Automation in Construction 140 (2022) 104315

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Enhancing resilience in construction against infectious diseases using stochastic multi-agent approach

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ARTICLE INFO

Keywords:
Infectious diseases
COVID-19
Resilience
Risk management
Agent-based modelling
Monte Carlo simulation

ABSTRACT

To recover from the adverse impacts of COVID-19 on construction and to avoid further losses to the industry in future pandemics, the resilience of construction industry needs to be enhanced against infectious diseases. Currently, there is a gap for modelling frameworks to simulate the spread of infectious diseases in construction projects at micro-level and to test interventions' effectiveness for data-informed decision-making. Here, this gap is addressed by developing a simulation framework using stochastic agent-based modelling, which enables construction researchers and practitioners to simulate and limit the spread of infectious diseases in construction projects. This is specifically important, since the results of a building project case-study reveals that, in comparison to the general population, infectious diseases may spread faster among construction workers and fatalities can be significantly higher. The proposed framework motivates future research on micro-level modelling of infectious diseases and efforts for intervening the spread of diseases in construction projects.

1. Introduction

The outbreak of COVID-19 forced several governments around the world to impose various restrictions, such as mobility restrictions, socio-economic restrictions, and physical distancing regulations, in order to limit the spread of the disease [1]. Despite the positive impacts of these restrictions on the spread of COVID-19, they have caused immense losses to several industries, including manufacturing, hospitality, and construction [2–4]. Specifically, construction industry has been severely affected by the imposing of social distancing measures, since the execution of construction projects highly relies on the physical interactions between project team members (e.g., labours, equipment operator, engineers). Moreover, despite the stringent restrictions imposed [5] and their consequent losses, previous research confirm that the construction industry have experienced the highest rate of COVID-19 infections among several other industries, including healthcare, manufacturing, and transportation, with five times of the chance of hospitalization as compared to the average of other industries [6,7]. This might be caused due to the unique characteristics of construction projects, in which project team members commonly work in crews — rather than individually — and tasks are often executed in contained spaces. It should be noted that the temporary or permanent absence of the skilled workforce (i.e., absence or fatality) caused by COVID-19 infections has an additional adverse impact on the performance of construction projects.

To recover from the aforementioned losses, the construction research community and economists are focused on assessing these adverse impacts and developing recovery plans for construction industry. This can be only achieved by developing accurate predictive models to forecast the spread of COVID-19 in construction projects, then, determining its adverse impacts on the projects' performance [8,9], and finally, evaluate different interventions to contain the spread of the disease [10]. The development of such predictive model can ultimately help with enhancing the resilience of construction industry against infectious diseases in future pandemics. This paper responds to this need by introducing a novel stochastic multi-agent framework to forecast the spread of infectious diseases in construction projects using agent-based modelling (ABM) and Monte Carlo simulation (MCS). The applicability of the proposed framework is tested by simulating the spread of COVID-19 in a case study of a residential building project, and then, by assessing the effectiveness of using face masks for containing the spread of the disease. Although there are several interventions suggested for containing the spread of COVID-19, this paper only evaluates the effectiveness of face masks, since (1) using face masks is one of the most common interventions during the COVID-19 pandemic due to its low cost and high effectiveness; and (2) evaluating the effectiveness of other

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https://doi.org/10.1016/j.autcon.2022.104315
Received 10 August 2021; Received in revised form 18 April 2022; Accepted 29 April 2022
Available online 11 May 2022

interventions, such as vaccination, ventilation, testing, and shift changes, is associated with several modelling complexities and requires additional modelling efforts, which will be addressed in a future research. This paper evaluates the effectiveness of using face masks as an attempt to illustrates the framework's applicability for testing intervention strategies and to validate the model by running parameter sensitivity analysis.

In previous research, several efforts have been made to model the spread of COVID-19 and the effectiveness of different interventions in large-scale social environments — called macro-level models hereafter — [8,10–13]. The majority of these studies used ABM due to its unique capabilities for simulating the behaviour of individual agents within a complex system of interacting agents and determining the global behaviour of the system as an aggregation of these interactions [14–16]. These macro-level models though, cannot accurately predict the spread of COVID-19 in construction projects, since these models often have a large modelling scope and low level of details for their agents' definition. In other words, the macro-level models can model the spread of disease in large geographical areas but, for the cost of losing details on individual agents and considering a population of people as one agent in the model. Additionally, the unique characteristics of construction projects reduces the accuracy of these generic macro-level models for their application in construction projects, since in construction, site specifications and crews' characteristics can significantly affect the spread of infectious diseases. Accordingly, to accurately simulate the spread of infectious diseases in small social environments, such as construction projects, the ABM model need to capture the dynamic interactions made between individual humans within the model. These models are called micro-level models, hereafter. The few existing micro-level models developed for modelling the spread of COVID-19 [9,17] used deterministic ABM, which can be challenged by the random behaviour of infectious diseases. In fact, the spread of infectious diseases is extremely random, since it starts by a random set of infected agents and continues by the random movements of agents within the system [18]. This random behaviour is confirmed by the literature and several quantitative techniques were suggested to address it, such as Monte Carlo simulation (MCS) [18], probabilistic approaches [19], and Bayesian modelling [20]. However, these studies solely use statistical/probabilistic approaches and fail to capture the dynamic interactions between people, which may only be captured by the application of ABM [9,10]. Thus, there is a research gap for a modelling framework that simultaneously captures the random behaviour of infectious diseases, as well as the dynamic interactions between humans at micro-level. This research gap is addressed in this paper by combining ABM with MCS in a novel stochastic multi-agent framework, where the ABM component captures the dynamic interactions between humans at micro-level and MCS addresses the random behaviour of infectious diseases. Moreover, to enhance the usability of the proposed framework in future applications, the user is provided with the flexibility to alter the projects' site specifications, crews' specification, and disease specifications to allow modelling the spread of various infectious diseases in several settings of construction projects. The contributions of this paper are three-folds: (1) introducing a novel micro-level stochastic multi-agent framework — programmed in Python® — for modelling the spread of infectious diseases in construction projects; (2) modelling the spread of COVID-19 in a case study project and quantifying the adverse impacts of this disease on construction projects and compare them to general population; and (3) providing means to enhance the resilience of construction industry against the spread of infectious diseases by providing a platform to assess the effectiveness of different interventions.

The remainder of this paper is organized as follows. Section 2 presents a brief literature review on the impacts of COVID-19 on the construction industry and the research conducted on modelling the spread of infectious diseases. Section 3 introduces the proposed stochastic multi-agent framework and illustrates its spatiotemporal structure; then, Section 4 presents a case-study by modelling the spread of COVID-19 in a residential building project, evaluates the effectiveness of using face masks, and validates the proposed framework through multiple behavioural tests. Finally, Section 5 discusses the conclusions of this research, identifies its limitations and introduces the future extensions to the current study.

2. Literature review

2.1. The impacts of COVID-19 on the construction industry

While the outbreak of COVID-19 has left several impacts on construction industry, the construction research community initiated extensive efforts on analyzing, forecasting, and minimizing these adverse impacts from the very start of pandemic. Kamal [21] identified two types of disruptions in various industries, which were caused due to the rise of COVID-19: (1) the transformational disruptions, which occurs by adopting the new technologies introduced for dealing with the pandemic-related restrictions; and (2) hostile disruptions that were unexpected disruptions caused by the external sources. Alsharef et al. [22] have conducted interviews with 18 experts to identify the early impacts of COVID-19 construction industry in the United States (US) as well as the new opportunities created by the rise of COVID-19. Alsharef et al. [22] identified several adverse impacts of the pandemic on construction projects, including delayed material delivery, material price escalation, and reduced construction productivity. Their study also identified reduced transportation times and facilitated recruitment of skilled human-resources as the opportunities created by COVID-19 in the US. In another effort Jones et al. [2] identified several positive impacts of COVID-19 pandemic on construction industry, including improved housekeeping and tidiness of construction sites, improved planning, and reduced site congestion. Jones et al. [2] also identified the causes of these positive impacts as, (1) improved and more detailed task planning; (2) lower site congestion due to the reduced number of staff on-site; (3) avoiding double handling of material; (4) avoiding personal time [23] during the delivery of project tasks; (5) more streamlined worker flow; and (6) improved crew motivation. This brief review of the literature confirms the significance of COVID-19 impacts on the construction industry and reveals the need for an accurate assessment of such impacts for proper planning of the industry's recovery.

A study by Bsisu [24] shows that the majority of experts in Jordanian construction industry believe that the COVID-19 pandemic caused no transformational disruptions on their productivity (i.e., 68.3% believed that remote work settings had no impact on their productivity or even improved their productivity). Accordingly, the majority of the negative impacts imposed to the construction industry by COVID-19, are hostile disruptions rather than transformational ones [21]. To address these hostile disruptions by reducing the spread of COVID-19, the main challenges that construction practitioners dealt with are identified as sanitation of construction material, sharing construction tools and equipment, lack of compliance, and poor quality of personal protective equipment (PPE) [25]. Moreover, Simpeh and Amoah [5] have identified the main interventions for limiting the spread of COVID-19 as social distancing, housekeeping and sanitation, screening, use of PPE, creating awareness, restricting site access, handling of deliverable, and improving compliance. In a recent study in Ghana, Amoah et al. [25] found that COVID-19 have severely affected small construction firms by reducing their productivity, affecting their projects' cash flows and site management. In another effort [26] compared the impact of COVID-19 pandemics on the construction site-works and office-works, and consequently, identified the major causes of disruption to the performance of construction firms and suggested corrective actions to combat these cases. Although the identification of these positive and negative impacts is an essential step to plan for the recovery of the industry, developing predictive models to numerically analyze these adverse impacts and simulate the effectiveness of different recovery plans is also a critical step, which has not been fully addressed yet. This paper aims to address this research gap by introducing a hybrid ABM-MCS framework for modelling the spread of infectious diseases in construction projects using Python® programming language.

2.2. Modelling the spread and impacts of COVID-19

Since the outbreak of COVID-19, several studies attempted to model the different aspects of the pandemic, including the prediction of its infection patterns [27], forecasting its adverse impacts [8], and predicting the effect of interventions on the spread of the disease [10]. Different methodologies are used for the development of these predictive models, depending on the modelling contexts, scope, and objective variables. Truong and Truong [27] used statistical methods and time series analysis to forecast the travel patterns of US citizens at the national level and determined the rates of infections in the US. Similarly, Marmarelis [28] used statistical time series analysis and Riccati model to forecast the spread of COVID-19 in the US. In another effort, Xie [18] used MCS to model the spread of COVID-19 in the UK and Australia, while considering the probabilistic uncertainties that affect the spread of this disease. The statistical methods and MCS allows the modellers to capture the probabilistic uncertainties associated with the spread of COVID-19 and enables them to forecast the spread of COVID-19 in large geographical area with large population size [18,28–30] (called macro-level models hereafter). However, the application of these techniques are not suitable for simulating the spread of the disease in small areas with small number of occupants, such as those exits in construction projects, where the spread of diseases is being modelled in smaller scope with higher levels of details. Hereafter in this paper, these models are called micro-level models.

For modelling the spread of infectious diseases at micro-level, ABM is an appropriate technique, since it allows the user to model the detailed behavioural characteristics of individual agents (e.g., project team members) and the disease; and then, the ABM technique determines the spread of the disease based on the several interactions of the agents [14]. Additionally, the use of simulation techniques (including ABM), allows the user to test several strategies for limiting the spread of the disease (i.e., running what-if analysis) and determine the optimum strategies to contain the spread of diseases. Given the strengths of the ABM technique, it has been used by several researchers for modelling the spread of COVID-19 in different contexts. One of the early efforts was made by Kerr et al. [8], who developed an open-source ABM library in Python for simulating the spread of COVID-19 in open environments. Their ABM model is called Covasim [8] and has been used by several scholars to analyze the spread of COVID-19 in different contexts and test different interventions to curb its spread. Li and Giabbanelli [10] used Covasim [8]) to assess the effectiveness of two vaccination plans in the US. Contreras et al. [31] used Covasim to determine the challenges associated with the tracing and isolation of coronavirus patients and to determine an optimized intervention strategy to contain the spread of COVID-19. In another effort, Cuevas [11] developed a generic ABM model to analyze the spread of COVID-19 in facilities, such as universities, companies, and shops. Araya [9,17] developed an ABM model to simulate the spread of COVID-19 in construction projects, though with some limitations due to its simplifying assumptions, where the spread of COVID-19 is modelled only by categorizing the agents into low, medium and high-risk groups and assuming random interactions between them. The ABM model developed by Araya [9,17] lacks the human agent component for modelling individual construction workers and their behavioural patterns within the model and ignores several characteristics of projects' site, crews and the disease. Consequently, it does not allow the modeller to run what-if analysis to optimize the preventive strategies for containing the spread of the disease. In another effort, Thneibat et al. [32] have implemented the ABM technique to model the impact of COVID-19 on the value management practices in construction projects. Their modelling efforts provides an insight regarding the applicability of this technique for modelling the secondary impacts of COVID-19 pandemic however, it does not provide any information regarding the spread of the disease on construction sites.

Although the generic ABM models [8,11] are useful tools for simulating the spread of COVID-19 in different environments, the simplifying assumptions made for the generalization of the models reduces their accuracy in the construction context. As an instance, the ABM model developed by Cuevas [11], ignores construction sites' specifications (e.g., site layout, warehouses) and assumes all agents constantly move within the model in random directions and work individually. However, in construction projects, projects teams usually work in crews, rather than individually and commonly are static on the project site, where their tasks are being executed. Additionally, those models that solely rely on the ABM technique may produce inconsistent results with the real-world conditions, since the ABM technique is purely deterministic and lacks the capacity to capture the probabilistic behaviour of the several factors that affect the spread of infectious diseases. These limitations are addressed in this paper by developing a context-specific ABM-MCS framework for simulating the spread of infectious diseases in construction projects, which allows the modeller to alter the project, crews and disease specifications and facilitates the implementation of what-if analyses.

3. The stochastic multi-agent framework for infectious diseases in construction

The proposed stochastic multi-agent framework has two major components: the ABM, and the MCS component. The architecture and building blocks of the proposed framework, and the data flow between its different elements are presented in Fig. 1.

As shown in Fig. 1, there is a constant interaction between the two components of the framework, where the ABM component simulates the specifications of the project, crews, and disease; and the MCS component captures the probabilistic uncertainty of the system behaviour. The two components of the model are illustrated in further details in the following sub-sections.

3.1. The agent-based modelling component

As discussed in Section 1, ABM is a simulation technique with the capability to predict the aggregated behaviour of real-world systems, based on the behaviour of their individual elements and the interactions among them [16]. Accordingly, the main steps of modelling real-world systems with the ABM technique are: (1) definition of the agents of the model; and (2) defining the scope of the system. The macro- and micro-level ABM models of COVID-19 can be distinguished based on these two main modelling practices, where in the macro-level models [8], agents often represent a community or a population of people and the in micro-level models [9], agents often represent one person. Furthermore, the scopes of the macro- and micro-level models are different, where the macro-level models often have a large system scope (e.g., modelling the spread of a disease in a large geographical area with large population size), and the scope of micro-level models is often limited to a small population of people. As the result, the micro-level models can more accurately — as compared to the macro-level models — simulate the behaviour of each person within the system, though this capability comes with significant additional computational cost [33] and makes them inapplicable to large systems. Considering the small scope of the system that the proposed framework captures (i.e., the team members of a construction project), the ABM component is defined at micro-level and represents each individual member of the project team as an agent in the simulation model. Moreover, the scope of system being modelled is limited to a given project and its team members, meaning the boundaries of the system is limited to the construction project's site only and the movements and/or interactions of the agents outside the project site are not captured. Once the definition of the system agents and system scope are set, the inputs of the ABM component need to be

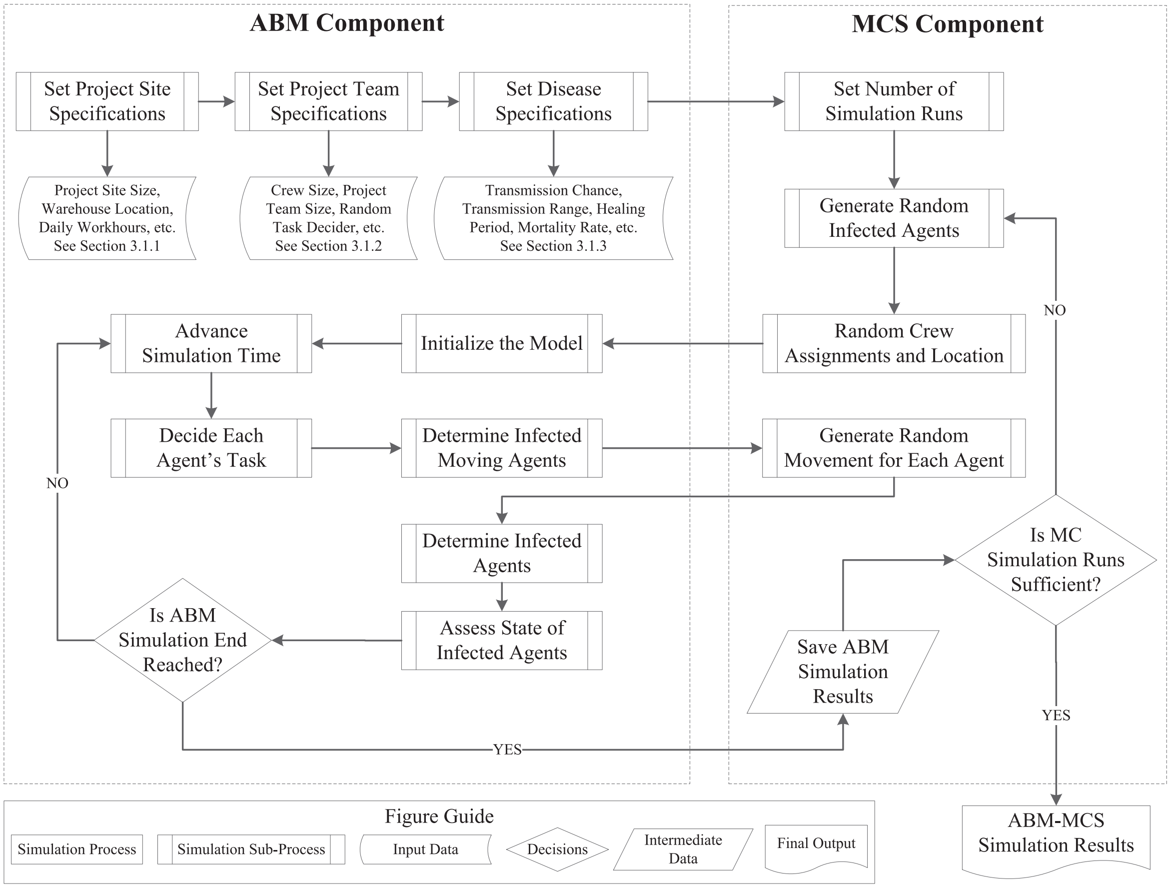

Fig. 1. The architecture of the proposed hybrid ABM-MCS framework and its data flow diagram.

specified by the modeller. The inputs of the ABM component (i.e., project site specifications, project team specifications, and disease specifications) gives this framework enough flexibility to model the spread of different infectious diseases in a variety projects' settings. The details of these inputs are illustrated in the three following sub-sections as the proper references are provided in Fig. 1.

3.1.1. *Project site specifications*

- Project site size: The proposed framework assumes a rectangular shape for the project site and using this parameter, the modeller can set the width and height of the rectangular project site. Once the size is set, the framework develops the spatial model of the project site, in which each grid cell has the width and the height equal to the disease transmission range (R_T) (see Section 3.1.3).
- Site warehouse location: This parameter specifies the project warehouse location, where the construction material and tools/equipment are stored. Earlier research reveal that the sites' warehouses are one of the hotspots for the transmission of infectious diseases, since site warehouses are usually crowded.
- Daily work-hours: Specifies the number work-hours per day.

3.1.2. *Project team specifications*

- Crews specifications: The proposed framework assumes that all project team members work in crews and it is also assumed that all crews are of the same size. The modeller can specify the the size of each crew and the overall project team size. This parameter can improve the accuracy of the proposed framework, as compared to the existing ABM models [9,17], which ignore the existence of crews in construction projects. Notably, working in crews is one of those characteristics that causes a higher rate of transmissions in construction as compared to the other industries [7].
- Probabilistic task decider: In the proposed framework, project team members (i.e., agents) may randomly take one of the three following actions at each simulation time-step: (I) working directly on the task in-hand (i.e., direct-work); (II) traveling to/from the site warehouse (i.e., traveling); or (III) doing personal travels on the site, such as using site facilities or hanging out with co-workers (i.e., personal). The probability of taking each action is specified by the modeller prior to the simulation run. The default values for this parameter are selected based on the research conducted by Tsehayae and Fayek [23] as follows: the probability of direct-work = 85%; traveling = 5%; and personal = 10%.

3.1.3. *Disease specifications*

- Infection rate: This parameter specifies the ratio of the project team members who are infected with the virus at the start of the project. The value of this parameter can be subjectively chosen by the modeller or can be set equal to the average infection rate of the general population, within which the project is being executed. In the case study presented in Section 4, the infection rate of COVID-19 is set to 5% according to the data provided by the Canadian Government at their weekly epidemiological report [34].

- General transmission chance (P_T): This parameter specifies the chance of infection transmission in a direct interaction between an infected and a healthy agent. The value of transmission chance maybe selected depending on several factors, including the disease, the specifications of the virus, and the mode of transmission. In the case of COVID-19, there are three modes of infection transmissions, (1) fomite transmission that refers to the transmissions caused by contacting contaminated surfaces; (2) droplet transmission, which is caused by the large repository droplets that carry the virus and are exhaled by the infected person through coughing, sneezing, breathing or speaking; and (3) aerosol transmission, which is caused by the small exhaled respiratory droplets that carry the virus [35–37]. The proposed framework in this paper only takes account for the droplet transmission of the disease (i.e., COVID-19), since the rate of fomite transmission depends on several factors (e.g., housekeeping, sanitation, level of tools sharing among the crew) and may not be accurately selected and modelling the aerosol transmission is associated with several modelling complexities, which will be addressed in future research. In the proposed framework, the default value of general transmission chance — assuming the transmission of COVID-19 is being modelled — is set to 10% based on the available research data [38].

$$P_t(a_i|a_h) = f_{P(a_i|a_h)} \times P_T \tag{1}$$

where $P_t(a_i|\, a_h)$ stands for the probability of disease transmission between an infected agent a_i and a healthy agent a_h; and f_P is the proximity function that is presented in Eq. 2.

- Transmission range (R_T): Specifies the maximum distance between two individuals, where the infection can be transmitted from the infected to the healthy individual. The value of transmission range is used for defining the proximity function as shown in Eq. 2.

$$f_P(a_j|a_k) = \begin{cases} 0 & \text{if } D(a_j|a_k) > R_T \\ 1 & \text{if } D(a_j|a_k) \le R_T \end{cases} \tag{2}$$

where the $D(a_j|\, a_k)$ stands for the distance between agent j and k; and T_r represents the transmission range of the disease. The default value for the transmission range is $2m$ according to the guidelines provided for the COVID-19 pandemic [39].

- Healing period: Using this parameter, the modeller specifies the number days each infected individual needs for the recovery from the disease. The default value for this parameter is 14 days, assuming the spread of COVID-19 is being simulated [40].
- Mortality rate: This parameter specifies the ratio of the fatal cases of the diseases to the total number of infections. The default value for this parameter is 2% based on the statistics reported by WHO [41], assuming the spread of COVID-19 is being simulated.
- Reinfection chance (P_{RI}): One of the main characteristics of infectious diseases is the immunity developed by the patients' body in post-recovery conditions and as a result, the chance reinfection is usually less the first time infection. In other words, once an individual is infected by a disease and healed completely, the chance of being infected by the same disease for the second time is less than the first time infection. This phenomenon causes herd immunity [11,39], where the mass population in a community develop immunity against an infectious disease through previous infections and the spread of the diseases stops. Herd immunity have stopped the spread of several infectious diseases in the history of epidemiology and is important factor modelling the spread of infectious diseases for the sake modelling accuracy. The reduced chance of reinfection may not be considered in macro-level models of COVID-19 accurately, since the individual people are not traced in these models. Conversely, in micro-level models, the simulation model tracks the individual people throughout the simulation run, thus, the reduced chance of reinfection may be accurately considered. Capturing the reduced chance of reinfection enables the micro-level models to simulate the phenomenon of herd immunity, as well as the assessing the effectiveness of vaccination on the spread of infectious diseases. However, the existing ABM models [9,10,17] failed to capture this phenomenon. The proposed framework allows the modeller to consider the reduced chance of reinfection using this parameter. The default value for the chance of reinfection — assuming the transmission of COVID-19 is being modelled — is set to 2% based on the findings of the research conducted by Cavanaugh et al. [42].

$$P_t^r(a_i|a_h) = P_t(a_i|a_h) \times P_{RI} \tag{3}$$

where $P_t^r(a_i|\, a_h)$ stands for the re-infection chance — of an agent recovered from the disease a_h —, who was in a direct contact with an infected agent a_i; and $P_t(a_i|\, a_h)$ is the general transmission chance that was previously defined in Eq. 1

- Infection states: The different states of an infectious disease and their duration are effective parameters for simulating its spread. Generally, there are three main states for infectious diseases: (I) the non-contagious asymptomatic state that refers to the period that the infected individual has not developed any symptoms yet and cannot transmit the disease; (II) the contagious asymptomatic state that refers to the period that the infected individual has not developed any symptoms yet but, can transmit the disease; and (III) the contagious symptomatic state refers to the period that the infected individual has developed symptoms and can transmit the disease. Ignoring the existence of these three states for modelling the spread of infectious disease, leads to unrealistic simulation results by either overestimating or underestimating their spread. In the real-world scenario, the spread of infectious diseases often occurs during the contagious asymptomatic state, since the infected individuals are not aware of their infections yet and freely interacts with other individuals. However, the existing micro-level ABM models [9,10,17] assume that the infected individuals transmit the disease throughout their infection period, an assumption that may lead to significant overestimation of simulation results. The proposed framework considers the three different states of infection and the default duration for each state is selected by assuming the spread of COVID-19 is being modelled and based on the findings of the research conducted by Shamil et al. [40] (see Fig. 2). In the case of COVID-19 infections, there are rare cases reported, in which the infected individual does not develop any symptoms throughout the infection period and stays in the asymptomatic state (i.e., contagious, or non-contagious) for the whole duration of infection [43]. However, due to the rarity of these cases and the lack of numerical and statistical evidence on them, the proposed framework ignores these cases and assumes all the infected people pass through the same three infection states

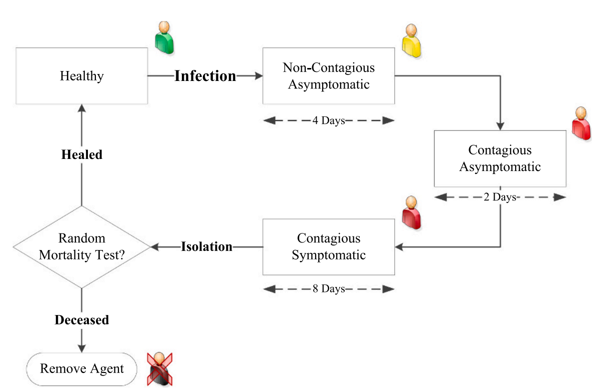

Fig. 2. The infection states and their default duration in the proposed framework.

presented in Fig. 2. However, the proposed framework and its associated Python® library provides enough flexibility for modellers to take these rare cases into account in future modelling efforts.

3.1.4. The spatiotemporal structure of the agent-based modelling component

Once the inputs of the ABM component are set, the proposed framework develops a spatial model of the project site based on the project site specifications given by the modeller (see Section 3.1.1), in which the width and the height of each grid cell is equal to the transmission range of the infectious disease R_T (see Section 3.1.3). Then, the ABM component, models each individual member of the project team by an agent and randomly assigns them to different crews (number and size of crews are specified by the modeller as discussed in Section 3.1.2). Finally, the workplace of each crew is randomly specified on the grid, assuming each grid cell can be occupied by an unlimited number of agents. To further illustrate the spatiotemporal structure of the ABM component, Fig. 3 graphically presents the spatial model of a hypothetical construction project in the proposed framework.

Once the simulation run starts, tasks undertaken by each individual agent at each simulation time-step is randomly selected based on the parameters of the probabilistic task decider given by the modeller (see Section 3.1.2). Referring to Fig. 3, there are three potential tasks each agent may undertake at simulation each time step and its movement is specified accordingly: (1) if the agent works directly on the task in hand, it will be moved to its pre-specified crew location; (2) if the agent travels to the site warehouse, it will be moved toward the warehouse through the route with the shortest Manhathan distance [44]; and (3) if the agent takes personal time, it will be moved to one of its six neighbour cells randomly until the next simulation time step (see Fig. 3). Further, those agents that travel to the site warehouse will not be assigned to any other tasks until after they arrive to the warehouse. At each simulation time step, once all agents' tasks are decided and their new position are assigned, the infected agents will be located on the grid and their cell mates (i.e., those agents that share the same cell with them on the grid) will be randomly infected. The random infection occurs, where the chance of infection of a healthy agent with no previous infections is equal to the general transmission chance (see Section 3.1.3), and the chance of infection of a healthy infection with previous infection is equal to $P_T \times P_{RI}$ (see Eq. 3). The pseudo code of the framework, which is presented in Fig. 4 illustrates the process of agents' movements on the project site, as well as the process of infection transmission between the infected agents and their cell mates.

The pseudo code presented in Fig. 4 is executed at each simulation

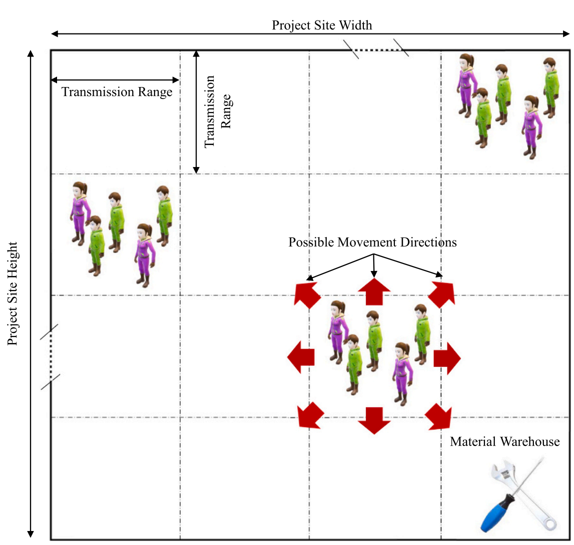

Fig. 3. The spatiotemporal structure of the ABM component.

Agents Positioning

```
for agent in model.agents:
    if agent.task != 'warehouse_travel':
        agent.task = agent.random_task_decider()
        if agent.task = 'direct':
            agent.pos = agent.work_loc
        elif agent.task = 'personal':
            agent.pos = agent.random_walk()
    else:
        agent.pos =agent.warehouse_travel()
```

Infection Transmission

```
for agent in model.agents:

    if agent.infection = True:
        cell_mates = [a in model.agents if a.pos == agent.pos]

        for a in cell_mates:

            if a.infection == False and a.pre_infection == False:
                if rand() <= transmission_chance:
                    a.infection == True

            elif a.infection == False and a.pre_infection == True:
                if rand() <= transmission_chance * reinfection_chance:
                    a.infection == True

            elif a.infection == True:
                pass
    else:
        pass
```

Fig. 4. The pseudo code of the ABM component for agents' positioning and infection's transmission.

time-step and once the predetermined time horizon of simulation is reached, the ABM component ends the simulation run and delivers the results to the MCS component. In each simulation run, the ABM component records the number agents at each infection state (recorded for at each simulation time-step), the location of each agent on the project site (recorded on a heat-map of the site), and the number of deceased individuals at each simulation time-step. It also records the infection log that includes the time and location of each occurrence of infection transmission, which assists with the identification of transmission's hot-spots and optimization of the site layout.

3.2. The Monte Carlo simulation component

The proposed framework captures the probabilistic uncertainties that affect the spread of infectious diseases by considering random behaviours of the system in six aspects. These random behaviours are modelled using pseudo random generator of NumPy library in Python®, which generates random numbers at the start of each simulation run or simulation time-step.

- Random external infections: This parameter determines the external infections by randomly selecting a pre-specified portion of agents (i.e., defined as infection rate) and changing their health state from healthy agents to the infected ones. This parameter simulate the start of the spread, where the first case(s) of infection enter the project's site. The occurrence frequency of random external infections is determined by the modeller based on the number of factors, including the relationships of the project team with the general population, project location, whether the project team reside in project camps or not.
- Random crew assignments: Prior to the project's start, project team members are randomly assigned to a given number of crews (see Section 3.1.2) and do not change their crews until the end of the project. Notable, all the project crews are equal in size.
- Random crew location: Once the crew assignments are completed, each crew is randomly located on project site and all its members are moved to the selected grid prior to the start of simulation.
- Random task decider: At each simulation time-step (i.e., takes 1 min long), this parameter randomly selects the task that each agent execute until the next simulation time-step. There three possible options (see Section 3.1.2) for this parameter: direct-work, traveling, or personal tasks.
- Random agent movements: At each simulation time-step, this parameter determines the direction of movement for those agents that travel on the site for personal reasons. Notable, those agents that travel to/from the warehouse do not move randomly nor instantly

relocated to the warehouse, instead the framework identifies their shortest path to the warehouse location using Manhattan distance measure and simulates their travel through this path. This capability (i.e., traveling from the shortest distance) is incorporated into the proposed framework to determine if the corridors toward the site warehouses are hot-spots of infection transmission or not.

- Random deaths: This parameter simulates the fatal cases of infections in the proposed framework by making a random decision regarding the death or recovery of each infected agent. This random decision will be made only once at the end of the symptomatic contagious state (see Fig. 2). Ultimately, agents' death is simulated by removing them from the ABM component for the rest of simulation run.

After each simulation run, the MSC component saves the results produced by the ABM component in a Python dictionary (or as a serialized object) and resets the ABM component parameters and runs the simulation until the user-defined number of simulation runs is reached. Then, the MCS component runs basic statistical analyses on the simulation results and delivers the global results. Further details regarding the programming aspects of the proposed framework are provided in the model documentations on the framework's Github page [45].

4. Construction case-study: spread of COVID-19 in a residential building project

4.1. Simulating the spread of COVID-19 in the project without interventions

In this section, the applicability of the proposed framework is tested through its implementation on a construction case study, which simulates the spread of COVID-19 in a residential building project. Moreover, to assess the behavioural validity of the proposed framework and test its application for developing strategies to contain the spread of infectious diseases, the effectiveness of using face masks is simulated in the case study project. Although the values for project site size, project team size, and crews' specifications are selected hypothetically, these numbers are intended to mimic the real-world conditions based on several years of experience of the author in construction industry. Moreover, the main reference for the disease specifications — the most important parameters for accurate simulation results — are provided in Section 3.1.3. The details of the construction case study are provided in Table 1.

Simulation of the current model is implemented using Python 3.8.9 on a desktop PC equipped with AMD® Ryzen 53,600 CPU, 32 GB of RAM, and Nvidia® GTX 1660 Super discrete graphics card. Each simulation run takes 16 s and for stochastic analysis of the results, the MCS component ran the model for 100 times. At each simulation run, the ABM component has run the model for 93,600 time-steps, which denotes six months of project execution with 5 days/week and 12 h of work per day.

Table 1
The specifications of the residential building case-study.

Project Site Specification		Project Team Specifications		Disease Specifications	
Description	Value	Description	Value	Description	Value
Size of project site	$45m \times 25m$	Project team size	100	Transmission chance	10%
Warehouse count	1	Number of crews	25	Transmission range	$2m$
Warehouse location	$22m \times 12m$	Size of crews	$4ppl$	Infection rate	5%
Project work-hours	$12hrs$	Task decider	[85%, 10%, 5%]	*Re*-infection chance	1%
		Time steps	Minute	Mortality rate	2%
		Site residence	Yes		

First, the number of fatal cases is analyzed and the histogram presented in Fig. 5 shows the results for 100 simulation runs. The average number of fatalities is 16.12 people and the standard deviation is 3.66, indicating that in a six months long project, 16% of project team members may lose their lives due to COVID-19 infections. This should be noted that the simulation model forecasts such a high rate of mortality among construction workers using the 2% mortality rate (see Section 3.1.3) given to the model based on empirical data that exists on general population [39] (see Section 3.1.3). In other words, the work behaviour in construction projects, which mandates the workers to work in crews rather than individually, causes several rebounds of infections among the project team members and increases the team's exposure to the chance of fatality in multiple occasions. Accordingly, the simulation results reveals that the mortality rate of construction workers can be up to 8 times of the general population. Notably, this case study represents building construction projects, in which the project's team work in confined space with no ventilation available. Although this is the common case in several building construction projects, the results produced in this case study cannot be generalized to the types of construction projects, which are executed in different external conditions (e.g., open-air, working individually). However, the flexibility of the proposed framework allows the users to model the different conditions that applies to the other types of construction projects and simulate the spread of COVID-19 in those projects as well.

The results presented in Fig. 5 confirms that the spread of infectious diseases has a random behaviour, which may be best modelled by a probabilistic distributions. Moreover, the number of agents at each health state — in each simulation time step — is determined in this case study and the results are presented in Fig. 6.

The simulation results, shown in Fig. 6, presents the average number of agents at each of the five health states (i.e., healthy, non-contagious asymptomatic, contagious asymptomatic, contagious symptomatic, and deceased) at each simulation time-step, in addition to the upper and lower limits of its 68.2% confidence interval. The upper and lower limits presented in Fig. 6 stand for the daily average value plus and minus the standard deviation respectively ($L_u = \mu + \sigma, L_l = \mu - \sigma$). On the first note, simulation results shows that the daily average number of healthy agents is 32.15 people with a standard deviation of 11.40, which indicates that on a daily basis 67.85% (almost two third) of the project team members are affected by the COVID-19 infections. Furthermore, results reveal that a rapid spike of infections occur in the early stages of the project, where the number of healthy individuals rapidly drops to zero at the first few days of the project. Interestingly, following the

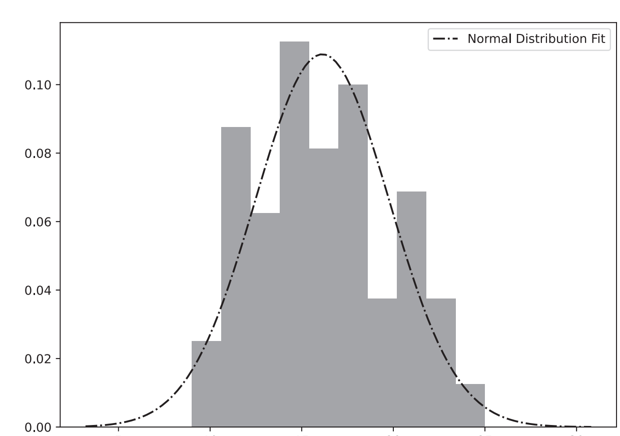

Fig. 5. Fatalities caused by COVID-19 in the case study project using the simulation inputs presented in Table 1.

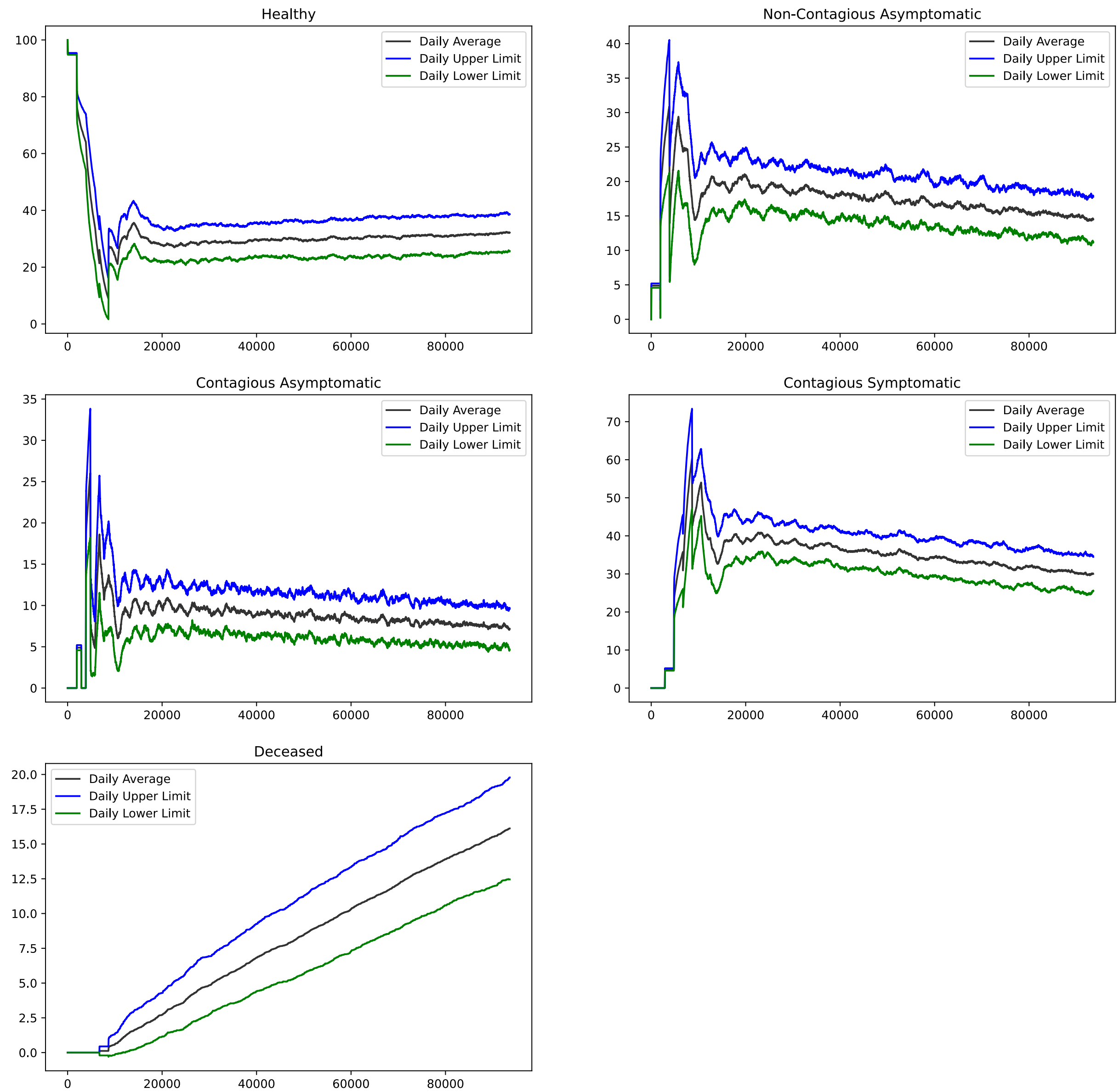

Fig. 6. Simulation results for daily average number of agents at each state of health, using the simulation inputs presented in Table 1.

initial spike of infections, the number of healthy individuals does not recover completely, which occurs due to the reinfection of the project team members. This means that reinfections still occur throughout the project life-cycle, even though, the chance of reinfection is only 2%. This phenomenon can be justified due to the close interactions of the project team members, since construction workers commonly work in crews.

As previously discussed, the spread of infectious diseases can significantly affect the performance of projects by causing temporary or permanent absence of the workforce at the job-site. To further investigate this impact, the average daily number of agents, who are present on the job-site (i.e., all agents who are not at contagious symptomatic state or deceased), is analyzed in this case study and the results are presented in Fig. 7. The simulation results shows that the average daily number of agents on-site is only 58.34 people and its standard deviation is 2.89. In other words, in the case study presented in this paper, the spread of COVID-19 can reduce the availability of human resources on the project site by 42%, which can cause significant increases to the project cost and time. Furthermore, as shown in Fig. 7, the normal distribution fitted on the simulation results reveals that the number of workforce on the site is randomly changing on daily basis and this can further challenge the project controlling and planning practices due to the inaccuracy of the workforce availability forecasts.

The proposed framework develops two types of heat-maps to support the site-layout planning practices with the objective of limiting the spread of infectious diseases. The first type of heat-map, shown in Fig. 8 (a), depicts the number of transmission occurrences in each grid cell of the project site, which is calculated cumulatively over the entire the simulation run. This type of heat-map helps to identify the hotspots of the disease transmission and to develop strategies to reduce the infection transmission in those locations. The second type of heat-map, shown in Fig. 8(b), pictures the accumulative number of agents observed on each grid cell over a number of simulation time-steps. This type of heat-map allows the project planners to detect the locations with the highest level of footfall on the site and change the project site layout or crews' work locations to avoid the generation of infection hotspots in those locations.

Fig. 8(a) shows the number of transmissions at each grid of the project site after six months of project execution in this case study. The results shows that the site warehouse location has the highest number of

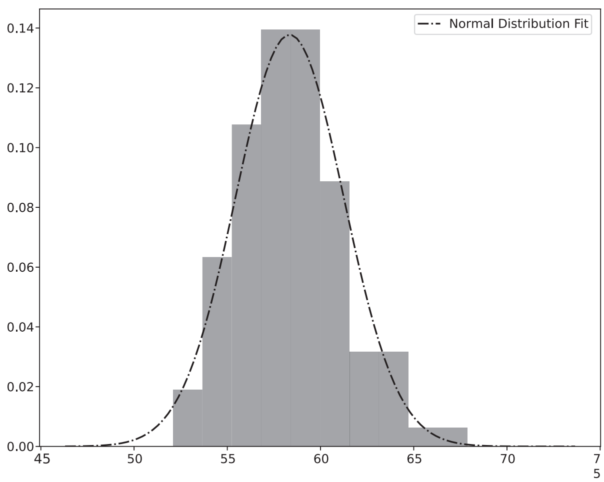

Fig. 7. Average daily number of project team members on the job-site, using the simulation inputs presented in Table 1.

infection transmissions, followed by the several crews' work locations. Accordingly, project site layout planning can play a key role for enhancing the resilience of construction projects against the spread of infectious diseases, since the site warehouses and crews' work locations are the hotspots for disease transmission. Fig. 8(b) shows the number of agents observed on each grid cell only after two days of project execution, which confirms the fact that the agents spent the majority of their time working in crews on their tasks; and routes to and from the site warehouse have experienced a higher than normal traffic of the agents.

4.2. Simulating the effectiveness of wearing face mask

In addition to predicting the spread of infectious diseases in construction sites, the proposed framework allows modellers to evaluate the effectiveness of different interventions on the spread of infectious diseases; and consequently, determine the optimal interventions to curb the spread. To test the application of the proposed framework in this capacity and investigate its parameter sensitivity for behavioural validation (see Section 4.3), the effectiveness of using face masks on preventing the spread of COVID-19 is simulated in the current case study. Several types of face masks have been suggested for limiting the spread of COVID-19 (e.g., surgical masks, N95, and 1 or 3 ply cloth masks), each of which have different characteristics and different levels of effectiveness in terms of reducing the rate of droplet and aerosol transmission modes [46]. In this case study, the use of surgical face masks are simulated, since they are one of the cheapest and most common types of face masks used during the COVID-19 pandemic [46]. To account for the effect of wearing surgical face masks in this case study, the general chance of transmission (P_T) is reduced from 10% to 1% according to [38] and the value of other parameters are unchanged, as presented in Table 1. Then, the model ran for 100 simulation runs and the simulation results — hereafter referred as post-intervention simulation results — are statistically analyzed. Fig. 9 shows the post-intervention simulation results regarding the average number of agents at each of the five health states, as well as the 68.2% confidence interval of the results.

The post-intervention simulation results shows significant improvements in terms of number of infections, as compared to the original simulation results presented in Fig. 6. Following the implementation of this intervention, the daily average number of healthy agents (refer to Fig. 9) is increased from 32.15 to 91.46 people and its standard deviation is only 1.47. This shows that the number of infections can be reduced by 87% ((67.85 − 8.54)/67.85 = 87%) by only mandating the

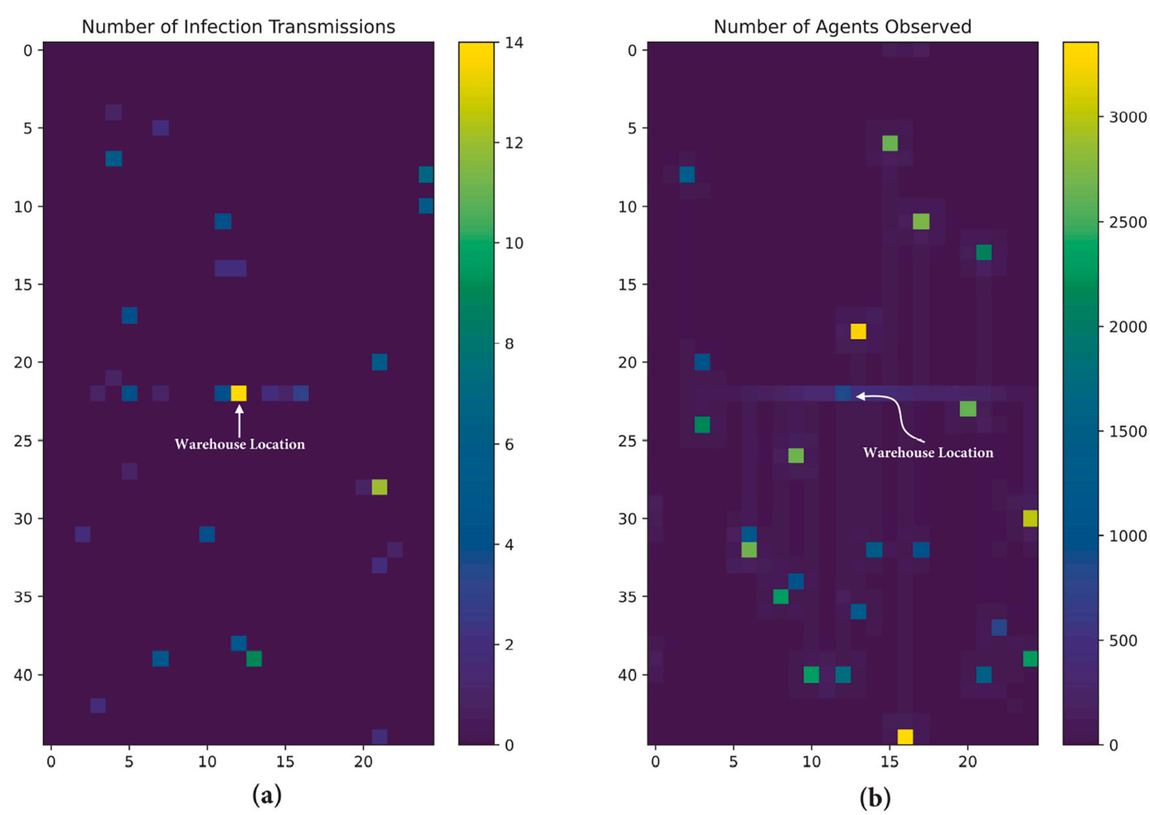

Fig. 8. Heat-maps of (a) the number of agents on each grid cell of the project's spatial model; and (b) the number of infection transmissions between an infected and a healthy agent.

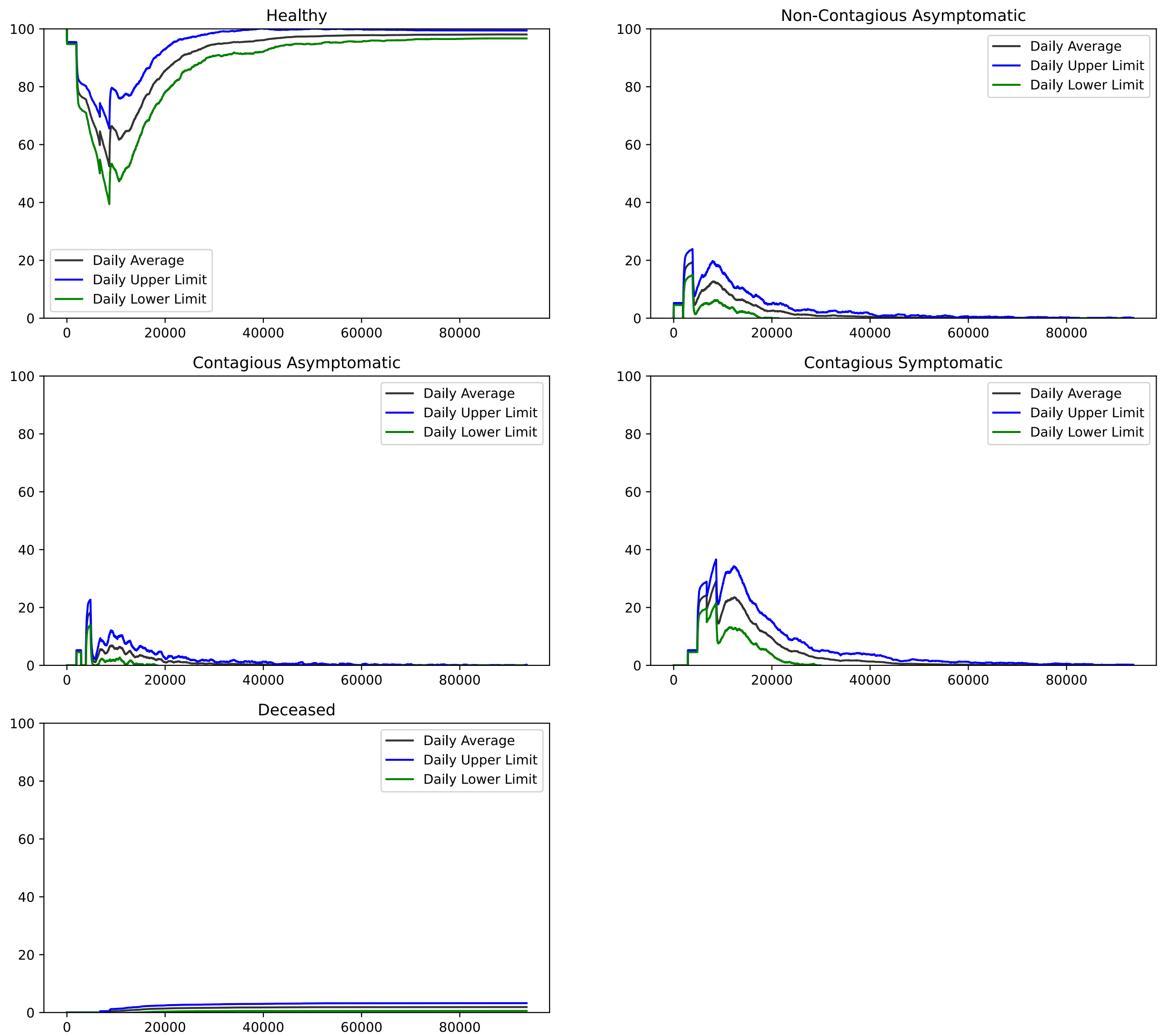

Fig. 9. Post-intervention simulation results for daily average number of agents at each state of health, using the simulation inputs presented in Table 1 and $P_T = 1\%$.

use of face masks in the project's site. The simulation results also reveal that the initial spike of infections still occurs in the project by infecting almost 50% of the project team members. However, the intensity of the initial spike is smaller in the post-intervention simulation results as compared to the original ones. Moreover, in the post-intervention simulation results, the spread of the disease slows down significantly, after the initial spike and the number of infected agents (i.e., non-contagious asymptomatic, contagious asymptomatic, contagious symptomatic, and deceased) tends toward zero (refer to Fig. 9) over time. On another observation, the average number of deceased agents in the post-intervention results is only 1.89 person with the standard deviation of 1.35, which indicates that wearing face masks can reduce the number of fatalities in projects up to 88% ((16.12 − 1.89)/16.12 = 88%). Finally, in the post-intervention simulation results, the average daily number of agents in the project's site — shown in Fig. 10 — is increased by 62%, with an average of 94.46 people, as compared to the 58.34 people in the original simulation results.

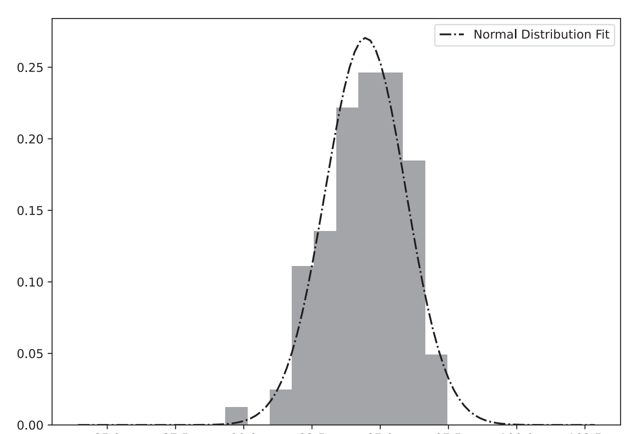

Fig. 10. Post-intervention simulation results for the average daily number of staff on the job-site, using the simulation inputs presented in Table 1 and general transmission chance = 1%.

4.3. Validation of the proposed framework

In this section, the validity of the proposed framework is investigated to build confidence in the results produced by the framework. For testing the validity of simulation models, first, the model need to be verified by ensuring that the implementation of the computer program is correct [47]; and then, the model need to be validated by ensuring that the model provides a satisfactory range of accuracy for predicting the behaviour the real-world system [47]. Accordingly, the validation tests of simulation models are different from those designed for other predictive modelling techniques (e.g., artificial neural networks technique), since simulation models are tested for predicting the system behaviour rather than their outputs only but, common predictive modelling techniques are only tested for predicting the systems' outputs [48,49]. There are several tests suggested for validating simulation models for predicting the different aspects of the real-world systems' behaviour, including the extreme conditions test [50], the parameter sensitivity test [51,52], and the degenerate validation test [47]. These tests often assess the behaviour of the computerized system (i.e., simulation model) in different scenarios (e.g., extreme conditions, the most common conditions, given events) and compares them to the behaviour that is expected from the real-world system [48,50–52]. In this paper, the model verification and parameter validation test are implemented to assure the model is simulating "the right phenomenon" and then, two validation tests are implemented to confirm the behavioural validity of the proposed framework, the extreme conditions test and parameter sensitivity test. Due to the novelty of the proposed framework and its application area, there are not sufficient empirical data to run statistical validation tests on the simulation outputs. However, with the application of the extreme conditions test and the parameter sensitivity test [47], the validity of the proposed framework is tested and further discussed in this section.

One of the key factors that affect the accuracy of the results produced by the proposed framework is the value of parameters used for modelling the spread of infectious diseases. More specifically, the parameters used for defining the disease specification (see Section 3.1.3) need to be accurately defined to produce accurate simulation results. To maintain the generality of the proposed framework, modellers are allowed to change the disease specification to simulate the spread of different infectious diseases or different variations of the COVID-19 in construction projects. However, for the sake of parameter validation, the default values for these parameters are set based on the assumption that the spread of COVID-19 is being simulated (i.e., the dominant variant in Canada at the time manuscript preparation was Delta according to Canadian National Collaborating Center for Infectious Diseases [34]) and the references used for determining the value of each parameter is provided in Section 3.1.3. Once the structural soundness of the framework is verified by the modeller and the values of the model parameters are validated through the literature review (parameter validation test), the behavioural validity of the model is tested using the extreme conditions and parameter sensitivity tests.

In extreme conditions test [47,49,53], the value of one system parameter is set to an extreme condition (i.e., maximum or minimum possible value), while the value of other parameters are kept unchanged, and then, the behaviour of the simulation model is compared to those expected from the real-world system. For the proposed framework, the behaviour of the framework is tested in the following four extreme conditions: (1) setting the value of infection rate equal to zero, which means there are no cases of COVID-19 at the project start; (2) setting the value of infection rate equal to one, which means that all project team members are infected at the project start; (3) setting the value of reinfection chance equal to zero that means the once an individual is infected with COVID-19 will be completely immunized against the disease; and (4) setting the transmission chance equal to zero, which means the the disease cannot be transmitted from an infected agent to a healthy agent. The results of extreme condition tests are presented in Fig. 11, where the number of healthy individuals in the project is plotted over time.

The results of extreme conditions tests presented in Fig. 11(a) shows that this framework accurately simulated the conditions of having no infections in the project, where the number of healthy agents are constantly equal to 100 (i.e., project team size). The simulation results for the second extreme conditions — shown in Fig. 11(b) — accurately

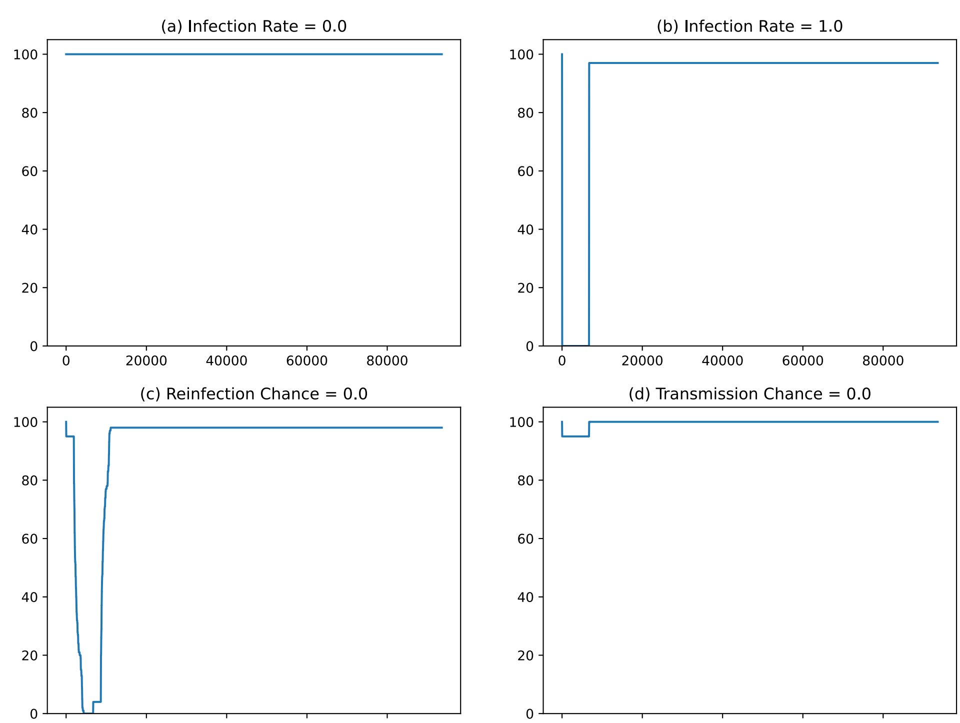

Fig. 11. Simulation results for the extreme conditions validation tests, using the simulation inputs presented in Table 1 and the extreme conditions labeled on the charts.

shows zero number of healthy agents at the project start and further predicts that all agents will be healthy after their infection period is over and there will be three moralities in this case. It should be noted that since all individuals are infected and healed at the exact same time, there are no cases of reinfection or secondary spikes of infection in this extreme condition, which has been accurately predicted by the framework. Next, Fig. 11(c) shows the simulation results for the extreme conditions of building complete immunity against COVID-19 after the first infection and these results confirm that there will not be any cases of reinfections in the project after the first spike, as the the number of healthy agents raised to its maximum value. Finally, the simulation results of the fourth extreme condition, in which there is no chance of infection transmission are shown in Fig. 11(d) and the results confirms that the framework accurately predicted no new cases of infection in the project. Accordingly, the results of extreme conditions test confirms the behavioural validity of the proposed framework for modelling the spread of infectious diseases. Furthermore, by comparing the simulation results for the two scenarios of using and not using face makes, confirms the parameter sensitivity of the proposed framework to the changes made in general transmission chance (see Section 3.1.3). Thus, the behavioural validity of the proposed framework can be confirmed by these two tests, the extreme conditions and parameter sensitivity tests. Although direct statistical validation tests cannot be implemented on simulation the results due to the lack of empirical data, the behavioural validation tests confirm that this framework can deliver accurate simulation results if accurate input parameters are given to the framework.

5. Conclusions and future works

The outbreak of COVID-19 and its following restrictions imposed by local health authorities have caused several losses to the construction industry. Construction industry needs a comprehensive playbook for an effective and timely recovery from these adverse impacts. The development of such playbook requires an accurate predictive model to analyze the impacts caused by the pandemic and assess several potential interventions for limiting the spread of the disease in construction projects. In this paper, a stochastic simulation framework is introduced for this purpose, which is developed by combining agent-based modelling (ABM) and Monte Carlo simulation (MCS) techniques. This proposed ABM-MCS framework is a generic solution for modelling the resilience of construction projects against the spread of infectious diseases. This generic framework has the capacity to model the spread of different diseases in different types of construction projects with different projects' site and crews' settings.

Using the proposed ABM-MCS framework, the spread of COVID-19 is simulated in a residential building project and the results reveals the followings: (1) infectious diseases spread faster in construction projects, as compared to the general population due to the fact that construction workers usually work in crews and commonly have physical interactions with each other; (2) herd immunity, where the mass population develop immunity against an infectious disease due to prior infections, may not occur in construction projects unlike in general population due to the high chance of transmission in construction projects and close physical interactions of the project team members; (3) non-compliance to the preventive guidelines laid out by the health authorities can cause higher rate of fatalities in construction projects, as compared to the general population; and (4) uncontrolled spread of COVID-19 on construction sites may increase the project time and cost due to the temporary/permanent absences of the project staff (e.g., up to 41.66% reduction in project staff size due to the infections). Moreover, the impacts of using face masks on the spread of COVID-19 in construction projects was tested and the results reveal that this intervention can significantly reduce the adverse impacts of COVID-19 infections in the following aspects: (1) it slows down the spread in construction projects and avoid potential project halts caused by the absence of project staff; (2) herd immunity is possible in case of using face masks as the number of infected agents tends toward zero as the project continues; (3) the number of fatalities can be reduced by 88%, as compared to the uncontrolled conditions; and (4) the average number of the absent project staff can be reduced by 62%, causing less hiccups in the project execution.

There are a few limitations in the proposed framework that will be addressed in future extensions. First, this framework can only simulate the droplet transmission mode of COVID-19 and ignores the aerosol transmission mode, although some recent findings confirm the key role of aerosol transmission mode on the spread of COVID-19 in indoor environments. This limitation will be addressed in future research by extending the capabilities of proposed framework to simulate the aerosol transmission of COVID-19 in addition to the existing available, droplets transmission mode. Moreover, this paper tests the effectiveness of using face masks on the spread of COVID-19, due to its modelling simplicity and the global acceptance of this intervention strategy for containing the spread of COVID-19. However, there are several other interventions suggested in the literature for containing the spread of COVID-19, the effectiveness of which have not been discussed in the current paper, since it was out of the initial scope of research. This research gap will be addressed in future by investigating the effectiveness of different interventions suggested to contain the spread of COVID-19 by the proposed framework and suggest the most effective strategies to enhance the resilience of construction industry against infectious diseases. Moreover, in future research, the proposed framework will be used to compare different types of construction projects (i.e., civil, industrial, residential, and commercial) in terms of their resilience against the spread of infectious diseases. Finally, the proposed framework will become publicly available to assist the construction research community with developing a comprehensive playbook for the recovery of the industry in the post-COVID-19 era.

The ABM-MCS framework proposed in this paper has some limitations, which will be addressed in future developments. Although it allows the modeller to specify the project-site characteristics, the shape of project site is always assumed to be in a rectangular shape. In future research, this Python library will be connected to Autodesk RevitÂ® to automatically import the project site specifications from Revit® into the simulation framework. Moreover, the proposed framework is limited in terms visualizing the simulation results. This limitation will be addressed in future extensions by incorporating a graphical user-interface for the model and including animations as an alternative format for the simulation results.

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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