THE IMPACT OF THE METRO SYSTEM ON THE SPREAD OF COVID-19

Chui-Sheng Chiu[1*], Pei-Fen Kuo[2]

Department of Geomatics, National Cheng Kung University, Taiwan

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ABSTRACT:

At the beginning of the COVID-19 pandemic, most scholars focused on how international transportation (such as airlines) spread the virus to different countries. At this point, scholars have begun to pay more attentions on how COVID-19 locally transmission via ground transportation systems. Because many people use these ground services to commute in urban areas, a high passenger volume may lead to a domestic large outbreak. Without detailed disease spreading path, healthcare professionals are still not sure where and how to apply these anti-epidemic measures. Therefore, this study chose the Taipei metro system as our study area to investigate the relationship between metro station passenger volume and COVID-19 transmission. By using the electric metro ticket data, we know the movement of metro passengers in Taipei, and this OD movement dataset was used to estimate the spreading path of the COVID-19. In order to simulate possible Covid-19 spreading cases in the real world, two different methods (the agent-based model (a micro-level simulation) and the effective distance method (a macro-level estimator)) were applied. Then, we compared the COVID -19 arrival order for each station. In our result, the average infectious order of stations of agent based model and shortest path effective distance is similar. Among all stations, Taipei Main Station is the first infectious station, and the top 15 infectious stations are similar according to result of the two method. Our result may help the authority choose proper methods to simulate the epidemic local transmission and then allocate resources effectively in the future.

[*] Corresponding author
1 : Email : san1.chiou@gmail.com
2 : Email : peifenkuo@gmail.com

1. INTRODUCTION

Approximately two years after the Covid-19 outbreak, this virus has not been eradicated and still affects our daily lives. In addition to the spread of new cases globally, the increases in local cases and local transmission rates have become an important issue recently. In most countries, the infection numbers have dropped; however, the accumulated cases are still on the rise. In other words, at the beginning of the pandemic, scholars focused on how international transportation (such as airlines) played a role in spreading the virus to different countries. At this point in the pandemic, researchers have begun to pay more attention to how ground transportation systems (trains, highways, and metro systems) play a role in the spread Covid-19. Because many people use these services to commute in urban areas, a high passenger volume may cause a large outbreak. It follows that the passenger volume of land transportation and potential transmission risk tend to increase the spread of Covid-19 (Yin et al., 2021; Liu et al., 2020; Ruan et al., 2015; Wu et al., 2021). Despite these findings, relatively few scholars have estimated the actual risk of such modes of transportation. Some researchers have even suggested that cities with high infection rates should consider shutting down public transportation to avoid further transmission (Patel et al., 2020). Otherwise, asymptomatic individuals are difficult to quarantine, and are more likely to continue using the transportation systems.

Risk of infection will surge during peak hours or travel for holidays. For example, Wong (2019) found that almost 440 million people traveled via Wuhan’s railway line during China’s New Year festivities, which clearly increased the spread of the disease. Interestingly, among the various ground transportation options, Zhao et al. (2020) showed that only trains and passenger volume are significantly related to the spread of COVID-19. That is, both air and highway travel were shown to be insignificant. These findings are convincing because the COVID-19 virus can survive for more than three hours in closed, humid environments, such as train cars, underground platforms, and stations. Although the studies discussed above provide some background information on how the metro system has increased transmission, the details of how it is spread remain unclear since most of these studies simply relied on a regression model or focused on defining the correlation coefficient. Therefore, these theorem results cannot be used to dictate the decisions of policymakers or metro station managers. In addition to developing more effective vaccines, other approaches may be used to curb the spread of the virus such as closing down some hub and commonly used stations to reduce exposure, disinfecting train cars as well as allocating more manpower to oversee these stations. Questions of where and in which order we should apply these anti-epidemic measures are still debated among healthcare professionals.

Among the existing studies of disease spreading simulation modeling, most of their approach could be classified as macro-level or micro-level analysis. Macro level analysis incorporates statistics and mathematical formulas, which are commonly referred to as equations-based models (EBM) to represent the macroscopic trends of disease spreading. For example, Lin (2020) utilized an effective distance model based on passenger volume to illustrate the regional transmission risk of COVID-19 in Chinese cities. By using mathematical formulas, the results show that COVID-19 spreads faster in cities with higher connection density. According to the above-mentioned literatures, the results of macro-level analysis could illustrate the general trend of disease spreading pattern, which is more meaningful to policymakers because it covers a larger study area with less detailed data (Jia et al, 2018). However, this kind of analysis could not simulate how the disease spread from individual to individual, nor could it show the movement pattern of infected people for more detailed analysis.

On the other hand, with regard to the micro-level analysis, the majority of current study utilized an agent-based model (ABM) to simulate the disease spreading from individual to other Individuals in this analysis are referred to as agents, and they have a variety of characteristics (e.g., age, health status) and behaviors (commute/stay at home). The characteristics of this agent may determine their actions, which may contribute to disease spreading. For example, agents can interact with one another when they are in the same station or train car. Under such circumstances, the infectious agent would be able to transmit the disease to the nearby susceptible agent (Gomez et al., 2021; Gaudou et al., 2020).

Furthermore, ABMs can capture various disease spreading scenarios that result from the combination of individual behaviors in a model governed by a set of coded rules. Tang et al. (2009) conducted a study that compared two different disease spreading scenarios to accurately demonstrate the transmission of Severe Acute Respiratory Syndrome (SARS). In the first scenario, they assumed that every agent's neighbor has the same chance of becoming infected because the agent (infected people) move randomly, which is known as random-diffusion While the second scenario assumed that only the neighbor along the shortest path can get infected by the agent and all the other neighbors have no chance where it referred as objective traveling. The results show that the second scenario infected a larger population because objective travel will most likely go through hubs (frequently visited places) and random diffusion will only go to neighboring nodes (Wang et al., 2014). Since the hubs get more infected people than other locations, traveling through them carries a higher risk of transmission (Rose et al., 2006; Gonzalez et al., 2008; Balcan et al., 2009). Moreover, this scenario may more accurately depict the real situation in which humans usually take the shortest path and do not engage in a random walk process (drunk man behavior). Such agent-based models were commonly used to test new anti-epidemic policies and estimate the outcomes of various transmission scenarios. However, these models mostly focus on travel modes such as buses, airplanes, cruise ships, rather than metro systems. In fact, very few researchers (Ben-Zion et al., 2010; Takeuchi et al., 2007; Zhou et al., 2012) have incorporated metro data into micro-level simulations that would include thousands of metro users clustered into several subgroups to increase the transmission disease risk.

After defining the scenario, some previous paper also suggest to use the mobility data to evaluate the transition risk, and emphasize the relative risk of the public transportation usage (Li et al., 2021; Kumar et al., 2021; Xu et al., 2013). Most related research used mobile phone data to investigate the migration of people. Furthermore, Wei et al., 2021 also used daily population flow of mobile phone to build city wise COVID-19 epidemic model. However, in our case, these kinds of data are expensive and hard to collect. Therefore, we utilized the Taipei metro ticket data to describe the movement of people/passengers through the various stations. In our data, hourly passenger volume data was utilized to generate the number of agents per hour and their aggregated O-D for each station was then determined. Following this default setting, we built an agent-based model that incorporates a susceptible and infectious individual who enter the metro station, wait, and then take the train to their destinations. The infectious individual, who will be assigned randomly, may transmit the disease to the susceptible one if they are at the same station at the same time. Then, according to the final simulation results out of over 100, the order of stations in which the infectious individual came into contact can be determined.

In comparison of macro and micro level methods, previous studies compared the equation-based model (EBM) and agent-based model (ABM) performance in simulating the infection disease spreading (Hunter et al., 2018; Skvortsov et al., 2007). The comparison was conducted by using a simulation data of human airborne infection diseases with population number in a town of Ireland. For the ABM, it followed the objective traveling scenario. While the EBM was based on the population compartmental model. This model is most common type of EBM used for infectious disease modelling, which included the susceptible, exposed, infected, and recovered (SEIR) population in their equation. The result shows that ABM was able to capture stochasticity of real world and agent interactions enables it to give a better overall view of an outbreak. However, Sreenivas et al., (2012) argue that EBM may produce similar conclusion compared to ABM when larger sample sizes were applied. Considering the ABM takes longer to setup and run, the EBM tend to be less computationally intensive and provides more general result which may preferred by the policy makers.

2. METHODOLOGY

The Taipei Metropolitan Mass Rapid Transit system (MRT), the site of our study, is the first and largest in MRT system Taiwan. This system includes six main lines (Wenhu Line, Tamsui Xinyi Line, Songshan Xindian Line, Zhonghe Xinlu Line, Bannan Line, and Ring Line.), two sublines, and 131 stations. Approximately two million passengers use the MRT system per day. With a total length of 152 km, its service area covers all of Taipei City and parts of New Taipei City. The hours of operation are from 5:00 am to 24:00 pm.

In order to simulate possible future Covid-19 spread scenarios, we used typical weekday ticket data (May 1, 2019). 1,780,712 trips took place during the study period. To illustrate the passenger movement and the possible paths of COVID-19 spread to various MRT stations, we assumed that the metro speed is 50 mph and used GIS to generate the metro line map based on the coordinates of the stations. It is shown as Figure 1.

Figure 1: MRT network (shape file with real world station location information, and green triangle is the MRT stations).

The MRT ticket dataset was provided by the Department of Transportation, Taipei City Government. The raw dataset was generated by MRT ticket sales records. In the record, the entry/exit station ID shows where these users enter/exit the metro system. Finally, the price column indicates the cost of the trip. This dataset was used to calculate the passenger volume of each MRT station during the study period. Otherwise, the descriptive statistic of passenger volume data is shown in Table 1, and the table summarized the passenger volume of in/out stations and OD pairs. The top 8 of maximum passenger volume in/out station are same, and it includes Taipei Main Station(Origin passenger volume : 126474; Destination passenger volume : 122568), Ximen(O:66470;D:67610), Taipei City Hall(O:51987; D:51499), Zhongxiao Fuxing(O:47507; D:47103), Zhongshan(O:40580; D:42528), Banqiao(O:35910; D:38480), Xinpu(O:34493; D:33103) and Dingxi(O:30387; D:31641), and the top six passenger volume OD pairs are composed of those station, such as from Taipei Main Station to Ximen and from Taipei City Hall to Taipei Main Station. The lowest in/out traffic volume station is Wanfang Community station(O:1759; D:1486), and there are 167 OD pairs only have one trip, such as Qizhang to Wanfang Community, Sanchong to Xinhai and Dahu park to Xiangshan. We utilized the effective distance method and the agent based model to calculate the O-D flow matric of each station in order to ascertain how COVID-19 spreads in the following three scenarios: (1) the disease source is randomly distributed; (2) the disease source passenger is weighted and randomly distributed.

Variable	Mean	SD	Min	Max
Origin Passenger Volume	16316.00	15365.59	1759	126474
Destination Passenger Volume	16316.00	15176.54	1486	122568
OD Passenger Volume	154.20	296.88	1	7394

Table 1: Descriptive Statistic of MRT trip data.

In order to describe the relationship between high dependence on the metro system and the spread of the coronavirus to various stations in Taipei, we used the agent-based model (a micro-level simulation) and the effective distance method (a macro-level estimator). The results were compared to the Covid -19 arrival order for each station.

ABMs are useful tools in epidemiology because they can simulate individual agents in complex systems who move through and interact with other agents and the environment by following a set of defined rules based on their own characteristics. Although ABMs are constructed from an individual point of view, the output of simulations speaks to a global perspective. Several scholars have developed these models specifically for Covid-19 scenarios. For example, Gaudou (et al., 2020) developed the COVID-19 Modeling Kit (COMOKIT) in order to simulate agents with complex social and geographical characteristics. This model can track detailed interactions between agents and estimate the effect of various policies. Gomez (et al., 2021) also built a detailed agent-based model to explore the risk of infection in crowded transportation routes. Unlike existing models, our agent-based model focuses exclusively on the Taipei MRT system to most effectively determine the order in which each station becomes infected with the Covid virus and compare this result with those obtained from the effective distance method. Due to the fact that large scale analysis of complex travel networks and modes are beyond the scope of this study, we chose GAMA software to obtain the agent-based simulations. Although there are other free and open-source ABM platforms, we prefer GAMA because it can read and is compatible with the GIS dataset. In addition, its simple code language (GAML: GAma Modeling Language) and user-friendly platform make it beneficial for future studies. It should be noted that in this study, the focus is on the spread of the virus in the MRT station not in the cars because there was no seating or detailed passenger location information available.

In this model, passenger agents enter the Taipei metro system and take the train to their destination stations. These agents were generated based on the hourly passenger volume of MRT data in order to make our simulation as realistic as possible. The simulation time was from 5:00 to 23:55, and the simulation cycle was set to five minutes. In order to speed up the simulation and reduce the burden on the computer, one agent represented 10 people moving through the MRT in the simulation video. The number of people entering and exiting each station was based on real O-D flow data. The agents walk to their destination stations at an average rate of 35 kilometers per hour, which is based on the average speed of MRT. Furthermore, the infection rate, the probability that the infected individual will transmit the disease, was set to 0.05. We assumed that the susceptible individual would be in the same location as the original disease source. For example, we assumed that one infected individuals would transmit Covid-19 via contact in the station with an infection rate of 0.05. Their entry points into various stations, including the Taipei main station, are random, and based on the passenger volume. According to our criteria, we performed the simulation 100 times to calculate the average order in which MRT stations become infected.

Proposed by Brockmann (2013), effective distance is based on passenger volume and the meta-population model, which incorporates the SEIR model and movement between cities or stations. It is assumed that the virus will appear more quickly in stations with higher instances of passenger interaction than those without.

$$d_{ij}^{eff} = 1 - \ln \frac{w_{ij}}{\sum_j w}, \quad (1)$$

where w_{ij} = the passenger flow from i to j
$\sum_j w$ = the total passenger flow from station j.

$$D_{ij}^{SP} = \min_{\Gamma_{ij}} \sum_{(k,l) \in \Gamma_{ij}} d_{kl}^{eff}, \quad (2)$$

where Γ_{ij} = the set of all possible paths from i to j
$\sum_j w$ = the total passenger flow from station j.

In Equation 1, $\sum_j \boldsymbol{w}$ is the total passenger flow from station j. In Equation 2, Γ_{ij} represents the set of all possible paths from station i to station j, through which all nodes cannot pass more than once. A path is composed of consecutive links (k,l).

3. RESULTS

Using the most basic setting, our results showed the order of infection at the top 15 MRT stations, according to three different methods. Because the agent-based model requires multiple simulations (100) times, the order of infection was based on the average of several simulations. It should be noted that the order value is relative and is only useful for ranking.

Table 2 shows the top 15 stations with the lowest average order, according to the agent-based model. The Taipei main station is the hub and the earliest to become infected, according to this model. Others include major commuting or transfer stations, such as Zhongxiao Fuxing and Zhongxiao Xinsheng. Some stations lead to tourist attractions or the central business district, such as Ximen.

Rank	Station Name	Average Order
1	Taipei Main Station	8.4
2	Ximen	13.49
3	Zhongxiao Fuxing	16.67
4	Zhongshan	17.61
5	Taipei City Hall	19.45
6	Zhongxiao Xinsheng	19.69
7	Guting	23.06
8	Chiang Kai-Shek Memorial Hall	23.7
9	Longshan Temple	24.36
10	Dongmen	24.4
11	Shandao Temple	24.83
12	Zhongxiao Dunhua	25.52
13	Shuanglian	25.55
14	NTU Hospital	26.47
15	Yuanshan	27.42

Table 2: a list of infection order, according to the agent-based model.

Table 3 shows the top 15 stations with the lowest average order, according to the effective distance method. The Taipei main station was determined to be infected first, according to both models. However, the results of random walk effective distance was slightly different than those of the agent-based model and the shortest path effective distance.

Rank	Shortest Path	Average Order	Shortest Path Passenger volume weighted	Average Order
1	Taipei Main Station	2.92	Taipei Main Station	2.02
2	Ximen	10.16	Ximen	6.46
3	Zhongshan	13.31	Zhongshan	11.40
4	Zhongxiao Fuxing	13.38	Zhongxiao Fuxing	12.39
5	Taipei City Hall	18.07	Taipei City Hall	15.64
6	Dingxi	21.94	Dingxi	17.20
7	Zhongxiao Xinsheng	22.23	Banqiao	19.79
8	Songliang Nanjing	24.07	Zhongxiao Xinsheng	20.20
9	Nanjing Fuxing	24.68	Guting	22.62
10	Dongmen	24.75	Dongmen	22.70
11	Banqiao	25.59	Jiantan	22.96
12	Guting	27.11	Longshan Temple	23.71
13	Xhongxiao Dunhua	27.50	Xhongxiao Dunhua	24.38
14	Jiantan	28.04	Xinpu	24.77
15	Chiang Kai-Shek Memorial Hall	28.42	Chiang Kai-Shek Memorial Hall	25.01

Table 3. the order of infection using effective distance models.

The results indicated that the hub station, Taipei main station, was one of the earliest to become infected, probably due to its extremely high passenger volume. Moreover, it is also a major transfer station to railway, high speed rail, and buses, which indicates that the infection rate should be even higher than our estimations. This station was the first to be infected in five different scenarios, meaning that no matter how many infectious individuals enter the Taipei metro system randomly, weighted by passenger volume, Covid-19 follows the shortest path or random walk. Therefore, Taipei main station was the first to be affected.

4. CONCLUSIONS

The order of infection results according to the macro (effective distance shortest path) and the micro (agent-based model) methods were similar. The top 15 infected MRT station includes high passenger volume stations, such as Taipei Main Station, Ximen, Zhongshan, Zhongxiao Fuxing, Taipei City Hall, Dingxi and Banqiao stations. To prevent the disease spreading, the authority can implement anti-epidemic strategies, such as more frequent and rigid cleaning of station seat and equipment surfaces, temperature checks for staff and passengers, and improving the ventilation of station. For the other stations with lower traffic volume but high covid-19 risk, we can stop-skipping strategy to decrease the transition risk.(Gkiotsalitis et al., 2021) However, those results from the macro method (effective distance random walk) were somewhat different. The reason for this may be that random walk accounts for all possible transmission paths, which also allow individuals to reach one station more than once. This kind of complexity is absent in the agent-based model. However, we might be able to ignore the random walk results because metro systems are different from other transportation systems, such as airplanes, which are affected by complicated routes due to the airline hubs and networks. In other words, most metro passengers tend to choose the shortest path to reach their destination. Therefore, it is reasonable that the agent of this study was designed to move from one station to another via the shortest path in the MRT network.

Future studies may include other scenarios, such as determining the disease source entry in different time periods, such as early morning, peak hours in the morning, noon, afternoon, and night. Scholars may also wish to analyze a longer timeframe, such as weekday/weekend and holidays/events. Infected individuals not only transmit disease to susceptible individuals in stations but also in train cars, which is a similar result to that found using the agent-based model in this study.

Our results indicate that the macro and micro models can accurately estimate order of infections in the Taipei metro stations. However, their estimator was different from that used for the random walk method. A limitation of our study was that it failed to account for external/internal environmental conditions within the stations and the risk of infection inside the cars of the metro system. Future scholars may wish to collect more data and design more complex settings to better simulate real world conditions.

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