Research Article

Passenger-to-Car Assignment Optimization Model for High-Speed Railway with Risk of COVID-19 Transmission Consideration

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Narrow and closed spaces like high-speed train cabins are at great risk for airborne infectious disease transmission. With the threat of COVID-19 as well as other potential contagious diseases, it is necessary to protect passengers from infection. Except for the traditional preventions such as increasing ventilation or wearing masks, this paper proposes a novel measurement that optimizes passenger-to-car assignment schemes to reduce the infection risk for high-speed railway passengers. First, we estimated the probability of an infected person boarding the train at any station. Once infectors occur, the non-steady-state Wells–Riley equation is used to model the airborne transmission intercar cabin. The expected number of susceptible passengers infected on the train can be calculated, which is the so-called overall infection risk. The model to minimize overall infection risk, as a pure integer quadratic programming problem, is solved by LINGO software and tested on several scenarios compared with the classical sequential and discrete assignment strategies used in China. The results show that the proposed model can reduce 67.6% and 56.8% of the infection risk in the base case compared to the sequential and discrete assignment, respectively. In other scenarios, the reduction lies mostly between 10% and 90%. The optimized assignment scheme suggests that the cotravel itinerary among passengers from high-risk and low-risk areas should be reduced, as well as passengers with long- and short-distance trips. Sensitivity analysis shows that our model works better when the incidence is higher at downstream or low-flow stations. Increasing the number of cars and car service capacity can also improve the optimization effect. Moreover, the model is applicable to other epidemics since it is insensitive to the Wells–Riley equation parameters. The results can provide a guideline for railway operators during the post-COVID-19 and other epidemic periods.

1. Introduction

In late December 2019, an infectious disease was first reported in Wuhan, China, named coronavirus disease 2019 (COVID-19) [1–4]. On 11 March 2020, the World Health Organization (WHO) announced a pandemic [5–7]. To halt the spread of the virus, many countries and regions have adopted national-wide travel restrictions and lockdowns [8]. Studies showed that these measures can reduce the spread rate of the virus in the early epidemic stage [9–11], but the lockdown strategy is too harmful to social economics to be a feasible option in the later stage [12–16].

However, the risk of recurrence of COVID-19 still exists after the lockdown status was loosened [17]. For example, Beijing's confirmation of a COVID-19 case on 11 June ended a run of 55 days without reported local transmission, and the number of cases finally stands at 335 [18]. Evidence indicated that the cold-chain food contamination was a possible origin of the outbreak in Beijing [19], which made it extremely difficult to prevent the epidemic. Under the risk of COVID-19 resurgence, easing travel restrictions and reopening public transport requires more caution since public transport is one of the main airborne infection transmission places [20–25].

To prevent the spread of the virus through public transportation, the operators take some measures such as temperature checks, wearing masks, and blocked seats. Strict temperature checks are usually performed on every passenger. However, this measure became failed in asymptomatic carriers of COVID-19 because they are infectious during the asymptomatic incubation period [26–29], and the incubation period is estimated at 5.2 days (mean value) and up to 12.5 days (95th percentile value).

It is essential to consider risk factors within vehicles and studies on this topic have yielded many practical conclusions. In epidemiological theory, the expiratory activity of infected people can introduce droplets with infectious doses into the indoor environment. Wells [30] first related the infection probability to infectious doses, where breathing one quantum infectious dose brings an average probability of 63.2% ($1 - 1/e$) of becoming infected. Riley et al. [31] applied this conclusion to study a measles epidemic in a school. They set the initial infector number as one and modeled the “chain reaction” of measles transmission. Latter studies in lots of scenarios (including airplane cabin [32], commute train [33], Internet café [34], gym [35], emergency department [36], and dental clinic [37]) followed this approach. That is, a certain number of susceptible people were in the same closed indoor environment with one initial infector in the beginning, and some of the susceptibles got infected after a given length of time. The number of infected people was used to judge the effect of protection measures or predict the trend of epidemics. These studies have found many effective measures to prevent the spread of airborne diseases, such as increasing ventilation rate [33–38], keeping social distance [32, 36, 39–42], lowering personnel density [33], and wearing masks [33, 43]. These findings are consistent with computational fluid dynamics simulations [21, 44, 46] and case studies [47, 48].

However, in regard to the preventive measures in a high-speed railway scene, things are different. First, a high-speed train usually serves multiple stations in a single trip, so we do not know how many infectors will appear and what their itineraries will be. Second, the infection probability of susceptible passengers depends on the cotravel trip of their journey and that of the infectors. Third, a high-speed train has many separated cars. Therefore, the infection risk can be reduced by not only the measures mentioned above but also assigning the infected persons in cars away from susceptible passengers.

To the best of our knowledge, existing studies did not discuss the feasibility that reducing the infection risk through the passenger-to-car assignment. To fill the gap, we attempt to model the overall infection risk of the number of passengers infected on the train and reduce the overall infection risk by adjusting the passenger-to-car assignment scheme. According to the above three characteristics of the train-based scenario, we summarize the key points of the model with three questions:

- (1) What is the probability of passengers boarding from a given station being contagious with COVID-19?
- (2) How to model the infection probability for the susceptible passengers when the contagious passengers board the train?

- (3) To what extent can optimal assignment schemes reduce the transmission risk?

For the first question, the probability can be estimated as the incidence of infection in the city where the station is located. For the second one, we model the infection probability considering the cotravel itineraries between susceptible passengers and infectors based on the non-steady-state Wells–Riley equation [49, 50]. Then, the overall infection risk can be calculated by multiplying these two probabilities. As for the third question, we make a sensitivity analysis of the model and compare it with two car assignment strategies used in the field in China [51]. Key contributions of the study are thus summarized as follows:

A passenger-to-car assignment is considered, modeled, and evaluated as a solution to reduce the risk of infection transmission.

The occurrence of contagious passengers is regarded as a probabilistic event when modeling the overall infection risk on the train.

Recommendations are found from the model optimization results for train operators' reference.

The remainder of this paper is organized as follows. In Section 2, the problem description and the model assumptions are stated. The proposed passenger-to-car assignment optimization model is presented in Section 3 in detail, which aims at reducing the overall infection risk on the train. LINGO software is introduced in Section 4 to solve the proposed model. Section 5 gives multiple numerical cases to explore the superiority of the model over existing assignment schemes and to analyze the sensitivity of the model. Finally, conclusions are drawn in Section 6.

2. Problem Description

Passenger-to-car assignment for high-speed railway passengers focuses on which car, instead of the seat, that passenger will be allocated. Consider a high-speed railway line with N stations. Station 1 represents the initial station, and Station N represents the terminal station. Each passenger might be a COVID-19 infector, and uninfected passengers in the same car with infected passengers are more likely to be transmitted. Thus, the problem can be stated as follows: given that the passenger flow x_{ij} ($i, j = 1, 2, \dots, N$ and $i < j$) for all itineraries (i, j) and the number of cars K of the train, our goal is to minimize the overall infection risk by adjusting $x_{i,j}^k$, which represents the number of passengers with itinerary (i, j) in car k ($k = 1, 2, \dots, K$). This paper refers to the problem as the passenger-to-car assignment optimization problem.

Several assumptions are made here to simplify the problem:

Assumption 1. The number of seats is preassigned to each origin-destination (OD) itinerary prior to sale. That is, we adopt the ticket preassignment strategy, which is one of the common ticket allocation methods used by the China Railway Customer Service Center [51]. It allows the model to focus upon coach assignments for passengers of OD itinerary without ticket assignment considerations.

Assumption 2. Each passenger who gets on the train from the same station is equally likely to be contagious. The probability depends only on the infection rate of the city where the station is located and independent of other passengers. Besides, only a few stations on the train route are at high risk of epidemic recurrence, which is corresponding to the actual situation.

This study adopts the city's incidence of infection with COVID-19 over the previous two weeks as the probability that a passenger is contagious. The two-week period is the maximum length of the coronavirus incubation period in "Diagnosis and Treatment Protocol for COVID-19" published by the China National Health Commission [26]. Actually, travelers are considerably less likely to be contagious than the citizenry as a whole considering temperature detection.

Assumption 3. Assumptions of the non-steady-state Wells–Riley equation [50] are adopted to model the indoor infection transmission: equal host susceptibility, the uniform size of droplets, uniform ventilation, homogeneous mixing of air, and the fact that ventilation is the main way to eliminate infective particles.

Assumption 4. The new infected passenger is not contagious during the rest of the ride, and passengers do not move between cars.

To facilitate the model presentation, the key notations used in this paper are listed in Table 1.

3. Passenger-to-Car Assignment Optimization Model

In this section, we first analyze the probability that contagious passengers with itinerary (i, j) board the car k . Then, the infection probability of susceptible passengers is formulated by the non-steady-state Wells–Riley equation. Next, the overall risk of infection is calculated. To facilitate the solution, we apply the approximation of the overall infection risk expression as the objective function.

3.1. Probability of Infectors with Itinerary (i, j) Assigned to Car k

3.1.1. The Estimation of α_i . For a passenger from a particular prefecture-level city where station i is located, the incidence is estimated by

$$\alpha_i = \frac{nc_i}{pop_i}, \quad (1)$$

where nc_i means the number of confirmed new COVID-19 infections in that city over the last 14 days and pop_i is the city's estimated population.

The peak of the first-wave epidemic in Wuhan reported 33,078 cases over 2 February 2020 to 16 February 2020. Equation (1) gives the incidence at 1/334 for a population of 11.08 million in Wuhan [52]. After March 2020, nc_i has

dropped to low levels in China, with small outbreaks in some prefecture-level cities. An exemplifying city was Beijing with a peak of 280 new cases from 11 Jun 2020 to 25 Jun 2020. The incidence was 1/76914 since the population in Beijing was 21.53 million [53]. Due to strict control measures, the incidence of higher-risk areas in the second-wave outbreak is possibly similar to that in Beijing and will not exceed the peak in Wuhan. In other words, the incidence of infection is about 10^{-5} and no more than 10^{-4} .

3.1.2. The Estimation of $P_{i,j}^k$. According to Assumption 2, $I_{i,*}^k$, which is the number of infectors boarding car k at station i , follows a binomial distribution $B(x_{i,*}^k, \alpha_i)$. The probability distribution function of $I_{i,*}^k$ is given by

$$\Pr\{I_{i,*}^k = n_i\} = \binom{x_{i,*}^k}{n_i} \alpha_i^{n_i} (1 - \alpha_i)^{x_{i,*}^k - n_i}, \quad (2)$$

where

$$\binom{x_{i,*}^k}{n_i} = \frac{x_{i,*}^k!}{n_i!(x_{i,*}^k - n_i)!}. \quad (3)$$

Then, for all nonnegative integers n_i ($i = 1, 2, \dots, N-1$) satisfying $n_i \leq x_{i,*}^k$ and $n_1 + n_2 + \dots + n_{N-1} = n$, we have

$$\begin{aligned} \Pr\{I^k = n\} &= \sum_{n_1+n_2+\dots+n_{N-1}=n} \Pr\{I_{1,*}^k = n_1, \dots, I_{N-1,*}^k = n_{N-1}\} \\ &= \sum_{n_1+n_2+\dots+n_{N-1}=n} \prod_{i=1}^{N-1} \Pr\{I_{i,*}^k = n_i\}. \end{aligned} \quad (4)$$

Specifically, the probability of $I^k = 0$ and $I^k = 1$ is given by equations (5) and (6).

$$\Pr\{I^k = 0\} = \prod_{i=1}^{N-1} (1 - \alpha_i)^{x_{i,*}^k}, \quad (5)$$

$$\Pr\{I^k = 1\} = \sum_{u=1}^{N-1} \frac{x_{u,*}^k \alpha_u}{1 - \alpha_u} \cdot \prod_{i=1}^{N-1} (1 - \alpha_i)^{x_{i,*}^k}. \quad (6)$$

However, the increment of I^k causes difficulties to model the infection transmission in a railway coach, and the probability of the event $I^k \geq 2$ can hardly be expressed analytically. Since α_i is small, we can consider the event $I^k \geq 2$ to be negligible if the probability of the event $I^k \geq 2$ is less than a given value δ (e.g., we set $\delta = 0.005$, which means the probability of $I^k \leq 1$ is greater than 99.5%), as shown in

$$\Pr\{I^k \geq 2\} < \delta. \quad (7)$$

The conditions required to satisfy equation (7) are discussed in the following. The equations (8) and (9) are given using the equivalent infinitesimals for small enough α_i (e.g., $\alpha_i < 10^{-3}$)

TABLE 1: Relevant notations.

Notation	Definition
K	Total number of cars of the train
N	Total number of stations
k	Car index; $k = 1, 2, \dots, K$
C^k	Service capacity of car k ; $k = 1, 2, \dots, K$
T_i^a	Time of train arriving at station i ; $i = 1, 2, \dots, N$
T_i^d	Time of train departing from station i ; $i = 1, 2, \dots, N$
α_i	The incidence of infection of the city where station i is located; $i = 1, 2, \dots, N$
$(*, *)$	OD itineraries, such as (i, j) and (r, s) in the following; $i, j, r, s = 1, 2, \dots, N$ and $i < j, r < s$
$x_{i,j}$	Passenger flow of itinerary (i, j)
$x_{i,j}^k$	The number of passengers with itinerary (i, j) boarding car k
$x_{i,*}^k$	The number of passengers boarding car k at station i , with $x_{i,*}^k = \sum_{j=i+1}^N x_{i,j}^k$; $i = 1, 2, \dots, N-1$
$I_{i,*}^k$	Total number of infectors boarding car k
$I_{i,*}^k$	The number of infectors boarding car k at station i ; $i = 1, 2, \dots, N-1$
$I_{i,j}^k$	The number of infectors with itinerary (i, j) boarding car k
V^k	Volume of space of car k , in m^3
Q^k	Ventilation rate of car k , in m^3/h
q	The quantum generation rate of an infected person, in quanta/s
$\rho_{i,j}^k(t)$	Quantum concentration of car k at time t if an infector with itinerary (i, j) boarding the car k , in quanta/ m^3
p	Breathing rate per person, in m^3/h
θ	Respirator penetration ratio, reflecting the reduction in the exposure term with the use of respirator or facemask
$p_{i,j}^k$	The probability that an infector with itinerary (i, j) assigned to car k
$p_{i,j;r,s}^k$	The probability of infection for susceptible passengers with itinerary (r, s) when infectors with itinerary (i, j) boarding car k
$p_{i,j;r,s;a}^k$	The conditional probability of infection for susceptible passengers with itinerary (r, s) when infectors with itinerary (i, j) boarding car k
$L_{i,j;a}^k$	The infected number of susceptible passengers of type a in car k when infectors with itinerary (i, j) boarding the car k , $a = 1, 2, \dots, 6$
$L_{i,j}^k$	The infected number of susceptible passengers in car k when infectors with itinerary (i, j) boarding car k

$$\lim_{\alpha_i \rightarrow 0} (1 - \alpha_i)^{x_{i,*}^k} = \exp(-x_{i,*}^k \alpha_i), \quad (8)$$

$$\lim_{\alpha_i \rightarrow 0} \frac{x_{i,*}^k \alpha_i}{(1 - \alpha_i)} = x_{i,*}^k \alpha_i. \quad (9)$$

Then, equations (5) and (6) can be approximated to

$$\Pr\{I^k = 0\} \approx \exp\left(-\sum_{i=1}^{N-1} x_{i,*}^k \alpha_i\right), \quad (10)$$

$$\Pr\{I^k = 1\} \approx \sum_{u=1}^{N-1} x_{u,*}^k \alpha_u \cdot \exp\left(-\sum_{i=1}^{N-1} x_{i,*}^k \alpha_i\right). \quad (11)$$

Define that

$$\xi^k = \sum_{i=1}^{N-1} \alpha_i x_{i,*}^k. \quad (12)$$

Actually, ξ^k is the expectation of the number of infectors boarding car k , because $I_{i,*}^k$ follows a binomial distribution $B(x_{i,*}^k, \alpha_i)$. Equations (10) and (11) are then rewritten as

$$\begin{aligned} \Pr\{I^k = 0\} &\approx \exp(-\xi^k), \\ \Pr\{I^k = 1\} &\approx \xi^k \exp(-\xi^k). \end{aligned} \quad (13)$$

The probability of $I^k \geq 2$ is calculated by

$$\Pr\{I^k \geq 2\} \approx 1 - (1 + \xi^k) \exp(-\xi^k). \quad (14)$$

If ξ^k is sufficiently small (e.g., $\xi^k < 0.1$), which can be satisfied under Assumption 3, then a Taylor expansion of $\exp(-\xi^k)$ is performed as

$$\exp(-\xi^k) = 1 - \xi^k + 0.5(\xi^k)^2 + O((\xi^k)^2), \quad (15)$$

where $O((\xi^k)^2)$ is the high-order remainder term. Substitute equation (15) into equation (14), and omitting the higher-order term, we have

$$\Pr\{I^k \geq 2\} \approx 0.5(\xi^k)^2. \quad (16)$$

The error between the results of equations (16) and (14) is 6.4% when $\xi^k = 0.1$; the error is 3.3% when $\xi^k = 0.05$. Equation (16) gives the condition that equation (7) can be satisfied approximately if and only if $\xi^k < \sqrt{2\delta}$. In this paper, the condition is $\xi^k < 0.1$ as we set $\delta = 0.005$.

Considering at most one infected person boarding a car, the probability of an infector with itinerary (i, j) boarding car k is formulated by

$$\Pr\{I_{i,j}^k = 1 | I^k \leq 1\} = \frac{\Pr\{I_{1,*}^k = 0, \dots, I_{i,*}^k = 1, \dots, I_{N-1,*}^k = 0\}}{\Pr\{I^k \leq 1\}} \cdot \frac{x_{i,j}^k}{x_{i,*}^k}, \quad (17)$$

where $\Pr\{I^k \leq 1\}$ equals the sum of equations (5) and (6). The expression of $\Pr\{I_{1,*}^k = 0, \dots, I_{i,*}^k = 1, \dots, I_{N-1,*}^k = 0\}$, as

$$\Pr\{I_{1,*}^k = 0, \dots, I_{i,*}^k = 1, \dots, I_{N-1,*}^k = 0\} = \frac{x_{i,*}^k \alpha_i}{1 - \alpha_i} \prod_{u=1}^{N-1} (1 - \alpha_u)^{x_{u,*}^k}. \quad (18)$$

Substituting equations (5) and (6) and equation (18) into equation (17), we can formulate the probability of one infector in the passengers with itinerary (i, j) as

$$\Pr\{I_{i,j}^k = 1 | I^k \leq 1\} = \frac{x_{i,j}^k \alpha_i / (1 - \alpha_i)}{1 + \sum_{u=1}^{N-1} x_{r,*}^k \alpha_u / (1 - \alpha_u)}. \quad (19)$$

3.2. Infection Transmission Model in a Car Based on Wells–Riley Model. The Wells–Riley equation is a commonly used indoor airborne infection transmission model [30, 32, 49, 50], which links the infection probability of a susceptible person with the infectious dose, outdoor air exchange rate, and exposure time. The equation gives the probability of infection for a susceptible person (P) by

$$P = 1 - \exp\left(-\theta p \int_0^t \rho(t) dt\right). \quad (20)$$

shown in equation (18), can be obtained by substituting $n_1 = 0, \dots, n_i = 1, \dots, n_{N-1} = 0$ into equation (4).

When an infector on itinerary (i, j) boards car k , the quantum accumulation rate function in the car can be divided into three parts by the time the infector boarding ($t = T_i^d$) and the time alighting ($t = T_j^a$), which can be represented as

$$V^k \frac{d\rho_{i,j}^k(t)}{dt} = \begin{cases} 0, & 0 \leq t < T_i^d, \\ q \cdot I_{i,j}^k - Q^k \cdot \rho_{i,j}^k(t), & T_i^d \leq t < T_j^a, \\ -Q^k \cdot \rho_{i,j}^k(t), & T_j^a \leq t \leq T_N^a, \end{cases} \quad (21)$$

where $q \cdot I_{i,j}^k$ is the quantum generation rate and $Q^k \cdot \rho_{i,j}^k(t)$ is the quantum removal rate. For an initial quantum concentration equal to 0, we have

$$\rho_{i,j}^k(t) = \begin{cases} 0, & 0 \leq t < T_i^d, \\ \frac{q \cdot I_{i,j}^k}{Q^k} \left[1 - \exp\left(-\frac{Q^k}{V^k}(t - T_i^d)\right) \right], & T_i^d \leq t < T_j^a, \\ \rho_{i,j;\max}^k \exp\left[-\frac{Q^k}{V^k}(t - T_j^a)\right], & T_j^a \leq t \leq T_N^a, \end{cases} \quad (22)$$

where Q^k/V^k is the outdoor air exchange rate. $\rho_{i,j;\max}^k$ is the quantum concentration when the infector leaves the car, as shown in

$$\rho_{i,j;\max}^k = \frac{q \cdot I_{i,j}^k}{Q^k} \left[1 - \exp\left(-\frac{Q^k}{V^k}(T_j^a - T_i^d)\right) \right]. \quad (23)$$

Considering a susceptible passenger with itinerary (r, s) boarding car k at $t = T_r^d$, and getting off at $t = T_s^a$, the

probability of infection of this passenger $P_{i,j;r,s}^k$ is given according to equation (20) by

$$P_{i,j;r,s}^k = 1 - \exp\left(-\theta p \int_{T_r^d}^{T_s^a} \rho_{i,j}^k(t) dt\right). \quad (24)$$

Note that $\rho_{i,j}^k(t)$ is a piecewise continuous function, so equation (24) requires a piecewise integral. Figure 1 shows the 6 types of integral calculation formulas of $P_{i,j;r,s}^k$ according to the cotravel situation of (i, j) and (r, s) . The

FIGURE 1: An illustration of 6 types of susceptible passengers when the itinerary of the infected passenger is (i, j) .

infection probability for the type of susceptible passengers

$P_{i,j;r,s;a}^k$ ($a = 1, 2, 3, 4, 5, 6$) is expressed as equation (25).

$$\left\{ \begin{array}{ll} P_{i,j;r,s;1}^k = 0, & r < s \leq i, \\ P_{i,j;r,s;2}^k = 1 - \exp\left(-\theta p \int_{T_i^d}^{T_s^a} \rho_{i,j}^k(t) dt\right), & r < i < s \leq j, \\ P_{i,j;r,s;3}^k = 1 - \exp\left[-\theta p \left(\int_{T_i^d}^{T_j^a} \rho_{i,j}^k(t) dt + \int_{T_j^a}^{T_s^a} \rho_{i,j}^k(t) dt\right)\right], & r < i < j < s, \\ P_{i,j;r,s;4}^k = 1 - \exp\left(-\theta p \int_{T_r^d}^{T_s^a} \rho_{i,j}^k(t) dt\right), & i \leq r < s \leq j, \\ P_{i,j;r,s;5}^k = 1 - \exp\left[-\theta p \left(\int_{T_r^d}^{T_j^a} \rho_{i,j}^k(t) dt + \int_{T_j^a}^{T_s^a} \rho_{i,j}^k(t) dt\right)\right], & i \leq r < j < s, \\ P_{i,j;r,s;6}^k = 1 - \exp\left(-\theta p \int_{T_r^d}^{T_s^a} \rho_{i,j}^k(t) dt\right), & j \leq r < s. \end{array} \right. \quad (25)$$

For a succinct representation, we define the functions $R_{i,j;1}^k(r, s)$ and $R_{i,j;2}^k(r, s)$ as follows:

$$R_{i,j;1}^k(r, s) = \frac{q \cdot I_{i,j}^k}{Q^k} \left[T_s^a - T_r^d + \frac{V^k}{Q^k} \left(\exp\left(-\frac{Q^k}{V^k}(T_s^a - T_i^d)\right) - \exp\left(-\frac{Q^k}{V^k}(T_r^d - T_i^d)\right) \right) \right], \quad (26)$$

$$R_{i,j;2}^k(r, s) = \rho_{i,j;\max}^k \frac{V^k}{Q^k} \left[\exp\left(-\frac{Q^k}{V^k}(T_r^d - T_j^a)\right) - \exp\left(-\frac{Q^k}{V^k}(T_s^a - T_j^a)\right) \right], \quad (27)$$

where $R_{i,j;1}^k(r, s)$ is the integral of $\rho_{i,j}^k(t)$ over the interval (T_r^d, T_s^a) as $i \leq r < s \leq j$ and $R_{i,j;2}^k(r, s)$ is the integral of $\rho_{i,j}^k(t)$

over the interval (T_r^d, T_s^a) as $j \leq r < s \leq N$. Substituting equations (26) and (27) in equation (25) gives

$$\begin{cases} P_{i,j;r,s;1}^k = 0, & r < s \leq i, \\ P_{i,j;r,s;2}^k = 1 - \exp(-\theta p R_{i,j;1}^k(i, s)), & r < i < s \leq j, \\ P_{i,j;r,s;3}^k = 1 - \exp[-\theta p (R_{i,j;1}^k(i, j) + R_{i,j;2}^k(j, s))], & r < i < j < s, \\ P_{i,j;r,s;4}^k = 1 - \exp(-\theta p R_{i,j;1}^k(r, s)), & i \leq r < s \leq j, \\ P_{i,j;r,s;5}^k = 1 - \exp[-\theta p (R_{i,j;1}^k(r, j) + R_{i,j;2}^k(j, s))], & i \leq r < j < s, \\ P_{i,j;r,s;6}^k = 1 - \exp(-\theta p R_{i,j;2}^k(r, s)), & j \leq r < s. \end{cases} \quad (28)$$

The number of types of passengers infected on the train $L_{i,j;a}^k$ ($a = 1, 2, 3, 4, 5, 6$) is shown in

$$\begin{cases} L_{i,j;1}^k = 0, \\ L_{i,j;2}^k = \sum_{s=i+1}^j \sum_{r=1}^{i-1} P_{i,j;r,s;2}^k x_{r,s}^k, \\ L_{i,j;3}^k = \sum_{s=j+1}^N \sum_{r=1}^{i-1} P_{i,j;r,s;3}^k x_{r,s}^k, \\ L_{i,j;4}^k = \sum_{s=i+1}^j \sum_{r=i}^{s-1} P_{i,j;r,s;4}^k (x_{r,s}^k - \delta_{i,j;r,s}), \\ L_{i,j;5}^k = \sum_{s=j+1}^N \sum_{r=i}^{j-1} P_{i,j;r,s;5}^k x_{r,s}^k, \\ L_{i,j;6}^k = \sum_{s=j+1}^N \sum_{r=j}^{s-1} P_{i,j;r,s;6}^k x_{r,s}^k, \end{cases} \quad (29)$$

where $\delta_{i,j;r,s}$ is the number of infectors with itinerary (r, s) , $\delta_{i,j;r,s} = I_{i,j}^k = 1$ when $(r, s) = (i, j)$; otherwise $\delta_{i,j;r,s} = 0$. Therefore, when an infected passenger on itinerary (i, j) boards car k , the number of infected susceptible passengers $L_{i,j}^k$ is given by

$$L_{i,j}^k = \sum_{a=1}^6 L_{i,j;a}^k. \quad (30)$$

3.3. Overall Infection Risk of Susceptible Passengers. Combining equations (19) and (30), the overall infection risk can be expressed as

$$\text{OIR} = \sum_{k=1}^K \sum_{j=2}^N \sum_{i=1}^{j-1} \Pr\{I_{i,j}^k = 1 | I^k \leq 1\} \cdot L_{i,j}^k \quad (31)$$

$$= \sum_{k=1}^K \sum_{j=2}^N \sum_{i=1}^{j-1} \frac{\alpha_i / (1 - \alpha_i)}{1 + \sum_{u=1}^{N-1} x_{u,*}^k \alpha_u / (1 - \alpha_u)} x_{i,j}^k L_{i,j}^k.$$

However, OIR is a complex nonlinear function, which brings some difficulties to the solution. Thus, we made an approximation by substituting the equivalent infinitesimal in equation (9) into OIR:

$$\text{OIR} \approx \sum_{k=1}^K \sum_{j=2}^N \sum_{i=1}^{j-1} \frac{\alpha_i x_{i,j}^k L_{i,j}^k}{1 + \xi^k}. \quad (32)$$

In equation (32), the denominator $(1 + \xi^k)$ is a linear function of $x_{i,j}^k$, which brings about a considerable amount of computation for the gradient calculation. However, as mentioned in Section 3.1., ellipses of the $(1 + \xi^k)$ would overestimate the overall infection risk of $|(1/1.1) - 1|/1.1 \times 100\% = 10\%$ at most but could reduce the computational burden because the objective function became a quadratic function. Therefore, this approximation is adopted and the Approximate Overall Infection Risk (AOIR) is given by

$$\text{AOIR} = \sum_{k=1}^K \sum_{j=2}^N \sum_{i=1}^{j-1} \alpha_i x_{i,j}^k L_{i,j}^k. \quad (33)$$

3.4. Passenger-to-Car Optimization Model. The passenger-to-car assignment optimization problem is formulated as a pure integer quadratic programming (PIQP) model:

$$\begin{cases} \min & \text{AOIR} = \sum_{k=1}^K \sum_{j=2}^N \sum_{i=1}^{j-1} \alpha_i x_{i,j}^k L_{i,j}^k \\ \text{s.t.} & \sum_{k=1}^K x_{i,j}^k = x_{i,j}; i, j = 1, 2, \dots, N; i < j \\ & \sum_{j=i_0+1}^N \sum_{i=1}^{i_0} x_{r,s}^k \leq C^k; i_0 = 1, 2, \dots, N; k = 1, 2, \dots, K \\ & x_{i,j}^k \in \mathbb{N}; i, j = 1, 2, \dots, N; i < j; k = 1, 2, \dots, K, \end{cases} \quad (34)$$

where three constraints are included: the first is the flow conservation constraint that states the total number of passengers assigned to each car equals the number of customers who purchase tickets, the second is the service capacity constraint that limits the number of in-car passengers not exceeding the vehicle capacity, and the last is the integer constraint ensuring that the decision variables are integers.

4. Solution Methods

The goal of the proposed model is to minimize the overall infection risk for susceptible passengers by optimizing the passenger-to-car assignment scheme. The model is a PIQP problem. Considering that the objective function is non-convex, while the itinerary flow and the number of cars are relatively large in actual cases, the model is not easy to solve. Besides, the global optimal solution of the model is not unique. For example, once the optimal passenger-to-car assignment scheme is obtained, multiple sets of optimal solutions can be obtained by exchanging the superscript k representing the car number.

Currently, the efficient global optimization algorithms that can solve nonconvex PIQP problems are still in the exploratory stage. The main local optimization methods for PIQP problems are the branch-and-bound method, the cutting-plane method, and some intelligent optimization algorithms. The Linear Interactive and General Optimizer (LINGO) solver is a software product that provides solution procedures, which was developed by LINDO systems Inc. (Chicago, IL, USA, <https://www.lindo.com>). Several programming solvers are integrated into LINGO software, such as the branch-and-bound method and the cutting-plane method.

The proposed model in this paper, which belongs to the PIQP problem, can be solved with LINGO software. More specifically, the branch-and-bound method was selected to solve the proposed model because it is a mature and effective method with a simple principle. The branch-and-bound method solves the QP relaxation subproblem corresponding to the PIQP problem at each branching step. As mentioned before, since there are multiple global optimal solutions for the proposed model, it will take quite a long time to find the global optimal solution. This paper sets the solving algorithm to terminate once a local optimal solution is found, which is a trade-off between the optimality of the solution and the operation time.

5. Case Study

To answer the third question that what extent can optimal assignment schemes reduce the risk of transmission and to find some characteristics of the optimal assignment scheme, we conduct several scenarios in this section. First, we present the parameter setting of the base case. Then, we draw the demonstration of the optimal assignment scheme to explore its characteristics. Meanwhile, the optimal assignment scheme is compared with two assignment strategies in the China Railway High-Speed System to answer how much the model reduced the overall infection risk. Finally, the sensitivity analysis was demonstrated.

5.1. Base Case Parameter Setting. We take the Beijing-Shanghai high-speed railway (HSR) as our base case, which serves eight stops, running from 8:50 a.m. to 14:33 p.m., as shown in Figure 2. There is a train stop plan in the Beijing-Shanghai HSR. For brevity, the eight stations are denoted by Station 1 to Station 8, and the average OD demand shown in Table 2 is derived from the literature [54], recorded from 20 July 2015 to 26 July 2015. Notice that the purpose of the literature is to maximize the railway revenue under random passenger demand, so the demand is greater than the train service capacity. To meet the train service capacity constraints, we reduced the OD demand in the literature by a certain proportion.

The train has eight homogeneous passenger cars, and the service capacity $C^k = 80$ for all $k = 1, 2, \dots, 8$. We set the incidence α_i at 1×10^{-5} (1 case per 100,000) for station 2 as a high-risk station and 1×10^{-8} (1 case per 100,000,000) for others.

The parameters in the Wells–Riley equation are shown in Table 3. Existing studies have indicated that the value of q for COVID-19 might vary from 0.1 to more than 1000 quanta/h for different respiratory activities and activity levels [55], and calibration methods have also a significant effect [41, 55, 56]. We apply the q value of 100 quanta/h. The breathing rate p is set as $0.3 \text{ m}^3/\text{h}$ when a person sits or conducts light indoor activities [57]. The respirator penetration ratio θ is set at 1, which means no respirator use. The space volume and ventilation rate of the car are selected within a reasonable range, and we adopted $V^k = 200 \text{ m}^3$ and $Q^k = 2000 \text{ m}^3/\text{h}$ (i.e., the outdoor air exchange rate was assumed 10 times per hour).

To evaluate the benefits obtained considering the transmission risk of COVID-19, we compared our solutions with two traditional assignment strategies in the China Railway High-Speed System, called sequential assignment and discrete assignment [51]. The specific steps to generate Sequential Assignment Schemes (SASs) and Discrete Assignment Schemes (DASs) are as follows:

Step 1: randomly generate 100 groups of ticket reservation request sequences according to the OD matrix. Each request contains an OD itinerary.

Step 2: apply the two strategies. The SAS searches candidate cars from cars with remaining tickets in the order of the car number and chooses the first one for a given passenger, and the DAS randomly picks a car with the remaining tickets. Then, 100 SAS and 100 DAS are obtained.

Step 3: calculate the AOIR of each scheme according to equation (33), and the average of 100 SAS and 100 DAS is then taken as the overall infection risk, respectively.

5.2. Assignment Scheme Analysis. We used the LINGO software to obtain the optimal assignment schemes (OASs). Then, the AOIR gap in percentage between SAS and OAS named S-O was calculated, as well as the gap between DAS and OAS, named D-O. Computational results in Table 4 indicate that the order of risk from low to high is OAS, DAS,

	Beijing	Tianjin	Dezhou	Jinan	Xuzhou	Nanjing	Suzhou	Shanghai
No.	1	2	3	4	5	6	7	8
T_i^a		9:11	9:54	10:42	11:51	13:07	14:02	14:33
T_i^d	8:50	9:19	9:57	10:47	11:53	13:11	14:09	

FIGURE 2: Train stop plan in the Beijing-Shanghai HSR.

TABLE 2: Passenger flow in each OD itinerary.

Departure station	Arrival station							NBT	NAT	NCB
	2	3	4	5	6	7	8			
1	36	46	28	28	25	104	112	379	0	379
2		5	4	10	46	6	22	93	36	436
3			13	3	4	8	12	40	51	425
4				24	8	12	10	54	45	434
5					41	19	43	103	65	472
6						48	22	70	124	418
7							47	47	197	268

Note: NBT: number of passengers boarding the train at station #; NAT: number of passengers alighting the train at station #; NCB: number of passengers currently on board.

TABLE 3: Parameters of transmission model in a rail car.

Parameter	Value	Unit	Note
q	100	Quanta/h	—
p	0.3	m^3/h	—
θ	1	—	—
V^k	200	m^3	$k = 1, 2, \dots, K$
Q^k	2000	m^3/h	$k = 1, 2, \dots, K$

and SAS. This is because SAS tends to assign passengers to cars more densely, which leads to a higher infection risk [33], while the DAS tends to assign passengers to cars evenly, resulting in a lower risk than the SAS.

By applying our optimization model, the AOIR of SAS and DAS can be reduced by 67.6% and 56.8%, respectively. The results suggest that optimizing the car assignment scheme can significantly reduce the overall infection risk.

The OAS is also visualized in Figure 3 to look for patterns of the scheme. Four main features can be concluded. (1) Passengers from higher-risk areas are apart from those from lower-risk areas. In Figure 3, passengers from station 2 (high-risk area) are assigned together, thus avoiding other passengers from exposure to them. (2) Passengers from higher-risk areas are supposed to be assigned evenly into cars. In the base case, the passengers from station 2 are evenly assigned to cars 1–3 with a total of 26 persons. (3) Long-trip and short-trip passengers with the same risk level are supposed to be separated. For example, the trip distance of passengers from station 1 becomes shorter from car 5 to 8 in turn, and those in cars 1–3 are the shortest. (4) The cotravel trip between passengers from lower-risk and higher-risk areas should be as short as possible. For instance, all passengers boarding cars 1–3 from station 1 alight at station 2. Thus, they have no cotravel itinerary with passengers boarding at station 2. Another example is that, because cars 5–8 are fully

loaded, some short-trip passengers from stations 4–7 and the higher-risk passengers of itineraries (2,3), (2,4), and (2,5) are assigned to car 4 together, but only a few cotravel time among these passengers.

5.3. Sensitivity Analysis. Based on the parameter setting of the base case, we analyzed the sensitivity of the incidence of infection, the number of cars, car service capacity, and the Wells–Riley equation parameters. The overall infection risks of SAS, DAS, and OAS are compared.

5.3.1. Sensitivity Analysis of the Incidence. To explore the influence of the incidence α_i , we set seven scenarios that changed α_i of each station in turn. In Scenario 1, the incidence in the city where station 1 is located (i.e., α_1) increased from 10^{-8} to 10^{-4} , while other stations were kept as 10^{-8} , so do other scenarios. The experimental results in Table 5 show the AOIR of the schemes in all designed scenarios from high to low, same as the basic case, are SAS and DAS.

Figure 4(a) shows the curves of AOIR of OAS under seven scenarios. Figure 4(a) shows the curves of AOIR of OAS under seven scenarios. As the incidence rises, the relative magnitudes of AOIR for each scenario tend to stabilize. By analyzing the order of AOIR at $\alpha_i = 10^{-4}$ (that is, Scenarios 1, 2, 5, 4, 3, 6, 7 decreases in turn), we found that the infection risk is the result of a combination of

TABLE 4: Computational results for the base case.

AOIR ($\times 10^{-3}$)				Gap (%)	
SAS	DAS	OAS	S-O	D-O	
3.662	2.750	1.187	67.6	56.8	

Note: the scheme obtained by our model (i.e., OAS) is highlighted in bold; the gap of S-O = (AOIR of SAS – AOIR of OAS)/AOIR of SAS $\times$ 100%; the gap of D-O = (AOIR of DAS – AOIR of OAS)/AOIR of DAS $\times$ 100%.

FIGURE 3: Optimized passenger-to-car assignment scheme for the base case.

TABLE 5: Sensitivity analysis of the incidence of infection α_i .

Scenario	Station i	$\alpha_i (\times 10^{-8})$	AOIR ($\times 10^{-3}$)			Gap (%)	
			SAS	DAS	OAS	S-O	D-O
1	1	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.159	0.119	0.105	34.4	12.1
		1×10^{-6}	1.51	1.13	0.964	36.1	14.6
		1×10^{-5}	15.0	11.2	9.56	36.4	14.9
		1×10^{-4}	150	112	95.0	36.7	15.3
2	2	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.0568	0.0425	0.0322	43.4	24.3
		1×10^{-6}	0.385	0.289	0.138	64.1	52.2
		1×10^{-5}	3.66	2.75	1.19	67.6	56.8
		1×10^{-4}	36.4	27.4	11.7	68.0	57.3
3	3	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.0347	0.0258	0.0220	36.7	15.0
		1×10^{-6}	0.141	0.105	0.0414	70.7	60.7
		1×10^{-5}	1.21	0.899	0.199	83.5	77.9
		1×10^{-4}	11.9	8.84	1.78	85.0	79.8
4	4	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.0355	0.0264	0.0227	36.1	14.1
		1×10^{-6}	0.150	0.111	0.0466	68.9	58.1
		1×10^{-5}	1.29	0.961	0.273	78.9	71.5
		1×10^{-4}	12.7	9.46	2.54	80.0	73.1
5	5	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.0428	0.0321	0.0272	36.4	15.1
		1×10^{-6}	0.230	0.174	0.0973	57.8	44.1
		1×10^{-5}	2.11	1.59	0.792	62.4	50.3
		1×10^{-4}	20.9	15.8	7.74	62.9	51.0
6	6	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.0304	0.0221	0.0203	33.3	8.4
		1×10^{-6}	0.094	0.0645	0.0372	60.4	42.3
		1×10^{-5}	0.729	0.488	0.196	73.1	59.8
		1×10^{-4}	7.08	4.72	1.78	74.8	62.2
7	7	1×10^{-8}	0.0241	0.0179	0.0176	27.0	1.8
		1×10^{-7}	0.0255	0.0185	0.0180	29.3	2.9
		1×10^{-6}	0.0396	0.0250	0.0202	49.1	19.2
		1×10^{-5}	0.181	0.0890	0.0364	79.9	59.1
		1×10^{-4}	1.59	0.730	0.197	87.6	72.9

Note: The scheme obtained by our model (i.e., OAS) is highlighted in bold.

station relative location and station passenger flow. On the one hand, the upper-stream stations have more impact on the overall risk. For example, the flow at station 2 (93 persons) is slightly less than station 5 (103 persons), but the AOIR of Scenario 2 was higher than Scenario 5 under the same incidence. On the other hand, a larger flow means a higher probability of occurring infected passengers and more contact opportunities to other passengers. Here, the AOIR of Scenario 5 is higher than Scenarios 3 and 4 and even station 5 is downstream of stations 3 and 4, which is because the passenger flow at station 5 (103 persons) is much higher than the latter two stations (40 and 54 persons). Therefore, rail operators are supposed to focus more on the upstream stations and high-demand stations. Passengers ought to be restricted or forbidden from boarding the train when their incidence of infection is high. On the contrary, when the incidence is higher at downstream or low-flow stations, optimizing the car assignment scheme is a feasible option.

In terms of the room for optimization, the scenario order of the D-O gap at $\alpha_i = 10^{-4}$ is the same as the passenger flow of stations (that is, Scenarios 1, 5, 2, 6, 7, 4, 3 decreases in turn). In other words, the smaller the passenger flow of a higher-risk station, the greater the optimizable space of overall infection risk for DAS. The S-A gap is not described since it shares the same trend as the D-A gap.

Additionally, the sequential assignment strategy should be avoided since the AOIR of SAS is much higher than the other two schemes.

5.3.2. Sensitivity Analysis of Car Parameters. The sensitivity of car parameters, including the number of cars and car service capacity, is further explored. The number of cars increases from 6 to 12 in turn. This is realistic because electric multiple units in China's high-speed railway operation can achieve the flexible composition of 2^{-16} cars [58, 59]. The car capacity changes from 60 to 120 with a step

FIGURE 4: Sensitivity analysis of the incidence of infection α_i . (a) AOIR of OAS. (b) Gap of D-O.

FIGURE 5: Sensitivity analysis of the number of train parameters.

size of 10, which can be achieved by replacing first-class cabins with second-class cabins or selling standing tickets.

As drawn in Figure 5, the S-O and D-O increase as the number of cars and car service capacity grows. It suggests that increasing the car number and car capacity is a feasible approach to reduce overall infection risk, which is a trade-off between epidemic prevention and economic cost. Once again, the sequential assignment strategy is strongly advised against for its high infection risk in all the scenarios.

5.3.3. Sensitivity Analysis of Wells–Riley Equation Parameters. To study the optimization effect under different settings of Wells–Riley equation parameters, we select the

ventilation rate (Q^k) and respirator penetration ratio (θ) for sensitivity analysis. The former not only influences the virus quantum concentration in the cabins but also can be regarded as the change of quantum generation rate q , which represents different types of airborne diseases. The latter models the protective measures.

As shown in Figure 6, the AOIR of all assignment schemes is greatly affected by ventilation rate and respirator permeability. However, the curves of S-O and D-O gaps are nearly horizontal. Thus, the optimization effect is not sensitive to the parameters of the Wells–Riley model. In other words, the proposed model thus can adapt to different cabin environments, protection levels, and types of airborne diseases.

FIGURE 6: Sensitivity analysis of the ventilation rate.

6. Conclusions

In this paper, we investigated the potential of minimizing the overall infection risk on a railway train by optimizing the passenger-to-car assignment scheme. Different from classical protective measures, our approach reduces the risk by assigning potential virus carriers and others to separate cars. The results demonstrate that the approach can reduce the overall infection risk and provide meaningful advice to railway operators.

In the study, since a train serves many stations, we estimated the occurrence of virus carriers by a probability model. Then, the infection probability considering the cotravel itineraries between susceptible passengers and infectors was calculated based on the non-steady-state Wells–Riley equation. An optimization model was established to minimize the overall infection risk, that is, the expected number of passengers infected on the train. The model, as a pure integer quadratic programming problem, was solved by LINGO software. The superiority of our model was tested by comparing it with the traditional sequential assignment scheme (SAS) and discrete assignment scheme (DAS).

Through the case study and sensitivity analysis, some meaningful findings are addressed:

- (1) The assignment scheme obtained by our model significantly reduces the overall infection risk. In the base case, it reduced infection risk by 67.6% and 56.8%, respectively, compared with the SAS and DAS. In other scenarios, the reduction is mostly between 10% and 90%
- (2) The optimized assignment scheme separates the passengers from higher-risk and lower-risk areas, as well as passengers with long and short trips. The cotravel trip between passengers from higher-risk and lower-risk areas was compressed to the minimum

- (3) Optimizing the car assignment scheme is a feasible option if the incidence is higher at downstream or low-flow stations. The smaller the passenger flow of a higher-risk area, the bigger the room for optimization
- (4) Increasing the number of cars (e.g., equipping the train with more cars within the cost burden) and car service capacity (e.g., selling standing tickets) can reduce the overall infection risk and improve the optimization effect
- (5) The optimization effect is not sensitive to the parameters of the Wells–Riley model, so the above results are advisable for different train cabin environments, prevention measures, and, more importantly, types of infectious diseases

However, our work is a static optimization model under the assumption that origin-destination demand is known. In practice, the ticketing process is dynamic, requiring a real-time allocation of cars and seats when passengers buy tickets. Therefore, further studies are needed on dealing with passengers' real-time ticket demand dynamically, as well as solving the problem of demand randomness and uncertainty. Another line of further research consists of collaborative optimization involving multiple trains and multiple lines.

Data Availability

The travel demand data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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