OPTIMIZATION MODEL FOR ONLINE HOTEL RESERVATION WEBSITE

BY

NAPAPORN RIANTHONG

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY (ENGINEERING AND TECHNOLOGY)
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Abstract

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by

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Online hotel reservation website has become an important reservation channel for the tourism service in recent years. However, in order to survive in the competitive online channel, an online hotel reservation website needs to provide the superior service on both of the product dimension (e.g., an appropriate price and special sale condition) and the website dimension (e.g., a usefulness of product sequencing functionality) to facilitate the searching process and satisfy the customer’s need.

In this dissertation, two aspects of online hotel booking were studied to response the current issues. That is, we studied (i) the sequencing decision of hotel room choices presented on the website and (ii) the pricing decision of sale conditions based on the no show and cancellation policy. We expected that, with the analysis of sequencing decision and pricing decision, the online hotel reservation website could deliver the online reservation service together with the hotel room service that meet the customer’s need. Also, the online reservation website and the hotelier could increase the reservation rate and gain higher profitability.
In the first study, we investigated customer behaviour during the process of searching for a hotel and making a reservation decision through an online hotel reservation website. We developed a stochastic programming model to design an appropriate sequence of hotel choices. Moreover, our proposed model could strategically determine a sequence with an appropriate number of hotel choices presented on the website to reduce the search cost for the customers. The multidimensional preferences of the heterogeneous customers (i.e., budget, expected hotel star, overall review rating) were considered in a hotel reservation decision. Accordingly, the objective of the proposed model was to propose the optimal sequence of hotel choices for overall customers gaining a satisfactory hotel at the maximum expected utility perceived from a hotel and minimum search cost. We conducted the numerical experiments using the hotel information and customer information appropriately collected from the customer survey and the online reservation website. The result shows the effectiveness of the sequence sorted by our proposed model, compared to the existing sequences sorted by the online reservation website (e.g., sequencing by price and star rating). Furthermore, we highlight a practical application of the proposed model that can provide an improvement suggestion for a hotel to compete in the current competitive market.

In the second study, we considered the pricing strategy, no-show and cancellation problem generally occurred in a hotel service reservation. To deal with the no-show possibility of heterogeneous customers, we proposed a pricing model which incorporates two sale conditions based on cancellation policy along two reservation periods. In the normal period, “Mild condition” is offered at the higher price with “full refund policy” or “partial refund policy for cancellation”. In the last minute period, “Restriction condition” is offered to sale an unsold room for the last minute customers at the lower price with “non-refund policy for cancellation”. The model determines the optimal price of sale conditions so that total profit of hotel is maximized. Our results lead to managerial insights that the amount of refund for cancellation is a strategic parameter. That is, when the amount of refund increases, a hotel is allowed to charge the higher price, thereby generating the higher total profit. Moreover, we suggested that the prominent strategy should focus on selling more rooms at a high price with a high refund for cancellation by “the mild condition” in
the normal period. Furthermore, our results make managerial insights for a hotel manager in practice.

**Keywords**: Online hotel booking, Online review, Sequencing, Stochastic programming, No show and cancellation, Pricing, Hotel revenue management
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Chapter 1
Introduction

1.1 Background and Motivation

The Internet has become a preferred platform for many business transactions adopted by almost industries. In 2016, overall e-commerce sales reached $1.92 trillion which was accounted for 8.7% of total retail spending worldwide. E-commerce sales have been estimated to reach $2.35 trillion in 2017, and continuously increase to $4.06 trillion in 2020 making up 14.6% of total retail sales (eMarketer, 2016). Interestingly, the tourism industry (e.g., hotel, car rental and airline) has greatest potential to adopt the Internet for an online service reservation which could generate additional sales successfully. As the fast-growing trend of e-commerce, the topic of online hotel booking has received attention by many researchers in the field of e-commerce, information technology, hotel revenue management, tourism management and marketing.

With the emergence of e-commerce, the customer tends to use the online reservation website due to the convenient transaction with usefulness functionality, the special price, and a variety of hotel choices with accurate hotel information and online review. However, the online reservation websites face with an excessive competition of online channel and thus, they needs to adapt them to gain the reservation rate from customers. We believe that, in order to survive in a competitive online channel, the online reservation websites need to provide superior service to satisfy such the customer’s needs. Obviously, in the searching process, most of customers tend to use the sorting tool to present the number of hotel choices and the price of hotel room is the major factor to determine the customer’s booking decision and the profitability of service providers. Therefore, both of the usefulness of website functionality (e.g., sequencing functionality for hotel choices) and the available products at the appropriate price need to be appropriately managed to response the
behaviour of customers at the profitability of service providers (i.e., hotel and online reservation website).

In this dissertation, two main aspects under an online hotel reservation were studied to response the current issues. That is, we studied (i) the sequencing decision of hotel room choices presented on the online reservation website and (ii) the pricing decision of sale conditions based on cancellation policy. In generally, both of the sequencing decision and the pricing decision can be separately decided but they have influence on each other. Specifically, each hotel needs to understand the need and behaviour of their target customers (i.e., no-show behaviour) and make the pricing decision for sale conditions to cooperate with the online reservation website at their profitability. Moreover, as the online reservation website presents the number of available hotel choices in the sorting feature, the sequencing decision for hotel choices is determined on the basis of the hotel characteristics including the hotel’s room price and other hotel attributes. Accordingly, the ranking position of hotel in the sequence and the room price with sale condition, presented on online reservation website, determine the customer’s choice decision and the profitability of hotel and online reservation website. Without the question, it is important that the pricing and sequencing need to be optimally decided to satisfy the customer’s needs and generate a higher profitability for hotel and online reservation website.

1.1.1 The tourism industry and the Internet

The tourism service is among the top three categories of products and services distributed through e-commerce. It is reported the overwhelming usage of the Internet for searching and booking the tourism service transactions. More than 114 million travellers searched the tourism services online as well as over 93.9 million customers performed a booking transaction online in 2012 (eMarketer, 2011). The 91% of the travellers used the search engine during the searching process (Hoteliers, 2017). Also, the survey of Toh et al. (2011) revealed that 67% of the respondents continued to make a hotel booking through an online channel whereas 26% of them made telephone calls and the remaining respondents walked in and relied on a travel agency. In the recent year, the tourism industry contributed up to 9.8% of GDP, thereby generating an opportunity of 227 million jobs for the global economy (World
Travel and Tourism Council, 2015). Without the question, the tourism industry has greatest potential to adopt the Internet for an online travel reservation (Kim et al., 2007). Many transactions have taken advantages from the growth of online channels whereas the hotel has been accounted to be the top travel products mainly distributed through an online channel, either through online travel agencies (OTAs) or directly on the hotels’ own websites. A number of hotels and other service providers in the tourism industry allow customers access the reservation directly through the hotels’ own websites. Moreover, to enlarge the distribution channel, many hotels consider cooperating with online travel agencies (OTAs). Accordingly, the hotels presented on OTA websites tend to generate additional sales by 7.5% to 26% (Anderson, 2011). Among the online reservation channels, online travel agencies (OTAs) or third-party websites, such as Agoda.com, Hotels.com, Expedia.com, have generated a large amount of reservation transactions by the worldwide visitors. Due to their ability to provide accurate and timely information, convenient transaction at the low search cost, deeply discount and promotion prices, opportunity to compare rates of popular hotels, online travel agencies (OTAs) have served as a one-stop service for the travel reservation transactions (Carvell and Quan, 2008; Senecal and Nantel, 2004). The 51% of online hotel market were accounted for OTAs (PhoCusWright, 2016). Accordingly, the development of the Internet plays a major role to facilitate the searching process of customers and enlarge the distribution channel in the tourism industry.

1.1.2 The sequencing of hotel choices presented on OTA website

Online travel agencies (OTAs) act as the distribution channel and marketing tool for a hotel to reach more customers. The customers conveniently access timely information and reservation service for a number of candidate hotels at a one-stop service. Typically, OTAs collect a number of available hotels and filter to present the candidate hotels for the customers. Therefore, the accuracy of hotel information, the website design as well as the useful functionality of website is the major factor to motivate the customer’s loyalty on the website.

The sequencing tool on OTAs is one of the useful OTA functionalities preferably used during the searching process of most customers. As shown in Figure
1.1. the current sequencing tool of OTAs allows the customers sorting the sequence of hotel choices by one dimension of hotel attribute (e.g., sorting by hotel star, price, distance from destination and overall review rating). Moreover, in the default page, each OTA independently offers a special deal for a specific hotel and recommend the popular hotels on the sequence sorted by the website favourite or popularity. Obviously, a number of candidate hotels are displayed on the website in the sequencing feature along with the necessary information of hotels (e.g., price, detail of room type, available rooms, hotel star and available facility) and online reviews rated by the historical customers (e.g., summary of overall review rating and review rating on each hotel attribute and customer’s text comment).
Due to the intangibility of the travel product during the searching process, most customers have relied on an online customer review to realize the hotel’s quality, thereby reducing the perceived risks of future service consumption such as the performance risk, physical risk and time risk (Lin et al., 2009). A number of customers have visited online review before making a hotel booking transaction (BrightLocal, 2016). As online review available on OTAs has rated by the historical
customers who have the actual staying experience on a hotel, most of customers realize the accuracy and reliability of online reviews to support the booking decision. As provided in Figure 1.2., the online review is displayed in the features of overall review rating, review rating on each hotel’s attribute and customer’s text comment. The review rating is scored by a range of 1 to 5 (i.e., 5 = very good, 3 = neutral, 1 = very poor). The review rating reflects the level of the hotel’s service performance. After staying at a hotel booked through OTA, the customers are invited to give comments and evaluate the service performance on each hotel’s attribute (e.g., cleanliness, service, comfort, condition and neighbourhood). A later customer can visit the customer review according to the type of customer and main attributes concerned by the customer.

Figure 1.2 Copy of the Hotels.com webpage describing online review on OTAs
1.1.3 No show and cancellation policy

In the travel and service industries (e.g., hotel, airline, restaurant), a typical customer makes an advance reservation for service to gain the special deal and ensures the service availability. However, a number of advance reservation transactions have often been cancelled in the last minute period. Moreover, some of customers fail to show up on the target date without any notice and cancellation. Due to scheduling conflict, uncertainty of business meeting, late fight schedule and other potential reasons, it is general for the customers to make the cancellation and no show for the hotel room reservation. Accordingly, as the perishable type of travel product, an unsold room of hotel in the specific date cannot be resold to other customers. Thus, the no show and cancellation behaviour of customers are the major problem leading to the significant loss of potential profit for the hotels.

In the recent year, most of the hotels offer various sale conditions based on the cancellation policy to sale the same room service. The example of different sale conditions for the same room service is provided in Figure 1.3. For instance, on Hotels.com website, “Anantara Hua Hin Resort” offered the “Premium Sea View Room with breakfast” for one night staying on April 18, 2017 with different two sale conditions, according to the booking dates and cancellation policy. In the normal period (i.e., booking date on April 7, 2017), “Anantara Hua Hin Resort” offered the “Premium Sea View Room with breakfast” at 7,362 Thai Baht with “a full refund policy for cancellation” (i.e., free cancellation before April 15, 2017; otherwise, cancellation fee is charged at one night price). Our study defines the sale condition with “a full refund policy for cancellation” that “the mild condition”. Note that at the normal period, the price and sale condition of the last minute period is unknown. On the other hand, in the last minute period (i.e., two day before arriving), the price of same room is adjusted to 6,462 Thai Baht with “a non-refund policy for cancellation”. Our study defines the sale condition with “a non-refund policy for cancellation” that “the restriction condition”. The similar setting of sale conditions can be practically found in many hotels presented on several OTAs.
Normal period: “Full refund policy for cancellation” or Free cancellation

Last minute period: “Non-refund policy for cancellation”

Figure 1.3 Copy of the Agoda webpage describing the example of sale conditions offered in the normal period & last minute period

Moreover, other scenarios of various sale conditions have been adopted as shown in Figure 1.4. For instance, on Agoda.com website, “Anantara Riverside Bangkok Resort” offered the “Deluxe premier room with breakfast” for one night staying on Feb 27, 2017 with different two sale conditions, according to the searching date on Feb 10, 2017. In the first sale condition, “Deluxe premier room” is provided at the special early booking of 4,887 Thai Baht with “the non-refund policy for cancellation”, called “the restriction condition”. In the second sale condition, the same room is provided at 5,749 Thai Baht with “the full refund policy for cancellation”, called “the mild condition” (i.e., a free cancellation before Feb 24, 2017). Moreover, most of hotels have adjusted the room price and cancellation policy in the last minute period (e.g., higher price or special discount for last minute price). Interestingly, many hotels provide the special discount to clear the unsold rooms to gain the last minute demand. The example of sale conditions offered in the normal period and last minute period is provided in Figure 1.5. For instance, “Shangri-La Hotel, Bangkok” offered the “Deluxe river view double or twin room” at 7,500 Thai Baht in the normal period whereas the price of the same room was adjusted to 7,000 Thai Baht in the last minute period. Our study defines the sale condition offered in the last minute period with a “non-refund policy for cancellation” that “the last minute condition”.

By offering various sale conditions for the same room service based on the cancellation policy, a hotel could better response the customer behaviour and reduce the effect of no show and cancellation. The customers holding a high uncertainty of trip (e.g., business travellers) could reserve the hotel room with the higher price but more flexible cancellation policy whereas the customers holding a low uncertainty of trip (e.g., leisure travellers) could reserve the hotel room with the lower price but the non-refund policy for cancellation. Accordingly, overall customers could gain the benefit according to their conditions.
Figure 1.4 Copy of the Agoda webpage describing the example of sale conditions based on cancellation policy

a). Sale condition offered in the normal period
b). Sale condition offered in the last minute period

**Figure 1.5** Copy of the Agoda webpage describing price adjusted in last minute period


1.2 Problem Statement

With the emergence of the Internet, the number of online travel agencies (OTAs) has continuously increased which leading to the excessive competition in an online reservation channel. Although the number of customers tends to book a hotel online, the reservation rate and profitability for each online travel agency might fluctuate. In order to survive in a competitive online channel, OTAs need to provide the superior service on both of product dimension and the website service dimension. According to overall online customer behaviour, an online travel reservation website needs to concentrate on the website dimension (e.g., sorting functionally) to facilitate the searching and booking processes and the product dimension (e.g., an appropriate price and special sale conditions) to meet the customer’s need.

The following problems occurring in an online hotel booking motivate us to investigate our study in two main aspects of (i) the sequencing decision of hotel room choices presented on the website and (ii) the pricing decision of sale conditions incorporating the no show and cancellation policy.
1.2.1 The sequencing decision of hotel choices presented on OTAs

- Since the customers could not realize the actual service performance of the hotels during the searching stage on the screen of website, they face with several potential risks from the poor choice decision which resulting to the unfavourable hotel experience. To better realize the service performance of the hotels, many customers rely on the online review and the OTA’s recommendation. Moreover, in practice, the sequencing tool for the hotel choice list is used to facilitate the searching process and booking decision. However, the existing sequencing tool on OTAs has some limitations to fulfil the demand of overall customer as discussed following.

  ▪ In general, most of customers consider the multidimensional preferences (e.g., their budget, expected review rating, hotel star) when making a hotel booking decision. Accordingly, OTAs sequencing tool that sorts a hotel choice list based on one attribute of hotels (e.g., room price or star rating) could not completely deliver a satisfactory hotel to fulfil the hotel selection criteria of heterogeneous customers.

  ▪ Due to the advertising fee imposed by OTA service, OTA might bias to show the sequence of hotel choices, sorted by the OTA website favourite or popularity, to promote some hotels in the top ranking position. Accordingly, the customers might fail to notice a satisfactory hotel if that hotel is presented in the bottom ranking position on the long sequence.

  ▪ In the searching process, the customers tend to search for a few hotels (e.g., 7 hotels on average) from top to bottom of the sequence before making a hotel booking decision. Moreover, the hotels presented in the upper ranking position are more attracting and thus considered to be the candidate hotel. Accordingly, the sequences of hotel choices shown by different sorting methods could create different results and thus, an ineffective sequencing of hotels can lead to an unfavourable hotel experience if customers unknowingly book an unfavourable hotel.
OTA presents a long sequence of available hotel choices (e.g. 1,000 available hotels located in the attractive destination) which take a searching effort and reduce the quality of booking decision. A customer may fail to notice a satisfactory hotel if that hotel is placed at the bottom of the long sequence.

Thus, the number together with the ranking positions of hotel choices presented on the website need to be strategically decided to deliver the quality of available hotels within an acceptable search cost.

- The emergence of online channel provides an opportunity for the service distribution whereas leading to the intensely competition in the hotel market. Many hotels need to improve their service performance but improvement consumes the time with the large investment for trial and error. Thus, the decision tool that could evaluate the marketing position and provide useful suggestion for potential improvement will be beneficial for a hotel to stand in the competitive market.

1.2.2 No show and cancellation policy

There are three main problems arising in hotel booking behaviour under our concerns.

- In the hotel industry, a number of reservations are cancelled before the target date and many customers fail to show up without cancellation. Due to the perishable characteristics of travel product, an unsold room of the hotel in the specific date cannot be resold to other customers. No show and cancellation is the common behaviour that leads to the significant loss of the potential hotel profit.
- The strict cancellation policy (such as 50% or 100% of room price charged) might reduce the demand for customers which influences on the potential profit of hotel.
- Overbooking creates over sale which damages the hotel’s reputation and customer’s loyalty when the number of customer’s arrivals exceeds the room availability.
Up to the present time, the revenue management (RM) has received attention by both practitioners and academic researchers. Pricing and room allocation are the key factors to determine the successful of revenue management in the travel and service industry. In practice, the hotel offers a same room service with various sale conditions based on price and cancellation policy. However, due to heterogeneous customer existing in the market, the pricing decision of sale condition and the cancellation policy need to be decided to response the customer behaviour at the hotel’s profitability. Therefore, our study on the pricing decision and cancellation policy will be more essential for the hotel industry in practice.

1.3 Objective of Study

The main objective of our research is provided as follow.

- We aim to provide the decision tools that could help OTAs and hotels making a better decision to increase the reservation rate and the profit.

To achieve such an objective, we divide our study into two studies and their detail objectives are as following.

In the first study, the main objective is as follow.

- To propose a new approach, based on a two-stage stochastic programming model (2SSP), for designing an appropriate sequence of hotel choices with an appropriate number of available choices presented on the website.

In the second study, the main objectives are as following.

- To propose a pricing model to optimally provide the prices of various sale conditions and the cancellation policies so that the total profit of hotel is maximized.
1.4 Overview of Dissertation

The remaining sections of dissertation are organized as following. Chapter 2 summarizes the review of prior literatures. Chapter 3 describes our first study under the sequencing decision of hotel room choices. Chapter 4 presents our second study under the pricing decision of sale conditions based on the no show and cancellation policy. Chapter 5 summarizes the studies and provides the contribution of research.
Chapter 2
Literature Review

Up to the present year, the topic of the online hotel booking has been received attention by a number of academic researchers and practitioners in the fields of tourism management, e-commerce, revenue management, business management and marketing, and information technology. In this dissertation, we present two aspects of online hotel booking consisting of (i) the sequencing decision for hotel choices presented on the hotel booking website and (ii) the pricing decision for various sale conditions based on no show and cancellation policy.

Regarding to our first aspect of the sequencing decision for hotel choices, we reviewed several related literatures which could be classified into the online channel selection, hotel selection criteria, online review, customer search behaviour, and sequencing and recommendation approach. Several literatures conducted survey and experimental study to examine an importance of website quality on an online booking intention of customers. The search theory tends to have an important role to understand the customer search behaviour along with the hotel choice decision. Prior literatures provided the comprehensive discussion to draw managerial insights for the tourism industry. To build the website quality to meet the customer’s expectation, the website design along with the sequencing tool were mainly focused in our study. In prior literatures, several approaches, based on a mathematical model, optimization model and information intelligence, for sequencing and recommending the online product choices have been widely proposed. However, the mathematical model approach, namely, a two-stage stochastic programming model (2SSP), has not been applied in an optimization problem of the sequencing decision in the context of tourism management.

Regarding to our second aspect of the pricing decision for sale conditions, we reviewed the related literatures which could be classified into the no show and cancellation policy as well as the hotel revenue management. Several literatures conducted survey to examine the influence of no show and cancellation on the hotel
revenue management. Moreover, several approaches and heuristics, based on mathematical and optimization model, have been proposed for deciding the pricing and room allocation to enhance the revenue management.

2.1 Online Channel Selection

In the recent year, the Internet has become the major channel for the travel service reservation. Many researchers have investigated the factors leading to the customer’s intention to book a travel service online, especially, through online travel agency websites (OTAs). The most of studies indicated that information quality, website quality in term of functionality and usability, website design and presentation, perceived price and customer commitment are the important factors to drive the online booking intention and satisfaction level of customers (e.g., Wen, 2012). The study of Liu and Zhang (2014) investigated on the influence of product-related factors (i.e., price, variety and review) and channel-related factors (i.e., website quality and customer relationship). Interestingly, they examined the channel selection criteria whereas two types of online channels, namely, hotel websites and online travel agent websites (OTAs), were considered. The result revealed that the website quality (i.e., information quality, privacy protection, service quality) is the main competitive aspect of hotel website over OTAs, but OTA websites perform better in other aspects from the customer’s perspective (i.e., price, review and variety). Kim et al. (2007) examined the website selection decision to determine the major attribute for online travel agency website. They revealed that providing the low fare and high security are the most important attributes when customers select the online travel agency websites. Using the survey of 311 respondents in U.S., Park et al. (2007) revealed that ease of use is a major dimension of website to motivate the customer’s booking intention, following with information quality, responsiveness, fulfilment, and security. Chiou et al. (2011) developed the strategic website evaluation framework to evaluate website consistency and intended strategic by examining 4PsC of product, promotion, price, place, and customer relationship. Agag and El-Masry (2016) proposed a model framework that incorporated Commitment–Trust theory and the Technology Acceptance Model (TAM) to determine customer’s intension to book a hotel through online channel. Using data analysis from 1,431 Internet users, they revealed that four
elements, consisting of commitment, trust, attitude, and customer’s antecedents, have significant effect to enhance the customer’s intention to book the hotels through online channel. Ozturk et al. (2016) considered the customer’s usage behavior intentions toward the mobile hotel booking (MHB) technology. They revealed that utilitarian (i.e., ease of use) and hedonic value have positive impact on the customer’s continued usage intentions. To motivate the continued usage of MHB users, the online travel agencies and hotel operators play a critical role to develop the marking strategies. They reported that four dimensions of website quality, consisting of usability, entertainment, ease of use and complementarily, have positive impact on e-trust and online booking intentions. Bilgihan and Bujisic (2015) supported the importance of website design features on e-loyalty in an online hotel booking marketing. They found that the utilitarian and hedonic website features are the major factors creating a customer commitment, trust, and e-loyalty. Abdullah et al. (2016) proposed a conceptual model to examine the importance of the hotel website interactivity on the perceived value and revisit intention of customers. Considering the competition among the hotel reservation websites, OTA websites and hotel websites need to adapt themselves to response the concentration of booking intention and satisfaction level of customers. Barreda et al. (2016) proposed the theory-based model to examine the relationship of website interactivity and brand value for the hotel reservation websites. They found that website interactivity, including the two-way communication and user control, have positive influence to build up brand awareness and brand image, which turn to brand value. The online travellers, who perceive reciprocal communication and control on the website, tend to perceive the hotel brand. Accordingly, the result suggested that user control contributes the positive brand image and plays an important role for hotel website design. The strategies to improve the OTA websites were examined by the study of Quintana et al. (2016).

2.2 Hotel Selection Criteria

Understanding the customers is one of the most important criteria to drive the prosperous business. In the tourism and hotel industry, the hoteliers need to understand the strength and weakness of their service and concentrate how customers perceive the hotel’s attributes in the hotel choice decision. Up to the present time, the
hotel selection criterion has been received attentions by a number of researchers. For instance, by surveying over 500 travellers who stayed at 19 Tehran hotels, Sohrabi et al. (2012) proposed two main hotel selection factors, including the comfort factors and compensatory factors. Specifically, the promenade and comfort attributes as well as the security and protection attributes were the most important factors representing the prerequisite of comfort factor in the hotel selection criteria in Tehran Hotels. Also, the results of factor analysis revealed that the promenade, comfort, security and protection, network services, pleasure, staff, news and recreational information, cleanliness and room comfort, expenditure, room facilities and car parking were the main hotel selection factors of Tehran hotels. Chu and Choi (2000) collected the hotel selection criteria from 343 travellers, classified into the business travellers and the leisure travellers, who stayed at the hotels located in Hong Kong. Through an Importance Performance Analysis (IPA), the travellers showed the perception on the importance of six hotel selection factors, consisting of service quality, business facilities, value for money, room and front desk, food and recreation, and security. Specifically, the service quality, room and front desk and security were rated to be the most critical factors for the hotel choice decision. Hsieh et al. (2008) reported that the abilities of staff on quick problem solving, room price, sanitary hot spring environment, convenience traffic route and shuttle, special promotions, convenience of reservation procedure, food and beverage service were the major factors in Taiwan hot-spring tourism industry. The study of Lockyer (2005) examined the importance of price on the hotel choice selection. The result revealed that cleanliness was rated as an important factor whereas price showed a complex relationship with the hotel selection decision. Moreover, price needs to be specially considered in the hotel booking process but should not be considered along with other hotel attributes such as staff service. The model of Chiang and Jang (2007) examined the influence of perceived price as well as brand image on the perceived quality, trust, perceived value and purchase intentions of customers in a hotel booking decision. By collecting data from the respondents in U.S., they found that brand image positively influenced on perceived quality and trust of consumers. Interestingly, they indicated that the price provided by a hotel was more affordable than competing prices. The results from several studies strongly supported the importance of brand image on the hotel booking
intention. For example, Lien et al. (2015) examined the effect of brand image, perceived price, trust and value on the hotel booking intentions of customers in Taiwan. Their results indicated that brand image has positive impact on perceived price and trust on a hotel to contribute the booking intention. Moreover, the perceived price and value showed positive impact on the hotel booking intention. Accordingly, the results provided insights for hotels to build up brand reputation with the reasonable room price meeting the customer’s expectation. Mauri and Minazzi (2013) conducted the experiment study on 349 young adults to investigate the influence of online reviews posted by customers on the hotel booking intention. Not surprisingly, the result indicated the effect of online review in term of valence (i.e., positive and negative tones) on the process of booking decision. However, they found that the presence of hotel manager’s responses to the online review has the negative impact on the customer booking intention. Not only the hotel attributes, but the destination image as well was found to determine the travel visit intention. Horng et al. (2012) and Ferns and Walls (2012) analysed the relationship between the travel involvement (i.e., travel activity and attraction) and the destination visit intention. They found that travel involvement could lead the travellers to aware and familiar with the destination, thereby motivating the destination visit intention.

However, the influence of hotel attributes on the hotel choice decision and booking intention has been varied depending on the customer characteristics (Prud’homme and Raymond, 2013), type of traveller (Yavas and Babakus, 2005; Korfiatis and Poulos, 2013), gender (Lien et al., 2015) and region (Li et al., 2013). For the type of traveller, the most of literatures examined the hotel choice decision of business travellers and leisure travellers as perceived as the major customer segment in the hotel industry. For example, the factor analysis of Chu and Choi (2000) revealed that business travellers concentrated on the room and hotel appearance whereas leisure travellers paid attention on security. Yavas and Babakus (2005) analysed the importance of hotel factors on the booking decision for business and leisure travellers. Five hotel factors were examined which were general amenities, convenience, core service, room amenities, and ambiance. The result revealed that the business travellers and leisure travellers have varied the importance of five factors. Specifically, general amenities were ranked to be the most important factor for both
traveller groups. Also, the business travellers perceived convenience whereas the leisure traveller perceived core service as the second important factor.

2.3 Online Review

The hotel industry offers the room service that customers could not evaluate the quality and satisfaction prior the purchase and consumption stages. Online review is one form of electronic word of mouth (eWOM) that plays an important role in the tourism and hotel sector (Litvin et al., 2008). The number of prior studies revealed the practical usage of online reviews for the customer’s hotel booking decision. The survey of BrightLocal (2016) reported that hotel; bed and breakfasts are the key business that consumers are interested in reading the customer reviews. The 37% of people visit the review site (e.g. TripAdvisor) to read online reviews whereas 84% people trust online reviews as much as a personal recommendation. Also, the 90% people read 10 reviews whereas overall rating were received attention by the 58% people. Tnooz (2014) supported that 80% of online travellers visited at least 6 to 12 online reviews before making a booking decision. The 65% of online review readers were likely to choose the hotels that get award from TripAdvisor whereas 53% of review readers would not book the hotel with the absence of online review history. TripAdvisor (2012) revealed that 87% of the respondents realized the accurate of online reviews observed from TripAdvisor. Most of online review readers perceived the online review as the valuable source of information to increase the hotel awareness and avoid risks from booking an unsatisfactory hotel (Cantallops and Salvi, 2014; Liu and Park, 2015). Through the eye-tracking approach, Noone and Robson (2014) observed that respondents looked at review rating and basis information of hotel choices during the searching and decision stages.

With the growing trend of online reviews, the number of prior studies confirmed the importance of online review in the customer’s hotel booking intention. The quality and performance of hotel service could be represented in form of review rating (i.e., scaled by 1 to 10 or 1 to 5) whereas the review text contents express the customer experiences (Fang et al., 2016). Review rating has been perceived more credible when appeared on the well-known online travel communities such as TripAdvisor and Facebook (Casaló et al., 2015). The positive relationship among
online reviews, popularity of hotels and hotel sales, was mentioned by several literatures (e.g., Singh and Torres, 2015). Öğüt and Taş (2012) indicated 1% increasing in the score of review rating could increase up to 2.68% of online hotel sales in Paris and up to 2.6% of hotel sales in London. Casaló et al. (2015) observed the influence of review rating on the customer’s attitude whereas the hotels appearing in the best review rating list were received the higher booking intention. Similar to the study of Torres et al. (2015), the impact of review rating and number of online reviews on the booking transactions were examined. The results found that review rating and number of online reviews rated on TripAdvisor has the positive effect on the number of online booking transactions. The total number of online reviews could represent the popularity of hotels. BrightLocal (2016) indicated that overall rating influenced to the customers in which the 74% of them will trust business from positive reviews and more than 60% will hesitate to use business from the negative reviews. Xie et al. (2017) examined the influence of online review in term of timeliness, volume, lengths, repetition of review topics on the financial performance of hotels. They pointed out that online review rating and review volume have moderate influence on management.

The influence along with the characteristics of online review has been examined by the sufficient number of literatures. It is commonly agreed that the review-related factors are important, including the valence of reviews (e.g., positive and negative review), the volume or number of online reviews, the target of review (e.g., service and facility categories), the variation of reviews, review quality (e.g., usefulness and understandability), period of time (e.g., recent), and the source of reviewers and websites (e.g., Ye et al., 2009; Casaló et al., 2015; Sparks and Browning, 2011). The valence of online review represents the tone of online reviews, normally divided into the negative review and positive review. In practically, the positive review expresses the favourable experience thereby leading the booking intention of other customers whereas the negative review shows the unfavourable experiences thereby stopping the booking transaction of review readers. However, the customers sometime give online review by rating an extremely satisfied and extremely dissatisfied. Sparks and Browning (2011) studied four variables of online review including the framing, target of review, valence and variation from average
review rating. They found that the positive framing, service-targeted review, positive valences and lower variation of review rating from average review rating were all preferred to motivate the customer’s trust and booking intention. Interestingly, they found that the consumers are more sensitive by early negative information, especially when the negative valence is presented. Baek et al. (2015) examined the linkage between the review rating extremity and the review helpfulness in general e-commerce business. They revealed that an individual online review is perceived more helpfulness when the review rating is close to average review rating. Verma et al. (2012) supported that the positive valence of online reviews creates the positive effect on a hotel booking decision than the negative valence. On the other hand, Casaló et al. (2015) reported a strong effect of negative online review on the booking decision, especially for a higher risk aversion customer. Qazi et al. (2016) found that the number of concepts contained in a review, the average number of concepts per sentence, and the review type contribute to the perceived helpfulness of online reviews. Specifically, the review types and concepts have a varying degree of impact on the helpfulness of reviews. Wu et al. (2017) examined the factors of online review in term of review’s language style and expertise level of reviewers on the hotel booking intention. The findings showed the moderate effect of reviewer’s expertise level and language style on the attitude and booking intention of customers. The study of Karimi and Wang (2017) supported the positive influence of reviewer profile image, especially the review length, to determine the review helpfulness. In term of review categories, the study of Xie et al. (2014) pointed out that an average review rating was perceived as the most important factor representing the hotel performance. Interestingly, online review categories which include the value for money, cleanliness and location are prominent. In addition, Elwalda et al. (2016) examined the quality of online review, determined by the understand ability, perceived usefulness and enjoyment, to create trust and booking intention for the customers.

Several studies have analysed the content of online reviews to evaluate the product performance in the simplified version of text for an online review reader. In the recent years, the sentiment analysis and text mining techniques have become the prominent approaches used to extract the most essential information from a large number of original online reviews in the tourism industry and other e-commerce
business sectors. For instance, Hu et al. (2017) proposed the multi-text summarization technique designed for extracting and summarizing the hotel review contents. From online reviews of two subject hotels available on TripAdvisor, they identified the top-$k$ most informative sentences of reviews and showed the performance of proposed model that was able to provide the comprehensive information. Salehan and Kim (2016) proposed the sentiment mining approach to analyse the readership and helpfulness of online reviews. They found that review with higher levels of positive sentiment in the title was perceived more readerships while sentimental reviews with neutral polarity in the text were perceived to be more helpful. Guo et al. (2017) developed the data mining approach based on the latent dirichlet analysis (LDA) to analyse the online review for 25,670 hotels located in 16 countries. The results pointed out the differences among the demographic segments and importance of hotel’s star rating. Furthermore, the application of text mining and sentiment analysis can be found in other business sectors (e.g., Singh et al., 2017).

2.4 Sequencing and Recommendation Approach

In practically, the sequencing tool and recommendation system have been applied by many e-commerce practitioners and, thus, become an interesting topic in the field of e-commerce, website design, information intelligence, and decision support system. The sequencing tool and recommendation system are the useful functionality that presents an attractive product choices matching the customer’s preference. It supports the customer’s purchasing decision and facilitates the information searching process from a hug of information, thereby shortening the search time as well as tailoring the customer’s preferences (Nilashi et al., 2015). Senecal and Nantel (2004) supported that online product recommendation has an effect on the customer’s choice decision. Specifically, an online retailer recommender system has a higher impact than a human expert recommendation (e.g., online review).

In the context of the tourism management, the sufficient number of prior literatures proposed an approach for sequencing and recommending the hotel choices. For example, Ghose et al. (2012) proposed a hotel ranking system to recommend the best value hotel choices in the sequence feature for the customers. They considered
the multidimensional preferences of customers along with the hotel user-generated content. The proposed model was tested with a data set of U.S. hotel booking transaction made through Travelocity. Ngai and Wat (2003) developed a hotel advisory system (HAS) based on a fuzzy expert system for the selection of hotel. The usability and effectiveness of the proposed approach were examined by the selected practitioners in Hong Kong hotel industry. Literature review on the recommendation algorithms and key advances in collaborative filtering recommender systems can be found in Konstan and Riedl (2012). Korfiatis and Poulos (2013) proposed a demographic recommender system based on the user-defined preference criteria that concerned online review categories and different types of customers. The performance of the proposed model was analysed with the data obtained from OTA website, namely, Booking.com. Nilashi et al. (2015) proposed a hybrid method for the hotel recommendation based on the dimensionality reduction and prediction techniques. Also, the multi-criteria collaborative filtering recommender system was proposed to provide the high accuracy for the hotel recommendation. Yoon et al. (2013) indicated that the consumer product knowledge relationship between recommendations negatively impacts the recommendation quality and customer satisfaction.

The recommendation and sequencing approaches have widely investigated in other e-commerce business sectors. For example, Liu et al. (2017) proposed a ranking algorithm based on the sentiment analysis technique and the intuitionistic fuzzy set theory to rank the products through online review. The proposed model identified the positive, neutral and negative sentiment orientation on concerning the product feature in each online review. Krestel and Dokooohaki (2015) developed a ranking product review model based on the review sentiment by summarizing all online reviews with the top-K reviews in the ranking. They showed the proposed model for review ranking presentation on the topic models and language models. Applied in the Chinese restaurant industry, a novel recommendation algorithm based on online review analysis was proposed by Liu et al. (2013). The characteristics of online reviews in term of review rating and opinions were examined to determine the preferences of overall customers and provide the accurate recommendation. Celdrán et al. (2016) proposed the recommendation algorithm based on location, preferences
of users and content of items located close to such users. In order to measure the users’ interest for the recommended items, the proposed algorithm could provide implicit ratings considering the users’ movements after receiving recommendations. Lacerda (2017) developed the multi-objective ranked bandits algorithm based on four main components: a scalarization function, a set of recommendation quality metrics, a dynamic prioritization scheme for weighting these metrics and a base multi-armed bandit algorithm. They showed that the proposed algorithm could provide improvements, approximately 7.8 and 10.4% in the click-through rate compared to the single-objective state-of-the-art algorithm. Liao and Chang (2016) proposed a recommendation system based on a rough set based association rule approach and data mining approach for customer’s preference analysis. The approach determined patterns and rules for e-commerce platforms and product category recommendations. Cui et al. (2017) proposed the novel multi-objective evolutionary algorithm, namely PMOEA algorithm, for the recommendation systems in e-commerce. The results indicated that the combination of PMOEA and recommendation algorithm could provide a good balance between the precision and diversity.

Most of approaches for sequencing and recommendation systems recommend the product choices closing to the customer’s preferences. Developing such an accurate recommendation, the collaborative filtering has been the prominent approach in the context (e.g., Wei et al., 2017; Najafabadi et al., 2017). Other approaches for sequencing and recommendation problems can be found in many prior literatures (e.g., Mishra et al., 2015; Safran and Che, 2017; Bassiliades et al., 2017; Mashal et al., 2016). Literature review of the proposed recommendation approach can be found in Lu et al. (2015).

2.5 Customer Search Behaviour

With the emergence of virtual store over the Internet, the customer search behaviour has received more attention by a number of literatures in e-commerce and marketing contexts. The customer search models have been widely developed regarding to the search theory to understand the customer search behaviour and purchasing decision. In generally, two search models are mentioned which are the non-sequential model and the sequential model. Regarding to the first model of non-
sequential model (Grosfeld-Nir et al., 2009), it is assumed to have a single period in which the searchers search and select the best choice from the fixed number of choices. The decision of model aims to decide an optimal number of sample choices with concerning the linear search cost. On the other hand, regarding to the second model of the sequential model (Zwick et al., 2003), it is assumed that the searchers evaluate the candidate choices in the random order and select one from a set of candidate choices along the multi periods. At each period, the searchers need to decide either to accept the candidate choice at the expected search offer or to continue searching at the search cost. The decision of model aims to decide an optimal stopping rule (e.g., expected reservation level, required price and search utility) to balance the search cost and expected search offer. With concerning the constraint of search time along with the expected search offer, both of the non-sequential search and the sequential search scenarios are incorporated to balance the optimal number of sample choices and expected reservation level.

The non-sequential and sequential search theories have been assumed in the most search problems such as shopping online (Chhabra et al., 2014; Zwick et al., 2003; Grosfeld-Nir et al., 2009), job search (Lippman and McCall, 1976), choosing a mate (Cheng et al., 2014), and other search problems (Mak et al., 2014; Mauring, 2016). Regarding to searching through an online shopping marketplace, Grosfeld-Nir et al. (2009) incorporated the fixed-sample size and sequential search to determine an optimal control limit (e.g. acceptable price) and an optimal number of observed stores. In addition, the studies of Chhabra et al. (2014) and Zwick et al. (2003) proposed the customer’s choice model with sequential search scenarios mainly adopted in the case of searching for a used car and apartment in an online marketplace.

The discussion of customer search behaviour and choice decision can be found in marketing, customer behaviour and information technology literatures (e.g., Dutta and Das, 2017; Jun and Park, 2016; Liu et al., 2017).

2.6 Stochastic Programming Model Approach

Stochastic programming is a mathematical approach for dealing with uncertainties within a general optimization framework. The two-stage formulation is
widely used in the stochastic programming. The problems are formulated with known parameters real world problems almost invariably include some unknown parameters. In the formulation, the basic idea is that (optimal) decisions should be based on data available at the time the decisions are made and should not depend on future observations (Shapiro and Philpott, 2007). Many real-word decisions taking randomness or uncertainty into account, such as, supply chain management, production scheduling, resource allocation and energy and environmental management (e.g., Wang et al., 2012; Barik et al., 2014; Bagheri et al., 2016; Huang et al., 2016; Ahmadi et al., 2016; Bidhandi and Patrick, 2017; Yang et al., 2017) have been modelled with the stochastic programming model.

Several studies have widely developed an optimization model and theory for an optimal decision under uncertainty with stochastic programming. For example, Dillon et al. (2017) addressed an inventory management problem taking demand uncertainty by presenting a two-stage stochastic programming model. The focus of proposed model was to decide the optimal periodic review policies for red blood cells inventory management at the minimum of operational costs and blood shortage and wastage. Chang and Dong (2017) proposed a two-stage stochastic programming model which embedded uncertainty for the qualification management problem of parallel machines in semiconductor manufacturing. In the study of Hu and Hu (2016), a two-stage stochastic programming model was formulated to address a lot-sizing and scheduling problem with sequence-dependent setups, taking the challenge of random demand with backorders. Soares et al. (2017) proposed the two-stage stochastic programming approach for the energy resource scheduling taking the demand and renewable sources uncertainty. The proposed model was examined to decide optimal electricity pricing in a realistic case study projected for 2030. Simic (2016) presented the interval-parameter two-stage stochastic full-infinite programming model for end-of-life vehicles allocation management under multiple uncertainties. They examined the effectiveness of the proposed model that able to provide end-of-life vehicles allocation schemes under multiple uncertainties. Hu et al. (2016) presented the application of a two-stage stochastic programming model adopted in the micro grids energy management systems for the electricity market. The model was examined to indicate optimal investment and operating strategies in the case study of INER micro
grids in Taiwanese market. Zohrevand et al. (2016) addressed the uncertainty of cell formulation problem by using a stochastic programming. Bagheri et al. (2016) presented the application of a stochastic programming model to address the nurse scheduling problem taking uncertainties of demand and stay period of patients over time. The proposed model was examined with a case study of nurse scheduling in the Department of Heart Surgery at Razavi Hospital.

2.7 No Show and Cancellation Policy

Due to a perishable asset, “no show” and “late cancellation” can be a significant problem for the hotel industry that damages the potential hotel’s revenue, as an unsold room at the specific time cannot be resold later (DeKay et al., 2004). When dealing with “no show” and “late cancellation”, the usage for overbooking and cancellation policy has been a common practice adopted in the hotel industry to maximize the occupancy rate and protect the expected sale loss from an unused capacity (Guo et al., 2016; Sierag et al., 2015). Specifically, the cancellation policy has been successfully adopted to create an opportunity for multiple selling leading more profitability by motivating the customers cancel within a specific deadline, imposing the cancellation fee from an advance buyer who cancels and then reselling an unsold room to a late-arriving customer (Shugan and Xie, 2005; Xie and Gerstner, 2007).

Many researchers have examined the effect of no show and cancellation. The cancellation policy could stop searching for a better deal of the strategic customers. Chen et al. (2011) examined the impact of cancellation fee and deadlines on three booking behavior categories including “Book”, “Book and Search”, and “Search”. They found that the cancellation deadline has impact on the customer behavior but the size of cancellation fee has no effect. The most common practice of cancellation policy is that the cancellation must be made at least 24 hours before 6.00 p.m. of the arrival date; otherwise the cancellation fee at the first night’s stay including taxes will be charged from the customer’s credit card (Chen and Xie, 2013; DeKay et al., 2004). However, the cancellation policy has been different based on hotel characteristics and other factors whereas the high-end hotel tends to have the less-strict policies (Chen and Xie, 2013). Park and Jang (2014) studied the effect of temporal sunk cost on the
potential cancellation intention. They revealed that a higher cancellation penalty reduces the cancellation intentions. Moreover, the model without cancellation could lead revenue loss up to 20% (Sierag et al., 2015).

2.8 Hotel Revenue Management

In the revenue management, the reservation policy with cancellation and overbooking has been received attention by many researches. Mandelbaum (2016) reported that cancellation has been the important source of revenue averaged 0.9% of total revenue at resort hotels, followed by 0.8% at convention hotels and 0.5% at full-service properties. Georgiadis and Tang (2014) proposed a model to determine the optimal reservation policy with a non-refundable deposit. They considered the capacity constraints, customer heterogeneity along two dimensions of “valuation” and “show-up probability”, overbooking and multiple reservation options. Koide and Ishii (2005) developed a model for the optimal room allocations with early discount, cancellation and overbooking. Two types of room prices were examined. The early discount price was offered in a limited booking period with the restricted cancellation policy and then the normal price was offered later until the arrival date with the less restricted cancellation policy. Sierag et al. (2015) proposed a revenue management model that incorporated cancellation and overbooking limit into the customer’s choice behavior. Courty and Hao (2000) considered the price discrimination where the customers deal with an uncertainty of show-up possibility or their service valuation. Examining a menu of refund contracts, they showed that a customer with a higher show-up possibility (e.g., leisure traveller) finds it optimal to purchases a low refund ticket whereas a customer with a lower show-up possibility (e.g., business traveller) purchases more flexible contracts at a higher price. Guo et al. (2016) analysed the overbooking problem with the influence of service denial on the perspective of customer. The Stacklberg model was developed to determine an optimal overbooking pad. The competition and equilibrium choices for a refund policy were investigated by Guo (2009). In his model, the partial refund policy and the zero refund policy were examined. Gosavi et al. (2007) proposed a simulation-based model for solving a seat allocation problem with cancellation and overbooking. Also, forecasting the
cancellation rate for the service revenue management using a data mining based two class probability estimation methods was studied by Morales and Wang (2010).

Pricing has been an important vehicle to sell the products, thereby generating the revenue for almost industries, including the service and tourism industry. Several tourism literatures have proposed a pricing model for the revenue management. Among the pricing strategies, the dynamic pricing strategy can be widely found in practice and academic literatures. For example, Abrate et al. (2012) analysed the dynamic pricing strategy in the European hotels. They found that 20% of hotels changed the price during the day immediately before the check-in date whereas the pricing structures depending on the type of customer, the star rating, and the number of suppliers with available rooms. Van der Rest and Harris (2008) investigated the pricing strategy under unknown demand and cost function. Their analysis revealed that a differential pricing and discounting could generate a higher profit. Guo et al. (2013) proposed a dynamic pricing model which incorporated the lead time of the reservation period so that the hotel’s profit was maximized. The linear case and non-linear case of demand were analysed. Other pricing strategies can be found in the travel industry such as BAR pricing model (Rohlfs and Kimes, 2007; Noone and Mattila, 2009; Guizzardi et al., 2017; Ling et al., 2012), a low price guarantee model (Carvell and Quan, 2008), the pricing based on hotel’s attributes (Collins and Parsa, 2006; Hung et al., 2010) and pricing strategy for cooperation with the third party websites (Long and Shi, 2017). For example, Noone and Mattila (2009) studied the hotel best available rate (BAR) pricing in which a blended and a non-blended rate approaches were analysed. Guizzardi et al. (2017) examined the daily online best available rates (BAR) for 357 hotels in Milan and Rome, up to an advance booking of 29 days. The effects of advance booking, room quality, services, competition, seasonality and fairs were incorporated to underline their different importance on the leisure and business destinations. They revealed that hotel quality (e.g., star rating) has an important positive effect on the online BAR whereas the sale condition for the “breakfast included in the room rate” and “full refunding options” have no significant effect on the BAR. Moreover, Carvell and Quan (2008) developed a low-price guarantee model to provide the best rate guarantee. The objective was to maximize the hotel’s profit and eliminate the customer switch behaviour. Furthermore, Hung et
al. (2010) determined the major determinants of hotel room pricing strategies with data for 58 international tourist hotels in Taiwan. The analysis of quantile regression model shows that hotel age, market conditions, and proportion of foreign individual travellers have significant determinant in the high-price category whereas the number of housekeeping staff per guest room has no effect for hotel price at the low price quantile.

In addition, the pricing games based on cooperation with OTAs have been widely studied to support the majority role of OTAs. For instance, Long and Shi (2017) developed framework to examine the optimal pricing strategies of an online travel agency (OTA) and a tour operator (TO) under an online sale and offline service cooperation. The numerical study found that the cooperation parameters, including the service level, unit sale commission, service cost coefficient and unit service compensation coefficient, have an effect on TO and OTA price decision but at different influence. Guo et al. (2013) investigated the optimal pricing strategy for the hotels which operates their online distribution channel through a third party website. They compared the centralized scenario when the hotels and website are integrated as a single player and the decentralized scenario showing each player’s equilibrium actions. Ling et al. (2011) and Ling et al. (2014) proposed the optimal pricing model for cooperation with an online travel agency (OTA) whereas the commission fee was incorporated in the hotel revenue management.

Similar to the revenue management for airline, Yoon et al. (2017) proposed a new approximation model to decide the pricing and seat controls simultaneously. Also, they considered the cancellation and mark-up policy in the pricing strategy under an uncertain demand condition.
Chapter 3
Sequencing Model for Hotel Room Choices

In this chapter, the OTAs sequencing tool is applied to present the sequence of hotel choices to an online customer. Our study proposed a sequencing model, based on a two-stage stochastic programming (2SSP) model, to optimally determine the number of hotel choices suitably shown on the website together with the sequencing decision for hotel choices. Accordingly, the background is provided in Section 3.1 and the research methodology is presented in Section 3.2. The detailed problem description is elaborated in Section 3.3 and then the problem is converted into the mathematical model presented in Section 3.4. The sample data and the numerical experiment are then described in Section 3.5 and 3.6, respectively. In Section 3.7, we discuss the results and draw the implications.

3.1 Background

The sequencing tool available on online travel agencies (OTAs) has become the useful functionality for most online customers used during the hotel searching process. Typically, the current sequencing tool sorts the sequence of hotel choices according to one dimension of hotel attribute (e.g., sorting by star rating or price) as shown in Figure 3.1. Moreover, OTAs present a long sequence of available hotels (e.g. 1,000 available hotels in the destination) which requires an effort in the searching process and booking decision for the customers. Based on our survey, sorting the hotel choices by price (i.e., from the lowest price to highest price) is the most preferable sorting method and the most of respondents search seven hotels, on average, before a hotel booking decision. However, sorting method based on one attribute has limitation to fulfil the demand for heterogeneous customers who concern the multidimensional attributes (e.g., required review rating, price and star rating) when making a hotel selection decision. Also, even though the existing OTAs sequencing tool is already efficient in a timely aspect, OTAs biasedly provides the sequence of hotel choices sorted by website’s favourite to promote some hotels in the
top ranking position to attract more customers, due to the advertising fee. Accordingly, the customer fails to notice a satisfactory hotel if that hotel is assigned in the bottom position of a long sequence. Therefore, the sequence of hotel choices shown by different sorting methods generates different results in the customer’s choice decision and online booking experience. It is essential for OTAs to consider an effective sequence of hotel choices to satisfy overall customers.

![Copy of the Hotels.com webpage describing OTA sequencing tool and website feature](https://www.hotels.com)

**Figure 3.1** Copy of the Hotels.com webpage describing OTA sequencing tool and website feature


Developing an approach for online product sequencing and recommendation has been explored by many researches (e.g., Ghose et al., 2012; Nilashi et al., 2015). However, the existing researches ignored the number of available choices but it has effect on the human cognitive load and the decision process. To the best of our knowledge, our study is the first attempt to consider the optimal or suitable number of product choices presented on the website in the sequencing feature. These issues could promote the profitable design of OTAs to enhance the customer experience from the usage of OTAs.

The main study, presented in this chapter, focuses on the usage of OTA sequencing tool to present the sequence of hotel choices for the customer’s hotel booking decision. We developed the sequencing model, based on the stochastic
programming model approach, in which our objective aims to decide an optimal number together with sequence of hotel choices to speed up the customer’s choice decision and satisfy the customer’s multidimensional preferences. Apart from previous literatures, our study concerns four main issues. (1) A new approach, namely, a two-stage stochastic programming model, was applied to deal with the optimal product sequencing problem in the tourism area. (2) The optimal number of choices suitably presented on the website as well as an appropriate sequencing position was incorporated. (3) The sequencing model was proposed on the basis of customer search theory as well as the customer’s multidimensional preferences. In order to drive the proposed model and numerical results close to a realistic online hotel booking mechanism, the hotel information was taken from OTA, namely, Hotels.com, whereas the customer information was collected by survey. (4) The multi-objectives were fulfilled in the view of customers, consisting of search cost, utility derived from a selected hotel, and the effect of ranking position in the sequence.

The main contributions of our study are (1) a new approach for dealing with the product sequencing problem in the tourism perspective. The area of concerned problem reflects the current issues in practical usage whereas the proposed model could be adapted to other e-commerce business. (2) We provide the managerial insights and the practical implementation of the proposed model that could provide the improvement guidelines for a hotel to maintain an advantage over other hotels.

3.2 Research Methodology

This section describes the research methodology to summary overall process of research conductions. Specifically, our study applied an optimization model as the approach to solve the problem and then discuss the insights. In order to set the proposed model representing the realistic mechanism, we included the important assumptions and parameters from data collection and then simulated the numerical experiments with the survey data.

The main steps of research activities are drawn in Figure 3.2.

In the first step, we reviewed the related literatures and conducted survey through questionnaires and website observation. Accordingly, we could understand
overall online hotel booking mechanism, collect the real data and set the proposed model closely representing the realistic mechanism.

In the second step, we formulated the detailed problem as the mathematical model in which the important parameters and the model’s assumptions were appropriately adopted from the related literatures and data collection.

In the third step, after formulating a model, we simulated numerical experiment through a set of generated sample data. The sample data, including the hotel information and customer characteristics, was observed from OTAs (i.e., Hotels.com) and the analysis of survey data. To derive the optimal solution, the proposed model with the appropriate sample data was optimally solved by the optimization software, namely, IBM ILOG CPLEX version 12.6. The numerical experiments were conducted to derive the findings.

In the fourth step, the findings were discussed to draw the managerial insights for the practical implication.

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**Figure 3.2 Steps of research activities**
3.3 Problem Description

We studied an online customer who visits online travel agencies (OTAs) and makes a hotel booking decision. As provided in Figure 3.3, after a customer provides the necessary information (e.g., destination, arrival date), OTA provides the sequence of candidate hotel choices with hotel information (e.g., available room, price, room type, star rating and review rating). In the typical searching process, a customer observes the hotel choices sequentially from the top to bottom of the sequence whereas the hotel choice presented at the upper position is more attractive. We assumed that a customer has multidimensional preferences (e.g., budget, expected review rating, start rating) for the hotel selection decision whereas the preference and expectation are varied by the types of customers and an individual customer (e.g., solo traveller, business traveller, couple). Accordingly, the heterogeneous customers select the hotel choice of which all attributes satisfying their expectation at the maximum expected utility.

In the searching process, the customer incurs search cost from observing a hotel choice. The arrival of customer is random whereas each customer is assumed to arrive first equally. The customer who arrives first has priority to select the hotel choice. Due to the limited supply of available rooms, the later customers could select the hotel choice if the room is available. Therefore, with the unknown arrival and multidimensional preferences of heterogeneous customers, it is necessary for OTA to prepare one optimal sequence of hotel choices that could effectively serve all potential case of unknown customers.

With the current OTAs sequencing tool, the sequences of hotel choices are sorted by one attribute (e.g., sorting by price). A large number of available hotel choices (e.g., 1,000 hotel choices) are served on the website. However, sorting by one attribute might not be satisfied the multidimensional preference of heterogeneous customers and a large number of choices have impact on search cost and choice decision. In our study, we propose the sequencing model that aims to reduce the search cost and match the hotel choices with overall customer’s expectation.

Main decisions that could be derived through an appropriate proposed model consist of;
1) Decision on the number of hotel choices shown on the website.  
2) Decision on the sequence of hotel choices shown on the website.  
3) Decision on the customer’s hotel choice selection.

**Figure 3.3** Overall process of online hotel booking

### 3.4 Mathematical Model Approach

In this study, the sequencing problem was formulated by using a two-stage stochastic programming (2SSP) model approach.

#### 3.4.1 Two-stage stochastic programming model

Stochastic programming is a mathematical approach for dealing with uncertainties within a general optimization framework. Many real-word decisions taking randomness or uncertainty into account, such as, supply chain management,
production scheduling, resource allocation and energy and environmental management (e.g., Wang et al., 2012; Barik et al., 2014; Bagheri et al., 2016; Huang et al., 2016; Ahmadi et al., 2016; Bidhandi and Patrick, 2017; Yang et al., 2017) have been modelled with the stochastic programming model.

The two-stage formulation is widely used in the stochastic programming, called a two-stage stochastic programming (2SSP) model. Therefore, the decision variables are classified into two sets. The first-stage decision variables are decided in advance (before the actual realization of the uncertain parameters is known). After the random events are known, further decisions can be made at a certain cost, known as the second-stage decision variables (Sahinidis, 2004).

In this study, the optimization problem of sequencing decision taking the uncertainties of customers (e.g., arrival order, preferences) was formulated as a two-stage stochastic programming (2SSP) model. The notations and descriptions are provided in Table 3.1.

### Table 3.1 Input parameters

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t$</td>
<td>Average search cost per hotel</td>
<td>$w_i$</td>
<td>Weight of search cost</td>
</tr>
<tr>
<td>$N$</td>
<td>Total number of customers</td>
<td>$w_2$</td>
<td>Weight of utility</td>
</tr>
<tr>
<td>$n$</td>
<td>Total number of hotels selected to be shown in the sequence</td>
<td>$w_3$</td>
<td>Weight of ranking position</td>
</tr>
<tr>
<td>$u_{i,j}$</td>
<td>Expected utility of hotel $j$ perceived by customer $i$</td>
<td>$\xi_i$</td>
<td>Reservation price of customer $i$</td>
</tr>
<tr>
<td>$\overline{Ub}$</td>
<td>Maximum number of hotels shown on the Web site</td>
<td>$M$</td>
<td>A threshold number of customers arriving at the web site to re-optimize</td>
</tr>
<tr>
<td>$B_i$</td>
<td>Budget of customer $i$</td>
<td>$p_j$</td>
<td>Price of a room at hotel $j$</td>
</tr>
<tr>
<td>$EQ_i$</td>
<td>Expected star rating required by customer $i$</td>
<td>$Q_j$</td>
<td>Star rating of hotel $j$</td>
</tr>
<tr>
<td>$Er_i$</td>
<td>Expected review rating required by customer $i$</td>
<td>$r_j$</td>
<td>Overall review rating of hotel $j$</td>
</tr>
<tr>
<td>$D_i$</td>
<td>Number of rooms required by customer $i$</td>
<td>$S_j$</td>
<td>Available rooms at hotel $j$</td>
</tr>
</tbody>
</table>

$O_{i,j} = \begin{cases} 
1 & \text{if hotel } j \text{ satisfies all requirements (price, star rating, review rating, number of rooms) for customer } i, \\
0 & \text{otherwise}
\end{cases}$

$O_{i,j} = \text{RoundDown} \left[ \min \left\{ \frac{B_i}{p_j}, \frac{Q_j}{EQ_i}, \frac{r_j}{Er_i}, \frac{S_j}{D_i} \right\} \right] \quad \forall i, \forall j$
Decision variables and auxiliary decision variables are provided as follows.

First-stage decision variables
\[ x_{j,k} = \begin{cases} 1 & \text{if hotel } j \text{ is placed at ranking position } k \text{ in the sequence;} \\ 0 & \text{otherwise} \end{cases} \]
\[ z_n = \begin{cases} 1 & \text{if } n \text{ is the last ranking position in the sequence selected by all customers;} \\ 0 & \text{otherwise} \end{cases} \]

Second-stage decision variables
\[ y_{i,j,k} = \begin{cases} 1 & \text{if customer } i \text{ selects hotel } j \text{ placed at ranking position } k \text{ in the sequence;} \\ 0 & \text{otherwise} \end{cases} \]
\[ s_i = \text{The list position number of the hotel selected by customer } i \]

With 2SSP, the decisions under the stated problem are separated into two stage decision, based on decision order of realistic mechanism. A decision-stage diagram is drawn in Figure 3.4.

- In the first-stage decision, the sequence of hotel choices \( x_{j,k} \) with the number of choices selected to be shown on the website \( z_n \) needs to be prepared and posted on OTAs website prior realizing the customer’s arrival and preferences. The uncertainties of customers are incorporated as each customer is equally likely to arrive first with the random multidimensional preferences. Thus, in this stage, the sequence and number of hotel choices need to be decided to serve all potential future cases of customers.

- In the second-stage decision, after an actual customer arrives at the website, the preference of customer is known. A customer makes a hotel booking decision \( y_{i,j,k} \), from a given sequence of available hotel choices prepared in the first-stage decision. Then, the ranking position of hotel selected by customer \( i, s_i \) is determined.
3.4.2 Customer’s choice model

In order to decide the optimal sequence, it is essential to understand the customer search behaviour and booking decision. We assume that a customer has multidimensional preferences (e.g., price, required star rating, review rating, number of rooms, reservation price). These preferences are different depending on the individual and on the type of customer. Moreover, the expected utility gained from each hotel is perceived differently among customers. To imitate the customer’s decision-making process, we assumed that a customer searches all hotel choices available in the sequence and then selects the hotel with the highest utility gained above the reservation price (net utility gained) while all constraints of price, star rating, review rating, and availability are satisfied to his or her minimum expectation. We prepared the optimal sequence with the optimal number of hotel choices to close with the customer search behaviour and decision-making process. Our mathematical model of the consumer’s decision-making process is as follows.

Objective: Maximize expected utility gained from a selected hotel

\[ \sum_{i=1}^{N} \sum_{j=1}^{K} \sum_{k=1}^{K} (u_{i,j} - p_{j} - \xi_{i,j,k}) \times y_{i,j,k} \]  

(3.1)

Customer’s choice constraints:

\[ y_{i,j,k} \leq x_{j,k} \quad \forall i, \forall j, \forall k \]  

(3.2)

\[ y_{i,j,k} \leq (1 - z_{n}) \quad \forall i, \forall j, \forall k, \forall n = 1...k-1 \]  

(3.3)

Figure 3.4 A diagram of stages of decision
\[ \sum_{j=1}^{K} \sum_{k=1}^{K} y_{i,j,k} \leq 1 \quad \forall i \]  

(3.4)

\[ y_{i,j,k} \leq O_{i,j} \quad \forall i, \forall j, \forall k \]  

(3.5)

\[ \left( u_{i,j} - p_j - \xi_j \right) y_{i,j,k} \geq 0 \quad \forall i, j, k \]  

(3.6)

Eq. (3.1) represents the objective that aims to maximize the expected utility gained from a selected hotel above the reservation price. The customer’s choice decision is determined by Eq. (3.2) to (3.6). That is, Eq. (3.2) to (3.4) state that the customer will select a hotel from the sequence of hotel choices presented on the website. According to Eq. (3.5) to (3.6), the customer will select a hotel if all attributes meeting with his personal expectation and reservation price.

### 3.4.3 Second-stage decision: Approximated customer’s choice model

In the second stage, the random events (i.e., a customer with a given preference arrives) occurs. In this stage, we know the preferences of the next customer and therefore we know which hotel and which hotel position will be selected (on the basis of the sequence set earlier in the first stage) using the consumer decision model above. However, this choice selected by the customer occurs with an equal probability of \( 1/N \). Therefore, in the second stage, the model will first try to maximize the expected utility gain of the next customer (due to its larger weight \( w_2 \) in the objective function compared to the other weight) to represent the optimal choices of the next customer. This is the first goal of the second-stage model. However, to find the optimal sequence that ranks the popular hotels on the top of the list, the second-stage model needs to record the expected number of positions of hotels selected by the next customer. For example, suppose there are two customers: customer A and customer B. If customer A comes first (with probability = 0.5), he will select a hotel at position 3. If customer B comes first (with probability = 0.5), he will select a hotel at position 2. The expected number of positions selected by the next customer will be \( (0.5 \times 3) + (0.5 \times 2) = 2.5 \). To set up a good sequence, this expected step should be as small as possible because it means that the hotel selected by the next customer under any scenario is ranked mostly at the top of the list. Therefore, the
Second stage will record this expected step in the objective function as the second goal and pass this to the first stage to minimize while deciding the sequence.

Second-stage model

Objective: Minimize composite score

\[
-w_2 \times \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{K} \sum_{k=1}^{K} (u_{i,j} - p_j - \xi_j) \times y_{i,j,k} + w_3 \times \frac{1}{N} \sum_{i=1}^{N} s_i \tag{3.7}
\]

Customer’s choice constraints

\[
y_{i,j,k} \leq x_{j,k} \quad \forall i, \forall j, \forall k \tag{3.8}
\]

\[
y_{i,j,k} \leq (1-z_n) \quad \forall i, \forall j, \forall k, \forall n = 1, \ldots, k-1 \tag{3.9}
\]

\[
\sum_{j=1}^{K} \sum_{k=1}^{K} y_{i,j,k} \leq 1 \quad \forall i \tag{3.10}
\]

\[
y_{i,j,k} \leq O_{i,j} \quad \forall i, \forall j, \forall k \tag{3.11}
\]

\[
(u_{i,j} - p_j - \xi_j) \times y_{i,j,k} \geq 0 \quad \forall i, j, k \tag{3.12}
\]

\[
s_i = \sum_{j=1}^{K} \sum_{k=1}^{K} k \times y_{i,j,k} + (1 - \sum_{j=1}^{K} \sum_{k=1}^{K} y_{i,j,k}) \times K \quad \forall i \tag{3.13}
\]

Eq. (3.7) represents the composite score that combines two goals. The first goal aims to maximize the expected utility gained from a selected hotel above the reservation price whereas the second goal aims to minimize the expected position of hotels selected by the customer. The objective function aims to minimize the composite score so that both goals are satisfied. Eq. (3.8) to (3.10) state the customer’s choice decision, in which, the customer will select a hotel from the sequence of hotel choices presented on the website. According to Eq. (3.11) to (3.12), the customers will select a hotel if all attributes satisfying with their expectation and reservation price. The position of the hotel selected by each customer is determined by Eq. (3.13).

The first term in Eq. (3.7), \(-w_2 \times \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{K} \sum_{k=1}^{K} (u_{i,j} - p_j - \xi_j) \times y_{i,j,k}\), serves as the expected utility gained by the next customer weighted by the importance factor \(w_2\).

The second term in Eq. (3.7), \(w_3 \times \frac{1}{N} \sum_{i=1}^{N} s_i\) represents the expected positions of hotels.
selected by the next customer weighted by the important factor $w_3$. As the sequence is not set up in the second stage, the term $w_3 \times \frac{1}{N} \sum_{i=1}^{N} s_i$ will be minimized by the first-stage decision. However, the second-stage model will work as expected only when the customer’s hotel choices solved from the consumer’s decision model are exactly the same as the customer’s choices of hotels solved from the second-stage model. Potential differences could occur due to the difference in objective functions (from the second goal of the second-stage model). To minimize this effect, the weight $w_3$ should be set relatively very small compared to $w_2$. With a very small value of $w_3$ compared to $w_2$, the objective function of the second-stage model closely represents the objective function of the consumer decision model. In our numerical simulation test, $w_3$ selected is tested with 80 customers and 10 replications such that $w_3$ is small enough to ensure the customer’s choices from the consumer’s model and the second-stage model are identical.

3.4.4 First-stage decision: Sequencing model

According to the customer’s choice decision, if we know which customer comes first, we can arrange the optimal sequence of available hotels to satisfy all goals of the customer. However, in practice, we don’t know which customers will come first, so each customer is assumed to arrive first with equal probability. Therefore, in the first stage, we need to decide the optimal number of available hotels with the optimal sequence to serve all of the possible requirements of the next customers. The sequence should also put the popular hotels (selected by the majority of next customers) on the top of the list (to minimize the term $w_3 \times \frac{1}{N} \sum_{i=1}^{N} s_i$).
### 3.4.5 Two-stage stochastic programming (2SSP) model

The decision of two stages are incorporated into one two-stage stochastic programming (2SSP) model, described as follows.

**Minimize composite score =**

\[
\begin{aligned}
& \text{Minimize composite score } = \\
& w_1 \times N \times K \times \sum_{n=1}^{K} n \times z_n - w_2 \times \frac{1}{N} \sum_{n=1}^N \sum_{j=1}^{K} \sum_{k=1}^K (u_{i,j} - p_j - x_i) \times y_{i,j,k} + w_3 \times \sum_{i=1}^N s_i \\
& \text{(3.14)}
\end{aligned}
\]

**Subject to:**

**First-stage constraints: Sequencing constraints**

\[
\begin{aligned}
& \sum_{n=1}^{K} z_n = 1 \quad \text{(3.15)} \\
& \sum_{n=1}^{K} n \times z_n \leq \bar{u}_b \quad \text{(3.16)} \\
& \sum_{n=1}^{K} n \times z_n \geq \bar{L}_b \quad \text{(3.17)} \\
& \sum_{j=1}^K x_{j,k} = 1 \quad \forall j \quad \text{(3.18)} \\
& \sum_{j=1}^K x_{j,k} = 1 \quad \forall k \quad \text{(3.19)}
\end{aligned}
\]

**Second-stage constraints: Customer’s choice constraints**

\[
\begin{aligned}
& y_{i,j,k} \leq x_{j,k} \quad \forall i, \forall j, \forall k \quad \text{(3.20)} \\
& y_{i,j,k} \leq (1-z_n) \quad \forall i, \forall j, \forall k, \forall n = 1, \ldots, K-1 \quad \text{(3.21)} \\
& \sum_{j=1}^K \sum_{k=1}^K y_{i,j,k} \leq 1 \quad \forall i \quad \text{(3.22)} \\
& y_{i,j,k} \leq O_{i,j} \quad \forall i, \forall j, \forall k \quad \text{(3.23)} \\
& (u_{i,j} - p_j - x_i) \times y_{i,j,k} \geq 0 \quad \forall i, j, k \quad \text{(3.24)} \\
& s_i = \sum_{j=1}^K \sum_{k=1}^K k \times y_{i,j,k} + (1 - \sum_{j=1}^K \sum_{k=1}^K y_{i,j,k}) \times K \quad \forall i \quad \text{(3.25)}
\end{aligned}
\]

Given the sequence of hotel choices on the website, the customers perform searching and then select one satisfactory hotel from the given sequence. The composite score comprised of three main goals is minimized by using Eq. (3.14).
Three main goals include (1) minimizing search cost from searching all hotel choices presented on the website, (2) maximizing the utility gained from a selected hotel above the reservation price, and (3) minimizing the expected position of hotels selected by customers. Thus, the objective function is to minimize the composite scores so that three main goals are all satisfied. A sequencing decision for the hotel choices is set by using Eqs. (3.15) to (3.19). Eq. (3.15) determines an appropriate number of hotel choices selected to present in the sequence. The upper bound and lower bound of number of hotel choices presented on the website are limited by Eq. (3.16) to (3.17). The ranking position of each hotel is assigned in the sequence by using to Eqs. (3.18) to (3.19). Eq. (3.18) states that each hotel needs to be assigned to one ranking position whereas Eq. (3.19) states that each ranking position needs to be assigned by one hotel.

A customer’s choice decision is set by using Eqs. (3.20) to (3.25). Eq. (3.20) states that the customers can select a hotel at the given position from the sequence presented on the website. Eq. (3.21) states that the customers can select a hotel if presented on the website. According to Eq. (3.22), the customers can either book a hotel or leave without booking. Eqs. (3.23) and (3.24) determine the customer’s choice decision. According to Eq. (3.23), the customers will select a hotel if all attributes meeting with their personal expectation (e.g., expected star rating, review rating and room price). Moreover, the customers will select a hotel if the net utility gained from the hotel exceeds their reservation price, determined by Eq. (3.24). The expected position of a hotel selected by each customer is determined by Eq. (3.25). However, if the customers leave without booking, the position \( K \) will be assigned.

3.4.6 Steps for the proposed model

The proposed sequencing model with the two-stage decision is run to determine an optimal sequence and appropriate number of hotel choices to serve the coming customers. The customers arriving or deciding first have priority to book a hotel room whereas the later customers can book if the room is available. After a booking transaction occurs, the available supply of hotel rooms is adjusted and the updated sequence of hotel choices is then served for the next coming customers.
Moreover, a new sequence of hotel choices should be always re-optimized but re-optimizing after every booking transaction takes large computation time to be practical. In our proposed method, we proposed re-optimizing the sequence every $M^{th}$ customer’s arrival, where $1 \leq M \leq N$. For instance, if $M = 5$ and the total number of customers ($N$) = 30, it means that we run the model to determine a new optimal sequence every $5^{th}$ customer’s arrival. That mean, the sequence will be re-optimized after $5^{th}$, $10^{th}$, $15^{th}$, $20^{th}$, $25^{th}$ and $30^{th}$ customers arrive at the website or make a booking transaction. However, before the re-optimizing period, the supply of hotel rooms is updated after a booking transaction whereas the hotel with the sold out room is removed and shifted up with a next ranking hotel. An appropriate $M$ value will be tested and shown in the numerical experiments. In summary, we proposed that the optimal sequence should be re-optimized for the next customers every $M^{th}$ customer’s arrival. The steps to determine the sequence by the proposed model are summarized in Table 3.2.

**Table 3.2** Steps showing the sequencing decision by the proposed model

| Step 1: Initialize customer counter $m = 0$. |
| Step 2: First stage decision determines an optimal sequence of $n$ available hotels. |
| Solve for $x_{j,k}, z_n$. |
| Step 3: Second stage decision determines the customer’s hotel choice from a given sequence. |
| Given the solution of $x_{j,k}, z_n$, solve for $y_{i,j,k}$. |
| Step 4: After every customer’s arrival, update the supply of room and the customer counter. |
| After a customer arrives at the website, increase customer counter $m$ by 1 or let $m = m+1$. Then, update the available supply of hotel rooms. If the room is already sold out, remove it from the current sequence and shift up to next one. Then, serve the updated sequence of hotel choices to the next coming customers. |
| Step 5: Check if the number of customers’ arrival reaches $M$. |
| If the customer counter $m = M$ where $1 \leq M \leq N$, go to Step 1, |
| Otherwise, go to Step 4 until reaching $N$. |
3.5 Sample Data

In this section, we presented a set of sample data used to generate the characteristics of hotels and customers for the numerical experiments. Specifically, the hotel information in the selected destination (i.e., Chachoengsao Province, Thailand) were taken from a popular OTA, namely, Hotels.com, which was ranked number 524 in the eBizMBA ranking with 16,000,000 estimated unique monthly visitors (eBizMBA, 2015). Hotels.com was selected due to its adequate web site design along with the sufficient information of hotels and online reviews. Furthermore, our customer profiles were appropriately generated from the analysis of customer’s survey data.

3.5.1 Hotel characteristics in the selected destination

We selected a set of available hotels, located in Chachoengsao Province, Thailand. Chachoengsao Province is located on the east of Bangkok, the capital of Thailand. It is 80 kilometres from Bangkok and conveniently access by car and other public transport services including train and bus. The province has become a tourist attraction representing the old history and traditional culture of Thailand from the Ayutthaya period. Various attractions are located in Chachoengsao Province such as Monument of King Thaksin, traditional market of Talat Klong Suan Roi Pi, Great Mango Orchards, Bang Pakong River and several temples including Wat Chin Prachasamoson and Wat Sothon (Barrow, 2015). Moreover, several industrial parks are located within the province. The destination of hotels located in Chachoengsao Province was selected to conduct the numerical experiments as the number of booking transactions made by various customer types as well as the numbers of available hotels are large but their size can be managed to generate the set of data manually.

The information of available hotels, located in Chachoengsao Province, for the check-in dates of February 11 to 12, 2015, were collected. Specifically, the total number of 42 available hotels on Hotels.com was taken. The hotel characteristics, which are the room price (Thai Baht), number of available rooms, star rating (scaled by 1 to 5), overall review rating (scaled by 1 to 5), and review rating in the hotel’s service attribute (scaled by 1 to 5), were adequately collected. Table 3.3 shows the
descriptive data of subject hotels. Moreover, the existing sequences of hotels available on the OTA (e.g., sorting by price, star rating, overall review rating, and website favourite or popularity) were observed and compared with the effectiveness of sequences derived by our proposed model.

**Table 3.3** Descriptive data of the subject hotels located in Chachoengsao Province

<table>
<thead>
<tr>
<th>Hotel attributes</th>
<th>Mean</th>
<th>Std.dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (Baht)</td>
<td>1,228.1</td>
<td>1,013.5</td>
<td>361</td>
<td>5,760</td>
</tr>
<tr>
<td>Star rating</td>
<td>3.31</td>
<td>0.53</td>
<td>2.5</td>
<td>5</td>
</tr>
<tr>
<td>Number of available room</td>
<td>5.74</td>
<td>3.25</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>Overall review rating</td>
<td>3.58</td>
<td>0.41</td>
<td>2.8</td>
<td>4.6</td>
</tr>
<tr>
<td>Review rating in service</td>
<td>3.76</td>
<td>0.46</td>
<td>2.5</td>
<td>4.8</td>
</tr>
</tbody>
</table>

Note. Data source: [http://www.hotels.com](http://www.hotels.com)
Total number of hotels = 42 hotels; Location: Chachoengsao Province, Thailand;
Check-in date: February 11 to 12, 2015

### 3.5.2 Customer characteristics in the selected destination

To estimate the ratio of customers in the selected destination, we adopted the available history of online review as it could represent an actual reservation and hotel experience. Table 3.4 summarizes the ratio of customer types in Chachoengsao Province, classified into solo traveller, couple, business traveller, family, and friend. It seems that most of customers in this destination are solo traveller and couple, respectively. Thus, we adopted the estimated ratio of customer types to generate the sample set of customers. The arrival order of customer was random and customer characteristics were generated by the distribution described in Tables 3.7 and 3.8.

**Table 3.4** Estimated ratios of customers

<table>
<thead>
<tr>
<th>Type of customer</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solo traveller</td>
<td>32.46%</td>
</tr>
<tr>
<td>Couple</td>
<td>26.96%</td>
</tr>
<tr>
<td>Business traveller</td>
<td>20.37%</td>
</tr>
<tr>
<td>Family</td>
<td>14.23%</td>
</tr>
<tr>
<td>Friend</td>
<td>5.96%</td>
</tr>
</tbody>
</table>

Primary data of customers was collected through the survey with a number of Thai customers. To observe the customer’s online hotel booking behaviour, the questionnaire consisted of five main sections. At the beginning of questionnaire, the respondents were asked about their general profile (e.g., income). The second sections
asked the general hotel selection criteria. In the third sections, one screening question was asked to indicate the experience on OTA usage for an online hotel booking. Accordingly, only the respondents having the OTA usage experience completed the section, otherwise going for the next section. The fourth section asked the respondents to provide information and evaluate their recent hotel booking experience. The fifth section asked the respondents to express their attitude toward the online review. Throughout the questionnaire, a list of attributes in the hotel selection was adapted from OTAs such as Hotels.com and Agoda.com, and from prior literatures (e.g., Sohrabi et al., 2012). For the measurement scales, we applied a five-point Likert-type scale (1 = Very unimportant, 2 = Unimportant, 3 = Neutral, 4 = Important, 5 = Very important) to indicate the level of importance on each hotel and online review attribute. Furthermore, a five-point Likert-type scale (1 = Very poor, 2 = Poor, 3 = Neutral, 4 = good, 5 = Very excellent) was applied to evaluate a hotel. The detail of questionnaire (English version) can be found in Appendix A.

The customer data were collected through the survey to the Thai respondents during November 3 to 19, 2014. Accordingly, the total of 120 questionnaires was completed whereas female and male had made up 60.8% and 39.2%, respectively. Classified by the types of customer, most of respondents were family (43.57%) and friends (32.96%) whereas couples, solo travellers, and business travellers accounted for 15.08%, 5.59%, and 2.79%, respectively. Moreover, most of respondents had spent their time on the internet less than 3 hours per day and over half of the respondents indicated their online hotel booking experience. The descriptive statistics of the respondents are summarized in Table 3.5.
Table 3.5 Descriptive statistics of respondents

<table>
<thead>
<tr>
<th>Variable</th>
<th>Range</th>
<th>%</th>
<th>Variable</th>
<th>Range</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Female</td>
<td>60.8%</td>
<td>Family</td>
<td>43.57%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Male</td>
<td>39.2%</td>
<td>Friend</td>
<td>32.96%</td>
<td></td>
</tr>
<tr>
<td>Type of Traveller</td>
<td></td>
<td></td>
<td>Couple</td>
<td>15.08%</td>
<td></td>
</tr>
<tr>
<td>20-30</td>
<td>33.33%</td>
<td></td>
<td>Solo traveller</td>
<td>5.59%</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20-30</td>
<td>33.33%</td>
<td></td>
<td>Internet usage</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Above 50</td>
<td>19.66%</td>
<td></td>
<td>3-5 hours</td>
<td>31.4%</td>
<td></td>
</tr>
<tr>
<td>High school</td>
<td>0.8%</td>
<td></td>
<td>&gt; 8 hours</td>
<td>11.9%</td>
<td></td>
</tr>
<tr>
<td>Education level</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collage certificated</td>
<td>2.5%</td>
<td></td>
<td>Online hotel</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bachelor degree</td>
<td>71.2%</td>
<td></td>
<td>booking experience</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Master degree</td>
<td>24.6%</td>
<td></td>
<td>Yes</td>
<td>52.5%</td>
<td></td>
</tr>
<tr>
<td>Doctoral degree</td>
<td>0.8%</td>
<td></td>
<td>No</td>
<td>47.5%</td>
<td></td>
</tr>
<tr>
<td>Monthly income</td>
<td>&lt; 20,000Baht</td>
<td>31.6%</td>
<td>1-2 times</td>
<td>69.8%</td>
<td></td>
</tr>
<tr>
<td>(Baht)</td>
<td></td>
<td></td>
<td>Using OTAs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20,000-39,990 Baht</td>
<td>27.2%</td>
<td></td>
<td>3-4 times</td>
<td>15.9%</td>
<td></td>
</tr>
<tr>
<td>40,000-49,990 Baht</td>
<td>8.8%</td>
<td></td>
<td>5-6 times</td>
<td>9.5%</td>
<td></td>
</tr>
<tr>
<td>50,000-69,999 Baht</td>
<td>16.7%</td>
<td></td>
<td>&gt; 9 times</td>
<td>4.8%</td>
<td></td>
</tr>
<tr>
<td>≥ 70,000 Baht</td>
<td>15.8%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.6 presents the percentage of using the OTA sequencing tool to sort the sequence of hotels by different sorting method. From our survey result, we observed that sorting the sequence of hotels by price is the most preferred sorting method when the customers searching for a hotel on OTAs. However, in the numerical experiment, we will compare the effectiveness of the existing sequences obtained from OTAs with the effectiveness of the sequence obtained by our proposed model. We will point out that sorting by price might not be the best sorting method, in practice, when facing with the potential constraints such as multidimensional preferences and search cost. These provide insight for OTAs to investigate the importance of sequencing and website feature design.
Table 3.6 Study respondent’s preferred sorting methods

<table>
<thead>
<tr>
<th>Sorting method</th>
<th>Percent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>72.5%</td>
</tr>
<tr>
<td>Promotion</td>
<td>59.2%</td>
</tr>
<tr>
<td>Distance from destination</td>
<td>53.3%</td>
</tr>
<tr>
<td>Review score</td>
<td>40.8%</td>
</tr>
<tr>
<td>Popularity</td>
<td>40%</td>
</tr>
<tr>
<td>Hotel star rating</td>
<td>37.5%</td>
</tr>
<tr>
<td>Web site suggestion</td>
<td>19.2%</td>
</tr>
<tr>
<td>Hotel name (A–Z)</td>
<td>10.8%</td>
</tr>
</tbody>
</table>

Using the data analysis of our survey, we could capture the customer characteristics and their preferences that could adequately represent overall online customers. Table 3.7 summarizes the general characteristics of overall online customers, including the number of hotels that customers tend to observe before making a booking transaction, the reservation price and the number of required rooms. We found that a typical customer searches for the hotels between 2 to 30 hotels. From this observation, we adopted these estimated hotel numbers as the upper bound and lower bound to decide the appropriate (optimal) number of hotel choices presented in the sequence through our proposed model. Adopted from the study of Anderson (2011), we assumed that the customers incur search cost per searching one hotel at 0.3484 Baht, approximately.

Table 3.7 Summary statistics of customer parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std.dev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>All types of customer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of searched hotels</td>
<td>6.24</td>
<td>4.68</td>
<td>2</td>
<td>30</td>
</tr>
<tr>
<td>Reservation price</td>
<td>199.24</td>
<td>983.69</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of required room</td>
<td>2.02</td>
<td>2.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Search cost per hotel (Baht)</td>
<td>0.3484</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Moreover, we classified the customers into five main types whereas the characteristics of each customer types were adequately captured. Table 3.8 summarizes the characteristics of each customer type, including the budget for one room per night, expected star rating and overall review rating. From the results of data analysis, we then generated the sample sets of customers by using Monte Carlo sampling. That is, for an individual customer who relying on his or her type, the parameters for the customer characteristics were randomly generated by using a normal distribution with the mean and standard deviations shown in Table 3.8.
Therefore, the sample sets of customers were randomly generated and assigned in the numerical experiments to test the proposed model and derive the results.

**Table 3.8** Summary statistics of customer parameters classified by types of customer

<table>
<thead>
<tr>
<th>Type of customer</th>
<th>Budget (Baht)</th>
<th>Expected star rating</th>
<th>Expected review rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solo traveller</td>
<td>Mean 2,294.44</td>
<td>2.6</td>
<td>3.69</td>
</tr>
<tr>
<td></td>
<td>Std.dev 2,323.31</td>
<td>0.7</td>
<td>0.87</td>
</tr>
<tr>
<td>Couple</td>
<td>Mean 2,035.71</td>
<td>2.86</td>
<td>3.61</td>
</tr>
<tr>
<td></td>
<td>Std.dev 1,298.14</td>
<td>0.58</td>
<td>0.88</td>
</tr>
<tr>
<td>Business traveller</td>
<td>Mean 1,860</td>
<td>2.6</td>
<td>3.28</td>
</tr>
<tr>
<td></td>
<td>Std.dev 879.20</td>
<td>0.55</td>
<td>0.74</td>
</tr>
<tr>
<td>Family</td>
<td>Mean 2,151.30</td>
<td>2.91</td>
<td>3.71</td>
</tr>
<tr>
<td></td>
<td>Std.dev 1,042.367</td>
<td>0.67</td>
<td>0.79</td>
</tr>
<tr>
<td>Friend</td>
<td>Mean 1,983.93</td>
<td>2.86</td>
<td>3.72</td>
</tr>
<tr>
<td></td>
<td>Std.dev 1,196.09</td>
<td>0.72</td>
<td>0.82</td>
</tr>
</tbody>
</table>

In order to estimate the expected utility that heterogeneous customers perceive from a hotel, the values on the recent experience and hotel service were evaluated by the respondents (self-stated valuation). We then adopted the multiple regression analysis in which the dependent variable \( y \) is the expected utility of hotel whereas the seven independent variables, consisting of hotel room price, review rating on five attributes (i.e., cleanliness, location, hotel condition, comfort, and service) and start rating, are the independent variables \( x \). Table 3.9 summarizes the result of multiple regression analysis for estimating the expected utility gained from a hotel. The result indicates that our survey data fits the multiple regression models with an adjusted \( R^2 \) of 0.86. Also, the stepwise regression was performed to select the significant variables and thus, two out of seven independent variables were incorporated in the final model. The 86% of the variation in expected utility is explained by two variables of hotel price and review rating in the service attribute. Therefore, the expected utility gained from a hotel = \(-1,134.27 + 1.144 \times \text{(Price)} + 249.98 \times \text{(Service rating)}\). As the expected utility of similar hotel is differently perceived by the perceptions of individual customers, we adopted the standard error of estimation at 901.461 to randomly assign the expected utility gained from each hotel to heterogeneous customers.
Table 3.9 Multiple regression results, dependent variable: expected utility

<table>
<thead>
<tr>
<th>Variable</th>
<th>B</th>
<th>t-value</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−1,134.27</td>
<td>−3.79</td>
<td>298.97</td>
</tr>
<tr>
<td>Price</td>
<td>1.144**</td>
<td>27.95</td>
<td>0.041</td>
</tr>
<tr>
<td>Service rating</td>
<td>249.98**</td>
<td>3.26</td>
<td>76.88</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.864</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>0.862</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard error of estimation</td>
<td>901.461</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note:
*p<0.01; Ordinary least squares (OLS) regression is used with total number of observations of 120.

3.6 Numerical Experiment

In this section, the numerical experiments were conducted to show the performance of our sequencing model and discuss the managerial insight that arose from doing them. To optimally solve the stated problem, we used the optimization software, namely, IBM ILOG CPLEX Optimization Studio Version 12.6. The numerical experiments were conducted on a personal computer with a 64-bit Intel(R) Core(TM) i3-2348M CPU, 2.30 GHz clock speed, and 8.0 GB of RAM. The input data, used to run numerical experiments, was generated from the data analysis described in Section 3.5. Specifically, we used the practical example of 42 hotels located at Chachoengsao Province, Thailand, and a set of sample customers appropriately generated based on the survey results.

3.6.1 Example of sequencing decision made by the proposed model

This numerical experiment shows the sequencing decision derived from solving the proposed model with a practical example of hotels located in Chachoengsao Province, Thailand. According to Table 3.10, for the OTAs website, the six hotels out (i.e., shading area) from 42 available hotels are selected to show on the website at a given ranking position in the sequence. The customers with random arrival order select a satisfactory hotel from a given sequence presented on the website.
Table 3.10 Example of decisions made by the proposed model

<table>
<thead>
<tr>
<th>Ranking position</th>
<th>Hotel</th>
<th>Customer no.</th>
<th>Selected hotel</th>
<th>Ranking position</th>
</tr>
</thead>
<tbody>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt;</td>
<td>BS Premier Airport</td>
<td>1</td>
<td>Avion Apart-Hotel</td>
<td>2&lt;sup&gt;nd&lt;/sup&gt;</td>
</tr>
<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt;</td>
<td>Avion Apart-Hotel</td>
<td>2</td>
<td>BS Premier Airport</td>
<td>1&lt;sup&gt;st&lt;/sup&gt;</td>
</tr>
<tr>
<td>3&lt;sup&gt;rd&lt;/sup&gt;</td>
<td>Chon Inter Hotel</td>
<td>3</td>
<td>Paragon Inn</td>
<td>4&lt;sup&gt;th&lt;/sup&gt;</td>
</tr>
<tr>
<td>4&lt;sup&gt;th&lt;/sup&gt;</td>
<td>Paragon Inn</td>
<td>4</td>
<td>BS Premier Airport</td>
<td>1&lt;sup&gt;st&lt;/sup&gt;</td>
</tr>
<tr>
<td>5&lt;sup&gt;th&lt;/sup&gt;</td>
<td>Siam Place Airport</td>
<td>5</td>
<td>Airy Resort</td>
<td>6&lt;sup&gt;th&lt;/sup&gt;</td>
</tr>
<tr>
<td>6&lt;sup&gt;th&lt;/sup&gt;</td>
<td>Airy Resort</td>
<td>6</td>
<td>Avion Apart-Hotel</td>
<td>2&lt;sup&gt;nd&lt;/sup&gt;</td>
</tr>
<tr>
<td>7&lt;sup&gt;th&lt;/sup&gt;</td>
<td>Grand Pinnacle</td>
<td>7</td>
<td>BS Premier Airport</td>
<td>1&lt;sup&gt;st&lt;/sup&gt;</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
<td>8</td>
<td>Chon Inter Hotel</td>
<td>3&lt;sup&gt;rd&lt;/sup&gt;</td>
</tr>
<tr>
<td>42&lt;sup&gt;nd&lt;/sup&gt;</td>
<td>Sananwan Palace</td>
<td>9</td>
<td>BS Premier Airport</td>
<td>1&lt;sup&gt;st&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

3.6.2 Analysis of numerical result

In the proposed model, we generated a set of sample customers to represent various characteristics of potential customers and then used it to prepare an optimal sequence of hotel choices to serve future independent customers (i.e., actual customer). In this numerical experiment, total number of sample customers \((N)\) were varied, where \(N \in \{60, 80, 100, 150\}\), to prepare the sequence of hotels. The sequence was re-optimized every time a new independent customer (independently selected from the customer pool) arrives. To test the sequence effectiveness, we randomly generated another set of five independent customers, and test with the sequences determined by different total number of sample customers, \(N \in \{60, 80, 100, 150\}\). According to Table 3.11 and Figures 3.5 (a) to (b), the result shows that the larger size of \(N\) consumes the longer computation times but provides a slightly difference in composite score. The sample size of 80 customers generates the best composite score (i.e., lowest) within the acceptable computation time per customer. The computation time will increase significantly with the number of independent customers and with the problem size. Therefore, we selected the sample size of 80 customers to conduct our sequencing decision.
Table 3.11 Sample size of customers for making a sequence of hotels

<table>
<thead>
<tr>
<th>Sample size of customer</th>
<th>Total search cost</th>
<th>Avg. utility/customer</th>
<th>Total position of all booked hotels</th>
<th>Composite score (Lower preference)</th>
<th>Computation time/customer (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>19.51</td>
<td>1,230.79</td>
<td>17</td>
<td>-1,211.11</td>
<td>22.54</td>
</tr>
<tr>
<td>80*</td>
<td>17.42</td>
<td>1,391.21</td>
<td>27</td>
<td>-1,373.50</td>
<td>43.48</td>
</tr>
<tr>
<td>100</td>
<td>13.92</td>
<td>1,348.52</td>
<td>25</td>
<td>-1,334.34</td>
<td>60.01</td>
</tr>
<tr>
<td>150</td>
<td>9.41</td>
<td>1,174.05</td>
<td>14</td>
<td>-1,164.50</td>
<td>161.20</td>
</tr>
</tbody>
</table>

Note: The sample size of 80 is used in all subsequent numerical experiments.

Figure 3.5 Effect of sample size on the composite score and computation time

Figures 3.6 and 3.7 present the sorting criteria of proposed model to determine the sequence of hotel choices. According to our survey result, the most of respondents tend to search for the hotels between 2 to 30 hotels. Therefore, the number of hotel choices presented on the website (n) is limited at 30 hotels which placed in 30 ranking positions, in this numerical experiment. Numerical experiments were conducted with three replications using three different sets of independent customers. Another three sets of 80 sample customers were generated and used to prepare an optimal sequence to serve the sets of independent customers, and the average results of three replications were analysed. According to Figure 3.6, the proposed model suggests that the hotel with a higher possibility to attract more potential customers should be placed at the upper ranking position. Moreover, the ranking position of hotels in the sequence is determined by the multidimensional criteria to response the customer’s multidimensional preferences. Figure 3.7 indicates that the hotel with higher net
utility, price, review rating, and star rating should be assigned in the upper ranking positions of the sequence.

**Figure 3.6** Ranking position and number of potential customers

(a) Ranking position & Net utility  
(b) Ranking position & Price

(c) Ranking position & Star rating  
(d) Ranking position & Review rating

**Figure 3.7** Ranking position and hotel’s characteristics
Table 3.12 shows the effect of number of shown hotel choices on the composite score of customers. In this experiment, the total number of hotel choices selected to be presented in the sequence was varied, where \( n \in \{10, 20, 25, 30, \text{ and } 35\} \). A set of fifty independent customers were randomly generated to test each of them. The results show that both of the average utility per customer and the search cost increase with the larger number of shown hotel choices. These reflect that the larger number of available hotel choices increases the possibility to match a hotel with the customer’s preferences but requires the higher search cost. Therefore, OTAs need to consider an appropriate number of shown hotel choices together with a quality of shown hotels. Our results indicate the need for a suitable number of hotels to balance the utility and search cost. For example, to obtain the best solution (i.e., lowest composite score), the 25 numbers of hotel choices in the sequence should be served to the customers. Accordingly, with the proposed model, OTAs could determine the appropriate number of hotel choices together with the selection of candidate hotels placed in the sequence by the multidimensional sorting criteria.

<table>
<thead>
<tr>
<th>Number of hotels</th>
<th>Total search cost</th>
<th>Avg. utility/customer</th>
<th>Total position of booked hotel</th>
<th>Composite score (Lower is preferred)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>191.62</td>
<td>1,085.73</td>
<td>320</td>
<td>-890.91</td>
</tr>
<tr>
<td>20</td>
<td>348.40</td>
<td>1,263.91</td>
<td>445</td>
<td>-911.06</td>
</tr>
<tr>
<td>25</td>
<td>435.50</td>
<td>1,413.10</td>
<td>573</td>
<td><strong>-971.87</strong></td>
</tr>
<tr>
<td>30</td>
<td>522.60</td>
<td>1,417.50</td>
<td>492</td>
<td>-889.98</td>
</tr>
<tr>
<td>35</td>
<td>609.70</td>
<td>1,457.31</td>
<td>642</td>
<td>-841.19</td>
</tr>
</tbody>
</table>

3.6.3 Effectiveness of the proposed model

Table 3.13 compares the effectiveness of sequences designed by our proposed model with that provided by OTA sequencing tools. In this numerical experiment, each sequence method was tested by three replications with three different set of 50 independent customers and the average result was recorded. Specifically, the numerical experiment was divided into two parts. In the first part, our sequencing model determined the optimal number of \( n \) hotels presented in the sequence and the sequence was re-optimized every time a new customer arrives, or \( M = 1 \). As shown in
the result of proposed model, the 9.31 hotel choices were selected to present in the sequence.

Moreover, if all 30 hotels were to be assigned in the sequence, the gained utility from a selected hotel would increase whereas the search cost would be much higher. To reflect this, in the second part, we fixed the total number of hotel choices selected to be presented in the sequence \(n\) at 30 hotels for all sequences.

The results indicate that our proposed model with the optimal number of 9.31 hotels generates the highest utility gained from hotels above the reservation price, lowest search cost, and lowest position from booked hotels, resulting to the best solution (i.e., lowest composite score). Moreover, our proposed model with the fixed 30 hotels generates a higher utility and higher number of sold rooms, resulting to a lower composite score compared with the other sequences provided by OTA sequencing tool. These results show the effectiveness of proposed model and highlight how our proposed model could improve the quality of the sequencing to fulfil what the customer needs. However, compared among the sequences provided by OTA sequencing tool, we observed that sorting by review rating generates the best solution (i.e., lowest composite score). Interestingly, even though the sorting by price is the most preferable sorting method, according to our survey result, the results here indicate the lowest effectiveness.

**Table 3.13** Comparison of sequence sorting performance by our proposed model with that by Web site function

<table>
<thead>
<tr>
<th>Number of hotels</th>
<th>Sequence method</th>
<th>Total search cost</th>
<th>Avg. utility/customer</th>
<th>Total position of booked hotels</th>
<th>Composite score (Lower is preferred)</th>
<th>Total sold rooms</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Optimal</strong> (n = 9.31)</td>
<td>Proposed model</td>
<td>162.12</td>
<td>1,539.31</td>
<td>229.67</td>
<td>-1,374.89</td>
<td>66.67</td>
</tr>
<tr>
<td><strong>Fixed</strong> (n = 30)</td>
<td>Proposed model</td>
<td>522.60</td>
<td>1,460.75</td>
<td>833.00</td>
<td>-932.20</td>
<td>66.67</td>
</tr>
<tr>
<td></td>
<td>Price</td>
<td>522.60</td>
<td>1,301.22</td>
<td>677.33</td>
<td>-770.29</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>Review rating</td>
<td>522.60</td>
<td>1,456.96</td>
<td>711.67</td>
<td>-927.58</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Star rating</td>
<td>522.60</td>
<td>1,409.54</td>
<td>892.00</td>
<td>-879.82</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Popularity</td>
<td>522.60</td>
<td>1,434.65</td>
<td>595.00</td>
<td>-903.13</td>
<td>60</td>
</tr>
</tbody>
</table>
Figure 3.8 highlights the impact of number of hotel choices and sequencing method on the composite score. In this experiment, the sequence methods, consisting of our proposed model, sorting by price, sorting by review rating, sorting by star rating, and sorting by popularity, were examined and compared. Also, the total number of hotels selected to present in each sequence was varied, where \( n \in \{10, 15, 20, 15, \text{ and } 30\} \). Each of sequence in every certain \( n \) was run by three replications with three different set of 50 independent customers.

According to the result shown in Figure 3.8, we observed the significant effect of number of shown hotels on the composite score. Interestingly, for each sequence method, there are a certain number of shown hotel choices that produce the best solution (i.e., lowest composite score). For instance, the sequence sorted by star rating will reach the lowest composite score when presenting 15 hotels in the sequence whereas the sequence sorted by price will reach the lowest composite score when presenting 25 hotels in the sequence. Furthermore, we observed the significant effect of the sequencing methods on the composite score. The result indicates that the sequence designed by our proposed model (i.e., multidimensional sorting criteria) leads to the best solution (i.e., lowest composite score) in every case of certain number of choices. These results provide managerial insights to re-consider the sequencing method together with the number of available choices in the sequence, implemented in an online shopping context.

![Comparison of sequencing methods and numbers of shown hotels](image)

**Figure 3.8** Comparison of sequencing methods and numbers of shown hotels

60
Table 3.14 reports the effect of re-sequencing period on the composite score and computation time. We considered the period to re-optimize the new sequence as every $M^{th}$ customer’s arrival, $M \in \{1, 5, 10, 20, \text{and } 50\}$. Each of them was test with the set of 50 independent customers. Note that the description of the re-optimize steps can be found in Section 3.4.6. We observed that the sequence should always be re-optimized to deal with the customer’s uncertainties (e.g., arrival order and preference), as this result shown in the lower composite score. However, the re-sequencing period need to be optimally decided because it has influence on the required computation time. The more often a sequence is re-optimized, the longer the computation time takes. In our numerical experiments, we decided to re-optimize the new sequence every new customer arrives, $M = 1$, as it generates the lowest composite score. Moreover, we decided to re-optimize the sequence every five customer’s arrival, $M = 5$, as it generates the good solution at an acceptable computation time. However, in the future research, the computation time will be reduced by using an efficient proposed heuristic.

<table>
<thead>
<tr>
<th>Re-sequence (every $M^{th}$ customer’s arrival)</th>
<th>Composite score (Lower preferred)</th>
<th>Number of sequences</th>
<th>Computation time/customer (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1,341.66</td>
<td>50</td>
<td>28.68</td>
</tr>
<tr>
<td>5</td>
<td>-1,057.30</td>
<td>10</td>
<td>6.69</td>
</tr>
<tr>
<td>10</td>
<td>-930.48</td>
<td>5</td>
<td>4.14</td>
</tr>
<tr>
<td>20</td>
<td>-850.17</td>
<td>3</td>
<td>1.90</td>
</tr>
<tr>
<td>50</td>
<td>-798.52</td>
<td>1</td>
<td>0.91</td>
</tr>
</tbody>
</table>

*Note: Re-optimizing the sequence every 1st and 5th customer’s arrival is selected in the numerical experiments.

3.6.4 Practical implication of the proposed model

At present, it is important for any service providers to adapt their services to compete with other service providers and satisfy the customer’s needs. In the next numerical experiment, we highlight the practical implementation of our sequencing model that could suggest the improvement ways for a hotel to increase the reservation rate. The characteristics of a sample hotel are presented in Table 3.15. Using the proposed model, we analysed the competitive position of this hotel in the current
market, which was ranked in number 23 out of 42 hotels. This is essential as the proposed model could incorporate the actual competitors and characteristics of potential customers to analyse the market condition. Based on our assessment, this hotel failed to get any reservations. According to Table 3.16, our proposed model recommends that, under the current hotel and service conditions, this hotel should reduce a room price from 1,291 Baht to less than 1,100 Baht to attract more customers.

However, an improvement of just one attribute (e.g., star rating or review rating) might not be enough to attract customers and remain competitive in the market. Therefore, in Table 3.17, we offer the guidelines to improve two attributes of hotel at the same time. For instance, to generate the reservation of four rooms, the hotel needs to reduce the price 700 Baht, and, at the same time, improve its service quality in order to get a review rating of at least 3.8. Otherwise, the hotel needs to reduce the price to 700 Baht and, at the same time, improve the hotel’s facilities in order to enhance a hotel star rating of at least 4.5. Since our proposed model suggests the improvement ways on the basis of the analysis of the current market condition (e.g., the selected area, potential competitors, and characteristics of potential customers), this strategy has a lot of potential to create a competitive advantage. This will help the hotel managers evaluate the direction of improvement that is most practical for the hotel.

**Table 3.15** Selected hotel characteristics

<table>
<thead>
<tr>
<th>Hotel information</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>1,291</td>
</tr>
<tr>
<td>Star rating</td>
<td>3</td>
</tr>
<tr>
<td>Review rating</td>
<td>3.4</td>
</tr>
<tr>
<td>Available room</td>
<td>9</td>
</tr>
<tr>
<td>Sold room</td>
<td>0</td>
</tr>
<tr>
<td>Ranking position</td>
<td>23 out of 42 hotels</td>
</tr>
</tbody>
</table>

**Table 3.16** Suggestion for service improvement based on one attribute

| Expected Number of sold rooms | 500 | 700 | 900 | 1,100 | 1,291 | 3 | 3.5 | 4 | 4.5 | 5 | 3.4 | 3.8 | 4.2 | 4.6 | 5 |
|-------------------------------|-----|-----|-----|-------|-------|---|-----|---|-----|---|-----|-----|-----|-----|---|---|
| Price (Baht)                  | 9   | 3   | 2   | 2     | 0     | 0 | 0   | 0 | 0   | 0 | 0   | 0   | 0   | 0   | 0 | 0 | 0 |
| Star rating                   |     |     |     |       |       |   |     |   |     |   |     |   |     |   |   |   |   |   |
| Review rating                 |     |     |     |       |       |   |     |   |     |   |     |   |     |   |   |   |   |   |
Table 3.17 Suggestion for service improvement based on two attributes

<table>
<thead>
<tr>
<th>Review rating</th>
<th>Expected number of sold rooms</th>
<th>Star rating</th>
<th>Price (Baht)</th>
<th>Expected number of sold rooms</th>
<th>Star rating</th>
<th>Price (Baht)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>500 700 900 1,100 1,291</td>
<td>500 700 900 1,100 1,291</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.4</td>
<td>9 3 2 2 0</td>
<td>3</td>
<td>9 3 2 2 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.8</td>
<td>9 4 3 3 0</td>
<td>3.5</td>
<td>9 3 2 2 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.2</td>
<td>9 5 5 3 0</td>
<td>4</td>
<td>9 3 2 2 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.6</td>
<td>9 7 5 3 1</td>
<td>4.5</td>
<td>9 4 2 2 0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>9 7 5 3 1</td>
<td>5</td>
<td>9 4 2 2 0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.7 Conclusion

Online travel agencies (OTAs) have become a major distribution channel for a hotel to reach more customers. Matching a hotel with a customer’s preference is a challenge, especially when dealing with a number of heterogeneous customers holding the multidimensional preferences. When searching for hotel on OTAs, the customers tend to use a OTAs sequencing tool to sort the sequence of hotel choices. However, the existing sequences of hotels are sorted by just one attributes such as sorting by price. In an online travel reservation, the search cost and the multidimensional selection criterion have been the critical concern by an online customer.

In the study of this chapter, we proposed a mathematical model, based on a two stage stochastic programming model, to determine a suitable (optimal) number of hotel choices presented on the website. Also, the candidate hotels were optimally assigned in the sequence by using multidimensional sorting criteria. We incorporated three goals concerning the search cost, expected utility gained from the hotel and effect of ranking positions in the sequence.

With this study, we make several contributions to the e-commerce, tourism industry and academic literature. We proposed a new approach called a two-stage stochastic programming model for solving an optimization problem of sequencing decision taken the uncertainties of customers. This methodology has never before been applied to this problem. We collected actual customer data through a survey and actual hotel information from OTAs. The multidimensional preferences and heterogeneity of customers were realistically captured. Using survey data, we found that the numerical results closely represent the results to be expected from actual
usage of the model. Different from previous studies, an optimal number of hotels presented on the sequence were determined to reduce the search cost while maintaining a high utility gained from available hotels. Also, our model helps hotel managers to analyse a hotel’s competitive position in the market and is able to provide useful guidelines to improve the service performance. Moreover, our model can be applied to other types of online products; it is not limited to hotels.

From the numerical experiments on the simulated data, we showed that the sequence designed by the proposed model outperformed than the existing sequences provided by an OTA sequencing tool.

The interesting findings are summarized as following:

1. Multidimensional sorting criteria

We found that the sequence of hotel choices has impact to determine the customer’s choice decision. Specifically, the customers will reach different hotel choices when searching from different sequences, thereby generating the hotel experience levels. The multidimensional sorting criteria were suggested through the proposed model. That is, the hotel with a higher possibility to attract more customer, a higher net utility, a higher review rating, a higher star rating, and a higher price should be assigned in the upper positions in the sequence. Also, the sequence needs to be always renewed at the suitable period to deal with the customer’s uncertainties.

2. The optimal number of choices selected to present on the website

We found that the number of choices offered to the customers should be decided strategically together with the quality of candidate hotel choices to balance the search cost and gained utility from the candidate hotels.

3. Strategy to create the competitive advantage

In the competitive market, the hotels need to adapt their services to fulfil the customer’s need and compete with other hotels. It is essential to improve their weakness by analysing the current market conditions. The model suggests making an improvement at various attributes, such as price, star rating, and review rating, to drive the hotel more attractive relative to other hotels.
Chapter 4
Pricing Model of Sale Conditions based on Cancellation Policy

In this chapter, the no show and cancellation behaviours of customers in the hotel reservation were incorporated in the pricing decision of hotel room. Our study proposed a pricing model for a hotel who offers the same room service with various sale conditions based on cancellation policy and reservation period. The background of this study is provided in Section 4.1. The research methodology is summarized in Section 4.2. The detailed problem description along with the proposed model is elaborated in Section 4.3. The analysis of proposed model is performed in Section 4.4. The numerical experiment is then described in Section 4.5. In Section 4.6, we discuss the results and draw the managerial insights.

4.1 Background

In the hotel reservation, most of customers make an advance reservation to guarantee the room availability and get the special deal. However, the number of advance booked rooms has often been cancelled in the last minute period. Also, some customers fail to show up on a target date without any notice or cancellation. The potential no show of customers has impact on the hotel’s profit and the customer’s cancellation penalty. For a hotel, the no show and cancellation behaviours lead to a significant loss of potential profit because an unsold room on the specific date cannot be resold to other customers. It was reported that 3.4% of the hotel management problems occurred from the no-show rate (DeKay et al., 2004). Moreover, the no-show customers face with the penalty charged as the cancellation fee.

To deal with the effect of no show and cancellation, most of hotels allow overbooking, adopt the dynamic pricing strategy and offer various sale conditions based on the cancellation policy. Interestingly, we considered a hotel offering a same room service with different sale conditions along two reservation periods, as shown in Figure 4.1. For instance, on Hotels.com website, “Anantara Hua Hin Resort” offered the “Premium Sea View Room with breakfast” for one night staying on April 18,
2017 with different two sale conditions, according to the booking date and cancellation policy. In the normal period (i.e., booking date on April 7, 2017), “Anantara Hua Hin Resort” offered the “Premium Sea View Room with breakfast” at 7,362 Thai Baht with “a full refund policy for cancellation” (i.e., free cancellation before April 15, 2017). Our study defines the sale condition with “a full refund policy for cancellation” that “the mild condition”. On the other hand, in the last minute period (i.e., two day before arriving), the price of same room is adjusted to 6,462 Thai Baht with “the non-refund policy for cancellation”. Our study defines the sale condition with “a non-refund policy for cancellation” that “the restriction condition”.

Normal period: 7,362 Baht & “Full refund policy for cancellation”

Last minute period: 6,462 Baht & “Non-refund policy for cancellation”

Figure 4.1 Copy of the Agoda webpage describing the example of sale conditions based on cancellation policy and booking period
The sale scenario has been varied among the hotels and websites along two reservation periods. In Figure 4.2, we summary the potential sale scenarios with the definition of each sale condition, including “the mild condition”, “the restriction condition” and “the last minute condition”.

**Sale condition:**
- **Mild condition** \((n)\): Full refund policy or Partial refund policy
- **Restriction Condition** \((r)\): Non-refund policy for cancellation
- **Last Minute Condition** \((l)\): Non-refund policy for cancellation, offered in the last minute period,

**Potential sale scenarios:**

<table>
<thead>
<tr>
<th>Normal period</th>
<th>Last minute period</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mild condition ((n))</td>
<td>1. Mild condition ((n))</td>
</tr>
<tr>
<td>2. Restriction condition ((r))</td>
<td>2. Restriction condition ((r))</td>
</tr>
<tr>
<td>3. Mild condition ((n))</td>
<td>3. Restriction condition ((r))</td>
</tr>
<tr>
<td>4. Restriction condition ((r))</td>
<td>4. Last minute condition ((l))</td>
</tr>
<tr>
<td>5. Mild condition ((n))</td>
<td>5. Last minute condition ((l))</td>
</tr>
<tr>
<td>6. Restriction condition ((r)) &amp; Mild condition ((n))</td>
<td>6. Last minute condition ((l))</td>
</tr>
</tbody>
</table>

**Figure 4.2** Summary of potential sale scenarios

In the present study, we considered a hotel offering a same room service with different sale condition based on booking period and cancellation policy. Motivated by a common observation in practice, two sale conditions for a same room service were considered along two reservation periods. In the normal period, a hotel offers (i) “Mild condition” \((n)\) at the higher price with “a partial refund policy” or “a full refund policy for cancellation”. In the last minute period, if an unsold room is available, (ii) “Restriction condition” \((r)\) is offered at the lower price with “a non-refund policy for cancellation”. Thus, we proposed a pricing model that incorporates two sale conditions of “the mild condition and restriction condition” \((n,r)\) along two reservation periods. The objective was to determine an optimal price of two sale
conditions so that total profit of hotel was maximized. The customers were assumed as the myopic customer who will consider the sale condition available at the current period whereas the future sale condition is unknown. Moreover, we examined several potential scenarios when a hotel offers different sale scenarios including (1) “the mild condition” \((n)\), (2) “the restriction condition” \((r)\), (3) “the mild and restriction conditions” \((n,r)\), (4) “the restriction and last minute conditions” \((r,l)\), (5) “the mild and last minute conditions” \((n,l)\), and (6) “the restriction, mild and last minute conditions” \((r,n,l)\).

4.2 Research Methodology

This section describes the outline of research methodology to summary overall process of research conductions. Specifically, this study has applied a mathematical model as the main approach to represent the stated problem and solve to discuss the insights. The main steps of research activities are summarized as follows.

In the first step, we reviewed the prior literatures related to the revenue management, no show and cancellation policy in the tourism and other service industries. Also, we observed the sale conditions available on the OTAs website to understand the practical setting for the sale conditions and cancellation policy.

In the second step, we formulated the detailed problem as a mathematical model based on the one-dimensional Hotelling’s model whereas the important behaviours were appropriately assumed.

In the third step, after a model was formulated, we optimally solved the proposed model by using the optimization software, namely, Wolfram Mathematica 7. In this stage, the proposed model and findings were analysed and comprehensively discussed.

In the fourth step, we conducted the numerical experiments to graphically show the results and draw the managerial insights.

4.3 Problem Description and Proposed Model

We studied a hotel offering various sale conditions for a same room through the online travel agencies (OTAs). Taking the possibility of no show and cancellation
into account for the pricing model, a hotel differentiates various sale conditions in term of room price and cancellation policy along two reservation periods. Our focus on the no-show behaviour reflects the common practice in the hotel reservation and tourism literatures (Sierag et al., 2015; DeKay et al., 2004).

In the proposed model, we considered two sale conditions offered along two reservation periods. In the normal period, one sale condition, namely, “Mild condition” \((n)\), charges a higher price with “the full refund policy” or “partial refund policy for cancellation”. That mean, a customer will pay higher at the price of mild condition \((p_n)\) whereas he could get refund when making a cancellation at \(\beta_n v\) from the paid price of \(p_n\). Thus, the cancellation fee under the mild condition is imposed at \(\beta_n v - p_n\). Note that \(\beta_n\) reflects the proportion value of refund from cancellation, where \(0 < \beta_n < 1\) and \(v\) represents the value of room service. For instance, if \(\beta_n\) is 0, no refund is provided and thus, the cancellation fee is imposed at the full price of \(p_n\).

However, if \(\beta_n\) increases, the amount of refund increases and until some point that reaches to 1, a higher \(\beta_n\) leads to free cancellation at \(\beta_n v = p_n\). In the last minute period, another sale condition, namely, “Restriction condition” \((r)\), charges a lower price with the non-refund policy for cancellation. That mean, a customer will pay lower at the price of restriction condition \((p_r)\) whereas he cannot get any refund from the paid price if fails to show up or makes a cancellation. Thus, the cancellation fee under “the restriction condition” is imposed at the full price of \(p_r\).

Accordingly, the following conditions are required to set up two sale conditions. \(p_n\) is charged higher than \(p_r\) whereas the cancellation fee imposed by the restriction condition at \(-p_r\) is higher than that by the mild condition at \(\beta_n v - p_n\). The cancellation fee of mild condition at \(\beta_n v - p_n\) can be imposed from zero to a full price of \(p_n\), where \(0 < \beta_n < 1\) and \(\beta_n v - p_n \leq 0\). Moreover, the value of room service \((v)\) needs to be higher than price and cost of room service \((c)\) to gain the positive demand. Furthermore, the prices of sale conditions need to be suitably charged to cover the cost of room service \((c)\) at the hotel’s profitability. Thus, the following necessary conditions \(p_n > p_r, \beta_n v - p_n > -p_r, \beta_n v - p_n \leq 0, 0 < \beta_n < 1, v > p_n, v > c, p_r > c, p_n > c, c > 0\) were assumed.
We developed the pricing model that includes two decision stages. According to Figure 4.3, the marketing planner sets the proportion value of refund ($\beta_n$) in the cancellation policy of mild condition ($n$), where $0 < \beta_n < 1$. Given $\beta_n$, “the mild condition” ($n$) is offered in the normal period to overall customer in the market. At the first stage decision, the prices of mild condition ($p_n$) is optimally determined according to $\beta_n$. After that, if an unsold room is available, “the restriction condition” ($r$) is offered with the non-refund policy for cancellation in the last minute period to the remaining customers. At the second stage, the price of restriction condition ($p_r$) is optimally determined. In order to attract demand for the remaining last minute customers, the price of restriction condition ($p_r$) should be lower, thereby $p_r < p_n$.

![Marketing plan](image)

**Figure 4.3** Two stages of decision

By incorporating the possibility of no show and cancellation, we believe that the perception of customers toward the sale conditions is captured and thus, the sale conditions have impact on the customer’s choice decision. Using one-dimensional Hotelling’s model (Hotelling, 1929; Osborne and Pitchik, 1987; Balvers and Szerb, 1996), we assumed that the heterogeneous customers have different possibility to cancel the reservation which incurs the no-show case. The no-show possibility is represented by $\alpha$. For instance, a business traveller may have a higher possibility of no show than a leisure traveller due to the unexpected and uncertain business trip (DeKay et al., 2004). For different customers, $\alpha$ is randomly drawn from a uniform distribution on the line segment of $\alpha$, where $0 \leq \alpha \leq 1$. We modelled the customer’s utility for each sale condition as the function of price, cancellation fee, value of room...
service and no-show possibility. The utility function of each sale condition incorporates both (i) the possibility of no-show case ($\alpha$) and (ii) the possibility of show-up case ($1-\alpha$). The customer was assumed as the myopic customer who will consider the sale condition offered at the current period whereas the future sale condition is unknown. The customer’s choice decision in each reservation period is described as following.

In the normal period, “the mild condition” ($n$) is offered. For “the mild condition” ($n$), if a customer cancels the reservation with the probability of $\alpha$, he could get a refund at $\beta_nv$ from the paid price at $p_n$. That mean, he will be imposed the cancellation fee at $\beta_nv-p_n$. However, if a customer shows up to use a room service with the probability of $(1-\alpha)$, he will get the value of room service ($v$) and pay at the price of mild condition ($p_n$). Eq. (4.1) shows the expected utility of mild condition ($U_n$). Moreover, we assumed that the customer will choose “the mild condition” offered in the normal period if his expected utility is positive, where $U_n>0$. Let $U_n=0$ at $\alpha=\alpha^*$ where $\alpha^* = \frac{v-p_n}{v(1-\beta_n)}$ as shown in Eq. (4.2). Thus, the customer with $\alpha$ under $0<\alpha<\alpha^*$ will choose “the mild condition” ($n$) whereas the remaining customers with $\alpha$ under $\alpha^* \leq \alpha \leq 1$ will leave “the mild condition” available in the normal period as the expected utility is negative. The distribution of consumer in the normal period is provided in Figure 4.4.

$$U_n = \alpha(\beta_nv - p_n) + (1-\alpha)(v - p_n)$$  \hspace{1cm} (4.1)

$$\alpha^* = \frac{v - p_n}{v(1-\beta_n)}$$  \hspace{1cm} (4.2)

**Normal period: Mild condition ($n$)***

<table>
<thead>
<tr>
<th>$\alpha^*$</th>
<th>$U_n &gt; 0$</th>
<th>$U_n &lt; 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figure 4.4** The distribution of buyers in the normal period

71
After missing the first sale condition available in the normal period, the remaining customers, with \( \alpha \) where \( \alpha^* \leq \alpha \leq 1 \), will be offered with the new sale condition, namely, “the restriction condition” \((r)\), in the last minute period. However, offering “the restriction condition” \((r)\) is uncertain as it is offered if an unsold room is available. For “the restriction condition” \((r)\), if a customer fails to show up with the probability of \( \alpha \), he will be imposed the cancellation fee at the full price of \((p_r)\). However, if a customer shows up to use a room service with the probability of \((1-\alpha)\), he will get the value of room service \((v)\) and pay at the price of restriction condition \((p_r)\). Eq. (4.3) represents the expected utility of restriction condition \((U_r)\). Also, the customer will choose “the restriction condition” if \( U_r > 0 \). Let \( U_r = 0 \) at \( \alpha = \alpha^* \) where \( \alpha^* = \frac{v - p_r}{v} \) as shown in Eq. (4.4). Thus, the customer with \( \alpha \) where \( \alpha^* \leq \alpha < \alpha' \) will choose “the restriction condition” \((r)\). Moreover, the remaining customers with \( \alpha \) where \( \alpha' \leq \alpha \leq 1 \) will leave to book a hotel room as the expected utility is negative. So, the hotel will leave the group of customers with a very high \( \alpha \). The distribution of consumer in the last minute period is provided in Figure 4.5.

\[
U_r = \alpha(-p_r) + (1-\alpha)(v-p_r)
\]  
\[
\alpha' = \frac{v - p_r}{v}
\]

\begin{figure}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
 & \( U_r > 0 \) & \( U_r < 0 \) \\
\hline
\( D_r \) & & \\
\hline
\end{tabular}
\caption{Last minute period: Restriction condition \((r)\)}
\end{figure}

Figure 4.5 The distribution of buyers in the last minute period

After two sale conditions were offered, we derived the distribution of total buyers along \( 0 \leq \alpha \leq 1 \) as shown in Figure 4.6. We next developed the demand functions based on the customer’s choice model. As the myopic customer was assumed, the customer will book a room if the expected utility from the sale condition offered in the current period is positive. We assumed that the customers with \( \alpha \) are
along the line segment of $0 \leq \alpha \leq 1$, where $0 \leq \alpha^* \leq \alpha^{'} \leq 1$. According to the utility function, we derived that the customer with $\alpha$ where $0 \leq \alpha < \alpha^*$ will choose “the mild condition” ($n$) and the customers with $\alpha$ where $\alpha^* \leq \alpha < \alpha^{'}$ will choose “the restriction condition” ($r$) and other remaining customers with $\alpha$ where $\alpha^{'} \leq \alpha \leq 1$ the will leave without booking. The demand functions of the mild condition ($D_n$) and the restriction condition ($D_r$) are derived as Eq. (4.5) and Eq. (4.6). The total demand for two sale conditions ($D_{n,r}$) is shown in Eq. (4.7).

\[
\begin{align*}
D_n &= \alpha^* \quad 0 < \alpha^* \\
D_r &= \alpha^{' - \alpha^*} = \frac{v - p_r}{v} - \frac{v - p_n}{v(1 - \beta_n)} \\
D_{n,r} &= \alpha^{' - \alpha^*} = \frac{p_r}{v} 
\end{align*}
\]

(4.5)

(4.6)

(4.7)

Moreover, we examined the expected sold rooms from a show-up customer, representing by $(1 - \alpha)$. The expected sold rooms from two sale conditions are derived in Eq. (4.8). We also used Eq. (4.9) to calculate the show-up ratio and Eq. (4.10) to calculate the no-show ratio.

\[
\begin{align*}
ES_{n,r}(p_n, p_r) &= \int_{0}^{\alpha^*} (1 - \alpha)d\alpha + \int_{\alpha^*}^{\alpha^{'}} (1 - \alpha)d\alpha \\
Show-up ratio: \quad S_{n,r}(p_n, p_r) &= \frac{\int_{0}^{\alpha^*} (1 - \alpha)d\alpha + \int_{\alpha^*}^{\alpha^{'}} (1 - \alpha)d\alpha}{\alpha^{'}} \\
No-show ratio: \quad N_{n,r}(p_n, p_r) &= \frac{\int_{\alpha^{'}}^{\alpha^{'}} (\alpha)d\alpha + \int_{\alpha^{'}}^{\alpha^{'}} (\alpha)d\alpha}{\alpha^{'}}
\end{align*}
\]

(4.8)

(4.9)

(4.10)

In the next section, we will describe the pricing decision for offering “the mild and restriction conditions” ($n, r$) where the decisions are made from a pricing model.
Moreover, we will discuss the analysis for several scenarios from combining different sale conditions along two reservation periods.

### 4.4 Decision Analysis

In this section, we analysed our proposed model that offers two sale conditions of “the mild and restriction conditions” \((n,r)\) along two reservation periods. To compare the expected profit from sale conditions with that from our proposed model, we discussed other five sale scenarios in which a hotel makes an optimal price decision on different sale conditions. Thus, all six scenarios of offering sale conditions were discussed and compared. Six scenarios include offering one sale condition of (1) “the mild condition” \((n)\) and (2) “the restriction condition” \((r)\), offering two sale conditions of (3) “the mild and restriction conditions” \((n,r)\), (4) “the restriction and last minute conditions” \((r,l)\), (5) “the mild and last minute conditions” \((n,l)\) and offering three sale conditions of (6) “the restriction, mild and last minute conditions” \((r,n,l)\). Figure 4.7 summarizes the pricing decision for six sale scenarios along two reservation periods.
In Section 4.4.1, we begin with the analysis of our proposed model that focuses on “the mild and restriction conditions” \((n,r)\) along two reservation periods.

### 4.4.1 Decision for offering the mild and restriction conditions \((n,r)\) by the proposed model

In this case, a hotel offers a same room service with two sale conditions along two reservation periods. In the normal period, “the mild condition” \((n)\) is offered whereas, in the last minute period, “the restriction condition” \((r)\) is offered. Accordingly, a hotel could generate the revenue from selling two sale conditions. According to Section 4.3, “the mild condition” \((n)\) covers the demand at the range of \(\alpha\), where \(0 \leq \alpha < \alpha\). The revenue of no-show case \((\alpha)\) is generated from the cancellation fee at \((p_n - \beta_p v)\) and the revenue of show-up case \((1 - \alpha)\) is generated from the room service at the price of \(p_n\) deduct the service cost \((c)\). Moreover, “the

![Figure 4.7 Potential sale scenarios of offering sale conditions in two reservation periods](image-url)

<table>
<thead>
<tr>
<th>Stage 1: Normal period</th>
<th>Stage 2: Last minute period</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Mild condition ((n)) (p^*_n)</td>
<td>1. Mild condition ((n))</td>
</tr>
<tr>
<td>2. Restriction condition ((r)) (p^*_r)</td>
<td>2. Restriction condition ((r))</td>
</tr>
<tr>
<td>3. Mild condition ((n)) (p^*_n)</td>
<td>3. Restriction condition ((r)) (p^*_r)</td>
</tr>
<tr>
<td>4. Restriction condition ((r)) (p^*_r)</td>
<td>4. Last minute condition ((l)) (p^<em>_l = fp^</em>_r)</td>
</tr>
<tr>
<td>5. Mild condition ((n)) (p^*_n)</td>
<td>5. Last minute condition ((l)) (p^<em>_l = fp^</em>_n)</td>
</tr>
<tr>
<td>6. Restriction condition ((r)) &amp; Mild condition ((n)) (p^<em>_n, p^</em>_r)</td>
<td>6. Last minute condition ((l)) (p^<em>_l = fp^</em>_r)</td>
</tr>
</tbody>
</table>
restriction condition” \((r)\) covers the demand under the range of \(\alpha\), where \(\alpha^* \leq \alpha < \alpha'\). The revenue of no-show case \((\alpha)\) is generated from cancellation fee at \(p_r\) and the revenue of show-up case \((1-\alpha)\) is generated from the room service at the price of \(p_r\) deduct the cost of room service \((c)\). The hotel determines the optimal prices of two sale conditions \((p_n^*, p_r^*)\) so that total profit is maximized. The total expected profit of offering two sale conditions \((II_{n,r})\) is provided in Eq. (4.11).

\[
II_{n,r}(p_n, p_r) = \int_0^{\alpha^*} \left( \alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c) \right) d\alpha + \int_{\alpha^*}^{\alpha'} \left( \alpha(p_r) + (1 - \alpha)(p_r - c) \right) d\alpha
\]

(4.11)

Where \(\alpha^* = \frac{v - p_n}{v(1 - \beta_n)}\), \(\alpha' = \frac{v - p_r}{v}\).

**Lemma 1** For offering two sale conditions \((n,r)\), the optimal prices of \(p^*_n, p^*_r\) and optimal profit \((II_{n,r}^*)\) are.

The decision problem under “the mild and restriction conditions” \((n,r)\) is

\[
\text{Max } II_{n,r}(p_n, p_r) = \int_0^{\alpha^*} \left( \alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c) \right) d\alpha + \int_{\alpha^*}^{\alpha'} \left( \alpha(p_r) + (1 - \alpha)(p_r - c) \right) d\alpha
\]

Let use the first order condition to obtain the optimal price decision for mild and restriction conditions \((n,r)\). By \( \frac{\partial II_{n,r}(p_n, p_r)}{\partial p_n} = 0 \) and \( \frac{\partial II_{n,r}(p_n, p_r)}{\partial p_r} = 0 \), we obtain

\[
p^*_n = \frac{v(c + (-2 + \beta_n)v)}{(-2 + \beta_n)c + (3 - 2\beta_n)v}
\]

(4.12)

\[
p^*_r = \frac{(-1 + \beta_n)v^2}{(-2 + \beta_n)c + (-3 + 2\beta_n)v}
\]

(4.13)

Let plug in \(p^*_n\) and \(p^*_r\) into the profit function of \(II_{n,r}\), we obtain

\[
II^*_{n,r}(p^*_n, p^*_r) = \frac{(-2 + \beta_n)(c - v)^2}{2(-2 + \beta_n)c + (6 - 4\beta_n)v}
\]

(4.14)

**Proof** To ensure that the optimal prices in Lemma 1 leads to a unique global maximum total profit (Chiang, 1984), we require conditions that \(\frac{\partial^2 II_{n,r}(p_n, p_r)}{\partial p_n^2} < 0\), \(\frac{\partial^2 II_{n,r}(p_n, p_r)}{\partial p_r^2} > 0\), and \(\frac{\partial^2 II_{n,r}(p_n, p_r)}{\partial p_n \partial p_r} < 0\).
By solving all necessary conditions, we obtain
\[ \frac{\partial^2 H_{n,r}(p_n, p_r)}{\partial p_n^2} = \frac{-2 + \beta_n}{(1 + \beta_n)^2 v} \]
and
\[ \frac{\partial^2 H_{n,r}(p_n, p_r)}{\partial p_r^2} = \frac{c - 2v}{v^2} \]
which satisfy the required conditions of
\[ \frac{\partial^2 H_{n,r}(p_n, p_r)}{\partial p_n^2} < 0 \]
and
\[ \frac{\partial^2 H_{n,r}(p_n, p_r)}{\partial p_r^2} < 0 \]
where \( v > c \) and \( 0 < \beta_n < 1 \). Moreover, we obtain
\[ \frac{\partial^2 H_{n,r}(p_n, p_r)}{\partial p_n \partial p_r} = \frac{(-2 + \beta_n)c + (3 - 2\beta_n)v}{(-1 + \beta_n)^3 v^3} \]
which leads to the necessary condition of
\[ \frac{\partial^2 H_{n,r}(p_n, p_r)}{\partial p_n \partial p_r} > 0, \text{ where } v > c, 0 < \beta_n < 1. \]

**Proposition 1** As \( \beta_n \) increases, it allows a hotel to set the higher price of the mild condition and satisfy the larger demand, resulting in the higher total profit.

We analyse offering two sale conditions \((n,r)\) and hotel’s profitability as follow. As \( \beta_n \) increases, it allows a hotel to set the higher price and the higher refund of “the mild condition” and thus, gain more demand in the normal period. When more rooms are sold at the higher price, the total profit will increase. Interestingly, even though the price of mild condition is charged higher, a hotel still gains the larger demand for customers. This result could be intuitionally explained that the customer tends to be sensitive to the possibility of refund rather than the price of room.

**Proposition 2** Average total profit per customer from offering the mild and restriction conditions \((\text{Avg. } H^*_n, r)\) could be determined by the value of \( \frac{1}{2}(-c + v) \).

It is basically to determine an average total profit per customer by the total profit and total demand of two sale conditions, thus, \( \text{Avg. } H^*_n, r = \frac{H^*_n, r}{D^*_n, r} \). Although total demand and total profit increase in \( \beta_n \), the increasing ratio of total demand is higher than the increasing ratio of total profit. As discussed earlier, the profit for each customer is generated differently according to the no-show and show-up customers and thus, the no-show customer will give the lower profit at the higher \( \beta_n \). Accordingly, an average profit per customer \((\text{Avg. } H^*_n, r)\) tends to be the same in every
point of $\beta_n$ but it could be constantly determined by the cost and value of room service.

**Lemma 2** Total expected sold rooms from the mild and restriction conditions ($ES_{n,\beta}$) increases in $\beta_n$.

The expected sold rooms are obtained by the show-up customers who come to use the room service without cancellation. As $\beta_n$ increases, total expected sale room ($ES_{n,\beta}$) increases. It is intuitively explained that when the refund for cancellation in high, the demand for customers increases, thereby generating the higher possibility to sale rooms. These results lead to the insight that $\beta_n$ could be the mechanism to adjust the demand of occupied rooms from the show-up customers with the availability of rooms, as discussed in Proposition 3.

**Proposition 3** As the availability of rooms is limited, a hotel is able to adjust the demand of occupied room with the available rooms by using $\beta_n$.

Given $\int_0^{\beta_n} (1-\alpha) d\alpha \leq C \times (1-s)$,

$$\beta_n = \frac{2c^2 - 4c^2 C + 4c^2 Cs - 7cv + 14cCv - 14cCsv + 5v^2 - 12Cv^2 + 12Csv^2 + \sqrt{c^2v^3 - 2c^2 Cv^2 + 2c^2 Csv^2 - 2cv^3 + 4cCv^3 - 4cCsv^3 + v^4 - 2Cv^4 + 2Csv^4}}{(c^2 - 2c^2 C + 2c^2 Cs - 4cv + 8cCv - 8cCsv + 3v^2 - 8Cv^2 + 8Csv^2)}$$

Where $0 < \beta_n < 1$, $C$ is the available supply of rooms and $s$ is the ratio of safety stock.

According to Lemma 2, when $\beta_n$ increases, total expected sold room (i.e., total demand of occupied room) increases. However, when the demand of occupied room exceeds the hotel’s room availability, over sale might damage the hotel’s reputation and the customer’s loyalty. It is essential for a hotel to implement an appropriate $\beta_n$ and manage the expected sold rooms with the room availability. Therefore, where $\int_0^{\beta_n} (1-\alpha) d\alpha \leq C \times (1-s)$, $\beta_n$ is the maximum level of refund proportion that can increase the expected sale rooms but not exceed the available supply of room. Although the higher $\beta_n$ could lead to the higher price, the higher demand, and the
higher profit, it needs to be strategically implemented to correspond with the room availability and other hotel’s conditions. Thus, our proposed model can be the simple tool that helps a hotel implements $\beta_n$ to manage the room availability.

4.4.2 Decision for offering one sale condition

4.4.2.1 Mild condition ($n$)

In this case, a hotel provides one sale condition, namely, “the mild condition” ($n$), to satisfy all demand of customers along two reservation periods. With “the mild condition” ($n$), a hotel charges the price at $p_n$ and provides the some refund for the cancelled room at $\beta_n v$. Thus, the revenue of no-show case ($a$) is generated from cancellation fee at $(p_n - \beta_n v)$ and the revenue of show-up case ($1 - a$) is generated from the room service at the price of $p_n$ deduct the service cost ($c$). The hotel determines the price of mild condition ($p_n$) and the expected profit of offering mild condition ($\Pi_n$) is

$$\Pi_n(p_n) = \int_0^{x^*} (\alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c)) d\alpha$$

Where $x^* = \frac{v - p_n}{v(1 - \beta_n)}$

**Lemma 3** For offering one sale condition of mild condition ($n$), the optimal price ($p^*_n$) and optimal profit ($\Pi^*_n$) is

The decision problem under “the mild condition” ($n$) is

$$\max \Pi_n(p_n) = \int_0^{x^*} (\alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c)) d\alpha$$

Let use the first order condition to obtain the optimal price decision for the mild condition ($n$). By \(\frac{d\Pi_n(p_n)}{dp_n} = 0\), we obtain.

$$p^*_n = \frac{(\beta_n c - v) v}{c + (-2 + \beta_n) v}$$

(4.16)

Let plug in $p^*_n$ into the profit function of $\Pi_n(p_n)$, we obtain
\[ H^*_n(p^*_n) = -\frac{(c-v)^2}{2(c+(-2+\beta)v)} \]  \hspace{1cm} (4.17)

### 4.4.2.2 Restriction condition \((r)\)

In this case, a hotel provides one sale condition, namely “the restriction condition” \((r)\), to satisfy all demands of customers along two reservation periods. With “the restriction condition” \((r)\), a hotel charges the price at \(p_r\) with “the non-refund policy for cancellation”. Thereby, all of payments are counted as the revenue for the hotel. Accordingly, \(\alpha\) represents the no-show case which generates the revenue from cancellation fee at \(p_r\) and \((1-\alpha)\) represents the show-up case which generates the revenue from the price of \(p_r\) deduct with the cost of room service \((c)\).

The hotel determines the price of restriction condition \((p_r)\) and the expected profit from offering the restriction condition \((H_r)\) is provided as following.

\[ H_r(p_r) = \int_0^{\alpha^*} (\alpha(p_r)+(1-\alpha)(p_r-c))d\alpha \]  \hspace{1cm} (4.18)

Where \(\alpha^* = \frac{v-p_r}{v}\)

**Lemma 4** For offering one sale condition of restriction condition \((r)\), the optimal price \((p^*_r)\) and optimal profit \((H^*_r)\) are

The decision problem under “the restriction condition” \((r)\) is

\[ \text{Max} \ H_r(p_r) = \int_0^{\alpha^*} (\alpha(p_r)+(1-\alpha)(p_r-c))d\alpha \]

Let use the first order condition to obtain the optimal price decision for the restriction condition \((r)\). By \(\frac{dH_r(p_r)}{dp_r} = 0\), we obtain.

\[ p^*_r = -\frac{v^2}{c-2v} \]  \hspace{1cm} (4.19)

Let plug in \(p^*_r\) into the profit function of \(H_r\), we obtain

\[ H^*_r(p^*_r) = -\frac{(c-v)^2}{2(c-2v)} \]  \hspace{1cm} (4.20)
4.4.3 Decision for offering two sale conditions

4.4.3.1 Restriction condition (r) and Last minute condition (l)

In this case, a hotel provides two sale conditions, namely, “the restriction condition and the last minute condition” (r,l), to satisfy the demand of customers along two reservation periods. In the normal period, “the restriction condition” (r) is offered at the normal price of \( p_r \) with “the non-refund policy for cancellation”. In the last minute period, “the last minute condition” (l) is offered at the discount price of \( f p_r \) with “the non-refund policy for cancellation”, where \( f > 0 \). These two sale conditions impose the cancellation fee at a full price of \( p_r \) and \( f p_r \) from a no-show customer. Accordingly, a hotel can generate the revenue from selling two sale conditions along two reservation periods. That is, “the restriction condition” (r) covers the demand under the range of \( \alpha \), where \( 0 \leq \alpha < \alpha' \). While the revenue of no-show case (\( \alpha \)) is generated from the cancellation fee at \( p_r \), the revenue of show-up case (\( 1-\alpha \)) is generated from the room service at price of \( p_r \) deduct the service cost (c). Similarly, “the last minute condition” (l) covers the demand under the range of \( \alpha \), where \( \alpha' \leq \alpha < \alpha'' \). While the revenue of no-show case (\( \alpha \)) is generated from cancellation fee at \( f p_r \), the revenue of show-up case (\( 1-\alpha \)) is generated from the price of \( f p_r \), deduct the cost of room cost (c). The hotel determines the optimal prices of two conditions and the expected total profit of offering two sale conditions of the restriction and last minute conditions (\( II_{r,l} \)) is.

\[
II_{r,l}(p_r) = \int_0^{\alpha'} (\alpha p_r + (1-\alpha) (p_r - c)) d\alpha + \int_{\alpha'}^\alpha (\alpha (f p_r) + (1-\alpha) (f p_r - c)) d\alpha
\]

\[
\text{Where } \alpha' = \frac{v - p_r}{v}, \quad \alpha'' = \frac{v - f p_r}{v}
\]

Lemma 5 For offering two sale conditions of restriction condition (r) and last minute condition (l), the optimal prices of \( p_r^* \) and \( p_l^* \) and optimal profit (\( II_{r,l}^* \)) are.

The decision problem under “the restriction and last minute conditions” (r,l) is

\[
\text{Max } II_{r,l}(p_r) = \int_0^{\alpha'} (\alpha p_r + (1-\alpha) (p_r - c)) d\alpha + \int_{\alpha'}^\alpha (\alpha (f p_r) + (1-\alpha) (f p_r - c)) d\alpha
\]
Let use the first order condition to obtain the optimal price decision for restriction and last minute conditions \((r,l)\). By \(\frac{dH_{r,l}(p_r)}{dp_r}=0\), we obtain

\[
p_r^* = \frac{v^2}{-cf^2 + 2(1+(-1+f)f)v}
\]  
(4.22)

\[
p_l^* = fp_r^* = f \frac{v^2}{-cf^2 + 2(1+(-1+f)f)v}
\]  
(4.23)

Let plug in \(p_r^*\) into the profit function of \(H_{r,l}^*\), we obtain

\[
H_{r,l}^*(p_r^*) = \frac{-c^2f^2 - 2c(1+(-1+f)f)v + v^2}{2cf^2 - 4(1+(-1+f)f)v}
\]  
(4.24)

In the next section, we will incorporate “the mild condition” \((n)\) with “the last minute condition” \((l)\) along two reservation periods.

**4.4.3.2 Mild condition \((n)\) and Last minute condition \((l)\)**

In this case, a hotel provides two sale conditions, namely, “the mild condition and the last minute condition” \((n,l)\) for a same room along two reservation periods. In the normal period, “the mild condition” \((n)\) is offered at the normal price of \(p_n\) with “the full refund policy” or “the partial refund policy for cancellation”. In the last minute period, “the last minute condition” \((l)\) is offered at the price of \(fp_n\) with “the non-refund policy for cancellation”, where \(f >0\). Accordingly, a hotel can generate revenue from two sale conditions along two reservation periods. That is, “the mild condition” \((n)\) covers the demand under the range of \(\alpha\), where \(0 \leq \alpha < \alpha^*\). The revenue of no-show case \((a)\) is generated from cancellation fee at \((p_n - \beta_n v)\) whereas the revenue of show-up case \((1-\alpha)\) is generated from the room service at the price of \(p_n\) deduct the cost of service room \((c)\). “The last minute condition” \((l)\) covers the demand under the range of \(\alpha\), where \(\alpha^* \leq \alpha < \alpha'\). The revenue of no-show case \((a)\) is generated from cancellation fee at \(fp_n\) whereas the revenue of show-up case \((1-\alpha)\) is generated from the price of \(fp_n\) deduct the cost of service room \((c)\).

The hotel determines the optimal price of \(p_n^*\) and the expected total profit of offering two sale conditions of the mild and last minute condition \((H_{n,l})\) is
\[
\Pi_{n,l}(p_n) = \int_0^{\alpha^*} \left( \alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c) \right) d\alpha + \int_{\alpha^*}^{\alpha'^*} \left( \alpha(f p_n) + (1 - \alpha)(f p_n - c) \right) d\alpha
\]

(4.25)

Where \( \alpha^* = \frac{v - p_n}{v(l - \beta_n)} \), \( \alpha'^* = \frac{v - fp_n}{v} \).

The hotel’s objective is to determine the optimal price of \( p_n^* \) so that the total expected profit is maximized. First order condition gives the following decision.

**Lemma 6** For offering two sale conditions of mild and last minute condition \((n,l)\), the optimal prices of \( p_n^* \) and \( p_l^* \) and optimal profit \( \Pi_{n,l}(p_n^*) \) are.

The decision problem under “the mild and last minute conditions” \((n,l)\) is

\[
\max \Pi_{n,l}(p_n) = \int_0^{\alpha^*} \left( \alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c) \right) d\alpha + \int_{\alpha^*}^{\alpha'^*} \left( \alpha(f p_n) + (1 - \alpha)(f p_n - c) \right) d\alpha
\]

Let use the first order condition to obtain the optimal price for mild and last minute conditions \((n,l)\).

By \( \frac{d\Pi_{n,l}(p_n)}{dp_n} = 0 \), we obtain

\[
p_n^* = \frac{(1 + (1 + \beta_n)(\beta_n f)\nu^2}{-(1 + \beta_n)^2 cf^2 + (2 - \beta_n + 2(-1 + \beta_n) f + 2(-1 + \beta_n)^2 f^2)\nu}
\]

(4.26)

Given the discount ratio \((f)\)

\[
p_l^* = fp_n^* = f \frac{(1 + (1 + \beta_n)(\beta_n f)\nu^2}{-(1 + \beta_n)^2 cf^2 + (2 - \beta_n + 2(-1 + \beta_n) f + 2(-1 + \beta_n)^2 f^2)\nu}
\]

(4.27)

Let plug in \( p_n^* \) into the profit function of \( \Pi_{n,l} \), we obtain

\[
\Pi_{n,l}^*(p_n^*) = \frac{-(1 + \beta_n)^2 c^2 f^2 + c(2 - \beta_n + 2(-1 + \beta_n) f + (2 - \beta_n)(-1 + 2 \beta_n) f^2)\nu - (1 + (2 + \beta_n)\beta_n f^2)\nu^2}{2(-1 + \beta_n)^2 cf^2 + 2(-2 + \beta_n - 2(-1 + \beta_n) f - 2(-1 + \beta_n)^2 f^2)\nu}
\]

(4.28)

In the next section, we will incorporate three sale conditions of “the restriction, mild and last minute conditions” along two reservation periods.
4.4.4 Decision for offering three sale conditions

4.4.4.1 Restriction, Mild and Last minute conditions \((r, n, l)\)

In this case, a hotel offers a same room service with three sale conditions at different prices along two reservation periods. In the normal period, “the restriction condition” \((r)\) and “mild condition” \((n)\) are offered. In the last minute period, if an unsold room is available, “the last minute condition” \((l)\) is offered. Accordingly, a hotel can generate the revenue from selling three sale conditions. That is, “the restriction condition” \((r)\) covers the demand under the range of \(\alpha\), where \(0 \leq \alpha < \alpha^*\). The revenue of no-show case \((a)\) is generated from cancellation fee at \(p_r\) and the revenue of show-up case \((1-\alpha)\) is generated from the room service at the price of \(p_r\) deduct the cost of room service \((c)\). Also, “the mild condition” \((n)\) covers the demand at the range of \(\alpha\), where \(\alpha^* \leq \alpha < \alpha'\). The revenue of no-show case \((a)\) is generated from cancellation fee at \((p_n - \beta_n v)\) and the revenue of show-up case \((1-\alpha)\) is generated from the room service at the price of \(p_n\) deduct the cost of room service \((c)\). Moreover, “the last minute condition” \((l)\) covers the demand at the range of \(\alpha\), where \(\alpha' \leq \alpha < \alpha''\). The revenue of no-show case \((a)\) is generated from cancellation fee at \(f p_r\) and the revenue of show-up case \((1-\alpha)\) is generated from the room service at the price of \(f p_r\) deduct the cost of room service \((c)\), where \(f > 0\).

The hotel determines the optimal prices of three sale conditions \((p_n^*, p_r^*, p_l^*)\).

The total expected profit of offering three sale conditions \(\Pi_{r,n,l}\) is provided as follows.

\[
\Pi_{r,n,l}(p_r, p_n)= \int_0^{\alpha^*} (\alpha(p_r )+(1-\alpha )(p_r-c))d\alpha + \int_{\alpha^*}^{\alpha'} (\alpha(p_n - \beta_n v)+(1-\alpha )(p_n-c))d\alpha \\
+ \int_{\alpha'}^{\alpha''} (\alpha(f p_r )+(1-\alpha )(f p_r-c))d\alpha
\]

where \(\alpha^* = \frac{p_n - p_r}{\beta_n v}, \alpha' = \frac{v - p_n}{v - \beta_n v}, \alpha'' = \frac{v - f p_r}{v}\)

To maximize the total expected profit, a hotel set the following optimal prices.
Lemma 7 For offering three sale conditions \((r,n,l)\), the optimal prices \((p_r^*, p_n^*, p_l^*)\) and optimal profit \(II_{r,n,l}^*\) are.

The decision problem under “the restriction, mild and last minute conditions” \((r,n,l)\) is

\[
\text{Max } II_{r,n,l}(p_r, p_n) = \int_0^\alpha (\alpha(p_r) + (1 - \alpha)(p_r - c))d\alpha + \int_\alpha^\alpha (\alpha(p_n - \beta_n v) + (1 - \alpha)(p_n - c))d\alpha \\
\int_\alpha^\alpha (\alpha(fp_r) + (1 - \alpha)(fp_r - c))d\alpha
\]

Let use the first order condition to obtain the optimal price decision for the restriction, mild and last minute conditions \((r,n,l)\). By \(\frac{dII_{r,n,l}(p_r, p_n)}{dp_r} = 0\) and \(\frac{dII_{r,n,l}(p_r, p_n)}{dp_n} = 0\), we obtain

\[
p_r^* = \frac{v^2}{-(2 + \beta_n)v + f(cf + (2 + \beta_n(-2 + f) - 2f)v)'} \tag{4.30}
\]

\[
p_n^* = \frac{v(-v + \beta_n f(v - \beta_n v + f(c + (-2 + \beta_n)v)))}{-(2 + \beta_n)v + f(cf + (2 + \beta_n(-2 + f) - 2f)v)'} \tag{4.31}
\]

Given the adjusted ratio \((f)\),

\[
p_l^* = fp_r^* = \frac{v^2}{-(2 + \beta_n)v + f(cf + (2 + \beta_n(-2 + f) - 2f)v)} \tag{4.32}
\]

Let plug in \(p_r^*\) and \(p_n^*\) into the profit function of \(II_{r,n,l}(p_r, p_n)\), we obtain

\[
II_{r,n,l}^*(p_r^*, p_n^*) = \frac{c^2 f^2 + c(\beta_n(-1 + f)^2 - 2(1 + (-1 + f)f))v + v^2}{2((-2 + \beta_n)v + f(cf + (2 + \beta_n(-2 + f) - 2f)v))} \tag{4.33}
\]

Proof To ensure that the optimal prices in Lemma 7 leads to a unique global maximum total profit, we require conditions that

\[
\frac{\partial^2 II_{r,n,l}(p_r, p_n)}{\partial p_n^2} < 0, \quad \frac{\partial^2 II_{r,n,l}(p_r, p_n)}{\partial p_r^2} < 0, \quad \text{and} \quad \frac{\partial^2 II_{r,n,l}(p_r, p_n)}{\partial p_n \partial p_r} > 0.
\]

By solving all necessary conditions, we \(\frac{\partial^2 II_{r,n,l}(p_r, p_n)}{\partial p_r^2} = \frac{\beta_n f^2 (c - 2v) - v}{\beta_n v^2}\)

and \(\frac{\partial^2 II_{r,n,l}(p_r, p_n)}{\partial p_n^2} = -\frac{1}{(-1 + \beta_n)^2 \beta_n v}\) which satisfy the necessary conditions of
\[
\frac{\partial^2 H_{r,n,d}(p_r,p_n)}{\partial p_n^2} < 0 \quad \text{and} \quad \frac{\partial^2 H_{r,n,d}(p_r,p_n)}{\partial p_r^3} < 0, \text{ where } v > c, 0 < \beta_n < 1, f > 0. \quad \text{Moreover, we obtain}
\]
\[
\frac{\partial^2 H_{r,n,d}(p_r,p_n)}{\partial p_n \partial p_r} = \frac{(-2 + \beta_n)v + f(cf + (2 + \beta_n(-2 + f) - 2f)v)}{(1 + \beta_n)^2 \beta_n v^3}
\]
which leads to the necessary condition of
\[
\frac{\partial^2 H_{r,n,d}(p_r,p_n)}{\partial p_n \partial p_r} > 0, \text{ where } v > c, 0 < \beta_n < 1, f > 0.
\]

To ensure the existence of three sale conditions, each sale condition has the positive demand, and all three sale conditions cover the market. Each sale condition covers the demand in different ranges of \(\alpha\), where \(0 \leq \alpha \leq 1\). Accordingly, it is assumed that \(0 \leq \alpha^* \leq \alpha' \leq \alpha'' \leq 1\) so that three sale conditions exist in the market. Also, the sale conditions that
\[
p_n > p_r, \beta_n v - p_n > -p_r, \beta_n v - p_n \leq 0, 0 < \beta_n < 1, v > p_n, v > c, p_r > c, p_n > c, c > 0, f > 0\]
were assumed to differentiate three sale conditions.

### 4.4.5 Comparison of different sale conditions

We compared the optimal total profits derived from six scenarios of offering sale conditions whereas our proposed model focuses on offering two sale conditions of “the mild and restriction conditions” \((n,r)\).

**Proposition 4 (Comparison of total profit derived from different sale conditions)**

A hotel could generate the highest profit by offering two sale conditions of the mild and restriction conditions \((\Pi'_{n,r})\), compared with total profits derived from other five scenarios \((\Pi''_{n', \Pi'_{n', r', n'}, n', r', n', n', n', n'}, \Pi'_{r,n,l})\).

The result confirms that with our proposed model, a hotel could generate the highest total profit from offering “the mild and restriction conditions” \((n,r)\) along two reservation periods, compared with other potential scenarios. The detail proof is shown in Appendix B.
4.5 Numerical Studies

In this section, we presented the numerical examples to illustrate our findings and provide managerial insight based on the analysis of our pricing model. In the first section, we focused on the sale conditions under our proposed model. We studied the effect of proportion value of refund from cancellation under the mild condition \( \beta_n \) on the decision of offering “the mild and restriction conditions” \((n,r)\) along two reservation periods. Also, we examined the impact of the cost of room service \(c\) as it is related to the decision. In the second section, we discussed and compared the various scenarios of offering the sale conditions.

To conduct numerical studies, we used input parameters as shown in Table 4.1. The parameters were hypothetical but were reasonably selected by our assumptions so that they could represent the situation in practice. In each numerical study, we observed findings by varying a major parameter of \( \beta_n \), where \(0 < \beta_n < 1\), while keeping other parameters constant. Note that as \( \beta_n \) represents the proportion value of refund from cancellation. That mean, when \( \beta_n \) increases, the amount of refund increases, thereby decreasing of cancellation fee under “the mild condition” \((n)\).

<table>
<thead>
<tr>
<th>(v)</th>
<th>(c)</th>
<th>(\beta_n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4</td>
<td>(0 &lt; \beta_n &lt; 1)</td>
</tr>
</tbody>
</table>

4.5.1 Offering two sale conditions of mild and restriction conditions

Figure 4.8 shows the effect of \( \beta_n \) on the prices for two sale conditions of “the mild and restriction conditions” \((n,r)\) when offered in different reservation periods. The result reveals that the price of mild condition \(p_n\) is typically charged higher than the price of restriction condition \(p_r\). When \( \beta_n \) increases, the prices of mild condition \(p_n\) increases whereas the price of restriction condition \(p_r\) decreases. This finding leads to the insights that the hotel could add the value for the same room service by charging the higher price with “a full refund” or “a partial refund policy for cancellation” at “the mild condition” \((n)\).
Figure 4.8 Effect of $\beta_n$ on the prices of mild and restriction conditions

Table 4.2 and Figure 4.9 show the effect of $\beta_n$ on the price decision ($p_n$) and amount of refund for cancellation ($\beta_n v$) under “the mild condition” ($n$). Figure 4.9 shows that as $\beta_n$ increases, the amount of refund for cancellation ($\beta_n v$) increases and the hotel is allow to increase the price of mild condition ($p_n$). For “the mild condition”, if a customer cancels the reservation, he could gain some refund at $\beta_n v$ from the paid price at $p_n$. That mean, the customer will be imposed the cancellation fee at $\beta_n v - p_n$. Therefore, it is intuitively assumed that the amount of refund ($\beta_n v$) have to be less than or equal to the price paid by the customer (i.e., $\beta_n v \leq p_n$ or $\beta_n v - p_n \leq 0$) so that the customer is imposed the cancellation fee ($\beta_n v - p_n < 0$) or promoted with “the full refund policy for cancellation” ($\beta_n v - p_n = 0$). Table 4.2 shows that, at any points of $\beta_n$, the amount of refund ($\beta_n v$) is not higher than the price of mild condition ($p_n$). Specifically, when $\beta_n$ reaches to 1, the customer tends to gain a full refund amount or free cancellation.
Figure 4.9 Effect of $\beta_n$ on price and amount of refund under the mild condition

Table 4.2 The price and amount of refund under the mild condition

<table>
<thead>
<tr>
<th>$\nu$</th>
<th>$\beta_n$</th>
<th>$c$</th>
<th>Amount of refund ($\beta_n\nu$)</th>
<th>Price ($p_n$)</th>
<th>Cancellation fee ($\beta_n\nu - p_n$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.05</td>
<td>0.4</td>
<td>0.05</td>
<td>0.7311</td>
<td>-0.6811</td>
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<tr>
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<td>0.4</td>
<td>0.1</td>
<td>0.7353</td>
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<td>0.4</td>
<td>0.2</td>
<td>0.7447</td>
<td>-0.5447</td>
</tr>
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<tr>
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<td>0.4</td>
<td>0.4</td>
<td>0.7692</td>
<td>-0.3692</td>
</tr>
<tr>
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<td>0.4</td>
<td>0.5</td>
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</tr>
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<td>0.6</td>
<td>0.8065</td>
<td>-0.2065</td>
</tr>
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</tr>
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<td>0.9</td>
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<td>-0.0211</td>
</tr>
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<td>-0.0003</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>0.4</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 4.10 shows the effect of $\beta_n$ on the demands for two sale conditions of “the mild and restriction conditions” $(n,r)$. As shown in Figure 4.10 (a), when $\beta_n$ increases, $D_n$ increases but $D_r$ dramatically decreases. As $D_n$ covers the largest demand of customers in the market whereas $D_r$ could gain the small portion of the
remaining demand in the last minute period, the increasing of $\beta_n$ leads to the increasing of total demand ($D_{n,r}$). That mean, the most of customers prefer “the mild condition” ($n$) at the cheaper cancellation fee. Interestingly, when $\beta_n$ increases (e.g., at $\beta_n > 0.9$), almost customers are motivated to make an advance booking in the normal period and thus, no customer will remain for the last minute period as $D_r$ reaches to zero. These results show that $\beta_n$ is a good mechanism to motivate a full occupancy rate in the normal period. Accordingly, it is not necessary for a hotel to sell an unsold room at a discount price in the last minute period which reduces the potential profit.

Figure 4.10 (b) shows the expected sale of rooms from a show-up customer. As $\beta_n$ increases, the expected sale rooms from the mild condition ($ES_n$) increases whereas the expected sale rooms from the restriction condition ($ES_r$) decreases. As a result, the total expected sale of rooms ($ES_{n,r}$) increases. These results are corresponding to the demand for the mild and restriction conditions. These imply that $\beta_n$ could be the mechanism to adjust the demand of occupied rooms with the supply of rooms.

![Graph](image)

(a) Total demand of two sale conditions
Figure 4.10 Effect of $\beta_n$ on the demand for two sale conditions $(n,r)$

Figure 4.11 shows the effect of $\beta_n$ on total profit from offering two sale conditions of “the mild and restriction conditions” $(n,r)$. As $\beta_n$ increases, the profit from the mild condition increases whereas the profit from the restriction condition decreases, resulting in the increasing trend of total profit. These trends are corresponding to the prices and demands for each sale condition as shown in Figures 4.8 and 4.10 (a). Obviously, the major source of profit is generated from the rooms sold to the show-up customers under “the mild condition” $(n)$ and the second source of profit is generated from imposing the cancellation fee under “the non-refund policy” of “the restriction condition”. These observations lead to the insights that as $\beta_n$ increases, it allows a hotel to charge the higher prices of $p_n$ and generate the higher demand at the higher profit. Note that the hotels were assumed to be the risk neutral. Thus, although the hotels will gain less or nothing if the booked rooms are cancelled, they could generate a higher profit from the show-up customers who pay at a higher price under the mild condition ($p_n$). Moreover, the hotels provide “the restriction condition” at a lower price ($p_r$) with “the non-refund policy” for the last minute customers who have high cancellation possibility (e.g., $\alpha^* \leq \alpha < \alpha^*$). In this

(b) Expected sale of rooms from the show-up customers
scenario, the hotels will get nothing from selling rooms at the low price but they could generate the profit from imposing a high cancellation fee charged for the no-show customers. However, the hotels need to leave the customers having a very high cancellation possibility (e.g., $\alpha' \leq \alpha \leq 1$) as a deep discount leads to the loss of total profit. Accordingly, the interesting observations from Figure 4.11(b) are that a hotel could generate the revenue from cancellation fee imposed from a no-show customer, and from the room service paid by a show-up customer.

Figure 4.11 Effect of $\beta_n$ on total profit from offering the mild and restriction conditions

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Table 4.3 and Figure 4.12 show an average profit per customer from offering “the mild and restriction conditions”. The result shows that when $\beta_n$ increases, total demand increases, thereby increasing of total profit. However, an average total profit per customer tends to be the same in every point of $\beta_n$. Moreover, when $\beta_n$ increases, the average profit per customer from the mild condition $(n)$ tends to slightly decrease whereas that from restriction condition decreases dramatically. It is intuitively explained that as the profit is differently generated from the no-show and show-up customers, an average profit per customer slightly decreases. For “the restriction condition”, as the demand and profit decreases, an average profit per customer decreases. Not surprisingly, “the mild condition” could generate a higher average profit per customer due to the trend of its profitability in the market.

**Table 4.3** Effect of $\beta_n$ on an average profit per customer

<table>
<thead>
<tr>
<th>$\beta_n$</th>
<th>Total demand</th>
<th>Total Profit $(n,r)$</th>
<th>Avg. Profit $(n)$</th>
<th>Avg. Profit $(r)$</th>
<th>Avg. TotalProfit $(n,r)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.05</td>
<td>0.55</td>
<td>0.166</td>
<td>0.381</td>
<td>0.215</td>
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<tr>
<td>0.1</td>
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<tr>
<td>0.2</td>
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<td>0.204</td>
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<td>0.3</td>
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<td>0.195</td>
<td>0.30</td>
</tr>
<tr>
<td>0.4</td>
<td>0.62</td>
<td>0.185</td>
<td>0.369</td>
<td>0.185</td>
<td>0.30</td>
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<tr>
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<td>0.193</td>
<td>0.364</td>
<td>0.171</td>
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<tr>
<td>0.6</td>
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<td>0.203</td>
<td>0.358</td>
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<tr>
<td>0.7</td>
<td>0.72</td>
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<td>0.350</td>
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<td>0.063</td>
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<td>0.295</td>
<td>0.303</td>
<td>0.008</td>
<td>0.30</td>
</tr>
<tr>
<td>0.99901</td>
<td>0.998</td>
<td>0.300</td>
<td>0.300</td>
<td>0.001</td>
<td>0.30</td>
</tr>
</tbody>
</table>
Figure 4.12 Effect of $\beta_n$ on an average profit per customer

Figure 4.13 shows the effect of $\beta_n$ on the show-up ratio and no-show ratio from offering two sale conditions of “the mild and restriction conditions”. As $\beta_n$ increases, the show-up ratio of two sale conditions ($S_n, S_r, S_{n,r}$) decreases. That mean, a hotel could increase the no-show ratio of two sale conditions ($N_n, N_r, N_{n,r}$).
Not only the proportion value of refund ($\beta_n$), the cost of room service ($c$) has the impact to determine the pricing decision offered by different hotels. In this numerical experiment, we varied the value of $c$ from a low to high level, where $0.5 \leq c \leq 0.75$ whereas other parameters were constant. Also, $\beta_n$ was selected to fix at 0.9 to represent a low cancellation scenarios imposed by “the mild condition” ($n$). Figure 4.14 shows the effect of the cost of room service ($c$) on the price decision. The result shows that when $c$ increases, the prices of two sale conditions increase, especially, the price of restriction condition increases significantly. It is commonly that the hotel needs to increase the price of sale conditions to cover the cost at the hotel’s profitability. In practice, these results reflect that the different hotels could charge the prices differently according to the cost and expense (e.g., staff salary).

Figures 4.15 and 4.16 show the effect of the cost of room service ($c$) on the demand and total profit from offering “the mild and restriction conditions”, respectively. The result shows that when $c$ increases, $D_n$ and $D_r$ decrease, thereby decreasing of total demand ($D_{n,r}$). It could be intuitively explained that the customers might not buy the hotel’s rooms due to the higher price of sale conditions. Accordingly, the decreasing of demands together with the higher cost lead to the decreasing trend of total profit from offering two sale conditions.
Figure 4.14 Effect of the cost of room service \( (c) \) on prices

Figure 4.15 Effect of the cost of room service \( (c) \) on demand
4.5.2 Comparison of offering different sale conditions

In this numerical experiment, we incorporated six scenarios of offering different sale conditions and compared the results. Six scenarios of offering sale conditions include offering one sale condition of (1) “the mild condition” \((n)\) and (2) “the restriction condition” \((r)\), offering two sale conditions of (3) “the mild and restriction conditions” \((n,r)\), (4) “the mild and last minute conditions” \((n,l)\), and (5) “the restriction and last minute conditions” \((r,l)\), and offering three sale conditions of (6) “the restriction, mild and last minute conditions” \((r,n,l)\).

Figure 4.17 compares a decision for the price of mild condition \((p_n)\) under the different scenarios of sale conditions. Thus, the pricing decision of \(p_n\) from offering sale conditions of \((n)\), \((n,r)\), \((n,l)\), and \((r,n,l)\) were compared. “The mild condition” from all scenarios is offered in the normal period. As \(\beta_n\) increases, all of \(p_n\) tend to increase. Offering one sale conditions \((n)\) charges the lowest \(p_n\) whereas offering two sale conditions of \((n,l)\) charge the highest \(p_n\). Thus, the strategy for offering the sale conditions has effect on the pricing decision.
Figure 4.17 Comparison of $p_n$ on different scenarios of sale conditions

Figure 4.18 compares a decision for the price of restriction condition ($p_r$) under the different scenarios of sale conditions. Thus, the pricing decision on $p_r$ from sale conditions of $(r)$, $(n,r)$, $(r,l)$, and $(r,n,l)$ were compared. Note that “the restriction condition” in $(n,r)$ scenario is offered in the last minute period whereas others are offered in the normal period. As $\beta_n$ increases, most of $p_r$ increase whereas the $p_r$ from offering two sale conditions $(n,r)$ significantly decreases. Moreover, $p_r$ from $(n,r)$ is charged at the lowest price. This result could be explained as “the restriction condition” under $(n,r)$ is offered in the last minute period which needs to be offered at an attractive discount price to sale an unsold room for the remaining customers with high uncertainty. Furthermore, we observed that a hotel is allowed to charge a highest price of $p_r$ when offering three sale conditions of “the restriction, mild and last minute conditions” $(r,n,l)$.
Figure 4.18 Comparison of $p_r$ on different scenarios of sale conditions

Figure 4.19 compares the demand for offering different scenarios of sale conditions. Thus, the total demand from six scenarios of sale conditions $(n)$, $(r)$, $(n,r)$, $(r,l)$, $(n,l)$, and $(r,n,l)$ were compared. As $\beta_n$ increases, the demands for $D_n$ and $D_{n,r}$ significantly increases whereas the demands for $D_{n,l}$ and $D_{r,n,l}$ decreases. Also, the demand for $D_r$ and $D_{r,l}$ remain constant. Obviously, the hotel could generate the highest demand from offering the mild and restriction conditions $D_{n,r}$ at the highest $\beta_n$. This scenario is beneficial for the hotel to reach a fully occupied room and generate a higher profit. However, the hotel could consider an adequate $\beta_n$ and other sale conditions to adjust the demand for the occupied rooms with the limited supply of rooms.
Figure 4.19 Comparison of demand for different scenarios of sale conditions

Figure 4.20 compares the profit from offering different scenarios of sale conditions. As $\beta_n$ increases, the profit from offering sale conditions of $(II_n)$, $(II_r)$ significantly increases and $(I_{r,n})$ slightly increases whereas that from $(I_{r,l})$ slightly decreases. Also, as “the restriction condition” provides “the non-refund policy for cancellation”, when $\beta_n$ changes, the profits from offering sale conditions of $(II_r)$ and $(II_{r,l})$ have no effect and remain constant. Obviously, a hotel could generate the highest total profit from offering the mild and restriction conditions $(II_n)$ at the highest $\beta_n$. Also, offering one conditions of “the restriction condition” $(r)$ has the lowest profitability and offering one condition of “the mild condition” $(n)$ might lead the lowest profit when setting low $\beta_n$. 

![Graph showing comparison of demand for different scenarios of sale conditions]
Figure 4.20 Comparison of total profit from different scenarios of sale conditions

Table 4.4 shows the percentage of the profit raised from offering “the mild and restriction conditions” over others scenarios. The result indicates that a hotel could increase the profit from offering the mild and restriction conditions ($II_{r,n}$) by 43.70%, on an average, compared with $II_{r}$, by 14.94% compared with $II_{n}$, by 19.29% compared with $II_{r,l}$, by 18.24% compared with $II_{r,n,l}$, and by 13.73% compared with $II_{n,r,l}$.

### Table 4.4 Comparison of total profit from different scenarios of sale conditions

<table>
<thead>
<tr>
<th>$\beta_n$</th>
<th>Profit from different sale conditions</th>
<th>% Increasing profit of mild and restriction conditions ($II_{r,n}$) over others</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$II_{r,n}$</td>
<td>$II_{r}$</td>
</tr>
<tr>
<td>0.05</td>
<td>0.16557</td>
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</tr>
<tr>
<td>0.1</td>
<td>0.16765</td>
<td>0.113</td>
</tr>
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<td>0.113</td>
</tr>
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</tr>
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<td>0.9</td>
<td>0.26053</td>
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</tr>
<tr>
<td>0.99</td>
<td>0.29513</td>
<td>0.113</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
According to the proposed model, our study suggests that offering two sale conditions of “the mild and restriction conditions” \((n,r)\) is the prominent strategy to generate the highest profit. The hotel could add the value of room by charging a higher price and thus, generate a higher profit. Also, our results confirm our observations that an effective marketing strategy should focus on selling more rooms at a higher price with a higher refund for cancellation by “the mild condition” \((n)\) in the normal period. Moreover, “the restriction condition” at the lower price with “the non-refund policy for cancellation” should be offered for the last minute customers. However, the hotels should leave the customers having a very high cancellation possibility as a deep discount leads to the loss of total profit.

The sale scenarios along the normal period and last minute period have been varied by the hotels and OTAs websites. In the last minute period, “the last minute condition” \((l)\) is offered at the adjusted price with “the non-refund policy for cancellation” to sell an unsold room. The adjust ratio is determined by \(f\), where \(f > 0\). For example, the sale scenario of “the mild condition and last minute condition” \((n,l)\). As “the last minute condition” charges the price of last minute condition \((p_l)\) at \(fp_n\), a higher \(f\) means that a higher price of \(p_l\) is charged. In the numerical experiment, we varied the value of \(f\) from a low to high value where \(0 < f < 2\) whereas other parameters were constant. Also, \(\beta_n\) was fixed at 0.9 to reach “a full refund policy for cancellation” at “the mild condition” \((n)\).

Figures 4.21, 4.22 and 4.23 show the effect of the adjust ratio \((f)\) on the price, demand and total profit from offering two sale conditions of “the mild and last minute conditions” \((n,l)\), respectively. As \(f\) increases, the price of mild condition \((p_n)\) increases and the price of last minute condition \((p_l)\) increases significantly. Accordingly, as the price of room increases, the demands for customer \((D_n,D_l)\) decrease and reach to be zero at the very high price, thereby dramatically decreasing of total profit. According to the result, we suggest that the adjust ratio \((f)\) should be between \((0 < f < 1)\) to charge a suitable price while could generate the demand at the profitability. However, we found that a last minute customer is sensitive to the price and may not book a room at the high price.
**Figure 4.21** Effect of adjusted ratio \((f)\) on the prices of sale conditions

**Figure 4.22** Effect of adjusted ratio \((f)\) on the demand
Comparing the sale scenarios of “the mild and restriction conditions” \((n,r)\) with “the mild and last minute conditions” \((n,l)\), “the restriction condition” at \((n,r)\) and “the last minute condition” at \((n,l)\) are similarly offered with “the non-refund policy for cancellation” in the last minute period. Figures 4.24, 4.25 and 4.26 show that if the adjusted value of \(f\) can be effectively selected, the pricing decision and total profit from “the sale scenario \((n,l)\)” could reach the optimal price and profit as that of the prominent “sale scenario \((n,r)\)”. In this experiment, we considered the selected value of \(f = 0.143\) at \(\beta_n = 0.9\). Figure 4.24 shows that when \(\beta_n\) increases, the prices of mild condition at both sale scenarios increase but the prices are charged at the different rate. Moreover, Figure 4.25 shows that, in the last minute period, the price of last minute condition and the price of restriction condition are charged at the different rate, thereby generating different profit. The profits of sale scenarios are shown in Figure 4.26. However, at \(\beta_n = 0.9\), if the value of \(f\) can be effectively selected (i.e., \(f = 0.143\)), the prices offered by “sale scenario \((n,r)\)” and “sale scenario \((n,l)\)” tend to be the same, thereby generating the same high profit for “the sale scenario \((n,l)\)” with “the sale scenario \((n,r)\)”. Therefore, the values of \(\beta_n\) and \(f\) could determine the price and profit for the sale scenarios. It is important for a hotel to select the appropriate \(\beta_n\) and \(f\) in “the sale scenario \((n,l)\)”.

**Figure 4.23** Effect of adjusted ratio \((f)\) on the profit
Figure 4.24 Pricing decision of mild condition by different sale scenarios

Figure 4.25 Pricing decision of sale conditions offered in the last minute period by different sale scenarios
4.6 Conclusion

We studied a hotel that differentiates a same room service with various sale conditions based on cancellation policy. Regarding to the no-show possibility of customers, we developed a model that considered two sale conditions along two reservation periods. That is, (i) “Mild condition” (n) is offered in the normal period at a higher price with “a full refund policy” or “a partial refund policy for cancellation”, and (ii) “Restriction condition” (r) is offered in the last minute period to sale an unsold room at a lower price with “a non-refund policy for cancellation”. The optimal prices of sale conditions were optimally determined to maximize total profit of hotel. Our objectives were to use a model to understand the customer’s choices and examine that how various sale conditions have an impact on the hotel revenue management. With an optimal price decision, the interesting observations from our analysis are summarized as follow.

- The proportion value of refund from cancellation (βn) is a strategic parameter affecting on an optimal price decision, thereby determining a profit. Moreover, βn has an effect on total demand and thus, the hotel could adopt an adequate βn to adjust the demand of occupied rooms with the supply of rooms.

![Figure 4.26 Comparison of profit by different sale scenarios](image-url)
• Offering “the mild condition” with a higher $\beta_n$ could motivate an advance booking in the normal period. As almost customers are motivated to book in the normal period, a hotel could sell more room at a high price without any discount in the last minute period.

• With “the refund policy” and “the non-refund policy for cancellation”, a hotel could generate the higher profit from the price of sold rooms imposed from a show-up customer and from the cancellation fee imposed from a no-show customer. Based on our analysis, the prominent strategy focuses on selling more rooms at a high price with a high refund for cancellation by “the mild condition” ($n$) in the normal period. Although the hotels will gain less or nothing if the booked rooms are cancelled, they could generate a higher profit from a higher price with more demand of the show-up customers. Moreover, the lower price with “the non-refund policy” under “the restriction condition” should be offered to attract the last minute customers. In this scenario, the hotels will get nothing from selling rooms at a low price but they could generate the profit from imposing a high cancellation fee charged for the no-show customers. However, the hotels should leave the remaining customers who have a very high cancellation possibility as a deep discount leads to the loss of total profit.

• The decisions on offering sale conditions and charging a room price are optimally determined on the basis of proportion value of refund ($\beta_n$), number of sale conditions available in the market, the cost of room service ($c$), and other hotel conditions. Our proposed model is a simple tool that could help a hotel to make a better decision.

• We showed that, offering two sale conditions of “the mild and restriction conditions” ($n,r$), a hotel could generate the highest profit, compared with other potential scenarios of sale conditions.

With this study, we make several contributions to the hotel industry. That are, our new model incorporates pricing issue for the revenue management and the important factors such as the no-show possibility of heterogeneous customers, “the full refund policy”, “the partial refund policy” and “the non-refund policy from
cancellation”. Moreover, various sale conditions, adopted in practice, have been modelled and then numerically analysed to make several managerial insights responding to the current business issues. We believe that our study could provide a useful insight for a hotel manager to challenge in the practical business.
Chapter 5
Conclusion and Research Contribution

5.1 Conclusion

Online hotel reservation is a major transaction that relies on the fast-growing trend of e-commerce. Among the online channels, online travel agency website (OTA) offers a one-stop service of timely information and reservation transaction for the tourism industry. The customers could access a large number of available hotel choices, seek for the best deal and use the useful functionality of OTAs to facilitate the searching process and booking decision. However, matching a number of available hotels with the heterogeneous customers varying in expectation (e.g., budget, preference, and potential cancellation) is a challenge for the hotel and OTAs.

In this dissertation, two main aspects of online hotel booking were studied to response the current issues in the hotel and travel industry. That is, we studied (i) the sequencing decision of hotel room choices presented on the website and (ii) the pricing decision of sale conditions based on the no show and cancellation policy.

In the first study, we studied the customer behaviour during the process of searching and making a hotel reservation through OTAs. Specifically, we focused on the hotel selection criteria and the adoption of a sequencing tool to search for a satisfactory hotel. We developed a new approach, based on a two-stage stochastic programming model (2SSP), to design an appropriate sequence of hotel choices. Different from prior literatures and existing OTAs mechanisms, our proposed sequencing model could decide an appropriate number of hotel choices with the ranking position presented on the website so that the search cost of customers could be reduced. Under our sequencing model, the sequence of hotel choices was sorted to satisfy the multidimensional preferences of overall heterogeneous customers with multidimensional preferences (i.e., budget, expected hotel star, overall review rating). Using the appropriate hotel and customer information collected from the customer survey and the online reservation website, we could generate the numerical
simulations and derived findings closely representing a realistic online booking mechanism. The numerical result confirms the effectiveness of the sequences derived by our proposed model, compared to the existing sequences derived by the OTA sequencing tool (e.g., sequencing by price). With an importance of sequencing and appropriate number of hotel choices, the main results suggest that OTAs should consider a small number of hotel choices but a quality of hotel choices presented on the website. Specifically, the hotels with a higher possibility to attract more customers, a higher price, a higher review rating, a higher star rating and a higher expected utility, should be placed in the upper position of the sequence.

In the second study, we studied the hotel offering a same room service with different sale conditions based on no show and cancellation policy. Taking the no-show possibility of customers in decision, we developed a pricing model that incorporated two sale conditions for a same room service along two reservation periods. In the normal period, “the mild condition” is offered at the higher price with “the full refund policy” or “the partial refund for the cancellation” (e.g., free cancellation or first night fee charged). In the last minute period, the price of room and the cancellation policy are adjusted. That is, “the restriction condition” is offered at the lower price with “the non-refund policy for the cancellation”. The main objective was to determine the optimal prices of mild and restriction conditions so that the total profit of hotel was maximized. The analysis of result shows that a hotel could generate the higher profit from offering two sale conditions of “the mild and restriction conditions”. Interestingly, we found that the proportion value of refund for the cancellation is the strategic parameter that could add the value for the same room service, increase total profit, adjust demand with supply and motivate an early booking. Moreover, the effective strategy focuses on selling more rooms by “the mild condition” at a high price and low cancellation fee.
5.2 Achievement

In order to provide the superior online hotel booking experience for the customers, the OTAs and hotels need to improve both of adequate website’s functionality (e.g., sequencing functionality) and hotel’s room choices (i.e., price and quality).

- In this dissertation, we achieved the above mentioned issues to derive the decision models for making a better decision on (i) the sequence of hotel’s choices and (ii) the prices of hotel’s room. Based on the numerical study, we make several managerial insights for hotels and OTAs to implement in practical way.

In the first study, the main achievements are as follows.

- To achieve to provide the sequencing model that could provide the adequate sequence to achieve the higher reservation rate and customer’s expectation. Moreover, based on numerical results, we reach the effectiveness of sequence designed by the proposed model, compared with the existing sequences designed by OTAs.

In the second study, the main achievements are as follows.

- To achieve to provide a pricing model to optimally decide the prices of various sale conditions at the maximum profit of hotels. Based on numerical results, we reach the effectiveness of sale scenario under the proposed model that can generate the higher profit over other sale scenarios.

5.3 Significance of Research Output

We expect that the combination of the following contributions drives our study and proposed model satisfying the expectations of the current issues in the tourism industry. With this research, we make several contributions to academic community and industry. The main contributions are discussed as following.
5.3.1 Contribution to academic community

• Operation research in application

In this dissertation, the mathematical model is the main approach used to formulate and solve an optimization problem. With the optimization models, consisting of a two-stage stochastic programming model (2SSP) and Hotelling’s model, we show the practical implementation of the academic knowledge and operation research that suitably used to make the sequencing decision and pricing decision for the business management decision.

• Theoretical study

We provide a new framework to promote the understanding of profitable design of OTAs. A typical practitioner could adopt it to learn and simply run on the model to get the managerial insights.

Moreover, our framework incorporates a new perspective of OTA website design (e.g., sequencing based on the multidimensional attributes and the appropriate number of presented choices) that could differentiate but fulfil the gaps of prior literatures.

Also, our studies focus on the topics of no show, revenue management, e-commerce, tourism management and customer’s choice behaviour that could fulfil the current issue of theoretical research and practical implication.

5.3.2 Contribution to industry

With the study in this dissertation, we make several contributions to the e-commerce, tourism industry and other service industries. Specifically, the scope of our study hits on the current problems arising in an online hotel booking through OTAs (e.g., search cost, no-show, and revenue management). We focus to deliver the superior hotel booking experience by analysing and enhancing the existing operation of OTAs in practice. We draw an insight to motivate OTAs and hotels concentrating on the importance of (ii) the website’s sequencing functionality and (ii) the pricing and sale condition for hotel’s room. As both of sequencing and pricing have been
practically implemented in OTAs, our findings could support the decision for OTAs and hotels. The contribution of each study is described as follows.

OTAs have implemented “the sequencing functionality” to sort the number of hotel choices presented on the website. However, a new and effective sequencing method has been continuously required to serve the heterogeneous worldwide customers. Our framework incorporates a new perspective of OTA website design (i.e., sequencing based on multidimensional attributes and appropriate number of available hotel choices) that could better response the multidimensional preferences and expected search steps of customers in practice. Our sequence solved by the proposed model is expected to be adopted by OTAs to serve the customers together with other existing sequences of OTAs. By considering our sequencing model, OTA could provide an appropriate sequence of hotel choices to facilitate the customer’s searching process. Unlike exiting methods, the optimal number of hotel choices available on the sequence will be decided to reduce the search cost. Moreover, our study provides the practical application of the proposed model that could analyse the marketing position and provide a useful improvement suggestion for a hotel to increase the reservation rate. These could help a hotel to understand how customers evaluate their hotel compared to other hotels and then could compete in the current competitive market. Furthermore, our model can be applied to other types of online products presented in the sequence feature; it is not limited to hotels.

“Pricing decision” has been an important vehicle to sell the products; thereby generating the revenue for almost industries. To response the hotel industry, our new model incorporates pricing issue for revenue management and important factors such as the no-show possibility of heterogeneous customers, “the refund policy” and “the non-refund policy”. We provide an approach to help a hotel and OTAs optimally offering sale conditions based on cancellation policy. Based on our analysis, we compare the sale scenarios practically adopted in practice and suggest the effective sale scenario to draw an insight into the hotel and OTA’s motivation in offering the sale conditions with “the full refund policy”, “the partial refund policy” and “the non-refund policy for cancellation” at the suitable price. The optimal price of sale conditions could be simply decided by the proposed model according to the hotel conditions. Moreover, various sale conditions, adopted in practice, have been
analysed to make insights responding to the current business issues (e.g., profit, expected sale room and over sale). Therefore, we believe that the combination of these contributions drives our pricing model very suitable for practitioners and could provide a useful insight for a hotel and practitioners to challenge in the practical business.

5.4 Limitations and Future Research

For the study of sequencing model, our work has fallen into a category of theoretical study that might have some limitations to completely replace an existing mechanism of OTAs. For example, the parameters might not cover overall realistic mechanism. Thus, in the future study, a full-scale survey and other realistic parameters will be incorporated to extract the customer behaviour and online reservation service mechanism. Also, the proposed sequencing model requires large computation time to optimally solve a complex and large-scale problem which might be difficult to implement to response realistic mechanism. However, in the future study, these problems could be addressed by implementing a more powerful computer system and considering an efficient heuristic to speed up the sequencing decision.

Moreover, the topic of hotel revenue management and e-commerce has been continuously discussed by the academic researchers and practitioners. However, the researches on these fields are very broad and still necessary to fulfil the fast-growing trend of the tourism industry and e-commerce. For the study of cancellation policy and pricing model, our current work has some limitations to fulfil the problem gaps in the competitive online market. For example, the distribution of customers with the no-show possibility might not be effectively estimated due to uncertainty of customers. Moreover, there is a competition among the online hotel reservation website and hotel’s own website to offer the better deal for the customers. In the future research, we will consider the competition among the online reservation channels (e.g., among OTAs and hotel’s own website).
References

Books


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Appendices
Appendix A

Questionnaire

“Factor affecting on online hotel booking decision”

**Instruction:** The purpose of this questionnaire is to study the customer behavior and observe factors that affect on hotel booking through online travel agencies. The analysis of result will be adopted to improve the website design of OTAs. This study has been mainly conducted by undergraduate students from the school of management technology, Sirindhorn International Institute of Technology, Thammasat University, Thailand, as the partial fulfillment of requirement of senior project. We would like to thank all of respondents who kindly participate in this study.

**PART 1: PERSONAL BACKGROUND**

*Direction: Please provide your general background by marking ✓ on the appropriate choices for each question.*

1) Gender:  □ Male  □ Female
2) Age:  □ 20-30 years  □ 31-40 years  □ 41-50 years  □ more than 50 years
3) Average monthly income (Thai Baht)
   □ Lower than 20,000 Baht  □ 20,000 - 39,999 Baht  □ 40,000-49,999 Baht
   □ 50,000-69,999 Baht  □ 70,000 Baht and above
4) How much time you spend on the Internet per day?
   □ Lower than 3 hours  □ 3-5 hours  □ 6-8 hours  □ More than 8 hours
PART 2: QUESTIONS ON HOTEL BOOKING DECISION

Direction: Please give the information about your hotel booking decision by marking ✓ on the appropriate choices for each question.

1) What is your type of traveller?
   □ Family  □ Couple  □ Friends  □ Solo traveller  □ Business traveller

2) Please provide your budget per room per night: ________ Baht

3) What is the minimum acceptable level for hotel star rating?
   □ 1 star  □ 2 star  □ 3 star  □ 4 star  □ 5 star

4) What is the minimum acceptable level for overall review rating?
   □ 1 review rating  □ 2 review rating  □ 3 review rating  □ 4 review rating  □ 5 review rating

5) What is your concern about location of hotel?
   □ Near tourist attraction  □ Near downtown  □ Near public transportation
   □ Near airport  □ Near restaurant and shopping centre

6) Please rate the important level of hotel attributes on the hotel selection criteria?

<table>
<thead>
<tr>
<th>Hotel attribute</th>
<th>Not important</th>
<th>Neutral</th>
<th>Very important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Security</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Cleanliness</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Location</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Service</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Environment</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Facilities</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Booking condition</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Food</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Price</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Review</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Hotel reputation</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Room type</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>
PART 3: QUESTIONS ON HOTEL BOOKING EXPERIENCE THROUGH ONLINE TRAVEL AGENCIES

Direction: Please give the information about hotel booking experience using online travel agencies by marking ✓ on the appropriate choices

1) Do you have the hotel booking experience through online travel agencies?
   □ Yes  □ No (Finish the interview)

2) How many times per year do you book a hotel through online travel agencies?
   □ 1 time  □ 2 times  □ 3 times  □ 4 times  □ 5 times
   □ 6 times  □ 7 times  □ 8 times  □ 9 times  □ More than 9 times

3) What are the purposes of using online travel agencies?
   □ Search information  □ Online booking transaction  □ Read reviews
   □ Review on hotel experience  □ Others ..............................

4) Please rate the important level of website’s elements on hotel booking decision?

<table>
<thead>
<tr>
<th>Element of website</th>
<th>Not important</th>
<th>Neutral</th>
<th>Very important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hotel information</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Hotel photo</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Variety of hotel choices</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Hotel’s sorting list</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Review and comment</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Convenient booking transaction</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Required information for booking</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

5) Please indicate the number of hotels you observe before making a booking decision

.............................Hotels

6) What is your preferable sorting method to sort the hotel list on online travel agencies?
   □ Sorting by price  □ Sorting by promotion and special deal
   □ Sorting by distance from destination  □ Sorting by review rating
   □ Sorting by popularity  □ Sorting by hotel star rating
   □ Sorting by website suggestion or favourite  □ Sorting by name of hotel
PART 4: QUESTIONS ON RECENT HOTEL BOOKING EXPERIENCE

Direction: Please give the information about your recent experience of hotel booking on the following questions. Use the scale provided for each question to guide your response.

1) When was your recent trip?
   - ☐ Last week   ☐ Last two weeks   ☐ Last month   ☐ Last two to three months
   - ☐ Last six months   ☐ One year   ☐ More than one year

2) How you book a hotel?
   - ☐ Walk in to a hotel   ☐ Via telephone   ☐ Hotel’s website
   - ☐ Online travel agencies   ☐ Others ………………………

3) Please provide the hotel information on your recent trip
   - Hotel name:________________________ Location:________________________
   - Star rating:________________________ Review rating:________________________
   - Number of rooms:________ Rooms
   - Room type:
     - ☐ Standard room   ☐ Superior room   ☐ Deluxe room
     - ☐ Suit room   ☐ Others……………………

4) Please give the score to evaluate hotels in the following point of view

<table>
<thead>
<tr>
<th>Hotel attribute</th>
<th>Very poor</th>
<th>Neutral</th>
<th>Very Excellent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value for money</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Location</td>
<td>1</td>
<td>2</td>
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</tr>
<tr>
<td>Facility</td>
<td>1</td>
<td>2</td>
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<tr>
<td>Staff and service</td>
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<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Cleanliness</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Food</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

133
5) After booking but not yet stay at a hotel, how would you rate the value for money compared with the actual price?

<table>
<thead>
<tr>
<th>Very worthy, the price should be increase 50%</th>
<th>Worthy</th>
<th>Worth for money</th>
<th>Unworthy</th>
<th>Very unworthy, the price should be reduced 50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6) After stay at a hotel, how would you rate the value for money compared with the actual price?

<table>
<thead>
<tr>
<th>Very worthy, the price should be increase 50%</th>
<th>Worthy</th>
<th>Worth for money</th>
<th>Unworthy</th>
<th>Very unworthy, the price should be reduced 50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
PART 5: QUESTIONS ON ATTITUDE TOWARD ONLINE REVIEW

Direction: Please give the information that best represents your attitude toward online review during online booking transaction. Use the scale provided for each question to guide your response.

1) What is your preferable sorting method to present online review on online travel agencies?
   - □ Type of traveller
   - □ Sorting from most recent review
   - □ Sorting from highest review rating
   - □ Sorting from lowest review rating

2) How many online review you read per hotel: ________ Reviews

3) Please indicate the minimum acceptable level for review rating in the following attributes

<table>
<thead>
<tr>
<th>Hotel attribute</th>
<th>Very poor</th>
<th>Neutral</th>
<th>Very Excellent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value for money</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Location</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Facility</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Staff and service</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Cleanliness</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Food</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

4) Please indicate the important level of each review indicator you will read.

<table>
<thead>
<tr>
<th>Hotel attribute</th>
<th>Very unimportant</th>
<th>Neutral</th>
<th>Very important</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value for money</td>
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<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Location</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Facility</td>
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<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Staff and service</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Cleanliness</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Food</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>
Appendix B

Proof of Decision

Proof of Proposition 1. We prove that \( p_n^* \), \( D_{n,r} \) and \( II_{n,r}^* \) increases in \( \beta_n \) . Thus, we can differentiate them with respect to \( \beta_n \) and get a clearly positive result of

\[
\frac{d p_n^*(\beta_n)}{d \beta_n} = \frac{(c - v)^2 v}{(2 + \beta_n)c + (3 - 2\beta_n)v^2} > 0, \text{ where } v > c > 0
\]

\[
\frac{d D_{n,r}(\beta_n)}{d \beta_n} = \frac{v(c + v)}{(2 + \beta_n)c + (3 - 2\beta_n)v^2} > 0, \text{ where } v > c > 0
\]

\[
\frac{d II_{n,r}^*(\beta_n)}{d \beta_n} = \frac{(c - v)^2 v}{2(2 + \beta_n)c + (3 - 2\beta_n)v^2} > 0, \text{ where } v > c > 0
\]

Proof of Proposition 2. We prove to find the parameters determining \( \text{Avg} \cdot II_{n,r}^* \). We have

\[
II_{n,r}^* = \frac{1}{2} \frac{(-2 + \beta_n)(c - v)^2}{(2 + \beta_n)c + (6 + 4\beta_n)v^2} \quad \text{and} \quad D_{n,r} = (v - \frac{(-1 + \beta_n)^2}{(2 - \beta_n)c + (3 - 2\beta_n)v}) / v.
\]

By using \( \text{Avg} \cdot II_{n,r}^* = \frac{II_{n,r}^*}{D_{n,r}} \), we get

\[
\text{Avg} \cdot II_{n,r}^* = \frac{(-2 + \beta_n)(c - v)^2}{(2 + \beta_n)c + (6 + 4\beta_n)v^2} \frac{v}{v - \frac{(-1 + \beta_n)^2}{(2 - \beta_n)c + (3 - 2\beta_n)v}}
\]

which can be simplified as \( \text{Avg} \cdot II_{n,r}^* = \frac{1}{2} (-c + v) \).

Proof of Proposition 3. For the room’s availability management problem, we require

\[
ES_{n,r} \leq C \times (1 - s) \text{ or } \int_0^s (1 - \alpha)d\alpha \leq C \times (1 - s) \text{ to fit the demand of occupied room with the hotel room’s availability. Where } C \text{ represents capacity or available supply of rooms and } s \text{ is the ratio of safety stock.}
\]

Thus, given \( ES_{n,r} = C \times (1 - s) \) at \( \beta_n^* \), we obtain optimal values of \( \beta_n^* \)

By using,

\[
\int_0^s (1 - \alpha)d\alpha = C \times (1 - s)
\]

We obtain that under the condition of \( \frac{c - v}{c - 2v} < \beta_n < \frac{2c - v}{c - v} \) and \( v > 0 \),

\[
0 < c < \frac{3v}{2} - \frac{1}{2} \sqrt{5v^2}
\]
\[ \beta_n^* = 2c^2 - 4c^2C + 4c^2Cs - 7cv + 14cCv - 14cCsv + 5v^2 - 12Cv^2 + 12Csv^2 + \sqrt{c^2v^2 - 2c^2Cv^2 + 2c^2Csv^2 - 2cv^3 + 4Cv^3 - 4Csv^3 + v^4 - 2Cv^4 + 2Csv^4} / (c^2 - 2c^2C + 2c^2Cs - 4cv + 8cCv - 8cCsv + 3v^2 - 8Cv^2 + 8Csv^2) \]

**Proof of Proposition 4.**

The proposed model focuses on offering the sale conditions of “the mild and restriction conditions” \((n, r)\). We require the conditions as follows to ensure the superior of hotel’s profit ability generated from the sale conditions under our proposed model. \(H_{n,r}^*(p_n^*, p_r^*) - H_n^*(p_n^*) > 0, H_{n,r}^*(p_n^*, p_r^*) - H_r^*(p_r^*) > 0, H_{n,r}^*(p_n^*, p_r^*) - H_{r,n}^*(p_r^*, p_n^*) > 0, \)

\[ H_{n,r}^*(p_n^*, p_r^*) - H_{n,l}^*(p_n^*) > 0, H_{n,r}^*(p_n^*, p_r^*) - H_{r,n}^*(p_r^*, p_n^*) > 0. \]

Plug in the optimal price of each sale condition to the profit function; we derive the optimal profit of each scenario. Therefore, we obtain

1. \(H_{n,r}^*(p_n^*, p_r^*) = -\frac{(2 + \beta_n)(c - v)^2}{2(-2 + \beta_n)c + (6 - 4\beta_n)v} \) (The proposed model)
2. \(H_n^*(p_n^*) = -\frac{(c - v)^2}{2(c + (-2 + \beta_n)v)} \)
3. \(H_r^*(p_r^*) = -\frac{(c - v)^2}{2(c - 2v)} \)
4. \(H_{r,l}^*(p_r^*) = -\frac{c^2 f^2 - 2c(1 + (1 + f)v + v^2)}{2c^2 - 4(1 + (1 + f)v)} \)

5. \(H_{n,l}^*(p_n^*) = -\frac{(-1 + \beta_n)^2 c^2 f^2 + c(2 - \beta_n + 2(-1 + \beta_n)f + (-2 + \beta_n)(1 + \beta_n)(-1 + 2\beta_n)f^2)v - (1 + \beta_n)(1 + f)^2 f^2 v}{2(-1 + \beta_n)^2 c f^2 + 2(-2 + \beta_n - 2(-1 + \beta_n)f - 2(-1 + \beta_n)^2 f^2 v} \)
6. \(H_{r,n,l}^*(p_r^*, p_n^*) = -\frac{c^2 f^2 + c(\beta_n(-1 + f)^2 - 2(1 + (-1 + f)f)v + v^2)}{2(-2 + \beta_n)v + f(c + \beta_n(-2 + f) - 2f)v)} \)

We assume that \(v > c, c > 0, f > 0, 0 < \beta_n < 1 \). By solving all necessary conditions, we obtain

\[ H_{n,r}^*(p_n^*, p_r^*) - H_n^*(p_n^*) = -\frac{(2 + \beta_n)(c - v)^2}{2(-2 + \beta_n)c + (6 - 4\beta_n)v} + \frac{(c - v)^2}{2(c + (-2 + \beta_n)v)} \] Which satisfy

condition of \(H_{n,r}^*(p_n^*, p_r^*) - H_n^*(p_n^*) > 0 \).
\[ H_{n,r}(p^*_n, p^*_r) - H_{r,f}(p^*_r) = \frac{(c-v)^2}{2(c-2v)} - \frac{-(2 + \beta_n)(c-v)^2}{2(-2 + \beta_n) c + (6 - 4 \beta_n) v} \quad \text{Which satisfy the condition of } \quad H_{n,r}(p^*_n, p^*_r) - H_{r,f}(p^*_r) > 0. \]

\[ H_{n,r}(p^*_n, p^*_r) - H_{r,l}(p^*_r) = -\frac{-(2 + \beta_n)(c-v)^2}{2(-2 + \beta_n) c + (6 - 4 \beta_n) v} - \frac{c^2 f^2 + 2(1 + (-1 + f)f)v + \lambda^2}{2c f^2 - 4(1 + (-1 + f)f)v} \quad \text{Which satisfy the condition of } \quad H_{n,r}(p^*_n, p^*_r) - H_{r,l}(p^*_r) > 0. \]

\[ H_{n,r}(p^*_r, p^*_n) - H_{r,l}(p^*_n) = -\frac{-(2 + \beta_n)(c-v)^2}{2(-2 + \beta_n) c + (6 - 4 \beta_n) v} - \frac{c^2 f^2 + c(\beta_n(-1 + f)^3 - 2(1 + (-1 + f)f))v + \lambda^2}{2c(2 + \beta_n)v + f(c + (2 + \beta_n(-2 + f) - 2 f)v)} \quad \text{Which satisfy the condition of } \quad H_{n,r}(p^*_r, p^*_n) - H_{r,l}(p^*_n) > 0. \]

Thus, offering the sale conditions of “the mild and restriction condition” (by the proposed model) could generate the highest profit.
Appendix C
Program Source Code

- Source-code of CPLEX (Sequencing Model in Chapter 3)

The first-stage decision: Sequencing decision

/// PART I: DEFINE TYPES OF PARAMETERS AND VARIABLES \"\n
int N=...;
int K=...;
range i = 1..N;
range j = 1..K;
range k = 1..K;
range n= 1..K;
float p[j]=...;
float u[i][j]=...;
float E[i]=...;
float w1=...;
float w2=..;
float w3=...;
float t=...;
float o[i][j]=...;
float Ub=...;
float Lb=...;

/// PART II: DECISION VARIABLES \"\n
dvar boolean x[k][j];
dvar boolean y[i][j][k];
dvar boolean z[n];
dvar float s[i];
dvar float obj;

/// PART III: OBJECTIVE FUNCTION \"\n
minimize obj;
subject to
{
  obj==((w1*N*t*(sum(n in n)z[n]))-(w2*(1/N)*(sum(i in i,j in j, k in k)(u[i][j]*P[j])*y[i][j][k]))+(w3/N*sum(i in i)s[i]);

/// PART IV: CONSTRAINTS \"\n
//Second-stage constraints: Customer’s choice constraints
forall (i in i) sum(j in j, k in k)y[i][j][k]<=1;
forall (i in i) sum(j in j, k in k) y[i][j][k]<=o[i][j];
forall (i in i) sum(j in j, k in k) u[i][j][j]-E[i])*y[i][j][k]>=0;
forall (i in i) sum(j in j, k in k) y[i][j][k]<=x[k][j];
forall (i in i) sum(j in j, k in k, n in 1..k-1) y[i][j][k]<=1-z[n];
forall (i in i) s[i]==sum(j in j, k in k)k*y[i][j][k]+(1-sum(j in j, k in k)y[i][j][k])*K;
// First-stage constraints: Sequencing constraints
sum(n in n)z[n] == 1;
sum(n in n)n*z[n]<=Ub;
sum(n in n)n*z[n]>=Lb;
forall (j in j)
sum(k in k)x[k][j]==1;
forall (k in k)
sum(j in j)x[k][j]==1;
}

/// PART VI: LINK TO EXCEL SPREADSHEET

For Example

N = 80;
K = 42;
SheetConnection sheet("SequenceDecision.xlsx");
p from SheetRead(sheet, "Sheet1!E5:E46");
u from SheetRead(sheet, "Sheet1!BN5:DC84");
E from SheetRead(sheet, "Sheet1!P5:P84");
o from SheetRead(sheet, "Sheet1!T5:BI84");
w1 from SheetRead(sheet, "Sheet1!E58");
w2 from SheetRead(sheet, "Sheet1!E59");
w3 from SheetRead(sheet, "Sheet1!E60");
t from SheetRead(sheet, "Sheet1!E61");
Ub from SheetRead(sheet, "Sheet1!E62");
Lb from SheetRead(sheet, "Sheet1!E63");

The second-stage decision: Customer’s choice decision (actual customer)

/// PART I: DEFINE TYPES OF PARAMETERS AND VARIABLES

int N=...;
int K=...;
range i = 1..N;
range j = 1..K;
range k = 1..K;
range n= 1..K;
{int} index_a=...;
float p[j]=...;
float u[i][j]=...;
float E[i]=...;
float w1=...;
float w2=...;
float w3=...;
float t=...;
float o[i][j]=...;
float Ub=...;
float Lb=...;
float x[k][j][index_a];

/// PART II: DECISION VARIABLES

dvar boolean y[i][j][k];
dvar boolean z[n];
dvar float s[i];
dvar float obj;

tuple result {
    int index_k;
    int index_j;
    int index_a;
    float x;
}

{result} Get_Actual_x =...;

execute {
    for (var g in Get_Actual_x){
        x[g.index_k][g.index_j][g.index_a]=g.x
    }
}

/// PART III: OBJECTIVE FUNCTION \/
minimize obj;
subject to
{
    obj=(w1*N*t*(sum(n in n)n*z[n]))-(w2*(1/N)*(sum(i in i,j in j, k in k)(u[i][j]-
P[j])*y[i][j][k]))+(w3/N*sum(i in i)s[i]);
}

/// PART IV: CONSTRAINTS \/
//Second-stage constraints: Customer’s choice constraints
forall(i in i) sum(j in j, k in k)y[i][j][k]<=o[i][j];
forall(i in i,j in j,k in k) y[i][j][k]<=o[i][j];
forall(i in i,j in j,k in k) (u[i][j]-p[j]-E[i])*y[i][j][k]>=0;
forall (i in i) s[i]==sum(j in j, k in k)k*y[i][j][k]+(1-sum(j in j, k in k)y[i][j][k])*K;
forall(i in i,j in j,k in k,a in index_a) y[i][j][k]<=x[k][j][a];

//First-stage constraints: Sequencing constraints
sum(n in n)z[n] == 1;
sum(n in n)n*z[n] == sum(j in j,a in index_a,k in k)x[j][k][a];
sum(n in n)n*z[n]<=Ub;
sum(n in n)n*z[n]>=Lb;
}