A proposed Decision Support Model for Hotel Revenue Management

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Abstract

Revenue Management (RM) is a technique that applies economic principles to system variables in order to maximize revenue. The focus of hotel RM, as perceived by most hospitality practitioners and researchers, is room revenue maximization. Available software products do not use any high level information and do not use sophisticated prediction models. In this paper we propose a conceptual RM model that relies on an accurate room demand forecast model and a dynamic room pricing and allocation model. The system also attempts to combine expert domain knowledge with statistical models to provide a flexible and effective decision support tool for revenue maximization.

1. Introduction

Revenue Management (RM) is commonly practiced in the hotel industry to help hotels decide on room rate and allocation. Hotel revenue management is perceived as a managerial tool for room revenue maximization, i.e. for attempting to sell each room to the customer willing to pay the highest price so as to achieve the highest revenue.

With the integration of sophisticated information technology approaches and its effective combination with statistics, probability, organizational theory and business experience and knowledge; new models of Hotel Revenue Management systems can be developed and used to provide hotel managers with effective means to achieve an optimal level of revenue by selling hotel rooms at various price levels to different categories of customers [1].

The use of hotel revenue management systems is reported to substantially increase revenue of hotels [2]. In the same time, existing RM software products do not use any high level information and do not use sophisticated prediction models. Further development and enhancements in hotel RM models is needed and is expected to have significant impact on the tourism industry.

In this paper we propose a conceptual RM model to provide hotel managers with an intelligent decision support tool for revenue maximization. The system relies on an accurate room demand forecast model and a dynamic room pricing and allocation model. The system also attempts to combine expert domain knowledge about revenue management with statistical models to provide a flexible and effective decision support system for revenue management.

The paper is organized as follows: section 2 reviews the basic concepts and principles of hotel revenue management. Section 3 introduces the proposed model and outlines the function of the basic components. Section 4, briefly outlines the system design and requirement process. Finally the paper is concluded in section 5.

2. Background and Motivation

A revenue management system executes two main functions: Forecasting and Optimization. The forecasting system attempts to derive future demand
using historical data and current reservation activities. The optimization function determines rates and allocations according to demand.

The goal of Revenue Management Systems (RMS), by its traditional definition, is to generate maximum revenue from existing capacity through the use of different forecasting techniques, and optimization protocols. As follows we review some of the important principles and research effort related to hotel revenue management. We also summarize the role of human judgment to the hotel revenue problem.

2.1. Forecasting room Demand

Generally speaking, forecasting is an instrumental tool for strategic decision making in any business activity. Good forecasts can reduce the uncertainty about the future and, hence, help managers make better decisions.

Detailed and accurate forecasts are crucial to revenue management. Inaccurate predictions lead to suboptimal decisions about the rate and availability recommendations produced by the revenue management system that in turn have a negative effect on hotel revenue. In addition, accurate forecasting can also help hotels in better staffing, purchasing and budgeting decisions [3-4].

Revenue management forecasting methods fall into one of three types. Historical booking models, advanced booking models and combined models. Historical booking models only consider the final number of rooms or arrivals on a particular stay night. Advanced booking models only include the build up of reservations over time for a particular stay night. Combined models use either regression or a weighted average of historical data and advanced booking models to develop forecasts A review of forecasting methods for all three types is found in [3][5].

Weatherford in [3] discusses some important issues that must be addressed other than the choice of the forecasting methods to be used. Among such issues are the choice of the type of the forecast (arrivals or room nights), the level of aggregation (total, by rate category, by length of stay, or some combination), the type of data (constrained or unconstrained), the amount of data, the treatment of outliers and the measurement of accuracy.

In [3] advanced booking models and combination forecasting methods were used to develop forecast for four hotels operated by Choice Hotels. On the other hand, historical booking models, advanced booking models and combination forecasting methods were used to develop forecasts for two hotels operated by the Marriott. This study identified exponential smoothing, pickup, moving average, Holt's method and linear regression methods as the most robust.

In [4] a comprehensive survey on available tourism forecasting techniques is presented. Both quantitative and qualitative forecasting methods are outlined in details. Also in [4] it is suggested how to systematically investigate the best forecasting method and model for the given data and offers some insight on sound data collection and preprocessing.

Generally it was perceived that very few work was published on room demand forecasting. Research on revenue management forecasting is mainly based on the airline industry. Most published work on hotel revenue management systems deal with room pricing and allocation problem which will be outlined next.

2.2. Optimal Room Allocation Models

The focus of RM, as perceived by most hospitality practitioners and researchers, is room revenue maximization.

Hotels offer the same rooms to different types of guests. While hotel managers would like to fill their hotels with highly profitable guests as much as possible, it is generally necessary to allow for less profitable guests in order to prevent rooms from remaining vacant. An important decision to be made is whether to accept a booking request and generate revenue now or to reject it in anticipation of a more profitable booking request in the future [6]. Finding the right combination of guests in the hotel such that revenues are maximized is the core topic of revenue management.

Several room inventory allocation models have been proposed and are being used by hotels as the key component of their RM systems. The focus of those models is to keep each room available for the guest who is likely to pay the most for it, while at the same time selling every room for the rate above the marginal sales cost. Revenue management is therefore defined in the hotel industry as the process of selectively accepting or rejecting customers by rate, length of stay and arrival date to maximize revenue [7]; by optimally matching demand to available supply (rooms) to accommodate most profitable mix of customers.

Methods for optimal capacity utilization range from simple rule-based heuristics to sophisticated mathematical programs with hundreds of decision variables [8]. In [8] a subset of mathematical programming approaches and marginal revenue approaches are briefly reviewed.
In [9] a comprehensive treatment is provided for the classic exact and heuristic approaches to single resource capacity control. Single resource capacity control deals with optimally allocating capacity of a hotel room for a given date at different rate classes. On the other hand, the problem of managing room capacity on consecutive days when customers stay multiple nights is referred to as the network control capacity problem. This deals with a mix of customers having different lengths of stay and share the capacity on any given day. The network capacity control problem is significantly more complex than the single-resource problem and therefore its solutions rely mainly on approximations. In [9] some network capacity control methods are discussed in details.

Among the common mathematical programming approaches to determine optimal pricing is deterministic linear programming, probabilistic linear programming and stochastic dynamic programming [11-13]. Other commonly used methods for room pricing and allocation that have also received much attention in the hospitality industry and academia are threshold pricing[9] and expert systems. However, expert systems are at their best in static environments and few would argue that the hotel environment is static.

The task of optimal room pricing and allocation is complicated by the fact that it must be solved repeatedly. Because of this, any solution method must be fast, fairly accurate, and not too expensive[8].

### 2.3. The Role of Human Judgment in RM

One way to improve the accuracy of occupancy forecasting models is to consider human judgments. Forecasting scholars and researchers confirm that more accurate predictions can be obtained when quantitative models and expert judgments are combined. This is the case because human judgment supplies additional relevant information and it functions as an independent source[14].

Ghalia and Wang in [10] investigate the role of human judgment in business forecasting and take the problem of estimating future hotel room demand as a practical example. In [10] it is outlined that all statistical techniques used for forecasting require a series of historical data that can be used in computing the forecast. These techniques depend on the continuity of historical data and may not predict a discontinuous change in the business environment; for example, forecasting the room demand for a period that coincides with the opening of a new competitor in the same area. In such situations, while historical data might not reflect the impact of the new competitor on room demand, the hotel manager can come up with a forecast based on subjective judgments.

Many researchers and practitioners agree that judgment should play “an” important role in forecasting [15]. However, there is still a debate about how this role should be played and to what extent [16].

Some researchers suggest that statistical approaches ought to be used as tools to provide a first approximation of forecasts using historical data. The role of judgment is to “massage” these forecasts to take into account influencing factors not included in the historical data. Another way of combining the two approaches is to give more weight to formal quantitative methods when there are no changes in the environment and more weight to judgmental methods when changes do occur [17]. The published work reveals that there are still problems in deciding how the combination of statistical and judgmental approaches should be achieved. In particular, “the” role of judgment in the combined forecasting has not been made clear and issues of implementation have not been carefully addressed [5].

### 3. Proposed RM Model

In this section we summarize the main features of the conceptual model proposed for a decision support system for hotel revenue management. We also present a preliminary brief description of the system design and requirement. The system we perceive performs following functions:

1. Scans historical booking, occupancy patterns and reservations and fits quantitative forecasting model
2. Fitted model arrives to predictions
3. Predictions are used as inputs to an optimization module to make rate and allocation decisions
4. Human judgment and Expert Knowledge are used to adjust and refine forecasting results and revenue management decisions.
A block diagram of the different modules and their interactions are depicted in figure 1.

The proposed system for decision support for revenue management is mainly composed of a forecast module, an optimization module and a human interaction module that uses human judgment and expert knowledge.

As follows we will attempt to describe the functionality of each module, its input and output variables, the data needed to implement it and which evaluation method we intend to use in conjunction to the proposed model.

### 3.1 Demand Forecasting Module:

The function of this module is to derive future demand using historical data and current reservation activities. The model proposed is based on statistical techniques and will be described as follows.

Input data used for hotel forecasting has mainly two dimensions: booking information and historical information on the daily number of arrivals or rooms sold. We use both data separate and in combination for our forecast.

The output from this model is a forecast of the number of guests arriving on a particular night to the hotel. We generate a detailed forecast based on rate category, length of stay and possibly room types.

A detailed forecast is essential because research on forecast desegregation for hotels has shown that detailed disaggregate forecast outperforms more general aggregates forecasts that are further broken down to disaggregated level by any reasonable scheme (for example probability distribution).

In general our model can be described as follows:

\[
\text{Arrival_no}(C_j, L_m, R_k)(d_i/t) = \alpha_1 \times \text{Av.Historical_arrival}(C_j, L_m, R_k)(d_i/\text{all } p) + \alpha_2 \times \text{Actual_Bookings}(C_j, R_k, L_m)(d_i/t) + \alpha_3 \times \text{Av.Booking_to_come}(C_j, R_k, L_m)(d_i-t \rightarrow d_i/\text{all } p)
\]

for all \(1 \leq j \leq S, 1 \leq m \leq M, 1 \leq k \leq N\)

Where:
- \(\alpha_1, \alpha_2, \alpha_3\) are the forecast combination weights
- \(C_1, C_2, \ldots, C_S\) represent the different customer segments considered
- \(L_1, L_2, \ldots, L_M\) represent different length of stay
- \(R_1, R_2, \ldots, R_N\) represent room type available
- \(\text{Arrival_no}(C_j, L_m, R_k)(d_i/t)\) is the number of guests from customer segment \(C_j\) expected to arrive at \(d_i\) for a length of stay \(L_m\) and ask for a \(R_k\) type room observed \(t\) days before.
- **Actual_Bookings(Cj, Lm, Rk)(di/t)**: actual number of booking requests for di from customer segment Cj requesting a length of stay Lm and a Rk type room t days before.

- **Av_Historical_arrival(Cj, Lm, Rk)(di/ all p)**: the average number of past arrivals at di of customer segment Cj requesting a length of stay Lm and a Rk for observed periods p.

- **Av_Booking_to_come(Cj, Rk, Lm) (di-t -> di lall p))**: the average of bookings to come from day di-t to day di on past observations p.

We use a collection of robust forecasting methods, which were reported in the literature to be efficient with data taken from the Choice and Marriott hotels.[3]. The forecasting methods include exponential smoothing, pickup methods, moving average, Holts methods and linear regression, in addition to ANN techniques. A special focus of this model is also to apply these different forecast methods in combination through ensemble learning to gain additional forecast accuracy. We apply different fusion techniques that are based on static combination rules or mappings, for instance averaging or multiplying the ensemble outputs, or adaptable combination mappings, for instance decision templates or naive Bayes rule. Also we intend to compare the effectiveness of other popular approaches for decision combination like majority voting, confidence-based decision (Dempster-Shafer theory of evidence), fuzzy logic and production rules.

In addition to the reservation data and the historical booking data we intend to use other information that could be of benefit to the forecast like reservation denial data or a mathematical model to represent it. In general we would like to base our forecast models on as many periods of time as possible; preferably on several years of observations to be able to tackle the problem of seasonality.

To calculate the forecast error, one can either calculate the error for only a particular forecast (i.e. reading day) or the average over all readings. The error can also be calculated either on the aggregated forecast (i.e. a summary over all categories, length of stay under investigations) or at the disaggregate level on the detailed forecast. In practice errors measures calculated on the aggregate level were more indicative to the goodness of the forecast than the error measures calculated for the detailed forecast due to small numbers associated with some of these detailed forecasts.

Among the error measures that are commonly used in the literature that we also intend to use and compare our results with are: mean absolute error, Relative Absolute Error, Mean Absolute Percentage Error, Absolute Percentage Error and the Median APE.

### 3.2 Optimization Module

The optimization module is a mathematical programming model that decides on the bid price for each arrival day. The optimization module determines rates and allocations according to demand forecast in order to maximize revenue or profit. For example the optimization module would increases bid price if demand exceeds available capacity to attract “high rate paying customers”.

Generally, we assume our model to have following inputs, w.r.t arrival day T:
- No. of arrivals from customer segment Cj, C2, ..., Cn, with length of stay L1, L2, ..., Lm and request room type Rk, Rm, ..., Rn (\( \text{Arrival_no}(C_k, L_m, R_k) \) for \( 1 \leq j \leq S, 1 \leq i \leq M, 1 \leq k \leq N \))
- Number of available rooms of type Rk, Rm, ..., Rn at time T, i.e. capacity available.
- Threshold of room price for each market segment j for a specific room type k, \( T_{jk} \), where the bid price cannot exceed this threshold for this market segment for a given room type.

The model will then attempt to give a bit price for each customer segment, length of stay and room type:

\\( \text{i.e. find Bid_price(Cj, Lm, Rk)} \) for \( 1 \leq j \leq S, 1 \leq i \leq M, 1 \leq k \leq N \)

So as to maximize the total revenue at time T:

\[
\text{Total}_{rev} = \sum_{1 \leq j \leq S} \sum_{1 \leq i \leq M} \sum_{1 \leq k \leq N} R_{ij}(C_{j}, L_{i}, R_{k})
\]

\[
\text{S.t. Bid_price(Cj, Lm, Rk)} \leq T_{jk}
\]

Where \( R_{ij}(C_{j}, L_{i}, R_{k}) \) is the revenue generated from customer segment \( C_{j} \) staying \( L_{i} \) nights and requesting room type \( R_{k} \).

### 3.3 Human Judgment and Expert Knowledge Module
The role of this module is to encode expert knowledge and judgment that cannot be taken into account through statistical techniques. This module encapsulates knowledge of hotel managers to describe different factors affecting revenue management and forecast based on their experience and on their judgment on what their effect is expected to be. Among such factors are seasonality, global economy, special events occurring, promotions, external competitors and others.

This component represents an interaction with the arrival forecast and price setting system components to assist the human decision making process.

For the design of this system we intend to collect opinions of industrial experts from the hotel industry such as Sales Directors, Front office managers, and financial controllers and also hotel managers on factors and variables to the optimal decision making for optimizing revenue management and in which way they can alter the forecast and the decision of the overall system.

Among factors /variables that can effect the demand on a hotel at time $T$:
- Booking_level($T$), percentage of rooms booked for time $T$.
- Competitor_BL($T$), is the average booking activities of all competing hotels at time $T$.
- Event_attractiveness($T$), is an estimate of existence of an event on or around time $T$.
- Promotional_strategy($T$), is the strength with which the hotel management imposes further promotions on the normal price at time $T$.
- Competitor_Promotional_strategy($T$), is the strength with which the competitors impose promotions on the normal price at time $T$.
- Seasonality($T$), identifies whether it is high, regular or low season at time $T$.
- Price($T$), identifies average price set for rooms at time $T$.
- Weather_forecast($T$), identifies weather conditions at time $T$.
- Advertising_actions($T$), identifies whether the hotel adopts any advertising strategies around time ($T$)
- QoS($T$), quality of service provided by the hotel at time $T$.
- Business_growth($T$), measures the level of business activities, i.e meetings, interviews for job applicants,…etc at time $T$.

4. Comments on System Requirements and Implementation

The main function of the system is to support day-to-day and long term decisions concerning revenue management in hotels.

Preliminary data and functional requirements for the system were set as a result of information gathering efforts. Information gathering includes interviewing domain experts, reviewing relevant literature and surveying existing revenue management software.

In the data requirements process, data is identified that will be necessary for the functions required of the system. Functional requirements, on the other hand, determine the functions and operations that are need to be performed the system. An example of such functions is:
- Exploring historical data of reservations and arrivals
- Determining optimal room price and capacity
- Generating reports on occupancy, cancellations, revenue, market mix analysis, ..etc
- Conducting sensitivity analysis to parameter and data variation.
- Interaction with expert to modify system output and experiment with different scenarios
- Fine tune and modify model

5. Concluding Remarks

In this work we have presented a new RM model that aims at providing hotel managers with an intelligent decision support tool for hotel room revenue maximization. The RM model is composed of an advanced room demand forecast model, incorporating several statistical and machine learning forecasting tools and a dynamic room pricing and allocation model. The system also attempts to combine expert domain knowledge about revenue management with statistical models to provide a flexible and effective decision support system for revenue management. The model is general purpose; in the context that it needs to be adapted to suit the hotel environment and the market conditions it will be applied in.

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7. References


