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

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ABSTRACT. Short term load forecasting is fundamental for the safety and reliability of the electric system. Exponential smoothing methods and, in particular, the Holt-Winters method and its variations, are appropriate in this context, since they are highly adaptable and robust tools to forecast different horizons. This paper presents an univariate model to forecast very short term demand for a large electricity distributor in the southeast of Brazil. The model produces 15-minute-ahead forecasts for the next 15 days, i.e., a total of 1440 steps ahead forecasts and uses a variation of the Holt-Winters approach with double cycles (daily and weekly).

Bank holidays were considered separately with an exogenous intervention. Separate rules were proposed for each 15 minutes period of the holiday and also for the days before and after the holiday. In addition, another exogenous correction was included in the model, to account for extreme temperatures.

KEYWORDS. Short-term load forecasts; Double Seasonal Exponential Smoothing Methods; Exogenous Interventions; Holiday Effects; Temperature Effects.

1. INTRODUCTION

In Brazil, electricity consumption has grown at an average 7% yearly rate for the past 30 years. Hydroelectric plants are responsible for roughly 80% of the country's total energy production and thermal plants had been built on the past few years to serve as a hedge against unfavorable hydrological conditions.

In the mid-nineties, the government decided to privatize the sector, inspired by the model used in the United Kingdom. However, 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, including the difficulty of attracting new investments. Until the mid-nineties, the Brazilian electric sector was primarily a government-owned enterprise. Expansion planning was centralized and determined by government-made demand forecasts (Kawabata, 2002). Investment and capital needs were projected based on historical consumption growth rates, often as a function of projected GDP growth rates. The primary objective of the privatization process was to define a model capable of transferring the responsibility for the new enterprises to the private initiative.

The liberalization process is still incomplete. Currently, the Brazilian power sector includes a mix of publicly held companies controlled by the state and federal governments and privately held companies.

The inability to attract new and much needed 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” 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. 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 the maximum amount of overbought energy allowed is 103% of actual demand. 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. Electricity distributors, thus, are subject to immense risks derived from inaccurate medium and long term load forecasts. However, their operational and financial feasibility is also affected by short-term load risks.

Short-term demand forecasting, the subject of this paper, is essential for the reliable and efficient operation of electrical grids, and it can point out local anomalies, such as those due to 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 companies seeking profitability in an environment of higher financial constraints. Good short term forecasts are also fundamental to improve current internal processes in distribution companies and to ensure the smooth operation of the electric grid.

In this work we apply a version of Holt-Winters method, originally developed by Taylor (2003b). Exponential smoothing methods provide a robust strategy to forecast series of different characteristics and periodicities. The models developed in this work are currently in their final testing stage to be implemented in real time in one of Brazil’s largest electricity distributors. Thus, the choice of exponential smoothing methods was also a choice for simplicity – we needed a class of models that would be relatively easy to implement and maintain, and that would be robust and provide reasonable forecasts even if the model would not be re-adjusted for a couple of days. Current specification requires us to provide quarter hourly forecasts up to 15 days in advance. When in operation, models should be re-adjusted on a daily basis, in the morning. The first forecast produced corresponds to 00:15h, so that when the model is “run” (say, typically at 10:00), the shorted term forecasts will not actually be used for scheduling purposes, just for comparison with the actual, already observed loads in the first morning. However, the electricity distributor considers these forecasts as important, as their comparison with the actual, recently observed load, may provide hints as how the load should behave in the first predicted afternoon, and how it would be expected to deviate from the produced forecasts.

It is widely known that short-term load is severely influenced by temperature. However, from a practical standpoint, it is no trivial task to incorporate such information in a system designed to run in almost real time. Moreover, temperature forecasts in Brazil are inaccurate and unavailable with the desired degree of geographical granularity. Here we present an exogenous correction of the load forecasts produced by the Holt-Winters procedure that takes into account deviations from monthly averages computed from maximum and minimum daily data since, as previously noted, high frequency temperature data is unavailable.

We include interventions to account for holiday effects. These are treated exogenously, and we correct the forecasts after they've been produced by the model. Holidays that occurred on Sundays were considered "regular" Sundays, and not accounted for. 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. Thus, for example, a Monday holiday would always lead to the same percentage decrease in load, irrespective to the month when the holiday occurred. This is, in our opinion, undesirable, but it was the only possible choice at present. The holiday rules were applied in quarter-hour periods, that is, different quarter-hours in a holiday suffered different percentage load reductions. Also, holiday corrections were applied to the preceding and following days. It should be noted that holidays are often ignored when developing forecasting models and accessing their accuracy. In our application, however, it was considered essential to obtain adequate forecasts for such unusual days, since the primary aim of our work was to produce forecasts to be used in an Operations Center for a large distributor. Thus, we couldn't simply ignore holidays as an "academic nuisance" as some researchers often do, as the production of poor load forecasts in holidays could lead to severe operational problems.

2. DOUBLE SEASONAL EXPONENTIAL SMOOTHING METHODS

The standard Holt-Winters method is capable of handling a series with level, trend and a single cycle (seasonal pattern). Hourly (or quarter-hourly) load series possess two seasonal cycles: weekly and daily. Taylor (2006, 2003a, 2003b) conceived a multiple cycle version of Holt-Winters method capable of handling such series (Esteves, 2003). Taylor (2003b) also presented an adaptation of a multiplicative ARIMA model to forecast hourly load.

Consider a quarter-hourly series. Let t denote the time index. The daily and weekly seasonal periods are, respectively, s_1 = 96 (24 times 4) and s_2 = 672 (168 times 4). Let X_t denote the observed load, $X_t(k)$ the k-step ahead forecast at time t and let D_t and W_t represent the daily and weekly seasonal factors. Let S_t be the local level, and T_t be the local trend. Let α, γ, δ, ω denote the smoothing constants. Then, the updating equations for the multiplicative Holt-Winters Double Seasonal Model are given in Table 1 below, (Taylor, 2003b):

Table 1. Updating and Forecasting Equations – Double Seasonal Holt-Winters

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

The smoothing hyperparameters $\alpha, \gamma, \delta, \omega$ are optimized using the minimum one step ahead mean squared error criterion. In this application, optimal values of the smoothing hyperparameters were obtained through a genetic algorithm search procedure. One should keep in mind that "naïve" forecasts are obtained when these parameters are set to one, which means that the forecast consists uniquely on the information contained in the most current observation. An additive Double Seasonal Holt-Winters Model can be obtained in a similar fashion from the basic ("usual") additive Holt-Winters Model, by the addition of the corresponding seasonal effects and updating equations.

3. APPLICATION

In this study we present results for one of the largest electricity distributors in Brazil, located in the Southeast part of the country. The original data consisted of three years of quarter-hourly loads. However, 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. Forecasting horizon consists of 15 days on a quarter-hourly basis, a total of 1440 forecasts. As mentioned earlier, these shall be produced daily, and the first forecast will always correspond to 00:15h.

3.1. Holiday Treatment

In Brazil, as in other countries, the occurrence of holidays affects load in a dramatic fashion, and leads to a very different "daily load profile" than that observed on a weekday of the same month. However, holidays are often ignored when developing models and accessing their forecasting ability. A few publications address the need of correcting load for holiday effects, and they attempt to detect unusual behavior patterns in the load, for example: Cancelo, Espasa & Grafe (2007), Cancelo & Espasa (1996) and Papalexopoulos & Hesterberg (1990).

However, it was observed that the occurrence of a holiday not only distorts the load of this day. Depending on the day of the week when the holiday occurs, it will alter the profile of the last hours of the preceding day and of the first hours of the following day, and sometimes it will completely change the load characteristics of several days before and after the holiday.

We develop a database of load reduction factors to be applied to the forecasts in an exogenous fashion. This database contains the corrections to be applied to the forecasts generated by the Holt-Winters model of each 15 minutes period of holidays, preceding and following days. The corrected forecasts, after the application of these exogenous factors, should reduce forecast errors.

Different load reduction factors were created for each weekday, and we also analyze the days (or portions of days) that are influenced by a given holiday, namely – the first hours of the day following the holiday and the last hours of the day before the holiday.

The methodology consists in computing, for each 15 minutes period, the percentage variation in load between a holiday and a "regular" weekday. This allows us to verify the range of variation between holidays and non-holidays. The same calculation was done considering only regular (non-holiday) weekdays. Thus, we could estimate the reduction factors due to holidays and the effects on adjacent days. Figure 1 next presents the load reduction factors (in percentage points) computed for a holiday occurring on a Tuesday; we notice that the previous day is also affected and, to a lesser extent, the earlier portion of the Wednesday. It was assumed that the load variations, estimated for regular weekdays for each 15 minutes follow, approximately a normal distribution, with zero mean and constant variance, whose unbiased estimator was obtained from the load variations for regular data mentioned above. Therefore, the significance of the variations between regular and holiday periods could be checked at the 95% level of confidence.

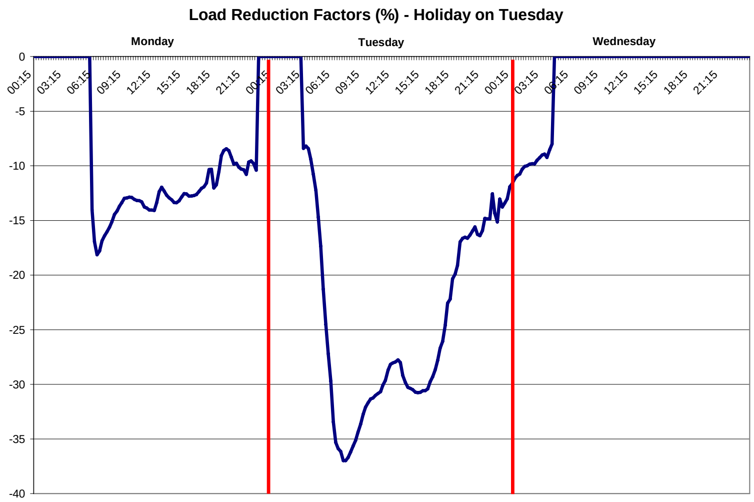

Figure 1. Load Reduction Factors – Holiday Occurring on Tuesday

3.2. Holt-Winters Double Cycle Exponential Smoothing

For the time horizon considered (15-day-ahead), there was no need to assume a linear growth for the trend model. Therefore, a further simplification in the formulation was considered, i.e., a constant model for the trend implying that only one smoothing constant for the trend need to be estimated. Thus, we use a more simplified structure than that on Table 1 was used, with smoothing constants α, δ and ω.

Figure 2 below presents observed and forecasted loads for the period 15-29 July 2005. The in sample period used to obtained the smoothing parameters was June 15th, 2005 to July 14th, 2005. The smoothing constants found by the optimization procedure were: $\alpha = 0.08$, $\delta = 0.137$ and $\omega = 0.627$.

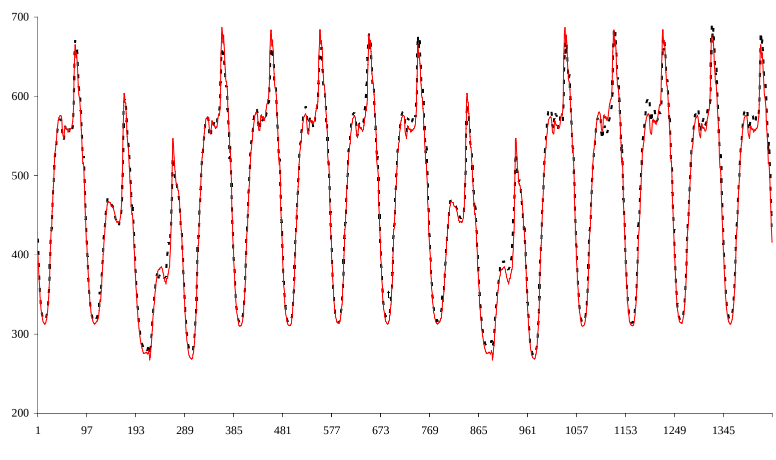

Figure 2. Real and Predicted Loads – 15/07/2005 to 29/07/2005

Figure 2 reveals a fairly good fit. The average MAPE (mean average percent error) for the entire forecasting horizon is 1.54%. Figure 3 presents average MAPEs over the entire forecasting interval. One can clearly notice that average daily errors, as measured by MAPE, do not uniformly increase with the forecasting horizon. In fact, the average error for the 15 day ahead forecast is 2.15%, below the 2.17% observed for the three day ahead forecast error. In fact, six and seven day ahead forecast errors (0.96% and 1.00%) are slightly below the forecast error for the first day (1.02%).

Moreover, the model seems to perform differently at different times of the day, as shown in Figure 4 next, which presents the average MAPE at every hour during the entire 15 day out of sample forecasting period. For example, the value corresponding to hour 01:00h is the average of MAPEs for the following periods: 00:15h, 00:30h, 00:45h and 01:00h.

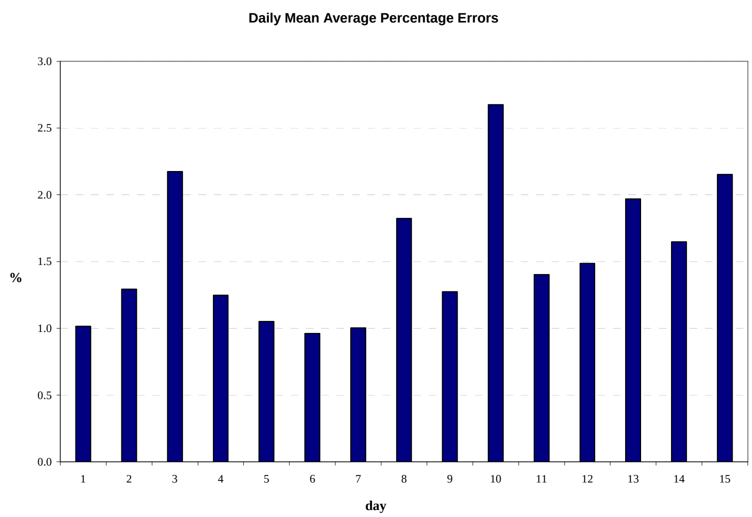

Figure 3. Daily Averages – Mean Absolute Percentage Error

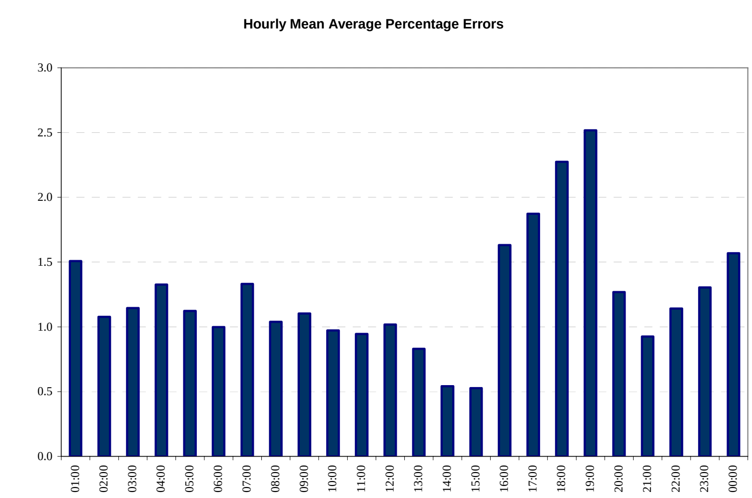

Figure 4. Hourly Average – Mean Absolute Percentage Error

Clearly, forecasting errors are larger at around 16:00-20:00h. This corresponds to the daily peak load for the system.

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 $\alpha = 0.1089$, $\delta = 0.0225$ and $\omega = 0.7618$**.** This particular out of sample period was chosen to test the validity of our empirical, exogenous rule to account for holidays. September 7th is a fixed national holiday in Brazil, and we were interested in checking the effect of the holiday correction procedure.

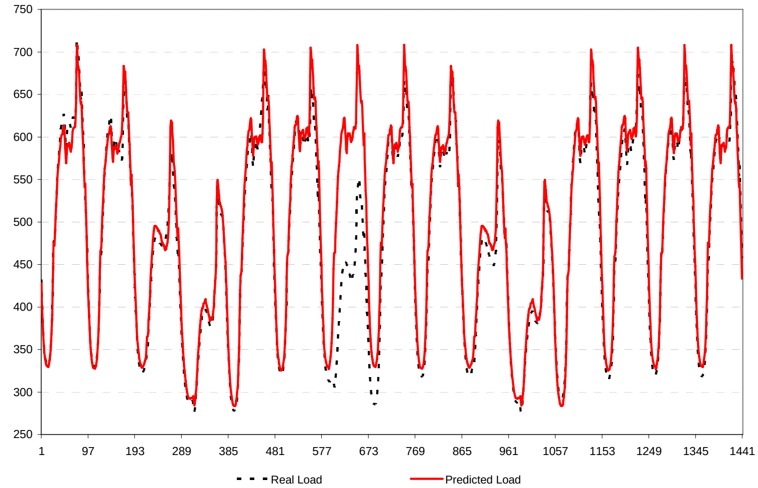

Figure 5. Real and Predicted Loads – 01/09/2005 to 15/09/2005

Figure 5 reveals a worse fit than that of Figure 2, especially on September 7th, the above mentioned holiday. The average MAPE for the period was 4.22%, and on the holiday alone, the average percentage error reached 27.97%. The application of the holiday correction rule improved significantly the quality of the forecasts. Overall MAPE for the 15 day period decreased to 2.30% and on the holiday the average MAPE fell to 2.92%. Figure 6 below compares the average hourly errors for the corrected and original (uncorrected) forecasts.

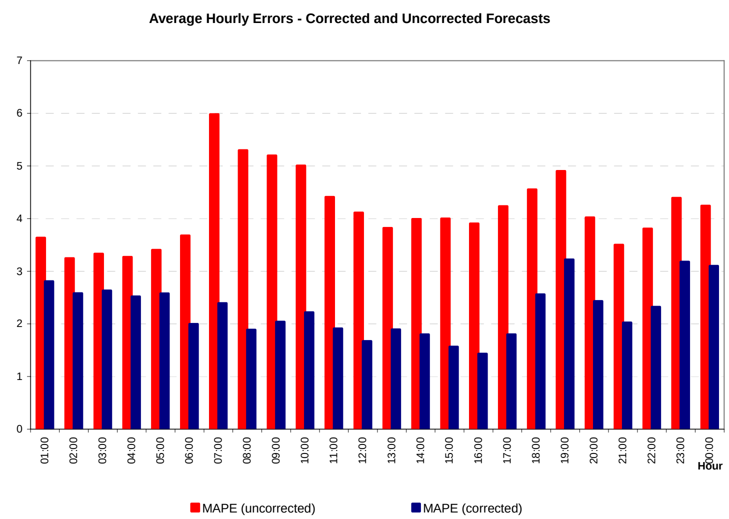

Figure 6. Hourly Average MAPEs – Corrected and Uncorrected Forecasts

As shown in Figure 6, the effect of the holiday correction is dramatic, and average hourly errors decrease substantially at all periods. Next, figures 7 and 8 present average hourly and daily MAPEs for the out of sample period after the application of the holiday correction.

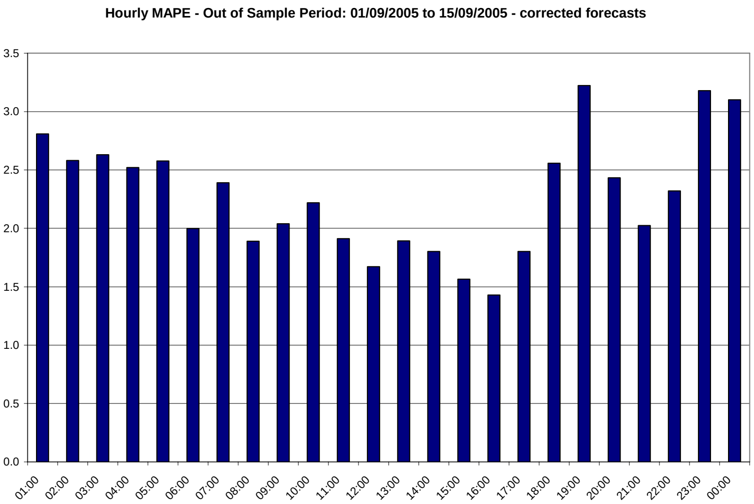

Figure 7. Hourly Average MAPEs – Corrected Forecasts

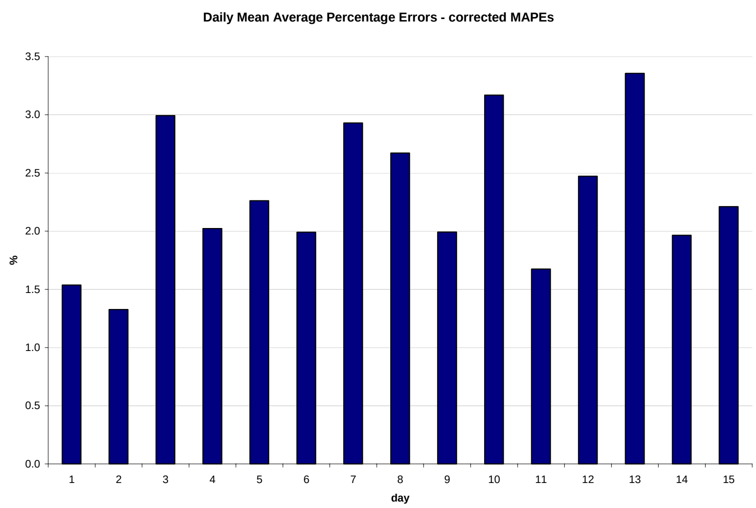

Figure 8. Daily Average MAPEs – Corrected Forecasts

3.3. Temperature Effects

Several previous studies (Cancelo& Espasa (1996), Cancelo, Espasa & Grafe (2007), Valor, Meneu & Caselles (2001), Engle, Mustafa, Rice (1992), Yan (1998), Taylor & Buizza (2003)) have shown that electricity consumption is affected by climate variables, particularly temperature. The effect of climate changes cannot be captured by univariate models, and we adopt an exogenous treatment of these effects, in a similar fashion to what was done to account for the effect of holidays.

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. 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. Other studies, such as the one performed by Valor, Meneu & Caselles (2001) used temperature data in 30 minute intervals for an 8 year sample.

It is a known fact that the relationship between energy consumption and temperature is nonlinear, and depends on the temperature level. For example, a $1^{o}C$ change in temperature (from 27ºC to 28ºC, for example, 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. 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. Basically, 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.

When analyzing the effect of temperature on load in Brazil, one should note a major difference with respect to European countries and the USA. In the Northern hemisphere, seasons are clearly defined, and the differences between them are very marked. Moreover, 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, and tropical weather characterizes most of the country. In the concession area of the distribution company under study, the use of heaters is uncommon, and the same applies to air-conditioning in residential units. Thus, the effect of temperature on electricity consumption tends to be felt in warm days – its effect is negligible in colder days.

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. It is necessary to separately analyze months due to the effect of the seasons of the year, and also it would be interesting to analyze the effect in the hours, but to do so we would need temperature data in higher frequencies than currently available. As only the daily maximum and minimum temperatures are available for this work, we decided to verify their impact on two distinct moments: in light load and heavy load hours.

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.

Next we identify the days whose temperatures were below the threshold level. In those days, the temperature is assumed to have no influence on the load.

Let: $\bar{C}_{m,y}$ denote the average of maximum loads at month m and year y computed only from those days where the temperature was BELOW the threshold level for month m. Next, for each month, we compare the difference in loads between those days whose temperatures were below and above the threshold point.

Let $d_{m,y,j} = \frac{G_{m,y,j}}{\bar{C}_{m,y}}$ where $G_{m,y,j}$ is the maximum load at day j of month m and year y, and j is a day whose temperature was ABOVE the threshold level, and $\bar{C}_{m,y}$ was previously defined, the average of maximum loads in the "cold" days of the same month and year.

For each month, a threshold temperature level has to be established, denote it by $\bar{T}_m$. For any given day whose temperature exceeded the threshold in month m, the "excess in temperature" for day j in month m and year y is written as:

$$t_{m,y,j} = \frac{TM_{m,y,j}}{\bar{T}_m}$$

Where $TM_{m,y,j}$ is the temperature (daily maximum or daily minimum, depending of the model to be used) in day j, month m and year y and $\bar{T}_m$ is the temperature threshold defined for the m-th month.

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

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

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.

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.

Table 2 below exhibits the results of the temperature correction (in terms of daily MAPE) for February 2006. Two different time periods (medium and heavy loads) are examined and corrections based on rules created using minimum or maximum temperatures are shown. One should notice that "uncommon" days, in terms of temperature effects, depend on which temperature rule is being used. For example, when we base the temperature rule on daily maximum temperatures, day 3 is considered extreme – this does not occur when the minimum temperature rule is used. Overall, both temperature rules seem to work equally well for the heavy load. However, when we look at medium load periods, the rule based on the minimum temperature seems more effective and results in a larger decrease of forecast errors.

	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

Table 2. Rules for Temperature Effect – February 2006

Next on table 3 we present the analysis for September 2005. Only one point had temperature above the threshold level and therefore was subject to the correction.

	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

Table 3. Rules for Temperature Effect – September 2005

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.

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, as the previous results show, even a very simple exogenous rule, that does not use high frequency temperatures, can substantially improve the forecasting ability of the model. One of its main advantages is ease of use and the ability to incorporate weather forecasts generated externally.

4. CONCLUSIONS

In this paper 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 also presented two exogenous corrections, one for holiday effects and another to account for extreme temperatures. Both corrections are useful and substantially improve forecasts.

Overall, the model performs well, and it does not seem to produce significant deterioration of the forecasts as the forecast horizon increases, even when we use a small "in sample" period to estimate the smoothing constants in the model.

The results obtained are promising, and we feel there can be further improvement, especially as more weather data becomes available and we can further improve the corrections for temperature effects. In summary, we believe exponential smoothing methods are a robust and adaptable methodology that can yield reliable forecasts in critical situations, such as the operations of electrical systems.

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