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Modelling effectiveness of COVID-19 pandemic control policies using an Area-based SEIR model with consideration of infection during interzonal travel

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ABSTRACT

This paper studies the effectiveness of several pandemic restriction measures adopted in Singapore during the COVID-19 outbreak. To this end, the classical Susceptible-Exposed-Infectious-Recovered (SEIR) model widely used to describe the dynamic process of epidemic propagation is extended to an area-based SEIR model with the consideration of exposure to infections during commute and quarantine. The proposed model considers infections within areas and infections occurred during the commute of individuals. A case study of the Singapore MRT system is presented to show the effectiveness of pandemic restriction policies implemented in Singapore, namely social distancing, work shift and Circuit Breaker (CB) and phase advisories. A long-term investigation of COVID-19 pandemic in Singapore is performed, and the disease transmission dynamics in 2020–2021 (which covers the first wave and second wave of COVID-19 pandemic in Singapore) is modelled.

1. Introduction

Infectious disease outbreaks have been haunting the human civilization since time immemorial. The Black Death, which started in 1340s and continued to spread in the following decades, had resulted in about 200 million deaths (DeLeo and Hinnebusch, 2005) in Eurasia and North Africa. Smallpox, an infectious disease with about 30% fatality death rate, has killed up to 300 million people in the 20th century (Henderson, 2011). Since the 20th century, the H1N1 influenza virus has led to two flu pandemics, the well-known Spanish Flu (1918 to 1920) and the 2009 swine flu pandemic. The outbreak of SARS (Severe Acute Respiratory Syndrome) from 2002 to 2004 has caused many deaths and the virus spread to different countries and region within a short period time because due to intensified human activities in urban environments.

As transport technologies have significantly advanced over the years, long distance travel has become more affordable and convenient and frequent than ever before. Such development has enabled movements via air (especially with the advent of low-cost travel and budget airlines) and via land (especially high-speed rail between cities and countries) (Kwok and Yeh, 2004) and have reshaped cities (Waddell, 2002). In addition, cities have become more urban (and densified) and public transportation systems (be it public bus or public rail systems) have become dominant mode of transport in cities such as Hong Kong, Taipei, and Singapore (Chang and Phang, 2017). The recent COVID-19 pandemic has basically highlighted how such enhanced transport connectivity (which is the
paramount importance for intercity or international travel) and urban density may cause pathogens to spread at large scale and across cities borders in a short span of time (Wang et al., 2018). Since COVID-19 was discovered in late 2019, the virus has resulted in up to 281.8 million infections and 5.4 million deaths globally (by December 30, 2021) (World Health Organization, 2021). To respond to this crisis, governments around the world have enforced various kinds of intervention measures. These include travel advisories and entry restrictions, restrictions on social gatherings, social distancing, quarantine, working from home and online teaching for schools, closure of public places, lockdown. For example, Wuhan, China has taken unprecedented measures in response to the outbreak, including physical distancing measures, workplace closures and lockdown (Prem et al., 2020). New Zealand enforced a full-scale shutdown of social and economic activity, while Australia responds to the crisis by increasing restrictions and assistance measures (Beck and Hensher, 2020). In Singapore, COVID-19 has caused about 278,750 infections and 826 deaths (as of December 30, 2021) since its outbreak in March (Ministry of Health of Singapore, 2021). Although the Singapore government has responded immediately to the pandemic and have taken actions such as intensive contact tracing (manual tracking, using SafeEntry - a check-in check-out-based system, and TraceTogether - a Bluetooth based system) (Government Technology Agency of Singapore, 2020), banned public gathering, imposed social distancing and wearing masks, and imposed the national Circuit Breaker (i.e. stay-at-home order and cordon sanitaire), such measures have created a tremendous impact on the society and the economy. In fact, Singapore has seen its gross domestic product dropped by 13.2% in the quarter before the national Circuit Breaker was implemented and 7.0% when the national Circuit Breaker was implemented (Ministry of Trade and Industry of Singapore, 2020). This is similar to global trends where many countries have seen their national GDP dropped in the range between 3.8% and 9.6% for the period of July to September 2020 (Organization for Economic Cooperation and Development, 2020).

The outbreak of epidemics propels the need to understand the propagation of disease and predict the process of disease outbreak for epidemic control and prevention. Several epidemic models were proposed in the literature to describe the dynamic process of disease propagation. The basic mathematical model for epidemic propagation is the compartment model proposed by Kermack and McKendrick (1927). More advanced compartment models were further developed over the years, e.g., epidemic models with consideration of time delay (Beretta and Takeuchi, 1995), with consideration of the effect of quarantine (Hethcote et al., 2002), and metapopulation models (Wang et al., 2018). For example, Wang et al. (2018) modeled disease transmission among different groups (metapopulation) with the interaction between a group of separated sub-population considered, and applied interaction strengths to describe the interactions between different groups of individuals. Three infection sources were considered in their study. For any given group, the authors assumed that a susceptible individual may be exposed to disease from (i) infected individuals in the same group, (ii) infected visitors from other groups, and/or (iii) from his/her visit to other groups and getting exposed to infected individuals. Besides the compartment models, network epidemic models were also adopted in the literature to consider disease transmission within the network of a population. These models combine both network and epidemiological theories and consider actual networks or idealized networks such as random graphs, small-world network, and scale-free network to study the dynamics of disease transmission (Keeling and Eames, 2005).

For megacities with high public transport ridership amidst a highly dense environment, potential infections during commute and at activity zones at origins and destinations should also be considered in the modeling of pandemics. Many past research studies have found that most people travel between a few of their desired locations and their travel distances tend to be bounded by the scale of the city (Gonzalez et al., 2008; World Health Organization WHO, 2020; Song et al., 2010; Hasan et al., 2013; Sun et al., 2013). Such an environment is an ideal hotbed for disease propagation if proper control strategies are not implemented, as pathogens can easily migrate from infected individuals to adjacent travellers through droplets and/or airborne transmissions, thereby causing secondary infections during regular and non-regular commute (Salathe et al. 2010). As such, there is a strong need to consider how diseases may be transmitted during travel when modelling the propagation of communicable disease.

In addition to pandemic spreading, there is also the need for models that can include various control and management strategies so that appropriate policies (especially transport-related strategies) can be implemented. For instance, Mu et al. (2019) investigated the effects of different government intervention measures (such as disinfection, culling of poultry and adopting a threshold policy) on mitigating the transmission of H7N9 virus using their developed disease propagation model. Zhang et al. (2005) proposed a compartmental model that mimicked the Severe Acute Respiratory Syndrome (SARS) control strategies which was eventually implemented by the Chinese government during SARS, and thereafter applied to study the effects of policies including quarantine, isolation, restriction on the flow of individuals, and contact tracing. These past studies serve as a useful guidance for governments to decide on appropriate policies in response to the current COVID-19 pandemic. In particular, the ability to quantify the impact on various COVID-19 intervention measure can help in understanding how policies perform during epidemic control stage and aid governments in developing proper epidemic prevention plans against future disease outbreaks. There are some recent studies on such quantification of the effectiveness of various control measures against the transmission of COVID-19, such as that for physical distancing (Jarvis et al. 2020), for quarantine control (Dandekar and Barbastathis, 2020), contact tracing (Elmokashfi et al., 2021), lock down (Mégarbane et al., 2021), combined control measures (Sharma et al., 2021; Zhao et al., 2021). However, these studies mainly focus on clinical surveys during the early stages of pandemic or merely consider the effect of a single control measure. Hence, there is a need to evaluate the impact of multiple intervention measures using appropriate epidemic modelling.

Recognizing the need for a model that can aid in public transport policy for pandemic control and management, this paper proposes an epidemic transmission model for megacities using an area-based Susceptible-Exposed-Infectious-Recovered (SEIR) model. This model is capable to model infections during travel commute, and the effect of control and management policies such as (work-from-home, quarantine and social distancing) on infection risk. First, we extend the classical metapopulation-based epidemic model to an area-based SEIR model with consideration of infections within areas (or activity zones) and infections occurred during travel commute of individuals. The proposed model is then applied to model the COVID-19 transmission in Singapore from February to August 2020.
with consideration to the public rail network in Singapore. Last but not the least, pandemic control measures to curb the spread of COVID-19 such as contact tracing, social distancing, work-from home, and the national Circuit Breaker are modeled and studied to understand their effectiveness in controlling and managing the pandemic. This would offer insights in how such strategies (including transport related policies) can help in pandemic control and management. As a result, the main contributions of this paper can be summarized as follows:

(a) We extend the classical metapopulation model to an area-based SEIR model to study epidemic propagation and COVID-19 pandemic control in Singapore. The proposed model can consider infections within areas and infections during the commute of individuals. This provides a possible means to study disease transmission in public transportation systems, which could be further used for managing transportation operations for pandemic resiliency.

(b) The effectiveness of pandemic restriction policies used in Singapore, namely social distancing, work shift and Circuit Breaker, are investigated using the proposed model. Disease transmission in the Reopening phases in Singapore are further investigated to assess the effectiveness of pandemic control measures adopted in 2020 and 2021. The study can also serve as validation studies and sensitivity analysis can be performed to assess the robustness of such control measures.

The remainder of the paper is organized as follows: Section 2 provides the literature review on epidemic models and pandemic control measures. Section 3 proposes the methodological approach to the area based SEIR model with the consideration of exposure to infections during commute and quarantine. Section 4 presents the nation-wide case study in Singapore using the model developed in Section 3. Finally, Section 5 concludes the study and provides an outlook on future research directions.

2. Literature review

This section reviews past works in the literature that are related to epidemic models, pandemic control measures and measurement of the effectiveness, transport policy’s role in pandemic control and management.

2.1. Epidemic models

The application of mathematical models to epidemic transmission was perhaps first initiated by Bernoulli (1760) in his study on the spread of smallpox. Two centuries later, Hamer (1906) proposed a discrete time model to investigate the spread of measles in England. However, it was the study by Kermack and McKendrick (1927) which proposed the compartment model (Susceptible- Infectious-Recovered (SIR) model) and the concept of epidemic threshold that established the foundation for modern epidemic dynamic modeling. With the compartment model as its fundamentals, a huge variety of epidemic models have been formulated in the literature which involved aspects such as age structure (Salathé, M. et al. 2010), passive immunity and vaccination (Hethcote, 2000), sexually transmitted disease (Castillo-Chavez et al., 1996), community structure (Begon et al., 1992), immigration (Brauer and van den Driessche, 2001), metapopulation (Wang et al., 2018), etc.

Besides the compartment model, the network epidemic model is also widely adopted in the literature to model epidemic transmission. Network models are mainly used to present the relationship between individuals in a population. Individuals are modeled as nodes in the contact/interaction network, while the interactions and contacts are presented as edges. Network epidemic models are preferable for infection tracing and contact tracing, such as determining the source of infection for each case and identifying all potential transmission contacts from a source individual (Brauer et al., 2001; Haydon et al., 2003). With a network of social connections given by generated data (Halloran et al., 2002) or census data (Meyers et al., 2005), the dynamics of disease outbreak can be easily simulated with network epidemic models. However, collecting actual network data related to human–human contact is time-consuming, and ascertaining the sensitivity of the epidemiological results to the details of the network structure remains challenging to date (Keeling and Eames, 2002). Therefore, computer-generated networks, such as random graphs, small-world network, and scale-free network, are idealized networks to simulate the dynamic of disease transmission (Keeling and Eames, 2002).

Several studies have investigated disease spread via large-scale transportation networks. These studies can be roughly classified as model-based and simulation-based studies. For model-based studies, (public) transportation network is assumed to connect several locations, and therefore contribute to the spatial spread of infectious diseases in a city. For example, Xu et al. (2013) study the spatial spread of an epidemic through a public transportation system with a hub. In their study, infections among several locations and occurred in the transportation system are considered via the Susceptible-Infectious-Recovered (SIR) model. Knipl et al. (2013) investigated epidemic spread due to travel-related infections in connected regions and considered the variation of peak hour travel demand within the transportation system. Simulation-based studies focus on the human–human interactions within the transport network and hence model the network-wide dynamics of disease propagation. These studies include the simulation work by Mei et al. (2015) to study the city-level disease propagation given a road network and the agent-based approach proposed by Perez and Dragicevic (2009) to consider the geospatial context of disease propagation. However, most studies focus on the spatial spread of diseases, and they seldom investigated disease spread via transportation network especially with the implementation of various intervention measures considered.

2.2. Pandemic control measures and measurement of the effectiveness

There are several measures for infection control and prevention during the outbreak of diseases and the selection of the appropriate
measures is primarily determined by the characteristics of the disease or virus. For example, SARS is a severe, rapidly spreading respiratory illness with high mortality rate. Infection control measures like reducing social gathering, monitoring close contacts, isolation of individuals and implementing precautions in hospitals are proved to be effective in mitigating its transmission (Skowronske et al., 2005). The West African Ebola epidemic can only spread when people come into contact with infected blood or body fluids, and hence travel/border restrictions, quarantine and contact tracing were the main control measures adopted by governments (Moon et al., 2015). During the H1N1 pandemic, geographically targeted non-pharmacological measures such as early case isolation, household quarantine, school/workplace closure and restrictions on travel are found to be effective only at its early phase, while clinical measures played an important role in keeping low mortality rate (Waterer et al., 2010). While for rapidly spreading virus with low mortality, like seasonal influenza, the most effective way for prevention is vaccination (World Health Organization, 2020).

Since the outbreak of COVID-19 in early 2020, the World Health Organization (WHO) has proposed recommendations for infection prevention and control. These include personal protective measures and advisories for communities (World Health Organization WHO, 2021). Governments around the world have also enforced different forms of infection control policies. These policies include travel advisories and entry restrictions, restrictions on social gatherings, social distancing, quarantine and isolation for possible infections, working from home and online teaching for schools, closure of public places, and lockdown of cities, regions or country. Several researchers have investigated the impact of such epidemic control measures on the disease transmission. Teslva et al. (2020) evaluated the impact of self-imposed prevention measures and short-term government-imposed social distancing on the transmission of COVID-19. Davies et al. (2020) used a stochastic age-structured transmission model to study the effects of non-pharmaceutical interventions on COVID-19 cases, such as school closures, physical distancing, shielding of older people. Other studies explored the effectiveness of quarantine and border control on the spread of COVID-19 (Hou et al., 2020; Hossain et al., 2020; Di et al., 2020; Ding et al., 2021; Yang et al., 2021). The efficacy of contact tracing strategies and the impact of time delays on COVID-19 have been also investigated (Keeling et al., 2020; Kretzschmar et al., 2020; Kariuki et al., 2021; Rossello et al., 2021). There are also studies in the literature regarding the impact of intervention measures on the transmission of other diseases. For example, De Vlas et al. (2009) tracked the effective reproductive number over time to assess the impact of important public health control measures during the SARS epidemic. Mu et al. (2019) investigated the effects of different government intervention measures on mitigating the transmission of H7N9 virus, including disinfection, culling of poultry and threshold policy.

2.3. Role of transport policy in pandemic control and management at the cities scale

Intensified human interaction and human mobility in megacities can contribute to the outbreak of epidemics. For megacities with high public transport ridership amidst a highly dense built environment, transport in cities can potentially contribute to the spatial spread of diseases (Knip1 et al., 2013). During the outbreak of pandemics, the highly dense built environment can potentially be a hotbed for disease transmission. On the other hand, appropriate transport policies during this period can help mitigate the spread of disease in cities and thus control infections.

There are few research studies in the literature that explored the impact of transport policy on pandemic control or spread. Instead, many studies have investigated the role of transportation systems in the spatial spread of diseases and studied the effectiveness of transportation-related measures on mitigating disease transmission. Kuzdeuov et al. (2020) proposed a network-based stochastic epidemic simulator to study the geographic spread of the disease and showed that transportation limitations can not only reduce the number of infections but also postpone the occurrence of infection peak. Chong et al. (2012) found that restrictions on travel can delay the peak time of pandemics. Zhang et al. (2015) modeled the diversity of traveling purposes in public transportation and investigated the effectiveness of several intervention measures with different levels of compliance. For experiment-based studies, von Braun et al. (2015) have investigated the quantity of influenza A (H1N1) virus in public transport systems, while so far there have not been similar studies of COVID-19 virus. However, it has found that COVID-19 virus can persist on inanimate surfaces for relatively long time (which is environment-dependent) (Kampf et al. 2020), and frequent disinfection in public transport can help in mitigating infections due to such contacts.

Although the role of transport policy in pandemic control has not been comprehensively studied, several transportation-related measures (e.g., travel restrictions, public transportation avoidance, closure of public transport) are shown to be effective in mitigating the spread of disease in the cities. Therefore, this study will quantify how transportation-related pandemic control policies can help to mitigate disease transmission. This understanding on the effectiveness of such measures can help transport operators and government agencies to decide proper transport policies in response to pandemics.

3. Methodology

In this section, we first introduce the basic Susceptible-Exposed-Infectious-Recovered (SEIR) model which is widely used to describe the dynamic process of epidemic propagation. Then, we extend the SEIR and metapopulation models to consider the effect of quarantine and the probability of infections that can occur to individuals during commute (be it regular or non-regular).

3.1. Classical Susceptible-Exposed-Infectious-Recovered (SEIR) model

The classical SEIR model is commonly used in the literature to study the propagation of communicable diseases (Hethcote, 2000). Implicitly, it assumes a homogeneous population of individuals, and divides these individuals into four compartments: \( S \) for the susceptible individuals, \( E \) for the exposed individuals, \( I \) for the infectious and \( R \) for the recovered or dead. The SEIR model assumes that
due to the interaction between individuals, all individuals are “well-mixed”, meaning that they have the same probability to contact each other (denoted as $a_1$). Let $P$ be the total number of individuals in the population, we can define $s(t), e(t), i(t)$ and $r(t)$ to denote the number of susceptible, exposed, infectious and recovered individuals respectively in the four compartments at time $t$. Assuming that the infection probability of a contact is $a_2$ and the incidence rate is bilinear, the number of susceptible individuals that will get infected at time $t$ (i.e., changing to $I$) can be described as $a_2s(t)i(t)$ where $a = a_1a_2$. By further assuming an incubation rate $\sigma$ (i.e. individuals switching from being exposed (i.e., state $E$) to being infected (i.e., state $I$)) and a recovery rate $\beta$ (i.e., individuals switching from being infected $I$ to being recovered or died $R$), the dynamics of the SEIR model are given by:

$$
\frac{ds(t)}{dt} = -\alpha s(t)i(t)
$$

$$
\frac{de(t)}{dt} = \alpha s(t)i(t) - \sigma e(t)
$$

$$
\frac{di(t)}{dt} = \sigma e(t) - \beta i(t)
$$

$$
\frac{dr(t)}{dt} = \beta i(t)
$$

$$
s(t) + e(t) + i(t) + r(t) = P
$$

It is noted that the classical SEIR model assumes a homogeneous infection propagation among individuals and is therefore applicable to only a single population. It could not consider the metapopulation scenario (Wang et al., 2018), nor could it account for the spatial distribution of the population.

3.2. Extension to Area-Based Susceptible-Exposed-Infectious-Recovered (SEIR) model

Recognizing the limitations of the model presented in Eqs (1) to (4) in modeling a metapopulation (i.e., a group of separated sub-populations of the same species which interact at some level), Wang et al. (2018) extended the classical SIR model to metapopulation SIR model by considering the interaction between a group of separated sub-populations. We adopted this principle and further extended the model to an area based SEIR model, taking into account exposure of airborne diseases that may occur during commute (which could be regular or non-routine). The proposed area based SEIR model can present the spatial distribution of epidemic situations since movement individuals between different areas and disease propagation within these areas (or activity zones) are considered. In addition, in order to model how control and management measurements can affect pandemic spread, we adopt the following assumptions in model formulation for the case of COVID-19:

1. Due to the characteristics of COVID-19 virus, exposed individuals and latent cases that have not been confirmed (i.e., state $E$) are also infectious.
2. Infected individuals (i.e., state $I$) are quarantined immediately after they are confirmed by government health agencies as COVID-19 infection. This means that susceptible individuals (i.e., state $S$) can only be infected by exposed and latent individuals (i.e., state $E$) when they are within the origin and destination activity zones (or areas) and during commute.

The problem formulation of the area-based disease propagation model is described as follows. Assuming that an urban area is divided into $N$ zones $\mathcal{Z} = \{z_i, i = 1, \ldots, N\}$, the adjacent matrix $A$ can be derived to describe the connectivity between activity zones (or areas). The number of individuals in zone $z_n$ is denoted as $P_{n}$, and the number of susceptible, exposed (latent), infected and recovered individuals at time $t$ are denoted as $s_{n}(t), e_{n}(t), i_{n}(t)$ and $r_{n}(t)$ respectively. The interaction strength between two activity zones (or areas) $n$ and $m$ is denoted as $a_{nm}$, where $m \in \{1, 2, \ldots, N\}$. In the area-based model, $h_{mn}$ is defined as the average number of commuters from zone $n$ to zone $m$ within a defined time interval (i.e. travel demand or volume). The interaction strengths can be estimated by two methods: (1) trip attractions from zone $n$ to $m$ (which can be obtained from gravity models), or (2) actual OD demand from zone $n$ to $m$. Assuming that an urban area divided into a given set of zones, the interactions between individuals within zones and between zones could result in disease transmission. A susceptible individual originating from zone $n$ may contact infectious (exposed) individuals from any of four sources as listed below:

Source I: Exposed individuals in the same activity zone at the origin (i.e zone $n$) with a total number of exposed individuals in the zones being $e_{n}(t)$;
Source II: Exposed visitors that originate from other zones but is at destination zone $n$;
Source III: The susceptible individual in question is at destination activity zone $m$ and comes in close contact with the exposed individuals from activity zone $m$;
Source IV: The susceptible individual in question comes across any other exposed individuals during his or her trip to destination zone $m$;

According to the SEIR model (Eqs (1) to (4)), we know that Source I result in $a_{n}(t)e_{n}(t)$ new infections in zone $n$. The probability for

\[s(t) + e(t) + i(t) + r(t) = P\]
an individual traveling from zone \( m \) to \( n \) (visitors from zone \( m \)) can be estimated as \( \frac{a_{mn}}{P_m} \). Hence, infections due to Source II become \( \alpha_n(t) \sum_{m: e_m(t)} \left( \frac{a_{mn}}{P_m} \right) e_m(t) \) new infections in zone \( n \). Similarly, Source III leads to \( \alpha_n(t) \sum_{m: e_m(t)} \left( \frac{r_{mn}}{P_n} \right) e_m(t) \) new infections in zone \( n \). For infections caused by Source IV (i.e., during commuting), and the number of new infections can be modelled with the following considerations:

1. An individual traveling from zone \( n \) to zone \( m \) may follow the path \( p_{n \rightarrow m} = \{z_n, ..., z_m\} \). We further assume that individuals will choose to take the shortest path to their destinations, and \( p_{n \rightarrow m} \) denotes a sequence of zone given by the adjacent matrix \( A \). During the trip, the individual meet commuters from other zones and hence close contact can occur.
2. If the commuters’ path sequences have common zones, it means that individuals will meet during their trips. In this paper, we consider only commuters originating from other zones and arriving at destination zone \( m \) to estimate the number of meet ups and the chance of infection. We use \( p_{m,k} \) to denote whether this individual will come across an individual from zone \( k \) during his/her trip to zone \( m \), and it is obvious that we have \( p_{m,k} = 0 \) if \( p_{n \rightarrow m} \cap p_{k \rightarrow m} = \emptyset \). The number of infectious travelers from zone \( k \) to zone \( m \) can then be estimated by \( \frac{h_{km}}{P_k} \), and therefore the estimated number of exposed (latent) individuals from zone \( k \) that an individual taking path \( p_{n \rightarrow m} \) will come across is \( \frac{h_{km}}{P_k} e_k(t) \cdot p_{m,k} \).
3. Unlike disease propagation that occurs within zones, disease transmission during commute tends to be different as it is dependent on intervention measures that are put in place (such as wearing of mask and social distancing) and the contact duration between the susceptible individual and the exposed individuals. In order to account for such measures and definition of close contact, we define a commute contact probability in this paper, instead of assuming the traditional assumption of a contact probability \( \alpha_1 \) in classic SEIR models (Eqs (1) to (4)). For simplicity, we apply a scaling ratio \( \gamma \) to this contact probability \( \alpha_1 \) and this value needs to be calibrated from actual infection data.

Given the above considerations, the number of new infections (for zone \( n \)) due to exposure occurred during commute can be expressed as:

\[
y_{as_n}(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} \right) e_m(t) = \gamma \alpha_n(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} \right) e_m(t) - y_{as_n}(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} \right) e_m(t) \sum_{k: e_k(t)} \left( \frac{h_{mn}}{P_k} \right) e_k(t)
\]

By considering the infections caused by Sources I to IV and defining \( h_{mn} = \frac{P_n}{2} \) (adopted from Wang et al. (2018)), the area-based SEIR model can be modelled as:

\[
\frac{dE_n(t)}{dt} = -\alpha_n(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} + \frac{h_{mn}}{P_n} \right) e_m(t) - y_{as_n}(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} \right) e_m(t) \sum_{k: e_k(t)} \left( \frac{h_{mn}}{P_k} \right) e_k(t)
\]

\[
\frac{dS_n(t)}{dt} = \sigma_n(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} + \frac{h_{mn}}{P_n} \right) e_m(t) + y_{as_n}(t) \sum_{m: e_m(t)} \left( \frac{h_{mn}}{P_m} \right) e_m(t) \sum_{k: e_k(t)} \left( \frac{h_{mn}}{P_k} \right) e_k(t) - \sigma_n(t) e_n(t)
\]

\[
\frac{dI_n(t)}{dt} = \sigma_n(t) e_n(t) - \beta_n(t)
\]

\[
\frac{dR_n(t)}{dt} = \beta_n(t)
\]

The first term of Eq. (6) represents the infections of susceptible individuals for zone \( n \) at time \( t \) caused by Sources I, II and III, and the second term models the number of individuals infected during commuting (i.e., Source IV). We further define the detection rate \( \sigma \) here not only presents the nature of pandemic i.e., the duration which symptoms begin to appear (i.e., the traditional definition of incubation rate), it also indicates the effectiveness or “strength” of control measures in isolating confirmed cases, such as active surveillance, stay home notice, and quarantine in specialized facilities. This means that its value is time-varying based on the actual point in time when the intervention measures are in effect. \( \beta \) is the recovery rate which indicates the rate at which individuals switch from being infected I to being recovered or died \( R \).

3.3. Initial states and estimation of interaction strength

Given the model developed in the previous sub-section, we introduce here how it is possible to determine the initial states and update the four compartments (susceptible, exposed, infectious and recovered individuals) for modeling and application (i.e., studying the impact of pandemic control policies on epidemic transmission).

Newly exposed individuals and initial states. We discretize the timeline into several time intervals \( t = 1, 2, ..., T \), and therefore \( e_{S_n(t)}(t), e_{E_n(t)}(t), e_{I_n(t)}(t) \) and \( e_{R_n(t)}(t) \) denotes the number of susceptible, exposed (latent), infectious and recovered (or died) individuals at time \( t \) respectively. According to Equation (6), the number of susceptible individuals getting infected during time \( t \) to \( t + 1 \) (changing from state \( S \) to state \( E \) ) is:
\[ \delta_n(t) = \alpha s_n(t) \sum_{m=1}^{N} \left( \frac{h_{nm}}{P_n} + \frac{h_{mn}}{P_m} \right) c_n(t) + \gamma \alpha s_n(t) \sum_{m=1}^{N} \sum_{k=m,n}^{N} \frac{h_{nk}}{P_n} p_{mk} c_k(t) \]  

(10)

The initial states \( s_n(0), r_n(0) \) and \( e_n(0) \) are given by the statistic of the disease situation in the early stage. For \( r_n(0) \), we set it as the same \( s_n(0) \). With the initial states, the number of susceptible, infectious and recovered (or died) individuals at time \( t + 1 \) can be calculated recursively:

\[ s_n(t+1) = s_n(t) - \delta_n(t) \]  

(11)

\[ e_n(t+1) = (1 - \sigma) e_n(t) + \delta_n(t) \]  

(12)

\[ i_n(t+1) = \sigma e_n(t) - \beta i_n(t) \]  

(13)

\[ r_n(t+1) = r_n(t) + \beta i_n(t) \]  

(14)

**Interaction strength.** The interaction strength between zone \( n \) and zone \( m \) can be estimated from actual origin–destination demand extracted from smart card data or other appropriate data collection sources. For a given activity zone (or area) with \( P_k \) individuals, the probability for an individual traveling to activity zone \( m \) is estimated as \( h_{km}/P_k \). Since demand is time-dependent, the interaction strength between any two zones is also time-varying. This time-dependent property of interaction strength can help explain the dynamics of disease transmission in a granular manner.

**Other parameters.** In this paper, we first set \( \gamma = 1 \) i.e., the intervention measures or population behavior do not increase or decrease contact probability \( \alpha \). Recovery rate \( \beta \) is estimated from regression analysis, while infection rate \( \sigma \) and incubation rate \( \sigma \) are estimated with the historical COVID data and an optimization model. The details are provided in the case study.

Given the initial states \( s_n(0), e_n(0), i_n(0), r_n(0) \) and interaction strength, we can recursively predict the dynamic of disease propagation in cities and quantify the impact of disease control policies on epidemic transmission.

### 3.4. Additional remarks on proposed model

Even though our proposed model is developed based on the metapopulation model by Wang et al. (2018), our model as discussed earlier is unlike the model developed by Wang et al. (2018) and further allows the consideration of the below items:

1. Infections caused by exposed individuals and latent cases.
2. Quarantine policy adopted to combat against the spread of air-borne pandemics such as COVID-19, hence allowing for quantification of the impact of such policies on disease transmission.
3. Infections occurred during trips within the public transportation systems. This consideration makes it possible to investigate how some operation strategies under pandemic in the public transportation system may help to curb the transmission of diseases.

Our model further provides a more straightforward and intuitive approach to determine the value of interaction strength by considering the interaction between different (geographical) zones/areas with actual OD demand of these areas. It should be noted that the use of OD data can reflect the influences of pandemic control measures on travel demand, which can further be used to quantify the effectiveness of the various adopted control measures.

### 4. Case study of Singapore during the COVID-19 pandemic

In this section, we applied the developed area-based SEIR model to understand how Singapore’s COVID-19 response in terms of national policies and transport-related policies have aided in managing the pandemic. The proposed model shall be calibrated against data collected in the country to reveal the infection trends for: (i) the first COVID-19 outbreak in Singapore (from January 2020 to August 2020); (ii) the second wave of the pandemic due to the transmission of the Delta variant (from April 2021 to October 2021). This section provides a quantitative analysis on the effectiveness of disease control measures based on the model, and further investigates the impact of adjusting intervention and re-opening dates of control measures, as well as other control measures in public transport for pandemic control and management.

#### 4.1. Measures for pandemic control and management in Singapore

Since the first COVID-19 case in Singapore on January 23, 2020, the Singapore government have successively enforced a series of infection control measures to curb disease transmission. The first round of control measures is focused on imported COVID-19 infection cases. Since the outbreak of COVID-19 in Wuhan, China and the lockdown of the city, Singapore immediately released travel advisories and entry restrictions in late January 2020 (Ministry of Health of Singapore, 2020a). Thereafter, Singapore started an extensive contact tracing program to trace people at risk of infection after close contact with confirmed COVID-19 cases and implemented diagnostics test in early February 2020 in response to increasing number of imported infections (Ministry of Health of Singapore, 2020a). Precautionary measures such as Stay-Home Notice (SHN) and health advisories were released subsequently. On March 13, 2020, the
Singapore Ministry of Health (MOH) announced various safe distancing measures for implementation in order to reduce the risk of local spread of COVID-19. These measures include limitations on gatherings, work from home and alternate shift arrangements. Such measures are to limit close contact and large gatherings of people in close proximity over a prolonged duration (Ministry of Health of Singapore, 2020b). Due to the continued increase of COVID-19 cases in Singapore in March 2020, MOH has enforced stricter safe distancing measures (Ministry of Health of Singapore, 2020b) on March 24, 2020 including stricter regulations for events and gatherings, workplaces, suspension of some activities. On April 7, 2020, the government enforced Circuit Breaker (CB) measures, a stay-at-home order and cordon sanitaire measure (Ministry of Health of Singapore, 2020c) and it is compulsory to wear mask and keep safe distancing when outside of the home for critical essential services or for essential service workers.

Since then, Singapore has witnessed a significant decrease in the number of COVID-19 cases and CB officially ends on June 1, 2020 for a gradual and calibrated reopening towards the new normal. “Safe Reopening” (Phase 1 from June 1, 2020 to June 19, 2020) and “Safe Transition” (Phase 2 from June 19, 2020 2359 h) have been implemented to ensure a safe resumption of commercial, work and school activities (Ministry of Health of Singapore, 2020c). With a high penetration rate on the use of TraceTogether app (Government Technology Agency of Singapore, 2020) and adequate testing capacity (The Straits Times, 2020), Singapore then entered Reopening Phase 3 on Dec 28, 2020, until the second wave of COVID-19 pandemic occurred in late April 2021, thereby forcing a return to Phase 2.

In this study, we attempt to quantify the impact of pandemic control and management measures on curbing the spread of COVID-19 using the proposed model. Since the first COVID-19 outbreak in Singapore, there are four main types of policies proposed by the government to combat COVID-19 infection in the community and they are namely social distancing, work-from-home and/or work shift measure, Circuit Breaker (CB) and phase advisory (for reopening phases).

**Intervention Measure I. Social distancing.** This measure was proposed to reduce possible contact among individuals, have been adopted since the first wave of COVID-19 pandemic in Singapore (from March 2020). It leads to a lower commute contact probability (i.e., smaller scaling ratio $\gamma$) and a smaller contact probability $\alpha_1$ (and hence a smaller infection rate $\sigma$) in the area based SEIR model, as described in the previous section. In addition, during the early stage of the COVID-19 pandemic, contact tracing efforts are of utmost important and it is much easier to control and quarantine possible exposed individuals (due to the smaller number of infected and hence exposed individuals). This also results in a higher detection rate $\sigma$.

**Intervention Measure II. Work-from-home and/or work shift.** Work-from-home and/or work shift (i.e., flexible work schedule) was proposed in the early stage of the COVID-19 outbreak in Singapore (March 20, 2020) (Ministry of Health of Singapore, 2020b) as one of the countermeasures to control the spread of COVID-19. Employers are advised to allow to allow workers to work from home (WFH) or have flexible work arrangements, and if not possible, must maintain social distancing at the workplace. Workers with flexible work arrangements are divided into different work shifts and crews from one work shift are not allowed to be in contact with any worker from another shift. This measure greatly reduced travel demand (and commute traffic) in Singapore, and this means that interaction strength $h_{nm}$ for the proposed area based SEIR model is much lower for this scenario as compared to that in pre-COVID-19 days. In addition, there will also be a decrease in commuters density and this results in a smaller commute contact probability (i.e., a
Intervention Measure III. Circuit Breaker (CB). From April 7 to June 1, 2020, Singapore entered into the Circuit Breaker period to prevent further COVID-19 infections, especially to the community. All individuals are advised to stay home as much as possible. They are advised to leave the house only if they work in the essential service industry (such as healthcare workers), get essential goods and services, or to seek medical help (Singapore Government, 2020). CB has a great influence on mobility in Singapore, and basically dramatically decreases possible contact between individuals within zones and between zones. From a model perspective, this measure results in a low cross-area travel demand (or low interaction strength $h_{nm}$), and according to Land Transport Authority (LTA) of Singapore, the ridership is around 17% (Urbanagents, 2020) during the CB period.

Intervention Measure IV. Phase Advisory. From June 1, 2020, Singapore has come to the reopening phases. Singapore has gradually re-open economic activities that do not pose high risk of transmission, while social, economic and entertainment activities with a higher risk remain closed. However, work from home (WFH) is still required except essential services defined in the government document on Phase 1 (Ministry of Health of Singapore, 2020c). By June 18, 2020, Phase 2 (Safe Transition) have been enforced. Singapore then entered Reopening Phase 3 on Dec 28, 2020, until the second wave of COVID-19 pandemic occurred in late April 2021 and forced her to return to Phase 2.

During the reopening period, the Singapore Ministry of Health (MOH) have been changing and adjusting control measures as phase advisories according to the pandemic situations. The phase advisory includes the regulations on social gatherings, household visits, workplaces and malls/large stores. Fig. 1 shows how some measures in the phase advisory have been adjusted since June 2020. The adjusted measures and regulations will results in the change of commuters density and commute contact (i.e., different detection rate $\sigma$).

4.2. Data collection

In this paper we have adopted the Singapore mass rapid transit network (i.e., urban rail transit system) to model the movement of commuters between zones. Fig. 2 shows the urban rail transport network in Singapore (and Light Rail Transit (LRT) lines are also shown in the figure). In the study period, there were 5 MRT lines operating in Singapore (East-West, North-South, Circle, Northeast and Downtown, while Thomson-East Coast Line is under construction) with 122 stations in the city-state. In 2018, there is an average of approximately 3.3 million ridership per day on the MRT system (Land Transport Authority of Singapore, 2020a). Origin-destination data is collected from the online DataMall system published by the Land Transport Authority of Singapore (Land Transport Authority of Singapore, 2020b).
Singapore, 2020a) and also checked against the published reports from the media on ridership during the COVID-19 period (Urbanagents, 2020). The data allows the approximation of interaction strengths between zones.

The MRT stations are treated as 122 urban activity zones in our pandemic transmission model, and we attempt to model of COVID-19 for individuals within these zones and between the zones when commuting. In this study, the interaction strength $h$ is estimated from actual origin–destination demand data, which means that interaction strengths would vary when new control measures are adopted (as these could influence travel demand). In this section, we present the origin–destination demand data for representative areas in Singapore (based on land use type) (as shown in Table 1) to show the how the interaction between zones has changed from the first wave to the second wave of COVID-19 pandemic in Singapore. Fig. 4 illustrates the changes in the total number of trips during the outbreak of COVID-19 (from Jan 2020 to Oct 2021) in Singapore.

Fig. 3 presents the travel demand for these areas from Jan 2020 to Oct 2021, and this study period covers the first wave and the second wave of COVID-19 pandemic in Singapore. It is obvious from the figure that there was a sharp change in the number of trips when strict regulations were put into place, and this indicates the tremendous impact of pandemic control measures on travel demand. It was also observed that there is a sharp decrease in the number of trips from residential areas, CBD and commercial areas when stricter control measures took place, and there was a rebound in travel demand for these areas when Singapore entered Reopening phases. The number of trips to industrial estates was quite stable during the pandemic as compared to other areas, indicating lesser influence of pandemic regulations on the trips related to the industrial sector – many of which are either essential services or are activities where workers cannot work from home. It should be noted that travel demand depends on the type of pandemic control measures implemented nationwide, and this means that interaction strengths, which account for the influence of control measures on transmission dynamics, are also time-dependent (and intervention-dependent).

The population size $P_n$ (taken as the number of passengers originated from station $n$) is scaled to represent the entire population in

| OD demand | Types of land use* |
|-----------|--------------------|
| Toa Payoh – Ang Mo Kio | Residential – Residential (R-R) |
| Toa Payoh – City Hall | Residential – CBD (R-CBD) |
| Toa Payah – Orchard | Residential – Commercial (R-C) |
| Boon Lay – Gul Circle | Residential – Industrial (R-I) |
| City Hall – Toa Payoh | CBD – Residential (CBD-R) |
| City Hall – Orchard | CBD – Commercial (CBD-C) |
| Orchard – Toa Payoh | Commercial – Residential (C-R) |

Note. Land use and classification data are obtained from Urban Redevelopment Authority of Singapore (2019).

Fig. 3. Number of daily trips via MRT and OD demand for two typical MRT stations.
Singapore thereafter to simulate the disease spread in the city-state. The epidemiological data provided by Ministry of Health (MOH) of Singapore (Ministry of Health of Singapore, 2021) which contains detailed information on each confirmed case, including epidemiological investigations and contact tracing details. Fig. 4 presents the epidemic curve in Singapore, as provided by MOH (Ministry of Health of Singapore, 2021). It is obvious that there were previously two waves of COVID-19 pandemic in Singapore, the first wave covered from Jan 2020 to Sept 2020, and the second wave began from May 2021. In the following sections, the proposed model will be adopted to present the disease transmission in Singapore for these two waves of pandemic.

4.3. Parameter estimation

Since there is no information on the contact probability $\alpha_1$ and infection probability $\alpha_2$ for COVID-19 in Singapore, we adopted a parameter tuning approach to determine the value of infection rate $\alpha$ for the early stages during the pandemic with the scaling ratio $\gamma$ set as 1. Details of parameter tuning for the infection rate $\alpha$, detection rate $\sigma$, and recovery rate $\beta$ are provided as follows:

(I) Recovery rate is calculated as the percentage of infected individuals that would recover daily. It is estimated with regression analysis using Eq. (14):

$$\Delta r_n = \beta \sum_i$$

For a relatively short period, we have

$\Delta r = \beta \sum_i$

For example, the first recovered case in Singapore was recorded on Feb 4, 2020. Therefore, taking a week data starting from this date, we have $\beta = 6 / 243 = 0.0247$. Since the recovery rate will change as the disease and the treatment have been investigated, in the case study, the recovery rate is estimated in each stage.

(II) Infection rate represents that nature of the disease, and therefore it is assumed that it remains constant unless (1) different variants of the pathogen appear, or (2) the contact probability ($\alpha_1$) of individuals has changed (such as due to social distancing being implemented). Given this consideration, the model needs to estimate the infection rates before and after social distancing has been implemented.

We can estimate infection rate by selecting the epidemiological data in a short period of time (such as one week). In the initial stage of pandemic, we can approximate the number of exposed individuals with the number of infected individuals:

$\Delta s = a_se = asi$ (16)
The value of $\Delta s$ is calculated as the summation of the number of infected individuals and the number of individuals in quarantine. Using Eq. (16), we can estimate the infection rate before and after social distancing (where infection rates are different due to changes on contact probability) has been implemented. It should be noted that the values of infection rates are used under the circumstances that the model applies a discrete time approach to update the number of individuals for each state recursively.

(III) In the model, detection rate measures the effectiveness or “strength” of control measures. It represents the efforts made by relevant agencies to identify infected individuals from exposed individuals, and this value can not be directly estimated from the pandemic data. Therefore, we test different values of detection rate $\sigma$ and compare the model predictions with actual cases. In each stage, we choose the appropriate detection rate that produces the minimum prediction errors.

4.4. Model results and analysis

This section applies the developed area-based SEIR model to model the COVID-19 transmission in Singapore. We calibrate the proposed model with the epidemiological data to reveal the infection trends for: (i) the first COVID-19 outbreak in Singapore (from January 2020 to August 2020); (ii) the second wave of the pandemic due to the transmission of the Delta variant (from April 2021 to October 2021). After estimating the model parameters for various stages, the model can provide results to interpret the COVID-19 transmission in Singapore.

4.4.1. The first wave of COVID-19 pandemic in Singapore (from January 2020 to August 2020)

The first wave of COVID-19 pandemic in Singapore began in Jan 2020, and ended by Sept 2020, as presented in Fig. 5. To model the disease transmission in Singapore, we divide the study period into 6 stages, according to the policies and control measures adopted in Singapore from February 2020 to July 2020. The epidemiological data for this period are provided by the Ministry of Health (MOH) of Singapore.

Table 2
Parameter Estimation Results.

| Period (in 2020) | Jan 23 to Mar 13 | Mar 13 to Mar 20 | Mar 21 to Apr 6 | Apr 6 to Jun 1 | Jun 1 to Jun 18 | From Jun 19 |
|------------------|------------------|------------------|-----------------|----------------|----------------|------------|
| Intervention Measure | I                | I                | I + II          | II             | III            | Phase 1    |
| Infection rate $\alpha$ | 4.5e-6           | 3.1e-6           | --              | --             | --             | --         |
| Detection rate $\sigma$ | 0.4              | 0.35             | 0.14            | 0.20           | 0.25           | 0.45       |
| RMSPE between actual and predicted number of active cases | 19.90%           | 21.37%           | 10.33%          | 11.67%         | 8.17%          | 21.01%     |

Note. Infection rate is estimated using clinical data (Ministry of Health of Singapore. 2021) obtained in the early stage of pandemic, and remain unchanged in our model since social distancing is enforced.

The value of $\Delta s$ is calculated as the summation of the number of infected individuals and the number of individuals in quarantine. Using Eq. (16), we can estimate the infection rate before and after social distancing (where infection rates are different due to changes on contact probability) has been implemented. It should be noted that the values of infection rates are used under the circumstances that the model applies a discrete time approach to update the number of individuals for each state recursively.

(III) In the model, detection rate measures the effectiveness or “strength” of control measures. It represents the efforts made by relevant agencies to identify infected individuals from exposed individuals, and this value can not be directly estimated from the pandemic data. Therefore, we test different values of detection rate $\sigma$ and compare the model predictions with actual cases. In each stage, we choose the appropriate detection rate that produces the minimum prediction errors.

Fig. 5. Active and total COVID-19 cases in Singapore from January to October 2020 (Ministry of Health of Singapore. 2021).
Singapore (Ministry of Health of Singapore, 2021) and contains detailed information on each confirmed case, including epidemiological investigations and contact tracing details. The number of active infected COVID-19 cases and the total number of infected persons from January 2020 to October 2020 are shown in Fig. 5.

Table 2 shows the key parameter estimation results for the various stages of the COVID-19 pandemic in Singapore from January 2020 to August 2020. It can be observed that in the early stage of the pandemic, the detection rate is high, because it is much easier to control and quarantine possible exposed individuals in this period due to the small number of infected and hence exposed individuals. The increase in the number of infected individuals (and the number of unlinked cases) increased since Mar 18, 2020 (Ministry of Health of Singapore, 2021) and increased the burden on contact tracing, while reducing the detection rate. After the enforcement of CB, detection rate gradually increased, which means that the efforts of contact tracing are recovering (primarily also due to use of contact tracing apps such as SafeEntry and TraceTogether). Due to the small number of infected individuals in the early stage and in Phase 2 of the reopening, a relatively high RMSPE at around 20% is observed. The model performs well during the CB period and Phase 1 of reopening with a RMSPE of less than 10%.

Fig. 6(a) illustrates the trends between the the predicted number of cases (for both active and total cases) and the actual number of cases from January to August 2020 while Fig. 6(b) compares the model performance against actual daily COVID-19 active and total cases.
cases. It can also be seen that there is a relatively good fit between our model and the actual data.

We further investigate the number of exposed individuals and the number of infections by sources as predicted by the model. Fig. 7 shows the number of exposed (latent) individuals in Singapore along with the timeline of key intervention measures adopted from Mar to Aug 2020. It is clear from the figure that there is a sharp decrease in the number of exposed (latent) individuals after CB was enforced on April 7, 2020. This is a result of stricter quarantine policies and lower contact probability during this period. Further analysis on the number of recovered cases also indicated an increased recovery rate $\beta$ and this is due to a better understanding of COVID-19 among the general population along with an increase in medical facility capacity (e.g., community isolation facility) in Singapore.

As mentioned in Section 3, the proposed model considers infections by four sources. Fig. 8 shows the predicted number of infections by sources in the first COVID-19 outbreak. The predicted infections caused by individual commuting between activity zones from Mar 1, 2020 to June 1, 2020 are shown in Fig. 8(a). It can be seen from Fig. 8(a) that work-from-home and work shift measures (and in the meantime, active disinfection of public transport systems) is an active can reduce the increase of infections, and the number of infections reached a plateau during the CB period. Fig. 8(b) shows the number of infections caused by the four sources mentioned as predicted by our model. Although travel between zones can play a considerable part in the early stage of disease transmission (up to 16.3%), infection within activity zones play a much higher role in transmission much later in the pandemic progression, and this can account for as high as more than 90% of the infection cases. Minimizing possible long-duration contact in the public transportation system, wearing of masks, and safe distancing are found in our models to play and important role in reducing infections for traveling between zones as revealed by parameter estimates in the model presented in Table 2. There are also several possible pandemic control and management measures that could be adopted in practice to minimize the contact of commuter and this could include: (1) carry out special routes schedule – some stations would be skipped in corresponding routes; (2) strict diversion for passengers in the intersection stations to make sure the minimized contact among them; (3) increase the frequency of cleaning and disinfection of public transportation; (4) active contact tracing, such as use of SafeEntry and TraceTogether apps (Government Technology Agency of Singapore, 2020).

4.4.2. Reopening Phase 2 and Phase 3 (from September 2020 to April 2020)

The effectiveness of pandemic control measures and model performance during the Reopening Phase 2 and Phase 3 (from Sept 2020 to Apr 2021) is studied. Fig. 9 shows the number of imported cases and island-wide cases (dormitory cases and community cases) from Sept 1, 2020 to April 1, 2021. It can be observed from the figure that the number of island-wide cases remained zero for a long time since Nov 1, 2020, and there were few (less than 5) cases recorded daily when Singapore entered Reopening Phase 3. The main pandemic control measure during this period was Intervention Measure IV - Phase Advisory. In addition, the Singapore government would adjust control measures during different stages of the reopening phases, and the pandemic control measures during this period are summarized in Table 3.

We tune the model parameters in our proposed model and apply it to simulate disease transmission for this period, and the key parameter estimation results for the this time period are presented in Table 4. The infection rate is assumed to be the same as that in phase 2, since the dominant subvariant of COVID-19 had not changed during this period. In addition, the detection rate for phase 2 is the same as that in Table 2 (From Jun 19), because of the similar control measures adopted during this period. For the detection rate in Phase 3, we estimate it by minimising the prediction errors between the model results and the actual epidemiological data.
Fig. 10 compares the model predicted infections and actual infections from Sept 1, 2020 to Apr 1, 2021. It can be observed from the figure that the model results only slightly overestimate the number of cases, partly because the experiments cannot fully model the effects of imported cases.

4.4.3. Second wave of COVID-19 pandemic in Singapore (from May 2021 to October 2021)

Singapore’s vaccination (2 doses) coverage gets progressively higher over time with a nationwide coverage of 60% in Aug 2021 and 80% in Sep 2021. The second wave of COVID-19 pandemic in Singapore began in May 2021 as a result of the Delta variant. Fig. 4 has earlier shown that the second wave resulted in more infections compared to the first outbreak. Singapore went back to Reopening Phase 2 on May 8, 2021, and conducted stricter control measures. Table 5 summarizes the main control measures during this period.

The number of imported cases and island-wide cases (dormitory cases and community cases) from April 15, 2021 are shown in Fig. 11. Due to the high vaccination coverage, the Singapore government decided to relax the control measures on Aug 2021, resulting in an increase in the number of island-wide cases. The proposed model is applied to simulate disease transmission during this period. Table 6 presents the tuned parameters of the model and Fig. 12 compares the model predicted infections and actual infections from Apr 15 to Oct 31, 2021. Since the control measures were adjusted frequently during this period, the detection rates for each period must be
individually estimated by minimizing the errors between actual and predicted number of cases. In addition, as there was no detail information on the infection rate of Delta variant in Singapore, the infection rate used in our model is estimated by minimizing the prediction errors. It should be noted that although Singapore’s vaccination (2 doses) coverage is high, this may only lower infection rate among the non-Delta variants. A current study on the effectiveness of vaccination (Bruxvoort et al., 2021) implies that the infection rate among Delta variants (even with high vaccination coverage) may still be similar to the non-Delta variants in the early phase of the pandemic when vaccination is not yet available. This is observed in the infection rate obtained from our model as shown in Table 6.

4.5. Pandemic control measures on COVID-19 for the various phases

This section interprets quantitatively the effectiveness of pandemic control measures implemented in Singapore. Since there were few COVID-19 cases in Reopening Phase 2 and Phase 3, this section will mainly focus on the quantitative analysis on (1) the first wave of COVID-19 outbreak (from January 2020 to June 2020), (2) the Reopening Phases after Circuit Breaker (from June 2020 to August 2020 to April 2021)}
Fig. 10. Comparison between model predicted infections and actual infections (island-wide cases) from Sept 1. 2020 to April 1. 2021.

Table 5
Pandemic control measures in Singapore from April 15. 2021 onwards.

| Before May 8. 2021 | May 8-May 15. 2021 | May 16–July 11. 2021 | July 12–July 21. 2021 |
|-------------------|---------------------|----------------------|----------------------|
| Max Group Size    | 8                   | 5                    | 2                    | 5                    |
| Max Visitors      | 8                   | 5                    | 2                    | 5                    |
| Max Gatherings    | 2                   | 2                    | 2                    | 2                    |
| WFH               | ≤75% at the workplace | ≤50% at the workplace | Default              | Default              |
|                   | July 22–Aug 9. 2021 | Aug 10–Sept 26. 2021 | From Sept 27. 2021   |                      |
| Max Group Size    | 2                   | 5 (V) or 2(U)*       | 2                    | 2                    |
| Max Visitors      | 2                   | 5                    | 2                    | 2                    |
| Max Gatherings    | 2                   | 2                    | 1                    | 1                    |
| WFH               | Default             | Default              | Default              |                      |

* V – Fully Vaccinated U – not fully vaccinated.

Fig. 11. Number of imported cases and island-wide cases from Apr 15. 2021 to Oct 31. 2021.
4.5.1. Effectiveness of pandemic control measures on first COVID-19 outbreak in Singapore (from January 2020 to June 2020)

Intervention Measure I, II and III were the three main pandemic control measures in the first COVID-19 outbreak (from January 2020, and (3) the second wave of COVID-19 (from May 2021 onwards).

4.5.1. Effectiveness of pandemic control measures on first COVID-19 outbreak in Singapore (from January 2020 to June 2020)

Table 6
Parameter Estimation Results.

| Period                  | Before May 8, 2021 | May 8 to May 15, 2021 | May 16 to July 11, 2021 | July 12 to July 21, 2021 | July 22 to Aug 9, 2021 | Aug 10 to Sept 26, 2021 | From Sept 27, 2021 |
|-------------------------|--------------------|-----------------------|-------------------------|-------------------------|------------------------|------------------------|------------------|
| Infection rate $a$     | 4.4e-6*            | –                     | –                       | –                       | –                      | 4.0e-6**              | –                |
| Detection rate $s$     | 0.4*               | 0.44                  | 0.53                    | 0.40                    | 0.50                   | 0.40                   | 0.46             |
| RMSPE                   | 11.22%             | 18.16%                | 24.47%                  | 23.16%                  | 17.01%                 | 10.06%                 | 11.04%           |

* Detection rate is the same as that in Phase 3. and infection rate is estimated from prediction error minimization approach. New infection rate is adopted due to the appearance of a new subvariant of COVID-19 virus (Delta variant) in Singapore.

** We consider a decreased infection rate as the vaccination rate in Singapore exceeded 70%.

![Fig. 12. Comparison between model predicted infections and actual infections from Apr 15 to Oct 31, 2021.](image1)

![Fig. 13. Predicted infections in Singapore with implementation of various measures.](image2)
(2020 to June 2020) in Singapore, and their effectiveness is investigated in this sub-section. It can be observed from Fig. 4 that there is a huge increase in the number of confirmed cases right before Singapore entered into the CB period. This is primarily because by this time there had been already a sufficient number of exposed (latent) individuals within the dormitories and community to cause concern (shown in Fig. 7). Table 2 shows that the detection rate gradually decreased until the circuit breaker period, which means that the effectiveness or “strength” of control measures weakened. This is due to the increasing number of infected cases (unlinked cases) (Ministry of Health of Singapore, 2021) which creates burden on contact tracing efforts and pressure on available medical resources.

We simulated the dynamics of disease transmission and predict the number of infections during this period and the results are shown in Fig. 5 and Fig. 6(a) with the parameter estimates shown in Table 2. It can be observed that after Circuit Breaker period, the number of infection cases has dropped to a controllable level. In addition, detection rate increases to the same level as that of January 2020, which show the effectiveness or “strength” of control measures on identifying exposed individuals in the reopening period.

We further explore the consequences of (1) lack of adoption of certain intervention measures, and (2) delay in implementing pandemic control measures on the total number of infected COVID-19 cases. Fig. 13 shows the dynamic of disease transmission if one of the three intervention measures discussed in the earlier section was not adopted. It can be observed from the figure a lack of any of the three measures would result in a higher number of infections and all three intervention measures play an important part in curbing the transmission of COVID-19 in Singapore. Although social distancing measures and work shift arrangement could postpone the transmission of COVID-19 to a great extent in the early stage, Circuit-Breaker is the leading disease control policy in face of a rapid increase in COVID-19 transmission. It is further estimated that there would have been about 175,000 additional infections by June 1, 2020 should CB be not imposed.

Table 7
Effect of pushing forward or delaying the implementation of intervention measures on COVID-19 cases.

| Intervention Measure                        | Number of active COVID-19 cases on 1 June 2020 | Number of total COVID-19 cases on 1 June 2020 |
|--------------------------------------------|-----------------------------------------------|------------------------------------------------|
|                                            | I     | II     | III    | I     | II     | III    |
| Pushing Forward Intervention Measure by 1 day | 12,803 | 13,624 | 12,947 | 30,004 | 31,956 | 30,111 |
| Delaying Intervention Measure by 1 day     | 17,875 | 15,411 | 17,980 | 42,159 | 36,245 | 42,162 |
| Delaying Intervention Measure by 3 days    | 24,768 | 21,364 | 25,320 | 58,923 | 50,588 | 59,720 |

![Fig. 14. Number of active cases from June to August 2020](image)

![Fig. 14. Number of total cases from June to August 2020](image)
The impact of postponing the enforcement of various intervention measures on the COVID-19 cases in Singapore is also investigated. Table 7 shows the impact on the number of cases (i.e., predicted additional infections by June 1, 2020) should any of the three intervention measures were pushed forward by a day, postponed for 1 day, or postponed by 3 days. As can be seen from the table, social distancing measure (intervention measure I) and in the early stage of the pandemic can successfully postpone the transmission of COVID-19. As the disease continues to spread, the early enforcement of CB (intervention measure III) could also decrease the number of infections. Work-from home and work shift (intervention measure II) tends to be less effective than the above two intervention measure. In addition, delaying the enforcement of intervention measures could have resulted in a great number of additional infections, and therefore taking measures in time is crucial to pandemic control.

4.5.2. Impact of re-opening dates for Reopening phases (from June 2020 to August 2020)

This sub-section shows how the selection of re-opening dates may result in different pandemic control outcomes. On June 1, 2020, the CB came to an end and Singapore entered the post-CB period (Phase 1: Safe Re-opening). Singapore gradually re-opened economic activities that do not pose high risk of transmission, while social, economic and entertainment activities with higher risk remain closed. However, work from home (WFH) is still required except essential services defined in the government document on Phase 1 (Ministry of Health of Singapore, 2020c). By June 18, 2020, Phase 2 (Safe Transition) have been enforced. At this stage, most businesses are allowed to resume, with safe management measures, group size and capacity limits in place. Restricted social interactions are allowed, and schools can re-open.

Using the developed model, Fig. 14 explores the effect of changing the re-opening dates based on four scenarios: Scenario I: Postpone the start of Phase 1 and Phase 2 by a week; Scenario II: Postpone the start of Phase 1 and Phase 2 by two weeks; Scenario III: Start Phase 1 and Phase 2 a week ahead; and Scenario IV: Postpone the start of Phase 2 by a week. It can be observed from the figure that there would have been fewer number of infections if the start of Phase 1 and Phase 2 were postponed (i.e., Scenario I, II and IV). The delay in the start date of Phase 2 results in similar infections cases comparable to that in Scenario I, and both cases are deemed to be able to avoid possible infections. Scenario II would result in an obvious decrease of infections and there would be no signs of infection rebound, while Scenario IV would lead to the rapid increase in infection cases.

4.5.3. Effectiveness of pandemic control measures during the second wave of COVID-19 in Singapore (from May 2021 onwards)

Intervention Measure IV is the main pandemic control measures adopted during the second wave of COVID-19. Fig. 15 illustrates the number of island-wide cases (including dormitory residents cases and community cases) from May 2021 to Oct 2021. It is obvious that changes to the transmission trend occurred whenever pandemic advisories were adjusted, such as at three points in time i.e., July 22, 2021 (where the relaxed measures were terminated), Aug 10, 2021 (where enhanced measures were introduced to control the spread of Delta variant in the community) and Sept 27, 2021 (where stricter regulations were adopted to restrain increasing number of infected cases.

We thus investigate the effectiveness of these phase advisories with our model. Table 8 presents the number of cases (i.e., predicted additional infections by Oct 31, 2021) should the various measures implementation date be pushed forward by 1 day, postponed for 1
day, or postponed by 3 days. It can be clearly seen from the table that delaying the enforcement of intervention measures can result in a considerable number of additional infections, and therefore taking measures in time is crucial to pandemic control.

5. Conclusion

This paper studies the dynamics of disease transmission in Singapore during the outbreak of COVID-19 virus and quantifies the effectiveness of several pandemic restriction measures adopted in Singapore during the pandemic. In the study, we extend the classic Susceptible-Exposed-Infectious-Recovered (SEIR) model to an area-based SEIR model with consideration of infections within areas (or activity zones) and infections occurred during travel commute of individuals. The quarantine is modeled in the way that susceptible individuals can only be exposed to COVID-19 virus from exposed (latent) individuals. The exposure to infection during commute is considered with the addition of a commute infection term in our developed disease transmission model. A case study of Singapore during the COVID-19 pandemic is presented to quantify the effectiveness of pandemic restriction policies. This study further investigates the impact of re-opening date adjustment on pandemic spread. The pandemic control measures which could be adopted for public transport is discussed and can be adopted in practice to minimize the contact between commuters in the reopening period.

This paper provides the feasibility of a disease transmission model with travel commute consideration as a tool for long-term pandemic modeling. Using over two years’ worth of data during the COVID-19 pandemic in Singapore, the paper shows that transmission dynamics in the first wave and the second wave of COVID-19 pandemic are well modeled. This work is hence a significant extension of the existing disease spread models for megacities. The consideration of different areas and commuting enable us to consider the human mobility in megacities, which can be used to model the spatial distribution of transmission. The quantification of several disease control measure in different stages of disease transmission can help the government to decide proper control policies in response to pandemic, which is crucial to public health, society and economic. On the other hand, there are some important factors that are neglected in this paper. Due to the complicated nature of the COVID-19 virus, this model may not sufficiently model the dynamic of disease transmission. Second, the spatial distribution and the corresponding characteristics of transmission have not been investigated due to the lack of detailed information on infections cases (mainly because of privacy issue). These issues will be explored in our future research.

CRediT authorship contribution statement

Jielun Liu: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft. Ghim Ping Ong: Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. Vincent Junxiong Pang: Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Disclaimer

Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Singapore Ministry of Education and the Singapore government.

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