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Prevention and control of COVID-19 in subway stations: An optimization strategy for placing location QR codes

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A B S T R A C T

The outbreak of COVID-19 has had a significant impact on passengers’ travel. To study the layout of prevention and control facilities in subway stations under the influence of the pandemic, this paper establishes a queuing model and Vickrey’s model to study the queuing problem at subway station security check channels. In addition, simulating the queuing model at the security check channel for passengers without a bag (SCCP0B) and the security check channel for passengers with a bag (SCCPB) in subway stations during off-peak hours. The queuing problem at the security check channels affected by the pandemic and not affected by the pandemic is also compared and analysed. The results of the study show that only placing location QR codes at subway station security check channels will have a greater impact on passengers travelling during peak hours but will have little effect on passengers travelling during off-peak periods. To effectively prevent and control COVID-19 without affecting the normal travel of passengers, this paper suggests that it is more appropriate for subway stations to place the location QR code in the aisle of the subway station. This research can provide a reference for the subway station operation management during COVID-19.

1. Introduction

As of 2018, the urban population in the world exceeded 4.2 billion, and it is estimated that the urban population will reach 6.3 billion by 2050 (70% of the world population) (Qian and Ukkusuri, 2021). Public transportation systems satisfy the basic transportation needs of residents of large cities, and play an important role in transporting large numbers of commuters in urban areas (Sipetas et al., 2020). However, the COVID-19 outbreak has had a major impact on commuters’ daily travel and public transportation systems (Basu and Ferreira, 2021, Gutierrez et al., 2020, de Haas et al., 2020). In addition, there is evidence (Auad et al., 2021, Shen et al., 2020) that the COVID-19 outbreak has also posed serious challenges for public transit agencies in terms of providing safe travel for passengers.

Public transport service provision serves an important role in moving commuters but has been greatly impacted by COVID-19 (Gkiotsalitis and Cats, 2020), especially crowded public transport services, which are considered one of the factors contributing to the spread of the virus (Gkiotsalitis, 2021). Due to safety concerns, many epidemic prevention measures have been proposed or implemented in public transportation systems, such as maintaining appropriate social distancing (Chen et al., 2021, Cheng et al., 2020), facing facial mask (Guellich et al., 2021), and even reconstructing transportation infrastructure to enable treatment of patients (Valdenebro et al., 2021).

With the impact of COVID-19, it is necessary to formulate many policies and measures related to virus prevention for public transportation systems (Hirschhorn, 2021, Cho and Park, 2021, Dzisi and Dei, 2020). However, COVID-19 also presents a new challenge for health authorities to implement various contagion prevention policies and measures at the same time (Wang et al., 2021). Since the arrival of COVID-19, many prevention measures have been taken by health authorities all over the world to reduce the impact of the epidemic. For example, the health authorities of China have formulated many policies and have taken various measures to control the disease and to break its transmission chain, including reducing vehicle capacities, checking passengers’ health QR codes, and disinfecting the subway.

The subway system is an important part of public transportation, and it plays an important role in transporting passengers. Subway stations are public places that passengers must pass through when they get on and off the subway. Subway stations are also enclosed spaces that...
contribute to the spread of the virus (Bansal et al., 2022). In addition, subway stations are the main place where passengers often have to queue, especially during morning and evening peak hours, which has further led to the spread of COVID-19. Therefore, it is very important to prevent and control the spread of COVID-19 in subway stations. In this paper, we aim to use queuing theory and Vickrey’s model to study the queuing problem of security check channels in subway stations under the influence of COVID-19. On this basis, strategies for the prevention and control of COVID-19 in subway stations are proposed.

The contributions of this paper can be summarized as follows:

(a) A comparative analysis of the queue length of passengers in subway security check channels before and after the impact of COVID-19 by using a queuing model and Vickrey’s model is conducted.

(b) An optimization strategy for placing location QR codes in subway stations is proposed to reduce the queue length and wait time for passengers during COVID-19.

(c) An effective approach to control COVID-19 pandemic transmission and reduce the risks of contracting COVID-19 for passengers in subway stations is provided.

The rest of the paper is organized as follows: Section 2 presents the problem description and assumptions. Section 3 describes the proposed models, including the queuing model during the off-peak period and Vickrey’s model during the peak period. Section 4 presents a numerical example. Section 5 analyses the calculation results. Section 6 concludes the paper.

2. Literature review

The occurrence of COVID-19 has profoundly affected the lives of residents and their travel. Considering that public transportation, especially the subway, is the main mode of access in large cities in most countries, the impact of COVID-19 on subway travel is crucial to the normal operation of urban transportation. Therefore, the study of subway operation characteristics and access efficiency under epidemic prevention and control, layout optimization of subway station facilities and subway epidemic prevention measures has received attention from transportation studies. This paper presents and summarizes previous studies on the optimization of subway station facility layout and subway epidemic prevention and control and compares the results obtained related to COVID-19 through knowledge mapping network analysis.

2.1. Layout optimization of subway facilities

The layout optimization and setup of subway facilities involves several elements, such as ticket machines, security screening equipment, barrier fences, passenger walking paths and stairs, and evacuation signs. A good layout for subway station service facilities can reduce the total walking distance for passengers to and from various facilities and improve the overall service efficiency and quality of subway stations. There are a number of studies on the service facilities of subway stations, and they are mostly implemented with the help of optimization models and simulations. As the original layout of a subway station can become unsuitable as the number of passengers, type of passengers and surrounding environment change, a study by Lee (Lee, 2012) proposed an integrated model with simulations to estimate the total walking time for passengers and obtain the optimal layout through ant colony optimization. In contrast, a recent study by Khattak et al. (Khattak et al., 2018) proposed a phase-based distribution and optimization method based on integrated discrete event simulation (DES) for performance evaluation and determining the optimal configuration of service facilities in metro stations. The facilities such as ticketing facilities and elevators are represented as a queuing system, and a genetic algorithm is used to obtain the optimal configuration for service facilities using facility utilization, average ridership, and passenger waiting time in the facility as performance indicators. This study provides a more realistic and novel approach to simulation optimization. In addition, transportation simulation software, e.g., Anylogic, was used by Ghali et al. (Ghali et al., 2022) to simulate the inflow and outflow of passengers. The operational capacity of metro stations and the optimal number of operational ticket windows was determined by simulating three logical units of passenger inflow, passenger outflow and train arrival, which in turn enables the evaluation and improvement of the layout organization of metro station facilities.

Many accident data from China, U.S. and Europe has been analysed by previous studies (Xu et al., 2014, Abril et al., 2008, Baysari et al., 2008, Kyriakidis et al., 2012, Zhang et al., 2008, Shi et al., 2012), which find that the injuries of passengers during the process of boarding and alighting are related to the platform design. Moreover, a study by Cruz and Smith. (Cruz and Smith, 2007), Rb et al. (Cruz and Smith, 2007, Rb et al., 2010) suggested that the evacuation of people is closely related to the speed and density of pedestrians in the pedestrian space and that optimizing the width of passenger aisles and stairs in subway stations through the M/G/C/C queuing model can improve the evacuation capacity for passengers, while Zhong et al. (Zhong et al., 2022) suggested that installing guardrails near elevator entrances can reduce congestion in subway stations.

Meanwhile, the concept of pedestrian level of service was introduced into the metro pedestrian access capacity calculation by Jiang et al. (Jiang Y S et al., 2010), who constructed a queuing optimization model that gave a new method for considering the metro access width, and they also validated the model by simulation. The simulation results showed that the model can simulate any kind of aisle queuing system with arrival and service laws. Kim et al. (Kim et al., 2019) pointed out that by clarifying the evacuation signs for underground human defence facilities in subway stations, the type and location of evacuation signs can effectively alleviate passenger congestion in emergency situations.

2.2. Epidemic prevention in subway stations

As the core infrastructure of urban public transportation, the subway needs to bear both the travel needs of urban residents under the impact of the epidemic and to provide better safety for passengers to reduce and prevent the spread of the epidemic. A study by de Haas et al. (de Haas et al., 2020) suggested that the coronavirus crisis can lead to structural behavioural changes, with decreased subway use due to increasing popularity of walking or bicycling trips, progressively negative attitudes towards public transportation, and structural shifts in transportation modes resulting from the government’s epidemic prevention requirements. Next, Jin et al. (Jin et al., 2021) constructed a risk model based on the PageRank algorithm to accurately identify key nodes for subway epidemic transmission risk by ranking PageRank values. Through an empirical study of Hankou subway station, they found that the risk level spatial nodes are mainly stairs, escalators and platform transfer spaces, and the model can provide an intuitive assessment of epidemic prevention strategies. In addition, Chen et al. (Chen et al., 2022) used a social force model to simulate the process of pedestrians exiting from subway stations, and they found that reasonable isolation facilities, larger walking distances, and expected speed can reduce the number of infections, but increasing the total number of people leaving the station will reduce the effectiveness of the measures and that the number of new coronavirus infections can be reduced by up to approximately 23% through the reasonable installation of stairway barriers. At the same time, a study by Shen et al. (Shen et al., 2020) concluded that public transportation is still a high-risk area for COVID-19, and it is particularly important to improve the safety and utilization of the subway by implementing strict measures for public transportation under the normal epidemic control status. Therefore, the government should adopt comprehensive countermeasures to prevent and control neoplastic pneumonia by strengthening personnel management, personal protection, environmental cleaning and disinfection, and health education to improve the safety of subways through a multipronged strategy.
2.3. Analysis of the knowledge graph network

From the knowledge graph network shown in Fig. 1, a total of 3,491 studies related to queuing problems in the field of transportation are found, mainly divided into engineering civil (572/3,491), transportation science technology (494/3,491), public environmental occupational health (493/3,491), transportation (482/3,491), environmental sciences (423/3,491), and electrical and electronic engineering (226/3,491).

Each node in Fig. 1 represents the number of researchers or research institutions, and each line indicates the degree of connection between nodes. From Fig. 1, it can be observed that the keyword network can be divided into five main clusters, namely, a red cluster, yellow cluster, blue cluster, green cluster and purple cluster, and the co-occurring keywords mainly include new coronavirus (COVID-19), transportation (transportation) and health (health), with proportions of 10.62%, 6.47% and 4.90%, respectively, and each cluster has a significant correlation with the keywords. From the keyword network, a total of five major clusters can be derived, mainly including public health (red), building layout (yellow), public transportation (blue), transportation model (green), and new crown pneumonia (purple). These clusters are interlaced with each other, and there is a significant correlation between the keywords of each cluster, which has a greater similarity in the research questions. The keyword with the highest total link strength is “new coronavirus”, which co-occurs with other keywords 1,308 times, followed by “traffic”, “health”, “impact”, and “built environment”.

A review of the literature shows that there are several studies on the optimization of subway facility layout, and various optimization methods have been used, but the research objectives are mainly focused on congestion relief and emergency evacuation, and there are fewer studies on the optimization of subway facility layout based on the context of COVID-19 epidemic prevention and control measures.

The literature review indicates that previous studies have focused on public transportation epidemic prevention and control, but fewer studies are related to subway studies, and previous studies are mainly from Asia, especially China, which is related to the implementation of the epidemic prevention system in China in accordance with the national conditions. China currently has a “dynamic zero” epidemic prevention and control strategy, using technology such as place codes and trip codes to strengthen epidemic prevention and control efforts and adjust prevention and control measures in a timely and dynamic manner.

In this paper, we apply queuing theory to study the effect of COVID-19 epidemic prevention measures on the efficiency of subway station. We also carry out a quantitative assessment of the effectiveness of the epidemic prevention measures setting scheme, and we propose an optimized layout for subway facilities. The results can provide theoretical support and case studies for governmental epidemic prevention departments to develop reasonable and effective epidemic prevention strategies.

3. Problem description and assumption

3.1. Problem description

The subway system has been widely developed in many countries owing to its safety, efficiency (Zeng et al., 2021). The outbreak of COVID-19 has had a serious impact on passengers travelling by subway. To effectively prevent and control the virus, passengers must scan a location QR code before taking the subway.
Passengers must have a security check before boarding the subway. Due to the limited number of security check channels, queues form at the security check channels when there are too many passengers. During peak hours, the queuing problem is even more serious.

During the COVID-19 pandemic, many subway stations have utilized location QR codes. Passengers must scan the location QR code at the subway station before travelling on the subway. If the subway station only places the location code at the security check channels and does not place the location codes at other locations, the passenger’s queuing time during the security check and the queue length at the security check channels will both increase, which is detrimental to the prevention and control of the epidemic.

In this paper, the problem of the traffic capacity of the subway station affected by the location of the location QR codes is studied, and on this basis, a scientific epidemic prevention and control strategy is proposed.

3.2. Assumptions

(1) Passengers only queue at the security check channels, and after passing through the security check channels, they will not queue at the fare gates.

(2) The desired time for passengers to arrive at the subway station does not change before and after the outbreak of COVID-19.

4. Methodology

The steps taken to develop the optimal strategy for the layout of location QR codes in subway stations during the COVID-19 pandemic are shown in Fig. 2.

4.1. Notations

\( \lambda_j \): The number of passengers passing through the \( j \)-th fare gate of the subway station per unit time.

\( q_j \): The number of passengers passing through the \( j \)-th fare gate of the subway station (\( j = 1, 2, \ldots, n \)).

\( p_q(t) \): Probability that \( q \) passengers pass through the \( j \)-th fare gate of the subway station (\( j = 1, 2, \ldots, n \)).

\( \lambda_i \): The number of passengers arriving at the \( k \)-th security check channel of the subway station per unit time.

\( \lambda_i \): The number of passengers arriving at the \( i \)-th security check channel of the subway station per unit time.

\( \mu_i \): The number of passengers passing through the \( i \)-th security check channel per unit time without the impact of COVID-19.

\( \mu_i \): The number of passengers passing through SCCPOB per unit time without the impact of COVID-19.

\( \tilde{\lambda}_i \): The number of passengers arriving at SCCPB per unit time with the impact of COVID-19.

\( \tilde{\lambda}_i \): The number of passengers arriving at SCCPB per unit time with the impact of COVID-19.

\( n(t) \): The queuing time of passengers arriving at the security check channel at time \( t \) during the peak period.

\( t_i^* \): Passengers’ desired time for passing through security channel \( i \).

**Fig. 2.** The steps used to develop the optimal strategy for the layout of location QR codes in subway stations during the COVID-19 pandemic.
$t_i^*$: The start time of queuing for the $i$-th security channel during the peak period without the impact of COVID-19.

$t_i^e$: The end time of queuing for the $i$-th security channel during the peak period without the impact of COVID-19.

$t_i^p$: The maximum delay for passengers in the queue at SCCPOB when arriving at the fare gates.

$t_i^f$: The maximum delay for passengers in the queue at SCCPB when arriving at the fare gates.

$C_i$: Travel cost of passengers arriving at the security check channel at time $t_i$.

$Q_i$: The number of passengers passing through the i-th security check channel during peak hours.

$Q_i^*$: The number of passengers passing through SCCPOB during peak hours.

$Q_i^f$: The number of passengers passing through SCCPB during peak hours.

$C_i^f$: Travel cost of passengers arriving at the security check channel at time $t_i^f$.

$T$: Length of peak time without the impact of COVID-19.

$t_i^f$: The start time of queuing for SCCPB during the peak period with the impact of COVID-19.

$t_i^e$: The end time of queuing for SCCPB during the peak period with the impact of COVID-19.

$t_i^p$: The maximum delay for passengers in the queue at SCCPOB when passing through SCCPB.

$t_i^e$: The end time of queuing for SCCPOB during the peak period with the impact of COVID-19.

$t_i^p$: The start time of queuing for SCCPB during the peak period with the impact of COVID-19.

$t_i^e$: The end time of queuing for SCCPB during the peak period with the impact of COVID-19.

$t_i^p$: The start time of queuing for SCCPB during the peak period without the impact of COVID-19.

$t_i^e$: The end time of queuing for SCCPB during the peak period without the impact of COVID-19.

$t_i$: The time passengers arrive at the security check channels.

$C_i(t)$: Travel cost of passengers arriving at the security check channel.

$Q_i$: The number of passengers passing through the i-th security check channel during peak hours.

$Q_i^*$: The number of passengers passing through SCCPOB during peak hours.

$Q_i^f$: The number of passengers passing through SCCPB during peak hours.

$C_i^f$: Travel cost of passengers passing through the security check channel at time $t_i^f$.

4.2. The queuing model during off-peak periods

As shown in Fig. 3, when passengers arrive at the subway station, they must first go through the security check channels and then swipe their cards or scan the QR code on their mobile phone to pass through the fare gates. Since it takes a long time for passengers to pass through the security check channels, passengers will form a queue. When passing through the fare gates, it takes less time for passengers to swipe their cards or scan their QR code, so passengers will not form a queue.

Passengers arriving at the fare gates of the subway station are random and have no influence on each other. Thus, the passengers arriving at the fare gates obey the Poisson distribution. Assuming that the number of passengers arriving at the $j$-th fare gate of the subway station during time period $t$ is $q_j$, the probability is calculated as follows:

$$p_{q_j}(t) = \left( \lambda_j t \right)^{q_j} e^{-\lambda_j t}$$

$$q_j = 1, 2, \ldots, n$$

Before taking the subway, all passengers must go through the security check channels firstly and then pass through the fare gates. The process of passengers passing through the security check channels and the fare gates is the process of transforming $m M/M/1$ models to $n M/M/1$ models. The number of passengers passing through the security check channels is equal to the number of passengers passing through the fare gates; therefore, we can obtain:

$$\sum_{i=1}^{n} q_i = \sum_{j=1}^{m} q_j$$

(2)

In Eq. (2), the left side refers to the number of passengers passing through the security check channels, and the right side refers to the number of passengers passing through the fare gates.

The number of passengers passing through the security check channels and the queue length of passengers at the security check channels are calculated by counting the number of passengers passing through the fare gates. Assuming that the number of passengers arriving at security check channel $i$ during time period $t$ is $q_i$, the probability can be obtained as follows (see Appendix A):

$$p_{q_i}(t) = \begin{cases} \frac{\left( \sum_{j=1}^{n} \lambda_j - \sum_{i=1}^{m} q_i \right)^{q_i} \sum_{j=1}^{n} \lambda_j \sum_{i=1}^{m} q_i}{\sum_{j=1}^{n} \lambda_j - \sum_{i=1}^{m} q_i} e^{-\left( \sum_{j=1}^{n} \lambda_j - \sum_{i=1}^{m} q_i \right)^{q_i}} & i = 1 \\ \frac{\left( \sum_{j=1}^{n} \lambda_j - \sum_{j=1}^{m-1} \lambda_j - \sum_{i=1}^{m} q_i \right)^{q_i} \sum_{j=1}^{n} \lambda_j \sum_{i=1}^{m} q_i}{\sum_{j=1}^{n} \lambda_j - \sum_{j=1}^{m-1} \lambda_j - \sum_{i=1}^{m} q_i} e^{-\left( \sum_{j=1}^{n} \lambda_j - \sum_{j=1}^{m-1} \lambda_j - \sum_{i=1}^{m} q_i \right)^{q_i}} & i = 2, 3, \ldots, m - 1 \\ \frac{\left( \sum_{j=1}^{n} \lambda_j - \sum_{j=1}^{m-1} \lambda_j \right)^{q_i} \sum_{j=1}^{n} \lambda_j \sum_{i=1}^{m} q_i}{\sum_{j=1}^{n} \lambda_j - \sum_{j=1}^{m-1} \lambda_j} e^{-\left( \sum_{j=1}^{n} \lambda_j - \sum_{j=1}^{m-1} \lambda_j \right)^{q_i}} & i = m \end{cases}$$

(3)

$T$: Length of peak time with the impact of COVID-19.

$\epsilon_i$: The maximum delay for passengers in the queue without the impact of COVID-19.

$\epsilon_i^*$: The maximum delay for passengers in the queue at SCCPOB without the impact of COVID-19.

$\epsilon_i^f$: The maximum delay for passengers in the queue at SCCPB without the impact of COVID-19.

$\epsilon_i^o$: The maximum delay for passengers in the queue at SCCPOB with the impact of COVID-19.

$\epsilon_i^o$: The maximum delay for passengers in the queue at SCCPB with the impact of COVID-19.
According to queuing theory, the queuing length of the $i$-th security check channel can be calculated as:

$$L_i = \frac{\mu_i}{\mu_i - \alpha_i} \quad i = 1, 2, \ldots, m - 1, m$$  \hspace{1cm} (4)

From Eq. (3), the number of passengers arriving at security check channel $i$ within a unit time can be obtained as:

$$Q_i = \alpha(t) + \beta(t)$$  \hspace{1cm} (7)

where $\alpha$ and $\beta$ are the starting and ending times of the queuing process in which $\alpha(t)$ and $\beta(t)$ are the starting and ending times of the queuing process. Therefore, we can obtain:

$$T = \alpha(t) - \beta(t)$$  \hspace{1cm} (8)

The maximum delay that passengers in the queue incurred at time $\alpha(t)$ is (see Appendix C):

$$v_i = \frac{Q(t)}{\mu_i \alpha}$$  \hspace{1cm} (9)

Since the system is in a stable state, the travel cost of each passenger in the system is the same. The travel cost of passengers who pass through the security check channel at time $\alpha(t)$ is

$$c_i = \frac{Q(t)}{\mu_i \alpha} = \frac{Q(t)}{\mu_i}$$  \hspace{1cm} (10)

The total travel cost of passengers in each security check channel during the peak period is

$$C_i = \sum_{t=1}^{T} c_i$$  \hspace{1cm} (11)

The total travel cost of passengers in all security check channels during the peak period is

$$C_i = \sum_{t=1}^{T} C_i$$  \hspace{1cm} (12)

Table 1

| Time period     | Number of total passengers without bags | Number of total passengers with bags |
|-----------------|----------------------------------------|-------------------------------------|
| 5:00–6:00       | 82                                     | 49                                  | 33                                  |
| 6:00–7:00       | 395                                    | 237                                 | 158                                 |
| 7:00–8:00       | 933                                    | 560                                 | 373                                 |
| 8:00–9:00       | 711                                    | 427                                 | 284                                 |
| 9:00–10:00      | 366                                    | 220                                 | 146                                 |
| 10:00–11:00     | 275                                    | 165                                 | 110                                 |
| 11:00–12:00     | 272                                    | 163                                 | 109                                 |
| 12:00–13:00     | 316                                    | 190                                 | 126                                 |
| 13:00–14:00     | 321                                    | 193                                 | 128                                 |
| 14:00–15:00     | 270                                    | 162                                 | 108                                 |
| 15:00–16:00     | 296                                    | 178                                 | 118                                 |
| 16:00–17:00     | 321                                    | 193                                 | 128                                 |
| 17:00–18:00     | 474                                    | 284                                 | 190                                 |
| 18:00–19:00     | 269                                    | 161                                 | 108                                 |
| 19:00–20:00     | 153                                    | 92                                  | 61                                  |
| 20:00–21:00     | 102                                    | 61                                  | 41                                  |
| 21:00–22:00     | 72                                     | 43                                  | 29                                  |
5. Numerical studies

5.1. Data description

The models are validated with the card data of passengers in a subway station in Ningbo, China. The data are collected with each hour as the time period, and Table 1 gives the number of passengers in each hour. Data collection starts at 5:00 and ends at 22:00. Passengers are divided into two categories: passengers with bags and passengers without bags. According to the survey, the ratio of the number of passengers without a bag to the number of passengers with a bag is 3:2. An analysis of Table 1 indicates that 7:00–9:00 is the peak time for passengers to enter the subway station and that 9:00–17:00 is the off-peak period. Therefore, this paper uses data from 9:00 to 17:00 to validate the queuing model during the off-peak period and uses data from 7:00 to 9:00 to validate Vickrey’s model during the peak period.

5.2. Validation of the queuing model during the off-peak period

Analyzing the queuing model during the off-peak period with data from 9:00–17:00, we find that the average time for passengers to pass SCCPOB is 4 s, and the average time to pass SCCPB is 9 s through investigation. When the location QR codes are only placed at the entrances of the security check channels, it can be investigated that the average time for passengers to pass through the security check channels will increase by 1.8 s because passengers have to scan the location QR code with their mobile phones.

Therefore, the average number of passengers passing SCCPOB per minute is $\frac{60}{4} = 15$, and the average number of passengers passing SCCPB per minute is $\frac{60}{9} = 10.34$, and the average number of passengers passing SCCPB per minute is $\frac{60}{5.8} = 5.56$ under conditions affected by COVID-19.

Table 1 shows that the total number of passengers from 9:00 to 17:00 is 2437, of which the number without packages is $2437 \times 0.6 = 1462$ and the number with packages is 2437 × 0.4 = 975. The length of time from 9:00 to 17:00 is 480 min. Therefore, the average numbers of unpackaged passengers and packaged passengers per minute are $\frac{1462}{480} = 3.05$ and $\frac{975}{480} = 2.03$, respectively.

5.2.1. Length of passenger queues at the security check channels of subway stations without the impact of COVID-19

(1) The queue length at SCCPOB without COVID-19 effects

Through Eq. (4), we can obtain the queue length at SCCPOB without the impact of COVID-19 as

$$\frac{15}{15 - 3.05} = 1.2552 \quad (14)$$

The queuing process is simulated by MATLAB, with the result shown in Fig. 6. The average value of the queue length from the simulation results is calculated as 1.2594. Through comparison, the calculation result obtained by Formula (4) has a very small gap with the result obtained by the MATLAB simulation.

(2) The queue length at SCCPB without COVID-19 effects

By Eq. (4), we can obtain the queue length at SCCPB without the impact of COVID-19 as:

$$\frac{6.67}{6.67 - 2.03} = 1.4375 \quad (15)$$

Fig. 7 shows the simulation result from MATLAB. The average value of the queue length from the simulation results is 1.4374. The difference between 1.4374 and 1.4375 is also very small.

5.2.2. Length of passenger queues at the security check channels of subway stations with the impact of COVID-19

(1) The queue length at SCCPOB with COVID-19 effects

Fig. 6. Simulation result of the queuing process at SCCPOB without the impact of COVID-19.

Fig. 7. Simulation result of the queuing process at SCCPB without the impact of COVID-19.

Fig. 8. Simulation result of the queuing process at SCCPOB with the impact of COVID-19.

Fig. 9. Simulation result of the queuing process at SCCPB with the impact of COVID-19.
5.2.2. Length of passenger queues at the security check channels of subway stations with the impact of COVID-19

(1) The queue length at SCCPOB with COVID-19 effects

Using Eq. (4), the queue length at SCCPOB with the impact of COVID-19 can be obtained as follows:

\[ \frac{987}{10.34} = 65.8 \text{ min} \]  

(2) The length of the queuing time at SCCPOB with the impact of COVID-19

According to Eq. (9), the length of the queuing time at SCCPOB with the impact of COVID-19 can be calculated as:

\[ \frac{987}{10.34} = 95.45 \text{ min} \]  

Under the influence of COVID-19, the start time at SCCPOB during the off-peak periods is earlier than that without the influence of COVID-19. The advance time can be obtained from Eq. (7) as

\[ t_i^s - t_i^d = t_i^* - t_i - \frac{Q_i \tau}{\mu_i \beta} - t_i^* - \frac{Q_i \tau}{\mu_i \beta} - \frac{Q_i \tau}{\mu_i \beta} - \frac{1}{\mu_i} \]  

By Eqs. (20) and (21), we have

\[ t_i^s - t_i^d = t_i^d - t_i^d \]  

Through Eqs. (18) and (19), we can obtain:

\[ \langle t_i^s - t_i^d \rangle = 95.45 - 65.8 = 29.65 \text{ min} \]  

Thus, we have that

\[ t_i^s - t_i^d = 14.825 \text{ min} \]

Using Eq. (10), the maximum delay for passengers in the queue with the impact of COVID-19 is as follows:

\[ t_i^m = \frac{Q_i \tau}{\mu_i \alpha} \]

By Eqs. (10) and (24), the increase in maximum queuing time under the influence of COVID-19 can be deduced as follows:

\[ t_i^m - t_i^m = \frac{29.6 \tau}{\alpha} = 29.6 \times \frac{3.9 \times 15.21}{8} \times \frac{1}{6.4} = 14.36 \text{ sec} \]

5.3. Validation of Vickrey’s model during the peak period

From the data in Table 1, 7:00–9:00 is the peak period for passengers to enter the subway station, and the length of the peak period is 120 min. During peak hours, the number of passengers entering the subway station is 1644, of which 657 have packages and 987 do not.

5.3.1. The length of queuing time at SCCPOB

(1) The length of the queuing time at SCCPOB without the impact of COVID-19

By Eq. (9), the length of the queuing time at SCCPOB under the condition without the impact of COVID-19 can be obtained as follows:
Fig. 10 shows the change in queuing time at SCCPOB.

5.3.2. The length of the queuing time at SCCPB

(1) The length of the queuing time at SCCPB without the impact of COVID-19

Using Eq. (9), we can obtain the length of the queuing time at SCCPB under the condition without the impact of COVID-19 as follows:

\[ t_1 = \frac{Q_\alpha \tau}{Q_\beta \mu_1 - \mu_\beta} \]

(27)

(2) The length of the queuing time at SCCPB with the impact of COVID-19

Using Eq. (9), the length of the queuing time at SCCPB with the impact of COVID-19 can be obtained as:

\[ t_1^* = \frac{Q_\alpha \tau}{Q_\beta \mu_1 - \mu_\beta} - \frac{Q_\alpha \tau}{Q_\beta \mu_1 - \mu_\beta} = \frac{Q_\alpha \tau}{Q_\beta \mu_1 - \mu_\beta} \left( \frac{1}{\mu_2} - \frac{1}{\mu_1} \right) \]

(29)

Under the influence of COVID-19, the queuing start time at SCCPB during the morning peak period is also earlier than that without the influence of COVID-19. By Eq. (7), the advance time can be obtained as:

\[ t_s^1 = t_1 - t_1^* = \frac{Q_\alpha \tau}{\mu_1 \beta} - \frac{Q_\alpha \tau}{\mu_2 \beta} = \frac{Q_\alpha \tau}{\beta} \left( \frac{1}{\mu_2} - \frac{1}{\mu_1} \right) \]

(30)

By Eqs. (29) and (30), we have:

\[ t_s^1 - t_s^1 = \frac{Q_\alpha \tau}{\beta} \left( \frac{1}{\mu_2} - \frac{1}{\mu_1} \right) \]

(31)

Through Eqs. (27) and (28), we can obtain:

\[ (t_s^1 - t_1) + (t_s^1 - t_1) = 118.17 - 98.5 = 19.67 \text{ min} \]

(32)

Thus, we have that

\[ t_s^1 - t_s^1 = 8.935 \text{ sec} \]

Using Eq. (10), the maximum delay for passengers in the queue with the impact of COVID-19 is as follows:

\[ t_3 = \frac{Q_\alpha \tau}{Q_\beta \mu_1} \]

(33)

By Eqs. (10) and (33), the increase in maximum queuing time under the influence of COVID-19 can be deduced as follows:

\[ \tau_3 - \tau_2 = \frac{Q_\alpha \tau}{Q_\beta \mu_1} - \frac{Q_\alpha \tau}{Q_\beta \mu_1} = \frac{Q_\alpha \tau}{Q_\beta \mu_1} \left( \frac{1}{\mu_2} - \frac{1}{\mu_1} \right) = \frac{675 \tau}{(10.8 \times 9) \times 10.8} = 9.71 \tau \]

(34)

The values of \( \alpha, \beta, \gamma \) are also 6.4, 3.9 and 15.21 (Nie and Yin, 2013), respectively. Therefore, we have

\[ \tau_3 - \tau_2 = \frac{9.71 \tau}{\alpha} = \frac{9.71 \times 3.9 \times 15.21 \times 1}{3.9 \times 15.21} = 9.51 \text{ sec} \]

(35)

Fig. 11 shows the change in queuing time at SCCPB.

Analyzing the queuing model during the off-peak period and Vickrey’s model during the peak period by numerical studies, we find that if location QR codes are only placed at the security check channels, it will not have a large impact on the queuing of passengers during off-peak hours. However, it will have a great impact on the queuing of passengers during peak hours. The time for passengers to queue will be advanced, and the end of the queue will be delayed. The analysis shows that the times of advance and delay of passenger queuing at SCCPB are both 14.825 min, and the maximum waiting time in the queue will increase by 14.36 sec. It also shows that the times of advance and delay of passenger queuing at SCCPB are both 9.835 min, and the maximum waiting time in the queue will increase by 9.51 sec. We find that only placing location QR codes at the security check channels will have a significant impact on passengers’ commute during the morning peak period.

6. Discussion and conclusions

The COVID-19 outbreak has had a significant impact on passenger travel, especially on passengers travelling by public transportation. To prevent and control the epidemic, location QR codes have been placed in subway stations in many cities in China to record passenger travel information. In this paper, a queuing model and Vickrey’s model are established to analyze the queuing problems in subway stations with and without the impact of COVID-19. The queuing model is used to study the queuing problem during the off-peak period, while Vickrey’s model is used to analyze the queuing problem during the peak period. The main contribution of this paper is that an optimal location QR code allocation framework for subway stations is proposed for reducing the risks of passengers contracting COVID-19.

Placing location QR codes in subway stations is an effective measure to prevent and control the epidemic, but they should not be placed in security check channels. Through analysis, it can be found that if location QR codes are only placed at the security check channels, it will increase the queuing time for passengers during peak hours. The increased queuing time further increases passengers’ risk of contracting COVID-19 since public transportation leads to a higher risk of infection for passengers (Mouratidis and Peters, 2022). By studying the problem of location QR code placement in subway stations, the following optimal placement strategies for location QR codes in subway stations are recommended:

(a) The most reasonable solution is to place the location QR codes in the aisles of the subway station. In this way, passengers will save time at the security check channels, thereby reducing the length of the queue and the waiting time at the security check channels. This method not only benefits passengers throughout security check channels but is also conducive to epidemic prevention and control.

(b) A sufficient number of location QR codes should be placed in subway station aisles. Due to the large number of passengers taking the subway, if the number of QR codes is small, passengers will still form a queue or gather at the aisles. Queuing and gathering will increase passengers’ risk of contracting COVID-19. Due to the long tunnels of subways, passengers can scan the location QR codes with their mobile phones while walking through the subway tunnels based on a sufficient number of location QR codes placed in subway tunnels. Since passengers do not need to scan the code at the security check channels, the time required for passengers to pass through the security check channels is
Appendix A. Proof of Eq. (3)

According to Eq. (1), when \( i = 1 \):

\[
P_q(t) = \frac{(\lambda_1 t)^n}{n!} e^{-\lambda_1 t}
\]

(A.1)

When \( i = 2 \):

\[
P_q(t) = \frac{(\lambda_2 t)^{n-1}}{(n-1)!} e^{-\lambda_2 t}
\]

(A.2)

Assuming \( q_1 = q_1 + q_2 \) and according to Eqs. (A.1) and (A.2), we can reduce that:

\[
P_{(q_1 + q_2)}(t) = \sum_{n=1}^{\infty} \frac{(\lambda_1 + \lambda_2 t)^n}{n!} e^{-(\lambda_1 + \lambda_2 t)}
\]

(A.3)

\[
= e^{-(\lambda_1 + \lambda_2 t)} \sum_{n=0}^{\infty} \frac{(\lambda_1 + \lambda_2 t)^n}{n!} (0)^{n-1} q_2
\]

\[
= e^{-(\lambda_1 + \lambda_2 t)} \sum_{n=0}^{\infty} \frac{(\lambda_1 + \lambda_2 t)^n}{n!} (0)^{n-1} q_2
\]

Assuming \( q_{\text{in}} = \sum_{s=1}^{n} q_s \), through the same proof method we can get:

\[
P_{\text{in}} = \sum_{s=1}^{n} p_s(t) = \frac{[(\sum_{i=1}^{n} \lambda_i)^n]}{n!} \sum_{i=1}^{n} q_i
\]

(A.4)

When \( j = 1 \), we have:

\[
P_{(q_1 + q_2) + \cdots + q_j}(t) = \frac{[(\sum_{i=1}^{n} \lambda_i)^n]}{n!} \sum_{i=1}^{n} q_i
\]

(A.5)

When \( j = 2, 3, \ldots, n-1 \), it can be obtained:
Appendix C. Proof of Eq. (10)

From Fig. 5, We have

\[ e_i = (t_i' - t_i) - \frac{(t_i' - t_i') \cdot \mu_i}{\alpha - \beta} = (t_i' - t_i) - \frac{(t_i' - t_i') \cdot (\alpha - \beta)}{\alpha} \]

(C.1)

According Eqs. (7) and (C.1), we can obtain
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