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Report 3235

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Abstract. Pandemics such as Covid-19 have posed a set of questions concerning safe space usage given the risk of virus transmission in confined and open spaces. In this context, this report presents a risk analysis methodology for the use of crowd modelling tools as an aid to assess safety in confined and open spaces. Crowd models can be used to investigate people movement in the built environment, thus they have a great potential for the performance of proximity analysis. The report presented here addresses first the psychological and physical aspects linked to physical distancing (also called social distancing). Given the limited current knowledge on human behaviour and space usage during pandemics, the changes needed in crowd modelling tools to appropriately represent people movement are listed. This includes issues associated with modifications of the fundamental relationships between the key people movement variables (speed/flow vs density), and issues linked with interactions between pedestrians (e.g. collision avoidance, queuing mechanisms, route choice). Suggestions for new crowd modelling outputs are provided in order to enhance their use during pandemics. In addition, practical solutions concerning space usage are presented in light of the assessment of human safety through a risk evaluation based on proximity analysis and/or exposure assessment. This is deemed to help identifying design and management solutions to decrease the risk of virus transmission.

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1. Introduction

How many people could safely access a given building or event? How do we ensure appropriate physical distancing between people in public spaces? What modifications are required in the space design and crowd management solutions to minimize the risk of virus transmissions? Those are just examples of questions generated by the Covid-19 pandemic which concern the safe usage of spaces. In fact, stakeholders from all over the world dealing with crowds have been greatly affected by Covid-19 pandemic and face issues in safely hosting and managing crowds. To date, events involving large crowds have been cancelled or postponed worldwide, restrictions have been posed to public gatherings and different prevention and/or mitigation measures have been adopted to decrease physical interactions among people (Anderson et al., 2020). In fact, the threats to a crowd which affect safety are indeed now including the risk of virus transmission. This risk should be considered along with other concurrent threats which may affect a crowd (e.g. a fire, antagonistic attacks, crowd crush).

Several countries in the world (e.g. Italy, UK) have adopted drastic measures such as compulsory lockdowns which may have short- and long-term impact on how public spaces are used (Honey-Roses et al., 2020). In addition, the absence of a vaccine for Covid-19 has led to recommendations on physical distancing provided by the World Health Organization (WHO, 2020) that were implemented (to a varying degree) in several national regulations. It should be noted that there is no consistency in the adopted measures worldwide (e.g., different recommendations for physical distancing are available (Movement Strategies, 2020)) and those change over time in light of the phase of the pandemic in which a given jurisdiction is operating. The term physical distancing is used here as the alternative term *social distancing* may be linked to social isolation. Physical distancing can be implemented in several manners, but its main aim is to keep people apart from each other. Lockdowns are the most stringent form of enforcing physical distancing. Common alternatives include providing recommendations on a certain minimum distance to be kept between people in crowded places. Physical distancing is overall designed to reduce the physical interactions between people and its implementation relies on the assumption that the risk of virus transmission increases with the decrease of distance between people. This issue is also associated with the use of personal protective equipment (e.g. face masks), for which inconsistent recommendations are provided worldwide as their use and consequences on physical distancing is object of an ongoing debate (Cheng et al., 2020; Desai and Aronoff, 2020; Howard, 2020)

Modelling tools have been adopted in several instances to inform policy making and preventive/containing measures to prevent the spread of the SARS-CoV-2 virus. The main type of modelling findings used for this purpose are mostly obtained using macroscopic epidemiological models, among which the most used are different variations of the SIR model. The SIR model stems from early analytical approaches developed to study the spread of disease (Kermack and McKendrick, 1927) and is an epidemiological tool that estimates the evolution of the number of infected people in given conditions under a given set of assumptions. The SIR model divides the population into three groups: (1) susceptible, S; (2) infectious, I; and (3) recovered/removed, R. Differential equations can be used in mathematical epidemiology to consider also the (4) exposed class, E, to create the so-called SEIR model (Anderson et al., 1992). Over the years, several macroscopic epidemiological models have been developed, including stochastic transmission models (Kucharski et al., 2020) and mean-field epidemiological models (Giordano et al., 2020).

The great benefit of macroscopic epidemiological models is their applicability to large scales which make them very suitable to inform policy making of regional and national governments. Nevertheless, their focus is the macroscopic scale, thus their use at a much smaller scale may suffer from their lack in resolution, i.e., they may not comprehensively take into account the movement of people and how their interactions may affect the risk of virus transmission. The pedestrian and evacuation dynamics community is well aware of this issue, given a keynote presented on this topic back in 2012 (Johansson and Goscè, 2014) which initiated the discussion on the need to couple the field of crowd dynamics/modelling with mathematical epidemiology (Goscé et al., 2014). Even if the heterogeneity in population and movement patterns have been addressed at a macroscopic scale (especially in transport settings (Goscé and Johansson, 2018; Meloni et al., 2011; Saberi et al., 2020)), current disease spreading models do not specifically address the space usage of pedestrians at a microscopic scale. This makes it difficult for a stakeholder involved in hosting or managing a crowd in a confined space or at an event to use epidemiological models. To address this issue, another type of modelling tools can help to identify suitable solutions aimed at minimizing the risk of virus transmission at a microscopic scale: crowd models.

Crowd models, such as hydraulic models (Gwynne and Rosenbaum, 2016; Predtechenskii and Milinskii, 1978), microscopic continuous models (Helbing et al., 2000; Thompson & Marchant, 1995) and discrete models (Lovreglio et al., 2015; Pelechano and Malkawi, 2008), can be used to represent the movement and behaviour of pedestrians at an individual (microscopic models) or aggregate (macroscopic models) level in open and confined spaces. The term confined space is here used as it refers to several types of spaces in the built environment, such as buildings or transportation means (e.g. trains, bus, aircrafts, etc.). Crowd models have been used so far mostly to ensure comfort and safety of pedestrians (e.g. to investigate fire evacuation scenarios (Ronchi, 2020)) and identify crowd management solutions to optimize movement flows and reduce waiting times (Bellomo & Gibelli, 2016; Johansson, 2008). Crowd models generally allow the assessment of the time to clear a given space based on a set of fundamental pedestrian movement variables, such as flowrates, walking speeds, occupant characteristics and behavioural rules.

The simulation of people movement could provide a great help to decision makers as they could be used to perform a risk analysis related to disease spreading and in case of concurrent threats. During the Covid-19 pandemic, some of the most known and used crowd models (Lovreglio et al., 2019) have released new features aimed at performing proximity analysis, considering physical distancing or counting the interactions between pedestrians in a given physical distance radius. While these features are useful to evaluate space usage, given the lack of knowledge concerning the current spread of disease (with great uncertainty in the mechanism of virus transmission (Bahl et al., 2020; Lewis, 2020)), they do not allow a comprehensive quantitative understanding of the impact of different measures on occupant exposure. In addition, some of the fundamental assumptions adopted by crowd models would need to be re-evaluated in light of the possible changes in crowd dynamics and behaviour that could occur during a pandemic. In other words, crowd models cannot directly be applied to perform a proximity analysis or investigate occupant exposure without a careful evaluation of their assumptions. This is because crowd models have been developed and configured for another scope and make use of datasets which were collected prior to the surge of the pandemic. It should be noted that - to the time this report was written - no experimental data was available on crowd dynamics during pandemics, thus the authors discuss here a set of possible solutions to deal with this lack of information.

For this reason, it is crucial to perform a review of the assumptions currently used by crowd models which may impact the crowd model outputs relevant for virus transmission risk analysis. This is a required step to ensure credibility of a proximity analysis or occupant exposure assessment. Given the current (limited) knowledge on crowd dynamics and behaviour during a pandemic, it is important to assess whether there is a need for retrofitting existing crowd models with a different set of underlying assumptions, input configurations or new model outputs.

1.1. Aim and objectives

The overall aim of this work is to develop and present a risk analysis methodology for the use of crowd modelling tools during the Covid-19 pandemic. The use of crowd models during a pandemic requires a careful evaluation of the suitability of the assumptions they use given possible changes in crowd dynamics and human behaviour. This work investigates the key aspects concerning possible physical and behavioural changes linked to physical distancing and speculates on the subsequent modifications needed in the input calibration phase of crowd models. The guidance provided include both short-term and long-term solutions on crowd model use and development. In other words, guidance is provided both on the calibration of existing crowd models to represent crowd dynamics in times of pandemics (i.e. to attempt an appropriate calibration of crowd models relying on existing approaches/tools) as well as future changes needed at a more fundamental level. The end goal is to provide a methodology to perform a risk evaluation based on proximity analysis and occupant exposure assessment performed with a crowd model. This evaluation can be performed both to analyse the risk of virus transmission *per se* as well as the case of concurrent threats (i.e. multiple risks along with virus transmission, e.g. fire or antagonistic threats leading to evacuation scenarios). The risk analysis performed can eventually be used to assess the safety of a space (confined or open) to a given risk (or risks) and identify suitable design and management solutions aimed at improving human safety.

The type of crowd models investigated here include macroscopic flow-based models (e.g. the hydraulic model of the Society of Fire Protection Engineering (Gwynne and Rosenbaum, 2016)) to microscopic agent-based models able to track people movement at an individual level (Adrian et al., 2019). The steps needed for the calibration of crowd model inputs and the associated modifications in the underlying assumptions to be adopted by the models are provided. This work also advocates for the identification of new crowd modelling outputs which can be used for the performance of risk analysis linked to the risk of virus transmission. An example of such new outputs is provided through a new model for the estimation of occupant exposure which is here presented.

1.2. Report overview

This report presents a methodology developed for the use of crowd models during the Covid-19 pandemic. The report structure is here presented. The first chapter introduces the project (chapter I: Introduction) and the overall aim and objectives of the project. Chapter II (Method) introduces the general approach employed in the development of the methodology (considering virus transmission as a threat in isolation or in case of concurrent threats), including the domain of application of the methodology and the type of models under consideration. Chapter III (Psychological issues linked to physical distancing) presents a set of key crowd behaviour which are generally expected during people movement and how they may change in times of pandemics. Chapter IV (Physical issues linked to physical distancing) provides a critical analysis of the key aspects of space usage, route choice and movement that may change due to physical distancing. Chapter V describes the issues associated with proximity analysis and exposure assessment in light of the assumptions concerning the virus transmission mechanisms. Chapter VI (The methodology for crowd model usage) presents the steps that a crowd model user would need to undergo to make use of a crowd model in times of pandemics along with a checklist of aspects to be considered. This includes the analysis of possible changes needed to retrofit existing crowd models and input configuration. Chapter VI (Design and crowd management solutions) presents practical uses of the methodology to enhance safety in case of risk of virus transmission. Chapter VII presents an exemplary case study in which the methodology is applied to a stadium. Chapter VIII (Discussion and Conclusions) discusses the benefits of a systematic methodology for crowd model usage in times of pandemics, short-term and long-term needs for model developments and presents a set of final remarks concerning future research needs in this domain.

2. Method

The general approach employed in the development of the risk analysis methodology for the use of crowd models in times of pandemics included different steps (see Figure 1). First, the crowd dynamics literature was reviewed to identify the key psychological and physical variables/factors which may impact crowd dynamics and behaviour during a pandemic. This was by no means intended to be a comprehensive review of the field of crowd dynamics, as this type of reviews is already available in the literature and covers the whole spectrum of empirical research methods, e.g., see (Haghani, 2020a, 2020b). Instead, the study of key crowd dynamics variables was made here to identify the most crucial aspects which might affect people movement during pandemics. Subsequently, the issues associated with people movement during pandemics were analysed in light of their implementation in two of the most commonly adopted approaches in crowd modelling (Bellomo et al., 2016; Duives et al., 2013). First, a macroscopic flow-based approach (Gwynne and Rosenbaum, 2016) in which an homogeneous group of people move through space. Second, an agent-based modelling approach in which individual behaviours are represented through movement modelling (e.g. the steering model (Reynolds, 1999)) and the parametric equations of each agent can be obtained.

The identification of the key crowd dynamics variables which may be impacted by pandemics was followed by the identification of the relevant crowd modelling outputs for the study of virus transmission risk. Two main domains were analysed: 1) Proximity analysis and 2) Occupant exposure assessment. Although apparently similar, these two domains have a significant conceptual difference. A risk assessment based on proximity analysis assumes that risk increases with the decrease of distance between people. The study of occupant exposure does not instead necessarily rely on this assumption, i.e. different mechanisms could be used to estimate the risk of virus transmission, and those may not necessarily be based on distance criteria. Given the current uncertainty in understanding the mechanisms of the SARS-CoV-2 virus transmission (Lewis, 2020) and future possible applications of this methodology to other viruses with different transmission mechanisms, both domains are here included.

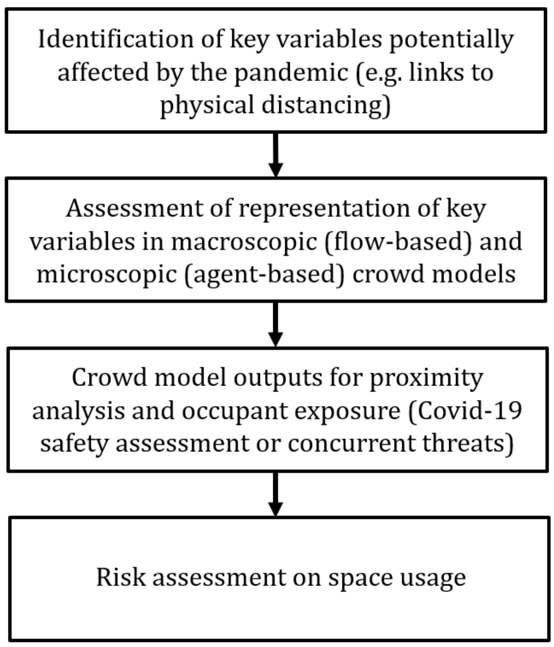


Figure 1. Steps for the development of the methodology for the use of crowd models in times of pandemic.

3. Psychological issues linked to physical distancing

Social identity theory (Tajfel and Turner, 2004) has been used in crowd dynamics research to investigate the behaviour of groups and individuals in a crowd. A common distinction is made between physical crowds and psychological crowds. Physical crowds are generally intended as groups of moving individuals that are co-present in a given space. In contrast, a psychological crowd include members of a group which share a social identity (Reicher, 2011). This is an important distinction during a pandemic as it may influence the sense of responsibility that people may take towards maintaining physical distance.

Crowds tend to self-organize themselves while moving in space, with a set of non-verbal cues which can influence crowd behaviour. Visual stimuli are known to be one of the key cues affecting crowd movement (Gibson, 1986; Warren, 2018). In normal situations, visual attention is estimated to occur primarily within a 2 m range and the likelihood to respond to a visual stimulus depends on spatial features (Gallup et al., 2012). Nevertheless, many aspects concerning how people monitor their environment strongly depend on the social context, and crowd dynamics alone cannot be used to interpret the processes associated with visual attention (Fotios et al., 2015; Gallup et al., 2012). This will likely have an impact on visual perception of individuals in a crowd during a pandemic, as the social context would differ significantly.

Researchers in the field of proxemics investigated the psychological factors associated with choices of interpersonal distances and personal spaces since the 50ies and 60ies (Hall, 1982; Sommer, 1962) through a number of research methods, including naturalistic and experimental studies (Hayduk, 1978). Several findings relevant to physical distancing in times of pandemics can be obtained from this field. For instance, individuals with high credibility are generally more accepted when they move closer to other individuals compared to individuals with low credibility (Burgoon and Jones, 1976). This information could be linked to the behaviour of a crowd towards staff members or emergency personnel.

Personal space is a common concept used in proximity analysis to study the willingness of people to get closer to other members of a crowd (Hecht et al., 2019). Personal space of an individual has been considered as rather stable over time (at least within a given instance of use of a space). During pandemics, personal space can be interpreted as a buffer zone, in which a person might see others as potential intruders, thus feeling potentially threatened by the presence of others. An important limitation of the concept of personal space is that it mostly relies on the analysis of a single individual rather than investigating the behaviour of collective groups. Psychological crowds do not move as individuals, and they tend to maintain closer proximity to others regardless of the number of people present in an areas (Templeton et al., 2018). These issues should be considered when studying physical distancing of a crowd.

Apart from the approach based on the analysis of personal space, it is here recommended to study physical distancing through the analysis of crowd identification and social identity (Tajfel and Turner, 2004). Approaches suggesting that crowding is inherently aversive have been in fact contradicted by recent studies (Novelli et al., 2013) which found out that, in normal situations, crowds may naturally tend to stay together in contexts in which social identification is present. In other words, people may tend to naturally go towards more crowded places. This means that there are conditions in which situations of high crowdedness can actually be enjoyed rather than being inherently aversive.

The psychological issues associated with physical distancing might get even more complex in case of concurrent threats (e.g. a pandemic plus a fire or antagonistic attack). To the authors knowledge, no data are currently available on the psychological factors impacting crowd movement and behaviour during concurrent threats. In this case, conflicting crowd needs would have to be taken into consideration, including the need to reach a safe place as soon as possible and the need to keep physical distancing while moving.

Pandemics such as Covid-19 have posed a great challenge for the stakeholders involved in managing crowds as they need to actively identify measures to provide an enjoyable crowded environment while ensuring a continuous monitoring of crowd safety. This highlights the importance of enhancing the feeling of being part of psychological crowd and promote responsible behaviour which leads to physical distancing. Different methods have been used to promote physical distancing measures, including education campaigns, persuasion, incentives, coercion, environmental modifications and restrictions (Bavel et al., 2020; Van Assche et al., 2020). Behavioural scientists (Bonell et al., 2020) advice on the use of instructions which aim at the feeling of being part of a psychological crowd (i.e., the *protect each other* message) while instructing people on keeping physical distance during pandemics. In fact, a psychological crowd with a shared social identity linked to the Covid-19 threat would likely follow more responsibly the physical distancing provisions received and attempt to coordinate movement to diminish the risk for themselves and for others. A physical crowd would instead likely be focused on the individual risk rather than the collective resilience.

The choice to keep physical distance in a crowd depends on group behaviour. In this context, consensus decision making in crowds has been largely investigated in the literature (Dyer et al., 2009). Different contrasting aspects are crucial when considering physical distancing. First, a known issue is that the collective behaviour concerning navigation may be influenced by a small proportion of individuals, i.e., small informed groups may steer decision-making of entire groups (Dyer et al., 2008). Conflicting information has also been investigated, showing that social influence can negatively affect movement behaviour in case of passive conflict (Kinateder et al., 2014a). In other situations, groups may tend to decide in favour of the majority, i.e. decision making always involve some form of designated or emergent leadership (Dyer et al., 2009). This is linked to informative and normative social influence (Deutsch and Gerard, 1955), which explains that people may tend to gather information from others and conform to the mass and "stick to the norm". In the context of physical distancing, this practically means that the choice of the distance kept of each individual would also be influenced by the distance kept by others. This would not be linked merely on physical proximity, but also to the tendency of people to conforming to the norm. In other words, a crowd including a given proportion of people maintaining (or not) physical distance would likely encourage the others in doing the same. To encourage a crowd in maintaining physical distancing, it is therefore crucial to ensure that an influential portion of the crowd intends to do so and that there is a leadership group which would exhibit exemplary behaviour. In this way, the rest will be encouraged to follow the norm.

4. Physical issues linked to physical distancing

Recommendations on physical distancing are deemed to have a significant impact on the physical aspects linked to the movement of people in normal and emergency situations. This section investigates these issues in light of the core components included in crowd models (International Standards Organization, 2020; Society of Fire Protection Engineers, 2019), considering aspects related to space usage, route choice, and movement.

4.1. The impact of physical distancing on space usage

Provisions on physical distancing between people can be given for a static or moving crowd and are prone to interpretation, including when they are implemented in a crowd model. This depends on several factors, among which it is important to note:

1. Crowd models may adopt different assumptions in the representation of people, i.e., their ability to represent their characteristics in terms of shape, size and grouping of the individuals may vary
2. Different reference points can be used when calculating physical distancing
3. Physical distancing provisions should generally be interpreted for dynamic implementation in crowd models (i.e. not for static positioning of the agents)

The assumptions on the dimensions of body size and their modelling representation can affect the impact of physical distancing. Crowd models generally calculate movement in bi-dimensional spaces which are connected with vertical elements (e.g. stairs, ramps, elevators). For this reason, people are generally represented in 2D for the calculations and then visualized in 3D for pure visualization purposes. In addition, while macroscopic crowd models may represent people as an homogenous crowd having the same characteristics (Gwynne and Rosenbaum, 2016), microscopic crowd models may be able to represent individual body shapes (e.g. generally an ellipsis or a circle with a given diameter, see the diameters *c* in Figure 2). It should be noted that this is currently possible mostly in continuous models, while most network-based models assume crowds of homogenous characteristics corresponding to the type of network elements in use (Ronchi, 2020). For this reason, microscopic continuous crowd models are likely more suitable for the study of the impact of physical distancing.

The reference points for physical distancing estimations may also be different. An example is provided in Figure 2, in which the same physical distancing provision may be interpreted differently in relation to the assumption adopted for the reference points from which the distance is considered. Reference points could be the centre of the person or different parts of the body, e.g., noses, arms or feet. As crowd models generally represent people as two-dimensional elements, the same physical distancing can therefore be calculated between the centre points (*a* in Figure 2) or between the closer points between people (*b* in Figure 2).

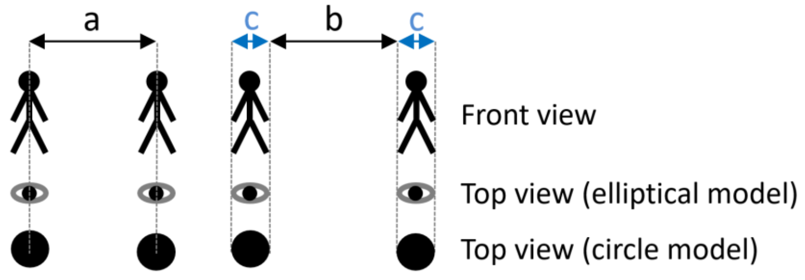


Figure 2. Possible interpretation of physical distancing considering distance between the centre point of people (a) or between the closest point between people (b). (c) indicates the diameter of the body size, which is generally represented in a continuous microscopic crowd model as an ellipse or a circle.

Crowd models may represent the variability of individual dimensions of the agents, thus their users should decide if taking this into consideration in a physical distance calculation which refers to the closer point between people.

Provisions on physical distancing (and their interpretation) can have a direct impact on global and local density, thus affecting occupant loads in a given space. A first clear impact regards how many people are allowed in a given area or building, but also how maximum density may change in a specific part of the area under consideration (maximum local density). Also in this case, the provisions themselves can be interpreted differently during their application for the analysis of space usage.

Since physical distancing provisions may relate to static or moving crowd, a physical distance that could be kept for a static crowd does not necessarily imply that it can be kept for a crowd in motion, as additional space may be required for movement. The implementation of a target physical distance might indeed require a higher physical distance provision when considering the movement of a crowd. This is particularly important for crowd modelling applications, as they generally refer to scenarios in which the crowd is in motion.

During the process of pedestrian navigation, collision avoidance mechanisms take place between pedestrians. Existing models are programmed and calibrated to represent collision avoidance (Kitazawa and Fujiyama, 2010) based on behaviour in which no pandemic was present. Depending on several variables, such as local crowd density (Plaue et al., 2012), modelled body size and personal space (Hayduk, 1978; Hecht et al., 2019), pedestrians may steer their direction of movement to a lower or greater extent when interacting with other individuals during a pandemic (or objects/obstacles (Alhawsawi et al., 2020)). This could be made in an attempt to minimize face-to-face interaction by changing the orientation of movement. This can be implemented in different manners in microscopic crowd models, including force-based approaches (Helbing and Molnár, 1995) or modifying steering behaviour (Ben Amor et al., 2006). The rules for local physical interactions between people may be greatly affected by a pandemic, in an attempt to keep higher physical distance than usual. Crowd models may be programmed to force pedestrians in keeping a given physical distance (e.g. 2 m) while in motion. This may have subsequent effects on crowd movement (affecting variables such as speed, acceleration, route choice, etc.) and during queuing, as people may be forced to wait until a space gets free from the presence of other people (or groups of people) before proceeding in a giving direction, or decide to re-route in another direction with lower congestion. While modelling capabilities of this kind are already available, real life data are lacking, thus there is still a limited understanding on how the actual crowd would behave in such situation.

An important aspect to highlight is that, regardless of the physical distancing provisions, grouping may substantially affect space usage (Moussaïd et al., 2010; Zanlungo et al., 2014). This is because established groups are generally not required to keep physical distancing, thus affecting the whole crowd dynamics and behaviour. Crowd models may allow the simulation of groups of different sizes and the priority they have during their movement (i.e. if the rules for collision avoidance can be weighted in relation to group characteristics such as their size). The selection of the size of the established groups and their behavioural characteristics (i.e. if they are likely to stick together during their movement and to which extent) is deemed to have an important impact on the density-related variables, among which, the maximum achievable local densities, the maximum achievable global densities and occupant load. It should be noted that estimations of local densities in crowd models may also change in relation to the type of assumptions adopted for the reference area assumed in the density calculations (Plaue et al., 2012). These issues are reflected in the dependent variables that crowd model users want to investigate (either the needed capacity of a space or the maximum number of people allowed in a given area).

In summary, different assumptions can be made for the calculation of the number of people allowed in a given area using a crowd model (or the space needed for a given crowd) in relation to the physical distancing provision provided. The final estimation can therefore depend on:

1) Static or moving crowd (e.g. extra space needed between people for movement of other people)
2) Space taken up by each individual, i.e. their shape (i.e., a virtually infinitively small dot, a fixed or varying space, type of shape, etc.)
3) Reference point for the calculation of physical distancing (centre or closer points between people)
4) Reference area for density estimations (e.g., with or without obstacles, approach in use for density calculations)
5) Positioning of people (e.g. uniform or not, individual vs presence of established groups)
6) Free area assumed around each pedestrian (e.g., circular, square, offset of represented person, etc.)

4.2. The impact of physical distancing on route choice

Route choice is currently represented in crowd models making use of different assumptions. Those are generally categorized into four types of modelling algorithms 1) Shortest distance, 2) Quickest time, 3) User-defined, 4) Conditional (Ronchi, 2020). A route choice algorithm based on *shortest distance* calculates the route which leads to the shortest travelled path walked by each agent. A *quickest time* algorithm modifies the routes of a shortest distance algorithm with some sort of optimization algorithm (Bladström, 2017) which represents the impact of congestions and queuing on movement time and yields the paths which lead to the shortest time. Crowd models may also give the opportunity to script the behavioural itineraries adopted by the agents; this method is often called as *user-defined*. Conditions may also be implemented in crowd models in order to modify the adopted routes of the agents (*conditional* method); these may include environmental conditions (e.g. smoke) or interactions between agents (e.g., social influence, collision avoidance).

The underlying route choice algorithm adopted by a crowd model is not explicitly designed to account for the behaviour which may occur during a pandemic. In fact, overall navigation in space generally does not consider the proximity to other people in itself as a deterrent for selecting a given route. For this reason, models should be re-calibrated (when possible) to represent possible re-routing due to the will of people to avoid congested areas. In this context, users should question the assumptions adopted by crowd models when representing queuing. As mentioned, current crowd models are not originally designed to account for proximity as a deterrent for queuing in a given space. Crowd models may implement direct or indirect variables to represent the patience levels of pedestrians (Heliövaara et al., 2013), intended here as their likelihood to change their route. Therefore, crowd model users may need to review their models to check if modifications of such inputs may lead to a more realistic representation of queuing in a given space. In fact, pedestrians may decide to not wait in a crowded queue, but to re-route towards a less congested space. This could generally be performed in microscopic agent-based models by scripting the behavioural itineraries adopted by the agents, which often make use of so-called way-points (i.e. intermediate points which the agents have to pass by before reaching their target destination).

An implicit representation of behavioural itineraries may become more cumbersome when performed manually by a user with increasing complexity of the underlying scenario and a higher number of agents. For instance, a circulation scenario may already require the representation of behavioural itineraries (to represent a set of actions, i.e. people navigating a supermarket while shopping), thus making it difficult for the crowd model users to represent appropriate route choice decisions aimed at keeping physical distancing on top of the underlying behavioural itineraries to be represented. In addition, given the uncertainty in route choice decisions, it is generally advisable to represent route choice adopting a stochastic approach. This leads to the need to investigate the impact of the variability in route choice decisions simulating multiple possible behavioural itineraries and evaluate their impact on results (Ronchi et al., 2014b). Given the complexity of those interactions, the number of scenarios required to perform a comprehensive assessment of the possible situations that may occur would rapidly grow.

In this context, the decision-making process concerning route choice in case of concurrent threats (i.e. a pandemic and a fire/antagonistic threat) is unknown. This means that we currently do not know under which conditions, people may choose a given route and what they would set as priority between reaching a safe place or staying away from a congested area due to the risk of virus transmission.

4.3. The impact of physical distancing on movement

Physical distancing can have a significant impact on the manner a crowd moves. This is linked to the attempts that a crowd can make to keep a given physical distance with other people or obstacles. This issue may relate to other people for a single individual moving or a group of people in case an already established group is moving in a given space.

In scenarios in which a pandemic is not present, crowds tend to follow a set of self-organising rules while moving, including shock waves in very dense crowds, lanes of uniform walking directions in counterflows, circulating flows at intersections or clogging effects at bottlenecks (Helbing et al., 2005). In this context, there are currently no experimental data to confirm if such self-organizing behaviour would occur as well during a pandemic. For this reason, crowd model users may need to review the assumptions adopted by a given model as certain assumptions on self-organizing rules might be questioned. An example is lane formation (Feliciani and Nishinari, 2016) (i.e. the tendency to follow people ahead when moving in a relatively dense crowd), as this behaviour might go against the principle of maximizing physical distance while walking.

The modifications in the physical distance kept between people may have a significant impact on crowd movement. Since no experimental data are currently available on this subject, and the possible great variability in pedestrian behaviour in response to physical distancing provision, it is recommended here to modify the fundamental relationships between speed/flow and density in relation to the assumed density range in which speed is deemed to be affected by others. The maximum density d_{max} will be a function of the physical distancing and it can be calculated in relation to the assumptions adopted concerning space usage (see section 4.1).

An example of a calculation method to perform a modification of the speed-density relationship is presented here, considering the starting assumptions and modelling approach presented in the hydraulic model of the Society of Fire Protection Engineers (SFPE) Handbook (Gwynne and Rosenbaum, 2016) to represent movement in a corridor. This has been chosen as it is currently implemented in evacuation models (Thunderhead Engineering, 2020) and sometimes used as benchmark testing for them (Ronchi et al., 2014a). Considering that in the original hydraulic model, a theoretical maximum density corresponding to an impeded speed equal to 0 m/s corresponds to 3.8 people/m^2, the new maximum density d_{max} depending on the physical distancing P_d will be equal or below that threshold value (see Equation 1).

$$d_{max} = f(P_d) \leq 3.8 \frac{people}{m^2}$$

[Equation 1]

Similarly, the minimum density d_{min}which corresponds to the start of a decrease in the unimpeded speed is 0.54 people/m^2 in the original hydraulic model, thus the new density to start the impeded speed can be assumed to be a number between 0 and 0.54 people/m^2 (see Equation 2). The speed reduction in relation to density 1) might be kept unimpeded until the same value of density adopted in the SFPE hydraulic model, 2) might start decreasing linearly from the value of unimpeded speed corresponding to density equal to 0 people/m^2 (the unimpeded speed is assumed 1.19 m/s in the SFPE model) or 3) might start decreasing from a given intermediate value between these two thresholds.

$$0 \geq d_{min} \geq 0.54 \ \frac{people}{m^2}$$

[Equation 2]

The range of densities in the fundamental relationships between speed and densities in which speed is impeded is therefore according to Equation 3.

$$d_{min} \leq d \leq d_{max}$$

[Equation 3]

Considering the two known points in the speed-density relationship A=(d_{max} ,0) and B=(d_{min}, v_{max}), it is therefore possible to calculate the speed based on the assumed physical distancing affecting density (see Equation 4).

$$v = v_{max} \qquad \text{IF } d < d_{min} \qquad \text{[unimpeded speed]}$$
$$v = v_{max}\left(\frac{d-d_{max}}{d_{min}-d_{max}}\right) \qquad \text{IF } d \geq d_{min} \qquad \text{[impeded speed]}$$

[Equation 4]

In case the assumption that d_{min}=0 is made (i.e. there is no unimpeded speed when densities are higher than 0), then Equation 4 becomes Equation 5.

$$v = -v_{max}\left(\frac{d}{d_{max}} - 1\right)$$

[Equation 5]

Similarly to movement and the fundamental speed-density relationships, also flowrates may need to be updated in accordance with the implications of physical distancing. The specific flow can be simply obtained by multiplying the speed obtained in Equation 4 with the corresponding density (see Equation 6).

$$F_s = vd$$

[Equation 6]

It should be noted that the shape of the flow-density relationship accounting for physical distancing might be different than the pre-pandemic one, as the limit for the so called capacity drop (Cepolina, 2009) might not be reached due to the lower achievable density levels. Given the lack of experimental data, the assumption adopted in the presented hypothetical relationships is that they follow a similar trend to the ones for pre-pandemic conditions. An alternative approach would be to consider just the left-hand side of the flow-density relationship, i.e., this will not be a quadratic curve but a monotonic function.

A set of examples of fundamental speed-density and flow-density relationships corresponding to different assumptions for d_{min} and d_{max} for movement in a corridor are presented in Figures 3 and 4.

In these examples, it is here presented:

1) Green curve: The existing SFPE relationships for corridors in which d_{min} =0.54 people/m^2 and d_{max}=3.8 people/m^2
2) Purple curve: hypothetical relationships for corridors in which d_{min}=0 people/m^2 and d_{max}=1.9 people/m^2 (half of the maximum density in the hydraulic model of SFPE)
3) Cyan curve: hypothetical relationships for corridors in which d_{min}=0 people/m^2 and d_{max}=1.0 people/m^2
4) Orange curve: hypothetical relationships for corridors in which d_{min}=0.54 people/m^2 and d_{max}=1.0 people/m^2

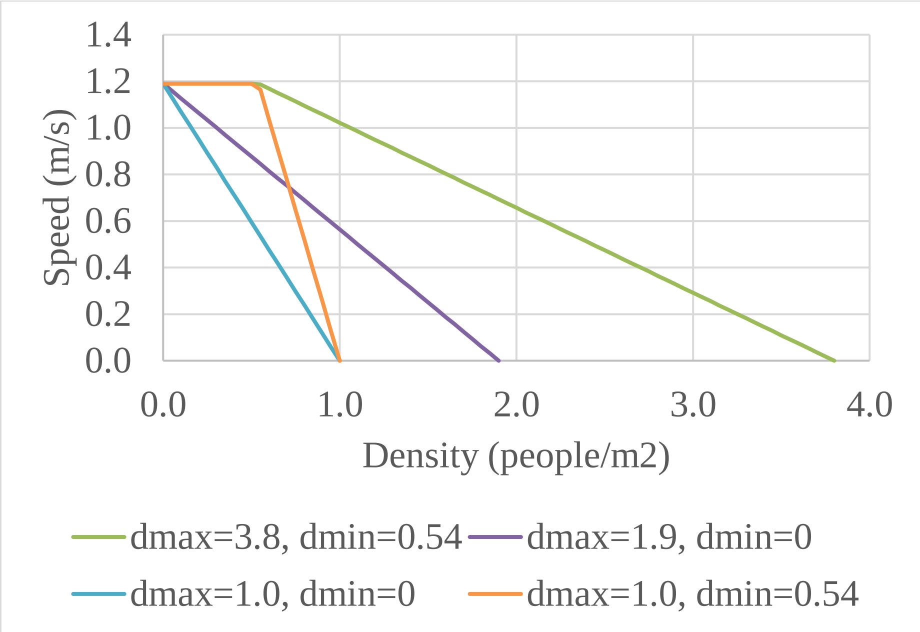


Figure 3. Examples of speed-density relationships in a corridor impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

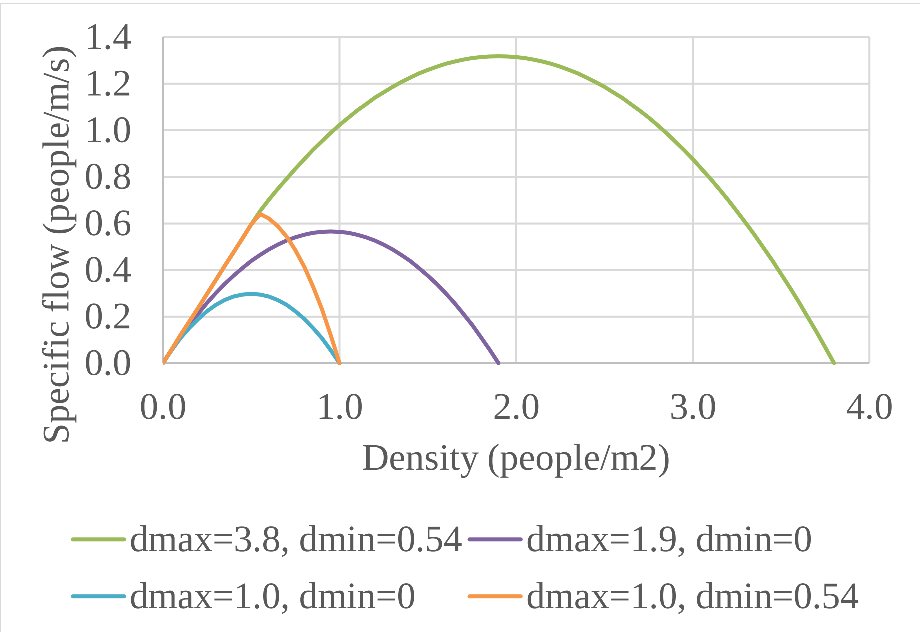


Figure 4. Examples of flow-density relationships in a corridor impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

Similar curves can be obtained for different staircase configurations using the same methodology. The curves can be obtained substituting in the equations the value of v_{max} as presented in Table 59.4 of the SFPE handbook chapter on the hydraulic model (Gwynne and Rosenbaum, 2016). The values are also reported in Table 1.

Table 1. Maximum unimpeded exit flow speeds for different stair configurations reported in the hydraulic model presented in the SFPE handbook (Gwynne and Rosenbaum, 2016).

Riser (inches)	*Tread (inches)*	*Max speed (m/s)*
7.5	*10*	*0.85*
7.0	*11*	*0.95*
6.5	*12*	*1.00*
6.5	*13*	*1.05*

The resulting relationships for the same examples early presented are plotted in Figures 5-12. Similar to the previous examples, it is here presented:

1) Green curve: The existing SFPE relationships for different staircase configurations in which d_{min}=0.54 people/m^2 and d_{max}=3.8 people/m^2
2) Purple curve: hypothetical relationships for different staircase configurations in which d_{min}=0 people/m^2 and d_{max}=1.9 people/m^2 (half of the maximum density in the SFPE relationships)
3) Cyan curve: hypothetical relationships for different staircase configurations in which d_{min}=0 people/m^2 and d_{max}=1.0 people/m^2
4) Orange curve: hypothetical relationships for different staircase configurations in which d_{min}=0.54 people/m^2 and d_{max}=1.0 people/m^2

Any other relationship can be obtained defining the values for d_{min}, d_{max} and v_{max}. It should be noted that crowd models may adopt different simulation approaches to represent these fundamental relationships. They may either be emergent, i.e. the result of underlying rules of interactions between pedestrians or they can be directly implemented within a given model. It should also be noted that the SFPE relationships are intended for design, i.e. they were designed making use of a conservative approach rather than directly reflecting experimental observations. In addition, these relationships were defined with demographics which may not fully reflect an ageing and less fit population of today (Spearpoint and MacLennan, 2012).

This simple calculation method of the fundamental relationship between speed-density and flow-density based on the hydraulic model can also be modified to directly implement the calculated value of d_{max} as a function of physical distancing P_d.

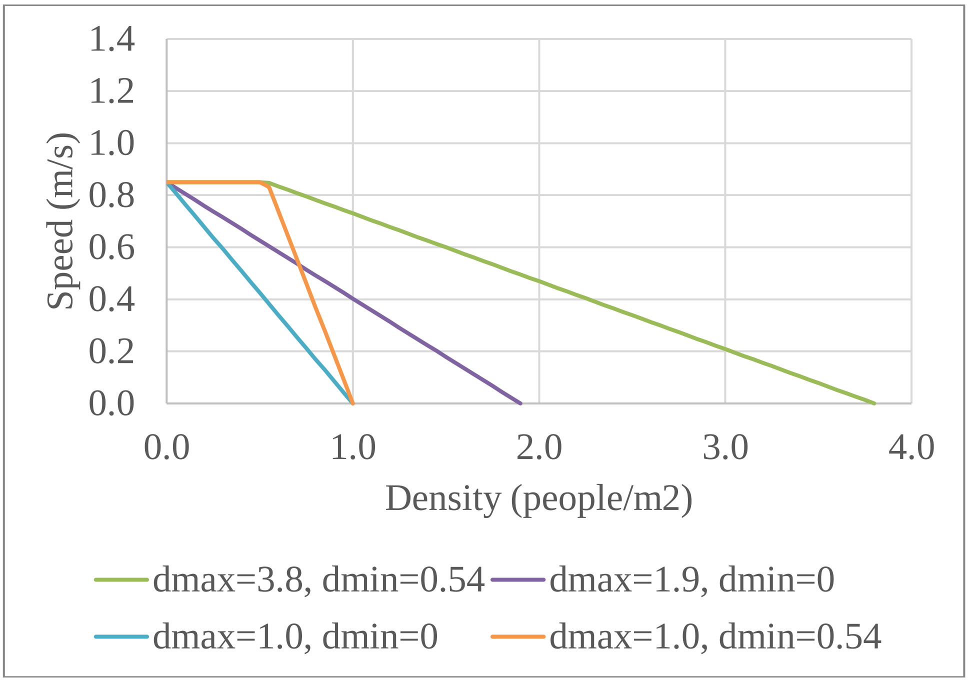


Figure 5. Examples of speed-density relationships in a staircase 7.5x10 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

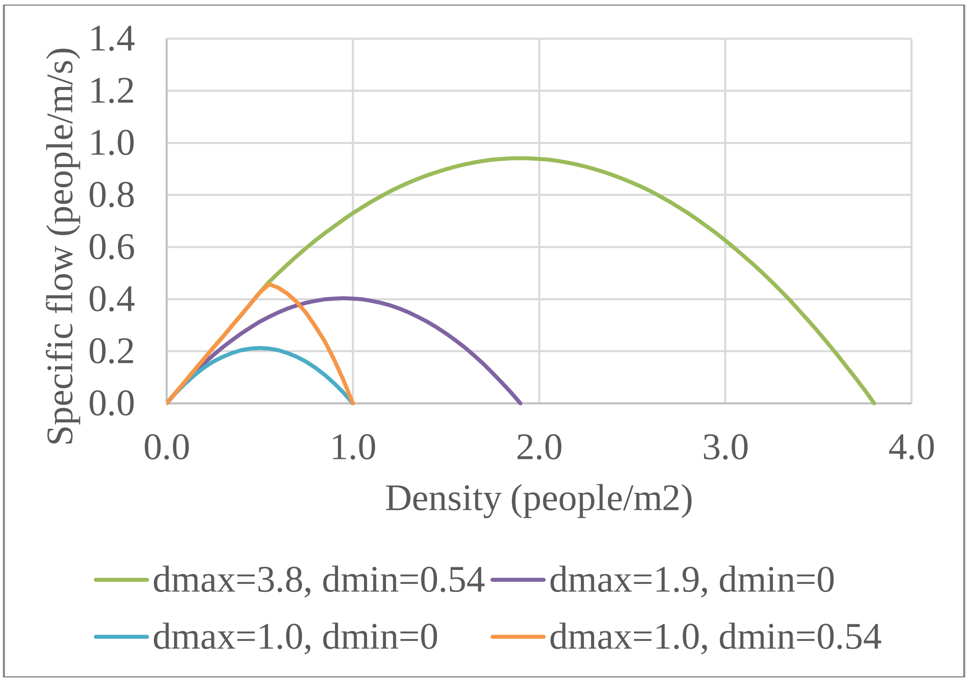


Figure 6. Examples of flow-density relationships in a staircase 7.5x10 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

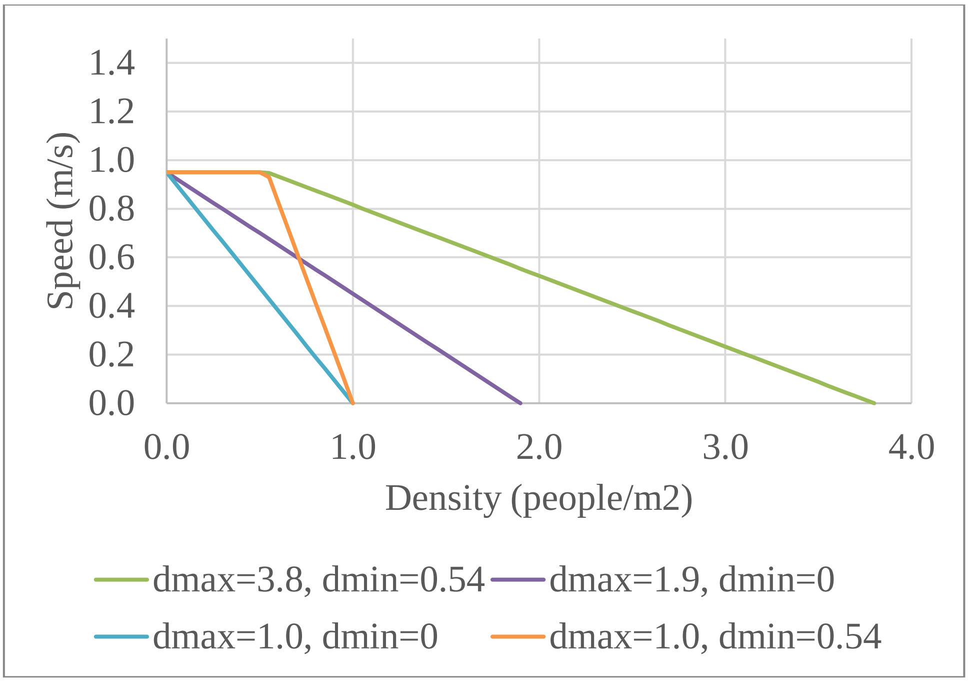


Figure 7. Examples of speed-density relationships in a staircase 7.0x11 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

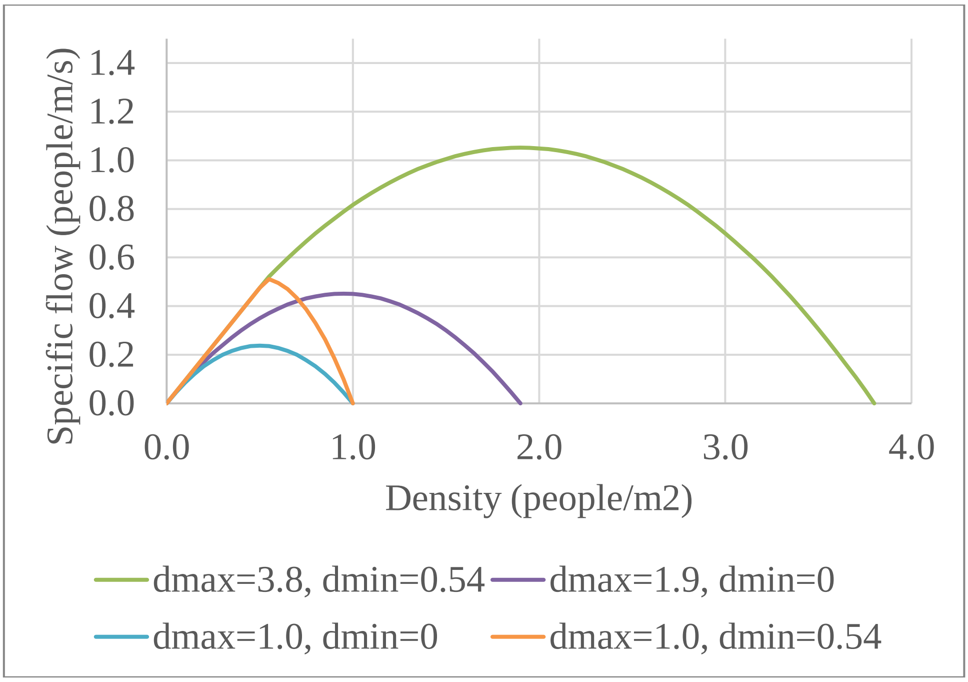


Figure 8. Examples of flow-density relationships in a staircase 7.0x11 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

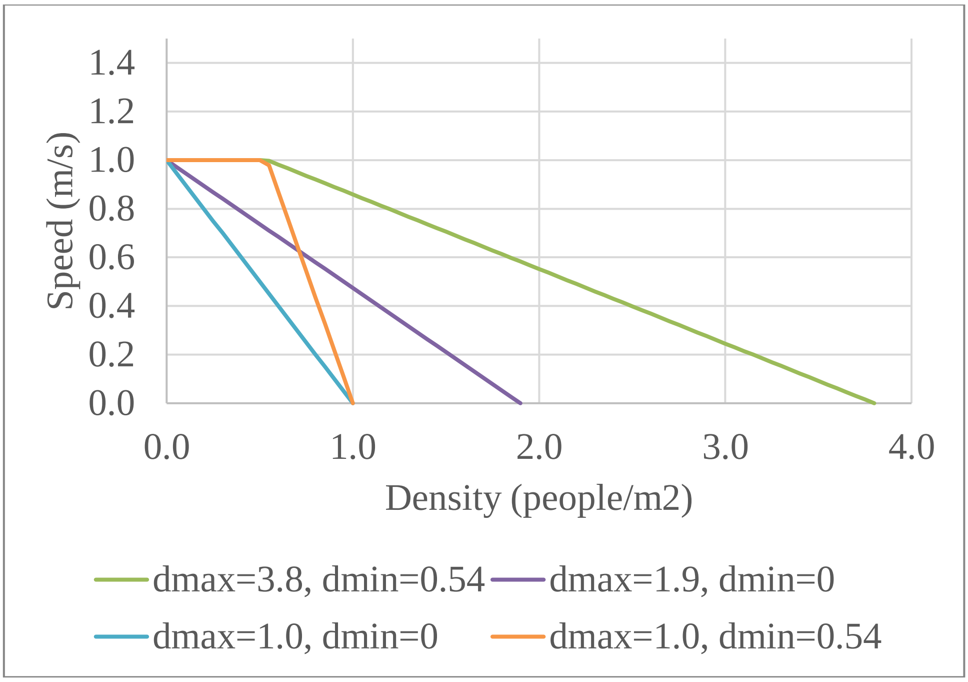


Figure 9. Examples of speed-density relationships in a staircase 6.5x12 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

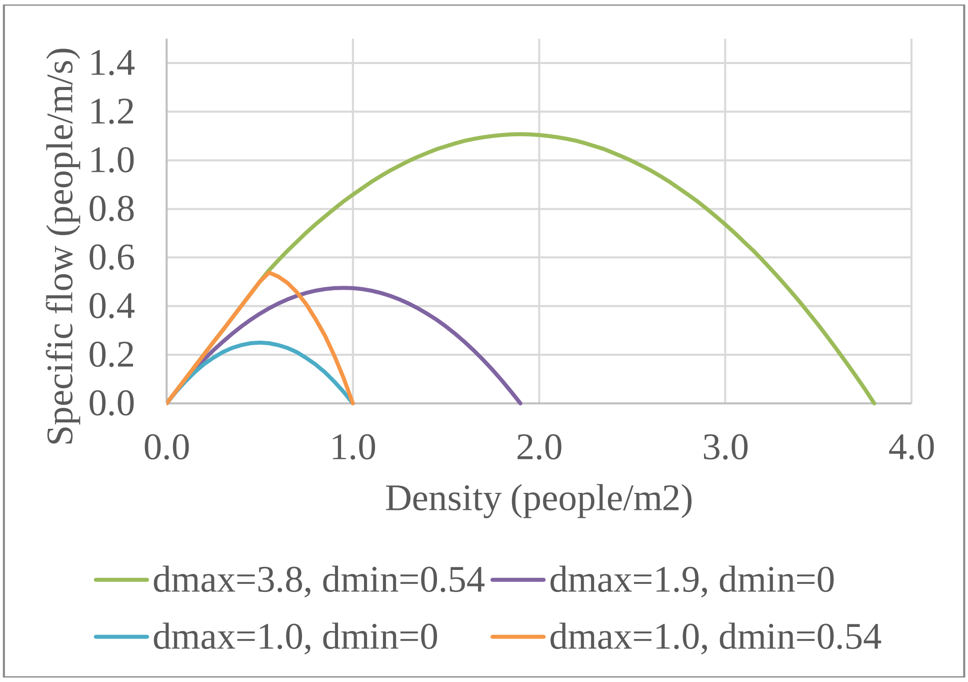


Figure 10. Examples of flow-density relationships in a staircase 6.5x12 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

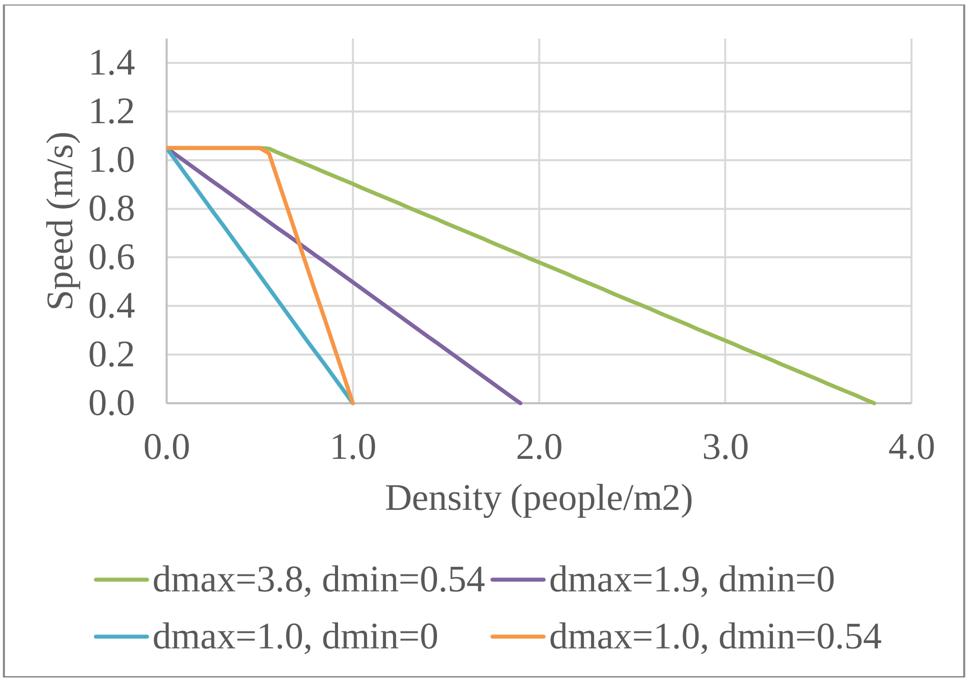


Figure 11. Examples of speed-density relationships in a staircase 6.5x13 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

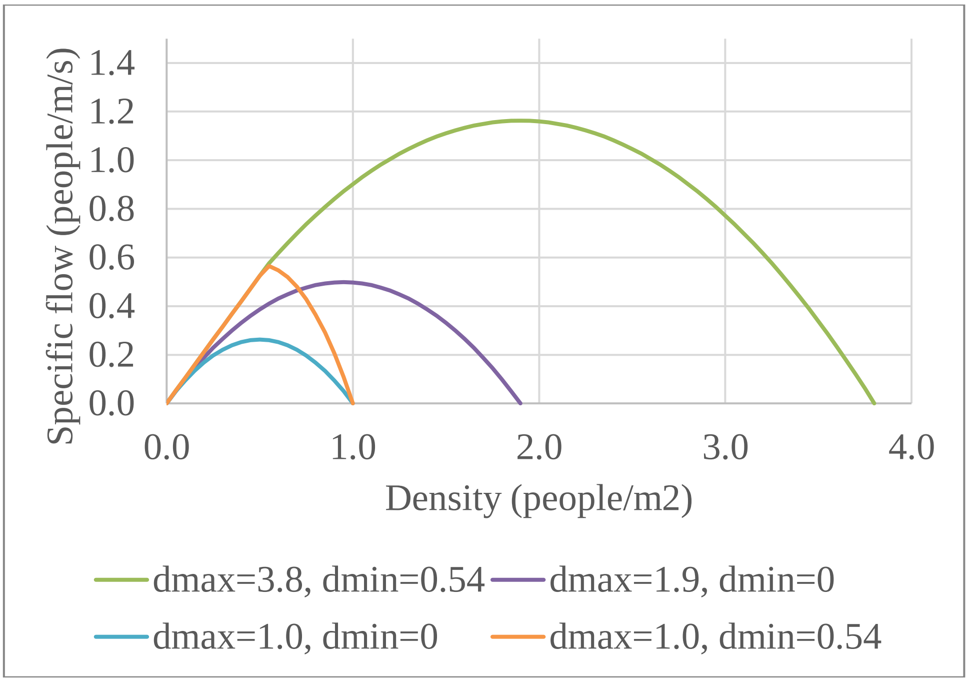
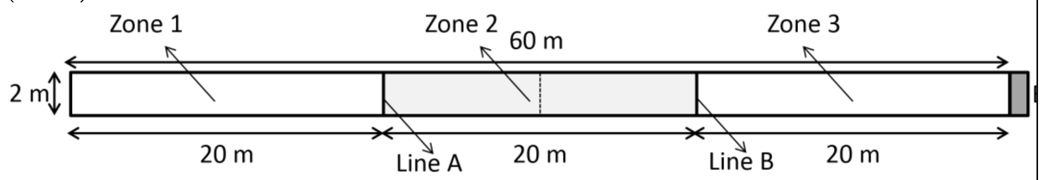


Figure 12. Examples of flow-density relationships in a staircase 6.5x13 inches impacted by social distance and considering different assumptions for minimum and maximum density for impeded speeds.

As the crowd model user may modify the relationship in use either directly or indirectly (e.g. enforcing a given physical distance between agents), they should make sure that the simulated relationship corresponds to the intended one. For this purpose, different tests are available in the literature, among which Test 4 in the RIMEA Guideline for Microscopic Evacuation Analysis (Rimea, 2016) or Test 13 in the protocol for testing crowd evacuation models provided by the international standards organization (ISO) (International Standards Organization, 2020), which could be modified to consider this issue. An example is provided here by modifying ISO Test 13 aiming at exploring the relationship between flow rate, density and walking speeds in a corridor considering physical distance.

In the test, the ability of crowd models to represent a uni-directional flow including physical distance shall be verified by showing the relationship between walking speed, flows, and densities. This test can help evaluating if the model results are implemented with enough accuracy given the intended use of the model. An example is provided here.

Test name	**Relationship between walking speed, uni-directional flow and density considering physical distance**
Objective	Assess qualitative consistency between the relationship between walking speed, uni-directional flow and density assignment and model representation in case of physical distance provisions.
Geometry	A corridor is represented in accordance to the following Figure 13 and it is divided in two zones, namely zone 1 (white), zone 2 (light grey) and zone 3 (white).  *Figure 13. Schematic geometric layout of the test (top view).*
Scenario(s)	Fill in the entire corridor (zone 1, 2 and 3 in Figure 13) with the maximum allowed number of people in accordance with your assumed starting physical distance (people can be placed at random in the space). They have pre-evacuation time equal to 0 s and a walking speed of 1 m/s is assigned to the entire crowd. Step 1: The occupants move to the right towards the exit of the corridor. Place the last occupant in zone 2 near line A and measure the time that it takes from line A to line B and estimate the associated walking speed. Measure the average occupant flows in line B (with a time interval decided by the tester) starting from the beginning of the simulation until the last occupant in zone 2 arrives to Line B. People densities in Zone 2 are recorded when the last occupant in zone 2 reaches the centre of zone 2. Step 2: Step one is repeated with a number of occupants equal to the double of the original number (i.e. to verify if the model allows an initial density higher than the physical distance provision in use and how people adjust their position to maintain the physical distance), three quarter of occupants, half the occupants, one quarter of occupants, and one eight of the occupants.
Expected result	The relationship between walking speeds and people densities in Zone 2 as well as the flows in line A vs people densities in Zone 2 are plotted and compared with the underlying assumptions used in the evacuation model.
Test method	The test method is a qualitative verification of the crowd movement.
User's actions	The tester may show results in relation to different time intervals adopted for the estimation of flows, people densities and walking speeds. Different methods for implementation of physical distance in the model can be used (e.g. enforcing distance between agents, setting up the speed/density relationship within the model). Further testing can be made by modifying this test to consider the impact of people with movement disabilities (i.e., some evacuees may have a slower speed and/or occupy a larger space) and attempting modifying the initial number of people further and their initial location.

5. Proximity analysis and exposure assessment

The use of crowd models in times of pandemics should take into consideration the risk of virus transmission. To date, there is no clear understanding on the mechanisms of transmission of SARS-CoV-2 (Lewis, 2020). While studies performed at the beginning of the Covid-19 outbreaks seemed to indicate that the disease spread was mostly linked to droplets (Bahl et al., 2020), more recent studies tend to indicate that airborne transmission may be considered as well (Morawska and Cao, 2020; Yu et al., 2004)

The main mechanisms to be considered for the SARS-CoV-2 virus transmissions are (1) physical contact, (2) droplets, and (3) airborne routes (Yu et al., 2004). This can be translated into different assumptions for the assessment of virus transmission. These are presented graphically in Figures 14 and 15. The transmission mechanisms in Figure 14 can be applied for both open spaces as well as confined spaces. The transmission mechanism in Figure 15 mostly relates to confined spaces (i.e. buildings or transportation means), as it is mostly linked with airborne transmission. The study of the risk of virus transmission would require at least the tracking of their individual trajectories in space over time. Therefore, macroscopic crowd models in which individual movement/behaviour cannot be tracked may not be suitable for this type of analysis.

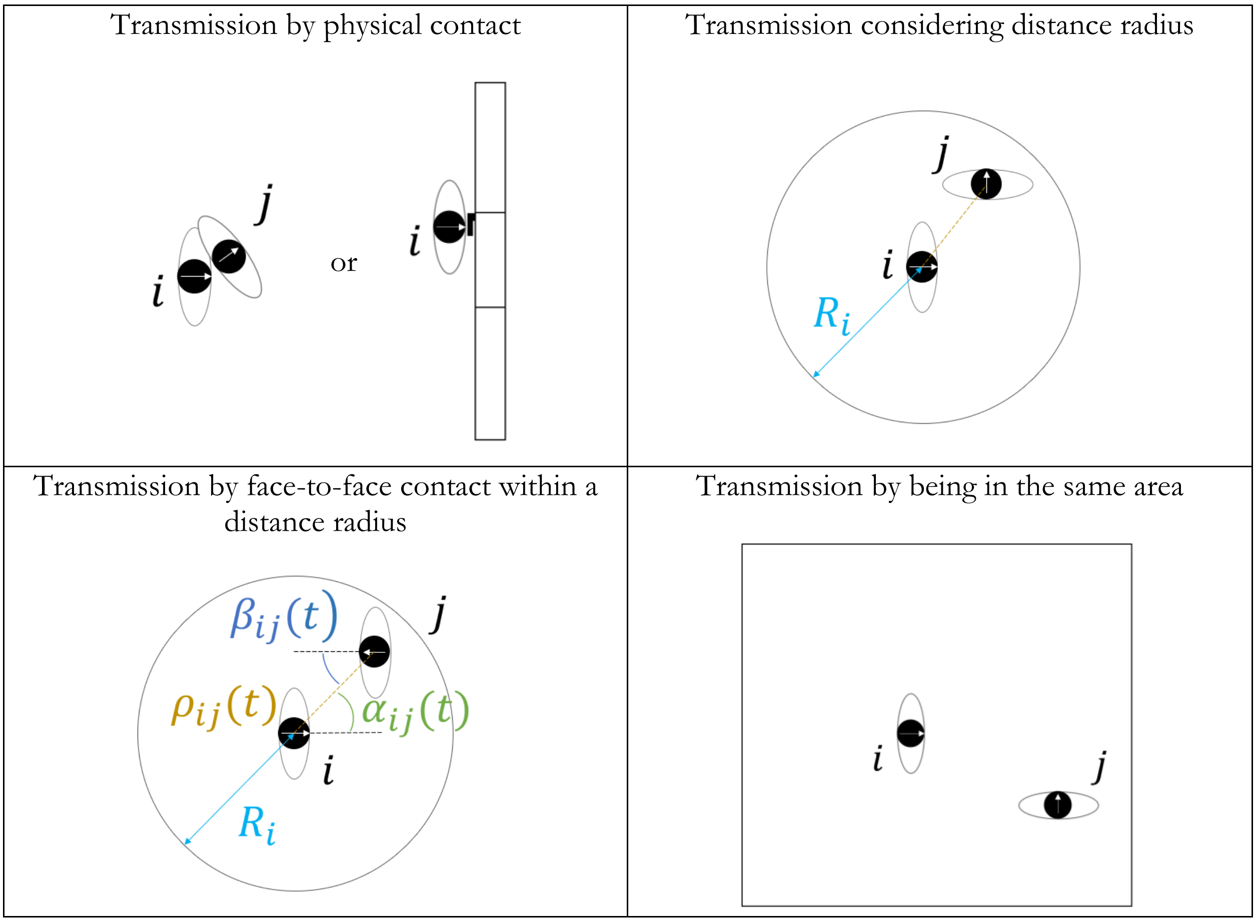


Figure 14. Possible assumptions on risk of virus transmission considering the simulated pedestrians in an open space or a confined space.

Transmission by physical contact (top left in Figure 14) can be considered in an open or confined space and is here accounted for when people are in direct physical contact to each other (i.e. pedestrians "touch each other") or they touch an object which could potentially transmit a virus (e.g. a door handle in the example in Figure 14). It should be noted that most microscopic crowd models generally assume rigid bodies representing only the head and shoulders of people (Duives et al., 2013), i.e. non-deformable pedestrian bodies (without any hand to hand contact) allow a simplified detection of collision and contacts between agents. Three-dimensional representations of the agents are generally for purely visual purpose and no use of upper extremities is generally simulated (Ronchi, 2020). Similarly, the resolution of existing crowd models generally does not include the representation of small objects or provide too many details on the elements in a given area. Therefore, this transmission mechanism is practically implemented considering the representation of the agents within the model (often represented in crowd models as circles or ellipses) and assuming contact with other people once their coordinate in space overlap with others or the assumed location of certain objects. The example in Figure 14 shows one agent i and one agent j that are in physical contact within a space or an agent i which is close to a door handle (this could similarly be assumed for other objects which agents could touch during their movement). This assumption requires from a crowd model the information concerning the pedestrian trajectories over time and the dimension of the agents.

The transmission by physical distance radius assumes the number of people in a given radius defined by the user (e.g., 1 or 2 m). The centre of the physical distance radius can be assumed to be the centre of the modelled pedestrian, its nose or the outer border of the shoulder. This is implemented by checking the coordinate in spaces of the pedestrians and evaluating if they are within the given radius of interaction. This can conservatively consider that if one agent has at least one part of its body within the social distance radius, it is assumed to be within that radius. The example in Figure 14 (top-right) shows one agent i and one agent j that are within a given social distance radius R_i. This assumption requires from a crowd model the information concerning the pedestrian trajectories over time (e.g. the parametric equations of pedestrian trajectories) and the reference point (i.e. centre, nose, outer boundary of an ellipse) for which the trajectories are provided.

Transmission can be assumed when people are in face-to-face contact to each other within a given angle of interaction in a physical distance radius defined by the user. To facilitate implementation, the polar coordinates $\alpha_{ij}(t)$ and $\rho_{ij}(t)$ can be used for defining the position of the agent j in the polar space in relation to each agent i (see the bottom-left in Figure 14), where ρ_{ij} changes over time. Zero is the case in which people physically touch each other, the max value for $\rho_{ij} = R_i$ within the assumed distance radius, so $\rho_{ij} = [0, R_i]$. $\alpha_{ij}(t)$ changes over time and it can vary from zero when the agent j is in front of the agent i to $\pm\pi$ when the agent j is right behind the agent i. $\beta_{ij}(t)$ is the orientation of the agent j in the polar space defined by the agent i. It can vary from zero when the agent j is facing the agent i to $\pm\pi$ when the agent j is turning its back on the agent i. As such, $\beta_{ij}(t)$ can be used to evaluate how many agents are at face-to-face contact within a distance radius at a given time. This can conservatively assume that if one agent has at least one part of its body within the distance radius, it is assumed to be checked for the face-to-face contact criteria. This assumption requires from a crowd model the information concerning both the pedestrian trajectories over time (considering a given position within the simulated agent, e.g., the centre of the agent), as well as the direction of movement of each pedestrian (in order to know the face orientation). The user would then need to make assumptions concerning the angles leading to face-to-face contact between pedestrians.

Transmission in an open or confined space can also be assumed when agents are in the same area or room/compartment (see bottom-right in Figure 14). This assumption requires the information from a crowd model concerning the number of people in a given area/room/compartment at each time-step.

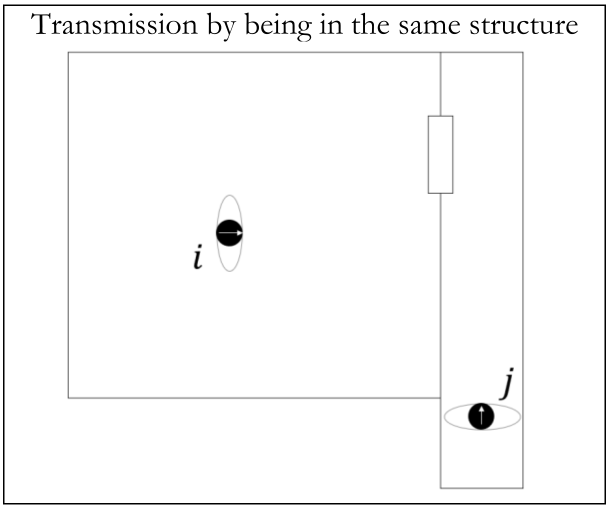


Figure 15. Possible assumption on virus transmission considering the simulated pedestrians in the same structure.

The last mechanisms for virus transmission (applicable only to a confined space) is when agents are in the same structure (see Figure 15). This is the simplest assumption from a crowd modelling implementation standpoint, as it only requires the information concerning how many people are in the structure in a given time-step. Nevertheless, a risk assessment based on this assumption would require information concerning the HVAC technology installed in the confined space under consideration along with its usage.

The information provided by a crowd model concerning the risk of virus transmission can then be used to perform different types of analysis. Two types of analysis are currently performed, namely 1) proximity analysis and 2) exposure assessment.

A proximity analysis is the study of the relationship between a selected element (a person in this case) and its neighbours (e.g., other people). The overall assumption used by this type of analysis is that the risk of virus transmission increases with lower distances. An exposure assessment is apparently similar, but it does not necessarily rely on the assumption of proximity as mechanism of virus transmission. For this reason, an exposure assessment could be considered as a more general method to address disease spread if compared with a proximity analysis. The latter could also make use of a deeper understanding on the physics of aerosol and droplet dispersion (Vuorinen et al., 2020).

Different variables can be considered in a proximity and exposure assessment, mostly related to time and space. Given an assumed mechanism of virus transmission (as mentioned above), the user would identify the interactions between people (and/or between people and objects), count them and obtain information concerning their duration. The needed information are the trajectories of people over time (generally available as parametric equations for each person in the simulation) and possibly (for the case of face-to-face transmission) the angle of direction of movement (representing the direction in which the face is pointing). A risk analysis can then be performed based on a set of metrics which quantify proximity or exposure.

Examples of metrics (based on different mechanisms of virus transmission) are provided below and they can be at individual or aggregate level:

1) Maximum number of people to which each individual is in proximity with/exposed to
2) Maximum number of objects to which each individual is in proximity with/exposed to
3) Time spent by each individual in proximity with/exposed to at least one other person

4) Longer time spent by each individual in proximity with/exposed to at least one other person
5) Time spent by each individual in proximity with a given object/objects
6) Longer time spent by each individual in proximity with a given object/objects
7) Distribution (including average and variance) of number of people to which each individual is in proximity with/exposed to
8) Distribution (including average and variance) of time spent in proximity with/exposed to a given number of people and how those times are spread among contacts with different people
9) Distribution (including average and variance) of time spent in proximity with a given object/objects
10) Total aggregated number of people to which all individuals are in proximity with/exposed to during the whole simulation time
11) Total aggregated time spent by all individuals in proximity with/exposed to others during the whole simulation time
12) Total aggregated time spent by all individuals in proximity with objects during the whole simulation time

These metrics are examples of outputs which can be obtained by a microscopic crowd models which is retrofitted to perform a proximity analysis or exposure assessment. They may be used in isolation or in conjunction with each other to derive information concerning the safe usage of a given space.

It should be noted that apart from the assumptions for the mechanism of virus transmission, crowd model users would also need to assess the possible impact of groups prior accessing the area under consideration. In fact, it is necessary to perform an assessment concerning the people who were already moving as a group. The people-to-people interactions within those groups may be removed (or given a lower weight) from the calculations of the metrics as those people would likely already be in contact (i.e. groups of family members, friends, etc. who access an open or confined space together). Another important aspect to take into consideration is that different types of interactions may be weighted differently. Examples of this issue may be interactions with a higher number of people, interactions occurring with different face-to-face angles, interactions with people wearing personal protective equipment (e.g. face masks) or interactions with people vs interactions with objects. The assumptions performed by the crowd model user should be clearly reported in order to be able to clearly interpret the results of the analysis performed.

5.1. Example of a model for exposure assessment

An example of a model which can be used to retrofit existing microscopic crowd models to perform an exposure assessment is presented. The model discussed here is called EXPOSED and it is designed to take into account of different mechanisms of virus transmission. It has been primarily designed for use in confined spaces, although the principles adopted could be extended to open spaces. Further information about the model can be found in the paper detailing its development and use (Ronchi and Lovreglio, 2020).

EXPOSED aims at estimating a set of metrics concerning occupant exposure in confined spaces. Considering that there is no information available on the initial number of agents who are susceptible, infected, or recovered, the model aims at quantifying the exposure of the pedestrians in a confined space. Assuming that each agent i can be exposed to a certain number of people based on the exposure assumption in use, it is possible to obtain the information concerning number of agents to which the agent i is exposed to at each time-step $\boldsymbol{t}$=[$t_0, t_1, \dots, t_q, \dots, t_f$] until it has left the confined space at the final time t_f. In this formulation we assume that the time-steps have the same magnitude (i.e., $t_{q+1} - t_q = \Delta t = constant\ \forall q)$. This information can be represented as a set $\boldsymbol{E^i}$ (see Equation 7) representing the number of people each agent is exposed to at each time-step t_q.

$$\mathrm{E^i} = \left\{\mathrm{e_{t0}, e_{t1}, \dots, e_{tq}, \dots, e_{tf}}\right\} \quad \forall\ \mathrm{i}$$

[Equation 7]

where e_{tq} is the k number of agents j to which each individual agent i is exposed at the time-step t_q.

The information concerning each occupant exposure at each time-step can be represented in the form of the matrix $\boldsymbol{E_t^i}$ in Equation 8.

$$\boldsymbol{E_t^i} = \begin{pmatrix} E^1 \\ \vdots \\ E^i \\ \vdots \\ E^n \end{pmatrix} = \begin{pmatrix} \mathrm{e}_{\mathrm{t0}}^{\boldsymbol{1}} & \cdots & \mathrm{e}_{\mathrm{tq}}^{\boldsymbol{1}} & \cdots & \mathrm{e}_{\mathrm{tf}}^{\boldsymbol{1}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathrm{e}_{\mathrm{t0}}^{\boldsymbol{i}} & \cdots & \mathrm{e}_{\mathrm{tq}}^{\boldsymbol{i}} & \cdots & \mathrm{e}_{\mathrm{tf}}^{\boldsymbol{i}} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathrm{e}_{\mathrm{t0}}^{\boldsymbol{n}} & \cdots & \mathrm{e}_{\mathrm{tq}}^{\boldsymbol{n}} & \cdots & \mathrm{e}_{\mathrm{tf}}^{\boldsymbol{n}} \end{pmatrix}$$

[Equation 8]

Since $\boldsymbol{E_t^i}$ presents the number of people each agent is exposed to at each t_q, it is therefore possible to obtain the information on the time T_k^i each i agent has been exposed to a given number of agents k (i.e. the exposure time to 0 occupants, 1 occupant, …, m occupants) by summing t_q^i, i.e., the number of time-steps t_q in which each agent i was interacting with a discrete number of people k, see Equation 9. The model user could assume that the exposure is considered either for any t or only counting the time-steps in case of a minimum exposure time (e.g. counting the t_q^i if the exposure last at least for a given number of seconds/minutes, i.e. a certain number of consecutive t_q^i are required). The maximum number of occupants that agents are exposed to correspond to a maximum of $n-1$ if the number of people in the confined space is restricted (i.e. if a maximum number of people is allowed in the confined space at the same time) or to a generic number of people m if we assume a transient space.

$$T_k^i = \sum_{t_0}^{t_f} t_q^i \ \forall\ i, k$$

[Equation 9]

Considering the total time t_f spent by all n agents in the confined space, it is therefore possible to obtain a set of distributions T_k of exposure times corresponding to a given discrete number of agents $k \geq 0$. Using a distribution from the two-parameter family of continuous probability distributions, T_k can be defined by its mean (μ_k) and standard deviation (σ_k) as shown in Equation 10.

$$T_k\ (\mu_k, \sigma_k^2)$$

[Equation 10]

The values reported in these distributions - corresponding to each k - range from a minimum possible value corresponding to no exposure (i.e. zero exposure) to a maximum time of exposure $t^i_{k,max}$ for each simulated agent i to each number of k agents they are exposed to. The summation over the data-points available for each of the values obtained $\forall\, k$ (see Equation 11) helps performing an assessment of the cumulative exposure C_k to a given number of people k. The higher is the value of the summation, the greater is the occupant exposure for $k > 0$. The value of the summation for $k = 0$ is an indicator of how long people have not been exposed to other agents in the confined space; this is called here C_0.

$$C_k = \sum_{i=1}^{n} T^i_k$$

[Equation 11]

The sum of all C_k with $k > 0$ provides a global assessment of exposure G for the total time t_f spent by all n agents in the confined space (see Equation 12). To obtain G, each C_k is multiplied by a factor γ_k which increases the exposure in relation to the value of k. For instance, γ_k can be assumed equal to 1 for $k = 1$ and with increasingly higher values when $k > 1$. The choice of the values for γ_k is left to the model user.

$$G = \sum_{k=1}^{m} \gamma_k \, C_k$$

[Equation 12]

The model user can therefore obtain different values for G in relation to the assumptions adopted for exposure. It should be noted that the matrix in Equation 8 can also be weighted considering the vulnerability of each individual occupant (e.g. considering their individual properties, such as age, physical abilities, etc. which can often be represented within a microscopic crowd model).

6. The risk analysis methodology for crowd model usage

A methodology for the usage of crowd models in times of pandemic is proposed and presented in accordance to Figure 16. This methodology could potentially be used either for the assessment of virus transmission risk in isolation or the case of concurrent threats (e.g. an evacuation scenario due to a fire during a pandemic). A set of steps are suggested, which would need to be repeated in an iterative way until an adequate level of safety is reached. These steps are followed by a checklist for crowd model users on the aspects which need to be taken into consideration.

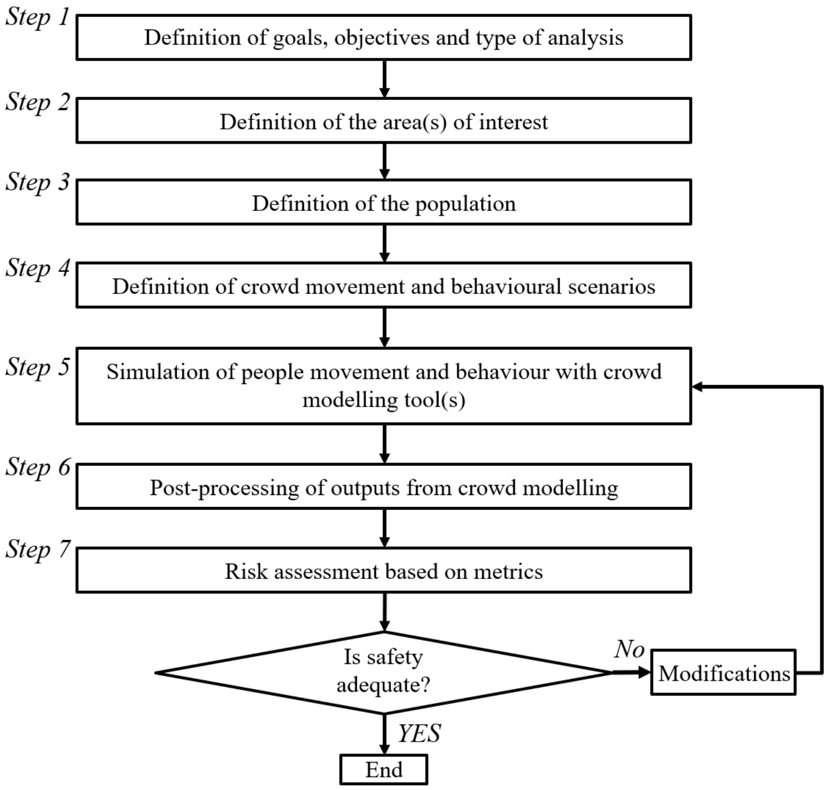


Figure 16. Steps to be followed for the methodology for the usage of crowd models in times of pandemic.

Step 1. Definition of goals, objectives and type of analysis

The first step consists in the assessment of the overall goal of the analysis performed with a crowd model, e.g. what is worth protecting and from which type of threats (and relative priorities in case of concurrent threats). The objectives provide specifications on how the given goal will be achieved, i.e., by identifying acceptance criteria or comparing different scenarios/solutions against each other. This is needed to identify scenarios to be represented within the crowd model. This includes the identification of the type of analysis (i.e., risk analysis of virus transmission or case of concurrent threats) and the subsequent implications on the scenarios. Therefore, the type of analysis to be performed (proximity analysis or exposure assessment) and the virus transmission mechanism assumed is also defined at this stage.

Checklist:

1. *What is the goal of the safety analysis? (virus transmission risk alone or concurrent threats)*
2. *What types of analysis are going to be performed? (e.g., performance-based design of fire safety, study of pedestrian flows, proximity analysis, exposure assessment, etc.)*
3. *Define the assumptions on virus transmission mechanism*

Step 2. Definition of the area(s) of interest
The crowd model user would also have to identify the area of interest given the goal and objectives of the overall analysis, and the area which is the object of the risk analysis on virus transmission (these may not necessarily overlap). This will be imported from an external model (e.g. a 2D/3D CAD or BIM) or directly represented within the crowd model. Depending on the mechanism of virus transmission assumed, the user may also take into consideration the need to modify the area under consideration (e.g. if airborne virus transmission is assumed, a given area under consideration might have air coming from an HVAC system in common with another area). Permanent or temporary design solutions adopted to keep physical distancing should be identified so that they can implicitly or explicitly be represented within the model.

Checklist:

4. *Define the area of interest for the safety analysis*
5. *Define the area of interest for the given assumption on virus transmission mechanism*
6. *Represent/Import the areas of interest in the crowd model*
7. *Identify design solutions for physical distancing*

Step 3. Definition of the population
In relation to the type of space under consideration (e.g. building use, type of event), possible people categories and their characteristics are identified. These will relate to physical and behavioural characteristics linked to the goal of the analysis (i.e. virus transmission alone or concurrent threats). In fact, on top of the considerations made concerning typical population characteristics determined for crowd modelling studies (e.g. body types, walking speeds, etc.), the crowd model users need to identify the behaviour (and possibly vulnerability) of people associated with the risk of virus transmission (e.g. the likelihood of keeping a certain physical distancing). This means that the definition of the occupant profiles might involve not only the features needed for crowd modelling, but also for the assessment of the risk of virus transmission. The possibility to practically implement the behaviour of people in relation to the risk of virus transmission would depend on the tool employed for the proximity analysis or exposure assessment to be performed. After the definition of people in the space under consideration, the crowd model users would have to identify the occupant load. This analysis could be performed differently in relation to the representation of a transient space (e.g. a metro station, an airport terminal) or a space with a fixed number of people (e.g. a residential building with a given number of people inside). While in a space with a fixed number of people the occupant load is defined up-front, occupant load assessment in a transient space would also need the assessment of the flows in the entry systems. The size and types of groups which are present in the population should also be assessed. This is particularly important as it will affect the overall physical distancing that can be achieved in the scenario (i.e. people moving in groups would not keep physical distance).

Checklist:

8. *Define people categories (who will be in the scenarios), including physical and behavioural aspects which may be linked to virus transmission and/or concurrent threats*
9. *Define people profiles (how to represent people in the crowd model), including features like walking speeds, body sizes, aspects linked to physical distancing, etc.*
10. *Define the type and size of established (or possibly emerging) groups*
11. *Define how many people are initially present (occupant load) in the scenarios, entry points (if present) and where they are initially located*

Step 4. Definition of crowd movement and behavioural scenarios
The overall use of the space and type of threat will influence crowd movement. In relation to the goal and objectives of the analysis (e.g. assessment of virus transmission or concurrent threats),

crowd movement and behavioural scenarios may include normal circulation or an emergency scenario. In addition, the movement may take place in a transient space or in a space with a fixed population number, thus affecting the behavioural itineraries and the target locations to be reached by people (e.g. a safe place in case of a fire or entering/exiting a building after shopping in a supermarket). Flows in entry and exit systems are identified along with any other components, features and procedural interventions that might impact crowd movement and behaviour. These aspects would have to be taken into account when defining the crowd movement scenarios. The aspects related to physical distancing (see Sections 3 and 4) that might impact crowd movement should be identified and their impact on crowd movement and behaviour assessed. In fact, when defining the movement and behavioural scenarios, the crowd model user also needs to decide the degree to which the crowd will follow the instructions provided on physical distancing during their movement (e.g. if the target physical distance is maintained, if chosen routes are according to the information given) in relation to the type of scenarios.

From the perspective of movement modelling linked to physical distancing, this may include the need to consider modifications on the fundamental relationships between speed/flow and density, collision avoidance, behavioural itineraries and route/exit choice (e.g., re-routing to avoid congested areas), queuing mechanisms (i.e. queuing involving spatial distances), impact of groups (groups of different sizes may not keep physical distance or may separate), maximum achievable densities, procedural solutions (e.g. only uni-directional movements allowed), etc. Concerning behavioural aspects, the crowd model user would have to identify the behavioural characteristics of the crowd which may impact their likelihood of maintaining physical distance and identifying a range of credible behaviour while moving in space and interacting with other people or objects.

The identified physical and psychological factors affecting crowd movement and behaviour would have to be implicitly or explicitly modelled through the process of model input calibration in which the methods available in the array of tools in use. In case the impact of a certain aspect cannot be (explicitly or implicitly) implemented within a model, appropriate conservative safety margins should be applied to take into account this limitation. Probabilistic approaches may be used to consider the variability in human behaviour.

Checklist:

12. *Define detailed scenarios (e.g., circulation, evacuation) and associated use of entry/exit points*
13. *Define components available for movement for each people type*
14. *Define behavioural profiles (e.g., responses to the threat(s)), behaviour in light of physical distancing)*
15. *Define behavioural itineraries, routes and exit usage in relation to physical distancing*
16. *Define impact of design and procedural solutions and likelihood of compliance in the given scenario (possibly with a probabilistic approach)*
17. *Define movement on each component, including issues related to physical distancing (e.g., fundamental speed-density and flow-density relationships, queuing mechanisms, collision avoidance, impact of groups)*
18. *Identify contrasting needs during movement in case of concurrent threats and subsequent priorities in behaviour exhibited by the agents*

Step 5. Simulation of people movement and behaviour with crowd modelling tool(s)

The crowd modelling tool(s) adopted for the analysis (crowd models and/or external models for importing inputs, post-processing, etc.) are identified in this step. The implementation of the modelling assumptions is refined in relation to the crowd modelling tool(s) in use. Subsequently, the simulations are conducted and crowd modelling outputs are obtained. The selection of the outputs to be analysed depends on the goals of the analysis (e.g., virus transmission or concurrent threats) and the specific methods adopted to achieve it (e.g. proximity analysis, exposure assessment, performance-based design for fire safety, etc.). The crowd modelling outputs include typical outputs obtained for performance-based design as well as outputs needed for proximity analysis or exposure assessment such as:

- Required Safe Egress Time (RSET) in fire safety engineering applications,
- Space usage (e.g., local and global densities, level of service (Fruin, 1987) queuing times, chosen routes, etc.)
- Parametric equations of agent movement
- Angles of interactions between agents

Checklist:

19. *Identify suitable crowd modelling tool(s)*
20. *Perform input calibration including issues associated with physical distancing based on crowd movement and behavioural scenarios*
21. *Run the simulations (using a probabilistic approach when needed)*
22. *Identify and obtain the crowd modelling outputs*

Step 6. Post-processing of outputs from crowd modelling

The crowd modelling outputs are now processed. In case of a probabilistic approach in use, the crowd model user would have to evaluate the convergence of the outputs and assess their variability. The crowd modelling outputs are therefore post-processed (e.g., with an external tool or spreadsheet) to obtain the metrics needed for the goals of the analysis.

Checklist:

23. *Post-process outputs obtained by the crowd modelling tool(s) in use and obtain the metrics needed for the goal of the analysis (e.g. proximity analysis, exposure assessment, fire safety engineering assessment, movement flow metrics, space usage metrics, etc.)*
24. *Analyse the variability in outputs in case of use of probabilistic approach*

Step 7. Risk assessment based on metrics

The metrics obtained are now used to perform a risk assessment in relation to the goal of the analysis. For example, results can be compared against acceptance criteria or used to compare different scenarios/solutions against each other. The crowd model user will then evaluate if the solutions performed are sufficient to meet the goal of the analysis or if changes are necessary to improve the safety conditions of the area under consideration. This is performed using an iterative process, i.e. performing modifications aimed at improving safety, returning to step 5 and continuing until step 7 and re-evaluate if an adequate safety level is achieved.

Checklist:

26. *Perform a risk assessment based on metrics*
27. *Check if an adequate safety level is reached. If this is met, the process is completed. If this is not met, perform modifications aimed at improving safety and return to step 5. The process ends when the target safety level is met.*

7. Design and crowd management solutions

Crowd modelling can be a useful tool to identify suitable solutions aimed at improving safety in times of pandemics. In particular, considering a virus transmission mechanism in which proximity leads to higher risks, solutions can be tested with crowd models aimed at increasing physical distancing and comparing different design and crowd management solutions. Design solutions and crowd management solutions may be environment-specific as for instance a confined space might have space constrictions which are stricter than in an open area. Crowd models are a powerful tool to evaluate the impact of a given solution on safety, its feasibility of implementations and possibly identify additional critical side effects which may be overlooked (e.g. a solution aimed at improving physical distancing that might decrease evacuation safety). Crowd models may or may not have the capabilities to implement detailed aspects concerning people movement. In any case, microscopic models often present enough flexibility to be able to represent such aspects implicitly (e.g. customizing a behavioural itinerary or a mechanism of interactions between people or between people and the environment).

Several design solutions can be implemented in crowd models. The first type of modifications relates to the geometrical space, i.e. attempting to modify it to improve distance between people. This can include footway widening, or modifications of entry and exit systems aimed at reducing queuing (by for instance improving flows). It should be noted though that any solution aimed at improvements in flow needs to consider if the modification has an actual impact on the ability of people passing through a given space (i.e., the need to keep physical distance might undermine the effect of the modification). Similarly, dedicated queuing areas might be designed to provide enough space for people to wait before reaching a given space. Temporary barriers or physical obstacles aimed at partitioning space and optimize flows can also be represented to study the interactions of people with the changed space (Alhawsawi et al., 2020; Helbing et al., 2005). This type of modifications can generally be explicitly represented within a crowd model in order to evaluate their impact on results.

While the impact of signage cannot often be explicitly implemented in crowd models (Filippidis et al., 2008; Ronchi et al., 2012), its impact may be represented implicitly. The use of signage (including marking/tapes) to instruct way-finding or to inform people on distance to be maintained in static or moving conditions can indeed have an important impact on crowd movement and behaviour.

From a crowd management perspective, an interesting set of solutions that can be tested with crowd models regard the implementation of phased movement or phased access strategies. These strategies can be aimed at minimizing the interactions between people in a given space (or between people at a given environment). Phased access would have the direct consequence of decreasing the number of people in a given space, thus directly impacting the metrics concerning proximity analysis and exposure assessment. Phased movement is a strategy generally adopted in evacuation (Ronchi and Nilsson, 2013) and circulation scenarios to minimize congestions and give priority to certain people or categories of people. Among other issues, its successful implementation relies on the level of training of people and staff in a given space and adequate means of communication. Another crowd management solution that can impact physical distancing is the use of one-way routes. Compared to two-way routes, counterflows would not take place, thus potentially minimize face-to-face interactions and increase physical distancing. Crowd models may allow to explicitly or implicitly model the direction of usage of a given movement component.

Both design and procedural solutions should be modelled taking into account the behavioural response of people. This means that crowd model users cannot always assume that people will strictly follow the instructions provided and that it is advisable to simulate different scenarios considering varying levels of compliance.

8. Case study

A case study is here presented to demonstrate the use of the risk analysis methodology for crowd model usage. The chosen setting is a European stadium with >40,000 seats distributed on two levels simulated with the crowd model Pathfinder (Thunderhead Engineering, 2020). As the methodology is deemed to be applicable for all types of facilities, the specific location of the case study under consideration is left deliberately anonymous.

8.1. The stadium layout

A schematic representation of the stadium is presented in Figure 17. A metal fence encloses the external areas of the stadium; gates are here available for the access of people. Once crossed the metal fence, people have to pass through the metal detectors to access the internal areas of the stadium. After passing the metal detectors, people are inside the stadium, and they can decide to which level are aiming for (upper or lower level). Finally, people have to pass through the turnstiles to access large corridors and the area in which toilets and food/beverage facilities are located. These areas are connected to the stands by means of vomitories. To sum up, people have to pass through three consecutive barriers, namely 1) a gate, 2) a metal detector and 3) a turnstile (see Figure 17). The stadium is split into portions served by different groups of gates/metal detectors/turnstiles, in order to keep different groups of people (e.g. different team supporters) separated.

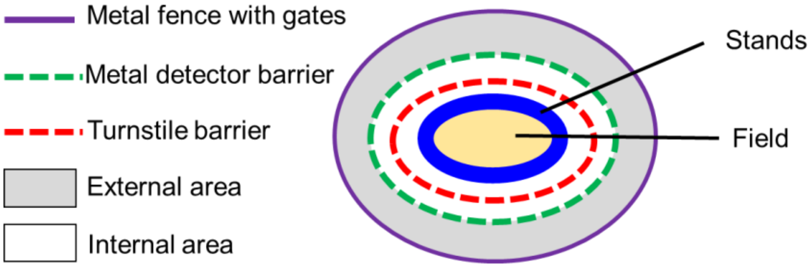


Figure 17. Schematic representation of the stadium.

8.2. Application of the methodology

The methodology for the use of crowd models is here applied listing each checklist bullet for each step along with the work performed

Step 1. Definition of goals, objectives and type of analysis

Checklist:

1. *What is the goal of the safety analysis? (virus transmission risk alone or concurrent threats)*
2. *What types of analysis are going to be performed? (e.g., performance-based design of fire safety, study of pedestrian flows, proximity analysis, exposure assessment, etc.)*
3. *Define the assumptions on virus transmission mechanism*

1. The goals of the analysis are: (i) to estimate the ingress phase duration in case of a pandemic scenario (this involves temperature checks at the entrance, physical distancing along ingress routes and stands), compared with the pre-pandemic situation using a microscopic agent-based model; (ii) estimate the interactions between people during the ingress phase using a microscopic agent-based model.

2. The analysis is based on the study of pedestrian flows inside the stadium, from the entrance gates to the stands, and on the proximity analysis.

3. It is assumed that virus transmission is triggered by proximity between people in a given distance radius.

Step 2. Definition of the area(s) of interest

Checklist:

4. *Define the area of interest for the safety analysis*
5. *Define the area of interest for the given assumption on virus transmission mechanism*
6. *Represent/Import the areas of interest in the crowd model*
7. *Identify design solutions for physical distancing*

4. The stadium can be accessed through different accesses in relation to the stadium portion under consideration. This is made to keep different groups of people (e.g. different team's supporters) separated. Ingress paths of different portions of the stadium are similar to each other, thus only a quarter of the stadium is analysed, including 3 entrance points (called here A, B, C) and their associated ingress paths. Table 2 shows the main features of this area, including number of seats and gates, metal detectors, and turnstiles for each entrance point considered in the analysis. In both the pre-pandemic and pandemic scenarios, each gate lets in 1 person every 15 s (240 persons/hour), each manual metal detectors lets in 300 persons/hour, each automated metal detector lets in 400 persons/hour, each turnstile lets in 750 persons/hour.

Table 2. Summary of the features of the area of interest under consideration in the stadium.

Entrance point	Number of seats	Number of gates	Number of metal detectors	Number of turnstiles
A	6398	16	10 (automated)	10
B	2099	8	4 (manual)	4
C	7519	24	10 (automated)	14

The analysis takes into account the stadium area included in the metal fence, so both external and internal areas, while the external area beyond the metal fence (public area) is not included in the analysis.

5. The stands are placed outdoor. The internal areas where toilets and other facilities are located are naturally ventilated by the openings on the walls. There are no HVAC systems, excluding toilets and other small enclosures (storage rooms, technical rooms), that are assumed here to be not relevant for the analysis.

6. The area of interest is reproduced in the crowd model, starting from a 2D CAD file. The crowd model permits to reproduce the stadium as a set of rooms, doors and stairs.

7. To keep physical distancing, the number of available seats (as reported in Table 2) is reduced to 42% of capacity in one scenario (this value was back-calculated assuming a 50% capacity in the stands of the tribune and 33% capacity in the tiers), while the full capacity is assumed in the baseline scenario. Further design solutions are evaluated by means of the analysis.

Step 3. Definition of the population

Checklist:

8. *Define people categories (who will be in the scenarios), including physical and behavioural aspects which may be linked to virus transmission and/or concurrent threats*
9. *Define people profiles (how to represent people in the crowd model), including features like walking speeds, body sizes, aspects linked to physical distancing, etc.*
10. *Define the type and size of established (or possibly emerging) groups*

11. *Define how many people are initially present (occupant load) in the scenarios, entry points (if present) and where they are initially located*

8. Since the analysis is related to a stadium, the population is assumed rather homogeneous, and it is made of individual sport supporters aiming at the stands to watch the event.

9. Typical profiles involve young men. Families with children and elderly people are possible users but, for the sake of simplicity, they have not been considered in the current analysis. Specific areas of the stadium are dedicated to people with disabilities, considering dedicated ingress paths (i.e. elevators are available rather than ramps). These areas are therefore excluded from the analysis domain. The assumed desired velocity of the agents is equal to 1 m/s. Since a continuous model has been adopted, the agent dimensions have to be defined by the user. These were assumed equal to a diameter equal to 0.45m, and a reduction factor (to resolve congestion and allow people to modify their size) equal to 0.25 with a minimum diameter equal to 20cm (to move through narrow geometries).

10. Groups are not explicitly modelled. This assumption was made to account for the conservative hypothesis of people walking alone.

11. The stadium is assumed empty at the beginning of the simulation. Stadium entrances are assigned as gates in the external metal fence. In the crowd model, occupant sources are located in correspondence of the entrance gates. The rate of agents' entrance is equal to the gate rate (240 person/hour), and the agents introduction in the domain is stopped as soon as their number have reached the number of available seats.

Step 4. Definition of crowd movement and behavioural scenarios

Checklist:

12. *Define detailed scenarios (e.g., circulation, evacuation) and associated use of entry/exit points*
13. *Define components available for movement for each people type*
14. *Define behavioural profiles (e.g., responses to the threat(s)), behaviour in light of physical distancing)*
15. *Define behavioural itineraries, routes and exit usage in relation to physical distancing*
16. *Define impact of design and procedural solutions and likelihood of compliance in the given scenario (possibly with a probabilistic approach)*
17. *Define movement on each component, including issues related to physical distancing (e.g., fundamental speed-density and flow-density relationships, queuing mechanisms, collision avoidance, impact of groups)*
18. *Identify contrasting needs during movement in case of concurrent threats and subsequent priorities in behaviour exhibited by the agents*

12. The analysis involves an ingress scenario. Entry points are defined as occupant sources in correspondence of metal fence gates. People destination are the stands. When those are reached the agents are assumed stopping their movement. Table 3 summarizes the key characteristics of the scenarios under consideration: (i) pre-pandemic scenario (100% seats, no physical distancing); (ii) pandemic emergency scenario (42% of available seats, reduced number of entrance gates, physical distancing equal to 1m which is enforced in the model). It should be noted that the gates that were excluded were next to other gates in use (i.e., since they are closely located, it would not be possible to ensure physical distancing if using adjacent gates). This means that it was assumed that despite increasing costs (as they are run by stewards), adding such gates would potentially create issues in ensuring physical distance from the side. (iii) An additional pandemic scenario was also conducted, in which additional measures reduced the ingress time to a value lower than the pre-pandemic scenario. This consisted in a procedural intervention in which trained stewards are placed at each vomitory to control the access to the stairs and the number of people in the stairs.

Trained stewards are placed in correspondence of each vomitory, in order to limit the access to the stairs, keeping the number of people in the stairs under a certain safety threshold, as shown in Figure 18.

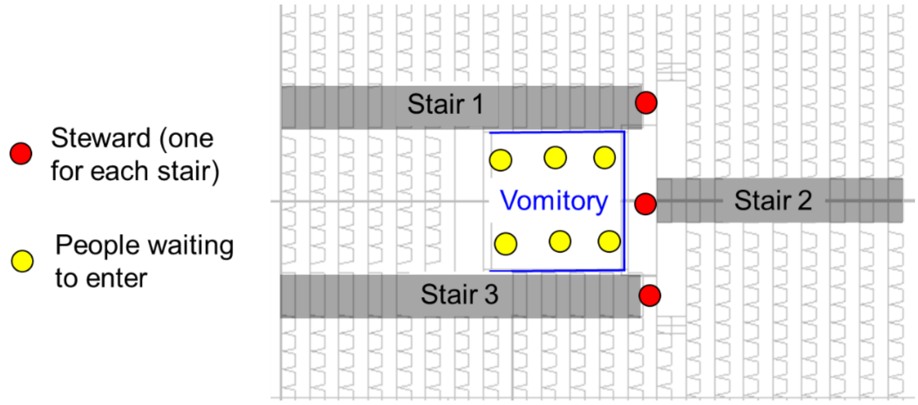


Figure 18. Schematic representation of the procedural intervention to improve safety.

Table 3. Summary of the features of the area of interest under consideration in the stadium in the pre-pandemic and pandemic scenarios.

Entrance point	Pre-pandemic scenario		Pandemic emergency scenario	
	Number of seats	Number of gates	Number of seats	Number of gates
A	6398	16	2783	7
B	2099	8	661	4
C	7519	24	3279	10

13. Ingress paths include ramps and stairs. The stands are the destinations of the simulated agents.

14. People are directly aiming at their target destinations and are forced to maintain a physical distance equal to 1m, calculated from the centre of their body. People were assigned to different routes in relationship to their assigned seat and vomitory.

15. Ingress paths are the same of the pre-pandemic situation.

16. It is assumed that all people maintain the physical distance. In scenario (iii) a procedural intervention was introduced

17. The fundamental speed-density relationships are not explicitly modified, but they are deemed to change compared to the default due to the enforced physical distancing. In particular, the high-density part of the speed-density relationship is not reached due to physical distancing. Queuing and collision avoidance mechanism are left as default although they are affected by the enforcing of the 1 m physical distancing. This implies that the resulting flow-density relationship is also deemed to not reach the high-density part and only the part on the left-hand side of the flow-density relationship is used (i.e. the descending part of the curve is not reached). No impact of groups is considered.

18. Since the analysis involves only the ingress phase, no concurrent threats are taken into account.

Step 5. Simulation of people movement and behaviour with crowd modelling tool(s)
Checklist:

19. Identify suitable crowd modelling tool(s)

20. *Perform input calibration including issues associated with physical distancing based on crowd movement and behavioural scenarios*
21. *Run the simulations (using a probabilistic approach when needed)*
22. *Identify and obtain the crowd modelling outputs*

19. The crowd modelling tool used for the analysis is Pathfinder 2020.2.0520.

20. The input calibration was performed by first observing the ingress phase duration in the pre-pandemic scenario. Empirical observations were used to estimate the order of magnitude of the ingress time (this time is approximately 2 hours). As in this type of scenarios the ingress is mostly driven by the flow restrictions, this was the variable likely having the higher impact on results. The procedural interventions in the pandemic scenario (iii) were implemented modifying the flowrates to access the vomitories.

21. No probabilistic approach was used, because the main driving factor was assumed to be the people flowrate. The desired velocity of agents was assumed as homogenous, no groups were considered, and it is assumed that people go from the entrance to the stands, neglecting possible deviations to the toilet or food and beverage facilities. This approach is due to the fact that no data were available on how many people use these facilities and for how long and it is deemed to be reasonable given the comparative scope of the analysis.

22. Crowd model outputs are the ingress phase duration (see Table 4), social usage vs time (see Figure 18), and jam time (see Figure 19).
Table 4 shows the ingress time in different scenarios. This includes pre-pandemic and pandemic scenarios. It includes an estimation of the ingress time based on empirical observation. This was measured in pre-pandemic conditions during an event with a typical turnout in the stadium. It can be seen that the simulation of pre-pandemic provides a slightly over-estimation of the ingress time. An ingress time larger than the one of pre-pandemic conditions can be observed considering the simulation results corresponding to the pandemic emergency scenario. The pandemic scenario with additional measures provided an ingress time comparable to the pre-pandemic scenario.

Table 4. Ingress time in different scenarios.

Scenario	Type of result	Ingress time [minutes]
Pre-pandemic	Estimation based on empirical observations	≈120±10
Pre-pandemic	Simulation	135
Pandemic emergency	Simulation	148
Pandemic emergency with additional measure*	Simulation	110
*Additional measure consists in the presence of trained stewards placed at each vomitory, with the aim of keeping the number of people in the stairs under a certain safety threshold.		

The social usage output is a metric for proximity analysis defined as follows: For every point on the mesh (conceptually a spot on the floor), the number of people within a 3D radius (equal to 1 m in this case) are calculated and assigned to that mesh point. The mesh of all values is then contoured. This corresponds to the highest values considering all occupants rather than evaluating the number of people within the radius of a single occupant.

Figure 19 presents an example of the social usage vs time in the stair that connects one vomitory with the stands. Social usage is the number of occupants within the 3D radius R= 1 m around a specific point in the middle of the stair. Figure 19 shows that the pandemic scenarios correspond to a social usage lower than in the pre-pandemic conditions due to the physical distancing. The additional measures introduced in the last pandemic scenario further reduce the social usage.

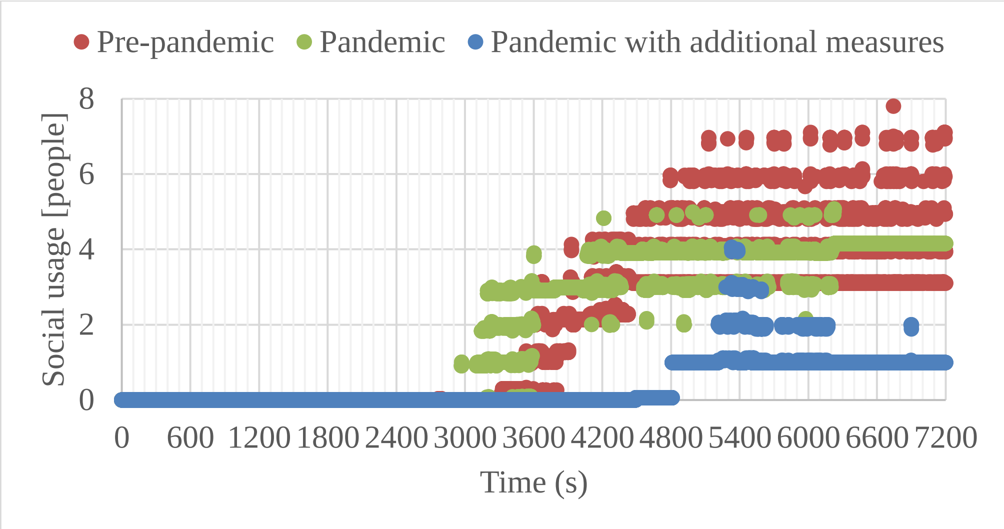


Figure 19. Social usage vs time for the pre-pandemic and pandemic scenarios under consideration.

The jam time output is defined as the total time people spend moving at less than the specified jam velocity (this is set in this case equal to 0.25m/s, the default value). Figure 20 shows the distribution of jam time in the scenarios under consideration. It can be seen that the pre-pandemic case is the one in which users experience the larger jam time. This is due to the fact that a larger number of people is allowed in the stadium if compared to the pandemic cases. Figure 20 also shows that the additional measures adopted in the pandemic scenario lead to a further reduction in the jam time. It is known that in pre-pandemic conditions, queuing people - especially for long and broad queues - tend to reduce their distance to others since this create the impression of progress (Helbing and Mukerji, 2012).

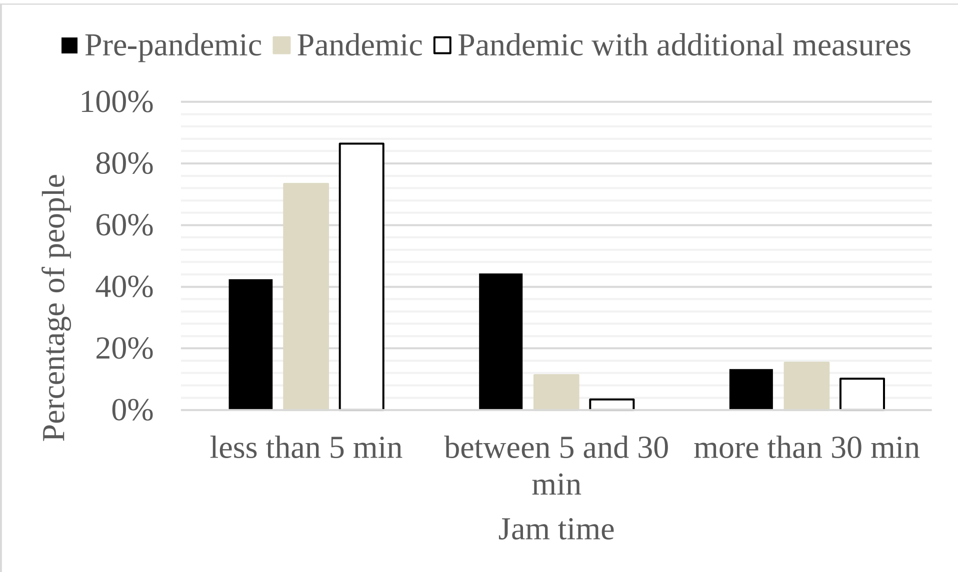


Figure 20. Jam time distributions for the pre-pandemic and pandemic scenarios under consideration.

Step 6. Post-processing of outputs from crowd modelling

Checklist:

23. *Post-process outputs obtained by the crowd modelling tool(s) in use and obtain the metrics needed for the goal of the analysis (e.g. proximity analysis, exposure assessment, fire safety engineering assessment, movement flow metrics, space usage metrics, etc.)*
24. *Analyse the variability in outputs in case of use of probabilistic approach*

23. A proximity analysis was done taking into account the social usage output.

24. Not applicable

Step 7. Risk assessment based on metrics

Checklist:

26. *Perform a risk assessment based on metrics*
27. *Check if an adequate safety level is reached. If this is met, the process is completed. If this is not met, perform modifications aimed at improving safety and return to step 5. The process ends when the target safety level is met.*

26. A risk assessment is made taking into account ingress time, social usage plots and jam time distributions. The ingress time estimation of pre-pandemic conditions based on empirical observations is comparable to the pandemic emergency scenario with additional measures, while it is approximately 19% lower than the pandemic scenario without measures. This means that it is deemed appropriate to adopt such measures to ensure that ingress times are comparable between pre-pandemic and pandemic conditions. Similarly, the social usage is decreased in the pandemic scenarios with additional measures compared to the pre-pandemic and pandemic scenarios. This indicates that the suggested procedural solution contributes to reduce the risk of virus transmission considering the proximity analysis method in use. In addition, the suggested measures also contribute to reduce the jam time. This is an important issue as it is assumed that - in the absence of empirical data related to pandemic situation - avoiding long jam time can prevent the people to move closer to each other and help keeping the physical distancing.

27. Social usage plots showed that the proximity is rather high (social usage > 4) in the pandemic conditions without measures along the stairs that connect vomitories with stands. Hence, the procedural intervention was evaluated to improve safety. The proximity analysis demonstrates that this additional measure reduces the proximity of people on the stairs. Furthermore, the percentage of people experiencing a jam time larger than 5 minutes is reduced (from 27% to 13%) between the pandemic scenarios without and with measures.

9. Discussion

This work analysed the usage of crowd modelling tools in times of pandemic (particularly focusing on aspects related to physical distancing) and presented a methodology which is deemed to guide crowd model users.

Several aspects have been identified as critical during the present work. First of all, given the current *status quo* of crowd models which are not originally designed for the study of the impact of physical distancing, it appears evident that users may not be able to use crowd models as they are. The process of input calibration would require a careful evaluation of the assumptions adopted by a given crowd model and the consequence that such assumptions may have on movement. In other words, users would need to perform a careful evaluation of the modelling assumptions to check that those hold also in times of pandemic. Modifications may be needed at different levels of the crowd modelling process, starting from the definition of the goals of the analysis (which include the risk of virus transmission) and ending with the methods to use crowd modelling outputs to perform risk assessment. During the process of scenario identification and input calibration, crowd model users may need to perform significant adjustments in the assumptions in use in order to consider the behavioural aspects linked to people movement modelling in times of pandemics. In this work, an example has been presented considering the modifications that can be performed in the fundamental relationships between speed/flow and densities and how those can vary in relation to the assumptions on minimum and maximum density for the calculations of the impeded speeds. Several other aspects should be investigated concerning pedestrian navigation behaviour at macroscopic (e.g. route choice, people re-routing to avoid congested areas) and microscopic (e.g., collision avoidance, people attempting the navigation around other people or obstacles keeping larger distances) scale. Similarly, the whole process of queuing may be affected by the willingness of people to keep physical distancing.

The situation is complicated even further by the fact that provisions on physical distancing (and subsequent instructions given to people) are prone to interpretation, thus crowd model users should review them in light of the assumptions adopted by the model in use for representing the simulated agents.

The use of crowd modelling tools in times of pandemic is also strictly linked to the assumptions adopted concerning the virus transmission mechanisms. To date, since no conclusive understanding exists on this matter (Bahl et al., 2020; Lewis, 2020), crowd model users may need to perform several types of analysis in relation to the assumption in use. In this context, the limitations of the models in representing particular mechanisms of interactions should be taken into consideration. A clear example of this issue is the currently inability of crowd models in predicting people interaction with objects.

The crowd modelling outputs themselves may need to be re-evaluated and new outputs may be needed. Currently, microscopic crowd models may give the opportunity to calculate the parametric equations of people trajectories (i.e. coordinate in space and time of the agents in the simulation). This information is surely useful to perform a proximity analysis or an exposure assessment, as they allow the obtainment of relevant metrics for risk assessment (as shown with the model EXPOSED (Ronchi and Lovreglio, 2020)). In relation to the mechanism of virus transmission assumed, additional needed outputs may include the tracking of the orientation of the agents, as this information could be used to study the face-to-face interactions between them or the likelihood of agents touching certain objects (e.g. a door knob). In other words, brand new outputs may be needed to be obtained using crowd modelling tools, so that proximity analysis and exposure assessment can be performed in a more accurate way. Nevertheless, the obtainment of these outputs would need to be based on experimental data for the development of dedicated sub-models addressing the behaviour to be modelled.

Limited research is currently available concerning the behavioural aspects affecting crowd movement in times of pandemic. For this reason, users may consider adopting conservative assumptions in their applications of crowd models and possibly evaluate different scenarios in which different levels of compliance to the instructions provided (either by design or procedural solutions). In this context, the impact of (established and emerging) groups cannot be neglected, as social influence is known to play a significant role in emergency scenarios, including issues related to route choice (Kinateder et al., 2014b). Physical distancing preferences may indeed vary both at an individual and group level and they can be influenced by the context in which movement is occurring. Also in this case, given the absence of experimental data concerning group behaviour, users are recommended to investigate the impact of group behaviour performing the simulation of different scenarios in which different group dynamics occur.

Future research efforts should focus on collecting experimental data concerning different aspects concerning people movement in times of pandemic. The first aspect to investigate is the space usage itself, i.e. how pandemics affect the number of people present in a given open or confined space. Subsequently, the movement dynamics of people should be studied by looking at behaviour at individual and group level, in a variety of contexts (both in terms of the type of space in which they take place as well as the type of people or groups of people involved). Until this type of information is not available, crowd model users should be very cautious in adopting crowd modelling assumptions developed in times in which no pandemic was present. For this reason, the methodology presented in this work along with a checklist of issues to be considered is deemed to be of help for crowd model users and stakeholders involved in the study of crowd movement in times of pandemic.

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