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Reliability and Resource Allocation and Recovery of Urban Transportation System Considering the Virus Transmission

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Abstract
The urban transport system is an integral part of a city and is essential for the proper functioning of other urban functional systems. To improve the resilience of urban transport systems under the background of the spreading COVID-19 epidemic, this paper predicts the number of patients of various types at each stage of epidemic development based on an improved infectious disease model for Wuhan and verifies the validity of the model using statistical methods. Then, a system reliability model is developed from the perspective of controlling the spread of the virus and reducing economic losses, and the optimal time points for urban traffic closure and recovery are determined. Finally, a resource allocation optimization model was developed to determine the number and location of resource allocation points which based on 19 hospitals to avoid the further spread of the virus. The results give a valuable reference for enhancing the resilience of urban transport systems and improving their performance in all phases.

Keywords- System reliability, Resilience, Urban transport, Resource allocation optimization, COVID-19 epidemic.

1. Introduction

Since the spread of the new coronavirus infection, China has been engaged in an unprecedented battle against the outbreak. At the beginning of the outbreak, shutting down urban transport was effectively in reducing the path and speed of transmission of the virus. However, travel became inconvenient and most people lost their jobs and incurred serious economic losses (Dui et al., 2022). With effective control by the government and relevant authorities, urban transport is gradually being restored and economic production is slowly recovering. We know that control of urban traffic plays an important role in curbing the spread of the virus, and that when traffic is shut down and restored are linked to the loss and recovery of the performance in the urban transport system.

Based on the above analysis, it is possible to model and analyze the urban traffic under the epidemic spread in COVID-19 according to the different stages of the general study on the resilience of urban traffic system (Dui et al., 2022).

Urban transport resilience refers to the ability to complete tasks after partial disruptions or performance degradation, and it is caused by traffic disruptions and unexpected events through the internal organization and maintenance of the system. Resilient transport systems are able to withstand disasters and extreme catastrophes due to climate change, ensuring the reliability of resilient transport systems by understanding the risk of urban outbreaks, planning alternative transport modes and routes, and applying new norms to improve emergency preparedness and response capabilities (Teng et al., 2020).

Referring to the system functional curve-based resilience assessment model constructed by Chen et al. (2022) for assessing the resilience of urban road public transport systems, a functional curve of the urban transport system under the epidemic transmission scenario is obtained as shown in Figure 1.

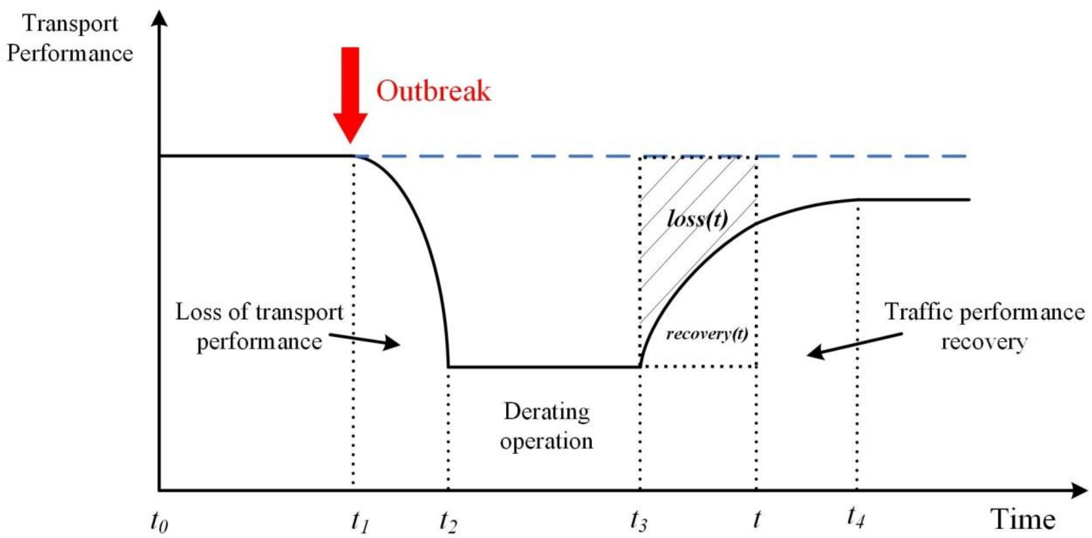

Figure 1. Functional curve of the urban transport system.

In order to build a resilient urban transport system, it is necessary to identify the stages through which the performance of urban transport changes before and after an outbreak. Therefore, according to Figure 1, the process of changing the performance of the urban transport system in the event of an epidemic spread can be divided into five stages as follows.

a. Prevention phase $(t_0 < t < t_1)$: the transport system is in a normal state of operation and appropriate decision support systems can be used to prevent and prepare for an epidemic during this phase.
b. Outbreak phase $(t_1 < t < t_2)$: the outbreak occurs at t_1 and the function of the transport system is affected to some extent, depending on the severity of the outbreak and the resilience of the transport system itself.
c. Derating phase $(t_2 < t < t_3)$: After the outbreak, the traffic system absorbs the effects of the outbreak and operates at a reduced level. Before traffic resumes, staff can help the transport system adapt to the epidemic through a series of optimization operations based on the fault state.
d. Recovery phase $(t_3 < t < t_4)$: At t_3, staff start to call on recovery resources to repair the traffic, and the repair is gradually completed and the system is gradually restored to its operational state.
e. Stable operation phase $(t > t_4)$: the fault repair work is completed and the system gradually returns to a stable operating state. The stable operating state may be lower than the original state and may take a long time to fully recover to the original state.

In order to accurately study the resilience of urban transport systems considering the spread of New Coronavirus, the modeling of epidemic transmission patterns needs to be analyzed, which requires the introduction of familiar infectious disease models. In Li et al. (2001), the authors studied a SEIR model of an infectious disease that spreads through a host population by horizontal and vertical transmission, demonstrating that global dynamics are determined by the basic regeneration number and also analyzed the contribution of vertical transmission to the basic regeneration number. In Khan et al. (2021), a stochastic epidemic compartmental model of covid-19 was proposed and analyzed based on the characteristics of NIV. Meanwhile, the existence and uniqueness were discussed using stochastic Lyapunov function theory. He et al. (2020) developed a SEIR epidemic model of COVID-19 was based on general control strategies such as hospital, isolation and external inputs. The system parameters were estimated using a particle swarm optimization (PSO) algorithm based on data from Hubei Province, and the control strategy of COVID-19 was discussed based on the structure and parameters of the proposed model. In Efimov et al. (2021), the COVID-19 pandemic course was analyzed for eight different countries using the SEIR model, and the identified model was then applied to predict the spread of the SARS-CoV-2 virus under various constraints, for which an interval predictor was designed to allow for variability and uncertainty in the model parameters.

In terms of system resilience, Bruneau et al. (2007) first introduced the resilience curve and applied it to earthquake engineering, and he argued that resilience can be expressed as the area enclosed by the system functional curve with the horizontal and vertical axes. In Ruiz-Martin et al. (2022), various open issues of organizational resilience as revealed by disasters and rapid environmental change are discussed, and the use of network theory to study the resilience of communication in organizations is explored with results showing that network theory provides a cost-effective method for analyzing the resilience of communication infrastructures and organizational relationships. Calvert et al. (2018) argued that both primary and secondary disturbances can have a considerable impact on the performance of traffic networks, and therefore proposed a resilient link performance index, which can be used to detect less resilient road segments and analyses which underlying road and traffic characteristics contribute to this non-resilience. In Dunn et al. (2016), the authors evaluate two strategies to improve the resilience of air traffic networks and show that adaptive reconfiguration strategies outperform permanent re-routing solutions, while finding that the geographical location of airports can make them vulnerable to spatial hazards if the traffic network has fixed routes.

In terms of resource allocation, Sangaiah et al. (2020) uses the Whale Optimization Algorithm (WOA) to solve the RA problem in the IoT, aiming to optimize RA and reduce the total communication cost between resources and gateways. In Yin et al. (2021), a multi-stage stochastic programming partitioning model for epidemic resource allocation is proposed that integrates uncertain disease progression and resource allocation to control infectious disease outbreaks, optimizing the allocation of treatment centers and resources. In Dangerfield et al. (2019), limited resources are considered to be allocated to treat pathogens in the independent target populations whose transmission is modelled using a susceptible-infectious-susceptible model.

In order to enhance the resilience of the urban transportation system and improve the performance of the urban transportation system in each stage, this paper selects Wuhan as the research area of the epidemic outbreak center, and the time range is from January 10th to March 8th, 2020. By consulting the data, the epidemic development can be roughly divided into three stages, and the urban traffic change process can be divided into three stages. Based on the improved SEIR infectious disease model, the model parameters are determined and the predicted values of the population numbers in each stage can be obtained. At the same time, the system reliability model is established from the perspective of controlling the spread of virus and reducing economic losses. Taking Wuhan subway traffic as the research object, the model parameters are determined. Based on the three stages of epidemic development, the optimal time nodes for opening and closing station outlets are determined. Finally, on the basis of 19 hospitals in Wuhan, the number and location of resource allocation points are determined to make medical resources meet the needs of hospitals. At the same time, unnecessary contact is reduced through resource allocation points to make the virus spread further.

The rest of this paper is organized as follows. In section 2, we established an improved SEIR epidemic model in COVID-19. In section 3, the reliability model of urban transportation system is established to analyze the reliability from the perspective of controlling the spread of virus and reducing economic losses. In section 4, because it is difficult to effectively allocate urban medical resources, we take Wuhan as an example to establish a resource allocation optimization model. In section 5, we discuss the results of the analysis. Finally, in section 6, we explain the conclusion of this paper.

2. Improved SEIR Virus Propagation Model

Since the outbreak of COVID-19, local outbreaks have occurred in Hubei, Hebei, Shandong, Heilongjiang and other parts of China. Due to the sudden nature of the COVID-19 outbreak and the lack of prior experience in traffic control, urban traffic was closed under emergency policies to avoid further spread of the outbreak. In this study, the time period for the spread of the novel coronavirus was from 10 January to 8 March 2020, and data on the outbreak were collected mainly from statistical yearbooks and literature.

The outbreak coincided with the flu season and fever clinics generally advised patients to wear masks in response to the seasonal flu, but these were not considered specific interventions for the COVID-19 outbreak and few people wore masks during this period. The mass movement of people could have led to the widespread spread of the new coronavirus within Wuhan and to other parts of the country and abroad, followed by the mass outbreak period from 23 January to 16 February, when strict control measures were implemented and the construction of a square hospital brought the outbreak under control, and then by 8 March when the outbreak gradually subsided. By isolating suspected patients and testing for the virus, the number of new cases was gradually reduced to zero (Mao et al., 2020). The various stages of outbreak transmission are shown in Figure 2.

Figure 2. Outbreak stages chart.

According to the spread of the epidemic, urban traffic under the epidemic can be divided into three stages. The first stage is the loss of traffic performance during the latent spread of the epidemic. In the second stage, when the epidemic broke out on a large scale, urban traffic operations were reduced. The operation of urban subways and public transportation were suspended, motor vehicles were banned, and residential communities in the city were closed. In the third stage, traffic performance will be restored when the epidemic gradually recedes. Wuhan will gradually resume rail transit operations. While implementing prevention and controlling measures strictly, passenger transportation organization will be optimized according to passenger flow, and they must wear masks when traveling. We will study the novel Coronavirus transmission model based on the three stages of urban traffic fault mode.

SEIR model is a classical dynamic model of infectious disease, which can show the process of an infectious disease from development to end (Radulescu et al., 2020). SEIR model of infectious diseases within the scope of the population is divided into four categories: susceptible (S), exposed (E) infections (I), recovery (R) in epidemic spread model, all kinds of people after the initial population, the number of people infected with the daily contact, contact transmission, of rehabilitation, and all can as a parameter to input into the model, so as to produce certain effect of spread of epidemic diseases.

To simplify the uncertainty and complexity of the spread of novel coronavirus epidemics in real life, this paper assumes that in the improved SEIR model, (1) the total number of people N in the examined area during the novel coronavirus epidemic is unchanged, (2) the contact rate of the population is constant for different epidemic phases, and (3) the number of daily infections is a continuous differentiable function of time. The model was further modified in light of the NOVEL coronavirus outbreak, and infected patients were further divided into ordinary infected patients (I), severe infected patients (H), removed patients into cured patients (C), and dead patients (D), as shown in the Figure 3 below.

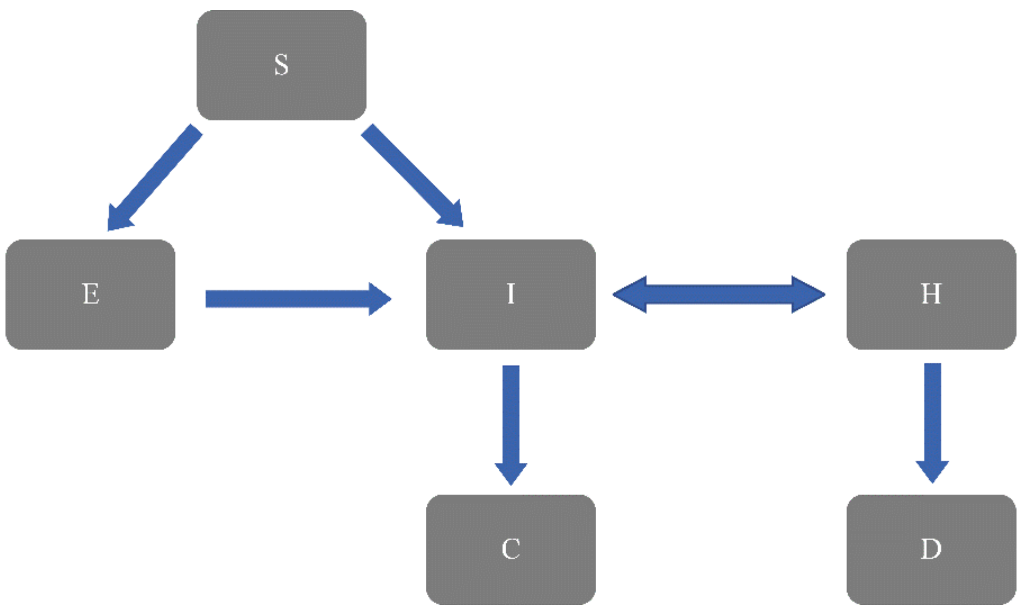

Figure 3. Diagram of the improved SEIR model.

There is a close relationship between various of groups. Latent patients are infectious, but severe patients are not. Latent patients are converted into ordinary patients with the probability of reciprocal incubation period, and the contact rate is constant. The iterative equation of the model is shown below:

$$\frac{dS(t)}{dt} = -\lambda_1 \frac{s(t)}{N} \beta E(t) - \lambda_1 \frac{s(t)}{N} \beta I(t), \tag{1}$$

$$\frac{dE(t)}{dt} = \lambda_2 \frac{s(t)}{N} \beta E(t) + \lambda_2 \frac{s(t)}{N} \beta I(t) - \alpha E(t), \tag{2}$$

$$\frac{dI(t)}{dt} = \alpha E(t) + \eta H(t) - \theta I(t) - \tau I(t), \tag{3}$$

$$\frac{dH(t)}{dt} = \theta I(t) - \eta H(t) - \mu H(t), \tag{4}$$

$$\frac{dC(t)}{dt} = \tau I(t), \tag{5}$$

$$\frac{dD(t)}{dt} = \mu H(t), \tag{6}$$

$$S(t) + E(t) + I(t) + H(t) + C(t) + D(t) = N. \tag{7}$$

N is the total number of people affected by the epidemic. $S(t)$, $E(t)$, $I(t)$, $H(t)$, $C(t)$, and $D(t)$ represent the total number of susceptible, exposed, infectious, severely infected, cured people and dead people on day t respectively. β refers to the probability of susceptible people into infected, α is the probability of exposed converting to normal infection, θ refers to the probability of ordinary people into severely infected, η refers to the probability of severe infection into ordinary, τ refers to the probability of ordinary population into cure, μ refers to the probability of severe infection turning into death, λ_1 refers to the contact rate of the exposed population, and λ_2 refers to the contact rate of common infected population.

3. System Reliability based on Economic Loss and Virus Transmission

Select the optimal time and mode of transportation according to the reliability of the transportation system: when any element of the transportation system composed of human-vehicle-road elements fails, the system will fail. The system is regarded as a series one (Dui et al., 2022). Due to the severe impact of the epidemic prevention and control on the economic development, the traditional series system has been revised, and the reliability of the revised system is:

$$R = K_m * R_d * R_v * R_r. \tag{8}$$

K_m is the economic impact of the COVID-19 outbreak in phase m, $m = 1,2,3$. And other model parameters have the following definitions.

(1) R_d is human reliability

$$Rd = 1 - k_1 * k_2 * (1 - R_0). \tag{9}$$

k_1 and k_2 represent the physical and mental state and environmental components respectively, and R_0 is the basic reliability of human.

(2) R_v refers to the reliability of the vehicle, considering the traffic density which is related to the station network. During the severity of the epidemic, the average daily traffic on expressways decreased by 61%, recovered only 62%, and then reached 80% as vehicle reliability.

(3) R_r is the reliability of the road

$$R_r = 1 - k_3 * (1 - \widehat{R_0}). \tag{10}$$

R_r refers to the road reliability under actual conditions, and k_3 is the reliability correction coefficient. During the epidemic period, it represents the traffic condition of the road that is whether the road is closed or not. In the serious stage of the epidemic in Wuhan, the city is closed, and this value is 0. $\widehat{R_0}$ is the base reliability of the road. The station network is closed when the reliability is lower than 0.5. Otherwise, the station network is opened.

4. Allocation Optimization of Resources

The epidemic development trend and mortality rate are closely related to the level of medical resource supply, so the study of medical resource allocation plan has certain reference value for other cities of the same size. Under the COVID-19 outbreak, many medical institutions will face the shortage of medical protective materials which caused by the sudden increase of patients at any time. Therefore, this study made a reasonable allocation of emergency medical resources in Wuhan during COVID-19, and provided the quantity of emergency medical resources which required under the response strategy. It is necessary to improve the emergency response speed of Wuhan medical resources and the emergency of handling the capacity of infectious diseases.

This article converted the epidemic resource allocation problem into the consideration of determining that under the condition of meeting the demand of emergency resources in Wuhan hospitals. Whether the location and number of resource allocation points can improve efficiency or reduce unnecessary contact of personnel. First of all, we need to investigate the number and location distribution of hospitals in Wuhan. In order to simplify the model, we only consider third-class A hospital in Wuhan, as shown in Figure 4.

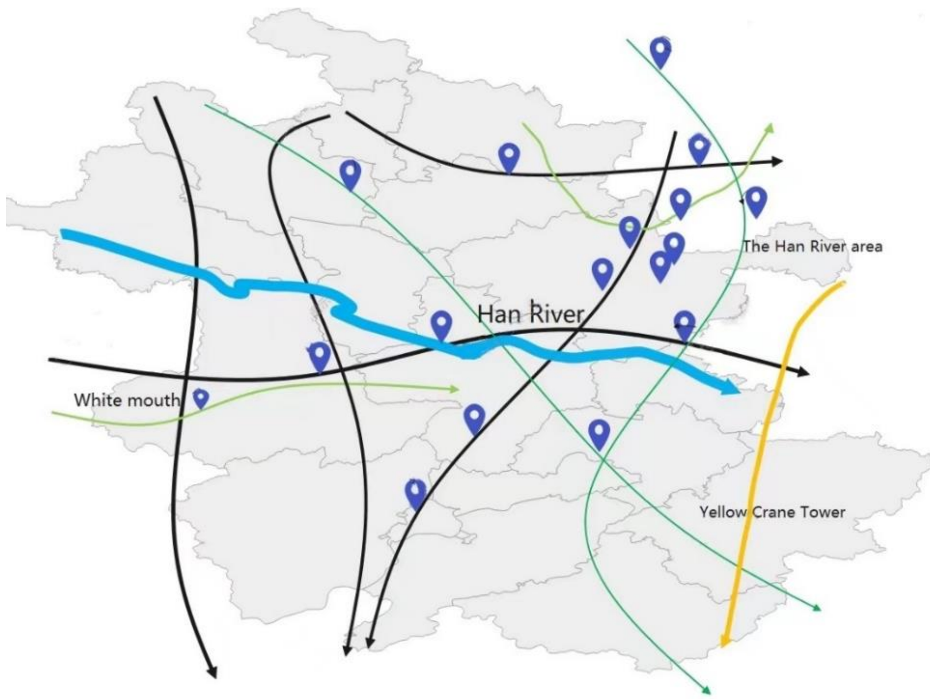

Figure 4. Distribution map of grade A hospitals in Wuhan.

Under the epidemic situation, hospitals bear huge responsibilities and face the risk of shortage of medical supplies at any time. Therefore, we mainly consider how to allocate resources to hospitals to simplify the model reasonably. This study calculates the distance between the allocation of resources, and setting its minimum product as objective function, so as to the constraint conditions. The resource configuration points need to meet the demand of resources, and the hospital resource allocation point of stored resources cannot exceed the space constraints which must select closer hospital to the allocation of resources firstly. The following optimization model is given.

$$min \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{n=1}^{N} d_{ij} a_i x_{nij} \tag{11}$$

$$\sum_{i=1}^{I} a_i x_{nij} \geq D_{nj} \quad n = 1,2,3, \dots, N, \tag{12}$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J} a_i x_{nij} \leq Q_i \quad n = 1,2,3,\ldots,N, \tag{13}$$
$$\sum_{i=1}^{q_w} a_i a_{ij} \leq \sum_{i=1}^{q_w} a_{i'} a_{i^i j} \quad i \neq i' \quad i, i' \in I, \tag{14}$$
$$\sum_{i=1}^{I} a_i = q_w, \tag{15}$$
$$D_{nj} = c_j a_{nj} \quad j = 1,2,\ldots,J \quad n = 1,2,3,\ldots,N, \tag{16}$$
$$a_i = \begin{cases} 1 \\ 0 \end{cases} \quad i = 1,2,\ldots,I. \tag{17}$$

where, A is the set of configuration points of medical resources mainly including masks and protective clothing, and we represented $A = \{a_i\}$, d_{ij} is the distance from resource configuration point i to hospital j, x_{nij} is the quantity of n material transported from resource allocation point i to hospital j, D_{nj} is the total demand of hospital j for the n material, Q_i is the storage space of resource allocation point j. W are different stages of the epidemic. Number of resource allocation points in the w stage of economic development under q_w epidemic. Number of patients treated at c_j hospital j.

5. Numerical Results

5.1 SEIR Model Parameters and Solutions

When we are determining the parameter values of each stage. According to the existing survey data and reference materials, we have considered the probability of transformation of various people under the traffic conditions at different stages, especially the impact on the contact rate. The different model parameters stages are as in Table 1.

Table 1. Model parameter values at each stage.

Parameters	N	β	α	θ	μ	η	τ	$\lambda 1$	$\lambda 2$
Stage 1	2000000	0.99	0.50	0.26	0.05	0.16	0.10	0.50	0.30
Stage 2	2000000	0.99	0.50	0.30	0.06	0.10	0.11	0.38	0.40
Stage 3	2000000	0.99	0.50	0.12	0.01	0.78	0.40	0.02	0.01

In Table 1, the number of people affected by the epidemic, N, was set mainly by referring to the government statistical yearbooks and government department releases. We also learn from the fit of parameters such as infection rate β, probability of exposed population converting to common infected population α, and cure factor τ using polynomial regression with multi-layer perceptron model by Li et al. (2021). Finally, due to the development of national interference and epidemic prevention policies, the exposed contact rate and the common infected contact rate λ_1 and λ_2 reduced to some extent, so this paper assumes the values of the two indicators at different three stages as shown in the table on the basis of the release data.

According to the above novel Coronavirus transmission model, the parameters in model are called for quantitative calculation of different urban traffic conditions. The parameters in the model, such as population base, contact rate, recovery probability and probability of latent infection conversion are all having the significant influence on the calculation results. Combining the survey data gives the initial data for each of these stages to solve the model. In Figure 5, the first stage was 1999959 for susceptible, 0 for latent, 31 for common, 7 for severe and 3 for cured as of January 10, 2020. The second stage was 1998095 for susceptible, 1410 for latent, 314 for common, 127 for severe and 31 for cured as of January 23, 2020.

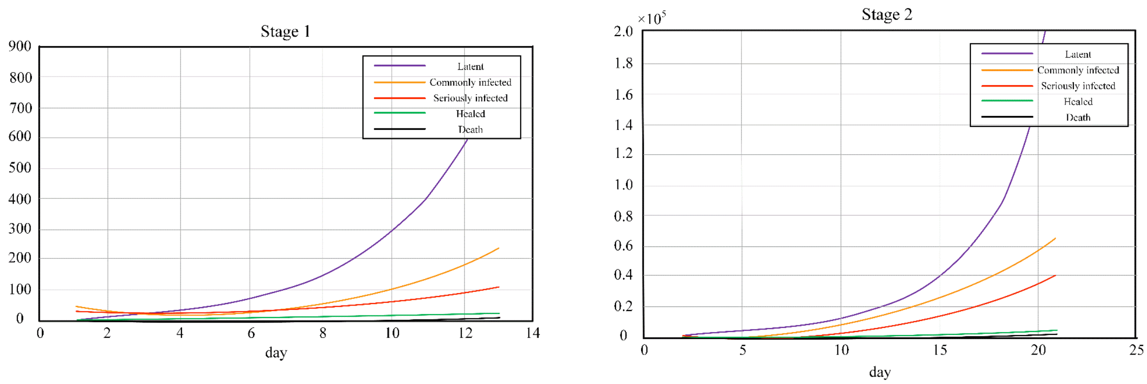

Figure 5. Number of different people in each stage.

As shown in Figure 6, in the third stage, as of 13 February 2020, the number of susceptible persons was 1955588, the number of latent persons was 8453, the number of common infections was 25467, the number of severe infections was 7492 and the number of cured persons was 2016.

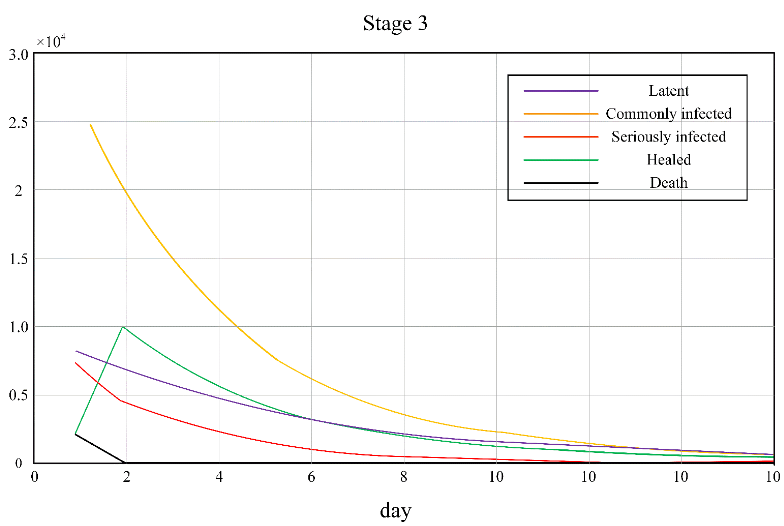

Figure 6. Number of different people in each stage.

The data collected were all at different stages after the corresponding traffic control measures were taken. In order to verify the validity of the model, the differences between the model predicted data and the actual data were compared and analyzed, and the results are shown in Figure 7. By comparing the number of infections predicted by the model at the three stages with the actual number of infections reported, they were generally consistent and the dates of the peak epidemic nodes also matched. The correlation coefficients were 0.992, 0.906 and 0.883 respectively, and the R-squares were 0.949, 0.856 and 0.710 respectively, indicating that the model fitted the actual number of infected persons well and verified the reliability of the modified SEIR model.

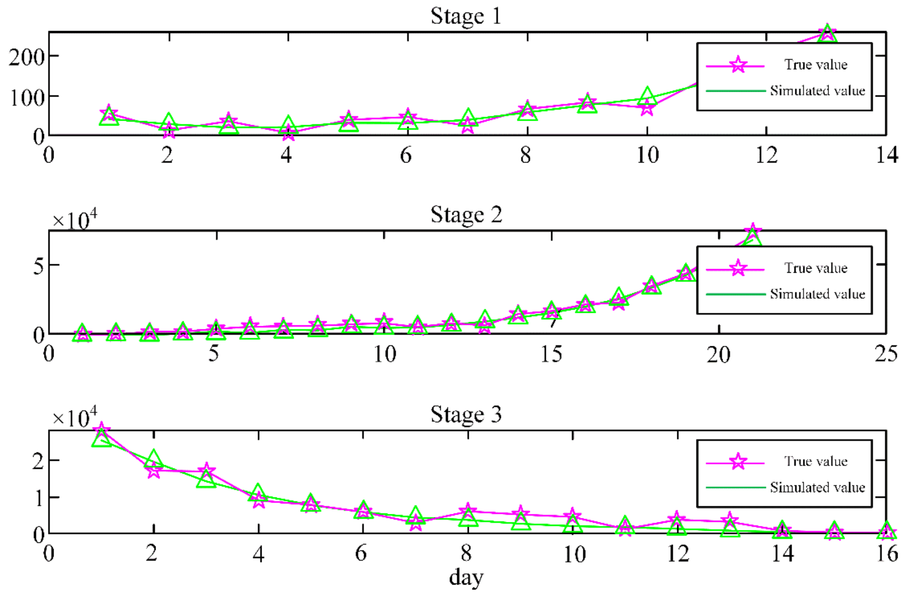

Figure 7. Model reliability test diagram.

5.2 Reliability Model Parameters and Solutions

Based on the above model and the initial selected mode of transportation is subway. We will determine the optimal time node and specific measures to close and open the station network. Firstly, we find the distribution of metro lines in Wuhan and simplify it appropriately, as in Figure 8.

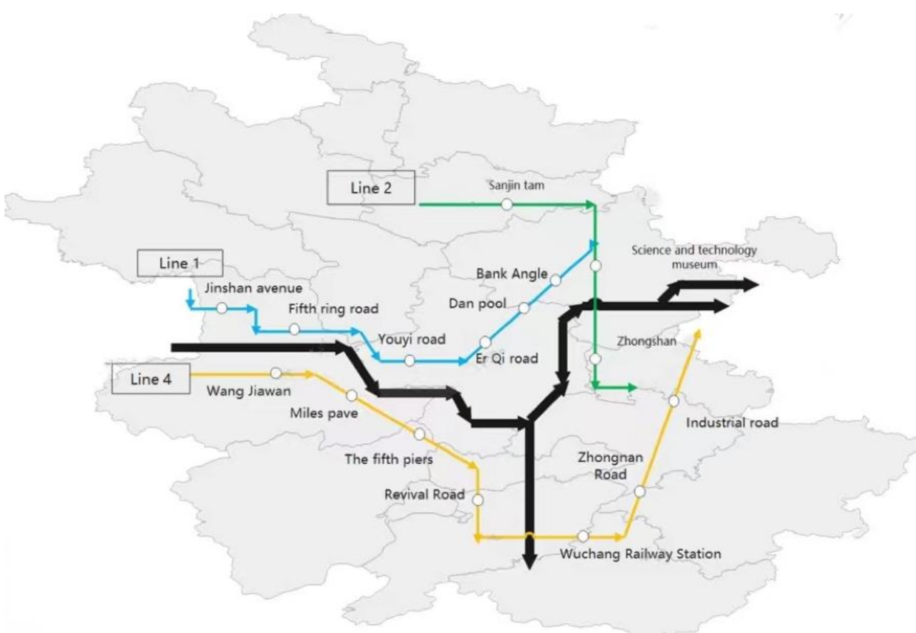

Figure 8. The subway line chart in Wuhan.

According to the above classification of epidemic stages, we further determine the closing time and opening time of subway lines. Each time node is optimized based on the model, t_1 is on January 11th, 2020, t_2 is on January 25th, 2020, t_3 is on February 12th, 2020, and t_4 is on March 7th, 2020. This paper discusses specific metro traffic measures using the traffic performance recovery phase as an example. The values of each model parameter were obtained from the information as shown in Table 2.

Table 2. Model parameter values for each stage.

R_0	R_d	R_v	R_r	$\widehat{R_0}$	k_1	k_2	k_3	k_m
0.80	0.856	0.89	0.84	0.80	0.90	0.80	0.80	0.93

Calculated according to the model parameter value

$R = 0.60 > 0.5.$

At this point, the reliability of the transport system is 0.6, and the railway operation is resumed with at least 60% recovery. In the same way, it is concluded that 60% of the subway is closed from t_1 to t_2, all of the subway is closed from t_2 to t_3, and the recovery starts from t_3 until 80% of the subway is recovered at t_4.

The response to Wuhan's metro traffic during the 2020 epidemic was obtained through a survey of actual data. Since 23 January 2020, rail traffic in Wuhan has remained low. According to preliminary statistics, the average daily rail traffic in Wuhan from 23 January to 10 February 2020 decreased by about 70%-90% compared to the same period last year. After some enterprises resumed work and production on 10 February, the average daily rail traffic in Wuhan rebounded, but generally remained at a low level. Wuhan Metro resumed operation of lines 1, 2, 3, 4, 6 and 7 on 28 March 2020 and line 8 phase 1 on 8 April. At this stage, passenger traffic is also at a low level, with average daily passenger traffic on weekdays down by approximately 85% and average daily passenger traffic on rest days down by approximately 90% compared to the same period last year. To some extent, the model results are very similar to the actual results.

5.3 Resource Allocation Model Solution

In the spread of the novel coronavirus epidemic, almost all medical institutions are faced with the problem of shortage of medical protective supplies, so the optimization problem for medical resource allocation is similar in all stages of the epidemic development, so only the resource allocation problem in the outbreak stage is solved here in this paper. The number of resource allocation points and locations were first determined based on the model described earlier to try to prevent further spread of the virus. Using Swan Lake Avenue in Caidian District, Wuhan as the origin, the coordinates of the other 19 hospitals were marked in kilometers, as shown in Figure 9.

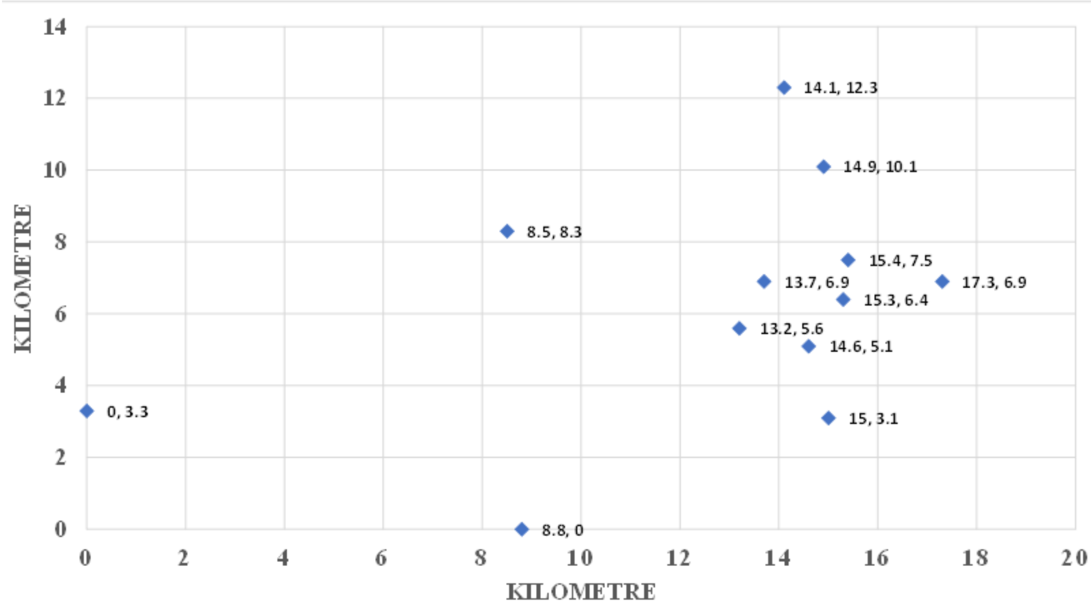

Figure 9. Coordinate distribution map of Wuhan 3A Hospital.

Using stochastic simulation to solve the optimization model, the optimal number of resources to be allocated is 3 and the specific locations are marked as shown in Figure 10.

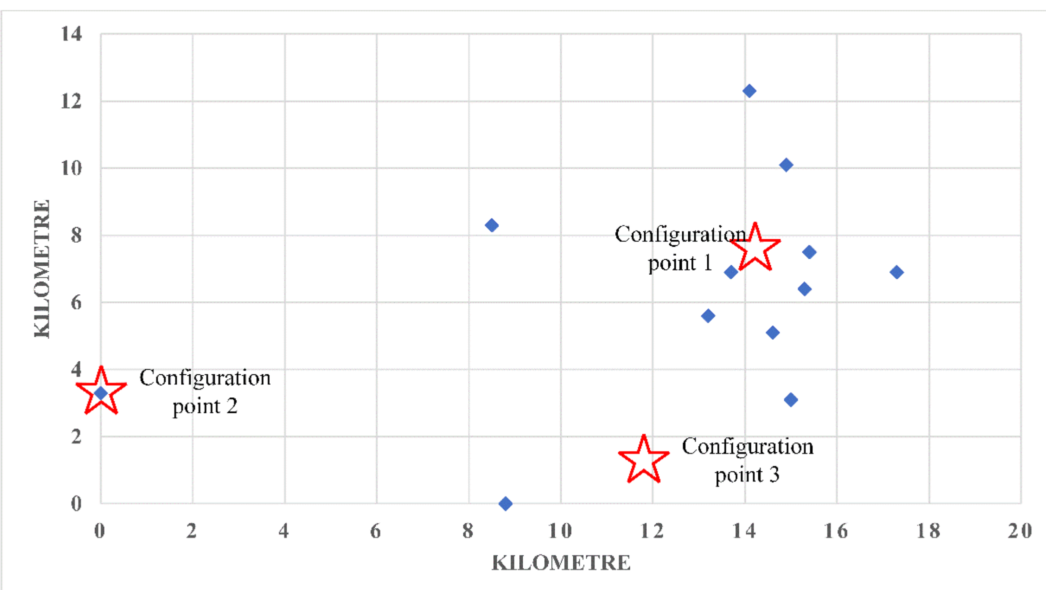

Figure 10. Distribution map of resource allocation points in Wuhan.

The resource allocation for each of the 19 hospitals was then solved for based on the resource requirements of each hospital, as shown in Table 3.

Table 3. The distribution map of the resources.

Hospitals	Masks	Protection suit (ten thousand)
1,2	300	1.2
3	295	1.5
4	302	2.1
5,6	290	1.5
7	330	1.8
8	320	1.4
9	280	1.6
10,11,12	315	2.1
13,14	295	2.25
15	309	1.95
16,17	298	2.05
18,19	301	1.23

6. Conclusions

The urban transport system is an integral part of a city, and it provides the basic transport services that are fundamental and critical to the proper functioning of the city's other functional systems. However, since the outbreak of the COVID-19 epidemic, transport networks in cities across countries have inevitably been disturbed and disrupted which causing the damage to the physical facilities of the transport system, and even the serious economic and property losses.

Therefore, in order to enhance the resilience of urban transport systems and improve the performance of urban transport systems at all stages of the epidemic. In the construction of the infectious disease model, this paper invoked the SEIR model, combined with the novel coronavirus epidemic, a novel virus that has never been seen in previous studies, and considered its characteristics of rapid transmission, long latent period, high death rate among the elderly, and high attention of the state and government, and constructed an improved SEIR infectious disease model that can accurately predict the number of various populations in this model, and further divided the infected and cured people, as well as Correlation analysis and R-square were used to verify the improved SEIR model was more applicable to the transmission description of the novel coronavirus outbreak. Subsequently, a reliability model of the urban transport system was developed from the perspective of controlling the spread of the virus as well as reducing economic losses. Taking the recovery phase of the epidemic as an example, a reliability analysis was conducted to accurately determine the optimal time point for the closure and recovery of urban transport. Finally, different from previous objective optimization studies, this paper converts the problem of rational resource allocation in the context of COVID-19 virus transmission into determining the number and location of resource allocation points based on 19 hospitals in Wuhan. The objective optimization model established in this paper can be solved to obtain the number and location of resource allocation points and the amounts of resources allocated to each hospital, and the results are visualized. The obtained results can effectively improve the emergency response speed of medical resources and handling the capacity of infectious disease epidemics in Wuhan.

This paper provides a valuable reference for enhancing the resilience of urban transport systems and improving their performance in all phases. In the future, cutting-edge strategies and sophisticated technologies from a wide range of disciplines should be integrated to build effective and resilient urban transport systems in the context of diseases, disasters and disturbances.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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