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The Role of China Rail Network in SARS-CoV-2 Transmission and Intervention

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***Abstract*—The rail can be competitive with car and air travel in terms of costs and journey time in countries with developed rail networks. However, it may potentially play a role in facilitating pandemic spread when encountering SARS-CoV-2. Mainly focusing on the role of rail traffic, this research constructs a 2-layer China rail network topological model based on collected China rail data, identifying 3 dynamic transmission scenarios. Then introduces the rail mobility rate into the traditional dynamic transmission model in epidemiology to fit the model for rail transportation. Finally, taking SARS-CoV-2 as an example, the transmission dynamics of sars-cov-2 is studied by simulation experiments, and the orbital movement rate control in different scenarios is measured as one of the potential interventions. Experiment outcomes lead to some managerial insights that (1) with an initial outbreak on the core layer, a faster response is required, while with an eruption on the periphery layer, more appropriate reactions and interventions are encouraged. (2) Adjusting the rail mobility rate of periphery transmission can be used to delay the local outbreak of SARS-CoV-2 in previously unaffected regions.**

Keywords-Complex network; rail; Pandemic dynamics; simulation;

I. INTRODUCTION

An outbreak of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has led to over 17 million confirmed cases as of August 2020 [1]. Until now, no approved vaccine to SARS-CoV-2 has been validated, and interventions are limited to contact tracing, quarantine, and social distancing. Compared to other coronaviruses, such as SARS-CoV-1 and MERS, higher infectiousness of SARS-CoV-2 makes it harder to control with case-based interventions. In this case, the effects of measures like intensive testing, isolation, and tracing become unstable and unpredictable. Therefore, looking into how the initial pandemic wave unfolds and on the subsequent transmission dynamics contributes to apply these measurements by defining their intensity, duration, and urgency, crucial for understanding pandemic transmission dynamic, evaluating the effectiveness of interventions, and assessing the potential for sustained transmission to occur in new areas as well.

More travelers in China show the propensity currently making interurban journeys by car and air to transfer to high-speed rail services. A possible preference lies in journeys within 6 hours by high-speed rail, where rail can be competitive with car and air travel in terms of costs and journey time [2]. Here, regular travelers are more likely than those elsewhere to use rail. This convenience of China rail network, however, may potentially play a role in accelerating transmission of SARS-CoV-2. Therefore, research on pandemic spread through China rail network helps to better understand the transmission paths, identify crucial influencing factors, and evaluate effective intervention measures, thus gaining time to enhance surveillance systems and allocate resources. On another note, it offers other rail transportation developed countries an alternative approach to estimate risks of pandemic transmission on the rail network and thus guide rail operators and policymakers on the design of effective interventions. In this paper, we present the results covering these issues to explore further in this area.

The contribution of this study is twofold. First, based on an empirical dataset, we construct the China rail network topological model with multiple layers. Thus, several dynamic transmission scenarios targeting rail passengers are defined, coming with various rail mobility rates. Second, the rail mobility rate is introduced into the SEIR model as a parameter, and then we apply this epidemical model tailored for rail

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transportation on the network in a set of experiments to simulate the pandemic transmission dynamics and feasible interventions. The outcomes with managerial insights offer values for decision-makers in rail sectors.

The rest of the paper is organized as follows. The second part overviews related theories in epidemiology and complex network. In the third part, it claims China rail network topological model construction and the corresponding epidemic dynamic model with rail mobility rate introduced. Then follows the stimulation experiments and result analysis in the fourth part. The whole research is concluded in the final part.

II. LITERATURE REVIEW

A. *Epidemiology and transportation*

Early research in epidemiology focused on compartmental models, the original important work of which came from Kermack and McKendrick in 1927 [3]. Compartmental models divide the population to compartments with labels in order, for example, S (Susceptible), I (Infectious), or R (Recovered). People may progress between compartments. Widely used compartmental models include SIS (Susceptible-Infected-Susceptible) model [4] and SIR (Susceptible-Infected-Recovered) model [5]. These compartmental models provide a theoretical framework that allows for the study of epidemic containment, which requires other factors in consideration to fill in high-resolution details. Factors such as increasing speed and reach of human mobility, increasing volumes of trade and tourism, and changing geographic distributions of disease vectors readily facilitate the global spread of infectious diseases. In particular, human travel and migration is now a major driving force pushing infections into previously non-endemic settings due to growing volumes of travelers and migrants year by year and thus stirred up interests and enthusiasm among researchers [6].

While the research on coping with an epidemic outbreak from the human mobility point of view provides a mature body of knowledge, the literature on analyzing epidemic outbreaks and transmission through rail travel, especially on China rail network is scarce. We consider this as a research gap and an opportunity to develop substantial contribution.

B. *Complex network and transportation*

With the emergence of small-world and non-scale network, the complex network has attracted lots of attention. Many researchers applied complex networks in transportation to further study structure characters of transportation networks, such as the civil aviation network, the railway network, etc. Recently there are some research combined dynamics and complex networks to explore passenger flow [7] or train delay [8] on transportation networks.

Most of the previous research focuses on random, scale-free, small world networks with the use of synthetic datasets based on theoretical models [9]. It creates space for the usage of other models and the need for real data collection is growing to better address real-world challenges. On the other hand, reaction to pandemic transmission and feasible interventions among cities on China rail network is still urgent and on-demand. Thus, to fill the research gap and further explore this area, this paper identifies a 2-layer China rail network topological model based on real datasets from China rail, and then simulates pandemic transmission and control on this network model. To better reflect the real scenarios, rail mobility rate is introduced as a novel parameter to further study pandemic diffusion and intervention, leading to some guides and references for policymakers in rail operating sectors.

III. METHODOLOGY

The dataset comes from China passenger rail timetable published on July 16th, 2019, on the website named 12306, an official e-ticking website launched by the China Railway. The giant component of the original network is used in this research to construct a fully connected graph model. The giant component dataset D_s contains 9569 items, including train number, departure station, and destination. Pandemic transmission caused by people traveling among rail stations in the same city or region goes beyond the scope of this research. And thus, this research combines those stations and transforms D_s to the dataset D_m, including 3054 items.

A. *China rail network topological model (CRN)*

Degree distribution of China rail network leads to an important question that concerns the degree to which mobility restrictions can achieve containment at the source of the pandemic, especially in combination with timely mitigation policies in the country of origin. To this end, we consider a simplified modeling framework based on a multi-layer scheme describing a network of cities (nodes) coupled with rail mobility (links) whose features reproduce the topological and mobility properties of real-world rail transportation systems. Since eigenvector centrality is widely used in the transmission network, such as pandemic transmission, this paper classifies nodes through eigenvector centrality and thus builds a 2-layer China rail network model, including the core layer, and the periphery layer respectively. Finally, 29 cities and their connections compose the core layer, and other cities and regions constitute the periphery layer. These two layers constitute the main body of the China rail network model, termed as CRN. For better understanding, the connection between these 2 layers, core cities and periphery cities on different layers are projected into the same space, called the connected layer. Figure 1 indicates geographical layers and their corresponding topological structures, constructed as the network model in the following simulation experiment.

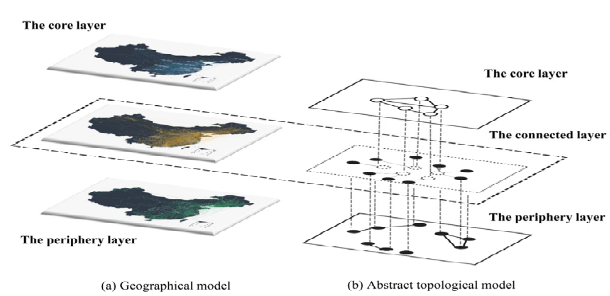

Figure 1. China rail network model (CRN)

China rail network model is an undirected weighted network graph, whose nodes represent cities, and edges dedicate quantities of the train traveling between two cities and regions. Specifically, the weight of the edge is the proportion of numbers of trains in dataset D_m. Based on the node position, dynamic transmissions on this network model can be classified as the following:

- Core transmission: pandemic spreads among nodes on the core layer
- Periphery transmission: pandemic diffuses among nodes on the periphery layer
- Connected transmission: pandemic transmits back and forth between the core layer and the periphery layer, or in other words, on the connected layer.

B. *Dynamic model in epidemics based on rail mobility rate*

This paper applies the SEIR model to simulate pandemic transmission among cities, which are assigned to the following categories: suspectable cities(S), exposed cities(E), infected cities(I), and recovered cities(R). Different from traditional epidemic models, this research introduces rail mobility rate m into the SEIR model to describe transmission routes among cities and reflect the spreading process on the complex China rail network. Rail mobility rate refers to the probability of travel by rail. Without considering the birth rate and mortality rate of the sample population, taking city i as an example, compartments of the city i and one of its neighbor city j change as below in figure 2.

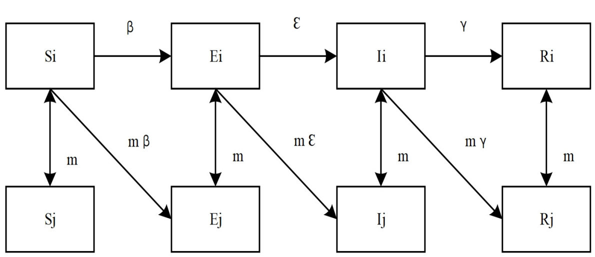

Figure 2. Dynamic transmission model based on rail mobility rate, where β, ε, and γ are the rates of contact, infection, and recovery in city i, respectively; m refers to rail mobility rate; correspondingly, mβ, mε, mγ are the rates of contact, infection, and recovery from city i to city j, respectively.

The corresponding dynamic calculus equation of every city i and its adjacent node j shows the following.

$$
\begin{cases}
\dfrac{dS_i}{dt} = mS_j - mS_i - \dfrac{\beta S_i I_i}{N_i} - \dfrac{m\beta S_j I_j}{N_j} \\
\dfrac{dE_i}{dt} = \dfrac{\beta S_i I_i}{N_i} - (\varepsilon + m)E_i + mE_j + \dfrac{m\beta S_j I_j}{N_j} - \dfrac{m\varepsilon E_j I_j}{N_j} \\
\dfrac{dI_i}{dt} = \varepsilon E_i - (\gamma + m)I_i + mI_j + \dfrac{m\varepsilon E_j I_j}{N_j} - \dfrac{m\gamma I_j R_j}{N_j} \\
\dfrac{dR_i}{dt} = \gamma I_i - mR_i + mR_j + \dfrac{m\gamma I_j R_j}{N_j}
\end{cases}
$$

C. *Model indicators and parameter calibration*

To clarify the outcomes, this research further defines measurements of pandemic transmission intensity and influence range in table 1, based on the common indicators.

TABLE I. MEASUREMENTS AND EXPLANATIONS

	Measurements	Explanations
Transmission intensity	Prevalence peak	The maximum value of prevalence
	Transmission speed	The time of prevalence showing the maximum value
Influence range	Recovered peak	The maximum value of recovered fraction
	Susceptible bottom	The minimal value of susceptible fraction

Specifically, prevalence peak and transmission speed can reflect eruption intensity on the network, and recovered peak and susceptible bottom mirror pandemic influence and spread range on the network, for they usually appear at the end of pandemic transmission and then stay stable values. These quantitative measurements describe the pandemic transmission process in a clear and comprehensive approach, echoing the corresponding influence on the population and region through transmission on China rail network.

Parameters involved in the simulation experiments are listed in table 2, some of which are set and calibrated according to empirical events and previous research.

TABLE II. MEASUREMENTS AND EXPLANATIONS

Parameter	Symbol	Specification and calculation	Calibration
Time	T	Describe transmission process, calculates by day	
Number of initial infected cities	In	The number of infected nodes when the experiment begins	
Positions of initial infected cities	Ip	Positions infected nodes locate when the experiment begins, on the core layer or the periphery layer	
Contact rate	β	$\beta = \beta_0 k$, β_0 denotes the probability of contact per exposure, k denotes the exposure frequency	1[a]
Infected rate	ε	$\varepsilon = 1/Te$, Te denotes the average latency	1/7[a]
Recovered rate	γ	$\gamma = 1/Ti$, Ti denotes the average recovery time	1/10.25[a]
Rail mobility rate	m	The proportion of population travel by rail	

a. According to Fang et al. [10], set the following parameters as β=1, Te=7, Ti=10.25

The following settings make the model more in line with the real situation:

Contact rate β declines with time

Usually, contact rates of most pandemic diseases decrease with time [11], while in SARS-CoV-2 the previous research verified this as well [12], thus, this proposed model sets the contact rate β the same way. During time T after pandemic outbreaks, from the initial point to 0.3T, the contact rate sets β, and then β equals to 0.8β from 0.3T to 0.6T. During the following 0.2T, from 0.6T to 0.8T, β decreases to 0.7β. In the final 0.2T, β sets half of the initial value, 0.5β.

Rail mobility rate m varies in different scenarios

Considering a higher flow of population migrates to core cities and areas compared to migration to periphery ones, and based on the assumption that China railway dispatching is designed according to the passenger demands, the rail mobility rate between two cities can be estimated through the number of trains traveling back and forth to these cities. Therefore, rail mobility rates are calculated under the three dynamic transmission scenarios of the core layer, the periphery layer, and the connected layer. Taking the core layer as an example, the number of trains traveling among cities on the core layer is divided by the number of trains in the dataset, calculating the rail mobility rate of the core layer is 0.346. The rail mobility rates of the periphery layer and the connected layer are computed in the same way, as 0.132, and 0.522, respectively.

IV. Simulation experiments and result analysis

This research conducts the simulation experiment in the following 2 aspects. The first part shows the pandemic transmission in the natural condition, analyzing the pandemic transmission pattern on the China rail network compared to the spreading process on the Erdos-Renyi (ER) graph. Taken initial outbreaks into consideration, the second part observes the differences of pandemic transmission process through manipulating rail mobility rates under 3 dynamic transmission scenarios, and thus digs into practical intervention measurements, providing guidance to policymakers and rail operating companies. All experiments use prevalence peak, transmission speed, recovery peak, and susceptible bottom as indicators to measure the pandemic impacts on the network. In order to verify the experiment results and reduce the randomness, the simulation experiment under each condition is repeated 100 times, with the mathematical average of results taken on records.

A. Transmission process in the natural condition

This part conducts a 100-day long experiment simulating SARS-CoV-2 outbreaks and spreads on the CRN model, with one initial infected city at a random position, and other calibrated parameters. The simulation experiment under the same condition is also conducted on the ER graph. Compared different transmission process on constructed China rail network and ER graph, shown in figure 3(a) and 3(c), this pandemic diffuses faster on CRN model, while it influences in a larger range on ER graph till pandemic comes to stable at the end of the transmission. However, this difference cannot count all on network structures, because rail mobility rates vary in the CRN model while it stays stable in the ER graph, which means inconsistency of rai mobility rates may lead to this result as well. To further figure out the role of network structures, set rail mobility rates the same value (m=0.346) in the CRN model and ER graph. Analyzing the results shown in figure 3(b) and 3(c), pandemic still disseminates as a leading speed on the CRN model with the stable rail mobility rate, meaning SARS-CoV-2 requires an urgent response and in-time interventions for its spreading trend after outbreaks.

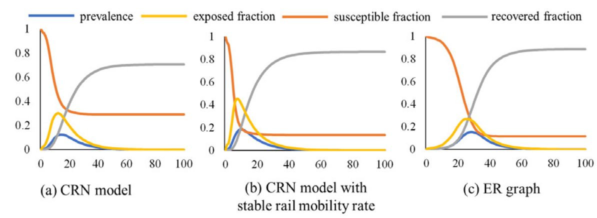

Figure 3. SARS-CoV-2 dynamic transmission on (a) CRN, (b) CRN with stable rail mobility rate and (c) ER graph

B. Intervention and control based on CRN

As mentioned in the first part of the experiment, various rail mobility rates contribute to different transmission patterns. Thus, through setting values of rail mobility rates under 3 dynamic scenarios, this part of the experiment probes roles of rail mobility rates in the pandemic spreading process, leading to potential intervention policies and measurements for rail transportation sectors.

To simplify the simulation conditions, this part sets the number of initial infected cities as 1, and thus initial conditions of the SARS-CoV-2 outbreak are limited to 2 kinds, node on the core layer and the periphery layer, respectively. Then taking the rail mobility rate as a variable, we adjust those of the core layer, the periphery layer, and the connected layer from 0.05 to 1 with each increment as 0.05 under above 2 initial conditions.

Experiment results reflect transmission strength from prevalence peak and transmission speed, respectively, visualized from figure 4 to figure 5. The influence on prevalence peak shows a similar pattern that prevalence peak increases with rail mobility rate growing. Figure 5 demonstrates that a large enough rail mobility rate may substantially facilitate an outbreak and the subsequent spreading, and meanwhile, the order of influences on spreading speed through adjusting the rail mobility rate is the core layer, the periphery layer, and then the connected layer. From the influence range, as shown in figure 6 with increasing rail mobility rate, the recovery peak mirrors an upward trend in various initial conditions. Further, changing the rail mobility rate of the periphery layer leads to the most obvious influence, then followed by the core layer, and the connected layer ranking at the least. Similar to the transmission speed, when the initial outbreak is located on the periphery layer, the corresponding alteration of the recovery peak becomes more significant.

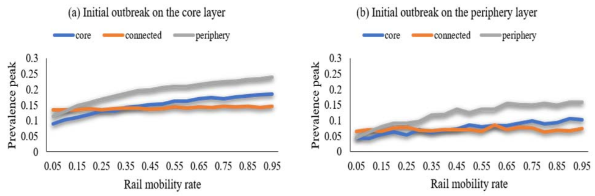

Figure 4. Influence of rail mobility rate on prevalence peak

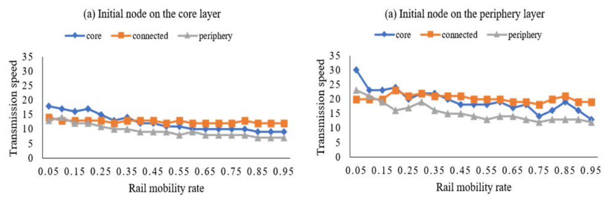

Figure 5. Influence of rail mobility rate on transmission speed

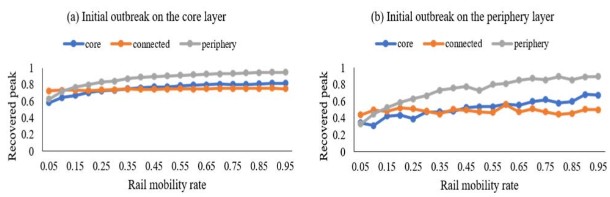

Figure 6. Influence of rail mobility rate on recovery peak

Experiment results mentioned above allow for the following insights:

a) Adjusting the rail mobility rate of the periphery layer is one of the potential interventions and measurements affecting pandemic transmission intensity and influence range. Experiment results show that with the rail mobility rate of the periphery layer increasing, prevalence peak and recovery peak grow at a significant pace. Moreover, pandemic intensity and influence range exceed those under other conditions when the rail mobility rate of the periphery layer reaches a certain value.

b) Changing the rail mobility rate of the core layer works more effectively with the purpose to delay the pandemic transmission. SARS-CoV-2 spreads rapidly on the China rail network, proposing a higher requirement to reaction speed and intervention efficiency. Therefore, taking the rail mobility rate of the core layer manipulation in the early phase of the pandemic outbreak can delay local spreads, allow additional time for preparation of the health system and further effective treatment, and thus mitigate pandemic risks, even if containment is ultimately impossible.

c) When the pandemic outbreak on the periphery layer, it needs more adjustment and control to rail mobility rates. For all scenarios, varying the rail mobility rate may more substantially delay the pandemic spread and limit the influence range on China rail network, when the initial infected node is located on the periphery layer.

V. CONCLUSION

In this research, we define a 2-layer complex network model for the China rail network, termed as CRN, based on an empiric China rail passenger dataset, leading to the core layer, the periphery layer, and the connected layer dynamic rail mobility scenarios. In addition, we introduce the rail mobility rate into the traditional epidemic SEIR model and then conduct simulation experiments through CRN. Our analysis reveals that the pandemic outbreaks start small but scale fast and disperse over many geographic regions with rail transmission which makes it comparatively difficult to fully estimate the impact of the pandemic outbreak on the China rail network and the right measures to react. To address this uncertainty, a set of experiments have been conducted to uncover how the pandemic spreads among cities and areas on the China rail network with time and further to offer the possibility of intervening the pandemic impact through adjusting the rail mobility rate of each dynamic transmission scenario.

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