Mindanao Journal of Science and Technology Vol. 19 (2) (2021) 164-183

Community Transmission of Respiratory Infectious Diseases using Agent-based and Compartmental Models

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Date received: January 7, 2021
Revision accepted: November 5, 2021

Abstract

Non-pharmaceutical interventions (NPIs) were the mainstay to control the spread of COVID-19 at the start of the pandemic. Mathematical modeling has played an important role in determining the effects of these NPIs. An agent-based model and a compartmental model (i.e., extended susceptible-exposed-infectious-recovered) were formulated to simulate the spread of a respiratory infection between two neighboring communities. The study aimed to determine the effects of non-pharmaceutical interventions such as social distancing, community lockdowns and the use of protective gears. The chance of traveling to another community and within the community during the lockdown, and an initial percentage of exposed and infected individuals in both communities influenced the increase in the number of newly infected individuals on both models. It was shown through simulations that an increase in exposed individuals increased the number of new infections; hence, the need for amplified testing-isolation efforts. Protection level of 75-100% effectiveness impeded disease transmission. Inter- or intra-community travels can be an option given that strict preventive measures (e.g., non-pharmaceutical interventions) were observed. The ideal setup for neighboring communities was to implement lockdown when there is a high risk of local transmission while individuals observe social distancing, maximizing protective measures and isolating the exposed. The results of the agent-based and compartmental models showed similar qualitative dynamics; the differences were due to different spatiotemporal heterogeneity and stochasticity. These models can aid decision-makers in designing infectious disease-related policies to protect individuals while continuing population movement.

Keywords: community transmission, disease transmission, infectious disease, mathematical models, simulation

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1. Introduction

Respiratory infections like the common cold, influenza and pneumonia are the most usual and widespread illnesses suffered by people of all ages (Chonmaitree and Mann, 1995; Monto, 2002; Saunders-Hastings and Krewski, 2016; Subbarao and Mahanty, 2020), which have brought havoc worldwide. In the last century, the worst global outbreaks of influenza happened in 1918, 1957, 1968 and 2009, with the 1918 pandemic resulting in nearly 50 million deaths (Saunders-Hastings and Krewski, 2016). Shortly after the turn of the millennium, the severe acute respiratory syndrome coronavirus (SARS-CoV) was identified to be caused by a novel coronavirus resulting in an epidemic in 29 countries and regions (Tong, 2006). In early January 2020, another respiratory illness, ascribed to the coronavirus called SARS-CoV-2 (more commonly known as Coronavirus Disease 2019 [COVID-19]), was identified and the outbreak of this disease was later announced by the World Health Organization (WHO) as a pandemic (Cheng *et al.*, 2007; Cucinotta and Vanelli, 2020; Zheng, 2020).

The proliferation of COVID-19 has driven change in mobility. According to studies, population movement is a major driver of transmission for infections like COVID-19 (Wang and Zhao, 2004; Cui *et al.*, 2006; WHO, 2020). Such movements are necessary for aspects like the economy but are not possible during a pandemic until a vaccine against the disease is developed (Leung *et al.*, 2020). Before a significant proportion of the population worldwide is vaccinated, non-pharmaceutical interventions (NPIs) are the mainstay to control the spread of COVID-19 (Anderson *et al.*, 2020; Chowdhury *et al.*, 2020; Ferguson *et al.*, 2020; Kissler *et al.*, 2020). Different forms of community lockdowns were enforced in affected areas as means to delay the virus transmission (Anderson *et al.*, 2020; Kissler *et al.*, 2020; Luo and Tsang, 2020). At the onset of the pandemic, lockdowns were implemented in almost all cities across the world. In the Philippines, lockdowns have evolved to target smaller communities but are tagged as critical zones (e.g., *barangay* or subdivision with a high number of active COVID-19 cases). Thus, this study focused on determining the dynamics of disease transmission between communities with different degrees of quarantine measures or lockdown stringency.

During community lockdowns, NPIs often include social distancing in public spaces, closure of schools and workplaces, which limit public transportation within and between communities and reduce the sizes of gatherings (Anderson *et al*., 2020; Kissler *et al*., 2020). These measures may need to be implemented for months to control the spread of infections (Lai *et al*., 2020). However, prolonging lockdowns may lead to unnecessary detriment to the economy (Chowdhury *et al*., 2020; Luo and Tsang, 2020). Thus, intermittent NPIs or rolling lockdowns are thought to be better options (Chowdhury *et al*., 2020; Ferguson *et al*., 2020; Ladha, 2020). One study suggested dynamic cycles of 50-day suppression followed by 30-day relaxation over 18 months or until a vaccine arrives (Chowdhury *et al*., 2020), while in another, the rolling lockdown was advised and implemented in some countries like India (Ladha, 2020).

Mathematical models are often used in studying the dynamics of disease transmission. Oftentimes, two types of models are used: differential equation-based model (EBM) and agent-based model (ABM) (Özmen *et al*., 2016). Simulation models like EBM and ABM are safe and efficient means for the analysis of real-world problems with complex dynamics like disease transmission.

The ABM is a micro-scale model used to demonstrate movements and interactions among agents in a complex system to simulate their behavior (Gustafsson and Sternad, 2010). It has been extensively used in various fields such as biology to study population dynamics and simulate the interaction among the individuals in the population (An *et al*., 2009). Other application areas include land-use planning (Matthews *et al*., 2007) and disaster management (Dawson *et al*., 2011; Wang *et al*., 2016). An ABM that factored in population, area, vaccination rates and age structure from openly available data was used to observe transmission of an airborne infectious disease (Hunter *et al*., 2018). Xiao *et al*. (2011) utilized the epidemic diffusion model to simulate transmission via road systems. Several ABMs about COVID-19 were also proposed to simulate its effect in a small town (Truszkowska *et al*., 2021) and transmission risks in facilities (Cuevas, 2020). Giacopelli (2021) made use of ABM to explore the impact of lockdown, social distancing and tax in Italy. Shamil *et al*. (2021) employed ABM to simulate the spread of COVID-19 in a community. While Shamil *et al*. (2021) included the transportation of individuals in the community as an avenue in spreading the infection, the ABM in this paper was specific to interactions within a closed transportation system.

Other studies employed EBMs in investigating the disease transmission between communities. Chen *et al*. (2014) used the susceptible-infected-recovered (SIR) epidemic model to observe transmission dynamics in two cities through transport. Mahmud *et al*. (2020) formulated a compartmental model where socioeconomic factors were used to determine the awareness level of people in each country and social consciousness was quantified and served as an input in the model. Other papers used well-known models such as the Malthusian and logistic growth models (Kamrujjaman *et al*., 2020a), a modified SIR model (Hassan *et al*., 2021) and delay differential equations (Kamrujjaman *et al*., 2020b) to investigate the trend of infections against actual data in different communities. However, these community transmission EBMs do not factor in immunity after recovery from a disease. There are diseases where the latency period plays a significant role in the dynamics of infection. In studying the dynamics of such diseases, an exposed group (E) is included since there is a latent period between being infected and becoming infectious (Bjørnstad *et. al*., 2020). Thus, the susceptible-exposed-infected-recovered (SEIR) model was utilized in this study to account for the latent period.

This study aimed to determine the dynamics of disease transmission between two communities with different rates of stringency in quarantine measures by studying the ABM and a compartmental model (extended SEIR) for a disease with a latency period. Quarantine measures in this study were defined to be NPIs such as the implementation of social distancing and lockdown in a community. The dynamics in the simulations considered other factors such as protective gears and practices, traveling to a nearby city, going out during lockdown and the initial percentage of infectious individuals. COVID-19 was considered as the example of respiratory infectious disease in the simulations. To the best of the authors' knowledge, the effects of this particular combination of factors in neighboring communities have not yet been investigated in other studies.

2. Methodology

2.1 ABM

The ABM was first used to simulate the transmission of respiratory infectious disease between two neighboring cities using the NetLogo simulation environment (Figure 1).

The model simulated the spread of respiratory infectious diseases such as (COVID-19) between two neighboring cities. The model explored the effects of factors such as the protection of individuals against infection, the chance of an individual traveling to another city, the chance of an individual leaving their houses during a lockdown, the initial number of exposed individuals and the initial number of infected individuals per city. These effects were determined under the presence or absence of social distancing protocol and the presence or absence of citywide lockdowns.

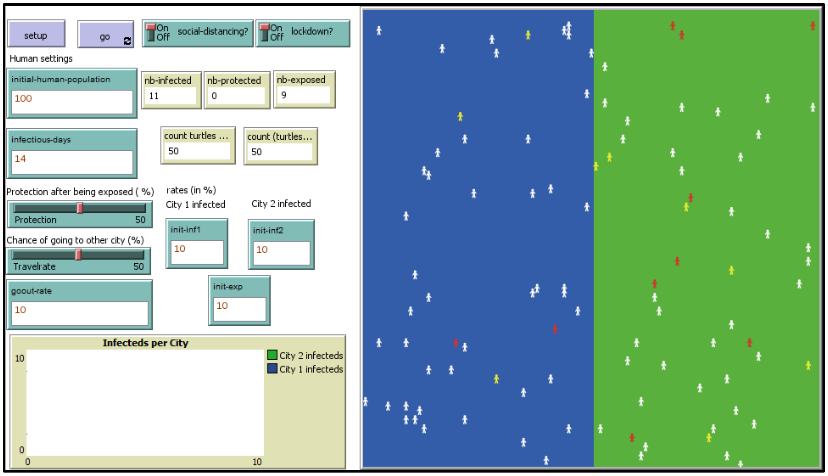

Figure 1. NetLogo simulation environment of transmission of respiratory infectious disease between two neighboring cities (blue and green areas) (Buhat 2020a, Buhat 2020b). Lockdown and social distancing may be set to on or off. The sliders for protection and the chance of going to other cities may be adjusted based on the desired level of each rate. The values in nb-infected, nb-protected, nb-exposed, count turtles, City 1 infected, City 2 infected and init-exp can be changed.

Individuals were initiated and placed randomly in each city. They may or may not travel to the neighboring city depending on their travel rate. In the presence of lockdown, an individual was expected to stay put but may leave their position depending on the going out rate. Their position determines if they would be infected or not. A person within 3 m from an infectious individual would have a 25% chance of being exposed, a person within 2 m from an infectious individual would have a 50% chance of being exposed while a person within 1 m from an infectious individual would have a 75% chance of being exposed. Exposed individuals may or may not develop into infected individuals depending on the protection. Protection (handwashing and use of alcohols or sanitizers) is the chance for an exposed individual to be an unexposed or uninfected individual again, while if the person fails to protect him or herself, the person would become infected. Infected individuals would then be infectious to those people surrounding them for 14 days.

The "setup" button created individuals according to the parameter values chosen by the user and these individuals were divided equally among each city. Each individual had a chance of initially being exposed depending on the init-exp value and being infected depending on the init-inf value (init-inf1 for City 1 and init-inf2 for City 2). Once the model had been set up, the "go" button started the model simulations. "Go" started the model and ran it continuously until: (1) all individuals were infected, or (2) no more infections could occur. Each time step can be considered as a day or any suitable time unit would do. Parameters and values used in the ABM are summarized in Table 1.

Table 1. Summary of variables used in the ABM

Variable	Description	Default value
Initial-human-population	Initial number of individuals to be divided equally in both cities	100
Infectious-days	Number of days (ticks) for an infected individual to be infectious to other unexposed or uninfected ones	14 days (ticks)
Protection	Chance for an exposed individual to be back to being susceptible again	0 to 100%
Travel-rate	Chance for an individual to travel to the neighboring city	0 to 100%
Go-out-rate	Chance for an exposed individual to move from his/her position during a lockdown	0 to 100%
Init-exp	Initial percentage of exposed individuals in both cities	0 to 75%
Init-inf1	Initial percentage of infected individuals in City 1	0 to 75%
Init-inf2	Initial percentage of infected individuals in City 2	0 to 75%
Social-distancing	If this switch is on, all individuals will try to stay 1m apart.	Yes/No
Lockdown	If this switch is on, all individuals will stay in their city and will only move based on the go-out-rate	Yes/No

The NetLogo file can be found online at Buhat (2020a) and a sample simulation can be viewed at Buhat (2020b).

2.2 SEIR Model

The most common type of EBM in studying the dynamics of infectious diseases is the compartmental model, which is composed of a set of differential equations. The extended SEIR compartmental model (Figure 2) was considered to study the dynamics and transmission of respiratory infectious disease between two neighboring cities. Similar to the ABM, the extended SEIR simulates the spread of respiratory infectious disease and explores similar factors under the same preventive measures used in the ABM.

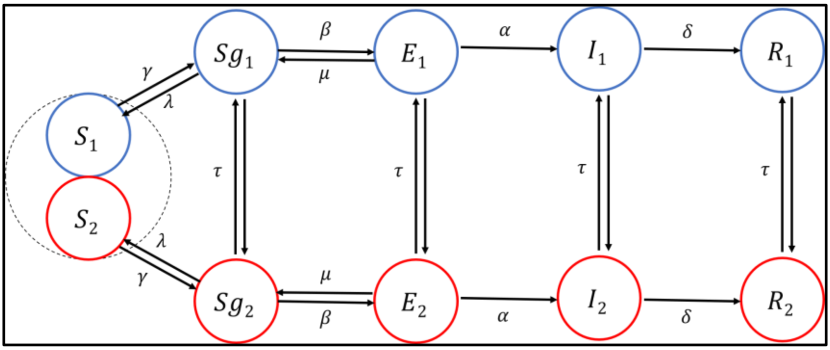

Figure 2. Extended SEIR model framework of transmission of respiratory infectious disease between two neighboring cities. The diagram describes the inflows and outflows of individuals in each compartment. The parameters aside from the arrows are rates for which the individuals transfer from a compartment to another compartment.

In the model, the residents of City 1 and City 2 were compartmentalized to susceptible, exposed, infected and recovered. Note that classes with subscript 1 were from City 1 and compartments with subscript 2 were from City 2. The susceptible residents were grouped into those that could not move around the city (S_1 *and* S_2) and the residents that may go out (Sg_1 *and* Sg_2). The individuals in S_1 and S_2 could not move around the city; hence, it was assumed in this study that they would not be exposed to the disease. Furthermore, individuals from S_1 could be transferred to S_2 or vice versa if the travel rate γ was non-zero. However, it was assumed that they could not roam around the city. The other classes included exposed individuals (E_1 *and* E_2), infected individuals (I_1 and I_2) and the removed individuals (R_1 *and* R_2), who were no longer infectious. Some of the susceptible individuals S_1 and S_2 may leave their location and were transferred to Sg_1 and Sg_2 at a rate γ. In this model, if the NPI lockdown was implemented in the community, the go-out-rate γ would be set to 0. A portion λ of those that can move around would be immobile. Let β be the exposure rate of the individuals to the respiratory infectious disease.

The exposure rate was the number of new exposed individuals caused by an infectious individual per unit of time. The rate at which an exposed individual in either of the cities became vulnerable or susceptible to the transmission of the virus was given by μ. Exposed individuals became infected with the disease at a rate of α for both City 1 and City 2 residents. Individuals in each city traveled to another city at a rate τ. Moreover, infected individuals became non-infectious and were transferred to the removed classes R_1 and R_2 at a rate δ. Table 2 shows the values that were used in the simulations performed in this study.

Table 2. Summary of variables used in the extended SEIR model

Variable/ parameter	Description	Default value	References
S_{i0}	Initial number of susceptible residents in City i (I = 1,2)	$100 - E_{i0} - I_{i0}$	Assumed
Sg_{i0}	Initial number of susceptible residents in City i (i = 1,2) that can move around their respective cities	0	Assumed
E_{i0}	Initial number of exposed individuals in City i (i = 1,2)	0 to 50%	Varied
I_{i0}	Initial number of infected individuals in City i (i = 1,2)	0 to 50%	Varied
R_{i0}	Initial number of removed individuals in City i (i = 1,2)	0	Assumed
γ	Go-out-rate of susceptible individuals	0 to 75%	Varied
β	Exposure rate (number of new exposed individuals caused by an infectious individual per unit time) of an individual to the disease	2/14	Buhat *et al.* (2021)
$1-\mu$	Rate at which an exposed individual in either of the cities	0 to 100%	Varied
λ	Rate at which mobile susceptible individuals will be immobile	1/2	Assumed
α	Rate at which exposed individuals become infected with the disease	1/2	Eikenberry *et al.* (2020)
τ	Rate at which mobile individuals travel to another city	0 to 100%	Varied
δ	Rate at which infected individuals become non-infectious	1/14	Eikenberry *et al.* (2020)

The dynamics in the extended SEIR compartment model are described in Equations 1 to 10.

$$S_1' = -\gamma S_1 + \tau S_2 - \tau S_1 - \lambda Sg_1 \tag{1}$$

$$Sg_1' = \gamma S_1 + \tau Sg_2 + \mu E_1 - \tau Sg_1 - \beta Sg_1 \frac{I_1}{S_1 + Sg_1 + E_1 + I_1 + R_1} - \lambda Sg_1 \tag{2}$$

$$E_1' = \beta Sg_1 \frac{I_1}{S_1 + Sg_1 + E_1 + I_1 + R_1} + \tau E_2 - (\alpha + \tau) E_1 \tag{3}$$

$$I_1' = \alpha E_1 + \tau I_2 - (\delta + \tau) I_1 \tag{4}$$

$$R_1' = \delta I_1 + \tau (R_2 - R_1) \tag{5}$$

$$S_2' = -\gamma S_2 + \tau S_1 - \tau S_2 - \lambda Sg_2 \tag{6}$$

$$Sg_2' = \gamma S_2 + \tau Sg_1 + \mu E_2 - \tau Sg_2 - \beta Sg_2 \frac{I_2}{S_2 + Sg_2 + E_2 + I_2 + R_2} - \lambda Sg_2 \tag{7}$$

$$E_2' = \beta Sg_2 \frac{I_2}{S_1 + Sg_1 + E_1 + I_1 + R_1} + \tau E_1 - (\alpha + \tau) E_2 \tag{8}$$

$$I_2' = \alpha E_2 + \tau I_1 - (\delta + \tau) I_2 \tag{9}$$

$$R_2' = \delta I_2 + \tau (R_1 - R_2) \tag{10}$$

3. Results and Discussion

Key parameters were varied in both the ABM and the extended SEIR model. The effect of each parameter on the number of newly infected individuals as the number of the initially infected populations in both cities increased was determined. Their behavior under different scenarios (with or without social distancing measures and with or without lockdown protocol) for up to 500 ticks was observed.

3.1 Initial Number of Exposed Individuals

With a fixed percentage of go-out-rate, protection and travel-rate, the initial number of exposed individuals and initial infected population of both cities were varied. Scenarios, where both lockdown and social distancing are present, were simulated – one of them was off and both were not applied.

It is exhibited in the ABM heatmaps (Figure 3) that with or without lockdown and social distancing, a larger infected population was observed when the initial exposed population was increased while keeping the other parameters constant.

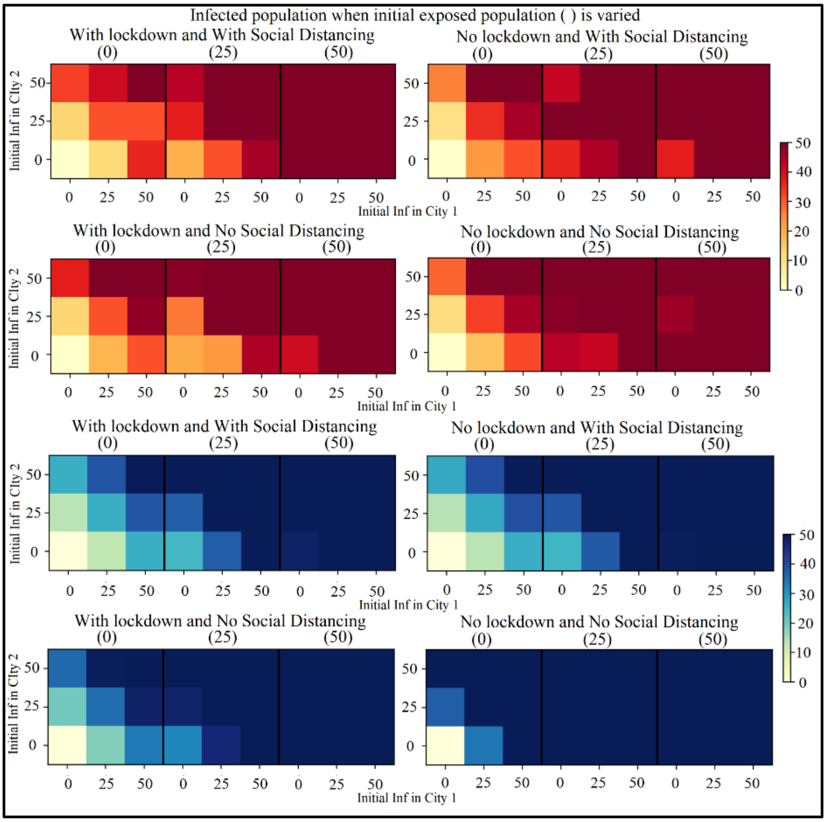

Figure 3. Resulting final number of infected individuals, from ABM simulations (red colorway) and extended SEIR model simulations (blue colorway), given various initial percentages of exposed individuals with a different initial percentage of infected individuals in City 1 (in %) and the initial percentage of infected individuals in City 2 (in %), with protection = 25%, travel-rate = 25% and go-out-rate = 25% (during lockdown)

This implies that lockdown and social distancing are useless if there is still a significant exposed population. Testing will play an important role here since identifying the infected ones and isolating them will lessen the number of exposed individuals. Comparing the scenarios when the initial exposure was 25% of the population, the case with no lockdown and with social distancing had a slightly bigger infected population compared with the case with lockdown and no social distancing. This suggests that minimizing the travel of individuals is still better than social distancing. It can also be noticed in each scenario that a larger number of initially infected in both cities (high prevalence) resulted in a further greater infected population. Similar to the ABM simulations, heatmaps from the extended SEIR simulations showed that in each scenario, a greater number of initially infected in both cities resulted in a larger infected population. Furthermore, as the initially exposed population increased, the infected population increased as well. This indicates that lockdown and social distancing may not be effective in controlling the spread of infection if there is still significantly exposed population. A lesser infected population was noticed when social distancing was enforced as compared with lockdown implementation. This means that moving within the city will not worsen the situation as long as strict physical distancing is followed.

An obvious difference in the result of the two models was that social distancing had a better effect in the extended SEIR model compared with lockdown (see blue heatmaps upper right and lower left subfigures). This is contrary to the result in ABM. This inconsistency was anticipated since interactions between individuals were removed in the EBM. Furthermore, disease progression in the SEIR was similar for all individuals. This property resulted in almost perfect employment of social distancing in the SEIR model when it was “on” (i.e., only a small part of the population transferred to the exposed compartment). On the other hand, applying social distancing in the ABM involved stochasticity – that is, social distancing will only lessen the probability of and will not eliminate exposure of each agent to the infection. Note that this probability varied for each agent.

3.2 Protection against Infection

In the previous subsection, it was observed that a larger initial exposed population increased the number of infections. Now, the effect of varying the protection rate from 0 to 100% was observed, with a fixed percentage of initially exposed individuals, travel-rate and go-out-rate.

Simulation results from ABM and extended SEIR model (Figure 4) showed that having individual protection was necessary to lessen the number of infections in two cities. Based on the results of ABM, additional NPIs were needed when protection was not 100% effective. It can also be seen that imposing a lockdown coupled with protection was better than social distancing with protection especially when the protection level was very low. These were not the case when the extended SEIR model was used. It is depicted from the heatmaps of the SEIR model simulations that increasing the protection fully was not enough to reduce the number of infections. When additional interventions were introduced, it was shown that protection with social distancing was better than protection with the lockdown. The results of having social distancing with lockdown were almost the same when there was no lockdown. This was again due to the employment of an almost perfect rate of physical distancing when it was "on" and the homogeneous mixing of individuals.

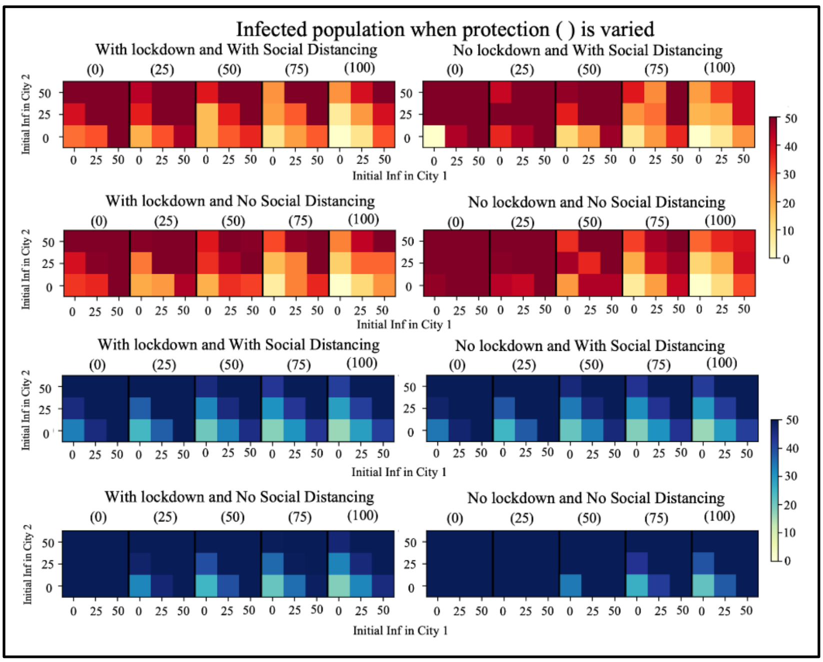

Figure 4. Protection level was varied. Resulting final number of infected individuals, from ABM simulations (red colorway) and SEIR model simulations (blue colorway), given various protection rate of individuals with a different initial percentage of infected individuals in City 1 (in %) and the initial percentage of infected individuals in City 2 (in %), with initial exposed percentage = 25%, travel-rate = 25% and go-out-rate = 25% (during lockdown)

It can also be inferred from the SEIR heatmaps that even though these control measures were observed, the number of infections was still high when there were at least 25% infected individuals present in each city. This implies that early detection of infected individuals and isolating them together with contact tracing are very important to keep the number of infected individuals at a minimum.

3.3 Effect of Traveling between Cities

In the previous subsection, it was observed that as protection increased, the number of infected individuals between the two cities decreased. In this phase, the effect of varying the travel-rate from 0 to 100% was examined with a fixed percentage of initially exposed individuals, protection and go-out-rate.

Both simulations from the ABM and SEIR model showed that increasing the travel-rate had no significant effect in all scenarios given that the other parameters were all constant (Figure 5).

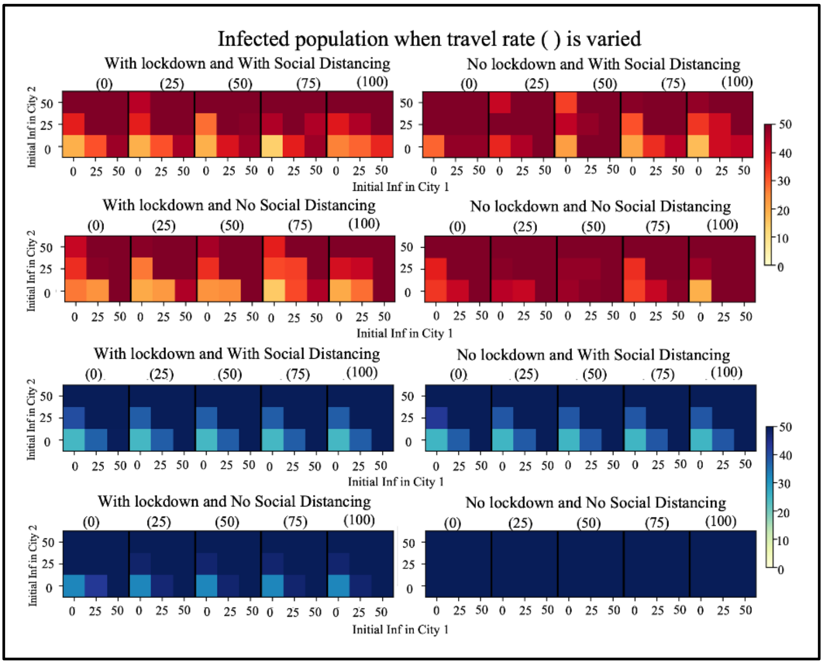

Figure 5. Travel rate was varied. Resulting final number of infected individuals, from ABM simulations (red colorway) and SEIR model simulations (blue colorway), given various travel rate of individuals with a different initial percentage of infected individuals in City 1 (in %) and the initial percentage of infected individuals in City 2 (in %), with initial exposed percentage = 25%, protection = 25% and go-out-rate = 25% (during lockdown)

Individuals could travel between two cities if there were at most 25% infected individuals present in both cities, protection against infection was present and at least social distancing was observed. Imposing a lockdown, social distancing or both was necessary to minimize the number of infections as what can be observed from the heat maps. Also, SEIR heatmaps showed that the infected population was greatest when social distancing was not employed. In all four scenarios, changes in travel-rates did not affect the infected population.

3.4 Effect of Traveling within the City during Lockdown

With a fixed percentage of travel-rate, the protection and initially exposed individuals, the go-out-rate and the initial infected population of both cities were varied. Scenarios such as lockdown within the city and application of social distancing were tested.

In both models projected in Figure 6, the infected population was greater when social distancing was not practiced. Go-out-rate had little (ABM) to no effect (SEIR) in terms of infected population when social distancing was in effect. This means that if the population follows proper social distancing protocols, the number of infected can be kept at a minimum. On the other hand, the effect of the go-out-rate was evident when there was no social distancing. Thus, in situations or places where social distancing is difficult to implement, the number of mobile individuals should be reduced.

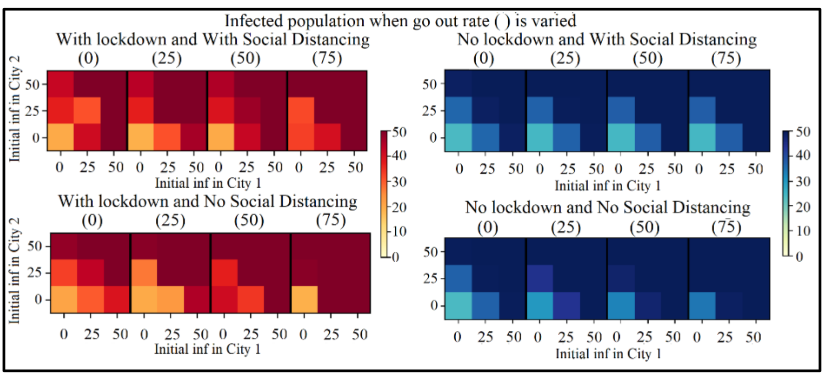

Figure 6. Go-out-rate was varied. Resulting final number of infected individuals, from ABM simulations (red colorway) and SEIR model simulations (blue colorway), given various go-out-rate of individuals during lockdown with a different initial percentage of infected individuals in City 1 (in %) and the initial percentage of infected individuals in City 2 (in %), with initial exposed percentage = 25%, protection = 25% and travel-rate = 25%

Comparing the upper red and the upper blue heatmaps, the go-out-rate affected the ABM and had very little to no effect in the extended SEIR model. This disagreement was again a consequence of the stochasticity (applied in ABM) in the exposure rate when social distancing was "on." Agents in the ABM were more likely to interact as go-out-rate was increased, which may heighten the infected population. On the other hand, since individuals in each group in EBM had the same behavior or followed the same pattern, go-out-rate had no impact when physical distancing was applied. In other words, since a high level of social distancing was set in the simulations, almost all individuals who moved around perfectly followed physical distancing.

4. Conclusion and Recommendation

Simulations for both ABM and SEIR model showed that isolation of infected individuals is necessary to reduce the exposed individuals since greater exposure means greater chances of infection. Mass testing will play an important role since isolating the infected ones will lessen the exposed individuals. Protection measures for individuals against infection are another vital step in reducing the chance of infection. A protection level of at least 75% together with the practice of social distancing and lockdown is recommended (and maximized to 100% if possible) to lessen disease transmission between cities. Frequent washing or cleaning of hands, wearing of a mask and other protective measures should then be a habit for each individual. During the lockdown, the go-out rate matters only when social distancing is not practiced. On the other hand, the travel rate exhibited a minimal effect on the number of newly infected individuals for both models. So long as NPIs are observed properly, mobility can be an option during pandemics.

Mathematical models in this study were tested for different combinations of NPIs to determine their efficacy. The application of the social distancing measure on the simulations proved to be an effective measure to decrease the number of newly infected individuals. The best scenario would still be an implementation of both social distancing and lockdown within cities. Relatively, the absence of both NPIs would generate the most number of new infections and is highly discouraged.

Both the ABM and compartmental (SEIR) model were favorable in simulating the transmission of infectious respiratory diseases in neighboring cities. Their simulations both exhibited akin behaviors when varying the parameters since both models were designed after each other. However, discrepancies in estimates occurred on the NPI comparisons for ABM and extended SEIR due to the heterogeneous and homogeneous mixing of individuals, respectively. Due to minimal heterogeneity and stochasticity effects, SEIR generated higher estimates of the infected population compared with the ABM. The ABM took a longer simulation time to reach similar outbreak values as SEIR since ABM considered both spatial and temporal aspects of the outbreak and each individual (agents) had their stochastic characteristic and interaction.

Overall, the study demonstrated that between two cities, the practice of NPIs, such as social distancing and lockdown is necessary to reduce the risk of infection. The practice of preventive measures, isolation of infected individuals and protection level of 75-100% effectiveness is the ideal setup to inhibit transmission of respiratory infectious diseases such as SARS-CoV-2, especially when community lockdown rules are to be relaxed. Policymakers can use the results of both models in designing infectious disease-related policies to protect individuals while continuing population movement.

The model only considered selected dynamics of individuals only when inside the two cities. Transmission of the disease was done through a distance function, and all infected individuals were assumed to recover after 14 days of infection. Death was not considered in the analysis of both model simulation results as the study focused on the transmission of the disease only. Results of the study showed the minimal effect of mobility during disease outbreaks but only through strict implementation and observance of the NPIs. Further extensions of the study may incorporate other temporal-only and spatial-temporal models. Results and dynamics from SEIR and ABM of this study can be a basis for comparison or improvement, and further include additional factors such as variants and vaccinations among others.

5. Acknowledgement

The authors would like to thank the anonymous reviewers for their valuable comments that helped in improving this manuscript. Jomar F. Rabajante is supported by the Associate Scheme of the Abdus Salam International Centre for Theoretical Physics, Italy. This research is funded by the UP System through the UP Resilience Institute.

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