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Understanding the Propagation and Control Strategies of Congestion in Urban Rail Transit Based on Epidemiological Dynamics Model

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Abstract: With the construction of the urban rail transit (URT) network, the explosion of passenger volume is more rapid than the increased capacity of the newly built infrastructure, which results in serious passenger flow congestion (PLC). Understanding the propagation process of PLC is the key to formulate sustainable policies for reducing congestion and optimizing management. This study proposes a susceptible-infected-recovered (SIR) model based on the theories of epidemiological dynamics and complex network to analyze the PLC propagation. We simulate the PLC propagation under various situations, and analyze the sensitivity of PLC propagation to model parameters. Finally, the control strategies of restricting PLC propagation are introduced from two aspects, namely, supply control and demand control. The results indicate that both of the two control strategies contribute to relieving congestion pressure. The propagating scope of PLC is more sensitive when taking mild supply control, whereas, the demand control strategy shows some advantages in flexibly implementing and dealing with serious congestion. These results are of important guidance for URT agencies to understand the mechanism of PLC propagation and formulate appropriate congestion control strategies.

Keywords: passenger flow congestion; propagation; control strategy; complex network theory

1. Introduction

Urban rail transit (URT) plays a critical role in the modern cities with its multiple advantages of large capacity, high speed, and low energy consumption. At present, there are over 100 cities all over the world that have been operating URT. As of December 31, 2016, a total of 4152.8 km of URT lines have been put into operation in Mainland China [1], which is shown in Figure 1.

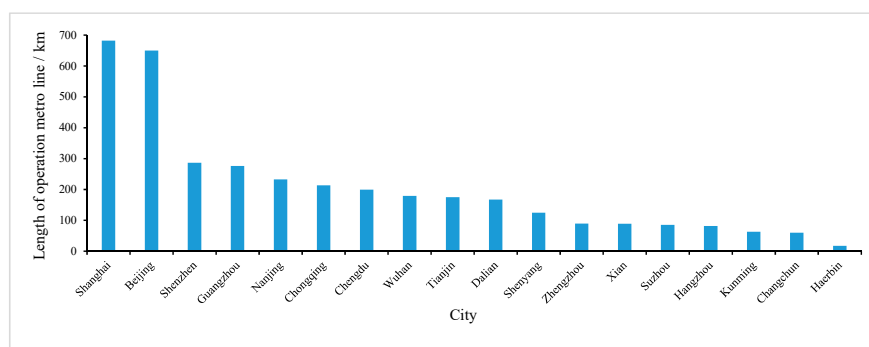


Figure 1. Urban rail transit (URT) line operated in Mainland China up to December 2016.

With the gradual construction of URT networks and rapid urbanization, many Chinese metro lines have reached the designed long-term maximum passenger flow volume [2]. It brings various problems to URT networks, among which the most visible symptom is passenger flow congestion. The level of crowdedness is an important indicator to measure the performance of URT networks. As passengers' desire for better travel environment and quality gradually increases, passenger flow congestion has become more of a concern in the literature. Most of the previous studies have focused on the route choice modelling for passengers [3,4], the detection technologies for abnormal passenger flow [5], and PLC organization schemes [6]; yet few researchers have investigated the propagation characteristic of passenger flow congestion. In this context, it is necessary to analyze the propagation of passenger flow congestion in the URT system and the effect of control strategies.

In this paper, we propose a model to simulate passenger flow congestion propagation based on the theories of virus propagation dynamics and complex network theory. The rest of this paper begins with reviewing prior work on analysis of congestion propagation. Section 3 develops a propagation model and the parameters of the model are analyzed in depth. Simulation experiments are given in the subsequent section. In Section 5, we analyze the passenger flow control strategy combined with the simulation results. The last section draws conclusions and recommends future research.

2. Literature Review

2.1. Passenger Flow Congestion Propagation and Control Strategy

Although congestion is an intuitive phenomenon, the literature presents various definitions of congestion, more complementary than distinct. According to the Transit Capacity and Quality of Service Manual [7], the level of service (LOS) concept was used to describe passengers' perceptions of the quality of demand-responsive service. It is quantified with many factors, such as service coverage, scheduling, capacity, reliability, travel time, safety, and so on. Among the factors, passenger loads (density) is the most direct measurement to describe that if stations or transit vehicles are crowded. Mokhtarian [8] proposed that congestion happens when the input volume (demand) exceeds the output capacity (supply). Oliveira et al. [9] considered that a segment of a road system is congested when the traffic demand approaches or exceeds the stable flow capacity of the road. In China, it is generally considered to be congested when the value of standing density exceeds 5 passengers/m² [10], which is significantly larger than 1.4 passengers/m² in the United States (i.e., LOS "D") [7].

In recent years, the study of topological and dynamical properties of traffic congestion and control strategy in the traffic networks attracted much attention. Zhang and Yan [11] conducted a study on the traffic congestion mechanism in big cities on the basis of economic theories. Zhang and Hua [12] appraised the performance of congestion solving strategy in Kunming city based on analytic hierarchy process (AHP). Wu et al. [13] analyzed the degree of congestion and the efficiency in different types of networks. They obtained that the formation and evolution of traffic congestion are mainly resulted from the increase of traffic demand. Based on the cell transmission model (CTM), Long et al. [14] proposed a congestion propagation model for the urban traffic and applied it to simulate the formation and dissipation of the traffic congestion. To the best of our knowledge, the first attempt to incorporate traffic dynamics in epidemic spreading was made by Meloni et al. [15] who introduced a theoretical approach to studying the result of an epidemic spreading process driven by the transport of a virus. Gao et al. [16] analyzed the process of traffic congestion spreading with the epidemiological dynamics model for a complex small-world network. It was found that the performance of the traffic system is tightly related to the average rate of infection, the average recovery rate and the topological properties of the traffic network.

At present, many scholars have put forward abundant control methods for urban traffic congestion. The existing methods of congestion control and prevention can be divided into four categories: traffic flow control and signal control [17,18], traffic demand management (TDM) [19], timetable scheme optimizing [20,21], and traffic guidance management [22].

2.2. Epidemiological Dynamics

Mathematical modelling of epidemic spreading has a long history of more than two hundred years [23]. Generally, the population is divided into three types: susceptible, infected, and recovered individuals. Susceptible individuals represent those who can contract the infection. Infected individuals are previously susceptible individuals and got infected by the disease. Recovered individuals are those who have recovered from the infection. In the susceptible–infected–susceptible (SIS) model [4], infected individuals can recover from the disease and become susceptible individuals again. While in the susceptible–infected–recovered (SIR) model [24], infected individuals no longer get infected after recovery from the disease, which are assumed to get the permanent immunity.

For a long time, scholars have made a great deal of effort in exploring and understanding the spreading processes on the field of epidemic, and the epidemic model has been used to simulate the spread of human and animal diseases (such as SARS and H1N1) among different cities. Recently, the focus has been transferred to a dynamic spreading process in temporal and multiplex networks [15,25].

Addition to diseases or viruses, there are usually many other substances spreading in networks like information packets, traffic flow, ideas, etc., which depend on the specific types of the networks. Epidemic spreading is often coupled with the delivery of these substances. For example, HIV spreads through the exchange of body fluids among individuals in contact networks. Computer viruses spread with the delivery of information packets in computer networks. Therefore, understanding the mechanisms of these coupled spreading processes and how these processes affect each other is significant for designing efficient epidemic immunization strategies. Meloni et al. [15] first studied the effects of traffic flow on epidemic spreading. They found that the epidemic threshold in the SIS model decreases as flow increases, and emergence of traffic congestion slows down the spread of epidemics. Then, Yang et al. [26,27] further studied the relation between traffic dynamics and the SIS epidemic model, and found that the epidemic can be controlled by fine tuning the local or global routing schemes. Furthermore, they obtained that the epidemic threshold can be enhanced by cutting some specific edges in the network [28].

3. Mathematical Model

3.1. Model Constructing

The susceptible-infected-recovered (SIR) model was formulated by Kermack and McKendrick [28], which is a simple deterministic model predicting the behaviour of epidemic outbreaks. In this section, we aim to describe and simulate the passenger flow congestion spreading progress with the classical SIR model.

The classical SIR model takes the following nonlinear system of ordinary differential equations:

$$\begin{cases} \frac{dS(t)}{dt} = -\beta S(t)I(t), \beta > 0 \\ \frac{dI(t)}{dt} = \beta S(t)I(t) - \lambda I(t) \\ \frac{dR(t)}{dt} = \lambda I(t), \lambda > 0 \end{cases} \quad (1)$$

Given the initial conditions:

$$S(0) = S_0 \in \mathbb{R}_+, I(0) = I_0 \in \mathbb{R}_+, \text{ and } R(0) = R_0 \in \mathbb{R}_+$$

where $S(t)$ is the number of susceptible individuals, $I(t)$ is the number of infectious individuals (i.e., individuals who are infected and capable of transmitting the disease), and $R(t)$ is the number of

recovered individuals at time t . The parameter β is infection rate (i.e., the infected probability for susceptible individuals), and λ is recovery rate (i.e., the recover probability for infectious individuals).

The corresponding differential equations can be written as:

$$\begin{cases} \Delta S(t+1) = -\beta S(t)I(t) \\ \Delta I(t+1) = \beta S(t)I(t) - \lambda I(t) \\ \Delta R(t+1) = \lambda I(t) \end{cases} \quad (2)$$

where $S(t)$, $I(t)$ and $R(t)$ represent the number of individuals in three different states at time t , respectively. Figure 2 illustrates the transition process of node state.

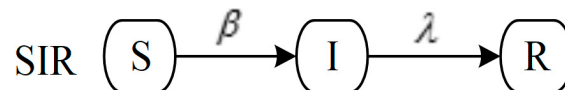


Figure 2. The transition process of node state.

3.2. Parameter Analysis

(1) The number of new congested stations affected by passenger flow congestion

The number of new congested stations and the total number of congested stations which varies over time are the main indicators of congestion propagation analysis.

At time t , the number of new stations in the network that will be affected by congestion can be expressed as the expected value:

$$E(-\Delta S) = N\beta - \lambda I(t) \quad (3)$$

where N is the number of stations directly connected to the congested station. Based on the Equations (2) and (3), the number of new congested stations can be deduced as:

$$\Delta I(t+1) = (N\beta(t) - \lambda(t)I(t))I(t) - \lambda(t)I(t) \quad (4)$$

Define $I(t+1)$ as the total number of infection stations at time $t+1$. It can be expressed as:

$$I(t+1) = \Delta I(t+1) + I(t) \quad (5)$$

Besides, the infection rate $\beta(t)$ and the recovery rate $\lambda(t)$ are the variables that change over time, however, the two variables are related to multiple actual factors which will be analyzed in more detail below.

(2) Degree of congested station

The number of stations directly connected to the station i can be expressed by (N_1, N_2) , where N_1 is the number of other stations in the line connected to the station i , N_2 is the number of stations in other lines connected to the station i . Based on the perspective of complex networks, the degree of station i can be calculate as $N = N_1 + N_2$. When the congestion occurs at the departure station, there are $N = 1$ and $N_1 = 1, N_2 = 0$; When the congestion occurs at the intermediate station, there are $N = 2$ and $N_1 = 2, N_2 = 0$; When the congestion occurs at the transfer station of two lines, there are $N = 4$ and $N_1 = 2, N_2 = 2$.

(3) Infection rate β

Infection rate β is the probability that congestion occurs at stations adjacent to the congested stations. It is a parameter to describe the diffusion phenomenon of PLC in the network. β_{ij} defines the infection rate for station j that is adjacent to i . Theoretically, β_{ij} is a non-negative and dynamic parameter which value is decided by the relative relationship between the number of passengers stranded on the platform and the remaining capacity of the train at the station i . The greater the value is, the greater impact the station i has on the station j .

For intermediate station, if there is a large number of passengers pouring into the train when the k th train arrives at the station i , the train will be operating full. For the station j in the upstream direction of the station i , the remaining capacity of the k th train is the number of alighting passengers at the station j . The number of assembling passengers in station j is equal to that of the passengers arriving within the interval between two trains.

$$P_{new,j}^{int} = K_{up}^j \times \int_{T_{k-1}}^{T_k} \Omega_j dt \quad (6)$$

where $P_{new,j}^{int}$ is the assembling passengers in intermediate station j within the interval between two trains, K_{up}^j is the direction imbalance coefficient of passenger flow at intermediate station j , T_k is the time for the k th train arriving at the station j , and Ω_j is the distribution function of passenger arrival rate.

For the transfer station j , there are two types of passengers gathered in the platform: one is the passengers entering the station in the operation interval, and the other is the passengers transferred from other lines to line l .

$$P_{new,j}^{trans} = K_{up}^j \times K_{up,l}^j \times \int_{T_{k-1}}^{T_k} \Omega_j dt + K_{up}^j \sum_{n=1}^{N^j-2} C_{trans}^{l,j,n} \quad (7)$$

where $P_{new,j}^{trans}$ is the assembling passengers in transfer station j within the interval between two trains, $K_{up,l}^j$ is the line imbalance coefficient of passenger flow at transfer station j , N^j is the degree of station j in the network, and $C_{trans}^{l,j,n}$ is the number of interchange passengers from other lines to the line l within the interval between two trains.

We assume that the actual cross-section passenger flow and the interval transmission capacity of each section in the initial state are known conditions. The surplus capacity of the k th train at station j can be calculated as:

$$C_{surplus,j} = C_{max,l} - \frac{Q_{ij}}{C_{ij}} \times C_{max,l} \quad (8)$$

where $C_{max,l}$ is the maximum capacity of trains in line l , Q_{ij} is the actual cross-section passenger flow in section l_{ij} , and C_{ij} is the section transport capacity in section l_{ij} .

Thus, the mathematical expression of infection rate β_{ij} can be obtained as:

$$\beta_{ij} = \begin{cases} 0 & P_{new,j} - P_{board,j} < 0 \\ \frac{P_{new,j} - P_{board,j}}{C_{surplus,j}} & P_{new,j} - P_{board,j} \geq 0 \end{cases} \quad (9)$$

where $P_{new,j}$ is the number of assembling passengers in intermediate or transfer station j within the interval between two trains, and $P_{board,j}$ is the number of boarding passengers at station j .

(4) Recovery rate λ

Recovery rate λ is the probability that infected station resumes as normal. It also is a non-negative and dynamic variable. We can infer that the more significant effect the organization method has on passenger flow, the greater value the recovery rate has. The main factors that affect λ are passengers' scale, congestion duration, the capacity of the train, etc.

For the intermediate congested station m , the number of passenger gathered on the platform when the k th train get in station m is the sum of the passengers arriving at station m within the interval and the passengers who fail to get on the previous train.

$$P_{new,m}^{int} = K_{up}^m \times \int_{T_{k-1}}^{T_k} \Omega_m dt + P_{delay,k-1}^m \quad (10)$$

where $P_{new,m}^{int}$ is the assembling passengers in intermediate station m within the interval, K_{up}^m is the direction imbalance coefficient at intermediate station, Ω_m is the distribution function of passenger arrival rate, and $P_{delay,k-1}^m$ is the passengers who fail to get on the $(k-1)$ th train.

For the transfer station m , there are three types of passengers gathered on the platform when the k th train arrived at the station: one is the passengers entering the station within the interval, the second is the passengers transferred from other lines, the third is the passengers who fail to get on the previous train.

$$P_{new,m}^{trans} = K_{up}^m \times K_{up,g}^m \times \int_{T_{k-1}}^{T_k} \Omega_m dt + K_{up}^m \sum_{n=1}^{N^m-2} C_{trans}^{g,m,n} + P_{delay,k-1}^m \quad (11)$$

where $P_{new,m}^{trans}$ is the assembling passengers in intermediate station m within the interval between two trains, $K_{up,g}^m$ is the line imbalance coefficient at transfer station m , N^m is the degree of station in the network, and $C_{trans}^{g,m,n}$ is the number of interchange passengers from other lines to the line g within the interval.

Thus, the mathematical expression of λ_m can be obtained as:

$$\lambda_m = \begin{cases} 0 & P_{new,m} - P_{board,m} < 0 \\ \frac{C_{surplus,m} - (P_{new,m} - P_{board,m})}{C_{surplus,m}} & P_{new,m} - P_{board,m} \geq 0 \end{cases} \quad (12)$$

where $P_{new,m}$ is the number of assembling passengers in intermediate or transfer station m within the interval between two trains, $C_{surplus,m}$ is the surplus capacity of the k th train at station m , and $P_{board,m}$ is the number of boarding passengers at station m .

(5) Propagation time t

In the SIR model, $S(t)$, $I(t)$ and $R(t)$ are functions of time t . In the process of PLC propagation, it will take some time for the congested state to spread to the adjacent stations.

$$\Delta t = \frac{L_{ij}}{\bar{V}} \quad (13)$$

where L_{ij} is the distance between adjacent stations i and j , and $\bar{V}$ is the average speed of the train in the section.

From Equations (9), (12), and (13), we can get the SIR model of PLC propagation.

$$\begin{cases} \frac{dS(t)}{dt} = -\frac{P_{new,j}-P_{board,j}}{C_{surplus,j}} S(t)I(t) \\ \frac{dI(t)}{dt} = \frac{P_{new,j}-P_{board,j}}{C_{surplus,j}} S(t)I(t) - \frac{C_{surplus,m}-(P_{new,m}-P_{board,m})}{C_{surplus,m}} I(t) \\ \frac{dR(t)}{dt} = \frac{C_{surplus,m}-(P_{new,m}-P_{board,m})}{C_{surplus,m}} I(t) \end{cases} \quad (14)$$

4. Numerical Experiment

In this section, we designed several simulation experiment networks based on the above analyses of the PLC propagation model in URT networks.

4.1. Sensitivity to Station Degree

The number of connected stations is a fundamental difference in the PLC propagation in the network. To ensure the accuracy of simulation results we set a unified assumption on the parameters of SIR model: $I_0 = 1$, $\beta = 0.3$, $\lambda = 0.25$. $I_0 = 1$ means that PLC occurs at a single station at initial time. β is the proportion of stations adjacent to congested stations which become congested per unit time. λ is the proportion of stations recovering from a congested state to a normal state per unit time. Before the simulation, the value of N (the number of connecting stations to the initial station) also should be first given. Considering the actual situation and the requirement for theoretical integrity, we assigned different values (i.e., 1, 2, 3, 4, 5, 6, 8, 10) to the variable N . The simulation results are shown in the Figure 3.

Figure 3 illustrates the process of change in the total amount of congested stations within 100-time lags. From Figure 3a ($N = 1$), it is obvious that the PLC dissipates quickly from the terminal or departure station. It may be explained by that the PLC at a single station can only spread in the single-line unilaterally and has little influence on the URT network. Figure 3b ($N = 2$) shows PLC spread in two directions within a single line. The number of congested stations increases before 20-time lags and then keep a stable state. Compare Figure 3a,b, it can be seen that when PLC occurs at intermediate station, the impact of congestion caused by the intermediate station is significantly greater than the terminal or departure station. Figure 3c–f illustrate that the number of congested stations converges to higher value with larger initial N . Besides, the time to reach the peak is getting shorter and shorter. The simulation results show that the higher the degree of the initial congested station is, the faster the congestion will spread in the network, and the larger influence scope the station has. When $N = 8$, the total number of crowded stations can reach peak value in a short period of time. However, the number of congested stations will not be flat curve, but fluctuates between two different levels. From Figure 3h ($N = 10$), it can be seen that the number of congested stations has a significant random fluctuation, which is similar to the period doubling bifurcation. The random fluctuation phenomenon indicates that the congestion in the network cannot be effectively controlled. It may ultimately affect the entire URT network and even cause network paralysis.

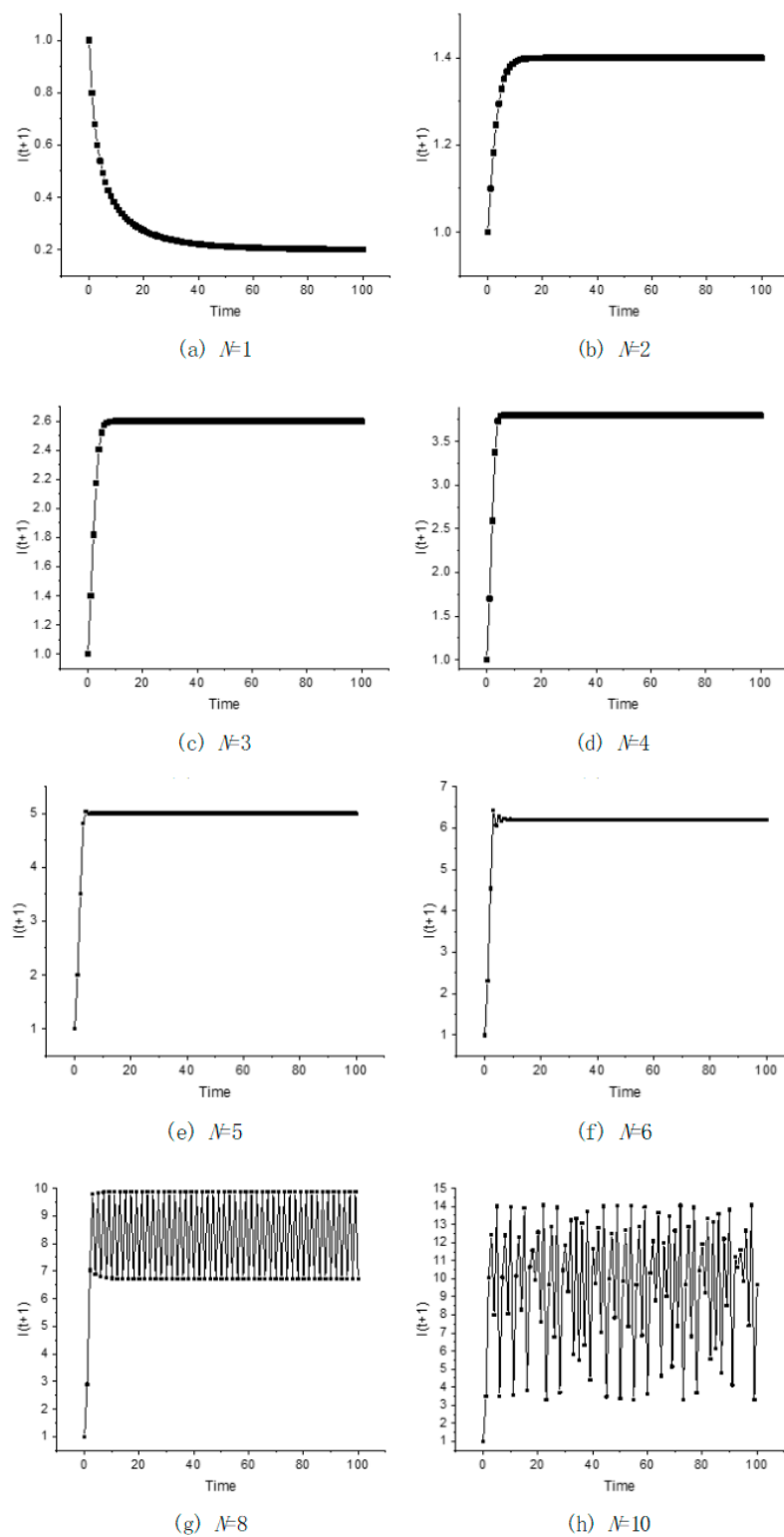


Figure 3. Simulation results for PLC propagation from a single station in different initial states.

4.2. Sensitivity to Initial Congested Stations

In this section, two different URT networks were selected to analysis the sensibility to the number of initial congested stations—a URT network with $\beta = 0.3$, $\lambda = 0.25$, $N = 4$, and the other one with

$\beta = 0.35, \lambda = 0.15, N = 4$. Six scenarios ($I_0 = 1, 2, 4, 5, 6, 7$) were simulated and the simulation results are shown in Figures 4 and 5, respectively.

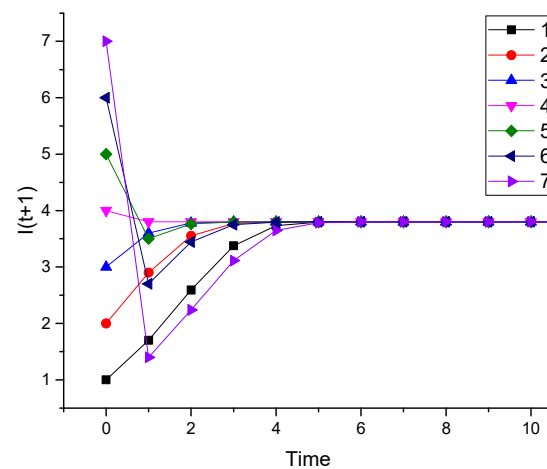


Figure 4. The convergence of the total number of congested stations with time when the urban rail transit (URT) network is not intensive.

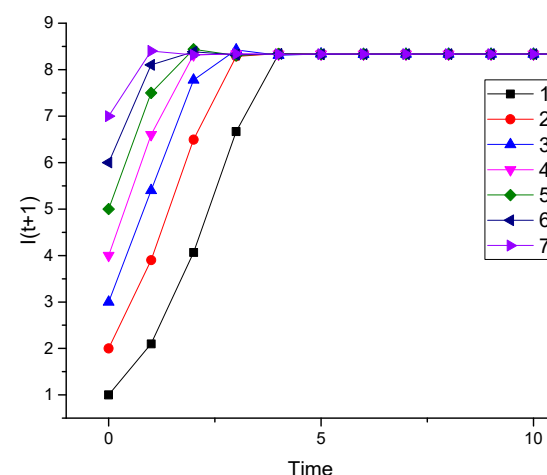


Figure 5. The convergence of the total number of congested stations with time when the URT network is dense.

Figures 4 and 5 present the propagation process of PLC from multiple stations in the initial state. The number of congested stations converges to a same fixed value under the same initial conditions including infection rate, recovery rate and topology structure, whereas, a larger number of initial congested stations can lead to a faster convergence process. It can be seen from Figure 4 that although a different number of stations are congested in the initial state, the eventual number of congested stations are the same, and a total of about 4 stations are affected by PLC. Figure 5 shows similar characteristics with Figure 4. The number of eventually affected stations are the same among different scenarios, and a total of about 8 stations are affected by PLC. Compared with the final convergence results of Figures 4 and 5, it suggests that PLC propagation is more difficult to dissipate in the dense URT networks.

4.3. Sensitivity to Infection Rate and Recovery Rate

In this section, we explored the impact of the infection rate and the recovery rate on the PLC propagation in the SIR model. Two scenarios of PLC propagation processes were simulated, and the numbers of the congested stations under the two scenarios were obtained as shown in Figures 6 and 7.

In the first case, we set the infection rate β with a fixed value and the recovery rate λ with different values; in the second case, we set the recovery rate λ with a fixed value and the infection rate β with different values.

In the first scenario, the recovery rate was assigned with a fixed value of 0.25, and the assigned values of infection rate are ordered from high to low: 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45. From Figure 6, we can infer that the number of eventually congested stations increases with the infection rate. The infection rate is determined by the number of passengers waiting on platform and the operating speed of trains to some extent according to Equation (9). The trains in URT are usually run at a fixed speed. In other words, the PLC can spread more widely throughout the network, if there are more passengers waiting on the platform. The second scenario was given with $\beta = 0.25$, and the assigned values of recovery rate are ordered from high to low: 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40. From the Figure 7, it can be concluded that with increasing recovery rate, less stations will be congested eventually. The number of congestion stations has a decreasing trend from the beginning if there is $\lambda > \beta$. On the contrary, if there is $\lambda < \beta$, the number of congestion stations increase from the initial state, and duration of PLC propagation process becomes longer with larger value of recovery rate. Particularly, when $\lambda < \beta$, a little decrease in the value of recovery rate λ may contribute to great serious congestion. It suggests that appropriate transport organization measures for the purpose of increasing recovery rate λ is a useful method to prevent the proliferation of PLC in URT networks.

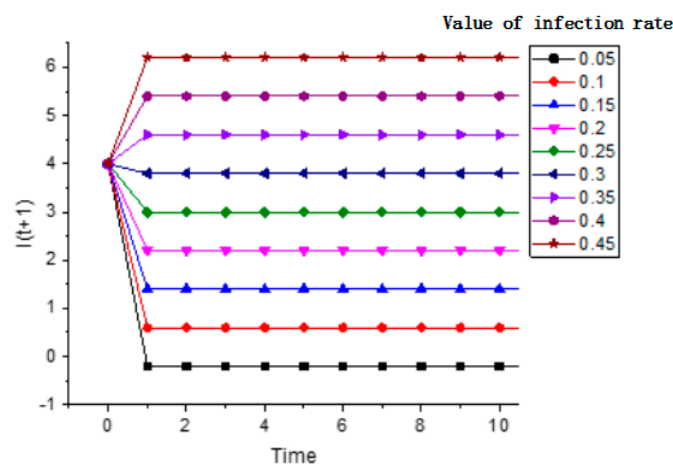


Figure 6. The total number of congested stations with the increasing of infection rate β while the recovery rate $\lambda = 0.25$.

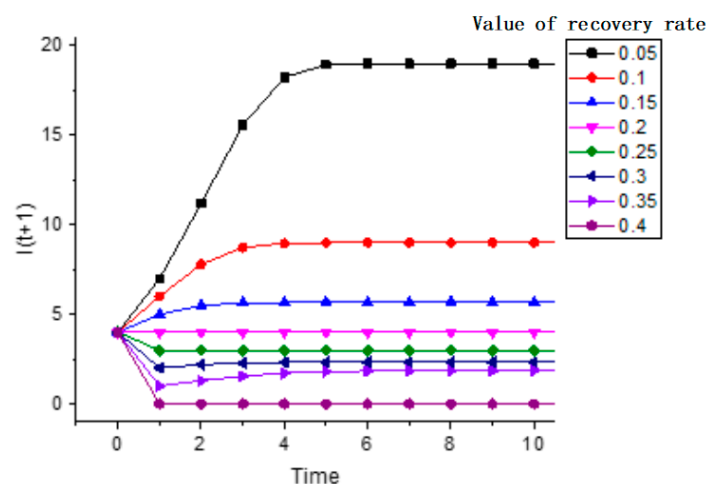


Figure 7. The total number of congested stations with the increasing of recovery rate λ while the infection rate $\beta = 0.25$.

5. Control Strategy

According to the type of object targeted at, the control strategies for URT networks can be divided into two categories: supply control and demand control.

5.1. Supply Control

(1) Train marshalling plan

Train marshalling can be categorized into three types: large grouping, small grouping, and mixed marshalling. For the rail transit lines, with long average travel distance and high travel demand, the train transport capacity can be improved by increasing the marshalling number and departure frequency of trains.

(2) Train routing plan

Train routing plan refers to the trace that the train operates on the rail lines. It has two different modes: conventional routing and special routing. Conventional routing scheme refers that a train travel along tracks between two terminal stations of the rail line. There are three typical kinds of special routing scheme, as shown in Figure 8. Figure 8a represents junction routing scheme that is able to take into account the various demands of different line sections. In the case of larger and more concentrated half passenger flow at the end of one line, the nested routing scheme, which is shown in Figure 8b, can reduce transportation costs and improve utilization of trains. Figure 8c is a staggered routing scheme, which is suitable for connecting the suburbs and the urban areas, and the passenger flow in each section is unbalanced and shows centripetal characteristic.

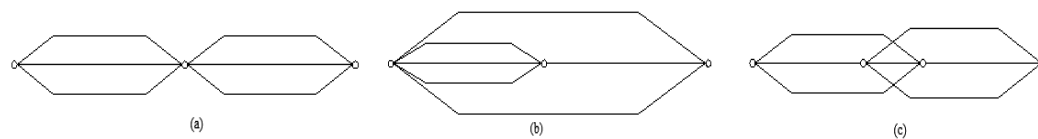


Figure 8. Special routing scheme.

(3) Stopping schedule

In URT networks, stopping schedule mainly includes stopping at each station and a skip-stop strategy. The skip-stop strategy represents that some determinate or stochastic trains could skip one or more stations. Compared with stopping at each station, the skip-stop strategy is able to reduce congested passengers' travel time by eliminating under-saturated stations' dwell time. It is usually applied during peak periods or when there is outburst mass passenger flow such as large sports tournaments.

As discussed above, supply control measures are able to increase the surplus capacity of trains by increasing train departure frequency and operating speed. According to Equations (9) and (11), the infection rate is negatively associated with the surplus capacity of trains, whereas the relationship between the recovery rate and the surplus capacity of trains is positive. Figure 9 displays the changes in infection rate and recovery rate versus different increased multipliers of surplus capacity given an initial parameters pair ($\beta = 0.45, \lambda = 0.1$). It can be seen that both the curves of infection rate and recovery rate tend to be flat with larger increased multiplier of surplus capacity. In other words, the variation of these two parameters is more sensitive when the surplus capacity begins to change. We conducted numerical tests here to assess the performance of the PLC propagation for four assumed supply control scenarios that the increased multipliers of the surplus capacity equal to 0.1, 0.2, 0.3, and 0.4, respectively. The corresponding parameters are shown in Table 1. Figure 10 presents the simulation process of these four scenarios. The simulation results indicate that supply control measures can not only reduce passengers' travel time but also relieve congestion pressure.

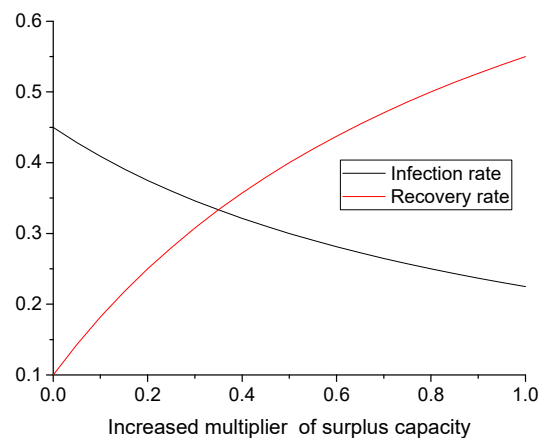


Figure 9. Changes in model parameters versus increased multipliers of surplus capacity.

Table 1. The related parameters of supply control measures.

Supply Control Measures	Infection Rate β	Recovery Rate λ	Max I (t + 1)
Without control measure	0.45	0.10	17.40
Control measure 1	0.41	0.18	8.40
Control measure 2	0.38	0.25	5.08
Control measure 3	0.35	0.31	3.52
Control measure 4	0.32	0.36	2.56

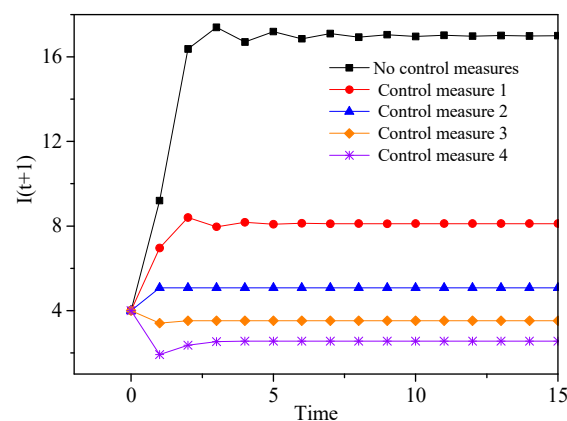


Figure 10. Comparison of supply control measures.

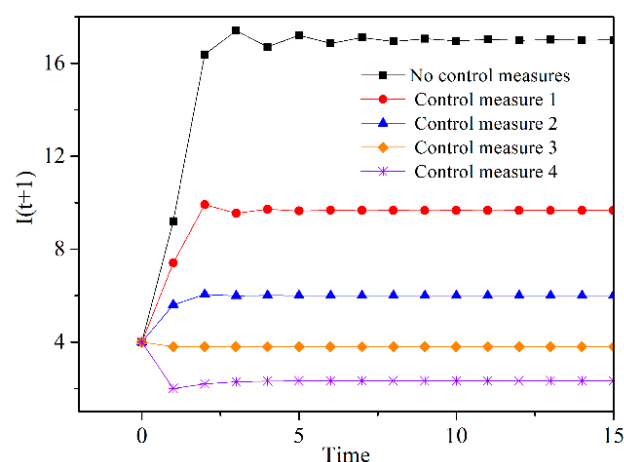
5.2. Demand Control

When the inbound and outbound passenger flow increases, the capacities of automatic ticket machines, security facilities, and tap-in/tap-out gates may be insufficient, where the bottleneck of PLC evacuation will occur. The basic strategies of demand control in URT networks include: outbound manual auxiliary and restricted entrance. The outbound manual auxiliary measures are as follows: ①manual ticket; ②manual fare collection; ③evacuation passenger flow through broadcasting. When the phenomenon of PLC does not alleviate, we can take three additional levels of restricted entrance measures to alleviate PLC pressure. The contents of the restricted entrance measures are shown in Table 2.

Table 2. The contents of the restricted entrance.

Level of Restriction	Action Position	Detailed Content
Level I	Platform/Platform channel	Intercept passenger flow, close channel or change escalator running direction
Level II	Subway hall/Gate	Control passenger flow continued to enter the payment area
Level III	Station entrances	Control passenger flow into the station

As distinct from supply control measures, demand control measures can lead to a reduction of the net platform-passenger variation (i.e., the assembling passengers minus boarding passengers within the interval between two trains). Based on Equations (9) and (11), there is positive correlation between the infection rate and the net platform-passenger variation, and the station with less crowded platform has a larger recovery rate. Although demand control measures can generate similar effects, namely less impact of congested stations and easier recovery to the normal state, both the two parameters present linear correlation with the net platform-passenger variation, as shown in Figure 11, which is different from the inverse proportion relationship for supply control measures. To evaluate the performance of demand control measures, four assumed universal demand control scenarios were simulated and compared with the initial parameters pair $\beta = 0.45$, $\lambda = 0.1$. For each of the scenarios, we reduced the same number of net platform-passenger variation for all stations. The related parameters of the assumed demand control scenarios are shown in Table 3, and the effect of demand control measures on PLC propagations is shown in Figure 11. The results indicate that demand control measures can significantly reduce the propagating scope of PLC.

**Figure 11.** Comparison of demand control measures.**Table 3.** The related parameters of universal demand control measures.

Demand Control Measures	Infection Rate β	Recovery Rate λ	Max I (t + 1)
No control measure	0.45	0.10	17.40
Control measure 1	0.40	0.15	9.92
Control measure 2	0.35	0.20	6.05
Control measure 3	0.30	0.25	3.80
Control measure 4	0.25	0.30	2.33

Compared with the simulation results in Table 1 and Figure 10, the decrease in maximum number of congested stations in demand control scenarios is smaller than that in supply control scenarios, when taking mild control measures. However, with evenly strengthening control measures, demand control measures can achieve better congestion control performance than supply control measures.

It suggests that supply control measures have advantages under the situation, when there is slight congestion. Nevertheless, demand control measures should be more effective if a serious congestion occurs at the metro network.

What is more, demand control measures can be implemented exactly to control specific stations, whereas supply control measures can only be applicable to rail lines or long routing sections. For example, we can only conduct demand control measures to the congested stations. It means that the infection rate will be fixed and the recovery rate will increase. We simulated four specific demand control scenarios that only have different recovery rates. The corresponding parameters and simulation results are given in Table 4. As shown in Table 4, the maximum numbers of congested stations for different specific demand control measures are approximate to the values for universal demand control measures. That is, the specific demand control measures are also effective in reducing congestion. Besides, the specific demand control measures are more easily implemented because it need less staff and management adjustment.

Table 4. The related parameters of specific demand control measures.

Demand Control Measures	Infection Rate β	Recovery Rate λ	Max I (t + 1)
No control measure	0.45	0.10	17.40
Control measure 1	0.45	0.20	8.35
Control measure 2	0.45	0.30	5.20
Control measure 3	0.45	0.40	3.58
Control measure 4	0.45	0.50	2.61

6. Conclusions

This study focuses on the analysis of PLC propagation and the effect of control strategies to alleviate congestion for URT networks. Based on theories of epidemiological dynamics and complex network, an SIR-based model is established to simulate the propagation process of PLC in URT networks. Combined with the characteristics of passenger flow and train operation organization in URT, the mechanism of each parameter in SIR model is discussed deeply in this paper. We simulated the process of PLC propagation under various situations and analyze the sensitivity of PLC propagation to model parameters. Finally, the control strategies of PLC propagation were discussed from two aspects, namely supply control and demand control, and the effectiveness of control measures was verified with the proposed model.

The results indicate that both of the two control strategies are able to contribute to relieving congestion pressure by reducing the infection rate and increasing the congestion recovery rate. The propagating scope of PLC is more sensitive when taking mild supply control, whereas the demand control measures show advantages in dealing with serious congestion. Besides, demand control measures can be flexibly implemented to specific stations with less staff and management adjustment. This work can help the URT agencies in understanding the mechanism of PLC propagation process and providing a helpful decision for congestion management.

Future work will concentrate on making the main characteristic parameters in the model more meticulous, as well as establishing the function of infection rate and recovery rate with time. Furthermore, the new model should also be tested with actual and dynamic situations.

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