New forecasting methods for hotel revenue management systems

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Abstract: An accurate forecasting module is a key element of any revenue management system. This module includes demand forecasting, which involves tasks of forecasting complex seasonal time series. The challenge of producing accurate demand forecasts requires the application of suitable forecasting methods to address that complexity. The aim of this paper is to evaluate a new innovation state space modeling framework, based on innovations approach, developed for forecasting time series with complex seasonal patterns. This modeling framework provides an alternative to existing models of exponential smoothing, since it is capable of tackling seasonal complexities such a multiple seasonal periods and high frequency seasonality.

Keywords: Hotel demand, forecasting, double seasonal Holt-Winters model, revenue management.

1. Introduction

Nowadays hotel companies face an ever growing and more competitive market, since new information and communication technologies are allowing hospitality customers to become better informed and more demanding. To deal with this increasing degree of competitiveness a hotel has, not only to provide an excellent service, but also, and above all, it is necessary that it knows how to create products which best meet the needs of its costumers.

Originating in the airline industry, revenue management (RM) was created as a management tool to maximize profits and maintain the competitive advantages of companies in the sector. The airline industry was a pioneer in the use of RM, and subsequently, its management was applied in other areas, such as the accommodation sector, car rental, casinos, rail transport, and cruise industry, among others (Chiang, Chen and Xu, 2007). These industries share some similar characteristics. All of their products are perishable, the demand for their products vary significantly over time, and they have large fixed costs while variable costs are small in the short run.

Just as Berman (2005) says, revenue management is an effective mechanism to allocate a service provider’s relatively fixed capacity and to provide discounts on a much broader scale. Demand forecasting is an integral element to this overarching strategy involving the application of different forecasting methods in order to provide the revenue manager with prognoses about the future development of RM metrics, demand and supply. A small business can use demand forecasting as part of revenue management to accurately predict the times throughout the year when the company has the chance to earn higher than normal revenue from sales. A demand forecast requires thorough research of sales records from previous years, study of the current marketplace, consideration of prevailing economic conditions and the performance of market competitors. The forecasts feed the mathematical models that produce recommendations for the optimal levels of prices, rate structures, overbooking and help the revenue manager take proper decisions.

Furthermore, accuracy if the forecast are crucial to the success of the RM model. Studies indicate that a 10% increase in forecast accuracy in the airline industry increased revenue by 0.5-3.0% on high demand flights (Lee, 1990). Also, Pölt (1998) estimated for the same industry that a 20% increase in forecast accuracy generated a 1% increase in revenue.

The motivation for this work is our strong belief that a new time series modeling framework, based on innovations approach, can be integrated with new technologies to maximize a particular firm’s revenue. Using a simplified architecture of the RM system, first a module of the RM system gathers the necessary data from internal and external sources and storages it in an appropriate data warehouse. Then, this data is analyzed using sophisticated and innovative models in order to provide revenue managers, and the system itself, with trends on key indicators for the forthcoming days or weeks. Finally, a module of the RM system addresses the problem of room pricing to provide hotel managers with a flexible and efficient decision support tool for room revenue maximization.

Although there are in the literature some studies dedicated to comparison of traditional forecasting methods for hotel RM (e.g. Rajopadhye et al., 2001; Weatherford and Kimes, 2003), less work (or no published work in the literature) has been done on exploring new time series methods to series with complex seasonal patterns. Thus, the aim of this paper is to evaluate, in the context of a revenue management system, new innovative forecasting models recently developed for forecasting time series with complex seasonal patterns. The well-known Holt-Winters model is used as a benchmark in the comparison. Using enormous amount of data, increasing computer power and new models, RM systems will be able to make more accurate forecasts and, consequently, to increase the profit generated from a limited supply.

In this paper we used data based in the total occupation rooms in a particular day of a particular hotel taken as an example, from January 2010 to December 2012, a total of 1068 observations.

Fig. 1 shows the demand of the total number of rooms, over time, in the period of the study. The figure suggests the presence of a complex seasonal patterns. It is also possible to check, not only, seasonality over the years but over the weeks as well, since this is a time series that presents two cycles of seasonality.

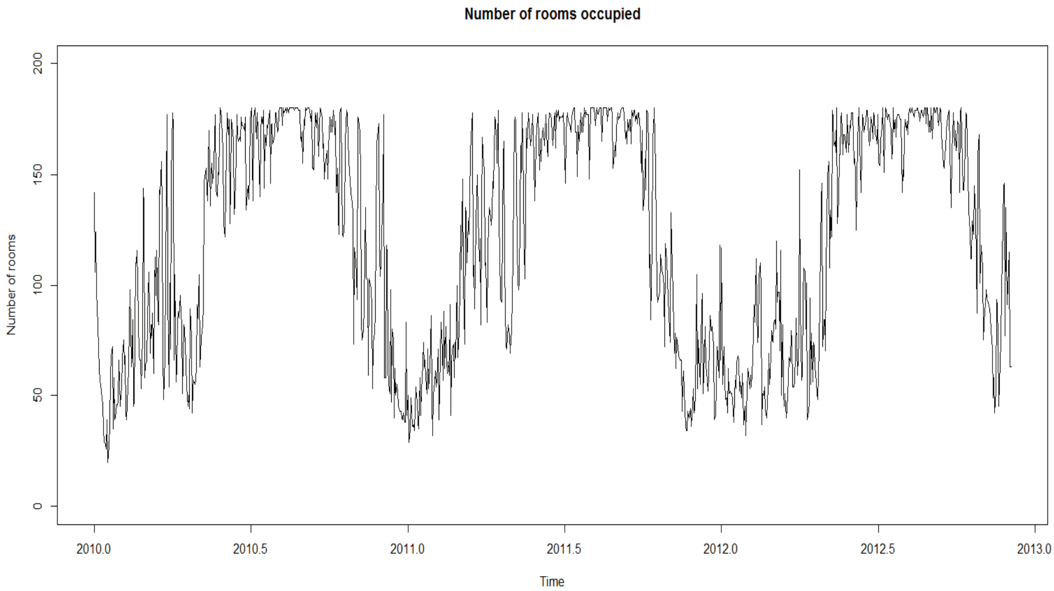

Figure 1: Time series of daily room demand of a hotel

Approaches to models of various seasonal patterns are not as frequent as those with a single seasonal pattern. To cite some examples we find: SSM with spline for daily series (Harvey and Koopman, 1993) exponential smoothing models for double seasonality (Taylor, 2003; Taylor and Snyder, 2009; Taylor, 2010) and innovations state space models for complex seasonal patterns (De Livera et al, 2011), BATS (Exponential Smoothing State Space model with Box-Cox transformation, ARMA errors, Trend and Seasonal Components) and TBATS (Trigonometric Exponential Smoothing State Space model with Box-Cox transformation, ARMA errors, Trend and Seasonal Components).

In this research, we compare the following three different forecasting methods: standard Holt-Winters, double seasonal exponential smoothing and BATS. In Section 2 we review these innovative methods. The results of applications of time series are shown in Section 3 and concluding remarks are stated in Section 4.

2. Forecasting Methods

Forecasting is a critical part of any revenue management system. The quality of revenue management decisions, such as pricing, capacity control, or overbooking, depend on an accurate forecasts. Pölt (1998) estimates that a 20% reduction of forecast error can translate into a 1% incremental increase in revenue generated from the revenue management system. Zaki (2000) notices, there are also many challenges that exist for practitioners to achieve a higher level of forecasting accuracy: the dynamic nature of revenue management, the unpredictable change of schedules, the size of the problem, the limitations of reservation systems, etc. The forecast is and always has been a tempting challenge for any system, especially in the field of time series where the behavior and future evolution of economic factors are often used, nowadays (Cordeiro, 2011).

Exponential smoothing was proposed in the late 1950s (Brown 1959, Holt 1957 and Winters 1960 are key pioneering works) and has motivated some of the most successful forecasting methods. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. This framework generates reliable forecasts quickly and for a wide spectrum of simple seasonal time series with a small integer-valued period (such as 12 for monthly data or 4 for quarterly data).

Single seasonal exponential smoothing methods, which are among the most widely used forecasting procedures in practice (Makridakis *et al*., 1982; Makridakis and Hibon, 2000; Snyder, Koehler and Ord, 2002), have been shown to be optimal for a class of innovations state space models (Ord, Koehler and Snyder 1997; Hyndman *et al.,* 2002). However, these kind of methods do not accommodate a double seasonal pattern. For example, a hotel room daily demand time series normally has a weekly seasonal pattern with a period 7 and an annual seasonal pattern with period 7×52=364.

Taylor (2003) extended the linear version of the Holt-Winters method to incorporate a second seasonal component. This involves the introduction of an additional seasonal index and an extra smoothing equation for the new seasonal index.

Articles of Pedregal and Young (2006) and Harvey and Koopman (1993) use models for double seasonal time series, but they have not been sufficiently developed for time series with more than two seasonal patterns, and are not capable of accommodating the nonlinearity found in many time series in practice. Similarly, in modeling complex seasonality, the existing exponential smoothing models (e.g., Taylor 2003, 2010; Gould *et al*. 2008; Taylor and Snyder 2009) suffer from various weaknesses such as overparameterization, and the inability to accommodate both non-integer period and dual-calendar affects. Therefore, De Livera et al (2011) introduced a new innovations state space modeling framework capable of tackling all of these seasonal complexities.

2.1. Double Seasonal Holt-Winters method

Exponential smoothing is a procedure for continually revising a forecast in the light of more recent experience. Exponential smoothing assigns exponentially decreasing weights are the observation get older. In other words, recent observation are given relatively more weight in forecasting than the older observation.

Single seasonal exponential smoothing methods are among the most widely used to forecast time series, either to produce smoothed data for presentation, or to make forecast providing good results (Makridakis *et al*. 1982).

Double Exponential Smoothing is a technique proposed by James Taylor (2003). He therefore proposed an adaptation of the Holt-Winters method to incorporate a second seasonal component than just the one in usual form of Holt-Winters method.

The formulation for double seasonal multiplicative patterns with additive trend is given by the following expressions (DSHW):

$$F_t = \alpha \frac{X_t}{D_{t-F_1} W_{t-F_2}} + (1-\alpha)(F_{t-1} + b_{t-1}) \quad (1)$$

$$b_t = \beta(F_t - F_{t-1}) + (1-\beta) b_{t-1} \quad (2)$$

$$D_t = \gamma \frac{X_t}{F_t W_{t-F_2}} + (1-\gamma) D_{t-F_1} \quad (3)$$

$$W_t = \omega \frac{X_t}{F_t D_{t-F_1}} + (1-\omega) W_{t-F_2} \quad (4)$$

$$\hat{X}_{t+k} = (F_t + k b_t) D_{t-F_1+k} W_{t-F_2+k} \quad (5)$$

where F_t and b_t are the smoothed level and trend; D_t and W_t are the seasonal indices; α, β, γ and ω are the smoothing parameters; and $\hat{X}_{t+k}$ is the k step-ahead forecast made from forecast origin t. The parameters $\alpha, \gamma, \delta, \omega$ and ϕ, are estimated in a single procedure by minimizing the sum of squared one step-ahead in sample errors.

When the number of seasonal components is long, it can be difficult to estimate the parameters and the seed values. Furthermore, if the seasonal period is long, the model obtained is likely to be overparametrized. For double seasonal time series Gould *et al*. (2008) attempted to reduce this problem by dividing the longer seasonal length into sub-seasonal cycles that have similar patterns. However, their adaptation is relatively complex and can only be used for double seasonal patterns where one seasonal length is a multiple of the other. To avoid the potentially large optimization problem, which is an important inconvenient in a revenue management system, the initial states are usually approximated with various heuristics (Taylor 2003, 2010; Gould *et al*., 2008), a practice that does not lead to optimized seed states.

2.2. A state space model for exponential smoothing

The exponential smoothing model assumes that the process of white noise is serially uncorrelated. This assumption is not always true in practice because it sometimes behaves as an AR (1) process. Thus, De Livera et al. (2011) proposed modifications to the ETS models in order to include a wide variety of seasonal patterns and solve the problem of correlated errors. To avoid falling into nonlinearity problems, these authors restricted the models to those homoscedastic and the Box-Cox transformation (Box and Cox, 1964) are used when there is some type of specific nonlinearity.

The model including the transformation of Box and Cox, ARMA errors, trend and multiple seasonal patterns (called BATS) can be expressed as follows:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega}, & \omega \neq 0, \\ \log y_t, & \omega = 0, \end{cases} \tag{6}$$

$$y_t^{(\omega)} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t, \tag{7}$$

$$l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t, \tag{8}$$

$$b_t = (1-\phi) b + \phi b_{t-1} + \beta d_t, \tag{9}$$

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t, \tag{10}$$

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{11}$$

where $m_1, \dots, m_T$ denote the seasonal periods, l_t is the local level in period t, b is the long-run trend, b_t is the short-run trend in period t, $s_t^{(i)}$ represents the i-th seasonal component at time t, d_t denotes an ARMA(p, q) process, and ε_t is a Gaussian white-noise process with zero mean and constant variance σ^2. The smoothing parameters are given by α, β and γ_i for $i = 1, \dots, T$. φ is the damping constant of the trend. This change ensures that the value of the short-term b_t trend converges on the value b (Long-term trend), rather than on zero.

The arguments $(\omega, \phi, p, q, m_1, m_2, \dots, m_T)$ are the Box-Cox parameter, damping parameters, ARMA model parameters (p and q) and seasonal periods ($m_1, \dots, m_T$). For example, BATS (1, 1, 0, 0, m_1) represents the underlying model for the well-known holt-winters additive single seasonal method. The double seasonal Holt-Winters additive seasonal model described by Taylor (2003) is given by BATS (1, 1, 0, 0,m_1, m_2), and that with the residual AR(1) adjustment in the model of Taylor (2003, 2008) is given by BATS (1, 1, 1, 0, m_1, m_2).

The BATS model is the most obvious generalization of the traditional seasonal innovations models that allows multiple seasonal periods.

The well-known Mean Average Percentage Error (MAPE) measure is used to estimate the efficiency of the models to forecast h steps ahead:

$$MAPE\ (h) = \frac{1}{h} \sum_{i=1}^{h} \left| \frac{x_t - \hat{x}_t}{x_t} \right| \times 100 \tag{12}$$

Because the MAPE captures the proportionality between the forecast error and the actual load, it is preferred and easily interpreted by those in the industry, particularly in the hospitality industry.

3. Results

The results obtained from the application of the standard Holt-Winters, DSHW and BATS methods to the time series showed in Fig. 1 are reported in this section. In this study were produced forecast with time horizon of 3 weeks and was conducted using the software statistical R (R 3.1.0).

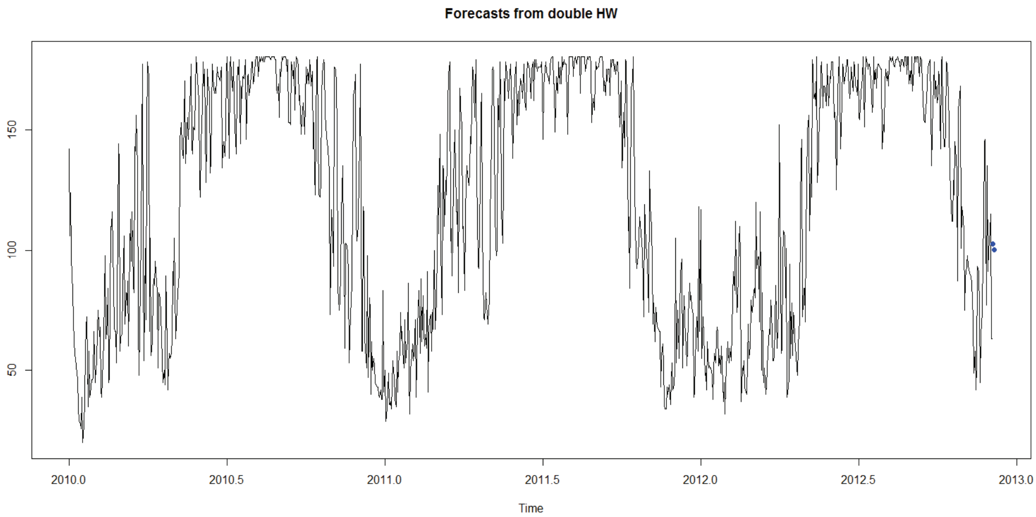

Figure 2: The variable modeling of a daily demand of a hotel room-DSHW

As stated before, Fig. 1 shows the demand of the total number of the rooms from January 2010 to December 2012. The data was observed daily and show a weekly and annually seasonal patterns. The series consists of 1068 observations. A sample was used to obtain the maximum likelihood estimates of the initial states, the smoothing parameters and ARMA errors. Fig. 2 shows the forecast results for the post-sample period of three weeks, using the DSHM method. Following the model proposed by De Livera et al. (2011), the following BATS model was fitted:

$$\text{BATS}(\omega = 1, \phi = 0.956, p = 3, q = 3).$$

The estimated values of 0 for β and 1 for φ imply a purely deterministic growth rate with no damping effect. The models also imply that the irregular components of the series is correlated and can be described by an ARMA(3,3) process, and a transformation is not necessary to handle nonlinearities in the series. The decomposition obtained from BAT, as shown in Fig. 3, clearly exhibits week and annual seasonal components. This figure also shows that the trend component is almost constant.

Table 1: Parameters from applications of the HW, DSHW and BATS models

PARAMETERS								MAPE	
MODEL	ω	φ	α	β	γ	p	q	1 week ahead	3 weeks ahead
BATS	1	0.956	0.405	0	--	3	3	26.3	32.6
DSHW	0.357	0.385	0.104	0	0.070	--	--	31.8	43.6

Table 1 also shows the post-sample forecasting accuracy of all methods, using the MAPE measure, for lead times up to a three weeks ahead for the time series. The one week ahead is the first week of the three-week post-sample evaluation period. It is possible to see that the standard Holt-Winters method is substantially outperformed by the other methods at both lead times (one and three weeks ahead). Off these three methods, the BATS approach performs particularly well.

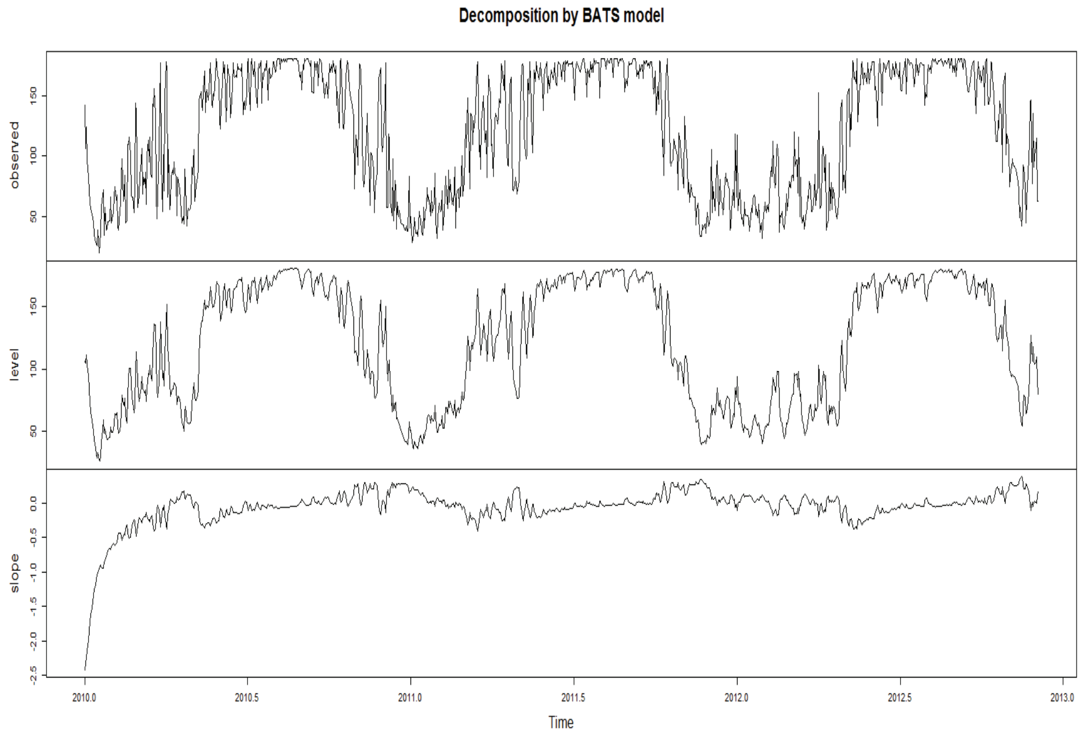

Figure 3: BATS decomposition of the daily demand of a hotel room

4. Conclusion

This paper evaluates new innovative forecasting models recently developed for forecasting time series with complex seasonal patterns. Of the three methods analyzed, the Holt-Winters seasonal smoothing with simple additive seasonality model has been the widely applied model in all revenue management systems. By contrast, both models with double seasonal patterns are newer formulations, particularly the BATS model, which have not been used in such systems.

A highlight of this study is the success of the later models. In addition to its performance, it is important to note that, of the two sophisticated methods that we analyzed, the BATS model has some advantages when compared with the DSHW in the context of a revenue management system. Indeed, it can take into account several seasonal periods with high frequency and it is as simple and quick to implement as the DSHW model.

Other important advantage regarding the BATS model (and also the exponential smoothing approach) is that, by contrast with seasonal ARIMA modelling and other approaches to short-term demand forecasting, there is no model specification involved. Note that a process of model identification is impractical in an online revenue management system. All of this gives the BATS model, which is simpler and quicker to implement online, a strong recommendation to be used in advanced revenue management systems.

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