Solving a Bi-objective Model for Hotel Revenue Management Considering Customer Choice Behavior Using Meta-heuristic Algorithms

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Abstract

The problem of maximizing the benefit from a specified number of a particular product with respect to the behavior of customer choices is regarded as revenue management. This managerial technique was first adopted by the airline industries before being widely used by many others such as hotel industries. The scope of this research is mainly focused on hotel revenue management, regarding which a bi-objective model is proposed. The suggested method aims at increasing the revenue of hotels by assigning the same rooms to different customers. Maximization of hotel revenue is a network management problem aiming to manage several resources simultaneously. Accordingly, a model is proposed in this paper based on the customer choice behavior in which the customers are divided into two groups of business and leisure. Customers of the business group prefer products with full price, whereas products with discounts are most desirable for leisure customers. The model consists of two objectives, the first one of which maximizes the means of revenue, and the second one minimizes the dispersion of revenue. Since the problem under consideration is Non-deterministic Polynomial-time hard (NP-hard), two meta-heuristic algorithms of Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multiple Objective Particle Swarm Optimization (MOPSO) are proposed to solve the problem. Moreover, the tuned algorithms are compared via the statistical analysis method. The results show that the NSGA-II is more efficient in comparison with MOPSO.

Keywords: Hotel Revenue management, Bi-objective model, Meta-heuristic algorithms, Customer choices.

1. Introduction

Revenue management, hereinafter regarded as RM, is a managerial technique which makes use of a number of strategies to manage the allocation of capacity to different fare classes over time in order that revenue would be maximized for different industries (Philips, 2005). This method, which was first suggested by Littelewood in 1987, was initially employed for time and fare control in Civil Aeronautics Board (CAB). It was, then, the airline industry which pioneered in revenue management in 1980, following the success of which the technique was utilized by many other industries including hotels, rental cars, freight transportation, and cruise line (Philips, 2005).

As shown by many scholars, hotel industries can potentially make use of the managerial techniques of airline industries due to their similar characteristics, making revenue management a significant subject of interest for hotel managers. The following characteristics are among the common characteristics of airline industries and hotels: a) products of both industries (hotel rooms and airline seats) are mortal and cannot be stocked; b) the volume of the products are stabilized; c) reserving in advance is permissible in both (Lai and Ng, 2005).

Goldman et al. studied the decision-making rules of multiple-day reservation in hotels based on stochastic and definitive mathematical programming methods in a paper in 2002, where they considered a flexible reserving schedule rather than a fixed schedule. A network optimization model in a stochastic environment was proposed by Lai and Ng in 2005 for hotel revenue management. Their proposed optimization approach presents a stochastic programming in order to obtain randomness of pathless demands. More recently, some researchers have been interested in deadly modeling of customer behavior in revenue management problems (Van Ryzin and Vulcano, 2008a). A single-leg model of revenue management with distinct elected model of order was introduced by Taluri and Van Ryzin (2004a). Gallego et al. developed elastic products in networks (2004). Moreover, a dynamic programming was introduced by Liue and Ryzin in 2008 based on decay heuristic. Based on dynamic planning,
Adelman presented a model for time-dependent pricing of base prices. Since the problem was complicated due to large dimensions, a column generation method was used to solve the problem. Tong and Topaloglu further developed Adelman’s network revenue management for an airline network in 2012 by making use of a linear model in which the number of constraints exponentially increases with increase in the number of flight legs.

Several exact methods have been proposed to solve this problem, most of which are considerably difficult and time consuming. Although the results of these exact methods are close to the optimal solution, they are not desirable due to their unreasonable computation time and complexity. In order to address the difficulties of the exact solution methods, other techniques such as simulation were proposed by the scholars which are more convenient but less accurate. More recently, meta-heuristic methods have been used as alternative solution techniques. Gosavi (2002) has made use of artificial intelligence methods for optimizing revenue in airline industries. The column generation algorithm has been used by Bront et al. in a research work in 2009 for solving choice-based linear programming models, where the greedy heuristic algorithm has been used to solve each column. It was proved by Etebari et al. in 2011 that this problem is an NP-hard, for which they applied the genetic algorithm to solve each column in a choice-based manner. The proposed model has two objectives. The first objective maximizes expected revenue (Liu and Ryzin, 2008) and the second one minimizes dispersion of revenue. In other words, a second objective function is proposed which minimizes the deviation from the mean value while maximizing the income via the first objective function. This approach has two real plus points; firstly, the determination rate changes in both objective functions, and it is dependent on the selected scenarios. Secondly, the aversion risk factor of revenue resulted from random demands under different scenarios is reduced which was one of the major difficulties of the problems of the proposed model of Liue and Ryzin (2008).

2. Customer Stochastic Behavior Programming

Renting the same room to different customers at different prices, which is one of the contributors that increase the revenue of the hotels, is one of the major challenges of hotel managers. In order to accomplish this, the product (the room) should be reserved in advance, especially when the supply exceeds the demand (Liu and Ryzin, 2008). This paper proposes a choice-based revenue management scheme in which the costumer priorities are taken into consideration such that in a multi-nominal logit model, each costumer can be assigned to more than one sector, and the booking horizon is divided into several intervals (Etebari et al., 2011). It is also assumed in the model that the hotel has only one type of room; however, the unit rate of the same room is different based on different booking periods. Moreover, it is worth mentioning that each reservation might cover several days in this model (Liu and Ryzin, 2008).

The major parameters of the proposed model are as follows:
- C is the room capacity of the hotel
- T represents the problem’s time horizon in which booking in advance takes place
- R_m shows the revenue resulting from renting a room on one day, with regards to capacity price of m.
- α represents the percentage of the allocated rooms to costumers of business type.
- β shows percentage of leisure customers who have rented a room at full price due to lack of enough rooms.
- D_{i,j,s} refers to the amount of room demand by business customers in scenario S, who intend to check-in on day i and check-out on day j.
- D_{i,j,s} is room demand from leisure customers in scenario S, who would like to check-in on day i and check-out on day j.

Parameter D_{i,j,s} is uncertain in most real situations. In order to address this problem, this uncertain parameter can be replaced by the expected value E (D_{i,j}). However, this sometimes does not result in acceptable answers. Accordingly, assuming that a decision-maker encounters a set of scenarios as s ∈ Ω= {1, s} with unknown parameters, and the corresponding probability for each scenario is P_s such that P_s ≥ 0 and ∑_{s=1}^{S} P_s = 1, the following variables are employed in this model:
- x_{i,j} is the number of business customers accepted for check-in on day i and check-out on day j (Integer decision variables)
- y_{i,j} is the number of leisure customers accepted for check-in one day i and check-out on day j (integer decision variables)
- y_{i,j} is the number of leisure customers, accepted to use second grade rooms for check-in on day i and check-out on day j (Integer decision variables)
- y_{i,j} is the number of leisure customers, accepted to use business class rooms, because second-grade rooms did not have enough capacity for check-in on day i and check-out on day j (Integer decision variables)

Where 0 < i < j ≤ T, i = {0, 1, 2, ..., T − 1}, is the check-in time and j= (1, 2, 3, T) is the check-out time, and z_p is the binary decision variable.

\[
z_p = \begin{cases} 
1 & \text{if hotel rooms are full,} \\
0 & \text{otherwise}
\end{cases}
\]
The first objective function is defined as the following:

\[
\begin{align*}
    \text{max } & Z \\
    & = \sum_{s=1}^{S} \sum_{i=0}^{T-1} \sum_{j=1}^{T-i} j(R_{1,s}x_{i,j} + R_{1}y_{i,j} + R_{2,s}y_{i,j}^2) \\
    & \quad - \sum_{s=1}^{S} \sum_{i=0}^{T-1} \sum_{j=1}^{T-i} (w_{1,ij} \max\{0, x_{i,j} - D1_{i,j}\}) \quad \forall j \\
    & \quad + w_{2,ij} \max\{0, y_{i,j} \} \\
    & \quad - D2_{i,j,s}) \\
\end{align*}
\]

(1)

The first term of the objective function defined by equation (1) is the expected revenue of the hotel, and the second term refers to the semi-variance of the revenue. Semi-variance is used in order to measure the robustness of the model, and parameters \(w_{1,ij}\) are penalty factors in case the constraints are violated.

The second objective function is defined as follows:

\[
\begin{align*}
    \text{Min } & Q \\
    & = \sum_{s=1}^{S} P_{s} \left( \max \left\{ 0, \sum_{s=1}^{S} \sum_{i=0}^{T-1} \sum_{j=1}^{T-i} j(R_{1,s}x_{i,j}) \\
    & \quad + R_{1}y_{i,j} + R_{2,s}y_{i,j}^2) \right\} \right) \\
    & \quad - \sum_{i=0}^{T-1} \sum_{j=1}^{T-i} j(R_{1,s}x_{i,j} + R_{1}y_{i,j}) \\
    & \quad + R_{2,s}y_{i,j}^2 \right\}^2) \\
\end{align*}
\]

(2)

The second objective minimizes the dispersion of different scenarios.

\[
\sum_{i=0}^{T-1} \sum_{j=1}^{T-i} (x_{i,j} + y_{i,j}^1) \leq \alpha C; \forall p = 0, ..., T - 1 (3)
\]

Constraint (3) is defined to prevent the sum of business customers and commercial customers who intend to use first class rooms from exceeding the maximum capacity allocated to commercial customers.

\[
\sum_{i=0}^{T-1} \sum_{j=1}^{T-i} y_{i,j}^2 \leq (1 - \alpha)C; \forall p = 0, ..., T (4)
\]

Constraint (4) prevents the model from accepting more leisure customers than the available capacity of the hotel.

\[
\begin{align*}
    \sum_{i=0}^{T-1} \sum_{j=p-i+1}^{T-i} y_{i,j} &= (1 - \alpha)C z_p; \forall p = 0, ..., T - 1 \\
    \sum_{i=0}^{T-1} \sum_{j=p-i+1}^{T-i} y_{i,j}^1 \leq \alpha C z_p; \forall p = 0, ..., T - 1 \\
    0 \leq y_{i,j}^1 \leq \beta (\max\{D2_{i,j,s}\} - y_{i,j}^2), \forall 0 \leq i \leq T - 1, \forall j = 1, ..., T \\
    y_{i,j} = y_{i,j}^1 + y_{i,j}^2; \forall 0 \leq i \leq T - 1, \forall j = 0, ..., T \\
\end{align*}
\]

(5) to (11)

Constraint (5) states that if \(z_p\) equals to one, then leisure customers will exceed the capacity of the hotel for this type of customers, in which case constraint (7) allows the model to allocate the excessive leisure customers to the business class rooms. Constraint (6), on the other hand, makes sure that the capacity of the hotel for business customers does not exceed its capacity for leisure customers.

\[
0 \leq x_{i,j} \leq D1_{i,j,s}, \forall 0 \leq i \leq T - 1, \forall j \\
0 \leq y_{i,j} \leq D2_{i,j,s}, \forall 0 \leq i \leq T - 1, \forall j \\
z_p \in \{0,1\}, \forall 0 \leq p \leq T - 1
\]

(9) to (11)

Equations (8) to (10) express limitations on variables.

According to the previous discussions, this problem is NP-hard (Eteberi et al., 2011). Hence, two meta-heuristic algorithms are proposed in this paper to address the problem.

3. Designing NSGA-II and MOPSO for the proposed model

Owing to the fact that the proposed model of this paper is bi-objective, a multi-objective optimization method must be applied. Two algorithms are proposed in this respect to solve the model. One of them is the NSGA-II optimization algorithm which is a popular non-domination based optimization algorithm for multi-objective optimization. This highly efficient algorithm is, however, often criticized for its computational elaboration (Srinivas and Deb, 1994). The second proposed algorithm is the multi-objective version of the particle swarm optimization algorithm (MOPSO) which elects the best local leader (the global best particle), and makes a set of Pareto-optimal solutions for every particle of the population. This algorithm is known to perform effectively in terms of both convergence and solution diversity (Mostaghim and Teich, 2003).

3.1. Common characteristic of these two algorithms

A population is exploited for both proposed algorithms (NSGA-II and MOPSO) in order to obtain an appropriate
solution, in which the population matrix is common between
the two algorithms.

3.2. Solution representation

This subsection is dedicated to defining a common
representation approach between the two proposed
algorithms. Accordingly, an initial solution must be defined.
Assuming that the considered horizon consists of \( m \) days, a
\( 2m \times m \) matrix can be defined, in which the first \( m \) rows (the
first 5 rows for the given example of the next section)
represent check-in days for business customers, and the
second \( m \) rows show the check-in days of the leisure
customers. The columns represent the length of stay in the
hotel for customers in terms of days. As an example, Figure
1 illustrates a solution in which \( g(i, j) = 4 \) indicates that the
demands of the business customers that have checked-in on
day \( i \) and checked-out on day \( j \), concerning \( 1 \leq i \leq m \), is
equal to four. It should be noted that if \( i \) is between \( m+1 \) and
\( 2m \), it is the demands of the leisure customers that equals to
four.

<table>
<thead>
<tr>
<th>Check-in day</th>
<th>Business customers</th>
<th>Leisure customers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4 2 4 4 4 1</td>
<td>2 4 5 6 0</td>
</tr>
<tr>
<td></td>
<td>3 3 2 0 0</td>
<td>2 2 0 0 0</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1 0 0 0 0</td>
</tr>
<tr>
<td></td>
<td>3 3 5 3 7</td>
<td>2 3 4 0 0</td>
</tr>
<tr>
<td></td>
<td>2 4 0 0 0</td>
<td>4 4 0 0 0</td>
</tr>
<tr>
<td></td>
<td>2 3 0 0 0</td>
<td>2 0 0 0 0</td>
</tr>
</tbody>
</table>

Fig 1. A sample chromosome

3.2.2. Objective function

The objectives of the present paper are defined according to
the solution matrix. Accordingly, each solution in the
proposed algorithm has a fitness value. However, some
solutions might be infeasible due to some constraints, in
which case the solution will be placed in the constraints of
the model, and the algorithm employs the following approach
to make such solutions feasible. Each infeasible solution will
be removed, and corresponding values of element \( g(1, 1) \) in
the solution matrix will be selected randomly. The other
elements of the matrix will continue to be randomly selected,
and the process will continue until the solution becomes feasible.

3.2. Non-dominated sorting genetic algorithm (NSGA-II)

First introduced by Srinivas and Deb in 1994, NSGA is used
for solving non-convex non-smooth single and multi-
objective optimization problems. Given that the performance
of NSGA was strongly dependent on some parameters such as
sharing and fitness, Deb et al. proposed a modified version
of the algorithm known as NSGA-II which can be
summarized in the following steps (2000):

Step (1): the primitive population is created,
Step (2): the value of the fitness function is measured,
Step (3): a rank (fitness) is determined for each solution in
each front and the non-dominate are sorted in the fronts,
Step (4): the crowding distance is estimated which is a control
parameter that extents how close an individual is to its
neighbors,
Step (5): the parents are selected from the population,
Step (6): new offspring are introduced by crossover and
mutation operations.

3.2.1. Definitions of the operators

Crossover and mutation operators are utilized in this
research. In order to select chromosomes via the crossover
operator, three methods are applied, all of which will be
combined with random probabilities. Besides, mutation,
which is a uniform method, is adopted as a selection
approach.

Crossover operator type I

The columns or rows are selected randomly from each parent
via this method, and two offspring are created by switching
the rows or the columns of the parent.

Crossover operator type II

In this crossover type, which is a uniform crossover, the fixed
mixing ratio is used between two parents. To build upon this
point a little more, if the mentioned ratio is, for example, 0.7,
then it means that the offspring inherits approximately 0.7 of its
genes from its first parent and 0.3 from its second parent.

Mutation operator

This operation is performed in two ways. The first mutation
method, called SWAP, randomly selects two elements of the
matrix and switches their places with each other to produce a
new offspring. The second mutation method, called mixed
mutation, subtracts the lower bound of the chromosomes
from the upper bound followed by multiplying the result by
a less than unit number; then it sums the result with one and
introduces the greatest integer of the resulting matrix as a new
offspring.

3.3. Multi-objective particle swarm optimization (MOPSO)

A powerful optimization tool introduced and commonly used
by many scholars is the particle swarm optimization (PSO), in
which the solution for each generation is the optimum
solution of the previous generation. The particles in this
algorithm are obtained via equation (12):
\[ v_{ij}[t+1] = w v_{ij}[t] \]
\[ + c_1 r_1 (p_{bestij}[t] - x_{ij}[t]) \]
\[ + c_2 r_2 (G_{bestij}[t] - x_{ij}[t]) \]
\[ x_{ij}[t+1] = x_{ij}[t] + v_{ij} \]
\[ \text{Horizon (day)} \mid \text{The Probability of a customer entering from each section} \]
\[ 5 \mid P_1 \mid 0.4 \]
\[ \mid P_2 \mid 0.5 \]
\[ \mid P_3 \mid 0.1 \]
\[ 10 \mid P_1 \mid 0.4 \]
\[ \mid P_2 \mid 0.5 \]
\[ \mid P_3 \mid 0.1 \]
\[ 15 \mid P_1 \mid 0.4 \]
\[ \mid P_2 \mid 0.5 \]
\[ \mid P_3 \mid 0.1 \]

The probability of length of stay is described in Table 2, after the determination of which the check-in day must be also determined. Assuming the length of stay as \( J \), the probability of selecting the check-in day is \( \frac{1}{J-j+1} \), which presumes that two types of customers are available with two types of price rates.

The first price rate type is applied on business customers. As it was mentioned before, in case the capacity of leisure customers is filled, leisure prices will be applied during their stay in business class suits.

Before solving the examples, the parameters of the algorithms must be tuned.

4.1. Tuning the parameters

Tuning of the parameters directly affects the quality of the solutions of an algorithm. Many techniques exist for tuning the parameters (Salimi and Najafi, 2018; Shahsavari et al., 2011; Amiri et al, 2008). In this research, to determine the best combination of parameters the Taguchi method is applied. This method was recently employed by many researches for algorithm parameters tuning (Rezaei et al, 2020; Arjmand et al, 2020). Taguchi is a statistical method in which some levels of parameters are considered for each algorithm followed by designing several experiments so that optimum parameters would be found by repeating the experiments several times via different parameter levels.

In the present work, four parameters and three parameter levels are considered for NSGA-II. The parameters include population size, crossover probability \( (p_c) \), mutation probability \( (p_m) \) and maximum number of generations. The results of the experiments obtained via Minitab 17 software are presented in Table 3, where the presented levels are the optimum levels of the parameters.

Furthermore, six parameters including population, repository, personal best \( (p) \), inertia factor \( (w) \), maximum number of generations, and global best position, and three parameter levels are taken into consideration for MOPSO algorithm. The optimum levels of these parameters are presented in Table 4.
Table 2
The probability of the duration of stay

<table>
<thead>
<tr>
<th>Duration of stay</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.012</td>
</tr>
<tr>
<td>2</td>
<td>0.01</td>
</tr>
<tr>
<td>3</td>
<td>0.03</td>
</tr>
<tr>
<td>4</td>
<td>0.04</td>
</tr>
<tr>
<td>5</td>
<td>0.1</td>
</tr>
<tr>
<td>6</td>
<td>0.03</td>
</tr>
<tr>
<td>7</td>
<td>0.04</td>
</tr>
<tr>
<td>8</td>
<td>0.2</td>
</tr>
<tr>
<td>9</td>
<td>0.1</td>
</tr>
<tr>
<td>10</td>
<td>0.02</td>
</tr>
<tr>
<td>11</td>
<td>0.01</td>
</tr>
<tr>
<td>12</td>
<td>0.01</td>
</tr>
<tr>
<td>13</td>
<td>0.02</td>
</tr>
<tr>
<td>14</td>
<td>0.03</td>
</tr>
<tr>
<td>15</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Table 3
Values of NSGA-II

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>60</td>
</tr>
<tr>
<td>Maximum generation</td>
<td>150</td>
</tr>
<tr>
<td>Crossover probability(pc)</td>
<td>0.95</td>
</tr>
<tr>
<td>Mutation generation(pm)</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table 4
Values of MOPSO parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population</td>
<td>40</td>
</tr>
<tr>
<td>Repository</td>
<td>30</td>
</tr>
<tr>
<td>Personal best(p)</td>
<td>1.5</td>
</tr>
<tr>
<td>Inertia factor(w)</td>
<td>0.3</td>
</tr>
<tr>
<td>maximum generation</td>
<td>150</td>
</tr>
<tr>
<td>global best position(g)</td>
<td>1.5</td>
</tr>
</tbody>
</table>

4.2. Performance measures

Given that the proposed model of this paper is a bi-objective model, evolutionary algorithms are used, the results of which are compared using a statistical analysis. In order to perform this comparison, convergence and dispersion criteria are applied. Convergence criterion includes a number of Pareto optimal solutions and the mean ideal distance (MID), and the dispersion criterion consists of spacing (S) and maximum spread (D). Time is yet another criterion for assessing the qualities of the algorithms.

4.2.1. Number of Pareto solutions

This index refers to the number of Pareto optimal solutions (Zitler & Deb, 2000).

4.2.2. Spacing (S)

Introduced by Schott in 1995, this index is used for measuring the extent of spread among the obtained solutions which is formulated by the following equation:

\[ S = \sqrt{\frac{1}{|n|} \sum_{i=1}^{n} (d_i - \bar{d})^2} \]  

\[ d_i = \min_{k \in n, \ k \neq i} \sum_{m=1}^{2} |f_i^m - f_k^m| \]  

The above-mentioned equation indicates that the efficiency of the algorithm increases with decrease in this index.
4.2.3. Maximum spread (D)

This criterion, formulated by the following equation, is employed to calculate the mean length of the hyper box (Zitler, 1999). The higher the amount of the metric, the better the efficacy of the algorithm.

\[
D = \sqrt{\sum_{m=1}^{M} (\max_{1<i<N} f_{m}^{i} - \min_{1<i<N} f_{m}^{i})^2}
\]  

(15)

4.2.4. Mean ideal distance (MID)

Mean ideal distance is a convergence criterion that measures the distance between the Pareto solution and the ideal point (0,0). This index is formulated as below:

\[
MID = \frac{\sum_{i=1}^{n} c_{i}}{n}
\]  

(16)

Where \(c_{i}\) is the distance between the Pareto solution and (0,0) (Zitler & Thiele, 1998).

4.3. Results

The two proposed algorithms, NSGA-II and MOPSO, will be compared in this subsection, and four indices presented in section 4.2 will be calculated using 40 examples for each algorithm. The results of the statistical analysis of NSGA-II and MOPSO are presented in Table 5. The results are then statistically evaluated via the paired sample t-test, which performs a parametric hypothesis test to assess the qualities of the two population means. The results of the t-test for two populations are given in Table 6. According to Table 5, it is clear that the results of NSGA-II algorithm are far more efficient than those of MOPSO in three criteria including mean ideal distance (MID), spacing (S) and maximum spread. However, MOPSO outperforms NSGA-II in terms of computation. On the other hand, the number of Pareto archive solutions is equal in both algorithms. The differences of the two algorithms are shown in Figure 4.

![Boxplot of Differences for S index](image1)

![Boxplot of Differences for Time index](image2)

![Boxplot of Differences for MID](image3)

![Boxplot of Differences for D index](image4)

Fig 4. Results of the algorithms
Several future recommendations are also proposed as the results show that NSGA-II algorithms are more powerful than heuristics. Moreover, the results of the statistical analysis indicate that increasing revenues in different scenarios in the second objective function will reduce the dispersions. Moreover, the results of the statistical analysis show that NSGA-II has been more efficient than MOPSO. Several future recommendations are also proposed as the following. First, canceled reservations can be taken into consideration. In this way, additional reserves would be considered for softening the hotel revenue. Secondly, different periods can be considered in future research work to make the problem more realistic.

5. Conclusions and Future Recommendations

The problem of revenue management was investigated in this research considering customer choice behavior. The customers were divided into two groups of business and leisure customers in the proposed model of this paper. Customer preferences are chosen from different price levels. The products (rooms) were presented in two price levels; leisure customers reserve a room at entire price. If 2nd level price products are not available in recreational customers’ first preference, products of the first level price...
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