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RESEARCH ARTICLE

Airplane Seating Assignment Greedy Algorithms That Separate Passengers Likely to Be Susceptible to Infectious Disease From Those Likely to Be Infectious

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ABSTRACT Although the COVID-19 pandemic has mostly ended, there may be future situations (e.g. future pandemics) in which infectious disease spread on airplanes should be minimized. The COVID-19 pandemic led to social distancing as a means of enhancing passenger safety. Methods were developed to separate homogenous passengers from each other on airplanes and in other settings. This paper presents three greedy methods that assign passengers to airplane seats so that those passengers most likely to be susceptible to infectious diseases are separated from those passengers who are most likely to be infectious. Stochastic simulation results show that the performance of the proposed greedy methods provide much higher values for the average distance of separation between susceptible and infectious passengers when compared to a random seat assignment. The improvements in the two best of the three greedy methods range from 152% to 343% across the selected scenarios. In addition to considering passengers who are likely to be infectious and those who are likely to be susceptible to the disease, the methods consider those passengers who are likely to be both infectious and susceptible. By accounting for variations in individual passenger infectiousness and susceptibility to infection, we illustrate how disease spread may be reduced during future pandemics or similar health crises, thereby improving the safety and resiliency of air travel.

INDEX TERMS Airplane seating assignment, greedy algorithm, COVID-19, pandemic, boarding strategies, NetLogo, Python.

I. INTRODUCTION

The COVID-19 pandemic precipitated the implementation of a range of measures to mitigate disease transmission risk and safeguard public health [1], [2], [3]. Notably, among these measures, social distancing has emerged as a focal point, garnering substantial attention and widespread implementation [4], [5]. The Centers for Disease Control and Prevention (CDC), an authoritative body in the United States, advocated for a recommended social distance, also known as "physical distance," of 6 feet, which roughly equates to 1.8 m [6]. Different nations embraced differing recommendations for the minimum physical distances to be maintained. For instance, countries like China, Italy, France, Denmark, and New Zealand endorsed a minimum distance of 1 meter, while Australia, Greece, Spain, Germany, and the Netherlands adopted a standard of 1.5 meters. Comparatively, the United Kingdom and Canada have advocated for a more extensive minimum distance of 2 m [7], [8].

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In their comprehensive systematic review encompassing 172 scholarly papers addressing COVID-19, SARS (Severe Acute Respiratory Syndrome), and MERS (Middle East Respiratory Syndrome), Chu et al. [9] conducted a sensitivity analysis to explore the impact of social distancing on virus infection rates. The researchers' findings underscored the significance of maintaining a social distance of greater than 1 m as important in curtailing virus transmission. Through a comparative assessment of various levels of social distancing, the researchers arrived at the conclusion that for each additional meter of separation distance observed, there was an estimated decrease of 2.02 times in the relative risk of infection [9].

The implementation of the minimum physical distancing measure in public spaces during the pandemic became widespread, aiming to mitigate the transmission of the virus. This preventive strategy had been adopted across various public settings, including indoor entertainment venues [10], [11], passengers from the same household traveling in a vehicle together [12], educational institutions and conference halls [13], places of worship [14], and transportation systems [15], [16], [17]. The CDC provided guidelines for schools. These guidelines suggest exploring innovative approaches to physically separate students, which can be as straightforward as arranging desks at greater distances from one another [10]. Additionally, when students travel on school buses, seating arrangements can involve assigning one student per row, alternating between window and aisle seats, and leaving empty rows whenever possible [18]. Moore et al. [12], advocate a comparable approach, differing in that these authors take into account the arrangement of students on the bus, which is influenced by their pick-up order. In cinemas and theaters, seating assignments have been complemented by the development of new features in booking systems. These features strategically block off adjacent seats to individuals or groups, simultaneously preventing seating in front of and behind the selected seats of a person or group [19].

The research community exhibited a keen interest in identifying optimal solutions for adhering to minimum social distancing requirements while maximizing the utilization of indoor spaces. This focus is evident in recent scientific literature. Murray [20] explores the feasibility of planning classroom layouts with physical distancing considerations using a spatial optimization model. By minimizing the risk of COVID-19 transmission, this model facilitates the arrangement of seats to accommodate students effectively. Dundar and Karakose [21] also investigate seat assignment in classrooms to minimize disease spread. The researchers propose optimization models and graph-based heuristic algorithms to arrange seat layouts, considering the safety of both students and university staff members. Romero et al. [22] examine various virus exposure levels in traffic scenarios within academic buildings. Their analysis highlights the impact of crowd density on infection risk. Bartolucci et al. [23] focus on students' exposure to COVID-19 and compliance with physical distancing measures inside university buildings. Through experimental analysis, the authors demonstrate that students perceive a higher risk of infection in university corridors, where the likelihood of close proximity interaction is high. D'Orazio et al. [24] consider three primary strategies—mask implementation, density control, and access control—employed by universities during pandemics. Using an agent-based modeling approach, the researchers analyze the efficacy of different risk mitigation strategies in preventing virus spread within university settings. Similarly, Bahl et al. [25] adopt an agent-based modeling approach to capture the unique features of viral transmission within a college environment. The authors' findings emphasize the necessity of robust policies for effectively reducing virus transmission.

Banon and Banon [7] delve into the reconfiguration of indoor spaces as a means to facilitate seat distribution in various settings, such as restaurants, libraries, and classrooms. The authors suggest that an equilateral triangle-based seat pattern may be more favorable than the traditional row-and-column arrangement when addressing the seat assignment challenge during pandemics [7]. Fischetti et al. [26] present an optimization tool designed to maximize area utilization in diverse public locations (e.g., restaurants, beach umbrella areas, theaters) while considering social distancing measures and minimizing the overall risk of infection. The authors demonstrate that their proposed approach can be effectively applied to the problem of seat selection for family groups. Despite initially appearing inefficient and counterintuitive, the resulting seating patterns successfully maximize space usage while minimizing the risk of infection [26]. Mokhtari and Jahangir [27] propose a strategy to minimize the risk of viral transmission through improved planning of occupant distribution within buildings throughout the day and the implementation of a higher air exchange rate. Simeone et al. [28] adopt an agent-based modeling approach to reevaluate the architectural design of spaces. The authors aim to explore how architecture can be adapted to mitigate the transmission of disease. Echeverria-Huarte et al. [29] conduct a laboratory experiment to demonstrate the influence of pedestrian density, walking speed, and prescribed safety distance on interpersonal distance—an essential measure for reducing the spread of the viral transmissions.

Benita [30] offers a comprehensive review that focuses on human mobility behavior, specifically examining the impact of disease spread on various aspects of transportation operations, road traffic demand, air transport, and the environment. The review provides a thorough analysis of the changes and challenges brought about by the recent pandemic in these domains.

Furthermore, concentrating solely on flight networks, Suzumura et al. [31] examines the repercussions of COVID-19 on these networks. The authors correlate the daily number of flights with the pandemic situation in various countries globally, thereby emphasizing the profound impact of the pandemic.

Additionally, Riquelme et al. [32] conducted a comprehensive survey on contagion modeling and simulation within transport and air travel networks during the COVID-19 pandemic. Their work underscores that, during the specified period, the scientific literature presented 15 models for the spread of COVID-19 contagion.

Mangili et al. [33] highlight that the airplane boarding and deplaning processes pose a higher risk of passengers coming into contact with each other and contaminated surfaces. Extensive research has examined various aspects of the boarding process, leading to notable findings. For instance, aisle seat passengers have a higher likelihood of contracting illnesses [34]. Conversely, passengers seated near the window are exposed to fewer infectious particles [35]. Additionally, passengers seated closer to the front of the cabin tend to have longer cumulative durations of contact, potentially due to the presence of lavatories located toward the rear of the airplane [36]. These studies shed light on the dynamics of disease transmission within the aircraft environment, providing insights for implementing strategies to mitigate risks during the boarding and deplaning processes.

Thus, social distance has been considered in the airplane boarding problem during the COVID-19 pandemic, airlines trying different policies for providing a safer environment for their passengers, such as: boarding first the passengers with seats in the rear rows of the airplane [37], [38], keeping the middle seats unoccupied [39], limiting the number of passengers when apron buses are used [40], using jet bridges when possible [40], suspending priority boarding [40], and filling the middle seats lasts [41].

Based on scientific literature, it has been asserted that keeping the middle seat empty during airplane boarding leads to a significant reduction in disease exposure [42]. The design of queues plays an important role in mitigating the spread of infectious diseases [43]. The scientific literature has addressed the issue of disease transmission during airplane boarding in various ways. Some studies have focused on determining the most effective boarding methods for minimizing disease spread [44], while others have adapted existing methods, such as the reverse pyramid boarding method, to account for social distancing requirements [45], [46]. Risk assessments related to passenger behavior during boarding have also been conducted [47], [48], aiming to understand the potential risks associated with specific actions or situations. Considering the groups of passengers boarding together has also been investigated as a potential strategy [49] to better manage the boarding process and mitigate the risk of infection. Strategies to manage the deplaning process of the patients with severe acute airborne disease have been explored by Xie et al. [50], aiming to reduce the risk of infection for healthy passengers, with the risk of sacrificing the deplaning process efficiency.

Additional researchers have explored seat assignment solutions that prioritize minimizing the risk of disease transmission on airplanes [51], [52]. Salari et al. [52] proposes a mixed-integer programming model, solved with a heuristic algorithm, that considers social distancing and passengers traveling together as a family group. Their method is superior to an alternative airline policy of blocking all middle seats, while taking into account the risk of disease transmission.

An important aspect to consider in the earlier works on airplane boarding and airplane seating assignments in the scientific literature is the assumption of homogenous passengers (except to the extent they form passenger groups such as families). While this assumption simplifies the analysis and modeling process, it does not capture the heterogeneity among individuals in terms of vulnerability to infection or infectiousness. In reality, some passengers may be particularly vulnerable to infection due to factors such as age, weight, underlying health conditions, or compromised immune systems. Likewise, certain individuals may be more likely to be infectious based on factors such as recent exposure to the virus or exhibiting symptoms of illness. Haque and Hamid [53] suggest reducing virus spread while boarding trains by reducing interaction among passengers from stations whose nearby populations have varying levels of infection. Their work reinforces the notion of segregating passengers based on their infection likelihood [53]. These variations in vulnerability and infectiousness can significantly impact the spread of diseases during the airplane boarding process.

Blackwood and Childs [54] present an introduction to models of infectious disease spread using the *susceptible-infectious-recovered* (SIR) framework. These models focus on the spread of disease within a population as a whole, considering different stages of infection and the transition between them. The SIR framework provides a foundation for understanding how infectious diseases propagate through populations and the impact of various factors on disease dynamics. In a similar vein, Gevertz et al. [55] develop an epidemiological model that explicitly characterizes individuals as belonging to specific compartments, such as susceptible individuals or compartments representing asymptomatic individuals. This compartmentalized approach allows for a more detailed representation of the different stages of infection and the interactions between individuals within a population.

Derjany et al. [56] adopt a perspective that considers passengers as either infectious or susceptible when analyzing the spread of infectious diseases during various stages of commercial air travel. By differentiating passengers based on their infection status, their study provides insights into the dynamics of disease transmission within the context of air travel. Similarly, Nakamura and Managi [57] offer valuable information for airlines to estimate the likelihood of passengers being infectious based on their airport of origin. This approach recognizes that passengers may vary in terms of their vulnerability to infection or their potential to spread diseases. The studies by Dollard et al. [58] on passenger screening in airports, and Mitra et al. [59] on temperature screening also emphasize the importance of considering different passenger characteristics in managing disease spread. These studies highlight the potential benefits of screening measures and the need to identify individuals who may pose a higher risk of spreading diseases.

In our research paper, we introduce a classification scheme that organizes passengers into four main groups based on their potential status with regards to the likelihoods of disease susceptibility and being infectiousness. These groups include:

- Susceptible to disease (unlikely to be infectious): Passengers in this category are considered vulnerable to contracting disease but are not likely to be actively infectious. They may exhibit certain characteristics that indicate a higher probability of becoming infected or incurring greater harm in the event of becoming infected. Potential indicators for this group could include advanced age, obesity, mobility impairment (requiring assistance from airline and airport staff, such as a wheelchair), no evidence of vaccination, no indication of a negative test result for the specific disease of concern, and a willingness to pay the airline for a seat that ensures enhanced safety measures.
- Infectious (not susceptible): Passengers in this category may have tested positive for a disease or exhibit symptoms that indicate an active infection. The characteristics of these passengers that could be taken into consideration include: being a young adult, being single (unmarried), as individuals in such circumstances may participate in more activities involving exposure risk, traveling alone on this flight or having a recent history of solo travel, having an airplane ticket with timings and destinations indicating a vacation rather than a business trip, particularly to locations known for a vibrant nightlife scene, no evidence of vaccination, no indication of a negative test result for the specific disease of concern, and residing in or departing from an area with a high infection rate and/or a significant positivity rate.
- Both susceptible and infectious. Passengers in this category are susceptible to disease and likely to infect others.
- Neither susceptible nor infectious: Passengers in this category are neither susceptible to the disease nor likely to be infectious.

To assess the likelihood of passengers belonging to different categories, airlines can employ various methods. These methods may include analyzing passenger demographics and characteristics, such as age and mobility status, checking vaccination records or test results, and offering enhanced safety measures for passengers who express a willingness to pay for them.

By implementing methods for assessing passenger vulnerability and infectiousness, airlines can enhance their ability to mitigate disease transmission risks during air travel. This approach allows for targeted measures and interventions to be applied, focusing on passengers who are more likely to be vulnerable, infectious, or both. As the emergence of a pandemic can be unpredictable, and the requisite response measures often necessitate a constrained timeframe for implementation, early preparedness can prove to be profoundly beneficial in ameliorating the consequences of such global health crises. While our study's approach draws inspiration from the lessons of the recent COVID-19 pandemic, the categorization of passengers into the four delineated groups can be applied to future pandemics or other circumstances in which minimizing disease spread becomes a priority.

In contrast to the approach employed by Derjany et al. [56], which relies on probability distributions to generate passenger attributes (susceptible and infectious) with uncertain likelihoods, our research paper operates under the assumption that these characteristics are known a priori. Each airline would independently determine these attributes using their own methodologies—potentially strengthened through future research and drawing inspiration from the aforementioned examples. The provided examples are not exhaustive, as airlines have the flexibility to incorporate additional factors and data sources to bolster the accuracy of their categorization process. The primary objective is to equip airlines with the necessary tools to make well-informed decisions regarding passenger placement, thereby mitigating the risk of disease transmission and increasing the safety of their passengers on board.

The original contributions of this paper include:

- The notion of classifying individual airplane passengers into one of four groups based on their likelihoods of infectiousness and susceptibility to infection
- Suggestions for data that may be useful in determining the classification of each individual
- Using that classification to assign passengers to seats that minimize harm from a contagious disease
- Evaluating the results of three greedy algorithms to provide insight into which ones perform better
- Provide a baseline for further research that leverages individual passenger differences to improve travel safety

II. METHODS

In this section, we present information regarding the proposed approach. First, we provide a list of assumptions. Subsequently, we discuss two greedy algorithms along with several examples showcasing passenger placements on the airplane.

A. ASSUMPTIONS

The following modeling assumptions are made:

- Each passenger is traveling as an individual (no groups of passengers traveling together)
- The airplane has 30 rows, each with 6 seats (3 on each side of a single aisle)
- Each seat of the airplane is occupied
- Each passenger is designated as belonging to exactly one of the following categories:

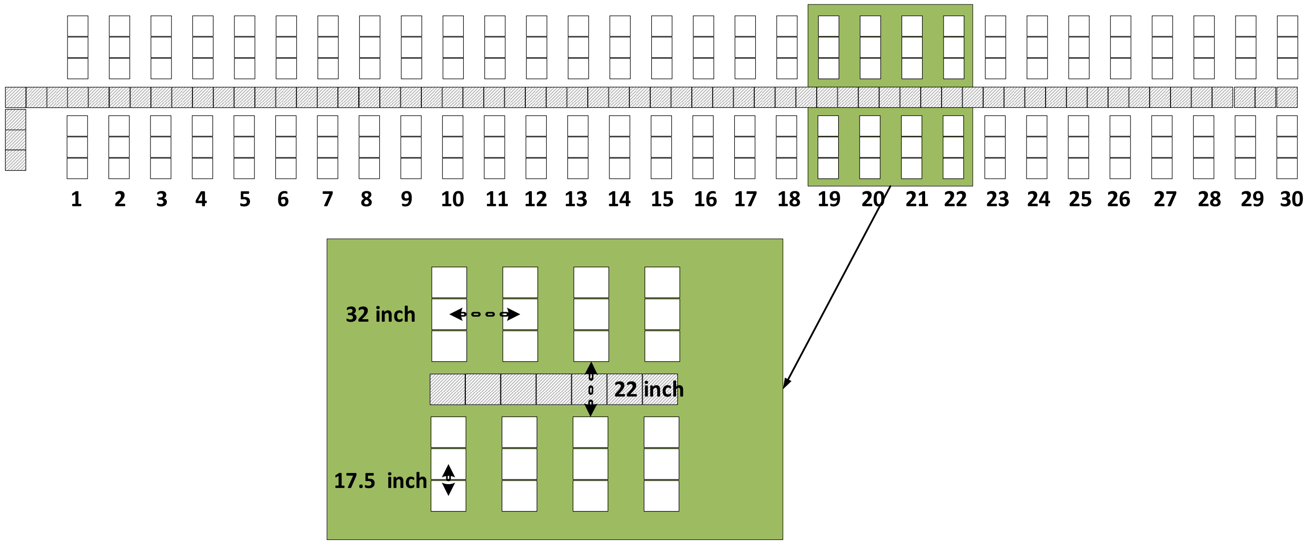

FIGURE 1. **Considered distances for the aircraft interior.**

- $s \in S$, passengers that are susceptible to infection but not likely to be infectious themselves
- $i \in I$, passengers that are likely to be infectious but not susceptible to infection
- $n \in \mathrm{N}$, passengers that are neither susceptible nor infectious
- $b \in B$, passengers that are both susceptible to infection and likely to be infectious

In addition to the seat assignment considerations, several distances related to the interior characteristics of the aircraft are taken into account [52]. These distances include a seat pitch of 32 inches, seat width of 17.5 inches, and aisle width of 22 inches, as depicted in Figure 1.

B. PROPOSED APPROACH

Table 1 describes a greedy algorithm for assigning the passengers to seats on the airplane.

The main idea is to separate infectious and susceptible passengers by assigning them seats on the airplane as follows. Susceptible passengers who are not infectious will be seated towards the back of the airplane, while infectious passengers who are not susceptible will be seated towards the front. Some passengers who are neither infectious nor susceptible will be assigned to seats directly in front of susceptible passengers near the back and directly behind infectious passengers near the front, acting as a buffer. Next, the passengers classified as both susceptible and infectious will be assigned seats in the middle of the airplane, spread apart and separated from those passengers who are infectious, susceptible, or both. Ideally, there will be enough passengers in the neither infectious nor susceptible category for them to surround and separate those who are both infectious and susceptible.

After assigning susceptible passengers who are not infectious to full rows of seats at the back of the airplane, there may be a partial row of these passengers to assign. In this case, the algorithm gives priority to assigning them seats on the right side of the airplane and closest to the right side's window. If there are any remaining susceptible passengers, they are assigned seats on the left side and closest to the left side's window. This arrangement aims to keep the susceptible passengers together and, secondly, seat them closest to the window. Recall that passengers seated near the window are exposed to fewer infectious particles [35].

On the other hand, after assigning infectious passengers who are not susceptible to full rows at the front of the airplane, there may be a partial row of these passengers to assign. The algorithm assigns them seats on the left side of the airplane and closest to the aisle. If there are any remaining infectious (but not susceptible) passengers, they are seated on the right side of the airplane, again, closest to the aisle. This arrangement clusters these infectious passengers together and, secondly, seats them closest to the aisle.

These seat assignments are influenced by the goal of having infectious passengers enter the airplane later than susceptible passengers. This implicitly considers common boarding methods where passengers with window seats typically board before those with middle seats, and those with middle seats board before those with aisle seats. Additionally, passengers seated near the rear of the airplane tend to board before those seated near the front. (If the airplane flight is long and if the lavatories used by passengers sitting near the front of the airplane are located near the back of the airplane, then essentially the same method could be used except with assigning the infectious (but not susceptible) passengers to seats near the back of the airplane and the susceptible (but not infectious) passengers towards the front of the airplane; assume for the remainder of this paper that this situation is not the case.)

In summary, the greedy algorithm works by first assigning the susceptible passengers, $s \in S$, to seats near the rear of the

TABLE 1. Greedy algorithm.

Greedy algorithm steps

```
// Assign all susceptible passengers to seats near
// the back of the airplane
   num_rows_s = |S| / 6  // the number of full
                         // rows that will have
                         // susceptible passengers
   integer_rows_s = floor (num_rows_s)
   num_back_row_passengers = integer_rows_s * 6
   assign num_back_row_passengers to the rearmost
        integer_rows_s of the airplane
   remaining_s_to_assign =
             |S| - num_back_row_passengers
   Assign these remaining_s_to_assign passengers
     to the rearmost seats on the right side of
     the airplane (in a window seat first, middle
     seat second, aisle seat third sequence) and
     then to the left side of the airplane (in a
     window seat first, then middle seat sequence)
// Assign all infectious passengers to seats near
// the front of the airplane
   num_rows_I = |I| / 6  // the number of full
                         // rows that will have
                         // infectious passengers
   integer_rows_I = floor (num_rows_I)
   num_front_row_passengers = integer_rows_I * 6
   assign num_front_row_passengers to the
      frontmost integer_rows_I of the airplane
   remaining_I_to_assign = |I| -
      num_front_row_passengers
   Assign these remaining_I_to_assign passengers
      to the frontmost seats on the left side of
      the airplane (in an aisle seat first, middle
      seat second, window seat third sequence)
      and then to the right side of the airplane
      (in an aisle seat first, then middle seat)
// Assign some of the passengers who are neither
// infectious nor susceptible to a row of
// seats in front of those passengers who are
// susceptible and to a row behind those who
// infectious. In many cases, this will result in
// 12 of these neither infectious nor
// susceptible passengers being assigned at this
// stage of the algorithm
    Until all |N| passengers have been assigned to
        seats or until (all susceptible passengers
        have a passenger assigned to a seat in
        front of them and all infectious
        passengers have a passenger assigned to a
        seat behind them)
    Do
        If there is an empty seat directly in
           front a passenger s ∈ S
            Then assign a passenger n ∈ N to that
                 empty seat
            Else If there is an empty seat
                 directly behind a passenger i ∈ I
                    Then assign a passenger n ∈ N
                         to that empty seat
                 End-if
        End-if
    End do
//Assign those passengers who are both infectious
//               and susceptible in a greedy manner
    If |B| > 1,
        then
           Assign passengers b ∈ B using
                  Method 1 (see Table 2)
                or Method 2 (Table 3)
                or Method 3 (see Table 4)
        End if
// There may be some passengers n ∈ N who have yet
// to be assigned seats.
// Assign them to the remaining empty seats
    Until all |N| passengers have been assigned to
                                    seats
         Assign a passenger n ∈ N to an empty seat
```

TABLE 2. Greedy algorithm for assigning B passengers – Method 1.

Greedy algorithm steps for assigning B passengers – Method 1

```
// Assign each passenger b ∈ B, in turn, to an
// empty seat that is farthest from the closest
// passenger that is either infectious,
// susceptible, or both.
While not all B passengers have been assigned to
seats do
    Assign a passenger b ∈ B to an empty seat that
       has the largest minimum distance from
       the closest seated passenger that is in set
       S, I, or B.
       In the case of ties, choose an equally
          maximum minimum distance seating
          assignment that is an empty seat that is
          furthest from the closet seat of
          a passenger that is in B.
End while
```

airplane, then assigning infectious passengers, $i \in$ I, to seats near the front of the airplane. Next, a buffer row (or partial row) of passengers that are neither infectious nor susceptible, $n \in N$, are placed in front of the susceptible passengers and also behind the infectious passengers. Subsequently, the passengers that are both infectious and susceptible, $b \in B$, are assigned to seats in the middle of the airplane, ideally so that each is assigned a seat that is far from other passengers who are infectious or susceptible or both. Finally, the remaining passengers, $n \in$ N, are assigned to the remaining empty seats on the airplane. The details of the greedy algorithm are outlined in Table 1.

As seen in Table 1, there are three approaches—Method 1, Method 2, and Method 3—for assigning the passengers who are both infectious and susceptible, $b \in B$, to seats in the middle of the airplane. The three methods use greedy algorithms.

In Method 1, each passenger $b \in B$ is assigned, in turn, to an empty seat that is farthest from the closest passenger that is either infectious, $i \in I$, susceptible, $s \in S$, or both infectious and susceptible, $b \in B$. This greedy approach ensures that the passenger $b \in B$ is assigned to a seat that is as far as possible from a passenger it should avoid. We refer to this as a *maximum minimum distance seating assignment* because it maximizes the distance from the closest passenger to be avoided. When there are multiple equally maximum minimum distance seating assignments, the algorithm will choose an empty seat that is farthest from the closest seat of

TABLE 3. Greedy algorithm for assigning B passengers – Method 2.

Greedy algorithm steps for assigning B passengers – Method 2

```
// Assign a single passenger b ∈ B to an empty
// seat that is farthest from another passenger
// that is either infectious or susceptible
      Assign a passenger b ∈ B to an empty seat
      that is the largest minimum distance from a
      seated passenger that is from set I or S
// Assign each passenger b ∈ B, in turn, to an
// empty seat that is farthest from another
// passenger that is both infectious and
// susceptible
        While not all B passengers have been
        assigned to seats do
           Assign a passenger b ∈ B to an empty
             seat that is the largest minimum
             distance from other passengers in B.
           In the case of ties, choose the equally
              Maximum minimum distance seating
              assignment that is farthest from the
              nearest seat's passenger that is in
              I or S
End while
```

TABLE 4. Greedy algorithm for assigning B passengers – Method 3.

Greedy algorithm steps for assigning B passengers – Method 3

```
// Assign each passenger b ∈ B, in turn, to an
// empty seat that is farthest from the closest
// passenger that is either susceptible (but not
// infectious) or both susceptible and infectious
While not all B passengers have been assigned to
seats do
    Assign a passenger b ∈ B to an empty seat that
       has the largest minimum distance from
       the closest seated passenger that is in set
       S or B.
    In the case of ties, choose an
       equally maximum minimum distance seating
       assignment that is an empty seat that is
       farthest from the closet seat of a
       passenger that is in S.
End while
```

TABLE 5. Algorithm for computing the average closest distance.

Algorithm steps for computing the average closest distance

```
total_distance = 0
For each passenger p:
    If the passenger p is in S or B // i.e. if the
                                    // passenger is likely
                                    // to be susceptible
       then
          find the nearest passenger that is
             in I or B // i.e. nearest infectious
                       // passenger
        set dist to the distance between passenger
           p and that nearest infectious passenger
        Add dist to total_distance
    End-if
End-for
average_closest_distance =
        total_distance / (|S| + |B|)
End while
```

a passenger $b \in B$. That is because an assignment close to a passenger $b \in B$, being both susceptible to infection and infectious itself, may be worse than being seated close to passenger $i \in I$ or $s \in S$, which is infectious or susceptible but not both. The details of Method 1 are described in Table 2.

Observe that Method 1 prioritizes the assignment of passengers $b \in B$ to empty seats that are farthest from seated passengers $i \in I$, $s \in S$, and $b \in B$, while favoring the avoidance of a seat assignment far from another passenger $b \in B$ as a secondary tie-breaking priority. With Method 2, the priorities reverse. Method 2 prioritizes most heavily the assignment of passengers $b \in B$ to empty seats that are farthest from another passenger $b \in B$, while favoring the assignment of passengers $b \in B$ to empty seats that are farthest from seated passengers $i \in I$ and $s \in S$, as a secondary tie-breaking priority.

Method 2 begins by assigning the first passenger $b \in B$ to an empty seat that is farthest from the closest passenger $i \in I$ or $s \in S$. This seat is typically located near the middle of the airplane, particularly if the number of infectious passengers in I is approximately equal to the number of susceptible passengers in S, that is, $|I| \sim= |S|$.

Method 2 continues by assigning each subsequent passenger $b \in B$, in turn, to an empty seat that is farthest from the closest passenger that is both infectious and susceptible, $b \in B$. This greedy approach ensures that the passenger $b \in B$ is assigned to a seat that is as far as possible from another passenger it should especially avoid as each of these two passengers can infect the other. When there are multiple equally maximum minimum distance seating assignments, the algorithm will choose an empty seat that is farthest from the closest seat of a passenger $i \in I$ or $s \in S$, as these latter passengers are not otherwise considered in this stage of Method 2. For further details on Method 2, please see Table 3.

Method 3 is similar to Method 1 in many respects. Whereas Method 1 most emphasizes the priority of the assignment of passengers $b \in B$ to empty seats that are farthest from seated passengers $i \in I$, $s \in S$, and $b \in B$, Method 3 most prioritizes the assignment of passengers $b \in B$ to empty seats that are farthest from seated passengers $s \in S$ and $b \in B$. The motivation for Method 3 is that is bad to seat passengers $b \in B$ near other passengers $b \in B$(because either passenger can infect the other) and very bad to assign them to seats near passengers $s \in S$ because many of the latter passengers sit near each other. When a passenger $b \in B$ is seated near one passenger $s \in S$, it is seated as close to other passengers $s \in S$ that may also become infected.

In Method 3, each passenger $b \in B$ is assigned, in turn, to an empty seat that is farthest from the closest passenger that is either susceptible, $s \in S$, or both infectious and susceptible, $b \in B$. When there are multiple equally maximum minimum distance seating assignments, the algorithm will choose an

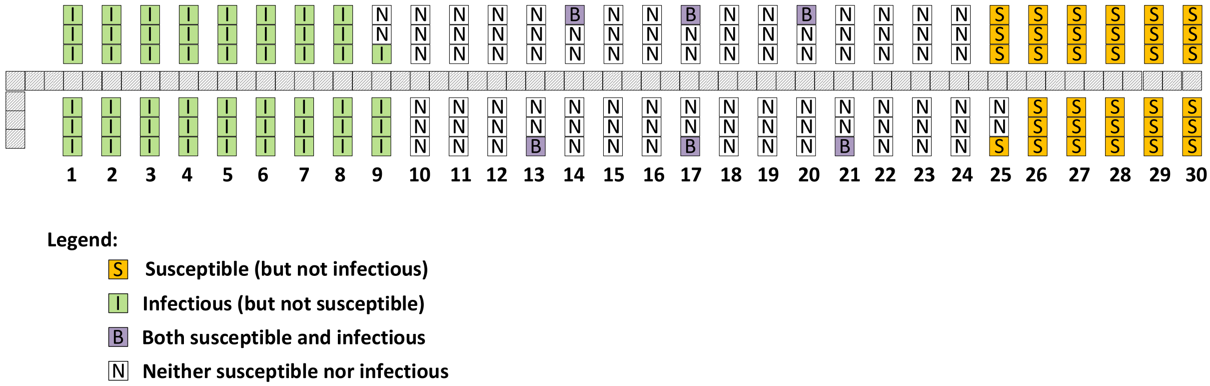

FIGURE 2. Example of seat allocation using Method 1.

empty seat that is farthest from the closest seat of a passenger $s \in S$. The details of Method 3 are described in Table 4.

To assess the effectiveness of the seat assignment methods, we calculate the average distance between each passenger that is likely to be susceptible $s \in S$ or $b \in B$ from the nearest passenger that is likely to be infectious $i \in I$ or $b \in B$. This evaluation is carried out by following the steps outlined in Table 5.

The proposed approach has been implemented in NetLogo [60], a software widely used in the scientific literature. The simulations, including random number generation, have been performed using Python while invoking NetLogo. Among the reasons for this choice, we aim in future research to simulate various aspects related to minimizing health risk indicators for various situations associated with airplane seat assignments and airplane boarding.

Figure 2 provides an example of seat assignments on an airplane using the greedy algorithm with Method 1. In this example scenario, there are 34 susceptible passengers $s \in S$, 52 infectious passengers $i \in I$, 6 passengers $b \in B$, and 88 passengers $n \in N$.

Consistent with the intended arrangement, the infectious passengers, $i \in I$, are assigned seats in the front section of the airplane, and the susceptible passengers, $s \in S$, are seated near the rear of the airplane. The passengers that are both susceptible and infectious, $b \in B$, are seated in the middle of the airplane and are far away from passengers other than those that are neither infectious nor susceptible, $n \in N$.

Figure 3 displays the seat assignments resulting from using Method 2 instead of Method 1 for the same example scenario depicted in Figure 2. Both Method 1 and Method 2 have the same seating assignments for the infectious passengers $i \in I$ and the susceptible passengers $s \in S$. Because Method 2 prioritizes the separation between pairs of passengers $b \in B$, the passengers $b \in B$ are seated farther apart from each other in Figure 3 than they are in Figure 2. The passengers $b \in B$ sitting in rows 10 and 24 of the airplane in Figure 3 are seated closer to the infectious passengers $i \in I$ and susceptible passengers $s \in S$ than the Method 1 passengers $b \in B$ sitting in rows 13 and 21 in Figure 3. The Method 2 assignment is particularly concerning for the 34 susceptible passengers $s \in S$ who are seated closest to the likely infectious passenger b sitting in row 24, unlike the Method 1 approach where row 21 contains the closest likely infectious passenger near the 34 susceptible passengers.

Figure 4 displays the seat assignments resulting from using Method 3 instead of Methods 1 and 2, for the same example scenarios depicted in Figures 2 and 3. The Method 3 seat assignments (Figure 4) are quite similar to the Method 1 seat assignments (Figure 2). The primary difference is that Method 3 assigns an additional passenger $b \in B$ to row 10, near the infectious passengers $i \in I$ of rows 1-9, whereas Method 1 assigns an additional passenger $b \in B$ to row 17. This stems from Method 3 being willing to assign passengers $b \in B$ close to the infectious passengers $i \in I$, whereas Method 1 tries to avoid them.

In this example scenario, the average closest distance was highest (best), 206.07 inches (with Method 1), 205.94 inches (nearly as good, for Method 3), and 125.24 inches (considerably worse for Method 2). Meanwhile a random seat assignment with this passenger data results in an average closest distance of 28.27 inches, much worse than using Method 1, Method 2 or Method 3.

III. NUMERICAL RESULTS

In this section, a series of scenarios (S_1 – S_{12}), outlined in Table 6, are designed to assess the proposed methods. These scenarios vary from those with only a few passengers designated as S, I, or B (scenario S_1), and gradually increasing the number of passengers in these categories. The scenarios continue until scenario S_{12} which has 50 or more passengers in each of the S, I, and B categories.

The performance of Method 1, Method 2, and Method 3 are compared with the results of random assignments determined by calculating the average over 1,000 stochastic simulation runs.

In the S_1 scenario, there are four passengers in each of the S, I, and B categories, with the remaining passengers in the N category. Figures 5, 6, and 7 illustrate the seat assignments, for the S_1 scenario, using Method 1, Method 2, and Method 3

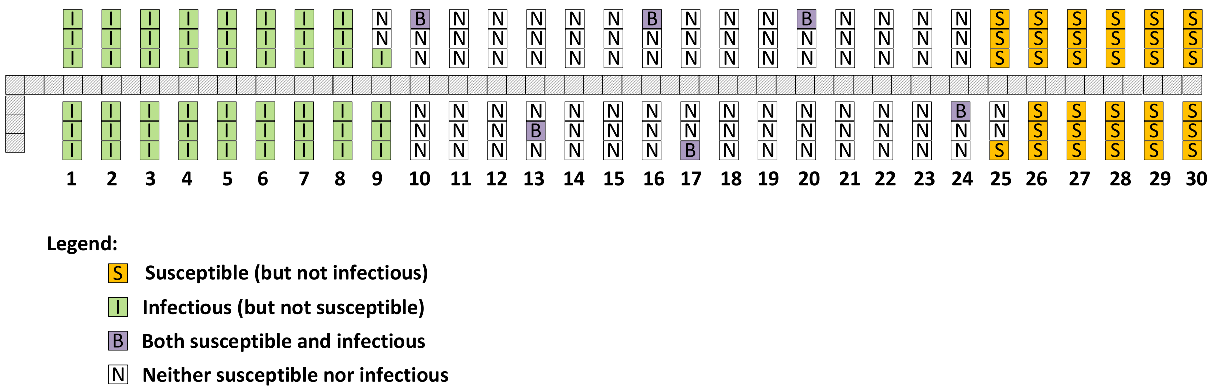

FIGURE 3. Example of seat allocation using Method 2.

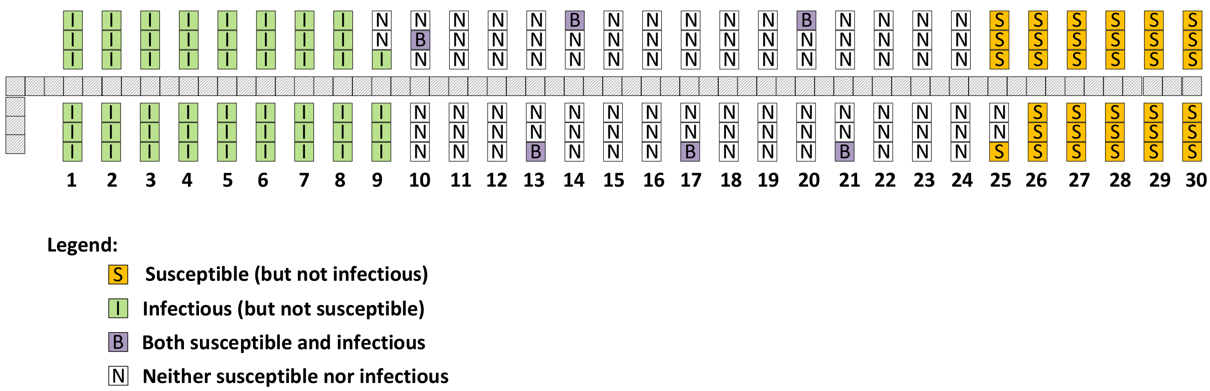

FIGURE 4. Example of seat allocation using Method 3.

respectively. Method 2 emphasizes separating passengers in B as can be seen in Figure 6, where the susceptible passengers $s \in S$ are seated in row 30 along with a passenger $b \in B$! The results show that Method 1 achieves an average closest distance of 221.41 inches, Method 3 does nearly as well at 220.87 inches, while Method 2 is considerably worse than both with an average closest distance of 126.72 inches. All three of these methods outperform the Random method, which has an average closest distance of 85.32 inches. When comparing the results of the S_1 scenario for Method 3 (see Figure 7), with the results for Method 1 (see Figure 5), we see that Method 3 provides greater separation between the passengers $b \in B$, which is good, but seats one of the passengers $b \in B$ in row 1 near the infectious passengers $i \in I$, which is bad (for that one passenger $b \in B$ in row 1), but not nearly as bad as the Method 2 result (see Figure 6) of seating a passenger $b \in B$ in row 30, which is bad for all four passengers $s \in S$ sitting near the infectious passenger $b \in B$ in row 30.

The results from all 12 scenarios are presented in Table 7. In Table 8 are the percentage improvements of Method 1, Method 2, and Method 3 versus the random method, followed by the percentage difference of those improvements between Method 1 and Method 2, and between Method 1 and Method 3.

TABLE 6. Scenarios for passengers' seat allocation.

Scenarios	Number of Passengers of Each Type			
	S	I	B	N
S1	4	4	4	168
S2	8	8	8	156
S3	10	15	12	143
S4	15	15	16	134
S5	20	20	20	120
S6	25	25	25	105
S7	25	25	30	100
S8	30	30	35	85
S9	35	35	40	70
S10	50	50	45	35
S11	50	50	50	30
S12	50	50	60	20

Based on the considered scenarios, as indicated in Table 8, Method 1, Method 2, and Method 3 all consistently and meaningfully yield superior seat assignment results when compared with the Random method. The improvement versus the Random method varies from 49% to 343%. In the final

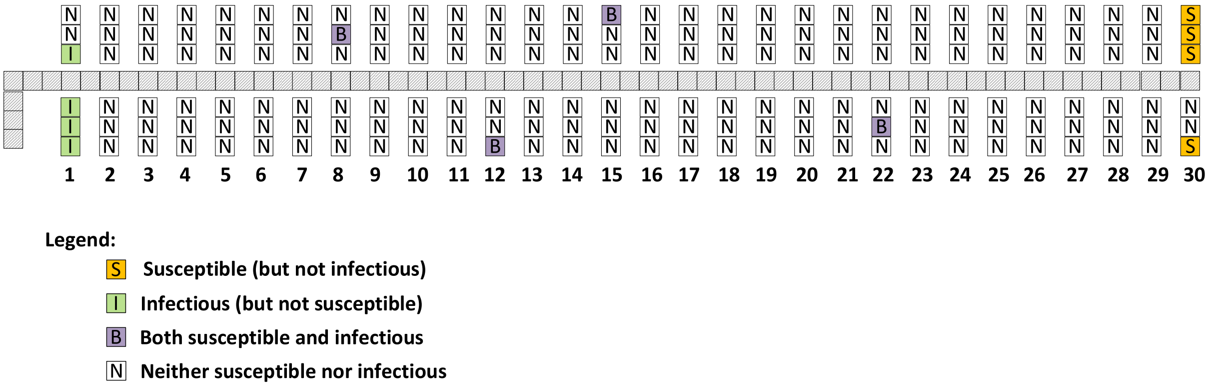

FIGURE 5. Scenario S1 seat allocation using Method 1.

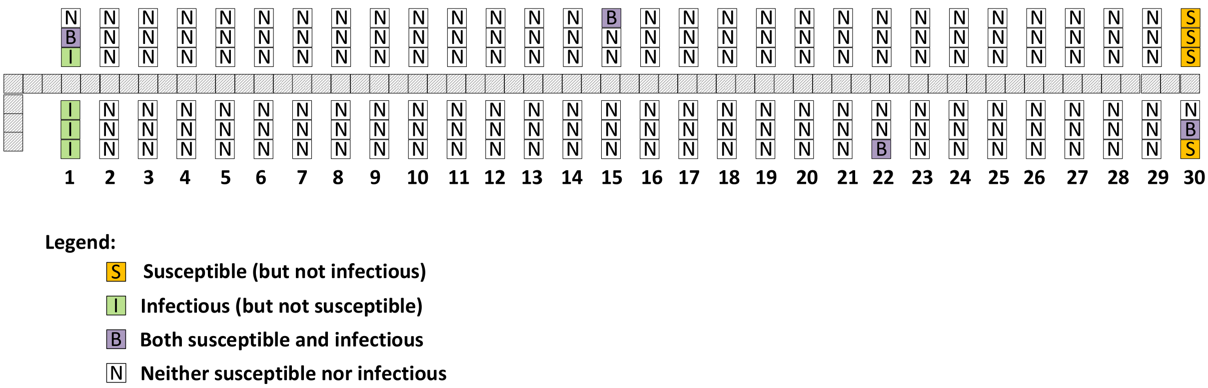

FIGURE 6. Scenario S1 seat allocation using Method 2.

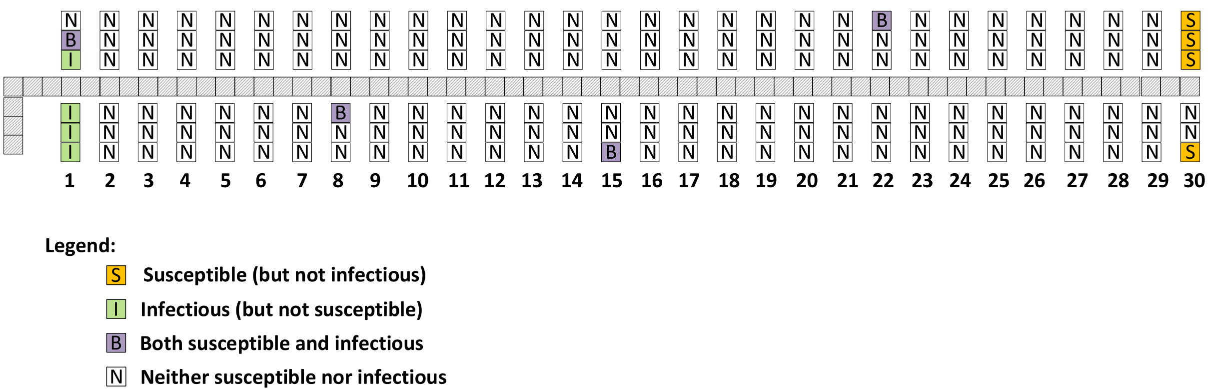

FIGURE 7. Scenario S1 seat allocation using Method 3.

two columns of Table 8, we see that Method 1 provides consistently provides better results than Method 2 for the 12 considered scenarios, with the difference most (least) prominent for the first (last) four scenarios. The final column of Table 8 indicates that Method 1 is sometimes better than Method 3, for instance, 17% better in scenario S_8, and sometimes worse, for instance, 47% worse in scenario S_5.

Method 1 so consistently provides better results than Method 2 that we had difficulty finding scenarios where Method 2 slightly outperforms Method 1. One such case is when there are 6 passengers in each of the categories S and I, 100 passengers in category B, and 68 passengers in category N (called S_{13} in the following).

In this particular situation, $S_{13,}$ Method 1 achieves an average closest distance of 30.65 inches, whereas Method 2 yields a slightly better average closet distance of 31.20 inches. The seat assignments for passengers using these methods are depicted in Figure 8 and Figure 9.

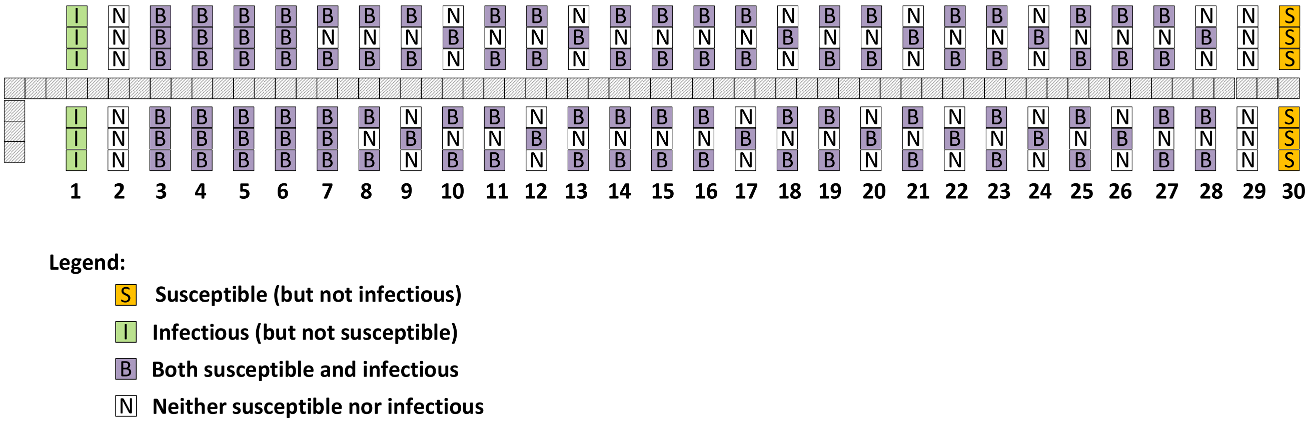

FIGURE 8. Scenario S_{13} seat allocation using Method 1.

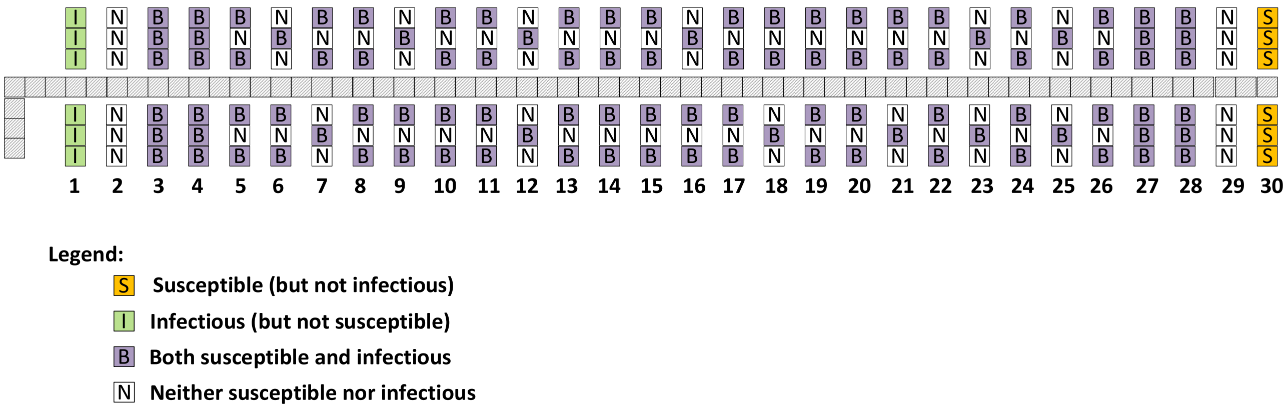

FIGURE 9. Scenario S_{13} seat allocation using Method 2.

TABLE 7. Numerical outputs of the average closest distances resulting from the seat assignment methods.

Scenarios	Seat Assignment Method			
	Random	Method 1	Method 2	Method 3
S1	85.32	221.41	126.72	220.87
S2	55.40	150.63	104.12	175.32
S3	41.77	115.33	91.86	113.73
S4	38.95	116.21	90.18	115.04
S5	34.40	86.65	84.19	102.77
S6	30.81	86.5	81.54	85.18
S7	29.65	79.78	74.97	76.12
S8	27.61	86.19	82.16	81.5
S9	26.04	77.77	77.61	77.66
S10	23.59	103.72	103.66	104.42
S11	23.12	98.58	97.81	98.97
S12	22.20	89.22	88.74	89.62

Figure 8 and Figure 9 reveal that Method 2 strategically assigns only *b* passengers in row 28 while Method 1 allocates some *n* passengers in row 28. The same situation can be seen in row 27.

This example demonstrates that in certain scenarios, Method 2 may have a slight advantage over Method 1 in terms of closest distance. The specific allocation decisions and their impact on passenger separation for this particular situation are shown in Figure 8 and Figure 9.

Indeed, even in the mentioned case, both Method 1 and Method 2 outperform the Random seat allocation, which recorded an average closest distance of 23.49 inches. This highlights the effectiveness of both greedy methods in enhancing passenger safety and reducing the risk of transmission compared to a randomly assigned seating arrangement. While Method 2 slightly outperforms Method 1 in this particular scenario, both methods offer significant improvements over the Random method in terms of average closest distance.

Considering the results obtained for the S_{13} scenario when Method 3 is used, an average closest distance of 31.19 inches is reported, slightly worse than in the case of Method 2. The seat allocation in this case, when Method 3 is used, is depicted in Figure 10.

In Figure 11, Figure 12 and Figure 13, we have represented the seat assignments for passengers in S_2 scenario when using Method 1, Method 2 and Method 3 respectively. The S_2 scenario has been chosen as in this case Method 1 performs 84% better than Method 2 and 46% worse than Method 3.

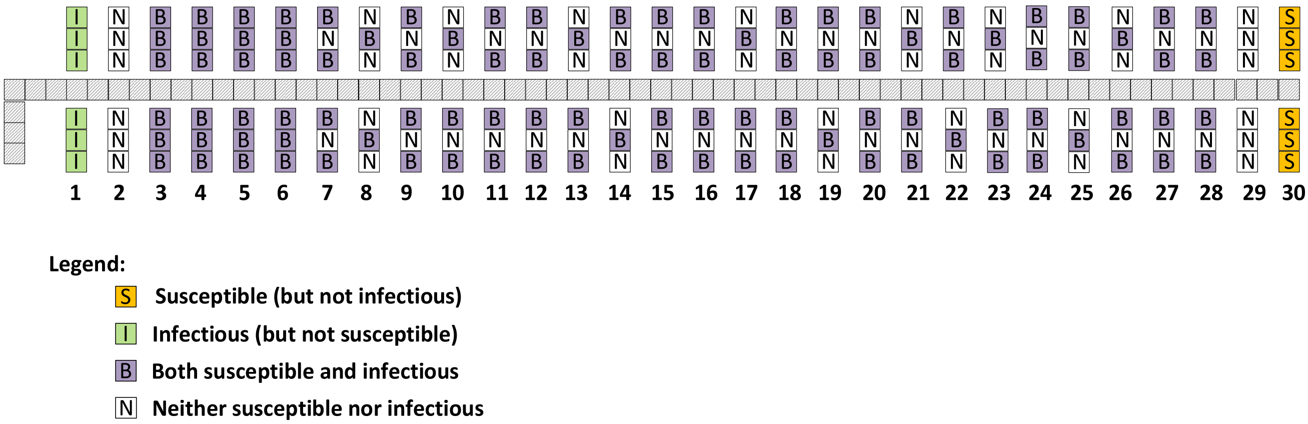

FIGURE 10. Scenario S_{13} seat allocation using Method 3.

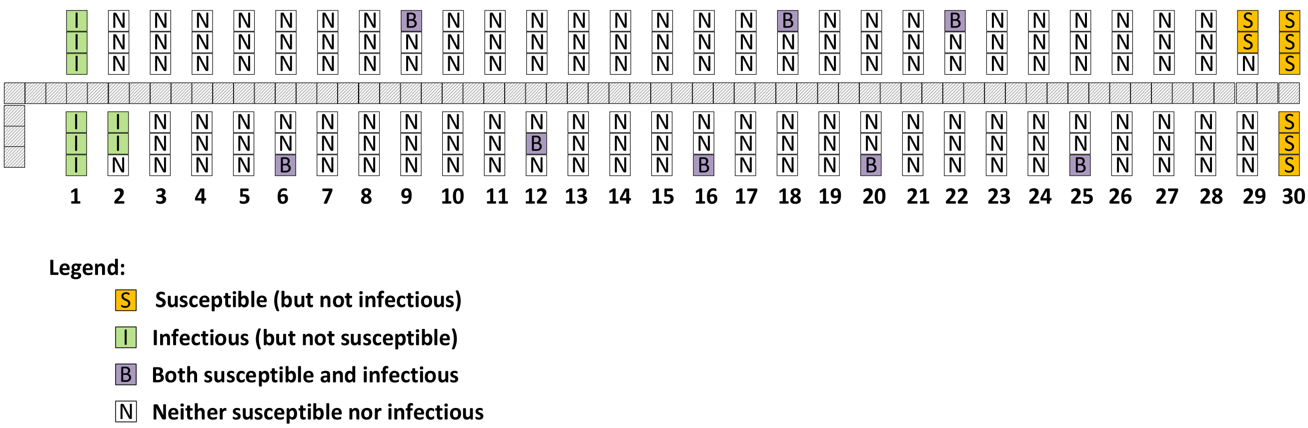

FIGURE 11. Scenario S_2 seat allocation using Method 1.

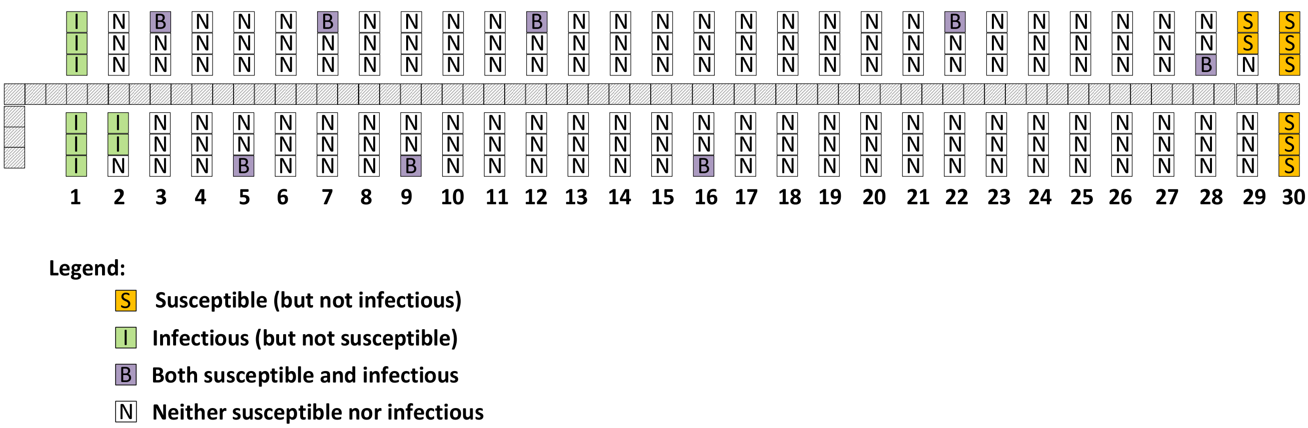

FIGURE 12. Scenario S_2 seat allocation using Method 2.

Upon comparing the outcomes of the S_2 scenario, there exists a more pronounced spatial separation between passengers b ∈ B and s ∈ S in the case of Method 3 when contrasted with the other two methods. In the context of Method 3, this difference is particularly significant when juxtaposed with Method 2. In Method 2, the assignment of a single passenger $b \in B$ to row 28 adversely affects the eight passengers $s \in S$ situated nearby in rows 29 and 30. Meanwhile, the closest single passenger $b \in B$ is assigned to row 23 with Method 3 (and slightly worse row 25 with Method 1). On the other hand,

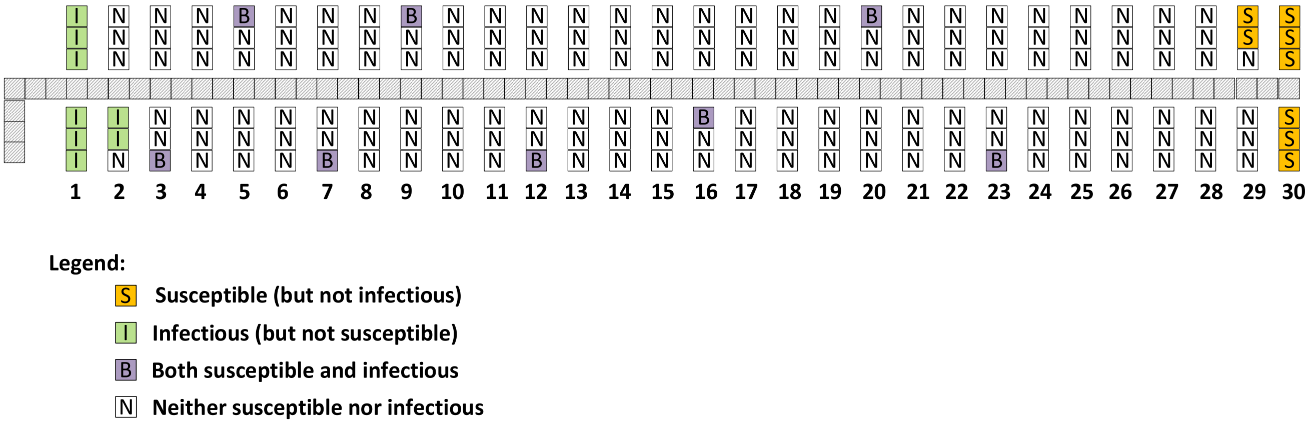

FIGURE 13. Scenario S_2 seat allocation using Method 3.

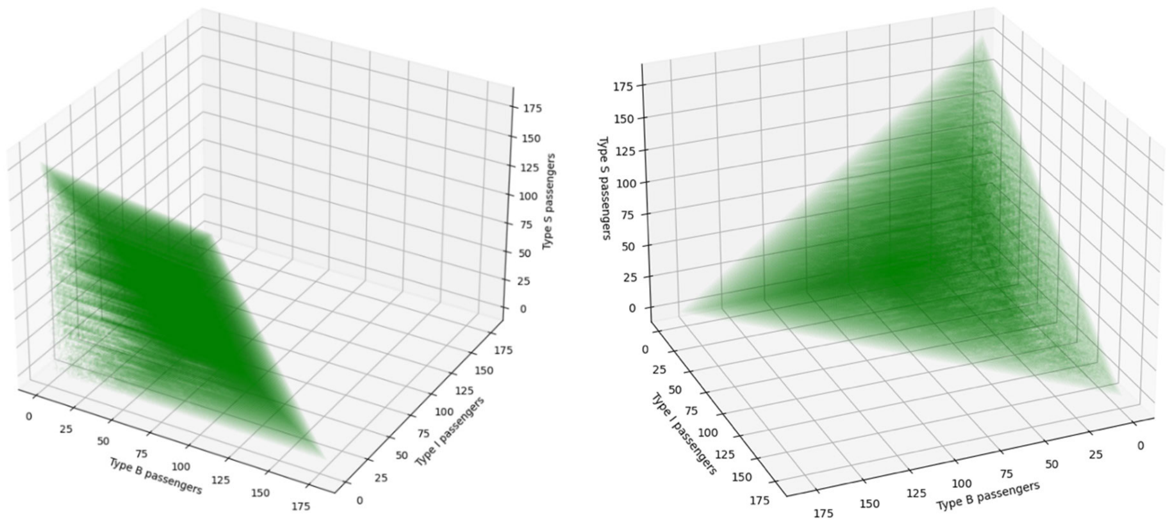

FIGURE 14. The cases in which Method 1 and Method 3 yield similar performance (view from different angles).

in comparison to both Method 1 and Method 2, there's an instance in Method 3 where one passenger $b \in B$ in row 3 is in closer proximity to the infectious passengers $i \in I$ – a situation that is disadvantageous for the aforementioned passenger $b \in B$ in row 1.

Furthermore, since both Method 1 and Method 3 have exhibit superior results in passenger seat assignments, we have been keen on ascertaining their relative performance across all potential scenarios involving varying passenger counts within each category, designed for a 180-seat airplane.

In light of this objective, we undertook simulations encompassing all conceivable scenarios using both Method 1 and Method 3. Subsequently, we evaluat and compare the performance of these methods in terms of the average closest distance.

The total number of feasible cases in which the number of passengers in categories B, I, and S each varies between 1 and 178 is 955,860. Among these, Method 1 outperforms in 291,862 cases (representing 30.54% of the total simulated cases), whereas Method 3 yields better results in 432,385 cases (45.24%). Both methods have demonstrated equivalent performance in 231,613 cases (24.22%).

Upon further investigation, we observe that there are 438,762 cases where the differences between the two methods are less than 1 inch. Consequently, we can conclude that in 670,375 cases (representing 70.14% of the total cases), the two methods perform nearly equally well. In the remaining cases, which amount to 101,393 of them, Method 1 outperforms Method 3, while Method 3 exhibits better performance in 184,092 cases. For the 101,393 cases, Method 1 performs better by an average of 5.25 inches. For the 184,092 cases, Method 3 performs better by an average of 21.63 inches.

From all the simulated cases, initially, we examine the 670,375 cases where both methods yield similar (equivalent or near-equivalent) performance outcomes. These cases are graphed based on the passenger counts within the B, I, and S categories, resulting in the generation of Figure 14.

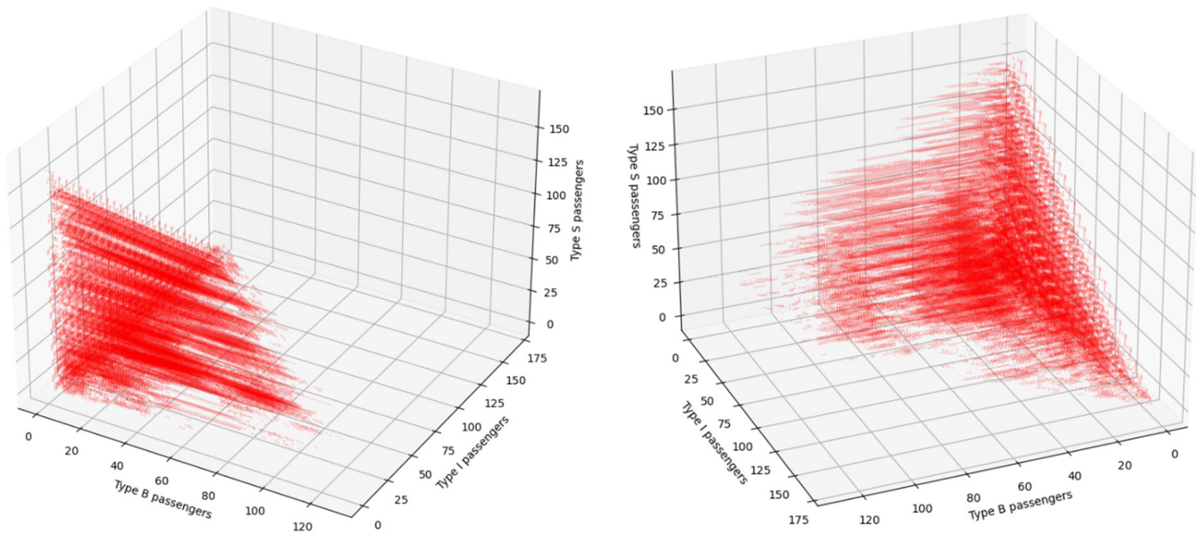

FIGURE 15. The cases in which Method 1 outperforms Method 3 (view from different angles).

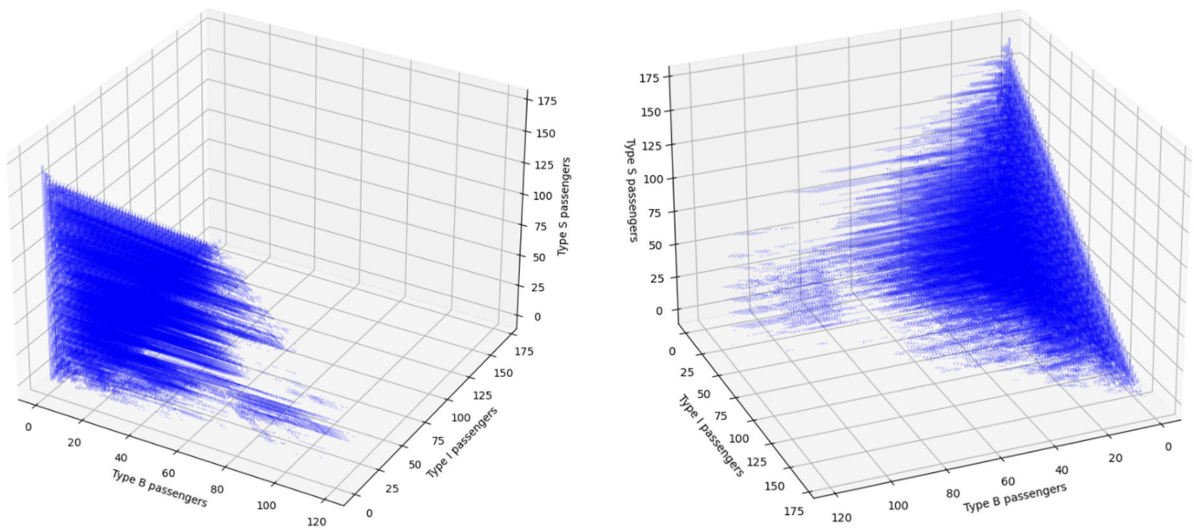

FIGURE 16. The cases in which Method 3 outperforms Method 1 (view from different angles).

Upon analyzing the simulation data, we observe that when the passenger count in the N category is less than or equal to 6, both methods consistently perform equally well in all 107,814 instances. However, as the passenger count N increases from 7 to 173, the instances in which one method outperforms the other become more prevalent. Beyond 173 passengers in the N category, no cases were found where the two methods perform equally well.

Regarding the other three passenger categories (B, I, and S), situations in which the methods perform equally well occur across the other passenger counts, and we did not identify a discernible pattern as to conditions when the two methods exhibit equal performance.

Through the analysis of the 101,393 cases in which Method 1 outperforms Method 3, these cases are plotted based on the B, I, and S categories, resulting in the creation of Figure 15.

The analysis of simulation data reveals that instances where Method 1 surpasses Method 3 are marked by a range of B passengers from 1 to 128, I passengers between 1 and 168, and S passengers between 1 and 165. However, we did not find a discernible pattern for passengers in the N category.

For the 184,092 cases where Method 3 outperformed Method 1, the outcomes are visualized in Figure 16.

Figure 16 highlights that instances where Method 3 outperforms Method 1 exhibit specific characteristics: the count of B passengers is less than 120, I passengers are fewer than 170, and S passengers are fewer than 171.

Drawing from the insights gleaned from both Figure 15 and Figure 16, we deduce that a subset of cases where the two

TABLE 8. Outputs showing the percentage improvements of Method 1, Method 2, and Method 3 versus the random method.

Scenarios	Percentage Improvement vs Random Method				
	Method 1 Improvement	Method 2 Improvement	Method 3 Improvement	Difference (Method 1 %– Method 2 %)	Difference (Method 1 %– Method 3 %)
S1	160%	49%	159%	111%	1%
S2	172%	88%	216%	84%	-46%
S3	176%	120%	172%	56%	4%
S4	198%	132%	195%	66%	3%
S5	152%	145%	199%	7%	-47%
S6	181%	165%	176%	16%	5%
S7	169%	153%	157%	16%	12%
S8	212%	198%	195%	14%	17%
S9	199%	198%	198%	1%	1%
S10	340%	339%	343%	1%	-3%
S11	326%	323%	328%	3%	-2%
S12	302%	300%	304%	2%	-2%

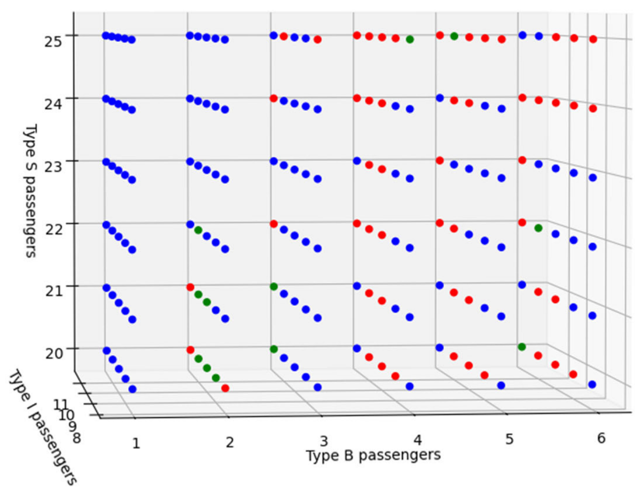

FIGURE 17. The performance of Method 1 and Method 3 for example passenger count values within the considered groups.

methods perform equivalently aligns with B passenger counts exceeding 128, comprising 22,100 cases. Additionally, within the range of B passengers from 120 to 128, Method 1 either performs better than or at least as well as Method 3, suggesting its favorable suitability in these scenarios.

Method 1 exhibits its most superior performance when B = 5, I = 10, S = 25, and N = 140, resulting in an average closest distance improvement of 76.41 inches. Conversely, Method 3 achieves its most superior performance when B = 1, I = 5, S = 16, and N = 158, yielding an average closest distance improvement of 394.01 inches.

For an example set of passenger count values within the considered groups (e.g., B ranging from 1 to 6, I between 8 and 12, and S from 20 to 25), we assess the performance of Method 1 and Method 3. The outcomes of this evaluation are depicted in Figure 17. In Figure 17 we have kept the color codes from the previous figures (please see Figure 14 – Figure 16, namely green for the situations in which the methods are equally good, red for the situations in which Method 1 outperforms Method 3, and blue for the situations in which Method 3 outperforms Method 1).

Analyzing Figure 17, it becomes evident that when B is equal to 1, Method 3 consistently outperforms Method 1 concerning the average closest distance. As B increases, Method 3 tends to exhibit superior, comparable, or inferior performance compared to Method 1.

Among the 180 cases illustrated in Figure 17, 12 cases (6.67%) exhibit equivalent performance between the two methods, 53 cases (29.45%) show Method 1's superiority, while 115 cases (63.89%) indicate Method 3's better performance. Once again, Method 3 emerges as the method with better performance in a greater number of cases compared to Method 1.

IV. LIMITATIONS

The proposed approach and the outcomes derived from simulations are subject to various limitations stemming from the assumptions delineated in Section II of the paper. Specifically, regarding passenger characteristics, we have assumed individual travel without consideration for passenger groups and without accounting for luggage carried onboard. Additionally, each passenger's category is presumed to be known to the airline. In terms of aircraft characteristics, the results are contingent upon a specific 30-row airplane configuration with three seats on each side of the aisle, and full occupancy. Altering any of these aforementioned characteristics may result in a different outcome.

In terms of methodology, while the approach may appear simplistic, it is applicable to the problem presented in the paper. As Papert [61] highlights, models can serve as "objects to think with," serving as initial frameworks for problem-solving in specific contexts. Moreover, the structure of this approach facilitates the facile manipulation of assumptions by interested parties, enabling the derivation of precise conclusions pertinent to the subject under scrutiny. According to Wilensky and Rand [60] certain forms of models are easier to manipulate than other forms, being helpful in easily making changes to the variables and observing the changes in the results, or providing a proof of concept that something is possible, thus offering knowledge that may not be readily available from real world observation.

A similar situation can be encountered in the case of the proposed approach, which combines elements used in similar researches in the pandemic / post-pandemic period – e.g. the paper of Blackwood and Childs [54] that presents an introduction to models of infectious disease spread using the *susceptible-infectious-recovered* (SIR) framework, the paper of Gevertz et al. [55] which develops an epidemiological model that explicitly characterizes individuals as being susceptible individuals or asymptomatic individual, and the paper of Derjany et al. [56] that adopts a perspective that considers passengers as either infectious or susceptible when analyzing the spread of infectious diseases during various stages of commercial air travel (though with a random assignment of passengers into such categories). As in the above-mentioned studies, this study provides insights into the dynamics of disease transmission within the context of air travel.

Airlines are limited in their airlines ability to ascertain passengers' viral infection status. However, Nakamura and Managi [57] detail estimations of airline passengers' infection likelihood based on airport of origin. Additionally, works by Dollard et al. [58] address passenger screening at airports, while Mitra et al. [59] focus on temperature screening. These studies underscore the potential benefits of screening measures and the imperative to identify individuals who may pose heightened disease transmission risks.

Additional information that may be attainable includes: evidence (or lack of evidence) of vaccination, indication of a negative test result for a disease of concern, and a willingness to pay the airline for a seat that ensures enhanced safety measures.

Furthermore, airlines already possess certain passenger information, such as date of birth. Thus, a straightforward method could be envisaged for categorizing passengers into the four aforementioned groups. For instance, passengers aged 15 to 25, being more likely to be socially active and unmarried, may be considered more likely to be infectious and assigned to category (I). Conversely, older passengers (e.g., aged 65 and above) may be deemed most susceptible and placed in category (S). The remaining passengers could be classified as (N).

V. CONCLUSION

Previous research established the effectiveness of social distancing as a means of reducing the spread of diseases. In the airline industry, social distancing has been implemented between passengers with previous research focused on airplane boarding methods and passenger seat assignments. However, this previous airplane research assumes homogeneous passengers—each equally likely of being infectious and equally likely of being susceptible to infection. We can do better.

This research paper recognizes heterogeneous passengers and describes greedy algorithms to assign them to seats on an airplane to improve passenger safety. We categorize passengers into four groups: susceptible, infectious, both susceptible and infectious, and neither susceptible nor infectious. We present three greedy methods for assigning these passengers to seats. While all three methods yield improved outcomes when contrasted with a random passenger boarding scenario, a notable observation has emerged: Method 1 and Method 3 consistently deliver superior results in comparison to the third method, denoted as Method 2 in the paper.

Method 1 contains the following themes to increase social distancing between pairs of passengers most likely to cause a susceptible passenger to become infected: assign susceptible and infectious passengers to seats in the back and front of the airplane respectively; institute a buffer of at least one row of passengers that are neither susceptible nor infectious in front of the susceptible passengers and in back of the infectious passengers. For those passengers that are both infectious and susceptible, spread them far apart from each other and from the susceptible passenger in the middle section of the airplane. The result provides improvements in the average closest distance between a pair of susceptible and infectious passengers that varies between 152% and 340% more than the average random assignment.

Conversely, Method 3 places the highest emphasis on allocating passengers who are both susceptible and infectious to vacant seats located at the maximum distance from passengers who are already seated and are either susceptible or both susceptible and infectious. The simulation outcomes for the chosen scenarios substantiate this approach by demonstrating improvements in the average closest distance that range from 157% to 343% in comparison to the outcomes of a random seating assignment.

Moreover, upon considering all 955,860 possible passenger placement scenarios categorized by susceptibility, infectivity, both, or neither, it becomes evident that Method 1 and Method 3 yield congruent outcomes in a substantial portion of these scenarios, specifically accounting for 70.14% of the total cases. However, the remaining scenarios feature instances where Method 1 outperforms Method 3 and vice versa.

Upon evaluating the average closest distance for scenarios where Method 3 prevails over Method 1 and vice versa, a key observation emerges: the average closest distance indicator is, on average, 4.12 times superior when Method 3 outperforms Method 1 than the reverse. Bolstering this observation is the fact that the number of cases favoring Method 3's superiority surpasses those where Method 1 excels over Method 3. These collective findings imply a preference for Method 3 in passenger assignment.

However, there exists a substantial number of cases where Method 1 outperforms Method 3, and given the potential variation in the average closest distance indicator (up to 76.41 inches), a balanced approach is warranted. This involves assessing both methods for each specific boarding instance and applying whichever seat assignment method provides the better result.

In this paper we have illustrated the tremendous opportunity from treating different passengers differently. Future research remains for airlines to determine how to estimate the probabilities of individual passengers being infectious, susceptible to infection, or both. We have mentioned demographic and other information—such as passenger age, travel history, marital status, vaccination and test records—within this paper that the airlines and academic researchers may use as a starting point for this investigation. The potential willingness of some passengers to pay for a safer seating assignment is another opportunity.

Additional research could be conducted to determine better algorithms than the one we propose and better means of evaluating seat assignments for passenger safety. For instance, our use of average closest distances does not reflect the possibility that having an infectious passenger sitting within two feet of a susceptible passenger is more than five times as bad as the pair sitting ten feet apart. Moreover, the proposed methodology holds the potential for expansion across diverse categories of aircraft and alternative modes of transportation susceptible to the impact of potential future pandemics, including trains and buses. This potential expansion serves the overarching aim of enhancing the safety and resilience of travel at large, with a particular focus on air travel in the event of pandemics.

In the meantime, this paper has revealed the opportunity and laid a foundation for further research in these areas.

ACKNOWLEDGMENT

The authors provided ChatGPT with initial drafts of many paragraphs (and sentences) within the manuscript. Sometimes they used the resulting ChatGPT output as-is. More often, they revised the output of ChatGPT. Other times, they disregarded the output of ChatGPT because they preferred their own writing. In all cases, their intention was to use ChatGPT to improve the grammar and writing style of the article rather than to introduce conceptual content resulting from ChatGPT.

REFERENCES

[1] D. Martínez, C. Parilli, C. Scartascini, and A. Simpser, "Let's (not) get together! The role of social norms on social distancing during COVID-19," *PLoS ONE*, vol. 16, no. 3, Mar. 2021, Art. no. e0247454, doi: 10.1371/journal.pone.0247454.

[2] P. Keskinocak, B. E. Oruc, A. Baxter, J. Asplund, and N. Serban, "The impact of social distancing on COVID19 spread: State of Georgia case study," *PLoS ONE*, vol. 15, no. 10, Oct. 2020, Art. no. e0239798, doi: 10.1371/journal.pone.0239798.

[3] N. B. Masters, S.-F. Shih, A. Bukoff, K. B. Akel, L. C. Kobayashi, A. L. Miller, H. Harapan, Y. Lu, and A. L. Wagner, "Social distancing in response to the novel coronavirus (COVID-19) in the United States," *PLoS ONE*, vol. 15, no. 9, Sep. 2020, Art. no. e0239025, doi: 10.1371/journal.pone.0239025.

[4] N. Shoari, M. Ezzati, J. Baumgartner, D. Malacarne, and D. Fecht, "Accessibility and allocation of public parks and gardens in England and wales: A COVID-19 social distancing perspective," *PLoS ONE*, vol. 15, no. 10, Oct. 2020, Art. no. e0241102, doi: 10.1371/journal.pone.0241102.

[5] K. Okabe-Miyamoto, D. Folk, S. Lyubomirsky, and E. W. Dunn, "Changes in social connection during COVID-19 social distancing: It's not (household) size that matters, it's who you're with," *PLoS ONE*, vol. 16, no. 1, Jan. 2021, Art. no. e0245009, doi: 10.1371/journal.pone.0245009.

[6] CDC. (2019). *COVID-19 Employer Information for Office Buildings*. Accessed: Aug. 09, 2021. [Online]. Available: https://www.cdc.gov/coronavirus/2019-nCoV/index.html

[7] L. Bañón and C. Bañón, "Improving room carrying capacity within built environments in the context of COVID-19," *Symmetry*, vol. 12, no. 10, p. 1683, Oct. 2020, doi: 10.3390/sym12101683.

[8] U.K. Government. (2021). *Review of Two Metre Social Distancing Guidance*. Accessed: Aug. 09, 2021. [Online]. Available: https://www.gov.uk/government/publications/review-of-two-metre-social-distancing-guidance/review-of-two-metre-social-distancing-guidance

[9] D. K. Chu, E. A. Akl, S. Duda, K. Solo, S. Yaacoub, and H. J. Schünemann, "Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: A systematic review and meta-analysis," *Lancet*, vol. 395, no. 10242, pp. 1973–1987, Jun. 2020, doi: 10.1016/s0140-6736(20)31142-9.

[10] CDC. (2009). *CDC H1N1 Flu|CDC Guidance for State and Local Public Health Officials and School Administrators for School (K-12) Responses to Influenza During the 2009-2010 School Year*. Accessed: Aug. 9, 2021. [Online]. Available: https://www.cdc.gov/h1n1flu/schools/schoolguidance.htm

[11] D. Blom, R. Pendavingh, and F. Spieksma, "Filling a theater during the COVID-19 pandemic," *INFORMS J. Appl. Analytics*, vol. 52, no. 6, pp. 473–484, Nov. 2022, doi: 10.1287/inte.2021.1104.

[12] J. F. Moore, A. Carvalho, G. A. Davis, Y. Abulhassan, and F. M. Megahed, "Seat assignments with physical distancing in single-destination public transit settings," *IEEE Access*, vol. 9, pp. 42985–42993, 2021, doi: 10.1109/ACCESS.2021.3065298.

[13] CDC. (2019). *Community, Work, and School*. Accessed: Aug. 09, 2021. [Online]. Available: https://www.cdc.gov/coronavirus/2019-ncov/community/large-events/considerations-for-events-gatherings.html

[14] Church England. (2020). *COVID-19 Safer Churches*. Accessed: Aug. 09, 2021. [Online]. Available: https://www.churchofengland.org/sites/default/files/2020-07/Covid-19

[15] J. De Vos, "The effect of COVID-19 and subsequent social distancing on travel behavior," *Transp. Res. Interdiscipl. Perspect.*, vol. 5, May 2020, Art. no. 100121, doi: 10.1016/j.trip.2020.100121.

[16] S. M. Iacus, F. Natale, C. Santamaria, S. Spyratos, and M. Vespe, "Estimating and projecting air passenger traffic during the COVID-19 coronavirus outbreak and its socio-economic impact," *Saf. Sci.*, vol. 129, Sep. 2020, Art. no. 104791, doi: 10.1016/j.ssci.2020.104791.

[17] M. Haghani, M. C. J. Bliemer, F. Goerlandt, and J. Li, "The scientific literature on coronaviruses, COVID-19 and its associated safety-related research dimensions: A scientometric analysis and scoping review," *Saf. Sci.*, vol. 129, Sep. 2020, Art. no. 104806, doi: 10.1016/j.ssci.2020.104806.

[18] U.S. Dept. Educ. *ED COVID-19 Handbook*. Accessed: Aug. 09, 2021. [Online]. Available: https://www2.ed.gov/documents/coronavirus/reopening.pdf

[19] Grand Cinema. *COVID-19 Guidelines and Procedures*. Accessed: Aug. 09, 2021. [Online]. Available: https://www.grandcinema.com/coronavirus-information/

[20] A. T. Murray, "Planning for classroom physical distancing to minimize the threat of COVID-19 disease spread," *PLoS ONE*, vol. 15, no. 12, Dec. 2020, Art. no. e0243345, doi: 10.1371/journal.pone.0243345.

[21] B. Dundar and G. Karakose, "Seat assignment models for classrooms in response to COVID-19 pandemic," *J. Oper. Res. Soc.*, vol. 74, no. 2, pp. 527–539, Feb. 2023, doi: 10.1080/01605682.2021.1971575.

[22] V. Romero, W. D. Stone, and J. D. Ford, "COVID-19 indoor exposure levels: An analysis of foot traffic scenarios within an academic building," *Transp. Res. Interdiscipl. Perspect.*, vol. 7, Sep. 2020, Art. no. 100185, doi: 10.1016/j.trip.2020.100185.

[23] A. Bartolucci, A. Templeton, and G. Bernardini, "How distant? An experimental analysis of students' COVID-19 exposure and physical distancing in University buildings," *Int. J. Disaster Risk Reduction*, vol. 70, Feb. 2022, Art. no. 102752, doi: 10.1016/j.ijdrr.2021.102752.

[24] M. D'Orazio, G. Bernardini, and E. Quagliarini, "A probabilistic model to evaluate the effectiveness of main solutions to COVID-19 spreading in University buildings according to proximity and time-based consolidated criteria," *Building Simul.*, vol. 14, no. 6, pp. 1795–1809, Dec. 2021, doi: 10.1007/s12273-021-0770-2.

[25] R. Bahl, N. Eikmeier, A. Fraser, M. Junge, F. Keesing, K. Nakahata, and L. Reeves, "Modeling COVID-19 spread in small colleges," *PLoS ONE*, vol. 16, no. 8, Aug. 2021, Art. no. e0255654, doi: 10.1371/journal.pone.0255654.

[26] M. Fischetti, M. Fischetti, and J. Stoustrup, "Safe distancing in the time of COVID-19," *Eur. J. Oper. Res.*, vol. 304, no. 1, pp. 139–149, Jan. 2023, doi: 10.1016/j.ejor.2021.07.010.

[27] R. Mokhtari and M. H. Jahangir, "The effect of occupant distribution on energy consumption and COVID-19 infection in buildings: A case study of University building," *Building Environ.*, vol. 190, Mar. 2021, Art. no. 107561, doi: 10.1016/j.buildenv.2020.107561.

[28] D. Simeone, A. Fioravanti, U. M. Coraglia, and S. Cursi, "A simulation model for building use re-thinking after the COVID-19 emergency," in *Blucher Design Proceedings, Medellín*. Sao Paulo, Colombia: Editora Blucher, Dec. 2020, pp. 412–417, doi: 10.5151/sigradi2020-57.

[29] I. Echeverría-Huarte, A. Garcimartín, R. C. Hidalgo, C. Martín-Gómez, and I. Zuriguel, "Estimating density limits for walking pedestrians keeping a safe interpersonal distancing," *Sci. Rep.*, vol. 11, no. 1, p. 1534, Jan. 2021, doi: 10.1038/s41598-020-79454-0.

[30] F. Benita, "Human mobility behavior in COVID-19: A systematic literature review and bibliometric analysis," *Sustain. Cities Soc.*, vol. 70, Jul. 2021, Art. no. 102916, doi: 10.1016/j.scs.2021.102916.

[31] T. Suzumura, H. Kanezashi, M. Dholakia, E. Ishii, S. A. Napagao, R. Pérez-Arnal, and D. Garcia-Gasulla, "The impact of COVID-19 on flight networks," in *Proc. IEEE Int. Conf. Big Data*, Dec. 2020, pp. 2443–2452, doi: 10.1109/BigData50022.2020.9378218.

[32] F. Riquelme, A. Aguilera, and A. Inostrosa-Psijas, "Contagion modeling and simulation in transport and air travel networks during the COVID-19 pandemic: A survey," *IEEE Access*, vol. 9, pp. 149529–149541, 2021, doi: 10.1109/ACCESS.2021.3123892.

[33] A. Mangili, T. Vindenes, and M. Gendreau, "Infectious risks of air travel," *Microbiology Spectr.*, vol. 3, no. 5, pp. 1–15, Sep. 2015, doi: 10.1128/microbiolspec.iol5-0009-2015.

[34] H. L. Kirking, J. Cortes, S. Burrer, A. J. Hall, N. J. Cohen, H. Lipman, C. Kim, E. R. Daly, and D. B. Fishbein, "Likely transmission of norovirus on an airplane, October 2008," *Clin. Infectious Diseases*, vol. 50, no. 9, pp. 1216–1221, May 2010, doi: 10.1086/651597.

[35] G. N. Sze To, M. P. Wan, C. Y. H. Chao, L. Fang, and A. Melikov, "Experimental study of dispersion and deposition of expiratory aerosols in aircraft cabins and impact on infectious disease transmission," *Aerosol Sci. Technol.*, vol. 43, no. 5, pp. 466–485, Apr. 2009, doi: 10.1080/02786820902736658.

[36] V. Stover Hertzberg and H. Weiss, "On the 2-Row rule for infectious disease transmission on aircraft," *Ann. Global Health*, vol. 82, no. 5, p. 819, Mar. 2017, doi: 10.1016/j.aogh.2016.06.003.

[37] L. Ash. *What Air Travel Might Look Like Post Covid*. Accessed: May 14, 2020. [Online]. Available: https://simpleflying.com/what-air-travel-might-look-like-post-covid/

[38] Delta Air Lines. *Delta Blocking Middle Seats, Pausing Automatic Advance Upgrades and More To Enable More Space for Safer Travel*. Accessed: May 19, 2020. [Online]. Available: https://news.delta.com/delta-blocking-middle-seats-pausing-automatic-advance-upgrades-and-more-enable-more-space-safer

[39] J. Walton. *Will Empty Middle Seats Help Social Distancing on Planes?*. Accessed: May 14, 2020. [Online]. Available: https://www.bbc.com/worklife/article/20200422-when-can-we-start-flying-again

[40] Alitalia. *Flying Safely*. Accessed: Jul. 07, 2020. [Online]. Available: https://www.alitalia.com/en_en/fly-alitalia/news-and-activities/news/info-flights/flying-safely.html?fbclid=IwAR1MrtLmqRdn-I9J-IYmYMCksLfeT-vTl7tfdO8DVZyszu_mkrvjkBz5FV4

[41] T. Pallini. (2020). *I Flew on the 4 Biggest U.S. Airlines During the Pandemic To See Which is Handling It Best, and Found One Blew the Rest Out of the Water*. Accessed: Aug. 09, 2021. [Online]. Available: https://www.businessinsider.com/what-to-expect-when-flying-on-united-american-delta-southwest-during-pandemic-comparison-2020-7

[42] T. Islam, M. Sadeghi Lahijani, A. Srinivasan, S. Namilae, A. Mubayi, and M. Scotch, "From bad to worse: Airline boarding changes in response to COVID-19," 2020, *arXiv:2006.06403*.

[43] P. Derjany, S. Namilae, D. Liu, and A. Srinivasan, "Multiscale model for the optimal design of pedestrian queues to mitigate infectious disease spread," *PLoS ONE*, vol. 15, no. 7, Jul. 2020, Art. no. e0235891, doi: 10.1371/journal.pone.0235891.

[44] L.-A. Cotfas, C. Delcea, R. J. Milne, and M. Salari, "Evaluating classical airplane boarding methods considering COVID-19 flying restrictions," *Symmetry*, vol. 12, no. 7, p. 1087, Jul. 2020, doi: 10.3390/sym12071087.

[45] R. J. Milne, C. Delcea, L.-A. Cotfas, and C. Ioanas, "Evaluation of boarding methods adapted for social distancing when using apron buses," *IEEE Access*, vol. 8, pp. 151650–151667, 2020, doi: 10.1109/ACCESS.2020.3015736.

[46] C. Delcea, R. J. Milne, and L.-A. Cotfas, "Determining the number of passengers for each of three reverse pyramid boarding groups with COVID-19 flying restrictions," *Symmetry*, vol. 12, no. 12, p. 2038, Dec. 2020, doi: 10.3390/sym12122038.

[47] M. Schultz and J. Fuchte, "Evaluation of aircraft boarding scenarios considering reduced transmissions risks," *Sustainability*, vol. 12, no. 13, p. 5329, Jul. 2020, doi: 10.3390/su12135329.

[48] R. J. Milne, L.-A. Cotfas, C. Delcea, L. Crăciun, and A.-G. Molănescu, "Adapting the reverse pyramid airplane boarding method for social distancing in times of COVID-19," *PLoS ONE*, vol. 15, no. 11, Nov. 2020, Art. no. e0242131, doi: 10.1371/journal.pone.0242131.

[49] M. Schultz and M. Soolaki, "Analytical approach to solve the problem of aircraft passenger boarding during the coronavirus pandemic," *Transp. Res. Part C, Emerg. Technol.*, vol. 124, Mar. 2021, Art. no. 102931, doi: 10.1016/j.trc.2020.102931.

[50] C.-Z. Xie, T.-Q. Tang, P.-C. Hu, and H.-J. Huang, "A civil aircraft passenger deplaning model considering patients with severe acute airborne disease," *J. Transp. Saf. Secur.*, vol. 14, no. 6, pp. 1063–1084, Jan. 2021, doi: 10.1080/19439962.2021.1873879.

[51] J. A. Pavlik, I. G. Ludden, S. H. Jacobson, and E. C. Sewell, "Airplane seating assignment problem," *Service Sci.*, vol. 13, no. 1, pp. 1–18, Mar. 2021, doi: 10.1287/serv.2021.0269.

[52] M. Salari, R. J. Milne, C. Delcea, L. Kattan, and L.-A. Cotfas, "Social distancing in airplane seat assignments," *J. Air Transp. Manage.*, vol. 89, Oct. 2020, Art. no. 101915, doi: 10.1016/j.jairtraman.2020.101915.

[53] M. T. Haque and F. Hamid, "An optimization model to assign seats in long distance trains to minimize SARS-CoV-2 diffusion," *Transp. Res. Part A, Policy Pract.*, vol. 162, pp. 104–120, Aug. 2022, doi: 10.1016/j.tra.2022.05.005.

[54] J. Blackwood and L. Childs, "An introduction to compartmental modeling for the budding infectious disease modeler," *Lett. Biomathematics*, vol. 5, no. 1, pp. 1–12, 2018, doi: 10.30707/lib5.1blackwood.

[55] J. L. Gevertz, J. M. Greene, C. H. Sanchez-Tapia, and E. D. Sontag, "A novel COVID-19 epidemiological model with explicit susceptible and asymptomatic isolation compartments reveals unexpected consequences of timing social distancing," *J. Theor. Biol.*, vol. 510, Feb. 2021, Art. no. 110539, doi: 10.1016/j.jtbi.2020.110539.

[56] P. Derjany, S. Namilae, D. Liu, and A. Srinivasan, "Computational modeling framework for the study of infectious disease spread through commercial air-travel," in *Proc. IEEE Aerosp. Conf.*, Mar. 2020, pp. 1–10, doi: 10.1109/AERO47225.2020.9172285.

[57] H. Nakamura and S. Managi, "Airport risk of importation and exportation of the COVID-19 pandemic," *Transp. Policy*, vol. 96, pp. 40–47, Sep. 2020, doi: 10.1016/j.tranpol.2020.06.018.

[58] P. Dollard, I. Griffin, A. Berro, N. J. Cohen, K. Singler, Y. Haber, C. de la Motte Hurst, A. Stolp, S. Atti, L. Hausman, C. E. Shockey, S. Roohi, C. M. Brown, L. D. Rotz, M. S. Cetron, and F. Alvarado-Ramy, "Risk assessment and management of COVID-19 among travelers arriving at designated U.S. airports, January 17–September 13, 2020," *MMWR. Morbidity Mortality Weekly Rep.*, vol. 69, no. 45, pp. 1681–1685, Nov. 2020, doi: 10.15585/mmwr.mm6945a4.

[59] B. Mitra, C. Luckhoff, R. D. Mitchell, G. M. O'Reilly, D. V. Smit, and P. A. Cameron, "Temperature screening has negligible value for control of COVID-19," *Emergency Med. Australasia*, vol. 32, no. 5, pp. 867–869, Oct. 2020, doi: 10.1111/1742-6723.13578.

[60] U. Wilensky and W. Rand, *An Introduction to Agent-based Modeling: Modeling Natural, Social, and Engineered Complex Systems With NetLogo*. Cambridge, MA, USA: MIT Press, 2015.

[61] S. Papert, *Mindstorms: Children, Computers, and Powerful Ideas*. New York, NY, USA: Basic Books, 1980.

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