Short Term Demand Forecasting Using Double Exponential Smoothing and Interventions to Account for Holidays and Temperature Effects

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Summary of the Presentation

- Overview of the Brazilian Power System
- Short Term Load Forecasting
- Overview of this work
- Temperature Effects
- Holiday Effects
- Double Seasonal Exponential Smoothing
- Application

Overview of the Brazilian Power System

- Until mid-90's, the Brazilian electric sector was primarily a government-owned enterprise. Expansion planning was centralized and determined by government-made demand forecasts.
- The liberalization process is still incomplete.
- Currently, the Brazilian power sector includes a mix of public companies controlled by state and federal governments and privately held companies.

Overview of the Brazilian Power System

- Electricity consumption growth rates = 7% yearly rate on average for the past 30 years.
- Hydroelectric plants are responsible for roughly 80% of the country's total energy production.
- Thermal plants had been built on the past few years to serve as a hedge against unfavorable hydrological conditions.
- Privatization of the sector started in the mid-nineties, inspired on the British model.

Overview of the Brazilian Power System

- The privatization process in the UK occurred at a stage of almost stagnant demand, while in Brazil it was carried out at a time of fast growing consumption.
- This might explain why the privatization process in Brazil has suffered drawbacks.
- The inability to attract new investments was one of the reasons that led President Lula's government to forsake the model conceived by the previous government and impose new rules, the so called "New Electric Sector Model".

Overview of the Brazilian Power System

- The electricity sector regulatory framework was further altered in 2004.
- When President Lula took office in 2003, there was concern about the small amount of new private investments in power generation brought about by the privatization model started in the previous government.
- The power rationing in 2001/2002 clearly exposed the weaknesses of the privatization process.
- The reform initiated in Lula's government transferred the liability of energy purchases from distributors to the Federal government.

Overview of the Brazilian Power System

- Distributors are required to inform their long term projected demands and the government acquires the total necessary amount of energy in auctions.
- There are severe penalties for distributors who under-purchase energy, and up to 103% of the actual demand can be over-purchased and passed-through to tariffs, so there is a bias towards over-purchasing energy, since penalties to distributors are highly assymetric.
- These limits are thought of as very narrow, especially in what concerns longer term forecasts, as distributors are forced to declare their demands ten years in advance.

Short Term Load Forecasting

- Short-term demand forecasts:
  - essential for the reliable and efficient operation of electrical grids,
  - can point out local anomalies, special events (holidays, major sport events) or unusual temperatures.
- The importance of such forecasts grows as safety limits and margins become tighter, as a consequence of competitive business environment.
- Also fundamental to improve current internal processes in distribution companies and to ensure the smooth operation of the electric grid.

Overview of this Work

- In this work we apply a version of Holt-Winters method, originally developed by J. Taylor.
- The choice of exponential smoothing methods was also a choice for simplicity. These methods are generally characterized by:
  - Ease of implementation and
  - Robustness
- These are important considerations when choosing among alternative models.

Overview of this Work

- Requirements:
- Quarter hourly forecasts up to 7 days in advance.
- When in operation, models should be re-adjusted on a daily basis, in the morning (at 10:00 a.m.).
- Short-term load is severely influenced by temperature.
- From a practical standpoint, it is no trivial task to incorporate such information in a system designed to run in almost real time.

Overview of this Work

- Moreover, temperature forecasts in Brazil are inaccurate and unavailable with the desired degree of geographical granularity.
- A future version of this work will attempt to incorporate daily temperature to improve our short term forecasts, but little hope remains on the use or the availability of high frequency temperature data.

Temperature Effects

- Electricity consumption is heavily affected by climate variables, particularly temperature.
- Temperature may be the most important climate variable to affect load, but it is certainly not the only one.
- Other variables, such as humidity, wind speed, rainfall and luminosity, could be considered. However, historical data for these variables is quite hard to obtain in Brazil, and even temperature data isn’t available in frequencies higher than daily observations.

Temperature Effects

- Moreover, forecasting these variables is no trivial task, and not readily available from weather data providers.
- On the other hand, temperature forecasts, up to 3 or 5 days ahead, are usually available free of charge for major Brazilian cities, with a reasonable degree of accuracy.
- In this study, the available weather data consisted of maximum and minimum daily temperatures during a 4 year interval.

Temperature Effects

- It is a known fact that the relationship between energy consumption and temperature is nonlinear, and depends on the temperature level.
- For example, a 1ºC change in temperature (from 27ºC to 28ºC, has an entirely different effect on load than a change from 34ºC to 35ºC).
- Moreover, the effect also depends on the season of the year; hence the temperature effect in the cold season is different than that during summer.

Temperature Effects

- We also believe on the existence of a saturation effect – above a certain temperature level, variations in temperature do no produce further increases in demand.
- One can summarize this effect by saying that, above a certain temperature, all refrigeration equipment has already been turned on.
- Finally, the temperature effect varies according with the day of the week, and also within the day of the week.

Temperature Effects

- One should note a major difference with respect to European countries and the USA.
- In the Northern hemisphere, there is a widespread use of heaters in the winter and air-conditioning in the summers, so the relationship between load and temperature is "U-shaped" – load tends to increase when temperatures are very low or very high.
- In Brazil, low temperatures are very rarely observed, the effect of temperature on electricity consumption tends to be felt in warm days.

Temperature Effects

- Thus, there exists a floor value for the temperature above which the temperature influences the load.
- There is also a ceiling level, which corresponds to the saturation effect already mentioned – if the temperature is above the ceiling, it has no further impact on the demand.
- The first step in the procedure is to define a temperature threshold (or floor level) above which the temperature effect on load will be felt.
- The threshold level chosen was the average monthly temperature.
- This procedure was done twice, as two different temperature models will be obtained, one for the minimum daily temperature and one for the maximum daily temperature.

Temperature Effects

- We propose the following model for the relationship between load and temperature:

$$\frac{G_{m,a,ka}}{\bar{C}_{m,a}} = 1 + (K_1 - 1)\left[1 - e^{-\lambda\left(TM_{m,a,ka}/T_m\right)}\right] + error_m$$

- In the previous equation, there are two parameters to be estimated, K_1 and λ. K_1 indicates the maximum effect of temperature on the load. After inspecting the data we set $K_1 = 1.2$, thus the maximum effect of temperature would be a 20% increase on consumption.
- Thus, only one parameter remains to be estimated, which is done by ordinary least squares.

Temperature Effects

- Next we present the results for medium and heavy loads for different seasons.
- The correction algorithm is implemented for both minimum and maximum daily temperatures.
- One conclusion clearly emerges: there is no single best answer – sometimes the correction factor based on the minimum temperature works better than that based on the maximum temperature and vice-versa.

Temperature Effects

	February 2006			
	Rule based on MAXIMUM temperature			
	Medium Load		Heavy Load	
	MAPE uncorrected	MAPE corrected	MAPE uncorrected	MAPE corrected
Day 3	1.48	1.51	4.68	4.24
Day 6	3.34	3.22	7.12	5.88
Day 7	3.77	3.64	2.57	1.96
Average	2.86	2.79	4.79	4.03
	Rule based on MINIMUM temperature			
	Medium Load		Heavy Load	
	MAPE uncorrected	MAPE corrected	MAPE uncorrected	MAPE corrected
Day 6	3.34	1.71	7.12	5.88
Day 7	3.77	1.77	2.57	1.96
Average	3.56	1.74	4.84	3.92

Temperature Effects

	September 2005			
	Rule based on MAXIMUM temperature			
	Medium Load		Heavy Load	
	MAPE uncorrected	MAPE corrected	MAPE uncorrected	MAPE corrected
Day 1	2.30	1.37	1.48	0.58
	Rule based on MINIMUM temperature			
	Medium Load		Heavy Load	
	MAPE uncorrected	MAPE corrected	MAPE uncorrected	MAPE corrected
Day 1	2.30	1.17	1.48	0.62

Temperature Effects

- Both rules are extremely effective in reducing forecast error, for both medium and heavy load periods.
- The rule based on the maximum temperature seems slightly more effective for the heavy load, and the other is slightly better for the medium load.

Temperature Effects

- The number of days which were candidates for correction varied according to the rule used and the month of the year.
- In some months, there were no "candidate days" using one set of rules or the other (sometimes both). This is certainly due to the fairly small sample of temperature data used to generate the "threshold" levels.
- Only 4 years of daily maximum and minimum temperatures were available, from which monthly averages were computed, and we believe the temperature threshold may be set more appropriately as more data becomes available.
- However, even a very simple exogenous rule, that does not use high frequency temperatures, can substantially improve the forecasting ability of the model.

Holiday Effects

- We include interventions to account for holiday effects.
- These are treated exogenously, and we correct the forecasts after they have been produced by the model.
- Initially, the bank holidays and the "normal days" are grouped into 14 different profiles; one for each day of the week, using the original 15 minutes observations.
- We created different rules for holidays in different weekdays, but we could not treat the monthly/daily holiday effect separately due to the insufficient amount of historical data.

Double Seasonal Exponential Smoothing

- Consider a quarter-hourly series.
- The daily and weekly seasonal periods are, respectively, $s_1 = 96$ and $s_2 = 672$.
- Let:
  - X_t = observed load,
  - $X_t(k)$ = k-step ahead forecast at time t,
  - D_t and W_t = daily and weekly seasonal factors.
  - S_t = local level,
  - T_t = local trend.
- Let α, γ, δ, ω denote the smoothing constants.

Double Seasonal Exponential Smoothing

- The updating equations for the multiplicative Holt-Winters Double Seasonal Model are given by: (Taylor, 2003)

Table 1

Level	$S_t = \alpha\left(\frac{X_t}{D_{t-s_1}W_{t-s_2}}\right) + (1-\alpha)(S_{t-1}+T_{t-1})$
Trend	$T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}$
Seasonality 1	$D_t = \delta\left(\frac{X_t}{S_t.W_{t-s_2}}\right) + (1-\delta)D_{t-s_1}$
Seasonality 2	$W_t = w\left(\frac{X_t}{S_t.D_{t-s_1}}\right) + (1-w)W_{t-s_2}$
Forecasting	$X_t(k) = (S_t + k.T_t)D_{t-s_1+k}.W_{t-s_2+k}$

Double Seasonal Exponential Smoothing

- The smoothing parameters α, γ, δ, ω are optimized using the minimum one step ahead mean squared error criterion through a genetic algorithm..
- The model has 96 parameters per day and 672 weekly parameters.

Application

- The original data consisted of three years of quarter-hourly loads.
- Due to the amount of time required for parameter optimization, we worked with much smaller samples.
- Our "in sample" periods ranged from one to six months, and we did not observe a significant improvement in forecasting ability when using larger samples.
- Thus, for the remainder of this work, we assume an "in sample" period of a single month.

Application

- As the required forecast horizon is only one week ahead we did not consider the trend term as the period is too short to observe any increment in the growth rate.
- Thus, we use a more simplified structure than that of Table 1, with only three smoothing constants: α, δ and ω.

Application

- The next figure shows the observed loads and forecasts for the period 15 to 21 July 2005.
- The in sample period used to obtained the smoothing parameters was June 15th to July 14th 2005 .
- The smoothing constants found by the optimization procedure were: $\alpha = 0.08$, $\delta = 0.137$ and $\omega = 0.627$.

Application

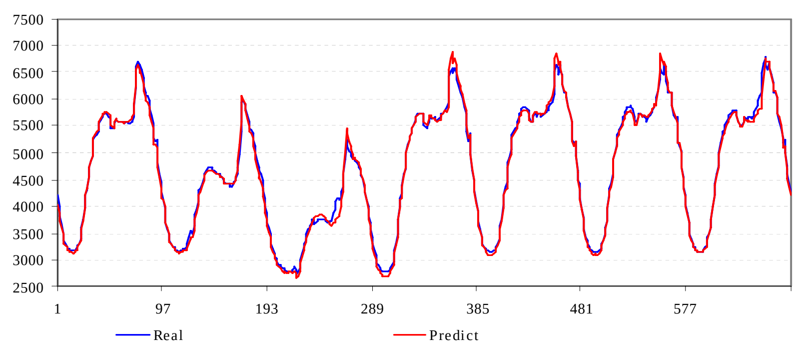

Figure 1. Real and Predicted Loads – 15/07/2005 to 21/07/2005

Application

- The MAPE for the entire forecasting horizon is 1.24%.
- It might seem surprising that the fit doesn't seem to deteriorate as the forecast horizon increases.
- The model seems to perform differently at different times of the day.
- The next figure exhibits the MAPE at every hour during the entire 7 day out of sample forecasting period.

Application

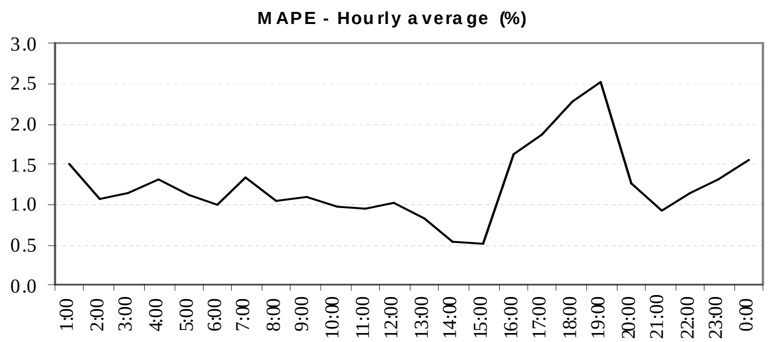

Figure 2. Hourly Average – Mean Absolute Percentage Error

Application

- Forecasting errors are larger at around 19:00-20:00h.
- This period is the part of the daily peak load for the system.
- The next figure presents average daily errors. Average errors, as measured by MAPE, do not increase with the forecasting horizon. The average error for the seventh day is very close to the corresponding error for the first day.

Application

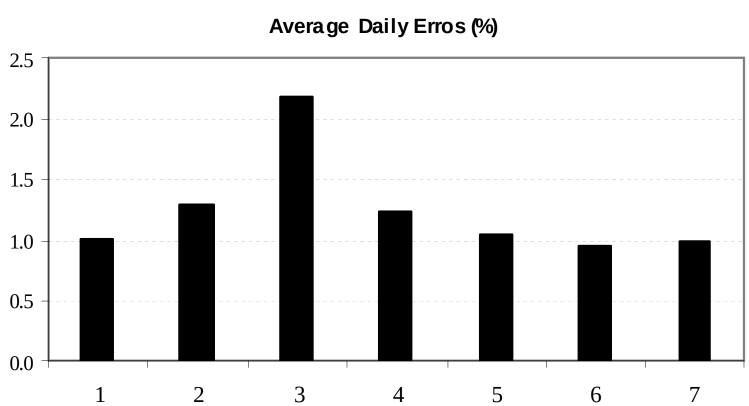

Figure 3. Average Daily MAPEs

Application

- We repeat the analyses using as an in sample period August 2005 to predict the first two weeks in September 2005.
- The optimization procedure yielded $\alpha = 0.1$, $\delta = 0.02$ and $\omega = 0.76$.
- This particular out of sample period was chosen to test the validity of our empirical rule to account for holidays. September 7th is a fixed national holiday in Brazil.

Application

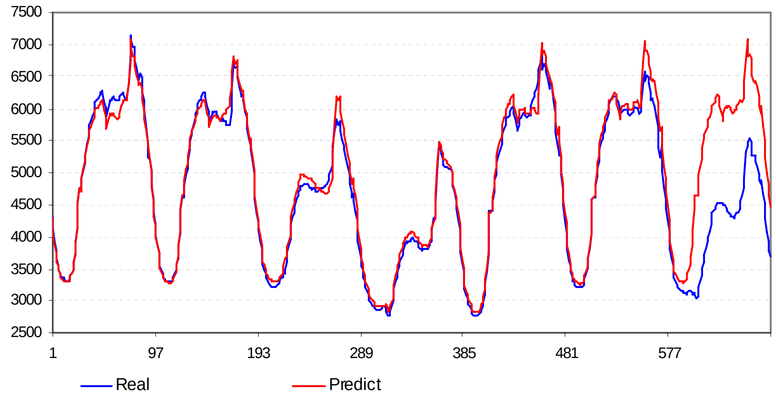

Figure 4. Real and Predicted Loads – 01/09/2005 to 07/09/2005

Application

- The MAPE for this period without the holiday correction was 5.82%, and the seventh day MAPE alone was 27.97%.
- On the other hand, with the holidays correction, this seventh day MAPE (i.e. the forecast for September, 7th) decreased to 2.92%. The MAPE for the whole period became 2.15%.
- Figure 6 displays the graph of the real and of the forecasted load on September 7th, with and without the holiday correction.

Application

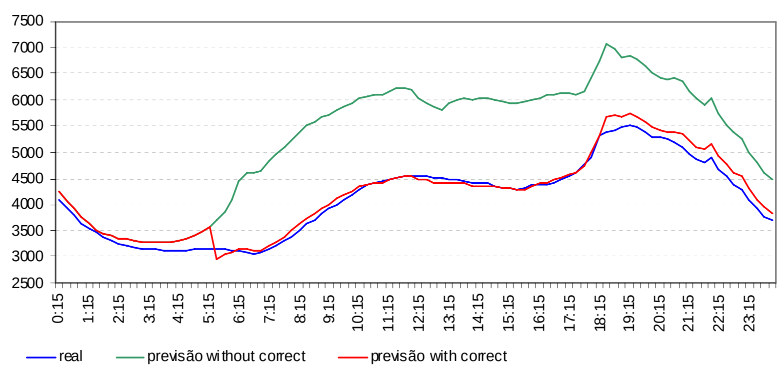

Figure 6. Real, Predicted without correction, Predicted with correction Loads – 07/09/2005

Conclusions

- We presented an application of Holt-Winters Double Seasonal Exponential Smoothing Model to forecast quarter-hourly loads in Southeast Brazil. The results for two “out of sample” periods were shown, and we addressed the validity of exogenous holiday and temperature corrections.
- Overall performance is good and forecasts do not seem to significantly worsen as the forecast horizon increases, even when we use a small “in sample” period to estimate the smoothing constants in the model.

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