Intelligent System to Support Judgmental Business Forecasting: The Case of Unconstraint Hotel Room Demand

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Abstract - In this paper, we describe the research and development of a fuzzy expert system and Economic system are characterized by increasing uncertainty in their dynamics hotel room demands. This increasing uncertainty is likely to incur bad decisions that can be costly in financial terms. This makes forecasting of uncertain economic variables an instrumental activity in any organization. This paper takes the hotel industry as a practical application of forecasting using the Holt-Winter method. The problem here is to forecast the uncertain demand for room at a hotel for each arrival dat. Forecasting is part of the revenue management system whose objective is to maximize the revenue by making decisions regarding when to make room available for customers and at what price .the forecast approach discussed in this paper is based on quantitative models and does satisfactory for certain days this is not the case for other arrival days. It is believed that human judgment when dealing with external event that may affect the variables begins forecasted. Actual data from a hotel are used to illustrate the forecasting mechanism.

Keywords -- Fuzzy expert system, Forecasting, Hotel Industry, Economic revenue management system, Holt-Winter approach.

I. INTRODUCTION:

Forecasting room demand is a very important part of modern day hotel revenue management systems. The objective of this system is to maximize the revenue under the constraint of fixed room capacity. To this end, most hostels have implemented some form of inventory optimization and controls. These optimization routines are carried out over several days prior to the arrival days, so an estimate of the demand for room for that particular target day is required to carry out the optimization. This paper deals with the problem of forecasting unconstrained hotel room demand. Unconstrained room demand is the number of rooms that can be rented if there is no capacity or pricing constraints. Room allocation and optimization are separate issues and not addressed in this paper.

Optimization of the inventory is very import to yield management system. The optimization problem involves selling the right type of room to the right customer at the right price, with the objective of maximizing the revenue. This is not a simple task, considering that there are multiple room types which can be sold at different rates to customers requesting multiple night Stay. This make forecasting and optimization, and consequently, increased revenue. Indeed, forecasting and optimization are among the primary components of the yield management system [1], and both components are vital for the performance of the system.

A lot of the work done on the hotel revenue management system deals with the optimization problem [2,3,4]. However, to the best of our knowledge, there has been little or no published work on the room demand forecasting aspect. In this paper, we show how a particular forecasting procedure can be applied to the hotel room demand problem.

Several methods have been used for the purpose of forecasting data in a variety of business application [5]. Different methods vary in the manner in which the historical data is modeled. ***Regression methods*** seek to explain the data with one or more input variables and model relates the data to the inputs with a set of coefficients [5].

An Application of this method is found in [5], which uses a liner regression model to the fit the monthly maintenance expense data of a manufacturing plant. Another method involves fitting a structural time series model to the data. Such a model is set up in terms of components which have a direct interpretation [6].

A very popular forecast method is ***Box-Jenkins approach*** to time series modeling and forecasting [7]. This approach does not assume that successive observations and errors An example of such a model can be found in [5], in which the viscosity of a product in a chemical process is model using VCP(2) model. However, these models are very complicated and difficult to implement. ***Smoothing methods,*** on the other hand, are Simple and give equivalent performance with the right choice of model. Smoothing procedures discount past observations in predicting future data, but the manner in which past data is discounted is ***ad hoc*** [6].

The ***exponential smoothing procedure*** is a simple method to forecast future data based on past observation [8] .In this method, pervious observation are discounted such that recant observation are given more weights and observations further in the past are given less weight. This weights decrease by constant ratio, and thus lie on an exponential curve. This method, however, can be used only for non seasonal time series showing no trend. Due to this certain adaptations are required in order to use it for time series that arise in real problems.

A more general variation of the simple exponential smoothing procedure is the Holt-Winters method [9].The latter considers the local linear trend and seasonality in the data. The trend represents the direction in which the time series is moving, while the seasonality explains the effects of different seasons in the data. This method owes its popularity to the fact that it is very simple to implement and is comparable with any other uni-variate forecasting procedure in terms of accuracy [10]. Also, the components of the forecast (viz. mean, trend and seasonality) lend themselves to an easy interpretation. These components are discussed in details in the next section.

In this paper, we apply *the **Holt-Winter procedure*** to forecast unconstrained room demand for an actual hotel. Data collected from an actual hotel is used in the initialization of the forecast components.

The objective of this paper is to apply and evaluate the ***Holt-Winters*** procedure to the forecast of hotel room demand. The forecast generated is based only on the hard data in the form of historical data and current booking activity. In this paper, no human input is accounted for in the forecast mechanism. The current study is part of an ongoing research aiming at developing a robust forecast system where both hard data and human input are combined. The motivation for this research comes from the fact that a good forecast would greatly enhance management decision making.

The remainder of the paper is organized as follows: We first present the Holt-Winters forecasting procedure in Section 2. Both, additive and multiplicative models are presented , and model selection criteria are discussed. Section 3 deals with the room demand forecasting. We discuss the reservation characterization and formulate the forecasting problem. Analysis of historical data and simulation of reservation request are also included in this section, followed by the forecast algorithm. Simulation results are presented in section 4. Finally, in Section 5, we present the conclusions and suggestions for further research work.

1) ***Holt-Winters forecasting method :*** The Holt-winters method is an extension of the exponentially weighted moving average (EWMA) procedure [6].The EWMA algorithm forecasts future values based on past observations, and places more weight on recent observations. In the Holt-Winters method, the forecast components are updated in a similar fashion, i.e. more weight are placed on recent values. The distinctive feature of the Holt-Winters procedure is that it incorporates linear trend and seasonality into the simple exponential smoothing algorithm [6].

The holt-Winters models the time series with three components: Mean local trend and seasonality. Depending on how the seasonal variation is included in the model, there are two version of the Holt-Winters forecast procedure: the additive model and multiplicative model. The additive model assumes that the forecast at time *t*, yt is given by ***yt = (mean at t - 1 + local trend) + (seasonality) + error*** While the multiplicative model assumes the forecast is given by ***yt = (mean at t - 1 + local trend) X (seasonality) + error***

Each component of the forecast is described below.

1.1) Mean : The mean component, denoted by *mt* , of the model gives the level of the time series at time instant *t*. It is the base component of the time series which is modified by the trend and seasonality effects to give the final values. For a constant, non seasonal process, the mean is taken as the forecast o future observations.

1.2) Trend : A majority of the time series does not fluctuate about a constant level, but exhibit shifts in either the upward or downward directions. This effect is modeled by the trend component , denoted by bt and it gives the general direction in which the series is progressing. The trend can be classified as global or local, liner or non liner, etc. The Holt-Winters procedure models locals, linear trend.

1.3 Seasonality : Time series generally show seasonal variations i.e. there is a period i.e. shifts in the level of the series. This is especially true in case of hotel room demand, which have distinct periods of high and low demand depending on the type of hotel property. Time of year etc, Seasonal effects are cyclic i.e. it repeats itself after a fixed interval time. The Holt-Winters method models a finite number of seasonal variations, and the seasonal component is denoted by c_t.

The seasonality component determines the version of the Holt-Winters forecast procedure. The additive version, in which the seasonal component is added to the base and trend components, is used when the amplitude of the seasonal variation is independent of the level of the time series.

The use of the multiplicative version is appropriate when the amplitude of the seasonal variation is proportional to the level of the time series. In the multiplicative version, the seasonal effect is multiplied to the base and trend components.

1.4) Additive Model : The time series is represented by the model $Y_t = m_t + b_t t + c_t + €_t$

where $€_t$ is the random error component with mean 0 and variance o2. We assume the length of a season to be s periods. The equations for updating the corresponding components are

$$\hat{m}_t = \propto (Y_t - \hat{C}_{t-s} + (1 - \propto)$$

$$(\hat{m}_{t-1} + \hat{b}_{t-1})$$

$$\hat{b}_t = \beta (\hat{m}_t - \hat{m}_{t-1}) + (1-\beta) \hat{b}_{t-1}$$

$$\hat{C}_t = \gamma(\hat{y}t - \hat{m}_{t-1}) + (1-\gamma) \hat{c}_{t-s}$$

Where ∝, β, γ are the smoothing constants for the base, trend and seasonal components respectively, and $\hat{m}_t$, $\hat{b}_t$ and $\hat{C}_t$ are the estimates of the base, trend and seasonal components respectively at time t. The forecast for any future time T = 1, 2,.... is given by

$$\hat{Y}_{t+T} = \hat{m}_t + b_t t) c_{t-s}$$

In the above equation, we use the estimate of the seasonal component at time t+T computed s period ago.

1.5) Multiplicative Model : The Multiplicative Model assumes the series to be of the form

$$Y_t = m_t + b_t t + c_t + €_t$$

Where, as above, $€_t$ is the random error component. The update equation is

$$\hat{m}_t = \propto Y_t / \hat{C}_{t-s} + (1 - \propto) (\hat{m}_{t-1} + \hat{b}_{t-1})$$

$$\hat{b}_t = \beta (\hat{m}_t - \hat{m}_{t-1}) + (1-\beta) \hat{b}_{t-1}$$

$$\hat{C}_t = \gamma(\hat{y}t / \hat{m}_{t-1}) + (1-\gamma) \hat{c}_{t-s}$$

where ∝ , β ,γ have the same meaning as in the additive model. The forecast for any future time T= 1,2,.... is given by

$$\hat{Y}_{t+T} = (\hat{m}_t + \hat{b}_t T) \hat{C}_{t+T-S}$$

As seen from equations, it is quite straightforward to implement the holt-winters method (either version) an a digital computer. We have used the multiplicative version to forecast rood demand, based on the assumption that the seasonal effects are proportional in size to the local mean. Initially, the smoothing constants are assigned values arbitrarily, and ∝ is optimized before each forecast run to minimize the most recent forecast error.

II .Forecasting unconstrained Room Demand

2.1 Characterizing Reservation Request : A reservation request is characterized by three quantities: the arrival day, market segment and length of stay. A request for room reservation always specifies a particular arrival date. Availability and /or price considerations may cause the customer to change the arrival day, but since we are interested in forecasting unconstrained demand, we assume that there is no change in the requested arrival day each reservation. Also, Hotels have different types of rooms(e.g. Suites, double rooms, economy etc.) and each of these is sold at different rates. Additionally, the same type of room may be sold at different rates to different customers, depending on promotional package, concessional rates for IT employees, etc. Thus, each reservation request is characterized by the market segment or rate category requested. Lastly, the demand for a room is also characterized by the number of night the reservation is requested for.

A reservation request may be for one night, two nights, or several nights. The length of stay is an important factor as it has a direct on the daily revenue, capacity, etc.

2.2 Characterizing Reservation cancelation Request: The forecast problem can then be defined as estimating the number of net reservations (reservations-cancelations) that will be received for each future arrival date per rate class for each possible length of stay. In this paper, we assume that the reservations are distributed over different stay durations according to historical data, and we focus our attention on forecasting the net demand for each future arrival day for each market segment.

These simulations are carried out for one rate class. Extending this work to forecast unconstrained demand for several rate classes is straight forward.

2.3) Analysis of Historical Data: We have used data from an actual hotel for the initialization and testing of the forecast algorithm. Reservation data for 58 week (406 days) was used for this purpose. The property from which the data was obtained is a business/convention center property. The methodology developed here is general, and can be applied to any type of hotel(e.g business traveler property, leisure traveler property).

The Seasonal effect is especially important in the hotel revenue management problem. Hotels generally have distinct high demand and low demand seasons, and different room allocation strategies are used in these different seasons. As an example, hotels may work with only a part of the room inventory during low demand season to reduce the overheads associated with excess rooms. Consequently, it is very important to be able to estimate the room demand based on the current season.

3.4) Simulating Reservation Request : To evaluate the performance of the forecast, we need to simulate the process of receipt of request for hotel rooms. The output of the forecast is the number of customers in each market segment that will actually show-up on any particular arrival day.

Thus, we need to simulate the build-up of net demand(reservations minus cancelations) for each market segment and each arrival day in the simulation period. Thus, the problem is that of generating random reservation and cancelation request based on historical data.

Reservation requests are generated using a Poisson distribution, while a binomial distribution is used to model cancelation requests. Modeling reservations and cancelations using Poisson distribution and binomial distribution respectively are very common in the literature and have been used by several researchers.

$$F(x) = \frac{\{e-^{t(^{t}})x}{X!}$$

^t = Number of Requests received in booking period
$$\frac{}{\text{Number of days in booking period t}}$$

3.5) Long Term and Short Term Forecasts: The forecasted value of demand is comprised of two components: the long term and the short term forecasts. As the name indicates, the long term forecast estimates the final demand for the different arrival dates/market segment combinations well in advance of the arrival dates.

The Short term forecast on the other hand, estimates the final demand only after the hotel property start receiving booking for an arrival day.

Typically, most of the advance booking request are received during the 60 days before the arrival day; hence the name short term forecast. The final forecast is a weighted combination of the long term and the short term forecasts.

3.6) Forecast Weight: The final forecast consists of combining the long term and the short term forecasts to produce a single composite forecast. This is achieved by taking a weighted sum of the two forecasts. The Objective is to give the long term forecast a higher weight than the short term forecast when the

Processing day is far away from the arrival day. Alternately, the short term forecast is given a higher weight when the processing day is close to the arrival day. The weight is normalized, i.e., their sum is unity.

Initially, the weights are set according to the number of booking and number of forecasted demand. During the execution of the forecast program, the weight is continually updated. The update factor depends on the mean square error (MSE) between each of the forecasts and the actual value. The new weight are given by

$$\text{New weight} = \frac{\text{ST forecast MSE}}{\text{ST forecast MSE + LT forecast MSE}}$$

The weights are themselves updated by taking a weighted average of the new weights and the old weights. The updated weights are given by
Update = weight N X old weight + (1- N) X new weight

The parameter o < n < 1 is fixed arbitrarily, depending on how much importance we wish to give to the new weights. We use n = 0.9 in the simulations.

3.7) Combined Forecast: After having calculated the short term and the long term forecast and the forecast weights, the final combined forecast can be calculated as
Final forecast = It – weight X LT forecast + St – weight X ST Forecast
The final forecast is calculated for each arrival days.

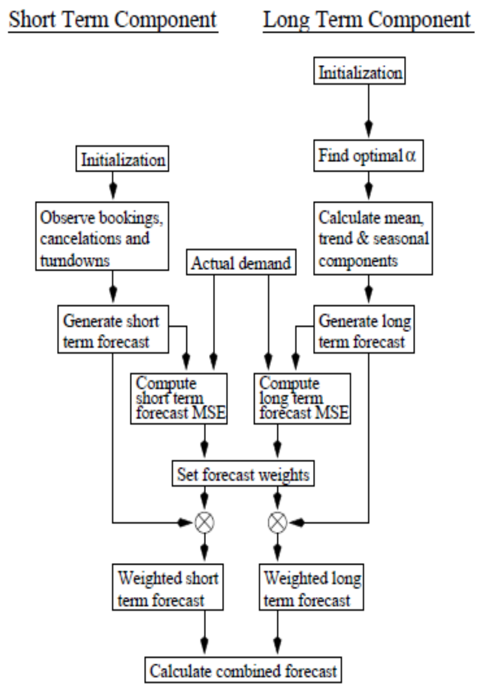

Fig.1: Long Term Short Term Component

III. CONCLUSION:

The role of the forecast should also seen in the proper perspective. As mentioned in the beginning of the paper, we feel that a good forecast will result in better inventory optimization and management. Thus, the objective is to be able to obtain a good forecast consistently for all future days, rather than having an exact prediction of the demand on some days. This logically takes us to the use of fuzzy logic in the forecast algorithm. These ideas are begin investigated and that certainly present a new approach of tackling the problem. Work along this line of thought will be reported in a future paper.

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REFERENCES

[1] Cross, R.G., Revenue Management, Broadway Books New York,

[2] Bitran, G.R., and Gilbert, S.M., Managing Hotel Reservations with Uncertain Arrivals, Opns. Res., Vol. 44, No.1

[3] Bitran, G.R., and Mondschein, S.V., An application of yield managemnt to the Hotel Industry Considering Multiple Day Stays Opns. Res., Vol. 43, No.3

[4] Ladany, S.P., Dynamic Operating Rules for Motel Reservations, Dec. Sci., Vol 7

[5] Montgomery, D.c., and Johnson, L.A., Forecasting and time Series Analysis,

[6] Harvey, A.c., time Series Model, MIT Press, Cambridge, MA, 2nd ed., 2011

[7] Gupta, P.c., and yamada, K., Adaptive Short-term Forecasting of Hourly Loads using Weather Information, IEEE Tran. Power Appar Vol Pas-2012

BIOGRAPHY

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