

# Seat Planning and Seat Assignment with Social Distancing

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## Abstract

This study tackles the challenge of seat planning and assignment with social distancing measures. Initially, we analyze seat planning under deterministic demand conditions. Subsequently, we introduce a scenario-based stochastic programming approach to formulate seat planning strategies. We also investigate the dynamic situation where groups enter a venue and need to sit together while adhering to minimum physical distancing criteria. Seat planning can serve as the foundation for assignment. Combined with relaxed dynamic programming, we propose a dynamic seat assignment policy for either accommodating or rejecting incoming groups. Our method outperforms traditional bid-price and booking-limit strategies. The findings furnish valuable insights for policymakers and venue managers regarding seat occupancy rates and provide a practical framework for implementing social distancing protocols while optimizing seat allocations.

Keywords: Social Distancing, Scenario-based Stochastic Programming, Seat Assignment, Dynamic Arrival.

## 1 Introduction

Social distancing is a proven concept for containing the spread of an infectious disease. It has been widely adopted worldwide, for example, during the most recent Covid 19 pandemic. As a general principle, social distancing measures can be specified from different dimensions. The basic requirement of social distancing is the specification of a minimum physical distance between people in public areas. For example, the World Health Organization (WHO) suggests social distancing as to “keep physical distance of at least 1 meter from others” [23]. In the US, the Center for Disease and Control (CDC) refers to social distancing as “keeping a safe space between yourself and other people who are not from your household” [6]. Note that under such a requirement, social distancing is actually applied with respect to groups of people. Similarly in Hong Kong, the government has adopted social distancing measures, in the recent Covid 19 pandemic, by limiting the size of groups in public gatherings to two, four, and six people per group over time. Moreover, the Hong Kong government has also adopted an upper limit on the total number of people in a venue; for example, restaurants can operate at 50% or 75% of their normal seating capacity.

The government hopes to implement some policies to reopen, but the requirement of social distancing is not applicable to all places. Strict physical distance requirements make some cinemas with small row spacing and seat spacing only able to accommodate fewer customers, making the implementation of this policy impractical. Therefore, we hope to develop a policy that is easy to implement and satisfies both the government and businesses to meet requirements, and evaluate the impact of these strategies, in order to provide insights for policy implementation and business operations.

The implementation of social distancing measures has an extended impact beyond disease control. In particular, social distancing may disrupt the usual operations in certain sectors. For example, a restaurant needs to change or redesign the layout of its tables in order to fulfill the requirement of social distancing. Such change implies smaller capacity, fewer customers and less revenue. In such a context, an affected firm faces a new operational problem of optimizing its operations flow under given social distancing policies.

The impact of enforcing social distancing measures on economic activities is also an important factor for governmental decision making. Facing an outbreak of an infectious disease, a government shall declare a social distancing policy based on a holistic analysis, considering not only the severity of the outbreak, but also the potential impact on all stakeholders. What is particularly important is the level of business loss suffered by the industries that are directly affected.

We will address the above issues of social distancing in the context of seating management. Consider a venue, such as a cinema or a conference hall, which is to be used in an event. The venue is equipped with seats of multiple rows. In the event, requests for seats are in groups where each group contains a limited number of people. Any group can be accepted or rejected, and the people in an accepted group will sit consecutively in one row. Each row can accommodate multiple groups as long as any two adjacent groups in the same row are separated by one or multiple empty seats, as the requirement of the social distancing measures. The objective is to accept the number of people as many as possible.

We will consider three models in managing the seats, referred to as seat planning with deterministic requests, seat planning with stochastic requests, and seat assignment, respectively. As we elaborate below, each of these models defines a standalone problem with suitable situations. Together, they are inherently connected to each other, jointly forming a suite of solution schemes for seating management under the social distancing constraints.

In seat planning with deterministic requests, we are given the complete information about seating requests in groups, and the problem is to find a seating plan which specifies a partition of the layout into small segments to match the seating requests. Such a problem is applicable for cases of which participants and their groups are known, such as people from the same family in a church gathering, and staff from the same office in a company meeting.

In seat planning with stochastic requests, we need to find a seating plan facing the requests in terms of a probabilistic distribution. This problem may find its applications in situations where a new layout needs to be made for serving multiple events with different seating requests. For example, there are theaters physically removing some seats during the Covid-19 outbreak. [19]

In seat assignment, groups of seating requests arrive dynamically. The problem is to decide, upon

the arrival of each group of request, whether to accept or reject the group, and assign seats for each accepted groups. Seat assignment can be used for those commercial applications where requests arrive as a stochastic process, for example, tickets selling in movie theaters.

The above three problems are closely related to each other with respect to problem solving methods and managerial insights. For example, seat planning with deterministic demand can provide an upper bound for the seat assignment problems. In studying the seat planning problem with deterministic requests, we identify some useful concepts such as the full patterns and largest patterns, which are important in the solution development for seat assignment.

We also address the dynamic seat assignment problem with a given set of seats in the context of social distancing. In the seat assignment, for the coming group, when accepting it, we assign the seats to the group, and the seats will not be used by others in the future. We intend to shed light on the problem described and propose a practical dynamic seat assignment policy. In particular, we investigate the following questions.

How to use the property of seat planning problem to design the dynamic seat assignment policy?  
How good is the performance of this policy compared with other policies?

What kind of insights regarding the social distancing and occupancy rates can we obtain when implementing the dynamic seat assignment policy?

We have the following insights:

Our policy outperforms traditional approaches in terms of the number of accepted individuals. While different probability distributions represent varying group profiles, our policy demonstrates consistent performance across different scenarios.

1. With the requirement of social distancing, there is no need for the government to set a separate attendance rate. We set the gap point to represent the size of the demand. The gap point is specifically the number of periods, and the demand is the product of the gap point and the probability distribution of customer arrival. It can be estimated by the average number of customers in each request. And it has little to do with different probability distributions.

2. When the demand is smaller than the demand corresponding to the gap point, social distancing will not have an impact. The occupancy rate corresponding to the gap point is the maximum occupancy rate when there is no impact.

3. The group size

For the choice of group size that allows sitting together, when the demand is high, we tend to allow more people to sit together, and when the demand is low, we can limit the number of groups that sit together to be smaller. For the choice of social distancing, when the demand is low, two seats can be chosen as the social distance.

4. Layout of venues also has the impact on the

Regarding the different layouts, we found that under the requirement of a single seat in social distancing, the occupancy rate of small venues is actually higher than that of large venues. When the total number of seats is the same, layouts with more rows have higher occupancy rates.

The rest of this paper is structured as follows. The following section reviews relevant literature. We

describe the motivating problem in Section 3. In Section 4, we establish the stochastic model, analyze its properties and obtain the seat planning. Section 5 introduces the dynamic seat assignment problem. Section 6 demonstrates the dynamic seat assignment policy to assign the seats for incoming groups. Section 7 gives the numerical results and the insights of implementing social distancing. The conclusions are shown in Section 8.

## 2 Literature Review

The present study is closely connected to the following research areas – seat planning with social distancing and dynamic seat assignment. The subsequent sections review literature about each perspective and highlight significant differences between the present study and previous research.

### 2.1 Seat Planning with Social Distancing

Social distancing in seat planning has attracted significant attention from the research community. This topic involves various applications and optimization techniques to address the challenges posed by the need for physical distancing in different settings.

In the context of layout design, i.e., determine the seats location in the given venue. For example, maximizing the social distancing between students in the classroom [5]. Fischetti et al. [10] consider how to plant positions with social distancing and apply it in restaurants and beach umbrellas. In some other applications, where the layout is predetermined, individuals are assigned seats while adhering to social distancing guidelines. For instance, in the field of air travel, seat planning with a given layout is addressed in the literature [12,21]. Additionally, the optimization of seating arrangements has also been investigated in the context of long-distance train travel [14].

Group seat reservation had two main applications in terms of revenue optimization and customer preference satisfaction. In the transportation domain, such as for passenger rail services, the primary focus of these studies was on maximizing capacity utilization or reducing the total capacity required [7,9]. Similar optimization techniques have also been applied in the context of seat planning for large events, such as weddings or dinner events [18]. In these cases, the focus was on satisfying customer preferences and enhancing the overall experience.

The pandemic has amplified the focus on and importance of group-based seat planning, especially within the framework of social distancing mandates. It has underscored the potential advantages of group reservations in curbing the spread of infections, as they can be structured to boost revenue without heightening transmission risks. The issue of group seat reservations has evolved into a more intricate problem with the constraint of social distancing. This complexity presents diverse applications across various industries, including: airplanes [21], trains [15], sports arenas [17], theaters [4].

The major difference in our study is that we consider group-based seat planning with stochastic demand not only the known specific demand. Meanwhile, we consider the dynamic seat assignment assuming the groups arrive in a certain probability.

### 2.2 Dynamic Seat Assignment

In dynamic seat assignment, the decision to either reject or accept-and-assign groups is made at each stage upon their arrival. This problem can be regarded as a special case of the dynamic multiple knapsack problem. When there is one row, the related problem is dynamic knapsack problem [16]. Our model in its static form can be viewed as a specific instance of the multiple knapsack problem [20]. To

the best of our knowledge, there are no existing studies that have specifically addressed the dynamic multiple knapsack problem.

Dynamic seat assignment has applications in the transportation industry, such as for airplanes, trains, and buses [2, 13, 25]. It is a process of assigning seats to passengers in a way that maximizes the efficiency and convenience of the seating arrangements.

Our problem is closely related to the group-based network revenue management (RM) problem [24], which is typically formulated as a dynamic programming (DP) problem. However, for large-scale problems, the exponential growth of the state space and decision set makes the DP approach computationally intractable. One of the characteristics we are studying is that the decision should be made on an all-or-none basis for each group, which is the real complication in group arrivals [22]. The group trait reflected in the RM is the hotel revenue management considering multiple day stays [1, 3].

Another characteristic in our study is the significance of seat assignment. This sets it apart from traditional revenue management focusing on accepting or rejecting a request [11]. The assign-to-seat feature introduced by Zhu et al. [25] also highlights the importance of seat assignment in revenue management. This trait addresses the challenge of selling high-speed train tickets in China, where each request must be assigned to a single seat for the entire journey and takes into account seat reuse.

Our work not only focuses on how to make the group-based seat assignment with non-reusable seats, also contribute the revenue insights with social distancing.

### 3 Seat Planning Problem with Social Distancing

This section integrates social distancing measures into the seat planning process. By introducing some concepts, we present the deterministic seat planning problem. For the seat planning that does not utilize all available seats, we propose to improve the seat planning.

#### 3.1 Concepts

Consider a seat layout comprising  $N$  rows, with each row containing  $L_j^0$  seats, where  $j \in \mathcal{N} := \{1, 2, \dots, N\}$ . There are  $M$  distinct group types, denoted by group type  $i$ , where each group type consists of  $i$  individuals. The set of all group types is denoted by  $\mathcal{M} := \{1, 2, \dots, M\}$ . The request of each group type is represented by a demand vector  $\mathbf{d} = (d_1, d_2, \dots, d_M)^\top$ , where  $d_i$  is the number of group types  $i$ .

We incorporate social distancing in the seat planning problem. To comply with the social distancing requirements, individuals from the same group must sit together in one specific row, while maintaining a distance from other groups. Since each group occupies only one row, we assume that social distancing does not impact different rows. If the social distancing requirement is more significant, an empty row can be implemented, as implemented by the theater in Berlin. [19]

Let  $\delta$  denote the social distancing, which could entail leaving one or more empty seats. Specifically, each group must ensure the empty seat(s) with the adjacent group(s). To model the social distancing requirements into the seat planning process, we define the size of group type  $i$  as  $n_i = i + \delta$ , where  $i \in \mathcal{M}$ . Correspondingly, the size of each row is defined as  $L_j = L_j^0 + \delta$ . By incorporating the additional seat(s) and designating certain seat(s) for social distancing, we can integrate social distancing measures into the seat planning problem.

For any feasible pattern  $h$ , the number of physical seats that can be taken is

$$\begin{aligned} \sum_i h_i i + (\sum_i h_i - 1)\delta &\leq L_j^0 \\ \sum_i h_i (i + \delta) &\leq L_j^0 + \delta \\ \sum_i h_i n_i &\leq L_j \end{aligned}$$

We introduce the term pattern to represent the seat planning arrangement for a single row. A specific pattern can be represented by a vector  $\mathbf{h} = (h_1, \dots, h_M)$ , where  $h_i$  is the number of group type  $i$  in the row for  $i = 1, \dots, M$ . A feasible pattern,  $\mathbf{h}$ , must satisfy the condition  $\sum_{i=1}^M h_i n_i \leq L$  and belong to the set of non-negative integer values, denoted as  $\mathbf{h} \in \mathbb{N}^M$ . Then a seat planning with  $N$  rows can be expressed by  $\mathbf{H} = \{\mathbf{h}_1; \dots; \mathbf{h}_N\}$ .

Let  $|\mathbf{h}|$  indicate the maximum number of people that can be assigned according to pattern  $\mathbf{h}$ , i.e.,  $|\mathbf{h}| = \sum_{i=1}^M i h_i$ . The size of  $\mathbf{h}$ ,  $|\mathbf{h}|$ , provides a measure of the maximum number of seats that can be taken due to the implementation of social distancing constraints. By examining  $|\mathbf{h}|$  associated with different patterns, we can assess the effectiveness of various seat planning configurations for accommodating the desired number of individuals while adhering to social distancing requirements.

**Example 1.** Consider the given values:  $\delta = 1$ ,  $L^0 = 10$ , and  $M = 4$ . By adding one seat to each group and the original row, we can realize the conversion, as shown in the following figure.

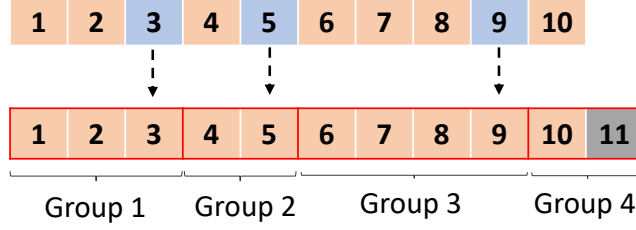


Figure 1: Illustration of Groups with Social Distancing

After the conversion,  $L = L^0 + 1 = 11$ ,  $n_i = i + 1$  for  $i = 1, 2, 3, 4$ . Then, the row can be represented by  $\mathbf{h} = (2, 1, 1, 0)$ . The maximum number of people that can be accommodated is  $|\mathbf{h}| = 7$ .

To formulate the deterministic model, let  $x_{ij}$  represent the number of group type  $i$  planned in row  $j$ . The seat planning problem with deterministic request is formulated below.

$$\begin{aligned} \max \quad & \sum_{i=1}^M \sum_{j=1}^N (n_i - \delta) x_{ij} \\ \text{s.t.} \quad & \sum_{j=1}^N x_{ij} \leq d_i, \quad i \in \mathcal{M}, \end{aligned} \tag{1}$$

$$\sum_{i=1}^M n_i x_{ij} \leq L_j, j \in \mathcal{N}, \tag{2}$$

$$x_{ij} \in \mathbb{N}, \quad i \in \mathcal{M}, j \in \mathcal{N}.$$

The objective is to maximize the number of people accommodated. Constraint (1) requires Constraint (2) requires the number of seats planned in each row does not exceed the size of the row.

In this context, the supply of a seat planning for group type  $i$  can be defined as  $\mathbf{X}_i = \sum_{j=1}^N x_{ij}$ . Then  $\mathbf{X} = (\mathbf{X}_1, \dots, \mathbf{X}_M)^T$  is the aggregate solution. In other words,  $\mathbf{X}$  captures the number of each group type that can be allocated to the seat layout by summing up the supplies across all rows. By considering the monotone ratio between the original group sizes and the adjusted group sizes, we can determine the upper bound of supply corresponding to the optimal solution of the LP relaxation of Problem (1), as demonstrated in Proposition 1.

**Proposition 1.** *For the LP relaxation of problem (1), there exists an index  $\tilde{i}$  such that the optimal solutions satisfy the following conditions:  $x_{ij}^* = 0$  for all  $j$ ,  $i = 1, \dots, \tilde{i} - 1$ ;  $\sum_j x_{ij}^* = d_i$  for  $i = \tilde{i} + 1, \dots, M$ ;  $\sum_j x_{ij}^* = \frac{L - \sum_{i=\tilde{i}+1}^M d_i n_i}{n_{\tilde{i}}}$  for  $i = \tilde{i}$ .*

For  $i = 1, \dots, \tilde{i} - 1$ , the optimal solutions have  $x_{ij}^* = 0$  for all rows, indicating that no group type  $i$  lower than index  $\tilde{i}$  are assigned to any rows. For  $i = \tilde{i} + 1, \dots, M$ , the optimal solution assigns  $\sum_j x_{ij}^* = d_i$  group type  $i$  to meet the demand for group type  $i$ . For  $i = \tilde{i}$ , the optimal solution assigns  $\sum_j x_{ij}^* = \frac{\sum_{j=1}^N L_j - \sum_{i=\tilde{i}+1}^M d_i n_i}{n_{\tilde{i}}}$  group type  $\tilde{i}$  to the rows. This quantity is determined by the available supply, which is calculated as the remaining seats after accommodating the demands for group types  $\tilde{i} + 1$  to  $M$ , divided by the size of group type  $\tilde{i}$ , denoted as  $n_{\tilde{i}}$ .



Hence, the corresponding supply associated with the optimal solutions can be summarized as follows:  
 $X_{\tilde{i}} = \frac{\sum_{j=1}^N L_j - \sum_{i=\tilde{i}+1}^M d_i n_i}{n_{\tilde{i}}}$ ,  $X_i = d_i$  for  $i = \tilde{i} + 1, \dots, M$ , and  $X_i = 0$  for  $i = 1, \dots, \tilde{i} - 1$ .

### 3.2 Seat Planning Composed of Full or Largest Patterns

The seat planning obtained from problem (1) may not utilize all available seats, as it depends on the given requests. To improve a given seat planning and utilize all seats, we aim to generate a new seat planning composed of full or largest patterns while ensuring that the original group type requirements are met.

**Definition 1.** Consider a pattern  $\mathbf{h} = (h_1, \dots, h_M)$  for a row with size  $L$ . We refer to  $\mathbf{h}$  as a full pattern if  $\sum_{i=1}^M n_i h_i = L$ . Refer to  $\mathbf{h}$  as a largest pattern if its size  $|\mathbf{h}| \geq |\mathbf{h}'|$ , for any other feasible pattern  $\mathbf{h}'$ .

In other words, a full pattern is one in which the sum of the product of the number of occurrences  $h_i$  and the size  $n_i$  of each group in the pattern is equal to the size of the row  $L$ . This ensures that the pattern fully occupies the available row seats. A largest pattern is one that either has the maximum size or is equal in size to other patterns, ensuring that it can accommodate the maximum number of people within the given row size.

**Proposition 2.** If the size of a feasible pattern  $\mathbf{h}$  is  $|\mathbf{h}| = qM + \max\{r - \delta, 0\}$ , where  $q = \lfloor \frac{L}{M+\delta} \rfloor$ , and  $r \equiv L \bmod (M + \delta)$ , then this pattern is a largest pattern.

The largest pattern is not unique, one form of largest pattern, other largest pattern has the same size.

Furthermore, according to the definition of the largest pattern, the size of one possible largest pattern is given by  $qM + \max\{r - \delta, 0\}$ .

When  $r = 0$ , the largest pattern  $\mathbf{h}$  is unique and full, indicating that only one pattern can accommodate the maximum number of people. On the other hand, if  $r > \delta$ , the largest pattern  $\mathbf{h}$  is full, as it utilizes the available space up to the social distancing requirement.

**Example 2.** Consider the given values:  $\delta = 1$ ,  $L = 21$ , and  $M = 4$ . The size of the largest pattern can be calculated as  $qM + \max\{r - \delta, 0\} = 4 \times 4 + 0 = 16$ . The largest patterns are the following:  $(1, 0, 1, 3)$ ,  $(0, 1, 2, 2)$ ,  $(0, 0, 0, 4)$ ,  $(0, 0, 4, 1)$ , and  $(0, 2, 0, 3)$ .

The following figure shows that the largest pattern may not be full and the full pattern may not be largest.

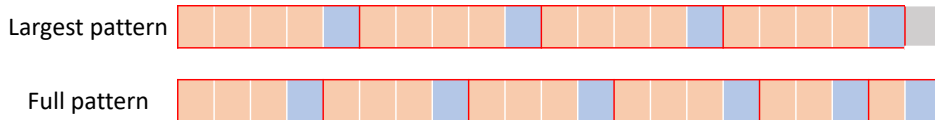


Figure 2: Largest and Full Patterns

The first row can be represented by  $(0, 0, 0, 4)$ . It is a largest pattern as its size is 16. However, it does not satisfy the requirement of fully utilizing all available seats since  $4 \times 5 \neq 21$ . The second row can

be represented by  $(1, 1, 4, 0)$ , which is a full pattern as it utilizes all available seats. However, its size is 15, indicating that it is not a largest pattern.

Having defined the full and largest pattern, we would like to obtain a seat planning from Suppose the original seat planning is  $\mathbf{H}$ , the desired seat planning is  $\mathbf{H}'$ . To meet the original group type requirements, for each group type  $i$ , the total quantity from group  $i$  to group  $M$  in  $\mathbf{H}'$  should be no less than the total quantity from group type  $i$  to group type  $M$  in  $\mathbf{H}$ . Mathematically, we aim to find a feasible seat planning  $\mathbf{H}'$  such that  $\sum_{k=i}^M \sum_{j=1}^N H_{ji} \leq \sum_{k=i}^M \sum_{j=1}^N H'_{ji}, \forall i \in \mathcal{M}$ . We say  $\mathbf{H} \subseteq \mathbf{H}'$  if this condition holds.

To utilize all seats in the seat planning, the objective is to maximize the number of people that can be accommodated. Thus, we have the following formulation:

$$\begin{aligned}
& \max \quad \sum_{i=1}^M \sum_{j=1}^N (n_i - \delta) x_{ij} \\
& s.t. \quad \sum_{j=1}^N \sum_{k=i}^M x_{kj} \geq \sum_{k=i}^M \sum_{j=1}^N H_{ji}, i \in \mathcal{M} \\
& \quad \sum_{i=1}^M n_i x_{ij} \leq L_j, j \in \mathcal{N} \\
& \quad x_{ij} \in \mathbb{N}, i \in \mathcal{M}, j \in \mathcal{N}
\end{aligned} \tag{3}$$

**Proposition 3.** *Given a feasible seat planning  $\mathbf{H}$ , the solution to problem (3) corresponds to a seat planning  $\mathbf{H}'$  such that  $\mathbf{H} \subseteq \mathbf{H}'$  and  $\mathbf{H}'$  is composed of full or largest patterns.*

This approach guarantees efficient seat allocation by constructing full or largest patterns while still accommodating the original groups' requirements. Furthermore, the improved seat planning can be used for the seat assignment when the demand arrives sequentially.

## 4 Seat Planning with Stochastic Demand

In this section, we aim to obtain a seat planning which is suitable to the dynamic seat assignment. Specially, we develop the Scenario-based Stochastic Programming (SSP) to obtain the seat planning with available capacity. Due to the well-structured nature of SSP, we implement Benders decomposition to solve it efficiently. However, in some cases, solving the integer programming with Benders decomposition remains still computationally prohibitive. Thus, we can consider the LP relaxation first, then obtain a feasible seat planning by deterministic model. Based on that, we construct a seat planning composed of full or largest patterns to fully utilize all seats.

### 4.1 Scenario-based Stochastic Programming Formulation

Now suppose the demand of groups is stochastic, the stochastic information can be obtained from scenarios through historical data. Use  $\omega$  to index the different scenarios, each scenario  $\omega \in \Omega$ . Regarding the nature of the obtained information, we assume that there are  $|\Omega|$  possible scenarios. A particular

realization of the demand vector can be represented as  $\mathbf{d}_\omega = (d_{1\omega}, d_{2\omega}, \dots, d_{M,\omega})^\top$ . Let  $p_\omega$  denote the probability of any scenario  $\omega$ , which we assume to be positive. To maximize the expected number of people accommodated over all the scenarios, we propose a scenario-based stochastic programming to obtain a seat planning.

The seat planning can be represented by decision variables  $\mathbf{x} \in \mathbb{N}^{M \times N}$ . Here,  $x_{ij}$  represents the number of group type  $i$  assigned to row  $j$  in the seat planning. As mentioned earlier, we calculate the supply for group type  $i$  as the sum of  $x_{ij}$  over all rows  $j$ , denoted as  $\sum_{j=1}^N x_{ij}$ . However, considering the variability across different scenarios, it is necessary to model the potential excess or shortage of supply. To capture this characteristic, we introduce a scenario-dependent decision variable, denoted as  $\mathbf{y}$ . It includes two vectors of decisions,  $\mathbf{y}^+ \in \mathbb{N}^{M \times |\Omega|}$  and  $\mathbf{y}^- \in \mathbb{N}^{M \times |\Omega|}$ . Each component of  $\mathbf{y}^+$ , denoted as  $y_{i\omega}^+$ , represents the excess supply for group type  $i$  for each scenario  $\omega$ . On the other hand,  $y_{i\omega}^-$  represents the shortage of supply for group type  $i$  for each scenario  $\omega$ .

Taking into account the possibility of groups occupying seats planned for larger group types when the corresponding supply is insufficient, we make the assumption that surplus seats for group type  $i$  can be occupied by smaller group types  $j < i$  in descending order of group size. This means that if there are excess supply available after assigning groups of type  $i$  to rows, we can provide the supply to groups of type  $j < i$  in a hierarchical manner based on their sizes. That is, for any  $\omega$ ,  $i \leq M-1$ ,

$$y_{i\omega}^+ = \left( \sum_{j=1}^N x_{ij} - d_{i\omega} + y_{i+1,\omega}^+ \right)^+, \quad y_{i\omega}^- = \left( d_{i\omega} - \sum_{j=1}^N x_{ij} - y_{i+1,\omega}^+ \right)^+,$$

where  $(x)^+$  equals  $x$  if  $x > 0$ , 0 otherwise. Specially, for the largest group type  $M$ , we have  $y_{M\omega}^+ = (\sum_{j=1}^N x_{Mj} - d_{M\omega})^+$ ,  $y_{M\omega}^- = (d_{M\omega} - \sum_{j=1}^N x_{Mj})^+$ . Based on the above mentioned considerations, the total supply of group type  $i$  under scenario  $\omega$  can be expressed as  $\sum_{j=1}^N x_{ij} + y_{i+1,\omega}^+ - y_{i\omega}^+$ ,  $i = 1, \dots, M-1$ . For the special case of group type  $M$ , the total supply under scenario  $\omega$  is  $\sum_{j=1}^N x_{Mj} - y_{M\omega}^+$ .

Then we have the following formulation:

$$\max \quad E_\omega \left[ (n_M - \delta) \left( \sum_{j=1}^N x_{Mj} - y_{M\omega}^+ \right) + \sum_{i=1}^{M-1} (n_i - \delta) \left( \sum_{j=1}^N x_{ij} + y_{i+1,\omega}^+ - y_{i\omega}^+ \right) \right] \quad (4)$$

$$\text{s.t.} \quad \sum_{j=1}^N x_{ij} - y_{i\omega}^+ + y_{i+1,\omega}^+ + y_{i\omega}^- = d_{i\omega}, \quad i = 1, \dots, M-1, \omega \in \Omega \quad (5)$$

$$\sum_{j=1}^N x_{ij} - y_{i\omega}^+ + y_{i\omega}^- = d_{i\omega}, \quad i = M, \omega \in \Omega \quad (6)$$

$$\sum_{i=1}^M n_i x_{ij} \leq L_j, \quad j \in \mathcal{N} \quad (7)$$

$$y_{i\omega}^+, y_{i\omega}^- \in \mathbb{N}, \quad i \in \mathcal{M}, \omega \in \Omega$$

$$x_{ij} \in \mathbb{N}, \quad i \in \mathcal{M}, j \in \mathcal{N}.$$

We use  $\text{SSP}(\mathbf{L}, \Omega)$  to represent the above stochastic programming, and similarly, we use  $\text{RSSP}(\mathbf{L}, \Omega)$  to represent the LP relaxation of SSP.

The objective function consists of two parts. The first part represents the number of people in the group type  $M$  that can be accommodated, given by  $(n_M - \delta)(\sum_{j=1}^N x_{Mj} - y_{M\omega}^+)$ . The second part represents the number of people in group type  $i$ , excluding  $M$ , that can be accommodated, given by  $(n_i - \delta)(\sum_{j=1}^N x_{ij} + y_{i+1,\omega}^+ - y_{i\omega}^+)$ ,  $i = 1, \dots, M-1$ . The overall objective function is subject to an expectation operator denoted by  $E_\omega$ , which represents the expectation with respect to the scenario set. This implies that the objective function is evaluated by considering the average values of the decision variables and constraints over the different scenarios.

By reformulating the objective function, we have

$$\begin{aligned} E_\omega & \left[ \sum_{i=1}^{M-1} (n_i - \delta) \left( \sum_{j=1}^N x_{ij} + y_{i+1,\omega}^+ - y_{i\omega}^+ \right) + (n_M - \delta) \left( \sum_{j=1}^N x_{Mj} - y_{M\omega}^+ \right) \right] \\ &= \sum_{j=1}^N \sum_{i=1}^M (n_i - \delta) x_{ij} - \sum_{\omega=1}^{|\Omega|} p_\omega \left( \sum_{i=1}^M (n_i - \delta) y_{i\omega}^+ - \sum_{i=1}^{M-1} (n_i - \delta) y_{i+1,\omega}^+ \right) \\ &= \sum_{j=1}^N \sum_{i=1}^M i \cdot x_{ij} - \sum_{\omega=1}^{|\Omega|} p_\omega \sum_{i=1}^M y_{i\omega}^+ \end{aligned}$$

Here,  $\sum_{j=1}^N \sum_{i=1}^M i \cdot x_{ij}$  indicates the maximum number of people that can be accommodated in the seat planning  $\{x_{ij}\}$ . The second part,  $\sum_{\omega=1}^{|\Omega|} p_\omega \sum_{i=1}^M y_{i\omega}^+$  indicates the expected excess supply for group type  $i$  over scenarios.

In the optimal solution, at most one of  $y_{i\omega}^+$  and  $y_{i\omega}^-$  can be positive for any  $i, \omega$ . Suppose there exist  $i_0$  and  $\omega_0$  such that  $y_{i_0\omega_0}^+$  and  $y_{i_0\omega_0}^-$  are positive. Subtracting  $\min\{y_{i_0\omega_0}^+, y_{i_0\omega_0}^-\}$  from these two values will still satisfy constraints (5) and (6) but increase the objective value when  $p_{\omega_0}$  is positive. Thus, in the optimal solution, at most one of  $y_{i\omega}^+$  and  $y_{i\omega}^-$  can be positive.

Considering the analysis provided earlier, we find it advantageous to obtain a seat planning that only consists of full or largest patterns. However, the seat planning associated with the optimal solution obtained by solver to SSP may not consist of the largest or full patterns. We can convert the optimal solution to another optimal solution which is composed of the largest or full patterns.

**Proposition 4.** *There exists an optimal solution to SSP such that the patterns associated with this optimal solution are composed of the full or largest patterns under any given scenarios.*

Proposition 4 is different from proposition 3. Proposition 3 can make sure that we can obtain a seat planning composed of full or largest patterns. Here, proposition 4 states that there always exists an optimal solution where the corresponding patterns are either full or largest. However, we may not be able to directly find such an optimal solution as described in Proposition 4. Instead, we try to obtain the seat planning composed of full or largest patterns, as stated in Section 4.3.

Then, we reformulate  $\text{SSP}(\mathbf{L}, \Omega)$  in a matrix form to apply the Benders decomposition technique. Let  $\mathbf{n} = (n_1, \dots, n_M)^\top$  represent the vector of seat sizes for each group type, where  $n_i$  denotes the size of seats taken by group type  $i$ . Let  $\mathbf{L} = (L_1, \dots, L_N)^\top$  represent the vector of row sizes, where  $L_j$  denotes the size of row  $j$  as defined previously. The constraint (7) can be expressed as  $\mathbf{x}^\top \mathbf{n} \leq \mathbf{L}$ . This constraint ensures that the total size of seats occupied by each group type, represented by  $\mathbf{x}^\top \mathbf{n}$ , does not exceed

the available row sizes  $\mathbf{L}$ . We can use the product  $\mathbf{x}\mathbf{1}$  to indicate the supply of group types, where  $\mathbf{1}$  is a column vector of size  $N$  with all elements equal to 1.

The linear constraints associated with scenarios, denoted by constraints (5) and (6), can be expressed in matrix form as:

$$\mathbf{x}\mathbf{1} + \mathbf{V}\mathbf{y}_\omega = \mathbf{d}_\omega, \omega \in \Omega,$$

where  $\mathbf{V} = [\mathbf{W}, \mathbf{I}]$ .

$$\mathbf{W} = \begin{bmatrix} -1 & 1 & 0 & \dots & \dots & 0 \\ 0 & -1 & 1 & 0 & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & -1 & 1 & 0 \\ 0 & \dots & \dots & 0 & -1 & 1 \\ 0 & \dots & \dots & \dots & 0 & -1 \end{bmatrix}_{M \times M}$$

and  $\mathbf{I}$  is the identity matrix with the dimension of  $M$ . For each scenario  $\omega \in \Omega$ ,

$$\mathbf{y}_\omega = \begin{bmatrix} \mathbf{y}_\omega^+ \\ \mathbf{y}_\omega^- \end{bmatrix}, \mathbf{y}_\omega^+ = [y_{1\omega}^+ \ y_{2\omega}^+ \ \dots \ y_{M\omega}^+]^\top, \mathbf{y}_\omega^- = [y_{1\omega}^- \ y_{2\omega}^- \ \dots \ y_{M\omega}^-]^\top.$$

As we can find, this deterministic equivalent form is a large-scale problem even if the number of possible scenarios  $\Omega$  is moderate. However, the structured constraints allow us to simplify the problem by applying Benders decomposition approach. Before using this approach, we could reformulate this problem as the following form. Let  $\mathbf{c}^\top \mathbf{x} = \sum_{j=1}^N \sum_{i=1}^M i \cdot x_{ij}$ ,  $\mathbf{f}^\top \mathbf{y}_\omega = -\sum_{i=1}^M y_{i\omega}^+$ . Then the SSP formulation can be expressed as below,

$$\begin{aligned} \max \quad & \mathbf{c}^\top \mathbf{x} + z(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x}^\top \mathbf{n} \leq \mathbf{L} \\ & \mathbf{x} \in \mathbb{N}^{M \times N}, \end{aligned} \tag{8}$$

where  $z(\mathbf{x})$  is defined as

$$z(\mathbf{x}) := E(z_\omega(\mathbf{x})) = \sum_{\omega \in \Omega} p_\omega z_\omega(\mathbf{x}),$$

and for each scenario  $\omega \in \Omega$ ,

$$\begin{aligned} z_\omega(\mathbf{x}) := \max \quad & \mathbf{f}^\top \mathbf{y}_\omega \\ \text{s.t.} \quad & \mathbf{V}\mathbf{y}_\omega = \mathbf{d}_\omega - \mathbf{x}\mathbf{1} \\ & \mathbf{y}_\omega \geq 0. \end{aligned} \tag{9}$$

We can solve problem (8) quickly if we can efficiently solve problem (9). Next, we will mention how to solve problem (9).

## 4.2 Solve SSP by Benders Decomposition

We reformulate problem (8) into a master problem and a subproblem (9). The iterative process of solving the master problem and subproblem is known as Benders decomposition. The solution obtained from the master problem provides inputs for the subproblem, and the subproblem solutions help update the master problem by adding constraints, iteratively improving the overall solution until convergence is achieved. Firstly, we generate a closed-form solution to problem (9), then we obtain the solution to the LP relaxation of problem (8) by the constraint generation.

### 4.2.1 Solve The Subproblem

Notice that the feasible region of the dual of problem (9) remains unaffected by  $\mathbf{x}$ . This observation provides insight into the properties of this problem. Let  $\boldsymbol{\alpha}$  denote the vector of dual variables. For each  $\omega$ , we can form its dual problem, which is

$$\begin{aligned} \min \quad & \boldsymbol{\alpha}_\omega^\top (\mathbf{d}_\omega - \mathbf{x}\mathbf{1}) \\ \text{s.t.} \quad & \boldsymbol{\alpha}_\omega^\top \mathbf{V} \geq \mathbf{f}^\top \end{aligned} \tag{10}$$

**Lemma 1.** *The feasible region of problem (10) is nonempty and bounded. Furthermore, all the extreme points of the feasible region are integral.*

Let  $\mathbb{P}$  indicate the feasible region of problem (10). According to Lemma 1, the optimal value of the problem (9),  $z_\omega(\mathbf{x})$ , is finite and can be achieved at extreme points of  $\mathbb{P}$ . Let  $\mathcal{O}$  be the set of all extreme points of  $\mathbb{P}$ . Then, we have  $z_\omega(\mathbf{x}) = \min_{\boldsymbol{\alpha}_\omega \in \mathcal{O}} \boldsymbol{\alpha}_\omega^\top (\mathbf{d}_\omega - \mathbf{x}\mathbf{1})$ .

Alternatively,  $z_\omega(\mathbf{x})$  is the largest number  $z_\omega$  such that  $\boldsymbol{\alpha}_\omega^\top (\mathbf{d}_\omega - \mathbf{x}\mathbf{1}) \geq z_\omega, \forall \boldsymbol{\alpha}_\omega \in \mathcal{O}$ . We use this characterization of  $z_\omega(\mathbf{x})$  in problem (8) and conclude that problem (8) can thus be put in the form by setting  $z_\omega$  as the variable:

$$\begin{aligned} \max \quad & \mathbf{c}^\top \mathbf{x} + \sum_{\omega \in \Omega} p_\omega z_\omega \\ \text{s.t.} \quad & \mathbf{x}^\top \mathbf{n} \leq \mathbf{L} \\ & \boldsymbol{\alpha}_\omega^\top (\mathbf{d}_\omega - \mathbf{x}\mathbf{1}) \geq z_\omega, \forall \boldsymbol{\alpha}_\omega \in \mathcal{O}, \forall \omega \\ & \mathbf{x} \in \mathbb{N}^{M \times N} \end{aligned} \tag{11}$$

Before applying Benders decomposition to solve problem (11), it is important to address the efficient computation of the optimal solution to problem (10). When we are given  $\mathbf{x}^*$ , the demand that can be satisfied by the seat planning is  $\mathbf{x}^* \mathbf{1} = \mathbf{d}_0 = (d_{1,0}, \dots, d_{M,0})^\top$ . By plugging them in the subproblem (9), we can obtain the value of  $y_{i,\omega}$  recursively:

$$\begin{aligned} y_{M\omega}^- &= (d_{M\omega} - d_{M0})^+ \\ y_{M\omega}^+ &= (d_{M0} - d_{M\omega})^+ \\ y_{i\omega}^- &= (d_{i\omega} - d_{i0} - y_{i+1,\omega}^+)^+, i = 1, \dots, M-1 \\ y_{i\omega}^+ &= (d_{i0} - d_{i\omega} + y_{i+1,\omega}^+)^+, i = 1, \dots, M-1 \end{aligned} \tag{12}$$

The optimal solutions to problem (10) can be obtained according to the value of  $\mathbf{y}_\omega$ .

**Proposition 5.** *The optimal solutions to problem (10) are given by*

$$\begin{aligned} \alpha_i &= 0 && \text{if } y_{i\omega}^- > 0, i = 1, \dots, M \text{ or } y_{i\omega}^- = y_{i\omega}^+ = 0, y_{i+1,\omega}^+ > 0, i = 1, \dots, M-1 \\ \alpha_i &= \alpha_{i-1} + 1 && \text{if } y_{i\omega}^+ > 0, i = 1, \dots, M \\ 0 \leq \alpha_i &\leq \alpha_{i-1} + 1 && \text{if } y_{i\omega}^- = y_{i\omega}^+ = 0, i = M \text{ or } y_{i\omega}^- = y_{i\omega}^+ = 0, y_{i+1,\omega}^+ = 0, i = 1, \dots, M-1 \end{aligned} \quad (13)$$

Instead of solving this linear programming directly, we can compute the values of  $\alpha_\omega$  by performing a forward calculation from  $\alpha_{1\omega}$  to  $\alpha_{M\omega}$ .

#### 4.2.2 Constraint Generation

Due to the computational infeasibility of solving problem (11) with an exponentially large number of constraints, it is a common practice to use a subset, denoted as  $\mathcal{O}^t$ , to replace  $\mathcal{O}$  in problem (11). This results in a modified problem known as the Restricted Benders Master Problem (RBMP). To find the optimal solution to problem (11), we employ the technique of constraint generation. It involves iteratively solving the RBMP and incrementally adding more constraints until the optimal solution to problem (11) is obtained.

We can conclude that the RBMP will have the form:

$$\begin{aligned} \max \quad & \mathbf{c}^\top \mathbf{x} + \sum_{\omega \in \Omega} p_\omega z_\omega \\ \text{s.t.} \quad & \mathbf{x}^\top \mathbf{n} \leq \mathbf{L} \\ & \boldsymbol{\alpha}_\omega^\top (\mathbf{d}_\omega - \mathbf{x}\mathbf{1}) \geq z_\omega, \boldsymbol{\alpha}_\omega \in \mathcal{O}^t, \forall \omega \\ & \mathbf{x} \in \mathbb{N}^{M \times N} \end{aligned} \quad (14)$$

Given the initial  $\mathcal{O}^t$ , we can have the solution  $\mathbf{x}^*$  and  $\mathbf{z}^* = (z_1^*, \dots, z_{|\Omega|}^*)$ . Then  $\mathbf{c}^\top \mathbf{x}^* + \sum_{\omega \in \Omega} p_\omega z_\omega^*$  is an upper bound of problem (14). When  $\mathbf{x}^*$  is given, the optimal solution,  $\tilde{\boldsymbol{\alpha}}_\omega$ , to problem (10) can be obtained according to Proposition 5. Let  $\tilde{z}_\omega = \tilde{\boldsymbol{\alpha}}_\omega^\top (\mathbf{d}_\omega - \mathbf{x}^*\mathbf{1})$ , then  $(\mathbf{x}^*, \tilde{\mathbf{z}})$  is a feasible solution to problem (14) because it satisfies all the constraints. Thus,  $\mathbf{c}^\top \mathbf{x}^* + \sum_{\omega \in \Omega} p_\omega \tilde{z}_\omega$  is a lower bound of problem (11).

If for every scenario  $\omega$ , the optimal value of the corresponding problem (10) is larger than or equal to  $z_\omega^*$ , which means all constraints are satisfied, then we have an optimal solution,  $(\mathbf{x}^*, \mathbf{z}^*)$ , to problem (11). However, if there exists at least one scenario  $\omega$  for which the optimal value of problem (10) is less than  $z_\omega^*$ , indicating that the constraints are not fully satisfied, we need to add a new constraint  $(\tilde{\boldsymbol{\alpha}}_\omega)^\top (\mathbf{d}_\omega - \mathbf{x}\mathbf{1}) \geq z_\omega$  to RBMP.

To determine the initial  $\mathcal{O}^t$ , we have the following proposition.

**Proposition 6.** *RBMP is bounded when there is at least one constraint for each scenario.*

From Proposition 6, we can set  $\boldsymbol{\alpha}_\omega = \mathbf{0}$  initially. Notice that only constraints are added in each iteration, thus  $UB$  is decreasing monotone over iterations. Then we can use  $UB - LB < \epsilon$  to terminate

the algorithm.

---

**Algorithm 1:** Benders Decomposition

---

**Input:** Initial problem (14) with  $\alpha_\omega = 0, \forall \omega, LB = 0, UB = \infty, \epsilon$ .

**Output:**  $\mathbf{x}^*$

```

1 while  $UB - LB > \epsilon$  do
2   Obtain  $(\mathbf{x}^*, \mathbf{z}^*)$  from problem (14);
3    $UB \leftarrow c^\top \mathbf{x}^* + \sum_{\omega \in \Omega} p_\omega z_\omega^*$ ;
4   for  $\omega = 1, \dots, |\Omega|$  do
5     Obtain  $\tilde{\alpha}_\omega$  from Proposition 5;
6      $\tilde{z}_\omega = (\tilde{\alpha}_\omega)^\top (\mathbf{d}_\omega - \mathbf{x}^* \mathbf{1})$ ;
7     if  $\tilde{z}_\omega < z_\omega^*$  then
8       Add one new constraint,  $(\tilde{\alpha}_\omega)^\top (\mathbf{d}_\omega - \mathbf{x} \mathbf{1}) \geq \tilde{z}_\omega$ , to problem (14);
9     end
10  end
11   $LB \leftarrow c^\top \mathbf{x}^* + \sum_{\omega \in \Omega} p_\omega \tilde{z}_\omega$ ;
12 end

```

---

However, solving problem (14) even with the simplified constraints directly can be computationally challenging in some cases, so practically we first obtain the optimal solution to the LP relaxation of problem (8). Then, we generate an integral seat planning from this solution.

### 4.3 Obtain The Feasible Seat Planning

We may obtain a fractional optimal solution when we solve the LP relaxation of problem (8). This solution represents the optimal allocations of groups to seats but may involve fractional values, indicating partial assignments. Based on the fractional solution obtained, we use the deterministic model to generate a feasible seat planning. The objective of this model is to allocate groups to seats in a way that satisfies the supply requirements for each group without exceeding the corresponding supply values obtained from the fractional solution. To accommodate more groups and optimize seat utilization, we aim to construct a seat planning composed of full or largest patterns based on the feasible seat planning obtained in the last step.

Let the optimal solution to the LP relaxation of problem (14) be  $\mathbf{x}^*$ . Aggregate  $\mathbf{x}^*$  to the number of each group type,  $\tilde{X}_i = \sum_j x_{ij}^*, \forall i \in \mathbf{M}$ . Solve the SPP( $\{\tilde{X}_i\}$ ) to obtain the optimal solution,  $\tilde{\mathbf{x}}$ , and the corresponding pattern,  $\mathbf{H}$ , then generate the seat planning by problem (3) with  $\mathbf{H}$ .

---

**Algorithm 2:** Seat Planning Construction

---

```

1 Obtain the optimal solution,  $\mathbf{x}^*$ , from the LP relaxation of problem (14);
2 Aggregate  $\mathbf{x}^*$  to the number of each group type,  $\tilde{X}_i = \sum_j x_{ij}^*, i \in \mathbf{M}$ ;
3 Obtain the optimal solution,  $\tilde{\mathbf{x}}$ , and the corresponding pattern,  $\mathbf{H}$ , from SPP( $\{\tilde{X}_i\}$ );
4 Construct the seat planning by problem (3) with  $\mathbf{H}$ ;

```

---



## 5 Dynamic Seat Assignment with Social Distancing

In many commercial situations, groups arrive sequentially over time, and the seller must promptly make group assignments upon each arrival while maintaining the required spacing between groups. When a group is accepted, the seller must also determine which seats should be assigned to that group. It is essential to note that each group must be either accepted in its entirety or rejected entirely. Once the seats are confirmed and assigned to a group, they cannot be changed or reassigned to other groups.

To model this problem, we adopt a discrete-time framework. Time is divided into  $T$  periods, indexed forward from 1 to  $T$ . We assume that in each period, at most one group arrives and the probability of an arrival for a group of size  $i$  is denoted as  $p_i$ , where  $i$  belongs to the set  $\mathcal{M}$ . The probabilities satisfy the constraint  $\sum_{i=1}^M p_i \leq 1$ , indicating that the total probability of any group arriving in a single period does not exceed one. We introduce the probability  $p_0 = 1 - \sum_{i=1}^M p_i$  to represent the probability of no arrival in a given period  $t$ . To simplify the analysis, we assume that the arrivals of different group types are independent and the arrival probabilities remain constant over time. This assumption can be extended to consider dependent arrival probabilities over time if necessary.

At time  $t$ , the state of remaining capacity in each row is represented by a vector  $\mathbf{L}^t = (l_1^t, l_2^t, \dots, l_N^t)$ , where  $l_j^t$  denotes the number of remaining seats in row  $j$  at time  $t$ . Upon the arrival of a group type  $i$  at time  $t$ , the seller needs to make a decision denoted by  $u_{i,j}^t$ , where  $u_{i,j}^t = 1$  indicates acceptance of group type  $i$  in row  $j$  during period  $t$ , while  $u_{i,j}^t = 0$  signifies rejection of that group type in row  $j$ . The feasible decision set is defined as

$$U^t(\mathbf{L}^t) = \left\{ u_{i,j}^t \in \{0, 1\}, \forall i \in \mathcal{M}, \forall j \in \mathcal{N} \mid \sum_{j=1}^N u_{i,j}^t \leq 1, \forall i \in \mathcal{M}; n_i u_{i,j}^t \mathbf{e}_j \leq \mathbf{L}^t, \forall i \in \mathcal{M}, \forall j \in \mathcal{N} \right\}.$$

Here,  $\mathbf{e}_j$  represents an  $N$ -dimensional unit column vector with the  $j$ -th element being 1, i.e.,  $\mathbf{e}_j = (\underbrace{0, \dots, 0}_{j-1}, 1, \underbrace{0, \dots, 0}_{n-j})$ . In other words, the decision set  $U(\mathbf{L}^t)$  consists of all possible combinations of acceptance and rejection decisions for each group type in each row, subject to the constraints that at most one group of each type can be accepted in any row, and the number of seats occupied by each accepted group must not exceed the remaining capacity of the row.

Let  $V^t(\mathbf{L}^t)$  denote the maximum expected revenue earned by the best decisions regarding group seat assignments in period  $t$ , given remaining capacity  $\mathbf{L}^t$ . Then, the dynamic programming formula for this problem can be expressed as:

$$V^t(\mathbf{L}^t) = \max_{u_{i,j}^t \in U^t(\mathbf{L}^t)} \left\{ \sum_{i=1}^M p_i \left( \sum_{j=1}^N i u_{i,j}^t + V^{t+1}(\mathbf{L}^t - \sum_{j=1}^N n_i u_{i,j}^t \mathbf{e}_j) \right) + p_0 V^{t+1}(\mathbf{L}^t) \right\} \quad (15)$$

with the boundary conditions  $V^{T+1}(\mathbf{L}) = 0, \forall \mathbf{L}$  which implies that the revenue at the last period is 0 under any capacity.

At the beginning of period  $t$ , we have the current remaining capacity vector denoted as  $\mathbf{L} = (L_1, L_2, \dots, L_N)$ . Our objective is to make group assignments that maximize the total expected revenue during the horizon from period 1 to  $T$  which is represented by  $V^1(\mathbf{L})$ .

Solving the dynamic programming problem described in equation (15) can be challenging due to the curse of dimensionality, which arises when the problem involves a large number of variables or states. To mitigate this complexity, we aim to develop a heuristic method for assigning arriving groups. In our approach, we begin by generating a seat planning, as outlined in section 4. This seat planning acts as a foundation for the seat assignment. In section 6, building upon the generated seat planning, we further develop a dynamic seat assignment policy which guides the allocation of seats to the incoming groups sequentially.

## 6 Seat Assignment with Dynamic Demand

In this section, we focus on the assignment of arriving groups in a dynamic context. Our policy involves making seating allocation decisions for each incoming group based on the seat planning strategy outlined in Section 4. This approach also integrates relaxed dynamic programming to inform the decision-making process.

### 6.1 DP-based Heuristic

To simplify the complexity of the original DP 15, we consider a simplified version by relaxing all rows to a single row with the same total capacity, denoted as  $\tilde{L} = \sum_{j=1}^N L_j$ . With this simplification, we can make decisions for each group arrival based on the relaxed dynamic programming. By relaxing the rows to a single row, we aggregate the capacities of all individual rows into a single capacity value. This allows us to treat the seat assignment problem as a one-dimensional problem, reducing the computational complexity. Using the relaxed dynamic programming approach, we can determine the seat assignment decisions for each group arrival based on the simplified problem.

Let  $u$  denote the decision, where  $u^t = 1$  if we accept a request in period  $t$ ,  $u^t = 0$  otherwise. Similar to the DP in section 5, the DP with one row can be expressed as:

$$V^t(l) = \max_{u^t \in \{0,1\}} \left\{ \sum_i p_i [V^{t+1}(l - n_i u^t) + i u^t] + p_0 V^{t+1}(l) \right\}$$

with the boundary conditions  $V^{T+1}(l) = 0, \forall l \geq 0$ ,  $V^t(0) = 0, \forall t$ .

After accepting one group, assign it in some row arbitrarily when the capacity of that row allows.

---

**Algorithm 3:** DP-based Heuristic Algorithm

---

```
1 Calculate  $V^t(l)$ ,  $\forall t = 2, \dots, T; \forall l = 1, \dots, L$ ;  
2  $l^1 \leftarrow L$ ;  
3 for  $t = 1, \dots, T$  do  
4   Observe group type  $i$ ;  
5   if  $V^{t+1}(l^t) \leq V^{t+1}(l^t - n_i) + i$  then  
6     Accept the group and assign the group to an arbitrary row  $k$  such that  $L_k^t \geq n_i$ ;  
7   else  
8     Reject the group;  
9   end  
10 end
```

---

Here, we encounter some straightforward scenarios. If the size of an arriving group exceeds the maximum remaining length of any row, we reject the group. Conversely, if the size of the arriving group exactly matches the remaining length of a particular row, we accept the group.

Since this policy does not provide guidance for specific assignment methods, we proceed with the assignment based on the planning strategy.

## 6.2 Assignment Based on Planning

In this section, we assign groups based on the planning derived from the LP relaxation of the SSP. Let the supply be represented as  $[X_1, \dots, X_M]$ . When the DP approach accepts an arriving group of type  $i'$ , if  $X_{i'} > 0$ , we allocate seats according to the break-tie rule. If  $X_{i'} = 0$ , we apply the group-type control policy to determine whether to assign the arriving group to a specific row. We will also discuss the break-tie rule for assigning specific rows. Finally, we address when to regenerate the seat planning.

### 6.2.1 Group-type Control

The group-type control aims to find the group type to assign the arriving group, that helps us narrow down the option of rows for seat assignment. The policy considers whether to use a larger group's supply to meet the need of the arriving group when given a seat planning. The group type is selected based on the tradeoff between the social distancing and the future demand. When a group is accepted and assigned to larger-size seats, the remaining empty seat(s) can be reserved for future demand without affecting the rest of the seat planning. To determine whether to use larger seats to accommodate the incoming group, we compare the expected values of accepting the group in the larger seats and rejecting the group based on the current seat planning. Then we identify the possible rows where the incoming group can be assigned based on the group types and seat availability.

Specifically, suppose the supply is  $(X_1, \dots, X_M)$  at period  $t$ , the number of remaining periods is  $(T - t)$ . For the arriving group type  $i'$  when  $X_{i'} = 0$ , we demonstrate how to decide whether to accept the group to occupy larger-size seats. For any  $\hat{i} = i' + 1, \dots, M$ , we can use one supply of group type  $\hat{i}$  to accept a group type  $i'$ . In that case, when  $\hat{i} = i' + 1, \dots, i + \delta$ , the expected number of accepted

people is  $i'$  and the remaining seats beyond the accepted group, which is  $\hat{i} - i'$ , will be wasted. When  $\hat{i} = i' + \delta + 1, \dots, M$ , the rest  $(\hat{i} - i' - \delta)$  seats can be provided for one group type  $(\hat{i} - i' - \delta)$  with  $\delta$  seats of social distancing. Let  $D_i^t$  be the random variable that indicates the number of group type  $\hat{i}$  in  $t$  periods. The expected number of accepted people is  $i' + (\hat{i} - i' - \delta)P(D_{\hat{i}-i'-\delta}^{T-t} \geq X_{\hat{i}-i'-\delta} + 1)$ , where  $P(D_{i'}^{T-t} \geq X_{i'})$  is the probability that the demand of group type  $i'$  in  $(T - t)$  periods is no less than  $X_{i'}$ , the remaining supply of group type  $i'$ . Thus, the term,  $P(D_{\hat{i}-i'-\delta}^{T-t} \geq X_{\hat{i}-i'-\delta} + 1)$ , indicates the probability that the demand of group type  $(\hat{i} - i' - \delta)$  in  $(T - t)$  periods is no less than its current remaining supply plus 1.

Similarly, when we retain the supply of group type  $\hat{i}$  by rejecting the group type  $i'$ , the expected number of accepted people is  $\hat{i}P(D_{\hat{i}}^{T-t} \geq X_{\hat{i}})$ . The term,  $P(D_{\hat{i}}^{T-t} \geq X_{\hat{i}})$ , indicates the probability that the demand of group type  $\hat{i}$  in  $(T - t)$  periods is no less than its current remaining supply.

Let  $d^t(i', \hat{i})$  be the difference of expected number of accepted people between acceptance and rejection on group type  $i'$  occupying  $(\hat{i} + \delta)$ -size seats at period  $t$ . Then we have

$$d^t(i', \hat{i}) = \begin{cases} i' + (\hat{i} - i' - \delta)P(D_{\hat{i}-i'-\delta}^{T-t} \geq X_{\hat{i}-i'-\delta} + 1) - \hat{i}P(D_{\hat{i}}^{T-t} \geq X_{\hat{i}}), & \text{if } \hat{i} = i' + \delta + 1, \dots, M \\ i' - \hat{i}P(D_{\hat{i}}^{T-t} \geq X_{\hat{i}}), & \text{if } \hat{i} = i' + 1, \dots, i' + \delta. \end{cases}$$

One intuitive decision is to choose  $\hat{i}$  with the largest difference. For all  $\hat{i} = i' + 1, \dots, M$ , find the largest  $d^t(i', \hat{i})$ , denoted as  $d^t(i', \hat{i}^*)$ . If  $d^t(i', \hat{i}^*) > 0$ , we will plan to assign the group type  $i'$  in  $(\hat{i}^* + \delta)$ -size seats. Otherwise, reject the group.

Group-type control policy can only tell us which group type's seats are planned to provide for the smaller group based on the current planning, we still need to further compare the values of the stochastic programming problem when accepting or rejecting a group on the specific row.

### 6.2.2 Break Tie for Determining A Specific Row

To determine the appropriate row for seat assignment, we can apply a tie-breaking rule among the possible options obtained by the group-type control. This rule helps us decide on a particular row when there are multiple choices available.

A tie occurs when there are several rows to accommodate the group. Suppose one group type  $i'$  arrives, the current seat planning is  $\mathbf{H} = \{\mathbf{h}_1; \dots; \mathbf{h}_N\}$ , the corresponding supply is  $\mathbf{X}$ . Let  $\beta_j = L_j - \sum_i (i + \delta)H_{ji}$  represent the remaining number of seats in row  $j$  after considering the seat allocation for other groups. When  $X_{i'} > 0$ , we assign the group to row  $k \in \arg \min_j \{\beta_j\}$ . That allows us to fill in the row as much as possible. When  $X_{i'} = 0$  and we plan to assign the group to seats designated for group type  $\hat{i}, \hat{i} > i$ , we assign the group to a row  $k \in \arg \max_j \{\beta_j | H_{j\hat{i}} > 0\}$ . That helps to reconstruct the pattern with less unused seats. When there are multiple rows available, we can choose randomly. This rule in both scenarios prioritizes filling rows and leads to better capacity management.

As an example to illustrate group-type control and the tie-breaking rule, consider a situation where  $L_1 = 3, L_2 = 4, L_3 = 5, L_4 = 6, M = 4, \delta = 1$ . The corresponding patterns for each row are  $(0, 1, 0, 0)$ ,  $(0, 0, 1, 0)$ ,  $(0, 0, 0, 1)$  and  $(0, 0, 0, 1)$ , respectively. Thus,  $\beta_1 = \beta_2 = \beta_3 = 0, \beta_4 = 1$ . Now, a group of

one arrives, and the group-type control indicates the possible rows where the group can be assigned. We assume this group can be assigned to the seats of the largest group according to the group-type control, then we have two choices: row 3 or row 4. To determine which row to select, we can apply the breaking tie rule. The  $\beta$  value of the rows will be used as the criterion, we would choose row 4 because  $\beta_4$  is larger. Because when we assign it in row 4, there will be two seats reserved for future group of one, but when we assign it in row 3, there will be one seat remaining unused.

In the above example, the group of one can be assigned to any row with the available seats. The group-type control can help us find the larger group type that can be used to place the arriving group while maximizing the expected values. Maybe there are multiple rows containing the larger group type. Then we can choose the row containing the larger group type according to the breaking tie rule. Finally, we compare the values of stochastic programming when accepting or rejecting the group, then make the corresponding decision.

By combining the group-type control strategy with the evaluation of relaxed DP values, we obtain a comprehensive decision-making process within a single period. This integrated approach enables us to make informed decisions regarding the acceptance or rejection of incoming groups, as well as determine the appropriate row for the assignment when acceptance is made.

### 6.2.3 Regenerate The Seat Planning

To optimize computational efficiency, it is not necessary to regenerate the seat planning for every period. Instead, we can employ a more streamlined approach. Considering that largest group type can meet the needs of all smaller group types, thus, if the supply for the largest group type diminishes from one to zero, it becomes necessary to regenerate the seat planning. This avoids rejecting the largest group due to infrequent regenerations. Another situation that requires seat planning regeneration is when we determine whether to assign the arriving group seats planned for the larger group. In such case, we can obtain the corresponding seat planning after solving the relaxed stochastic programmings. By regenerating the seat planning in these situations, we can achieve real-time seat assignment while minimizing the frequency of planning updates.

The algorithm is shown below.

---

**Algorithm 4: Dynamic Seat Assignment**

---

```
1 Obtain  $\mathbf{X} = [X_1, \dots, X_M]$ , calculate  $V^t(l)$ ,  $\forall t = 2, \dots, T; \forall l = 1, \dots, L$ ;  
2 for  $t = 1, \dots, T$  do  
3   Observe group type  $i'$ ;  
4   if  $V^{t+1}(l^t) \leq V^{t+1}(l^t - n_i) + i'$  then  
5     if  $X_{i'} > 0$  then  
6       Find row  $k$  such that  $H_{ki'} > 0$  according to the tie-breaking rule;  
7       Accept group type  $i'$  in row  $k$ , update  $L_k, H_{ki'}, X_{i'}$ ;  
8       if  $i' = M$  and  $X_M = 0$  then  
9         Generate seat planning  $\mathbf{H}$  from Algorithm 2, update the corresponding  $\mathbf{X}$ ;  
10      end  
11    else  
12      Calculate  $d^t(i', \hat{i}^*)$ ;  
13      if  $d^t(i', \hat{i}^*) \geq 0$  then  
14        Find row  $k$  such that  $H_{k\hat{i}^*} > 0$  according to the tie-breaking rule;  
15        Accept group type  $i'$  in row  $k$ ;  
16        Generate seat planning  $\mathbf{H}$  from Algorithm 2, update the corresponding  $\mathbf{X}$ ;  
17      else  
18        Reject group type  $i'$ ;  
19      end  
20    end  
21  else  
22    Reject group type  $i'$ ;  
23  end  
24 end
```

---

## 7 Computational Experiment

We carried out several experiments, including analyzing the performances of different policies, evaluating the impact of implementing social distancing, comparing different layouts, group sizes and social distancing. In the experiment, we set the following parameters.

The default setting in the experiments is as follows,  $\delta = 1$  and  $M = 4$ . The default seat layout consists of 10 rows, each with the same size of 21. The values of  $\delta$ ,  $M$  and the layout will change accordingly as we explore different layouts, group sizes and social distances. We simulate the arrival of exactly one group in each period, i.e.,  $p_0 = 0$ . The average number of people per period, denoted as  $\gamma$ , can be expressed as  $\gamma = p_1 \cdot 1 + p_2 \cdot 2 + p_3 \cdot 3 + p_4 \cdot 4$ , where  $p_1, p_2, p_3$ , and  $p_4$  represent the probabilities of groups with one, two, three, and four individuals, respectively. We assume that  $p_4$  always has a positive value.

## 7.1 Performances of Different Policies

In this section, we compare the performance of five assignment policies to the optimal one, which can be obtained by solving the deterministic model after observing all arrivals. The policies under examination are the dynamic seat assignment policy, DP-based heuristic, bid-price control, booking limit control and FCFS policy.

### Parameters Description

We consider three sets of probability distributions: D1: [0.18, 0.7, 0.06, 0.06], D2: [0, 0.5, 0, 0.5], D3: [0.2, 0.8, 0, 0], which are experimented in [4]. We also consider another probability distribution D4: [0.25, 0.3, 0.25, 0.2] for the extra experiments. The number of scenarios is  $|\Omega| = 1000$ . To assess the effectiveness of different policies across varying demand levels, we conducted experiments spanning a range of 60 to 100 periods.

The following table presents the performance results of five different policies: DSA, DP, Bid-price, Booking, and FCFS, which stand for dynamic seat assignment, dynamic programming based heuristic, bid-price, booking-limit, and first come first served, respectively. The procedures for the last four policies are detailed in the appendix 9. Each entry in the table represents the average performance across 100 instances. Performance is evaluated by comparing the ratio of the number of accepted individuals under each policy to that under the optimal policy, which assumes complete knowledge of all incoming groups before making seat assignments.

Table 1: Performances of Different Policies

Distribution	T	DSA (%)	DP (%)	Bid (%)	Booking (%)	FCFS (%)
D1	60	100.00	100.00	100.00	88.56	100.00
	70	99.53	99.01	98.98	92.69	98.82
	80	99.38	98.91	98.84	97.06	96.06
	90	99.52	99.23	99.10	98.24	95.37
	100	99.58	99.27	98.95	98.46	94.98
D2	60	99.45	97.23	96.58	99.09	96.49
	70	99.82	98.28	97.46	99.81	95.76
	80	99.92	98.60	98.86	100.00	95.66
	90	99.99	99.10	99.70	100.00	95.66
	100	100.00	98.74	99.99	100.00	95.66
D3	60	100.00	100.00	100.00	93.68	100.00
	70	100.00	100.00	100.00	92.88	100.00
	80	99.54	97.89	97.21	98.98	96.19
	90	99.90	99.73	99.44	99.61	94.53
	100	100.00	100.00	100.00	99.89	94.32
D4	60	99.61	99.68	99.63	94.01	99.61
	70	99.05	98.95	98.49	97.10	96.03
	80	98.96	98.84	98.71	97.99	93.80
	90	99.38	99.17	98.70	98.36	92.87
	100	99.62	99.45	99.13	98.56	92.35

We can find that DSA is better than DP-based heuristic, bid-price policy and booking limit policy consistently, and FCFS policy works worst. DP-based heuristic and bid-price policy can only make the decision to accept or deny, cannot decide which row to assign the group to. Booking limit policy does

not consider using more seats to meet the demand of one group. FCFS accepts groups in sequential order until the capacity cannot accommodate more.

The performance of DSA, DP-based heuristic, and bid-price policies follows a pattern where it initially decreases and then gradually improves as  $T$  increases. When  $T$  is small, the demand for capacity is generally low, allowing these policies to achieve relatively optimal performance. However, as  $T$  increases, it becomes more challenging for these policies to consistently achieve a perfect allocation plan, resulting in a decrease in performance. Nevertheless, as  $T$  continues to grow, these policies tend to accept larger groups, thereby narrowing the gap between their performance and the optimal value. Consequently, their performances improve. In contrast, the booking limit policy shows improved performance as  $T$  increases because it reduces the number of unoccupied seats reserved for the largest groups.

The performance of the policies can vary based on different probabilities. For the different probability distributions listed, DSA performs more stably and consistently for the same demand. In contrast, the performance of DP and bid-price fluctuates more significantly.

## Analysis of DSA

We explore the arrival path of one instance under DSA and the optimal solution. The figures show two arrival paths when  $T = 55$  and  $T = 70$  at the even probability distribution. In the figures, we plot four lines over periods, number of remaining seats, the expected future demand, optimal remaining seats and optimal remaining demand. The horizontal parts of remaining seats represent the rejection at the period. We can observe that when the demand is larger than supply ( $T = 70$ ), even at the beginning we still reject the group. When the demand is lower than supply ( $T = 55$ ), we will accept all groups.



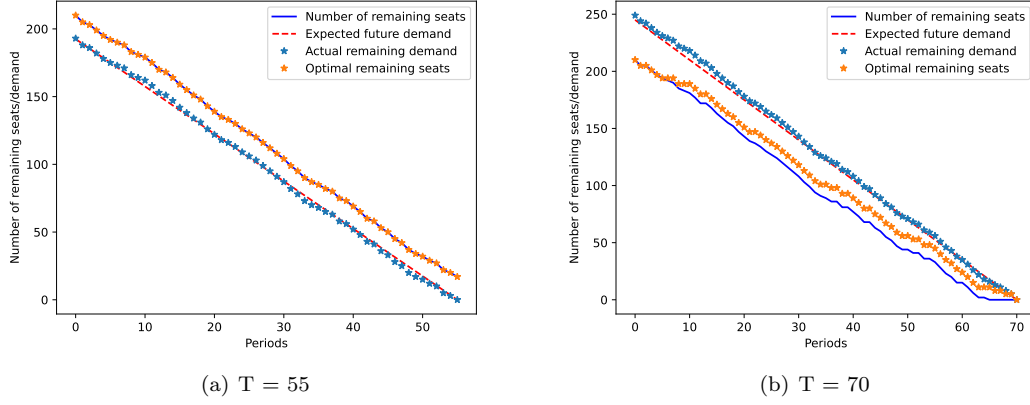


Figure 3: Remaining seats over periods under DSA and optimal policies

We also examine the situations where the actual demand is higher or lower than the expected demand.

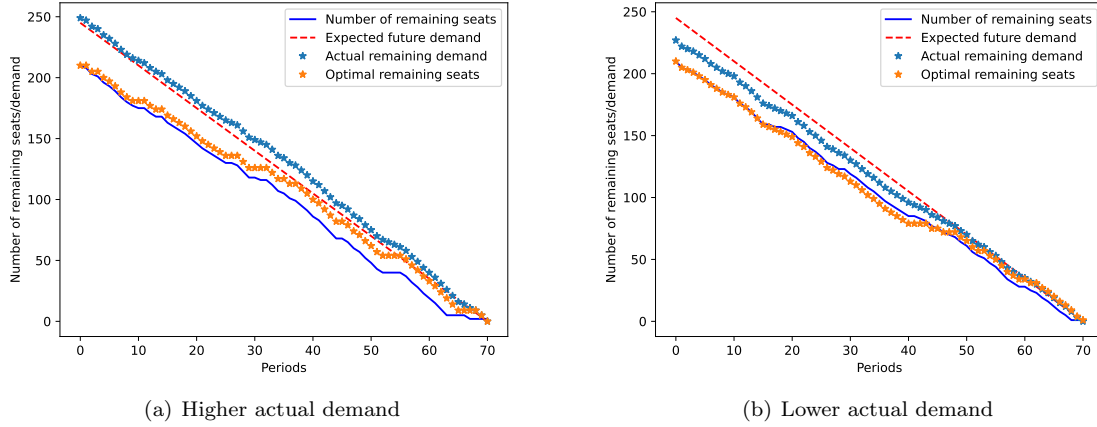


Figure 4: Remaining seats over periods when  $T = 70$

Based on the figures provided, we can draw several key conclusions:

1. When the demand is larger than supply, even at the very beginning of the time period, both DSA approach and the optimal solution reject some groups, as indicated by the horizontal segments in the lines.
2. DSA approach is inclined to accept groups earlier compared to the optimal solution. This is because DSA makes decisions based on the expected future demand, rather than the actual remaining demand.
3. When the actual remaining demand is lower than the expected demand, the optimal remaining seats will be lower than that of DSA approach. Conversely, when the actual remaining demand is higher than expected, the optimal remaining seats will be higher than DSA.

## 7.2 Impact of Social Distancing

Now, we explore the impact of social distance as the demand increases. Specifically, we consider  $D4$  as the probability distribution. In the next section, we also consider other distributions. Here,  $T$  varies from 30 to 90, the step size is 1. Other parameters are set the same as before.

The figure below displays the outcomes of groups who were accepted under two different conditions: with social distancing measures and without social distancing measures. For the former case, we employ DSA to obtain the results. In this case, we consider the constraints of social distancing and optimize the seat allocation accordingly. For the latter case, we adopt the optimal solution assuming that all arrivals are known and that there are no social distancing constraints. The occupancy rate at different demands is calculated as the average of these 100 instances. The figures depicting the results are presented below. The difference between these two figures is the x-axis, the left one is period, while the right one is the percentage of expected demand relative to total seats.

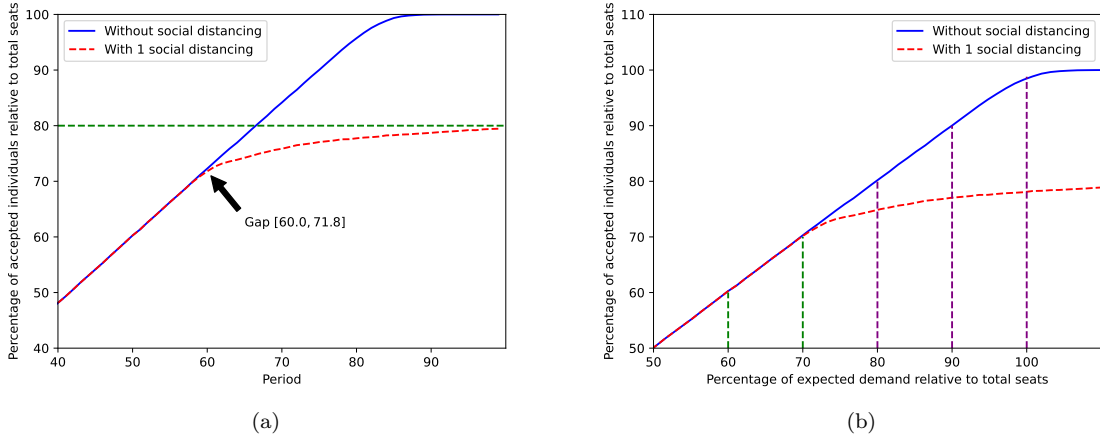


Figure 5: The occupancy rate over demand

Intuitively, when demand is low, we will accept all arrivals, and there will be no difference in the number of accepted individuals whether we implement social distancing or not. The interesting case is when the difference in the number of accepted individuals due to social distancing starts to occur.

We use  $E(T; DSA)$  to denote the expected number of individuals accepted across 100 instances by DSA with one seat as social distancing. Similarly, we use  $E(T; OPT)$  to denote the expected number of people accepted across 100 instances by the optimal solution when there is no social distancing. The gap point  $\tilde{T}$  is defined as the largest point  $T$  such that  $E(T; DSA) + 1 \geq E(T; OPT)$  holds. The occupancy rate at the gap point is denoted by  $\Gamma(\tilde{T})$ . This occupancy rate represents the maximum demand that can be satisfied when the difference in the number of accepted individuals is not affected by social distancing.

Under the probability distribution of  $D4$ , we obtain the gap point is 60, the corresponding occupancy rate is 71.8%. To better analyze the situation under different demands, we plot the second figure. When the capacity is sufficient, in this case when the expected demand is less than 71.8%, the outcome remains unaffected by the implementation of social distancing measures. When the expected demand is larger than 71.8%, the difference between the outcomes with and without social distancing measures becomes

more pronounced. As the expected demand continues to increase, both situations reach their maximum capacity acceptance. At this point, the gap between the outcomes with and without social distancing measures begins to converge. For the social distancing situation, according to Proposition 2, when the largest pattern is assigned to each row, the resulting occupancy rate is  $\frac{16}{20} = 80\%$ , which is the upper bound of occupancy rate. Therefore, the policy requires an occupancy rate larger than 80% will be invalid.

### 7.3 Estimation of Gap Points

To estimate the gap point, we aim to find the maximum period such that all the groups can be assigned into the seats during these periods, i.e., for each group type  $i$ , we have  $\sum_j x_{ij} \geq d_i$ , where  $x_{ij}$  is the number of group type  $i$  in row  $j$ . Meanwhile, we have the capacity constraint  $\sum_i n_i x_{ij} \leq L_j$ , thus,  $\sum_i n_i d_i \leq \sum_i n_i \sum_j x_{ij} \leq \sum_j L_j$ . Notice that  $E(d_i) = p_i T$ , we have  $\sum_i n_i p_i T \leq \sum_j L_j$  by taking the expectation. Recall that  $\tilde{L} = \sum_j L_j$  denotes the total number of seats, and let  $\gamma = \sum_i i p_i$  represent the average number of people arriving in each period. From this, we can derive the inequality  $T \leq \frac{\tilde{L}}{\gamma + \delta}$ . Therefore, the upper bound for the expected maximum period is given by  $T' = \frac{\tilde{L}}{\gamma + \delta}$ .

Assuming that we accept all incoming groups within  $T'$  periods, filling all the available seats, the corresponding occupancy rate at this period can be calculated as  $\frac{\gamma T'}{(\gamma + \delta) T' - N \delta} = \frac{\gamma}{\gamma + \delta} \frac{\tilde{L}}{\tilde{L} - N \delta}$ . However, it is important to note that the actual maximum period will be smaller than  $T'$  because it is impossible to accept groups to fill all seats exactly. To estimate the gap point when applying DSA, we can use  $y_1 = c_1 \frac{\tilde{L}}{\gamma + \delta}$ , where  $c_1$  is a discount factor compared to the ideal assumption. Similarly, we can estimate the corresponding occupancy rate as  $y_2 = c_2 \frac{\gamma}{\gamma + \delta} \frac{\tilde{L}}{\tilde{L} - N \delta}$ , where  $c_2$  is a discount factor for the occupancy rate compared to the ideal scenario.

To analyze the relation between the increment of  $\gamma$  and the gap point, we conducted an analysis using a sample of 200 probability distributions. The figure below illustrates the gap point as a function of the increment of  $\gamma$ , along with the corresponding estimations. For each probability combination, we considered 100 instances and plotted the gap point as blue points. Additionally, the occupancy rate at the gap point is represented by red points.

To provide estimations, we use the equations  $y_1 = \frac{c_1 \tilde{L}}{\gamma + \delta}$  (blue line in the figure) and  $y_2 = c_2 \frac{\gamma}{\gamma + \delta} \frac{\tilde{L}}{\tilde{L} - N \delta}$  (orange line in the figure), which are fitted to the data. These equations capture the relationship between the gap point and the increment of  $\gamma$ , allowing us to approximate values. By analyzing this relationship, we find that  $\gamma$  can be utilized to estimate the gap point. We employed an Ordinary Least Squares (OLS) model to fit the data and derive the parameter values. The goodness of fit is assessed using the R-squared values of 1.000 for all models, indicating a perfect fit between the data and the models. Here, the values of the discount factors are  $c_1 = 0.9578$  and  $c_2 = 0.9576$ .

Based on the above analysis, we also explore the results of different layouts, different group sizes and different social distances. Since the figure about the occupancy rate over demand is similar to Figure 5(a), we only use three metrics to show the results: the gap point and the corresponding occupancy rate, largest occupancy rate.

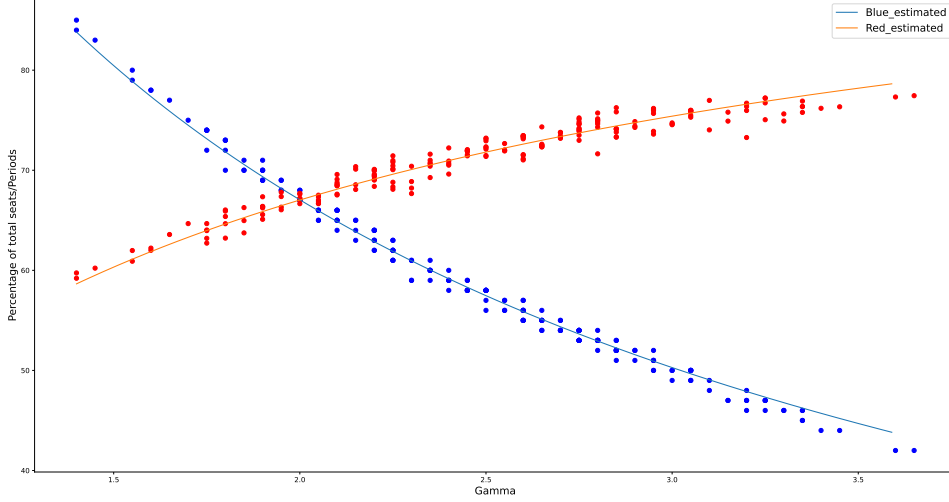


Figure 6: Gap points and their estimation under 200 probabilities

## Different Layouts

We experiment with four seat layouts. For the large room, we consider three configurations, each with the same total of 200 seats. Layout 1 consists of 20 rows with 10 seats each, Layout 2 features 10 rows with 20 seats each. Additionally, we include a fan-shaped Layout 3 with 10 rows, where the first five rows contain between 16 and 20 seats, increasing by 1 seat per row, and the last five rows contain between 20 and 24 seats, also increasing by 1 seat per row. This ensures that the total number of seats and the number of rows match those of the Layout 2. Layout 4 as the small room consists of 15 rows with 7 seats each. The same 100 instances with the probability of  $D4$  are experimented for each layout.

The occupancy rate over demand follows the typical pattern of Figure 5(a). The gap point, the corresponding occupancy rate and the largest occupancy rate are also given in the following table. The largest occupancy rate can be calculated from Proposition 2.

Table 2: Gap points and occupancy rates of the layouts

Seat Layout	Gap point	Occupancy rate	Largest occupancy rate
Layout 1	62.0	74.33 %	80 %
Layout 2	60.0	71.79 %	80 %
Layout 3	60.0	71.84 %	82 %
Layout 4	33.0	74.41 %	85.71 %

We have three observations. First, the gap point and occupancy rate of Layout 1 are higher than those of Layout 2 and Layout 3. This suggests that, when the total number of seats is the same, the layout with more rows yields a larger gap point and occupancy rate compared to the layout with fewer rows. Second, when the number of rows is the same, the fan-shaped layout exhibits a similar gap point and occupancy rate to the rectangular layout. However, the largest occupancy rates differ between the two layouts. Third, the occupancy rate at the gap point and the largest occupancy rate for the small room will be higher than those for the large room, comparatively.

For each row, a seat is designated for social distancing with every group accepted. Consequently, when each row follows a full pattern and the total number of seats remains constant, having more rows

results in a higher gap point and occupancy rate. Similarly, in a small room with fewer seats per row, the occupancy rate at the gap point will correspondingly be higher.

## Different Group Sizes

For group sizes of 3, 4 and 5, we present the gap point, the corresponding occupancy rate and the largest occupancy rate in the table below. The probability distributions for these group sizes all share the same value of  $\gamma = 2.4$ .

Table 3: Gap points and occupancy rates of the group sizes

Group Size	Probability distribution	Gap point	Occupancy rate	Largest occupancy rate
3	[0.2, 0.2, 0.6]	60.0	71.83 %	75 %
4	[0.25, 0.3, 0.25, 0.2]	60.0	71.79 %	80 %
5	[0.3, 0.3, 0.2, 0.1, 0.1]	58.0	70.00 %	85 %

We observe that larger group sizes correspond to higher largest occupancy rates under the same seat layout. However, the gap point and occupancy rate for larger group sizes do not necessarily increase correspondingly. The explanation for this is that as larger groups are allowed to be accepted, seat allocation makes it difficult to achieve a full pattern for each row. Thus, there will be a decrease in both gap points and occupancy rates, i.e., the impact of social distancing will manifest at an earlier period.

The insight is although allowing larger groups will increase the largest occupancy rate, the impact of social distancing will become evident at an earlier period. Specifically, if demand is low or if the managers wish to avoid rejecting a significant number of customers, they can set a smaller group size limit. Conversely, when demand is high, a larger group size limit can be set to accommodate more customers.

## Different Social Distances

The following figure illustrates the number of accepted individuals over time with social distancing set at 0, 1, and 2 seats, respectively.

We examine the impact of implementing social distancing on the occupancy rate and explore strategies to minimize revenue loss. Consider the situation where the gap point is  $\tilde{T}$  and is determined by the parameters  $\delta$ ,  $\gamma$ ,  $M$ , and  $\tilde{L}$ . The corresponding occupancy rate is  $\Gamma(\tilde{T})$ . When the actual number of people (demand) is less than  $\tilde{L} \cdot \Gamma(\tilde{T})$ , implementing social distancing does not affect the revenue. However, if the actual number of people exceeds  $\tilde{L} \cdot \Gamma(\tilde{T})$ , enforcing social distancing measures will lead to a reduction in revenue. The extent of this loss can be assessed through simulations by using the specified parameters. To mitigate the potential loss, the seller can increase the value of  $\gamma$ . This can be achieved by implementing certain measures, such as setting a limit on the number of single-person groups or allowing for larger group sizes. The government can set a requirement for a higher occupancy rate limit, for example, for family movies in cinemas,  $\gamma$  will be relatively large, so a higher occupancy rate limit can be set. By doing so, the objective is to minimize the negative impact of social distancing while maximizing revenue within the constraints imposed by the occupancy rate.

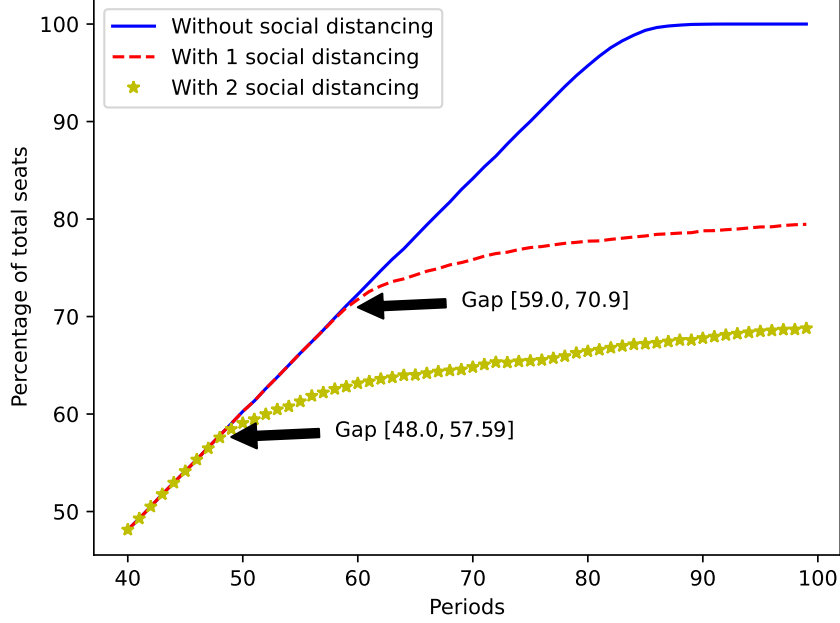


Figure 7: The occupancy rate over demand for different social distancing

## 8 Conclusion

Our paper focuses on the problem of dynamic seat assignment with social distancing in the context of a pandemic. To tackle this problem, we propose a scenario-based stochastic programming approach to obtain a seat planning that adheres to social distancing constraints. We utilize the benders decomposition method to solve this model efficiently, leveraging its well-structured property. However, solving the integer programming formulation directly can be computationally prohibitive in some cases. Therefore, in practice, we consider the linear programming relaxation of the problem and devise an approach to obtain the seat planning, which consists of full or largest patterns. In our approach, seat planning can be seen as the supply for each group type. We assign groups to seats when the supply is sufficient. However, when the supply is insufficient, we employ the dynamic seat assignment policy to make decisions on whether to accept or reject group requests.

We conducted several experiments to investigate various aspects of our approach. These experiments include analyzing different policies for dynamic seat assignment and evaluating the impact of implementing social distancing. In terms of dynamic seat assignment policies, we consider the classical bid-price control, booking limit control in revenue management, dynamic programming-based heuristics, and the first-come-first-served policy. Comparatively, our proposed policy exhibited superior performance.

Building upon our policies, we further evaluated the impact of implementing social distancing. By defining the gap point as the period at which the difference between applying and not applying social distancing becomes evident, we established a relationship between the gap point and the expected number of people in each period. We observed that as the expected number of people in each period increased, the gap point occurred earlier, resulting in a higher occupancy rate at the gap point.

Overall, our study emphasizes the operational significance of social distancing in the seat allocation and offers a fresh perspective for sellers and governments to implement seat assignment mechanisms that effectively promote social distancing during the pandemic.

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## 9 Policies for Dynamic Situations

### Bid-price Control

Bid-price control is a classical approach discussed extensively in the literature on network revenue management. It involves setting bid prices for different group types, which determine the eligibility of groups to take the seats. Bid-prices refer to the opportunity costs of taking one seat. As usual, we



estimate the bid price of a seat by the shadow price of the capacity constraint corresponding to some row. In this section, we will demonstrate the implementation of the bid-price control policy.

The dual of LP relaxation of problem (1) is:

$$\begin{aligned}
\min \quad & \sum_{i=1}^M d_i z_i + \sum_{j=1}^N L_j \beta_j \\
\text{s.t.} \quad & z_i + \beta_j n_i \geq (n_i - \delta), \quad i \in \mathcal{M}, j \in \mathcal{N} \\
& z_i \geq 0, i \in \mathcal{M}, \beta_j \geq 0, j \in \mathcal{N}.
\end{aligned} \tag{16}$$

In (16),  $\beta_j$  can be interpreted as the bid-price for a seat in row  $j$ . A request is only accepted if the revenue it generates is above the sum of the bid prices of the seats it uses. Thus, if its revenue is more than its opportunity costs, i.e.,  $i - \beta_j n_i \geq 0$ , we will accept the group type  $i$ . And choose  $j^* = \arg \max_j \{i - \beta_j n_i\}$  as the row to allocate that group.

**Lemma 2.** *The optimal solution to problem (16) is given by  $z_1, \dots, z_{\tilde{i}} = 0$ ,  $z_i = \frac{\delta(n_i - n_{\tilde{i}})}{n_{\tilde{i}}}$  for  $i = \tilde{i} + 1, \dots, M$  and  $\beta_j = \frac{n_{\tilde{i}} - \delta}{n_{\tilde{i}}}$  for all  $j$ .*

The bid-price decision can be expressed as  $i - \beta_j n_i = i - \frac{n_{\tilde{i}} - \delta}{n_{\tilde{i}}} n_i = \frac{\delta(i - \tilde{i})}{n_{\tilde{i}}}$ . When  $i < \tilde{i}$ ,  $i - \beta_j n_i < 0$ . When  $i \geq \tilde{i}$ ,  $i - \beta_j n_i \geq 0$ . This means that group type  $i$  greater than or equal to  $\tilde{i}$  will be accepted if the capacity allows. However, it should be noted that  $\beta_j$  does not vary with  $j$ , which means the bid-price control cannot determine the specific row to assign the group to. In practice, groups are often assigned arbitrarily based on availability when the capacity allows, which can result in a large number of empty seats.

The bid-price control policy based on the static model is stated below.

---

**Algorithm 5:** Bid-price Control Algorithm

---

```

1 for  $t = 1, \dots, T$  do
2   Observe group type  $i$ ;
3   Solve the LP relaxation of problem (1) with  $d_i^t = (T - t) \cdot p_i$  and  $\mathbf{L}^t$ ;
4   Obtain  $\tilde{i}$  such that the aggregate optimal solution is  $x e_{\tilde{i}} + \sum_{i=\tilde{i}+1}^M d_i e_i$ ;
5   if  $i \geq \tilde{i}$  and  $\max_j L_j^t \geq n_i$  then
6     Accept the group and assign the group to row  $k$  such that  $L_k^t \geq n_i$ ;
7   else
8     Reject the group;
9   end
10 end

```

---

### Booking Limit Control

The booking limit control policy involves setting a maximum number of reservations that can be accepted for each group type. By controlling the booking limits, revenue managers can effectively manage demand and allocate inventory to maximize revenue.

In this policy, we replace the real demand by the expected one and solve the corresponding static problem using the expected demand. Then for every type of requests, we only allocate a fixed amount according to the static solution and reject all other exceeding requests. When we solve the linear relaxation of problem (1), the aggregate optimal solution is the limits for each group type. Interestingly, the bid-price control policy is found to be equivalent to the booking limit control policy.

When we solve problem (1) directly, we can develop the booking limit control policy.

---

**Algorithm 6:** Booking Limit Control Algorithm

---

```

1 for  $t = 1, \dots, T$  do
2   Observe group type  $i$ ;
3   Solve problem (1) with  $d_i^t = (T - t) \cdot p_i$  and  $\mathbf{L}^t$ ;
4   Obtain the optimal solution,  $x_{ij}^*$  and the aggregate optimal solution,  $\mathbf{X}$ ;
5   if  $X_i > 0$  then
6     Accept the group and assign the group to row  $k$  such that  $x_{ik} > 0$ ;
7   else
8     Reject the group;
9   end
10 end

```

---

**First Come First Served (FCFS) Policy**

For dynamic seat assignment for each group arrival, the intuitive but trivial method will be on a first-come-first-served basis. Each accepted request will be assigned seats row by row. If the capacity of a row is insufficient to accommodate a request, we will allocate it to the next available row. If a subsequent request can fit exactly into the remaining capacity of a partially filled row, we will assign it to that row immediately. Then continue to process requests in this manner until all rows cannot accommodate any groups.

---

**Algorithm 7:** FCFS Policy Algorithm

---

```

1 for  $t = 1, \dots, T$  do
2   Observe group type  $i$ ;
3   if  $\exists k$  such that  $L_k^t \geq n_i$  then
4     Accept the group and assign the group to row  $k$ ;
5   else
6     Reject the group;
7   end
8 end

```

---

**Tie-Breaking Rule**

These policies will encounter ties when the group can be assigned to two or more rows. For the booking limit control, we assign the group according to the seat planning. The same tie-breaking rule

used in the DSA approach can be applied for the booking limit control policy. For the other policies besides the booking limit control, we adopt the following rule for assigning groups to rows. We prioritize assigning the group to rows that have at least  $n_M$  seats available. If the number of remaining seats for all rows are less than  $n_M$ , we assign the group to an arbitrary row that has enough capacity to accommodate the group.

### Proof of Proposition 1

First, we regard this problem as a special case of the Multiple Knapsack Problem (MKP), then we consider the LP relaxation of this problem. Treat the groups as the items, the rows as the knapsacks. There are  $M$  types of items, the total number of which is  $K = \sum_i d_i$ , each item  $k$  has a profit  $p_k$  and weight  $w_k$ . Sort these items according to profit-to-weight ratios  $\frac{p_1}{w_1} \geq \frac{p_2}{w_2} \geq \dots \geq \frac{p_K}{w_K}$ . Let the break item  $b$  be given by  $b = \min\{j : \sum_{k=1}^j w_k \geq \tilde{L}\}$ , where  $\tilde{L} = \sum_{j=1}^N L_j$  is the total size of all knapsacks. For the LP relaxation of (1), the Dantzig upper bound [8] is given by  $u_{\text{MKP}} = \sum_{j=1}^{b-1} p_j + \left(\tilde{L} - \sum_{j=1}^{b-1} w_j\right) \frac{p_b}{w_b}$ . The corresponding optimal solution is to accept the whole items from 1 to  $b-1$  and fractional  $(\tilde{L} - \sum_{j=1}^{b-1} w_j) \frac{p_b}{w_b}$  item  $b$ . Suppose the item  $b$  belong to type  $\tilde{i}$ , then for  $i < \tilde{i}$ ,  $x_{ij}^* = 0$ ; for  $i > \tilde{i}$ ,  $x_{ij}^* = d_i$ ; for  $i = \tilde{i}$ ,  $\sum_j x_{ij}^* = (\tilde{L} - \sum_{i=\tilde{i}+1}^M d_i n_i) / n_{\tilde{i}}$ . ■

### Proof of Proposition 2

First, we construct a feasible pattern with the size of  $qM + \max\{r - \delta, 0\}$ , then we prove this pattern is largest. Let  $L = n_M \cdot q + r$ , where  $q$  represents the number of times  $n_M$  is selected (the quotient), and  $r$  represents the remainder, indicating the number of remaining seats. It holds that  $0 \leq r < n_M$ . The number of people accommodated in the pattern  $\mathbf{h}_g$  is given by  $|\mathbf{h}_g| = qM + \max\{r - \delta, 0\}$ . To establish the optimality of  $|\mathbf{h}_g|$  as the largest number of people accommodated given the constraints of  $L$ ,  $\delta$ , and  $M$ , we can employ a proof by contradiction.

Assuming the existence of a pattern  $\mathbf{h}$  such that  $|\mathbf{h}| > |\mathbf{h}_g|$ , we can derive the following inequalities:

$$\begin{aligned} & \sum_i (n_i - \delta) h_i > qM + \max\{r - \delta, 0\} \\ \Rightarrow & L \geq \sum_i n_i h_i > \sum_i \delta h_i + qM + \max\{r - \delta, 0\} \\ \Rightarrow & q(M + \delta) + r > \sum_i \delta h_i + qM + \max\{r - \delta, 0\} \\ \Rightarrow & q\delta + r > \sum_i \delta h_i + \max\{r - \delta, 0\} \end{aligned}$$

- (i) When  $r > \delta$ , the inequality becomes  $q + 1 > \sum_i h_i$ . It should be noted that  $h_i$  represents the number of group type  $i$  in the pattern. Since  $\sum_i h_i \leq q$ , the maximum number of people that can be accommodated is  $qM < qM + r - \delta$ .
- (ii) When  $r \leq \delta$ , we have the inequality  $q\delta + \delta \geq q\delta + r > \sum_i \delta h_i$ . Similarly, we obtain  $q + 1 > \sum_i h_i$ . Thus, the maximum number of people that can be accommodated is  $qM$ , which is not greater than  $|\mathbf{h}_g|$ .

Therefore,  $\mathbf{h}$  cannot exist. The maximum number of people that can be accommodated in the largest pattern is  $qM + \max\{r - \delta, 0\}$ . ■

### Proof of Proposition 3

First of all, we demonstrate the feasibility of problem (3). Given the feasible seat planning  $\mathbf{H}$  and  $\tilde{d}_i = \sum_{j=1}^N H_{ji}$ , let  $\hat{x}_{ij} = H_{ji}$ ,  $i \in \mathcal{M}$ ,  $j \in \mathcal{N}$ , then  $\{\hat{x}_{ij}\}$  satisfies the first set of constraints. Because  $\mathbf{H}$  is feasible,  $\{\hat{x}_{ij}\}$  satisfies the second set of constraints and integer constraints. Thus, problem (3) always has a feasible solution.

Suppose there exists at least one pattern  $\mathbf{h}$  is neither full nor largest in the optimal seat planning obtained from problem (3). Let  $\beta = L - \sum_i n_i h_i$ , and denote the smallest group type in pattern  $\mathbf{h}$  by  $k$ . If  $\beta \geq n_1$ , we can assign at least  $n_1$  seats to a new group to increase the objective value. Thus, we consider the situation when  $\beta < n_1$ . If  $k = M$ , then this pattern is largest. When  $k < M$ , let  $h_k^1 = h_k - 1$  and  $h_j^1 = h_j + 1$ , where  $j = \min\{M, \beta + k\}$ . In this way, the constraints will still be satisfied but the objective value will increase when the pattern  $\mathbf{h}$  changes. Therefore, by contradiction, problem (3) always generate a seat planning composed of full or largest patterns. ■

#### Proof of Proposition 4

In any optimal solution where one of the corresponding patterns is neither full or largest, we can utilize the conclusion of Proposition 3 to obtain a seat planning that is composed of full or largest patterns meanwhile the constraints of SSP are still satisfied. ■

#### Proof of Lemma 1

Note that  $\mathbf{f}^\top = [-1, \mathbf{0}]$  and  $\mathbf{V} = [\mathbf{W}, \mathbf{I}]$ . Based on this, we can derive the following inequalities:  $\alpha^\top \mathbf{W} \geq -1$  and  $\alpha^\top \mathbf{I} \geq \mathbf{0}$ . According to the expression of  $\mathbf{W}$  and  $\mathbf{I}$ , we can deduce that  $0 \leq \alpha_i \leq \alpha_{i-1} + 1$  for  $i \in \mathcal{M}$  by letting  $\alpha_0 = 0$ . These inequalities indicate that the feasible region is nonempty and bounded. For  $i \in \mathcal{M}$ ,  $\alpha_i$  is only bounded by  $\alpha_{i-1} + 1$  and 0, thus, all extreme points within the feasible region are integral. ■

#### Proof of Proposition 5

According to the complementary slackness property, we can obtain the following equations

$$\begin{aligned} \alpha_i(d_{i0} - d_{i\omega} - y_{i\omega}^+ + y_{i+1,\omega}^+ + y_{i\omega}^-) &= 0, i = 1, \dots, M-1 \\ \alpha_i(d_{i0} - d_{i\omega} - y_{i\omega}^+ + y_{i\omega}^-) &= 0, i = M \\ y_{i\omega}^+(\alpha_i - \alpha_{i-1} - 1) &= 0, i = 1, \dots, M \\ y_{i\omega}^- \alpha_i &= 0, i = 1, \dots, M. \end{aligned}$$

When  $y_{i\omega}^- > 0$ , we have  $\alpha_i = 0$ . When  $y_{i\omega}^+ > 0$ , we have  $\alpha_i = \alpha_{i-1} + 1$ . When  $y_{i\omega}^+ = y_{i\omega}^- = 0$ , let  $\Delta d = d_\omega - d_0$ ,

- if  $i = M$ ,  $\Delta d_M = 0$ , the value of objective function associated with  $\alpha_M$  is always 0, thus we have  $0 \leq \alpha_M \leq \alpha_{M-1} + 1$ ;
- if  $i < M$ , we have  $y_{i+1,\omega}^+ = \Delta d_i \geq 0$ .
  - If  $y_{i+1,\omega}^+ > 0$ , the objective function associated with  $\alpha_i$  is  $\alpha_i \Delta d_i = \alpha_i y_{i+1,\omega}^+$ , thus to minimize the objective value, we have  $\alpha_i = 0$ .

– If  $y_{i+1,\omega}^+ = 0$ , we have  $0 \leq \alpha_i \leq \alpha_{i-1} + 1$ .

■

### Proof of Proposition 6

Suppose we have one extreme point  $\alpha_\omega^0$  for each scenario. Then we have the following problem.

$$\begin{aligned}
\max \quad & \mathbf{c}^\top \mathbf{x} + \sum_{\omega \in \Omega} p_\omega z_\omega \\
\text{s.t.} \quad & \mathbf{nx} \leq \mathbf{L} \\
& (\alpha_\omega^0)^\top \mathbf{d}_\omega \geq (\alpha_\omega^0)^\top \mathbf{x} \mathbf{1} + z_\omega, \forall \omega \\
& \mathbf{x} \in \mathbb{N}^{M \times N}
\end{aligned} \tag{17}$$

Problem (17) reaches its maximum when  $(\alpha_\omega^0)^\top \mathbf{d}_\omega = (\alpha_\omega^0)^\top \mathbf{x} \mathbf{1} + z_\omega, \forall \omega$ . Substitute  $z_\omega$  with these equations, we have

$$\begin{aligned}
\max \quad & \mathbf{c}^\top \mathbf{x} - \sum_{\omega} p_\omega (\alpha_\omega^0)^\top \mathbf{x} \mathbf{1} + \sum_{\omega} p_\omega (\alpha_\omega^0)^\top \mathbf{d}_\omega \\
\text{s.t.} \quad & \mathbf{nx} \leq \mathbf{L} \\
& \mathbf{x} \in \mathbb{N}^{M \times N}
\end{aligned} \tag{18}$$

Notice that  $\mathbf{x}$  is bounded by  $\mathbf{L}$ , then the problem (17) is bounded. Adding more constraints will not make the optimal value larger. Thus, RBMP is bounded. ■

### Proof of Lemma 2

According to the Proposition 1, the aggregate optimal solution to LP relaxation of problem (1) takes the form  $xe_{\tilde{i}} + \sum_{i=\tilde{i}+1}^M d_i e_i$ , then according to the complementary slackness property, we know that  $z_1, \dots, z_{\tilde{i}} = 0$ . This implies that  $\beta_j \geq \frac{n_i - \delta}{n_i}$  for  $i = 1, \dots, \tilde{i}$ . Since  $\frac{n_i - \delta}{n_i}$  increases with  $i$ , we have  $\beta_j \geq \frac{n_{\tilde{i}} - \delta}{n_{\tilde{i}}}$ . Consequently, we obtain  $z_i \geq n_i - \delta - n_i \frac{n_{\tilde{i}} - \delta}{n_{\tilde{i}}} = \frac{\delta(n_i - n_{\tilde{i}})}{n_{\tilde{i}}}$  for  $i = \tilde{i} + 1, \dots, M$ .

Given that  $\mathbf{d}$  and  $\mathbf{L}$  are both no less than zero, the minimum value will be attained when  $\beta_j = \frac{n_{\tilde{i}} - \delta}{n_{\tilde{i}}}$  for all  $j$ , and  $z_i = \frac{\delta(n_i - n_{\tilde{i}})}{n_{\tilde{i}}}$  for  $i = \tilde{i} + 1, \dots, M$ . ■