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Enhancing Covid-19 virus spread modeling using an activity travel model

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Abstract

Coronavirus 2019 (COVID-19) and its variants are still spreading rapidly with deadly consequences and profound impacts on the global health and world economy. Without a suitable vaccine, mobility restriction has been the most effective method so far to prevent its spreading and avoid overwhelming the health system of the affected country. The compartmental model SIR (or Susceptible, Infected, and Recovered) is the most popular mathematical model used to predict the course of the COVID-19 pandemic in order to plan the control actions and mobility restrictions against its spreading. A major limitation of this model in relation to modeling the spreading of COVID-19, and the mobility limitation strategy, is that the SIR model does not include mobility or take into account changes in mobility within its structure. This paper develops and tests a new hybrid SIR model; SIR-M which is integrated with an urban activity travel model to explore how it might improve the prediction of pandemic course and the testing of mobility limitation strategies in managing virus spread. The paper describes the enhanced methodology and tests a range of mobility limitation strategies on virus spread outcomes. Implications for policy and research futures are suggested.

1. Introduction

Since December 2019, Coronavirus disease (or COVID-19 in short) has caused havoc on the global public health with its rapid spreading over 220 countries and territories, resulting in more than 457 million people being infected and six million deaths (World Health Organization, 2021). While awaiting for a suitable vaccine to be developed against the COVID-19, different policies and interventions have been implemented to contain the escalation of the disease, including high rates of diagnostic testing, rapid isolation of suspected cases, and most notably, restrictions on mobility in high-risk areas (Zhu et al., 2020). Initial analysis suggests that the mobility restrictions resulted in an average 3-day delay of the COVID-19 spread to other cities (Tian et al., 2020); however, the full extent of the effect of mobility restrictions and other types of interventions on transmission has not been examined quantitatively (Wu et al., 2020; Zhao et al., 2020b).

COVID-19 has been found to have a longer incubation time and higher estimated reproduction number, as compared to SARS-CoV or MERS-CoV (Majumder et al., 2014; Zhao et al., 2020a; Read et al., 2020), so it can be more easily transmitted by individuals who have no or only mild symptoms (Wang et al., 2020). With these characteristics, mobility restrictions or even hard lock-down have been used by authorities around the world to stop or at least slow down the spreading of this pandemic.

Virus spread modeling is thus a critical element to COVID-19 management and mobility restrictions is a critical strategy within this field. In order to predict the viral transmission in the community, the SIR (Susceptible–Infectious–Recovered) mathematical...
model (Kermack and McKendrick, 1927) and its variants (Hethcote, 2000; Brauer et al., 2012; Anderson et al., 1992) have been widely applied to predict the course of the COVID-19 pandemic, and to describe possible stage transitions (e.g., from susceptible to infectious) with the consideration of clinical and biological features (e.g., incubation period or reproductive rate) in these compartmental models (CM). Depending on the disease, the SIR model could be extended by adding new stages of contagions as done in SEIR (Lin et al., 2020), SIRD (Anastassopoulou et al., 2020) or SIRDX (Giordano et al., 2020).

A major limitation of current approaches to virus spread modeling is that the SIR models and their variants do not include mobility in their structure and so cannot directly consider mobility limitation strategies as a policy measure. This is because in the conventional compartment models (i.e. SIR) individuals are assumed to be distributed evenly and behave homogeneously (Anderson et al., 1992; Bailey et al., 1975). Early works such as Sattenspiel and Dietz (1995) proposed a SIR model that incorporates geographic mobility patterns to model the measles epidemic. Even though the model simultaneously considers both epidemic and behavioral processes, it assumes traveler characteristics are static and the mobility patterns of different groups are independent of one another. This assumption is somewhat unrealistic because a person's mobility pattern depends not only on dynamic factors such as weather, traffic condition but also on other people's travel decisions (e.g., mode and departure time). Besides, Sattenspiel and Dietz (1995) also neglects the infections that might occur during traveling on shared public transport. This is crucial for epidemics such as COVID-19 in which a susceptible person might get infected while traveling together with infected individuals.

Some recent works use real mobility data to model the epidemic with promising results such as Chang et al. (2021). Nevertheless, large scale data availability and accessibility remain a challenging problem. Using a transport model to generate detailed and realistic synthetic data is thus an attractive alternative as proposed and shown in this paper. On that aspect, a similar work in Najmi et al. (2020) proposed to use the SydneyGMA transport model to provide the activity location of each individual to predict the pandemic impact for Sydney. The SydneyGMA is based on the TASHA model (Roorda et al., 2008), which generates activity schedules at zonal levels but without the exact location (within the zone) and time of the out-of-home activities due to unknown travel time delay. For this reason, the activities and time of agents within the zone were largely overlapped, and thus, to make it a realistic model, SydneyGMA randomly picked agents in the zone to model the interactions among a subset of agents only. This is crucial for studying infectious diseases closely related to human travel behaviors and serves as an approximate model only (Najmi et al., 2020). A similar framework was developed to study the trade-off between different levels of social distancing compliance and the transition of COVID-19 (Chang et al., 2020). This work was based on the ACEMod — an epidemiology model which employed a highly sophisticated calibration process that included: age-dependent attack rates, a range of reproductive numbers, age-stratified and social context-dependent transmission rates, household clusters (HCs) and other social mixing contexts, symptomatic-asymptomatic distinction, and other relevant epidemiological parameters. Further note that even though the results are quite close to reality, this model cannot trace specific spatial pathways and patterns of the epidemics.

Furthermore, recent research has also demonstrated how commuting behavior can relate to viral transmission using a microscopic agent-based simulation model combined with the SIR model to describe the infectious stages of traveling agents (Banos et al., 2015; Muller et al., 2020). Banos et al. (2015) studied the impact of integrating mobility factors with the traditional SIR model to study the spread of flu across different cities by proposing a hybrid model. Specifically, Banos et al. (2015) first established the metapopulation at the macro level with aggregated mobility, and then used the real flight data to model a more detailed (disaggregate) mobility at the micro-scale. As using deterministic flight data as source of mobility, this metamodel cannot include details relating to the heterogeneous populations and behaviors, as well as the incorporation of human’s intentions and adaptability. To this end, Banos et al. (2015) proposed the hybrid approach, which further modeled infections that occur both during the flight and at the destination (e.g., city), while metapopulation only focused on infections at destinations and modeled their transferring between destinations (Colizza and Vespignani, 2008) but not those occurred during the travel.

On the other hand, Muller et al. (2020) used Episim and a micro simulation of an agent-based model (MATSim) to study and evaluate different possible policies and interventions to combat the pandemic. While running MATSim, the pandemic evolved with infections took place in Episim with certain probabilities defined by a person-centric epidemiological model. This approach does not include a macro level but rather works entirely at the micro level. Furthermore, as the agents’ trajectories in this model do not change (i.e. the same interactions among agents) from day to day, this model often underestimate the viral transmissions (Muller et al., 2020) due to the low mixing contacts.

Departing from the existing literature, we propose in this study a new hybrid SIR model (SIR-M), which incorporates the transmission of the virus in both time and space by taking into account the travelers’ mobility and mode (e.g. private vehicle or public transport, PT). We propose to use an agent-based transport model, which is based on real data, including population and its characteristics, to generate the (disaggregate) mobility data at the micro-scale. We then aggregate them to create the metapopulation model at the macro level forming a hybrid model. In other words, the different policies and interventions can then be applied to the synthesized mobility data at the micro-scale to evaluate their impacts at the macro level using this metapopulation model. Similar to Banos et al. (2015), the proposed model is hybrid since it takes into account the infections due to mobility (including travel delay and mode choice) for specific travel mode (e.g. public transport) besides modeling the infection at each location, which similar to the metapopulation approach. The proposed hybrid model is able to spatially and temporally capture the spread of the viruses with lower complexity than that of the existing probabilistic microscopic approach in the literature. It is worth noting that the model is not limited to the agent-based model due to its hybrid nature and only requires the information from the transport model as OD flows between zones at the macro-level (similar to the metapopulation model). Furthermore, the issue of underestimated transmission due to low mixing contacts will be tackled here by considering the possible distribution of transmissions among the movements in a group of agents rather than modeling the probability of infectious transmission between contacting agents only. Therefore, it can be applied with any mobility models or simulations without the need of adapting to a particular implementation or platform, and
thus is more flexible and versatile. Table 1 summarizes the existing pandemic models and compares them with the model proposed in this paper.

In summary, our contributions are the following:

- We propose a new hybrid and more accurate epidemiological model (SIR-M) based on the conventional SIR model to study the course of the COVID-19 pandemic and its spatial impact considering the community’s mobility and mode of travel.
- We develop a framework to study the interactions between mobility and the transmissions of virus under different intervention policies and evaluate their impact on a network-wide transmission.
- We demonstrate the applicability of our model and framework via a case study using the Melbourne Activity-Based model (MABM) (Victoria, 2017) for the Melbourne city in Australia to demonstrate the impact of applying multiple types of mobility restrictions and their timing.

The paper is structured as follows; the following section presents background to the research, including an outline of the SIR model and the Melbourne Activity Based Model. The proposed methodology is then described. Results of application are then outlined. The paper finishes with an outline of key findings and a discussion of implications for both research and practice.

2. Background

2.1. The SIR model

The SIR (Susceptible–Infectious–Recovered) is a compartment model which contains a set of ordinary differential equations describing the infectious diseases evolution. In this model, the population is separated into distinct sub-populations based on the status of the disease. The SIR model, which was proposed in early twentieth century (Kermack and McKendrick, 1927), divides the population into three sub-classes: Susceptible ($S$), Infected ($I$) and Recovered ($R$). The sizes of these sub-populations are denoted as function of time $S(t)$, $I(t)$, and $R(t)$. The transition rate from $S$ to $I$ and from $I$ to $R$ are shown in Eqs. (1) to (3) as followed:

$$\frac{dS}{dt} = -\frac{\beta S I}{N}$$
$$\frac{dI}{dt} = \frac{\beta S I}{N} - \gamma I$$
$$\frac{dR}{dt} = \gamma I$$

$$\frac{dS}{dt} + \frac{dI}{dt} + \frac{dR}{dt} = 0$$

$$S(t) + I(t) + R(t) = N$$

$$R_0 = \frac{\beta}{\gamma}$$

where $N$ is the total population, $\beta$ is the average number of contacts per person per time. If an individual is infectious for an average time period $D$, then the rate of recovery is $\gamma = 1/D$. Eqs. (4) and (5) express in mathematical terms the constancy of population $N$. The reproductive number $R_0$ in Eq. (6) is the expected number of new infections from a single infected individual in a population.

2.2. Melbourne Activity Based Model (MABM)

Melbourne activity-based model (MABM) (Victoria, 2017) is developed by Infrastructure Victoria in the partnership with KPMG and Arup to simulate the activities and travel patterns in the large-scale Melbourne metropolitan network. The MABM utilizes the open source platform known as Multi-agent transport simulation (MATSim) which was developed incrementally since in the early 1990’s (Horni et al., 2016).

The geographic coverage of the MABM includes Greater Melbourne whose input is generated corresponding with the demographic of Melbourne by the following calibration process: Population synthesis, activity travel pattern and scoring function parameters.
### 2.2.1. Population synthesis

The synthetic population is a list of individuals in MABM that reflects the population of Greater Melbourne with unique demographic identifiers. Therefore, a combination of aggregated population, household census data and method of travel to work is used to create key demographic dataset for each region. This dataset is then used together with the total number of individuals within each region called ‘control total’ during population synthesis process to make the synthetic population proportionally match with demographic trend, and household totals. The ‘control total’ contains a list of demographic identifiers such as age, car ownership for each VITM zone in individual level. This factor functions as a constraint to ensures the final population is representative for Greater Melbourne.

The age profile and residential geographic distribution is estimated from the Victoria in Future (VIF) (Department of Environment Land Water and Planning, 2016). Since the method of travel to work data is obtained from 2011 Census, an ‘inflation factor’ is calculated by the number of household projected for the reference year (2016) with the number of household number in the Census 2011 for each VITM zone.

### 2.2.2. Activity travel pattern

After population synthesis, a virtual population was created for use in MATSim which demands each agent to be assigned with an activity plan representing its daily movements and activities. These plans are generated by using 2011 Census for journey to work and the 2012–14 Victorian Integrated Survey of Travel and Activity (VISTA) (Department of Economic Development, Jobs, Transport and Resources, 2017) for activity.

The activity travel pattern generation begins with assigning an activity plan to workers. The location of work is obtained from Method of Travel to Work Profile (MTWP) 2011 Census (Australia Bureau of Statistics, 2017b,a). From this location, nine combinations of mode choice are used to create the home to work trips and the control total generated from the population synthesis is used to scale up the population to match in the reference year.

Then, to assign the whole day activity plan to each worker, VISTA records are used to determine additional trips, trips lengths and timings. Each agent is matched with an activity plan from VISTA using a demographic signature which base on agent’s age (for non-worker), household location and employment status.

The trip purposes considered in MABM are:

- Home
- Work
- Business
- Education (Primary/Secondary/Tertiary/Drop-off/Pick-up)
- Others

The activity location assignment is dependent on the activity type itself. For example, the education trips for primary and secondary education activity type are ‘snapped’ to the school that is nearest to the trip distance reported in VISTA. For others activity types, the location is randomly chosen based on the trip length and the its occurrence (at an SA2 level) reported in VISTA.

### 2.2.3. Scoring function parameters

The plans in MATSim is scored with positive utility/dis-utility associated with activities and travel respectively. The scoring function are pre-defined within MATSim therefore they are modified to reflect the behavior of Greater Melbourne. The modification process is achieved by using multinomial logistic regression for existing travel data for Melbourne (VISTA data). The results from this process are the parameters that are used in utility function for travel by different modes in MABM.

### 3. Method

The proposed framework consists of two parts, namely the SIR-M and the mobility extraction process that can be customized. In our study, we used MABM for mobility extraction; however, this part can be modify according to the source of mobility data that is available (e.g., mobile data, social network data). Fig. 1 depicts how the two parts interact under the framework. Notations used in this section are defined in Table 2.

#### 3.1. SIR-M model

In this section, we will describe our proposed SIR-M model in more detail. The SIR with the mobility (SIR-M) model describes the evolution as well as the movement of the population in each stage through different zones over time. Let $D_I$ be the infectious duration per infected individual and $R_0$ be the reproductive number representing the expected number of cases that can be generated from an infectious individual in the susceptible population (Fraser et al., 2009). In SIR, the recovery rate (from stage I to stage R) is $\frac{1}{D_I}$ and the infectious rate (from stage S to stage I) is $\frac{R_0}{D_I}$. In addition, the reproductive rate $R_0$ remains unchanged until the pandemic dies out. Lastly, the probability of becoming susceptible again, after having already recovered from the infection is omitted, because this appears to be negligible based on the current evidence (Lan et al., 2020).

The model classifies the population in three compartments including “Susceptible” ($S$), “Infectious” ($I$), and “Recovered” ($R$) stages. In each zone $i$ at any time $t$, we denote the number of susceptible, infected, and recovered individuals by $S_i(t), I_i(t), R_i(t)$ who
Fig. 1. The proposed framework consisting of Melbourne Activity Based Model (MABM) and SIR-M. The framework begins by generating the synthetic population which required geographic data, survey related to occupation, transit network etc. Then, the optimal mobility under different policies is obtained by simulating this synthetic population iteratively with MATSim optimization framework which was calibrated with Melbourne data. The final step is simulating the SIR-M model with mobility extracted from MATSim optimal output.

use their private cars to travel, respectively. Similarly, for people traveling on public transport (or PT), we denote the corresponding quantities as $\bar{S}(t), \bar{I}(t), \bar{R}(t)$. Recovered individuals in $R(t)$ and $\bar{R}(t)$ are assumed to be immune, i.e. not contracting the disease again or transmitting the infection to others. The mobility generated by the population is aggregated within a time period $t$ (2 h was used in the above results), and categorized into public transport (PT) and non-public transport (non-PT). The infection can happen while conducting activities in a zone or during the time traveling on PT. Let $Q(t)$ and $\bar{Q}(t)$ be the total population in zone $i$ for non-PT (i.e. car) and PT users respectively at time $t$, therefore, we have

\begin{align}
Q(t) &= S(t) + I(t) + R(t) \\
\bar{Q}(t) &= \bar{S}(t) + \bar{I}(t) + \bar{R}(t).
\end{align}

3.1.1. Modeling the mobility in SIR

In each zone $i$ at any time $t$, the probability of getting infection by conducting activities is denoted by $p_i(t)$ and $\bar{p}_i(t)$ and is given as follows:

\begin{align}
p_i(t) &= \frac{I(t) + \bar{I}(t)}{Q(t) + \bar{Q}(t)} \frac{R_0}{D_I} \\
\bar{p}_i(t) &= \frac{\bar{I}(t)}{\bar{Q}(t)} \frac{R_0}{D_I}.
\end{align}

In this formulation, the transmission rate is defined by the product of reproductive number $R_0$ and the inverse of infectious period $D_I$. The probability $p_i(t)$ is applied to everyone conducting an activity (e.g., working, shopping etc.) in zone $i$; however,
Using PT have an additional probability $\tilde{p}_i(t)$ of getting infection by traveling on PT with others. Based on these probabilities, we estimate the number of susceptible individuals in each zone $i$ at any time $t$ for PT and non-PT users considering mobility as follows:

$$S_i(t + 1) = S_i(t) - S_i(t)p_i(t) + \sum_{j \in Y^+_i} s_{ij}(t) - \sum_{j \in Y^-_i} s'_{ij}(t)$$  \hspace{1cm} (11)

$$\tilde{S}_i(t + 1) = \tilde{S}_i(t) - \tilde{S}_i(t)(\tilde{p}_i(t) + \tilde{p}_i(t)) + \sum_{j \in Y^+_i} \tilde{s}_{ij}(t) - \sum_{j \in Y^-_i} \tilde{s}'_{ij}(t)$$  \hspace{1cm} (12)

$$\sum_{j \in Y^+_i} s_{ij}(t) \leq S_i(t)\left(1 - p_i(t)\right)$$  \hspace{1cm} (13)

$$\sum_{j \in Y^-_i} s'_{ij}(t) \leq S_i(t)\left(1 - \tilde{p}_i(t) - \tilde{p}_i(t)\right)$$  \hspace{1cm} (14)

Eqs. (11) and (12) are the numbers of susceptible people for non-PT and PT travelers in zone $i$ at time $t + 1$, respectively, which equals the number of susceptible people in or arriving into that zone at time $t$ subtracts the number of people who get infected or leaving that zone. Let $s_{ij}(t)$ and $\tilde{s}_{ij}(t)$ denote the numbers of susceptible people leaving at time $t$ from region $i$ to region $j$ for non-PT and PT travelers, respectively. At the downstream of link $(i, j)$, let $s_{ij}(t)$ and $\tilde{s}_{ij}(t)$ be the numbers of susceptible people from region $i$ and arriving the region $j$ at time $t$ for non-PT and PT travelers. Eqs. (13) and (14) ensure that the number of agents leaving zone $i$ does not exceed the current susceptible agents in this zone. The dynamic of infected people is formulated for each zone $i$ at any time $t$ as follows:

$$I_i(t + 1) = I_i(t) + \frac{I_i(t)}{D_i} + \sum_{j \in Y^+_i} h_{ij}(t) - \sum_{j \in Y^-_i} h'_{ij}(t)$$  \hspace{1cm} (15)
3.1.2. Proportion of S-I-R in movements

Eqs. (15) and (16) represent the numbers of infectious people and are calculated similarly to the number of susceptible people in Eqs. (11) and (12) at zone \( i \) by adding new infected cases (from stage S to I) and subtracting to the number of recovered people (from stage I to R). Furthermore, we also model the flow of infectious people entering and leaving zone \( i \) as the pair \((s_{ij}(t), h_{ij}(t))\) for non-PT travelers and \((\bar{s}_{ij}(t), \bar{h}_{ij}(t))\) for PT travelers. Eqs. (17) and (18) ensure that the number of infectious agents leaving zone \( i \) does not exceed the current infectious agents in this zone. Finally, for stage R, it is cumulatively raised from infected people with the recovery rate \( D_r^{-1} \) as follows:

\[
R_i(t + 1) = R_i(t) + \frac{I_i(t)}{D_r} + \sum_j r_{ij}(t) - \sum_j r_{ij}'(t)
\]

(19)

\[
\bar{R}_i(t + 1) = \bar{R}_i(t) + \frac{I_i(t)}{D_r} + \sum_j r_{ij}(t) - \sum_j r_{ij}'(t)
\]

(20)

\[
\sum_j r_{ij}(t) \leq R_i(t) + \frac{I_i(t)}{D_r}
\]

(21)

\[
\sum_j r_{ij}'(t) \leq \bar{R}_i(t) + \frac{I_i(t)}{D_r}
\]

(22)

Eqs. (19) and (20) show the numbers of recovered people on non-PT and PT modes and are calculated similarly to the number of susceptible and infectious agents in Eqs. (11), (12), (15) and (16). In addition, the notation for mobility of recovered people is the same for susceptible and infectious mobility. Particularly, let \( r_{ij}(t) \) and \( r_{ij}'(t) \) be the upstream and downstream flows of non-PT travelers on link \((i, j)\). Similarly, \( \bar{r}_{ij}(t), \bar{r}_{ij}'(t) \) are for recovered PT travelers. Eqs. (21) and (22) ensure that the number of recovered agents leaving \( i \) is not exceed the current number of recovered agents in this zone.

3.1.3. Day to day continuity of infection

We extend the definition of within-day variables in the above equations for each day \( n \) as \( S^n_i(t), I^n_i(t), R^n_i(t) \) denoting the number of susceptible, infectious and recovered individuals, respectively, in zone \( i \) at time \( t \) in day \( n \). In day \((n + 1)\), the status of infection is from the end of the previous day, as following:

\[
S^{n+1}_i(0) = S^n_i(T)
\]

(29)

\[
I^{n+1}_i(0) = I^n_i(T)
\]

(30)
4. Results

In our numerical results, we set the basic reproduction number $R_0$ equal to 2.4 and assume that the infectious period $D_i$ is 7 days according to the previous works in the literature (Majumder et al., 2014; Zhao et al., 2020a; Read et al., 2020). The chance of infected people requiring hospital care is assumed to be 10% of the infectious population. With the total population of more than 4.6M people in the Melbourne city, the study area is divided into 309 zones where the distribution of people in these areas follows the Victorian Integrated Survey of Travel and Activity (VISTA) (2017) (Department of Economic Development, Jobs, Transport and Resources, 2017), Method of Travel to Work census (2017) (Australia Bureau of Statistics, 2017b,a) and Victoria in Future report (2016) (Department of Environment Land Water and Planning, 2016). The mobility or travel demand for different scenarios (or policies) is extracted from the Melbourne Activity-Based Model (MABM). The MABM model is owned by the Infrastructure Victoria (Victoria, 2016) and uses an open source multi-agent transport simulation (MATSim Horni et al., 2016) platform to simulate the activities and travel patterns in the large-scale Melbourne metropolitan network.

4.1. Intervention policies

In this paper, we evaluate the different policy strategies on mobility to restrain the COVID-19 pandemic in the Melbourne city (Australia) including working restriction, school closure, and 5 km travel restriction rule. In particular, working restriction means certain jobs or works are carried out at home, i.e. working from home (WFH), and thus trips related to the working activities will be reduced while other trips, such as shopping or education, remain the same. Similarly, school closure will eliminate trips of picking up, dropping off children, or going to school. A study during COVID-19 estimated that 39 percents of all jobs in Australia can be done from home, and Canberra has the highest proportion of workforce for this teleworkability (Ulubasoglu and Onder, 2020). Therefore, WFH will be applied on 40 percents of commuters for all policies. The 5 km restriction rule, which was in place in Victoria, Australia from August till mid-October 2020, is the highest level of restriction in which all activities (except permitted work activities) have to be carried within the radius of 5 km from each individual’s home.

4.2. Comparison with the traditional SIR model

We will initially choose 5 random locations that have the first infected individuals, then compare the results from our framework (SIR-M) with the traditional SIR model as shown in Fig. 2. Without mobility, the virus appears to be contained within the proximity of the chosen locations, while with mobility consideration, it spreads out across all zones of the Melbourne network within the studied three month period.

We observe that the mobility prolongs the pandemic and raises its peak significantly higher (about 5 times compared to the result without mobility). The figure also shows that the mobility makes the pandemic more severe in some locations far from the original locations (e.g. Wyndham, Melton or Casey suburbs in the Melbourne city) where large shopping centers or industrial compounds located. Our results show the strong relationship between the activities, associating travel patterns and the transmission of the virus across the city of Melbourne.

In particular, Fig. 3, our model shows similar patterns in comparison with data published for Melbourne by the Victoria’s Department of Health and Human, where the eastern, western, and northern parts of the city have been heavily affected by COVID-19. These are densely populated areas and have the most traffic in the city (see Fig. 4).

4.3. Implementation of policies

The numbers of movements between locations (origin–destination data) representing Melbourne mobility data generated by MABM is demonstrated in Fig. 4. The mobility data incorporates four time periods as shown in Table 3 reveals that the city center, western and southern regions are the busiest areas in all time periods.

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1 This data contains all infected cases in the state of Victoria from the 2nd September 2021 to the 6th of March 2022. Before this period, the State of Victoria imposed local restrictions from the 20th of June before declaring a ‘State of Disaster’ which included the imposition of restrictions such as a nightly curfew, mandatory face coverings in public and the closing of schools and businesses on the 2nd of August 2020.
In this work, the MABM is used to evaluate various control strategies on mobility to prevent the spreading of the COVID-19 pandemic. The travel patterns under different control strategies are obtained and extracted in terms of aggregated flows as the input for the proposed SIR-M model. These policies in this study is mobility related to demonstrated the correlation with the outbreak growth cases.

4.4. Sensitivity analysis

We evaluate the sensitivity of the proposed SIR-M model by varying the infectious periods between 5 and 14 days, the initial locations of the first infected cases and the reproductive number between 2 and 7 (see Fig. 5). It shows that for longer infectious periods, the peak of infections do not change significantly in terms of the total number of cases; however, the health system is required to endure the pandemic for a considerably longer period of time (from two up to six months) in Fig. 5(a). It is expected because longer duration of infection allows infectious individuals more time to travel to other regions before they are diagnosed and isolated.

Fig. 5(b) shows that different initial infected locations only have a small effect on the transmission intensity and speed. However, when all the initial infections are concentrated in one location, it can delay the spread (up to 10 days) and the peak is lower, as compared to that of other scenarios where the spatial infections are distributed over the 15 or 20 different locations. Fig. 5(c) shows
that reproductive number $R_0$ strongly affects the transmission intensity and speed. Specifically, the pandemic’s peak is double with $R_0 = 7$ as compared to $R_0 = 2$ where the same spatial infections are distributed over 20 locations. In reality, the reproductive number reflects how infectious a disease is and can be influenced by control measures.

4.5. Impact of mobility restriction policies on infectiousness

Fig. 6(a, b) presents the number of infected cases over time for the different policies, including working from home (40%), 5 km restriction rule, school closure and a combination of school closure and working from home (40%). We observe that mobility restriction policies have positive impact on the growth rate by reducing the peak of the outbreaks. In particular, work intervention with 40% of workers carry out their job from home slightly reduces the peak and around 1% of the total infected cases compared to that of the base scenario. The policy only impacts 20% of Melbourne population, therefore the actual number of trips that are cut as implementing this policy is insignificant. Besides work restriction, shutting down school and other educational activities via school closure also reduces peak value and total infected cases. This policy reduces large number of trips (e.g., pick-up/drop-off, errands) to city center. Moreover, combining working from home with school closure can enhance this positive effect with a reduction of 15% at the peak compared to that of the base case. Furthermore, we observe that 5 km restriction rule has the lowest peak value and accumulated cases compared to the base scenario. The main reason is that this policy significantly reduced the mobility in crowded place such as city center and places where large shopping centers or industrial compounds are shown in Fig. 4. In overall, all policies can reduce the peak while the shapes remain similar in terms of the period of infectiousness.

In regard to the spatial distribution, Fig. 7 shows that reducing trips to the workplaces or school has a positive effect on preventing the transmission of the viruses with fewer new infected cases in most zones. And thus combining these policies together provides an effective control to contain the outbreak. Furthermore, the impact of these policies on outbreaks differs markedly by zone which shows the strong and significant correlation with mobility factor in containing the outbreak. In particular, city center and the south east areas are zones with highest reduction in total COVID-19 new cases. This is consistent with mobility data in Fig. 4 where these area are the busies zones of the city.

In overall, our results show that the SIR-M model is capable of better predicting the course of the COVID-19 pandemic taking into account the impacts of mobility, which in turn enables a more accurate evaluation of different control policies both temporally and spatially against the pandemic and its spreading.

5. Conclusions and discussion

This paper has proposed a new macroscopic epidemic virus spread model, SIR-M, which extends the traditional SIR model to consider the impact of mobility on the viral transmission and the evolution of the COVID-19 pandemic. The approach integrates a mobility model (e.g. the activity-based model in this paper) into the proposed framework to capture virus spread using the aggregated mobility of individuals between different (temporal) compartments and (spatial) regions within the city. The simulations used the mobility data from MABM where agent travel behavior is generated and optimized based on the framework of MATSim. We illustrated the application of the model in a case study of Melbourne city (Australia) where various control strategies or policies have been evaluated and the impacts of mobility on virus spread were assessed.
Results of the models application suggest that multiple simultaneous control policies can effectively prevent virus transmission, reducing stress on the public health systems, and acting to enhance pandemic recovery. Combining control strategies such as school closure and working from home can significantly reduce the peak of the pandemic and its duration. Results suggest that by reducing mobility to crowded locations such as workplaces or the city center can greatly reduce the total number of infected cases.

The proposed SIR-M model represents a significant improvement on the conventional SIR approach particularly in relation to COVID-19 since mobility restriction strategies are a major component of effective virus management. The approach also improves on previous suggestions for building mobility into SIR models by better representing virus contamination in travel and by providing a more consistent and flexible modeling approach which can be used with any mobility model that is available in cities. Besides, our model is able to reproduce a multi-peak distribution of cases. Specifically, since its study area consists of small zones that interact
**SIR-M with the effect of infectious periods, infected locations and reproductive number**

![Graphs showing the effect of infectious periods, initial locations and reproductive number](image)

(a) Different infectious periods  
(b) Different initial locations with infected agents  
(c) Different reproductive number with infected agents

Fig. 5. The effect of infectious periods, initial locations and reproductive number of infected agents. (a) The infected cases over a 250-day horizon for different infectious periods ranging from 5 to 15 days (the plotted lines from left to right respectively) with infected cases distributed over 5 locations initially. (b) The infected cases over a 250-day horizon for different scenarios of initial infected locations, ranging from 1 to 30 locations (the infectious period is 7 days for all scenarios). (c) The infected cases over a 250-day horizon for different reproductive number ranging from 2 to 7 with infected cases distributed over 5 locations initially (the infectious period is 7 days).

**SIR-M with intervention polices**

![Graphs showing the effect of intervention policies](image)

(a) Infected cases over time  
(b) Aggregated infected cases

Fig. 6. The effect of intervention policies. (a) The infected cases over time under different policies, including school closure, 5 km restriction rule, 40% WFH and the combined policy of 40% WFH and school closure where the line of combined policy has a lower peak of infected cases and a shorter spanning duration. (b) The accumulation of infected cases over time under different policies shown in (a). After 250 days, the total number of infected people is significantly reduced by applying the combined policy for mobility restriction. For these plots (a–b), initial infected individuals are initially placed in 5 random locations.

With each other through agents movements, the two (or multi) peaks pattern may emerge from different time delays at which the epidemic spreads in between zones. This pattern appears more clearly when the interaction between zones becomes weaker (see Fig. 5).

The obvious implication for virus management practices is that mobility management strategies can now be more accurately tested using SIR-M. In particular, the SIR-M is able to produce consistent predictions in terms of daily and active cases as well as their spatial distribution. Furthermore, our model also demonstrates its ability to study patterns of the outbreak spread under...
various mobility-control policies. Besides, the trend and evolution of the pandemic in our model are similar to the reality, which is sufficient to enable the studies of different mobility-related policies and interventions to combat the pandemic. For research, it would be particularly beneficial if modeling outcomes could be compared to post-implementation strategy outcomes to identify how accurate modeling is forecasting outcomes. As with all models, it seems likely that our proposed SIR-M model might be improved with a better experience in its use. Wider application of the model and reporting of outcomes seems an appropriate task for future research when sufficient data becomes available.

CRediT authorship contribution statement

Tri K. Nguyen: Conceptualization, Software, Methodology, Writing – original draft, Writing – review & editing. Nam H. Hoang: Methodology, Writing – original draft, Writing – review & editing. Graham Currie: Writing – original draft, Writing – review & editing. Hai L. Vu: Conceptualization, Methodology, Supervision, Writing – review & editing.

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