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Technology revenue management system for customer groups in hotels☆

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ABSTRACT

This paper discusses revenue management; a technique that focuses on decision making that will maximize profit from the sale of perishable inventory units. New technologies management plays an important role in the development of revenue management techniques. Each new advancement in technology management leads to more sophisticated revenue business capabilities. Today decision support revenue management systems and technologies management are crucial factors for the success of businesses in service industries. This paper addresses the specific case of customer groups in hotels. This paper introduces a new decision support system that sets the revenue maximization criteria for a hotel. The aforementioned system includes a set of demand forecasting methods for customers and addresses a general case considering individual guests and customer groups. The system also incorporates deterministic and stochastic mathematical programming models that help to make the best decisions. The actual revenue depends upon which reservation system the hotel uses. A simulation engine makes a comparison between different heuristics of room inventory control: the results include performance indexes such as occupancy rate, efficiency rate, and yield; it compares results and chooses one of them. The system proves its suitability for actual cases by testing against actual data and thus becoming an innovative and efficient tool in the management of hotels' reservation systems.

1. Introduction

Many firms seek to use revenue management techniques to maximize profitability in capacity-constrained situations. As firms seek out revenue management techniques to squeeze profits from increasingly more efficient business processes, researchers respond to these needs. In the past, different industries used most of the characteristics underlying this technique. Perishable firms, such as bakers, grocers, fresh fruit vendors, or theater managers regulated demand by varying prices during specific periods of time.

Following the US Airline Deregulation Act established in 1978, any airline can now operate any route at any time with whichever fares they choose, point out Smith, Leimkuhler and Darrow (1992). These facts have led the scientific community to develop a new management approach called revenue management. Initially, revenue management techniques assumed that passengers chose from one particular fare class, without moving to a lower fare if it became available. Companies adopted differentiated pricing in order to compete for price sensitive travelers, without giving up the revenue from their existing, full fare customers. The later extension of these techniques allows for passenger flexibility amongst fare classes. Bodily and Weatherford (1995) also consider overbooking and allowing for passenger adjustments. Belobaba and Weatherford (1996) perform a comparison of various decision making rules incorporating passenger adjustments.

In this way, they define revenue management as the sale of the right inventory unit to the right customer at the right time. Their research focuses on hotels' revenue management as hotels use this type of system to determine the number of available rooms at different rates. Rothsein (1971) performs the early work on overbooking of hotel reservations. Liberman and Yechiali (1978) consider customer cancellations in a 24-hour period. Orkin (1988) outlines some of the ideas behind revenue management for hotels and provides examples of the different types of calculations. Bitran and Mondschein (1995) model hotel reservations including multiple day stays, and Bitran and Gilbert (1996) extend previous models to incorporate uncertain arrivals.

Revenue management applies to the service industry when it meets the following five conditions (Kimes, 2000), each specifically adapted for hotels.

1. Limited capacity. The design of revenue management target capacity-constrained services firms. The units of inventory sell in a short period of time with a fixed capacity, measured by the number of rooms.
2. Market segmentation. Service industries make use of segmentation because they can choose between different types of customers. They do not allow arbitrary pricing, so the service should have some distinguishing characteristic so that it uses the same unit of capacity to deliver many different services. Hotels usually use

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purchase restrictions and refund requirements to help segment the market between leisure and business customers.
3. Future demand is uncertain. Revenue management must have the ability to forecast the demand variability so that managers can increase prices during periods of high demand and decrease prices during periods of low demand. Hotels must set aside rooms for business customers, to protect them from the lower prices acquired by leisure customers before they know how many business rooms will sell.
4. Perishable units of inventory. Inventory distinguishes service firms from manufacturing firms. The units of inventory unsold after a specific date go to waste in service industries, because services cannot be stored. This special characteristic leads to the sale of services in advance. Hotels cannot store rooms for use by tomorrow's customer.
5. Appropriate cost and pricing structure. Many service firms have a fixed cost capacity expense and a demand that cannot rapidly adjust. In the same way, the additional cost of adding a new customer to the available capacity is very low.

This paper studies revenue management models including group acceptance in hotels. Customer groups for hotels have their own set of characteristics that require a slightly different set of strategic levers from the typical approaches in use for the individual customer. Therefore, this study models the customer typology as an individual or as a group. The study tests a variety of different rooms' optimization algorithms, based on deterministic and stochastic programming techniques. The research intends to test a Technology Revenue Management (TRM) system in a hotel chain and to identify factors associated with the management of different customer typologies.

The hospitality industry needs to use technology management for its survival, and several studies show evidence of this necessity. Donaghy, McMahon-Beattie and McDowel (1997) raise a 10-step model which stresses the use of technology management in the segmentation of clients and the use of their characteristics in each market segment. Emeksiz, Gursoy and Icoz (2006) present a model in 5 steps comparing those hotels using the technology management and those not using the system. It is also necessary to devise an asset to clients as long term. Therefore, it is necessary to manage revenue management with CRM systems, Noone, Kimes and Renaghan (2003), to ensure the provision of quality service, and customer loyalty for the future.

However, businesses using different prices for the same service offer to customers should do it very carefully. An example of such an occurrence took place in 2000, Enos (2000), when Amazon.com sold DVDs at different prices, and was offering discounts between 20% and 40%, in accordance with the geographic area in which the customer was purchasing the product. The customers using ICTs and Internet could check the different prices for the same film. The experiment had a negative impact on the company. In other sectors, such as the airline or hotel industry, price variations are higher and have not created any negative perceptions of the companies so far. This is because the service that airlines and hotels offer at different prices is well differentiated by its characteristics, so that the customer receives tangible differences in the products or services offered.

Six hotels in Andalusia (Spain) become the test sites of the proposed decision support system, implementing the TRM system. These hotels are part of a 4-star hotel chain with an average of 160 bedrooms per hotel and with locations on the southern coast of Spain, a destination where the tourism industry is important on an international level, Guzman, Moreno and Tejada (2008). TRM system focuses on Marbella Hotels. These hotels stay open all year round, and the organization owns another hotel in Marbella. If necessary, guests can move from one hotel to another. This hotel chain obtains high customer satisfaction results, a necessary factor in service industries, Fullard (2007). Lindenmeier and Tscheulin (2008) address the same aspects in another paper, but dealing with the airline industry.

Sections comprise the remainder of the paper. Section 2 presents a new methodology used for tackling the problem in service industries. Section 3 addresses demand forecasting models that airlines traditionally use and their adaptation for the hotel sector. Section 4 presents the problem of optimizing room distribution. A new stochastic model is the basis of the problem, with or without groups' option. Section 5 describes a simulation model where it defines arrivals under three different policies for room inventory control. Section 6 discusses computational results and their comparisons. This section includes the comparison of performance indexes for heuristics, including occupancy rate, efficiency rate, and yield. Finally, Section 7 draws conclusions.

2. Methodology

The TRM system comprises of three management levels (Jones and Lockwood, 1998):

- Strategic level addresses the long-term and generally focuses at the head office. TRM system data establishes market segmentation criteria and overall pricing policy in long-term, structural decisions.
- Tactical level deals with the intermediate-term running of individual operating units. TRM system data establishes target occupancies for different market segments in the intermediate-term.
- Operational level concerns itself with the short-term conduct of the operating system, such as the sales office or the front desk. Human capital constitutes a key determinant of the operational office in service industries, Arribas and Vila (2007). TRM system data decides what price to offer and what reservations to accept in the short-term.

Following this structure, we propose an original methodology as described in the figure below that features a brief description of the architecture of the TRM system. Fig. 1 introduces the key components and gives an overview of information flows, decision and design, and the test stage. Shoemaker (2003) also includes "tactical level" within the "strategic management', distinguishing the use of price changes in the hotel. Later sections describe in detail each TRM system module.

TRM system follows four steps:

1. Demand forecasting must come from historical data. Based on occupation rates from historical data, the company can forecast future demand in a short-term period of time. The accuracy of forecasted demand is of special importance because it conditions the effectiveness of TRM system. Frequent updates to historical data improve the accuracy of the model. Results from this module.
2. Optimal room distribution. The system uses forecasted data as input to the application of the capacity models, so the forecasted quantity distributes among the different categories subject to the daily capacity of the hotel. A room distribution optimization model sets booking limits at diverse fare levels.
3. Room inventory control. Two differentiated phases make up this step: the arrival generation and the reservation system. First a simulation engine generates arrival processes of customers, whose data helps set up the arrival generation submodule within the room inventory control process. Conversely, the previously stated optimal room distribution process, along with the arrival generation submodule, are inputs for the reservation system submodule. The room inventory control process states the rooms' sell mode and the reservation system. The sales manager must receive the defined criterion to determine whether to accept or reject a request when a customer arrives.
4. Real assignment. As a final step, the sales office offers room prices to individual customers and negotiates rates for group customers with tour operators and travel agents.

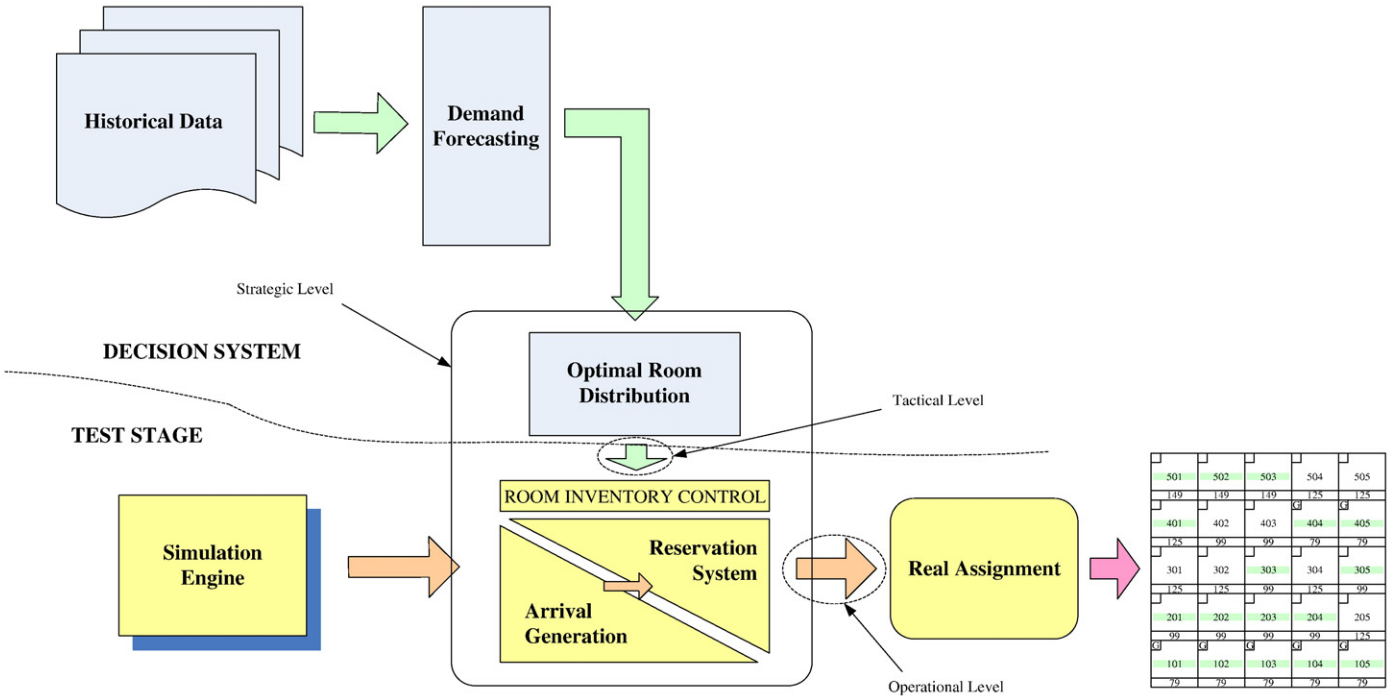

Fig. 1. Technology revenue management system process flow.

Vinod (2004) raises a revenue management system applicable to the hospitality industry, stressing the technology needs of each of the modules that comprise the aforementioned industry. Along the same line, Chiang, Chen and Xu (2007) address the importance of technology management in revenue management techniques.

Historical data module updates automatically by incorporating data from sales and reservations. Also, data updates thanks to Internet and technology management, play an important role in revenue and pricing management. Nowadays, it is easier for customers to compare prices amongst competitors, whilst service providers can get detailed information about customer behavior much quicker.

3. Demand forecasting

Revenue management depends highly upon an accurate forecasting needed for efficient reservation systems, and as input data for real-life oriented optimization models. For a comprehensive literature review on forecasting models see McGill and Van Ryzin (1999), Talluri and Van Ryzin (2004), Pai and Hong (2005) or Fernández-Morales and Mayorga-Toledano (2008).

The TRM system uses the customers' demand forecasting as input to obtain an optimal allocation of rooms. Usually the system calculates demand forecasting from historical arrival information taking into consideration the length of the stay and room category. Different methods can work, from traditional approaches to advanced and/or combined booking models, Lee (1990).

Traditional forecasting techniques include moving average bookings, exponential smoothing, or ARIMA time series models amongst other well known statistical approaches, Makridakis, Wheelwright and Hyndman (1998). Advanced booking models predict customer pickup. They consider the incremental booking received during a certain time interval. Hybrid models include regression methods in which the independent variable is the number of reservations on hand for a particular day and the dependent variable is the economics parameters from customer countries taking the final number of rooms sold.

There is not an agreement on the best method. In fact, every hotel has its own particular characteristics, and a hotel may use a forecasting method depending on the time of year due to the strong seasonal component. In general, regression model, linear, or loglinear regression should provide dependable data. Unpublished studies use combination forecasting or specific methods as a pick-up model.

Group forecasts calculate the number of rooms available to individual guests. There are two types of group demands; ad hoc and series. Ad hoc groups consist of guests that are not regular in terms of repetition of travel patterns (dates and/or services). They use a specified number of rooms and services for specific nights. A typical ad hoc request might be a single or a few one-time rooms. Series groups typically stay longer and come from tour operators or travel agencies. These customers might request rooms in specific blocks of time or nights and reallocate them through tour packages.

If the group forecast is inaccurate, the total number of rooms available will be inaccurate, and the TRM system proposals may lead to poor decisions. Inaccurate group forecasts have a greater impact during high occupancy periods of time. If group forecasts are too high, any mistake in the detection of such groups could lead to unused rooms. Unfortunately individual guests, had there been prior knowledge, could have booked these rooms, instead of leading to unnecessary waste. The experimental results section presents the results of the forecasting module for the different analyzed cases.

4. Optimal room distribution

Using the forecasting the guests' arrival, the system relies upon filling the available capacity by charging the highest price. This ensures that those customers most willing to pay for a room can do so. Most of the optimization models follow the Williamson (1992) models, maximizing revenue using a deterministic mathematical programming model, originally created for the airline industry. In the hotel industry, the objective is to allocate rooms to maximize revenue, while satisfying capacity constraints.

The optimal room distribution uses four models. The first is a deterministic model (DP), which accounts for the number of rooms in each category, taking into consideration individual guests only. The deterministic group problem (DGP) considers the DP scenario but also customer group arrivals. The system determines the opportunity cost

Table 1
List of parameters and variables of the models considered for optimizing the room distribution in the TRM system.

	DP		DGP[a]	
Data	k	Length of stay (in days)	λ_g	Length of group stay (in days)
	p_j	Fare price (category j)	μ_g	Group size (customers)
	b_i	Hotel capacity on day i	c_g	Fare group
	d_{ijk}	Forecasted demand on day i, staying k days at fare category j.		
Variables	x_{ijk}	Integer variable. Number of rooms reserved for the guest of ijk characteristics (arrival day i, fare j and length of stay k)	x_g	Binary variable. It represents the possible acceptance of group, g.
SP/SGP[a, b]				
Data	r	Number of alternative scenarios being considered depending on different customers' arrival process. It varies from 1 to S		
	$d_{ijk,r}$	Forecasted demand on day i, staying k days at fare category j according to scenario r.		
	D_{ijk}	Demand taken from a discrete set of values $\{d_{ijk,1}<d_{ijk,2}<\ldots<d_{ijk,r}\}$		
Variables	$x_{ijk,r}$	Integer variable. It represents the part of the demand D_{ijk} falling into the interval $(d_{ijk,r-1}, d_{ijk,r}]$		

[a] In DGP and SGP problems, subscript i^* means the arrival of a group on day i^* at difference from the subscript, i, applicable to arrivals of individual customers.

[b] SP considers the same set of data and variables in problem DP plus those specific for stochastic problems at the box below. The same happens with respect to SGP and DGP problems.

due to the assignment of a set number of rooms to a group instead of individual customers. Individual customers usually pay more expensive rates than customer groups, but individual customers have a higher probability of no-shows, so there is greater uncertainty of them arriving.

The stochastic problem (SP) considers the possibility of an arrival differing from the mean, taking into account the natural variability of demand. The main problem corresponds with situations where more requests exist than what appears as the mean value. In such cases, there are more customers willing to stay at the hotel than the expected amount. On such occurrences, the probability of customers accepting higher rates is greater than usual in deterministic models and therefore revenues would increase. Afterwards, it presents a stochastic demand model including groups of customers; this is the stochastic group problem (SGP) which considers the SP problem, plus group consideration.

To represent the mathematical formulation of the problem, Table 1 presents the data, parameters, and variables to deal with the different models to consider in the TRM system, and those previously presented.

Once introducing Table 1, one can formulate the different models previously described (Fig. 2).

To formulate the models, one follows the next hypothesis. Data updates automatically in order to solve the model with the latest information. This leads to a situation where cancellations have a very low impact because the system incorporates eventual cancellations into the demand forecasting module varying the input data of the optimal room distribution module that has the ability to re-run. Additionally, the system does not account for overbooking. Overbooking occurs when a hotel accepts more reservations than available rooms. Depending on the country it could cause different legal issues when hotel managers use airline overbooking as a justification for the practice. However, the legal framework of the airline and the hotel industries differs. In actual practice, hotels overbook less frequently than airlines.

Fig. 2 presents the four models dealt with in this paper. First, the DP model attempts to maximize average profit per available unit by anticipating the price sensitivity of different customers and by anticipating the possibility of reserving a room for the customers willing to pay the highest price. The model selects a number of rooms the guest can reserve of ijk characteristics, which stands for the arrival on day i, at a fare j, and for a stay of k days. The constraints of the model include the daily capacity (in rooms) of the hotel and the expected demand.

Svrcek (1991) introduces an extension of the DP model including group reservation. Groups are special clients because they make bookings in advance, include blocks of rooms, and sometimes need conference rooms. Groups are also sensitive about price. In actual situations, tour operators or travel agents negotiate the group rate. During negotiation, tour operators contact the reservation supervisor requesting a specific number of rooms for a specific period of time. In addition, the group usually needs extra services such as food and beverages, conference rooms, etc. With these requests the hotel requires the minimum amount for a room to remain profitable in order to accept or reject decisions. Group requests can replace individual customers that could pay higher fares. Some group customers may occupy rooms with higher expected marginal revenue than other

$$
\begin{aligned}
\text{(DP)}\quad & \text{Max} \quad \sum_{i,j,k} k \cdot p_j x_{ijk} \\
& \text{s.t.} \quad \sum_{l \le i} \sum_{j} \sum_{(l+k)>i} x_{ljk} \le b_i \qquad \forall i \\
& 0 \le x_{ijk} \le d_{ijk} \\
& x_{ijk} \quad \text{integer}
\end{aligned}
$$

$$
\begin{aligned}
\text{(DGP)}\quad & \text{Max} \quad \sum_{i,j,k} k \cdot p_j x_{ijk} + \sum_{g} \lambda_g c_g \mu_g x_g \\
& \text{s.t.} \quad \sum_{l \le i} \sum_{j} \sum_{(l+k)>i} x_{ljk} \le b_i \qquad \forall\, i \notin \{i^*, \ldots, i^* + \lambda_g\} \\
& \sum_{l \le i} \sum_{j} \sum_{(l+k)>i} x_{ljk} + \mu_g x_g \le b_i \qquad \forall\, i \in \{i^*, \ldots, i^* + \lambda_g\} \\
& 0 \le x_{ijk} \le d_{ijk} \\
& x_{ijk} \quad \text{integer} \\
& x_g \in \{0,1\}
\end{aligned}
$$

$$
\begin{aligned}
\text{(SP)}\quad & \text{Max} \quad \sum_{r=1}^{S} \sum_{i,j,k} k \cdot p_j \cdot \Pr(D_{ijk} \ge d_{ijk,r}) \cdot x_{ijk,r} \\
& \text{s.t.} \quad \sum_{r=1}^{S} \sum_{l \le i} \sum_{j} \sum_{(l+k)>i} x_{ljk,r} \le b_i \qquad \forall\, i \\
& x_{ijk,1} \le d_{ijk,1} \\
& x_{ijk,r} \le d_{ijk,r} - d_{ijk,r-1} \qquad \forall\, r=2,\ldots,S \\
& x_{ijk,r} \ge 0 \quad \text{integer}
\end{aligned}
$$

$$
\begin{aligned}
\text{(SGP)}\quad & \text{Max} \quad \sum_{r=1}^{S} \sum_{i,j,k} k \cdot p_j \cdot \Pr(D_{ijk} \ge d_{ijk,r}) \cdot x_{ijk,r} + \sum_{g} \lambda_g c_g \mu_g x_g \\
& \text{s.t.} \quad \sum_{r=1}^{S} \sum_{l \le i} \sum_{j} \sum_{(l+k)>i} x_{ljk,r} \le b_i \qquad \forall\, i \notin \{i^*, \ldots, i^* + \lambda_g\} \\
& \sum_{r=1}^{S} \sum_{l \le i} \sum_{j} \sum_{(l+k)>i} x_{ljk,r} + \mu_g x_g \le b_i \qquad \forall\, i \in \{i^*, \ldots, i^* + \lambda_g\} \\
& x_{ijk,1} \le d_{ijk,1} \\
& x_{ijk,r} \le d_{ijk,r} - d_{ijk,r-1} \qquad \forall\, r=2,\ldots,S \\
& x_{ijk,r} \ge 0 \quad \text{integer} \\
& x_g \in \{0,1\}
\end{aligned}
$$

Fig. 2. Optimal room distribution models.

customers. However, the total group revenue may be higher than selling these rooms to individual customers.

DGP model maximizes the profitability of individual guests and customer groups. The model modifies the capacity constraint for the days expecting groups of customers. The hotel must have a large enough capacity to lodge such groups along with individual guests. The model uses a variable binary to accept or reject the group requests.

However, in practice the demand is stochastic. Stochastic demand means that the number of allocated rooms could be different from the forecasted amount of requested rooms. The study considers a stochastic programming model, SP, with a simple resource problem. These particular stochastic problems do not cause severe computational difficulties, Kall and Wallace (1994). De Boer, Freling and Piersma (2002) introduce a stochastic model for the airline industry, assuming that discrete values are possible scenarios depending on customer demand.

Therefore, the model divides the number of rooms reserved x_{ijk} into possible scenarios, that they rename as decision variables $x_{ijk,r}$. Such variables differ from zero when $x_{ijk,r-1}$ is equal to $d_{ijk,r-1}$, that is $Pr(x_{ijk} = d_{ijk,r-1}) = Pr(x_{ijk} = d_{ijk,r-1})$. However, the sum of $x_{ijk,r}$ rooms sold to customers in S scenarios must agree with the daily capacity constraint.

Following De Boer et al. (2002), the assumption is that three demand scenarios are enough to capture most of the extra revenue generated by excess customers. The forecasted mean calculates these demands by adding up and taking away the standard deviation, thus generating a three-value band for every price.

Although the study presents a stochastic model for individual customers, we develop an original model for stochastic demand considering groups, SGP. This consideration does not appear in scientific literature thus far consulted. As an objective, the model searches for the better method for the assignment of rooms, taking into consideration the arrival of individual guests and customer groups, and accounting for the stochasticity of the demand.

The individual customer demands must agree with the three bands previously discussed, and corresponding constraints state such consideration. Additionally, the daily capacity of the hotel must be sufficient enough to lodge the stochastic arrival of individual customers and groups.

Integer programming models comprise all of the problems. However, the model can set the individual guests' variability to continuous due to the unimodularity property of the constraint coefficient matrix. Consequently, they can all reformulate as linear problems (cases of DP and SP) or mixed integer linear problems (cases of DGP and SGP), considering deterministic or stochastic demand depending on the model.

5. Room inventory control

In the previous section, the mathematical models allocated the finite rooms' inventory to the demand. The next step defines the operational work, when a customer requests a room. In such a situation, the reservation supervisor must decide whether or not to accept this guest. He/she must analyze the profit of reserving the room at that moment in time or waiting for another potential customer to arrive in the near future and pay a higher fare.

Below is a developed set of heuristics taking into account the acceptance or denial of such requests depending on a few parameters in the TRM system developed.

1. First-Come First-Serve (FC FS). This simple rule evaluates reservation request based on the well known first-come first-serve criterion. This rule disregards any room distribution. Whoever requests the room first gets the room.
2. Distinct. This heuristic considers the protection of rooms according to the optimal room distribution proposed by the four models. The arrival simulation engine allows for the selection of the better solution from the four models in the simulation.
3. Nested. This method clusters the number of fare prices into smaller buckets. Williamson (1992) proposes this method, suggesting a procedure to book rooms that considers higher fares and in turn utilizes the rooms reserved for the cheaper fare but charging the higher price. The highest fare price class has an inventory limit equal to the daily capacity.

Using a rolling horizon simulation of the reservation and a non-homogeneous Poisson arrival process they run tests using the three heuristic rules, suggested by Lewis and Shedler (1979) three decades ago, and still considered today a common basis for arrival generation. There is a comparison between the results of the heuristics simulations and a basic scenario case where they choose the arrival rate of individual customers function, $\lambda(t)$, from the historical daily pattern and positive correlates for fares (for example, the arrival rate of customers is higher during the afternoon than in the evening).

In the customer groups case, guests arrive in batches, instead of arriving one at a time. Using a discrete distribution that arranges successive batches into their sizes, they construct the arrival process of such groups. Also, they create the number of each customer batch with a random variable (Fig. 3).

6. Results and discussion

To test the suitability of the TRM system, the experiment uses historical data from an actual Spanish hotel chain with six hotels on

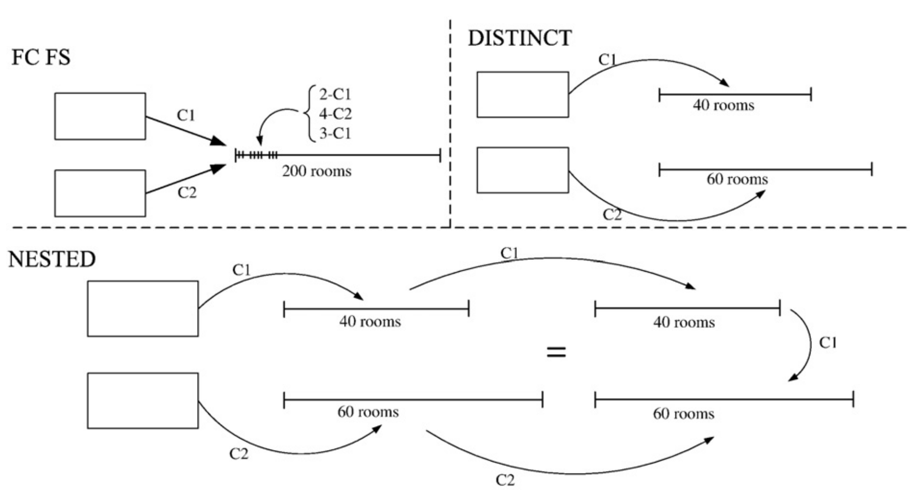

Fig. 3. Heuristics of room inventory control.

Table 2
Individual price classes.

Class	Price (€)
Premiere/luxury fare	250
Business/superior fare	175
Standard/normal fare	125
Economy/discount fare	90
Supereconomy/superdiscount fare	75

the southern coast of Spain. In the company, an analyst is responsible for making the daily decisions that the TRM system supports, and a sales team is responsible for checking the outputs of the system, using such information to deal with groups and negotiate prices.

The company provides historical data that is the input information needed for the demand forecasting module. The company carries out the forecasting for a 30 day-rolling-horizon because company managers consider a month as the longer horizon including reliable data to be forecasted and planned. The forecasting shows how great volatility makes it extremely difficult to achieve accurate forecasts.

They use the forecasted demand for each day to obtain the optimal room distribution, considering the four mathematical models: DP, DGP, SP, and SGP. Each model produces a different proposal that the TRM system considers. Models work using CPLEX 8.0.

They consider a target hotel of 200 available rooms because it represents the standard hotel of the company. The interval [0, 21] randomly generates the length of the stay, k in mathematical models. Individual guests have the ability to book at five different fares, which Table 2 describes.

For the stochastic models, they take into account three different scenarios: low track line, average, and high track line. It corresponds to the $r=1,\ldots,S$ in the models. Following De Boer et al. (2002) we set a probability for each scenario equal to p_1: 0.8/0.6/0.4; p_2: 0.6/0.4/0.2 and p_3: 0.7/0.5/0.3.

The arrival of customers provided by the demand forecasting module corresponds to the daily arrival. Therefore, they must distribute this value through the day by hours. They carry out this distribution by using a simulation engine based on ARENA simulation software.

These arrivals are a non-homogeneous Poisson process with an arrival rate $\lambda(t)$ depending on the time. They construct an actual daily pattern by taking into account the expert opinion of the people in-charge in the hotel chain.

The reservation system uses the arrival generation together with the four proposals from the optimal room distribution to propose the room assignments. To do so the systems use FC FS, distinct and nested heuristics for the four proposals from the optimal room distribution. The TRM system must analyze and compare twelve different proposals.

The expected incomes from the twelve alternatives are compared among them and with a value referred to as "real optimum distribution". Such real optimum distribution corresponds to better distribution after analyzing the "a posteriori" actual overall number of customer arrivals knowing all the information.

The following expressions calculate the percentages of occupancy, efficiency, and yield:

$$\text{Occupancy} = \frac{\text{number of rooms occupied}}{\text{maximum daily capacity}} \times 100$$

$$\text{Efficiency} = \frac{\text{number of customers accepted}}{\text{total number of rooms}} \times 100$$

$$\text{Yield} = \frac{\text{actual rooms income}}{\text{potential rooms income}} \times 100$$

Yield rate indicates the real incomes with respect to the maximum possible income assuming all of the rooms sell at the full rack rate.

Table 3 shows the average results for a 30 day period and the twelve alternatives and they compare with the real optimum distribution. The aforementioned table contains the obtained average daily incomes, sorted by capacity distribution model, and the room assignment method for a non-homogeneous Poisson process.

As Table 3 indicates, the best room distribution is a combination of group models (DGP/SGP) with assignment rule based on nested heuristic. The results of such a combination show an average error of less than 5% with respect to the actual optimal distribution. On the contrary, models not based on customer groups consideration report errors higher than an average of 8%, nearly 3,000 Euro daily. Also, the efficiency, occupancy, and yield factors reveal the convenience of such an approach because it provides more adjusted rates. In fact, group consideration is of higher importance when considering the groups of customers.

However, a detailed analysis is necessary. To do so, one must consider Figs. 4 and 5, which include the daily analysis. They consider the results for the four performance indexes: incomes, occupancy, efficiency, and yield. The figures analyze such results with respect to the optimal room distribution models (Fig. 4) and with respect to room inventory control heuristic rules (Fig. 5).

Fig. 4 depicts the daily evolution of the four indexes with respect to the four different optimal room distribution mathematical models. DGP and SGP (group models) lines are always on top of the DP and SP lines that consider only individual customers. DGP performs best most of the time. This result is mainly due to the consideration of all of the typologies of customers, and this allows for a better adaptation to the demand and the behavior of customers. However, some days show poorer results due to no-shows. For example, refer to day 6 in the figure in question.

Also, the deterministic approaches show better performance related to the occupancy, efficiency, and yield rates. The difference between deterministic and stochastic models is the expected value of perfect information, EVPI. It shows how much someone could expect to earn if they were told what would happen before making their decision. It measures the value of randomness, but it does not show that the deterministic models are dysfunctional. A small EVPI means that randomness will play a minor role in the model, whereas with a large EVPI randomness plays a major role.

Despite this, the stochastic model considering groups (SGP) obtains very good results regarding incomes, although not as good as the deterministic model, DGP. After analyzing the global behavior, one can see that the deterministic group room distribution model presents the best alternative of the analyzed options.

Fig. 5 presents the daily evolution of the four performance indexes related to the three assignment heuristics of the room inventory control. Generally, the nested line shows the better performance. However, the distinct method sometimes provides better assignments which is the case between approximately days 4 to 10 due to the fact

Table 3
Comparison of average results.

		DP	DGP	SP	SGP
FC FS	Incomes	20,670.70	22,837.50	20,670.70	22,837.50
	Occupancy	65.03%	69.75%	65.03%	69.75%
	Efficiency	78.21%	86.41%	78.21%	86.41%
	Yield	59.06%	65.25%	59.06%	65.25%
DISTINCT	Incomes	21,881.04	24,150.00	22,023.43	24,386.25
	Occupancy	67.67%	62.61%	67.98%	63.13%
	Efficiency	82.79%	91.38%	83.33%	92.27%
	Yield	62.52%	69.00%	62.92%	69.68%
NESTED	Incomes	22,782.86	25,278.75	22,972.71	25,291.88
	Occupancy	69.64%	65.07%	60.05%	65.10%
	Efficiency	86.21%	95.65%	86.92%	95.70%
	Yield	65.09%	72.23%	65.64%	72.26%
ROD[a]	Incomes	23,732.14	26,250.00	23.732,14	26,250.00

[a] Supposed real optimum distribution after real requesting by customers.

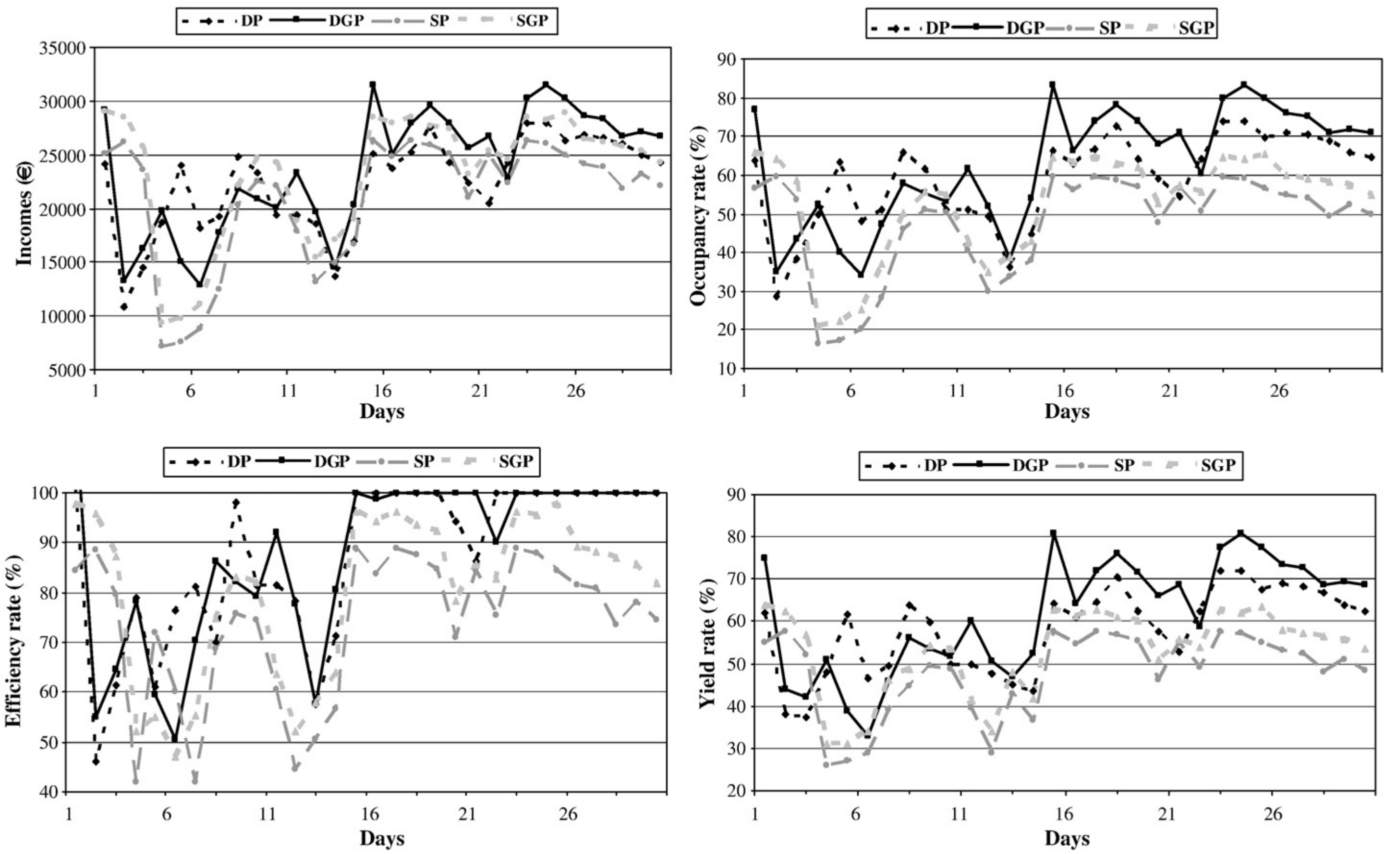

Fig. 4. Daily optimal room distribution models.

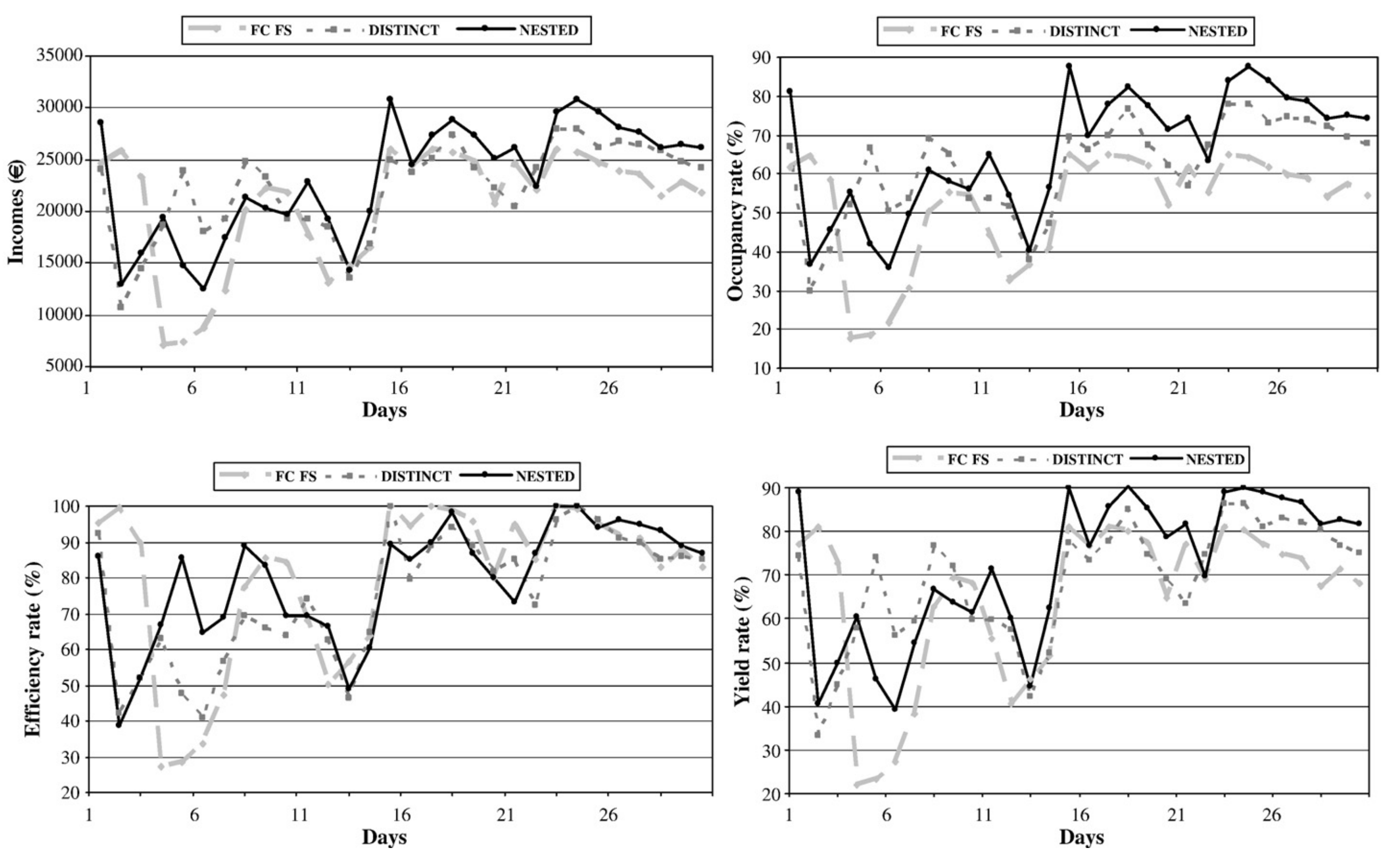

Fig. 5. Daily results for heuristic assignment in the room inventory control.

Table 4
Comparison of computational times (in seconds).

	Average time	Maximum time	Minimum time	Standard deviation
DP	0.91	2.45	0.51	0.65
DGP	1.41	2.25	0.93	0.42
SP	2.45	3.06	1.85	0.38
SGP	3.65	4.81	2.70	0.66

that ultimately they do not reach expected demand. Consequently, many rooms were not sold to first-come first-serve customers, mainly economy fare customers. Ultimately the rooms remain empty. The FC FS method is a basis method when one does not take action for distributing rooms. This method shows as having a worse trend than the others. The global behavior leads to the recommendation of the nested method as the best alternative.

Figs. 4 and 5 allow the observation of the daily evolution as function of the optimal room distribution models and the assignment heuristics. This analysis goes beyond the average results shown in Table 3 depicting daily limit situations that allows analysis based on maximum and minimum deviations and not only on average results.

The final interesting parameter of the models considered, is the computational time. The models run on a PC Pentium IV 3 GHz with 2 Gb RAM memory, and use CPLEX 8.0 as optimization software. All tested approaches obtain feasible times, all executed in less than 5 s. Table 4 summarizes the computational times related to the average time, maximum and minimum times, and standard deviations.

7. Conclusions and further research

This paper presents a decision support revenue management system as a sophisticated technology helping managers to make decisions in the framework of the hotel industry. The situation presented corresponds to an inventory perishable problem under limited capacity, which price policies differentiate.

The TRM system includes a demand forecasting module to estimate the arrival of customers from historical data, an optimal room distribution based on mathematical models to distribute the forecasted demand into different categories subject to the daily capacity of the hotel, a room inventory control module consisting of an arrival generation and a reservation system, and finally a real assignment module helping the sales office to offer room prices to individuals and group customers.

Literature on group customers is scarce by and less agreeable. First, we consider a special case for the problem, which models as deterministic programming. Then, we use stochastic programming to solve the same case. The consideration of such a customer groups model is an original idea in the scientific literature dealing with the hotel industry.

The study experiments with several models. The analysis of the experimental results concludes that the room distribution based on group models together with a nested inventory control assignment method provides the best results.

This TRM system needs a special implementation of IT department, special in the sense that it is based on particular models that are highly data-fragile. This IT system will not perform in good order without data or with not worth gathering data, and the system would not perform correctly as a consequence. TRM system needs data collected at lowest level and stored for a relatively long time in operational databases. The TRM system follows a wide spectrum of technology management focusing on planning, organizing, staffing, implementing, and monitoring and evaluating stages oriented on how to use technology to gain profit.

The proposed TRM system provides a suitable alternative for the management of any inventory perishable problem under limited capacity, concretely for every hotel located in every place of the world. Although some hotel chains usually focus their energy on selling rooms (volume of sales), on some occasions not making a sale could be more suitable, because it could increase revenues. In fact, this revenue objective can lead to lower room sales. The TRM system takes into account such aspects, and although the sales team could be recommending increases of room sales at their own discretion, TRM system would be preventing the former from offering such discounts to wait for customers willing to pay more in the near future.

In terms of future work we are focusing this approach on many other service industries, to which this system can adapt considering their particular characteristics. Another issue we are analyzing is conceiving group auction setting. This work will involve other functional areas of the company, as pricing analysts and product-design groups. In this way, we are exploring different alternatives of price negotiations among travel agencies, tour operators, and hotels owners. In addition, we are exploring customer behavior and demand models based on individual customer choice, random-utility models, and aggregate market-demand, product interactions with demand for other products and dependence on historical products attributes incorporated in its specification, Konecnik and Gartner (2007).

Another limitation of this system concerns knowledge management. Improving information processing that allows for an extensive use of knowledge transfer, knowledge reuse, storage and production of knowledge is necessary. Hallin and Marnburg (2008) suggest new lines to explore such aspects.

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