**	4.99	4.91	5.32	2.92	3.21	3.85	4.69	**4.70**	**4.74**	**4.97**	2.34	3.21	3.52	4.84	4.76	5.52	5.55	4.72	5.11	6.65	6.36	6.03	6.21	6.19
Dec	**3.31**	**4.14**	**5.02**	**5.21**	5.55	6.06	6.87	4.13	4.82	5.08	5.57	**5.07**	**5.37**	**5.93**	4.08	4.69	4.92	5.01	5.10	5.87	6.86	5.21	5.87	6.85	6.11	6.81	6.95	7.14
Minimum	1.56	2.05	2.76	3.42	4.30	4.66	5.14	2.13	2.77	3.12	3.50	4.04	4.51	4.95	1.99	3.17	3.11	3.82	4.60	4.89	5.31	4.03	4.98	6.03	6.00	6.03	6.21	6.19
Average	2.19	2.86	3.46	4.42	4.87	5.06	5.64	2.78	3.62	3.82	4.39	4.61	4.82	5.26	2.55	3.57	3.63	4.53	4.83	5.29	5.74	4.61	5.44	6.41	6.57	6.47	6.80	7.27
Maximum	3.51	4.14	5.02	5.21	5.55	6.06	6.87	4.13	4.82	5.08	5.57	5.07	5.37	5.93	4.08	4.69	4.92	5.01	5.10	5.87	6.86	5.21	5.87	6.96	6.95	7.33	7.78	7.95

5.4.2 Vector

In this section we will report the results for the vector conceptual, i.e., one model for each half hour. First the order p suggested by the AIC and BIC and the analysis of the autocorrelation function was 1 and 7. In some cases (half hour 2, 4, 6, 7, 8, 9, 10, 11 and 12) the lag 14 was significant; however, fitting the data with this lag the fit didn't increase much. Thus lags 1 and 7 were considered the correct order for all half hours.

Table 8 will present the results for the linearity test indicating the delay parameter d chosen for the transition variable when it was load or temperature. It also presents the number of harmonics selected using BIC as the information criteria.

The estimated model for the STPAR was like (31), that is,

$$y_t = \phi_{01} + \phi_{11} y_{t-1} + \phi_{21} y_{t-7} + \{(\phi_{02} + \phi_{12} y_{t-1} + \phi_{22} y_{t-7}) \times F(\gamma(s_t - c))\} + \varepsilon_t$$

where (31)

$$\phi_{ij} = \varpi_i + \sum_{k=1}^{h} \lambda_{ik} \sin(2k\pi(W(s)//7) + \kappa_{ik} \cos(2k\pi(W(s)/7)) + \tau_{ik} \sin(2k\pi(Y(s)/365)) + \omega_{ik} \cos(2k\pi(Y(s)/365))$$

In half-hour number 1, 3, 5, 6, 7, 8, 9, 47 and 48 the null hypothesis was not rejected in 95% confidence level. However, the nonlinear models were tested. Another interesting point is that load was selected the transition variable in late night and dawn. During the day, temperature was the choice. And in most half hours, 2 harmonics is enough according to BIC. In none of the series, 5 harmonics were picked.

Table 9 will present the MAPE results for all estimated models. As in the univariate format, the STAR model was estimated with the same transition variable as selected for the STPAR and again the temperature was included in the PAR and AR model with same lag as d when the transition variable was temperature.

Figure 33 show the graph for the estimated MAPES in the vector format. It is just a graphical representation of table 9.

Table 8 – Results for the linearity test and selection of the number of harmonics

Linearity Test				Number of Harmonics
Hour	P-value	Delay	Transition Variable	
1	0.058	1	Load	2
2	0.048	1	Load	2
3	0.061	1	Load	2
4	0.039	1	Load	2
5	0.077	1	Load	2
6	0.134	1	Load	2
7	0.141	1	Load	2
8	0.092	1	Load	2
9	0.076	1	Load	2
10	0.049	1	Load	2
11	0.031	1	Load	2
12	0.011	1	Load	2
13	0.018	1	Temp	2
14	0.009	1	Temp	3
15	0.010	1	Temp	3
16	0.005	2	Temp	3
17	0.011	2	Temp	3
18	0.024	2	Temp	2
19	0.014	3	Temp	2
20	0.016	2	Temp	2
21	0.009	3	Temp	2
22	0.004	3	Temp	2
23	0.001	3	Temp	2
24	0.007	3	Temp	4
25	0.013	3	Temp	4
26	0.000	3	Temp	4
27	0.000	2	Temp	4
28	0.000	2	Temp	4
29	0.000	2	Temp	3
30	0.001	1	Temp	4
31	0.002	1	Temp	2
32	0.000	2	Temp	2
33	0.005	2	Temp	2
34	0.002	1	Temp	2
35	0.018	1	Temp	3
36	0.018	1	Temp	3
37	0.000	1	Temp	4
38	0.012	2	Temp	4
39	0.019	3	Temp	4
40	0.020	3	Temp	4
41	0.029	1	Load	2
42	0.031	1	Load	2
43	0.033	2	Load	2
44	0.050	1	Load	2
45	0.042	1	Load	2
46	0.031	2	Load	2
47	0.061	1	Load	2
48	0.059	1	Load	2

Table 9 – Forecasting performance for the STPAR, STAR, PAR and AR models – MAPE – Vector (48 models)

Hour	PLSTAR	STAR	PAR	AR
1	3.72	3.97	3.11	**2.91**
2	3.82	3.03	**2.90**	2.94
3	3.83	3.10	3.07	**2.98**
4	4.03	3.22	**3.06**	3.13
5	3.94	3.31	**3.20**	**3.20**
6	3.84	3.25	**2.89**	3.11
7	3.80	3.21	**2.99**	3.05
8	3.84	3.19	3.22	**3.01**
9	3.90	3.24	3.26	**3.12**
10	4.22	3.44	3.40	**3.36**
11	5.07	3.77	**3.62**	3.66
12	**4.00**	4.01	4.03	4.01
13	**3.62**	3.70	4.92	5.21
14	**4.05**	4.26	6.06	6.09
15	**4.38**	4.51	6.60	6.78
16	**3.28**	3.58	6.08	6.28
17	**3.94**	4.48	5.60	5.73
18	**3.34**	4.09	5.17	5.94
19	**3.97**	4.34	4.95	6.37
20	**4.01**	4.63	5.04	5.45
21	**4.38**	4.78	5.18	5.60
22	**4.63**	4.63	5.48	5.79
23	**4.48**	4.72	5.76	5.94
24	**4.70**	5.01	6.07	6.31
25	5.01	**4.99**	6.33	6.55
26	5.21	**5.17**	6.68	6.85
27	**5.26**	5.47	6.99	7.08
28	**5.53**	5.67	7.25	7.31
29	**5.83**	5.95	7.46	7.48
30	**5.98**	6.01	7.55	7.57
31	**5.75**	6.07	7.60	8.57
32	**5.90**	6.20	7.67	8.08
33	**5.89**	6.01	7.60	7.44
34	**5.78**	5.92	7.42	7.35
35	**5.73**	5.91	7.20	7.32
36	**4.58**	4.91	6.92	7.14
37	**4.28**	4.42	6.64	6.83
38	**4.07**	4.39	6.28	6.52
39	4.68	**4.24**	6.12	5.37
40	4.38	**4.36**	5.84	5.25
41	**3.81**	3.98	5.81	5.12
42	3.86	**3.85**	5.60	4.92
43	**3.91**	3.94	5.36	4.58
44	**3.99**	4.14	4.87	4.15
45	3.47	**3.79**	4.30	3.81
46	3.99	**3.38**	3.82	3.41
47	3.76	3.09	3.51	**3.07**
48	3.60	2.94	3.38	**2.88**
Minimun	3.28	2.94	2.89	2.88
Average	4.40	4.34	5.29	5.30
Maximum	5.98	6.20	7.67	8.57

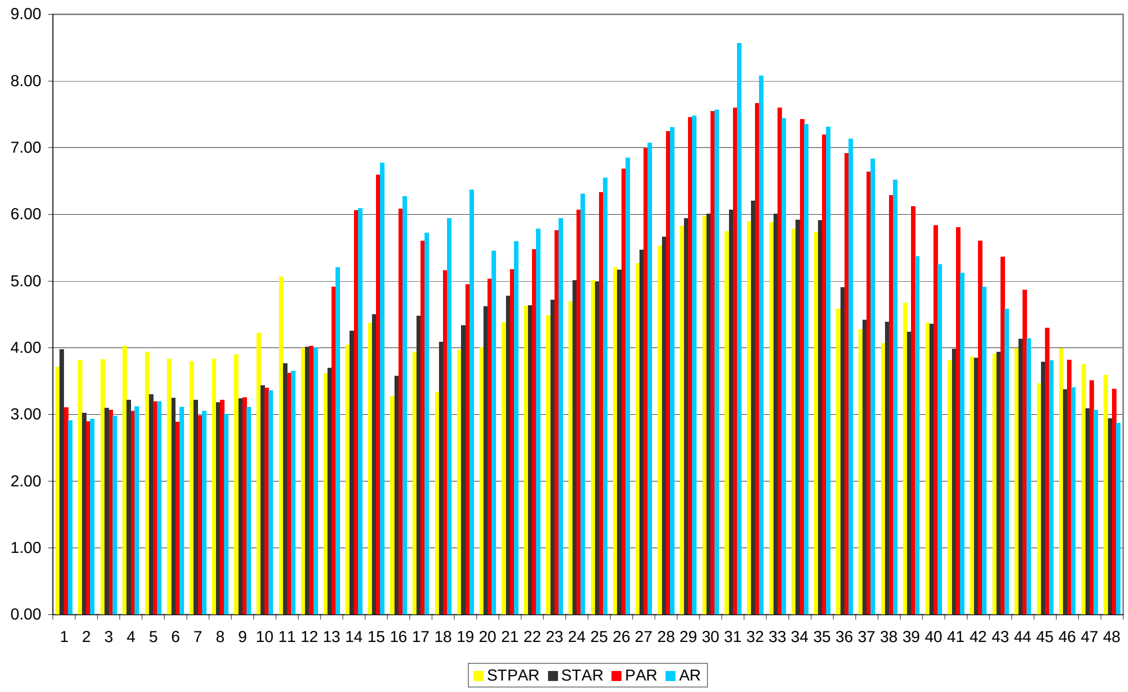

Figure 33 – Comparison of MAPES between STPAR, STAR, PAR and AR for each half-hour of the day (vector format)

During dawn, the best choices are the linear models. After 6 am, it is clear that the linear models (PAR and AR) perform worse than the others. And different from other countries, it looks that to predict dawn in New South Wales State is easier. The results for this period are quite good. The biggest MAPES for the best model were found between 14:30 and 17:30.

As a general conclusion, comparing the MAPES from the univariate format and the vector format, it looks that the univariate format using the STPAR is better than when using the vector one. A reason for that is that a possible advantage of STPAR model is that it captures well the intra-day behavior of a load series. And when one is dealing with 48 models, this intra-day pattern is excluded, remaining only the weekly pattern. Therefore, more periodicity in the time series, better the smooth transition periodic auto regressive will fit to data.