A Prescriptive Simulation Framework with Realistic Behavioural Modelling for Emergency Evacuations

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Emergency and crisis simulations play a pivotal role in equipping authorities worldwide with the necessary tools to minimize the impact of catastrophic events. Various studies have explored the integration of intelligence into Multi-Agent Systems (MAS) for crisis simulation. This involves incorporating psychological behaviours from the social sciences and utilizing data-driven machine learning models with predictive capabilities. A recent advancement in behavioural modelling is the Conscious Movement Model (CMM), designed to modulate an agent's movement patterns dynamically as the situation unfolds. Complementing this, the model incorporates a Conscious Movement Memory-Attention (CMMA) mechanism, enabling learnability through training on pedestrian trajectories extracted from video data. The CMMA facilitates mapping a pedestrian's attention to their surroundings and understanding how their past decisions influence their subsequent actions. This study proposes an efficient framework that integrates the trained CMM into a simulation model specifically tailored for emergency evacuations, ensuring realistic outcomes. The resulting simulation framework automates strategy management and planning for diverse emergency evacuation scenarios. A single-objective method is presented for generating prescriptive analytics, offering effective strategy options based on predefined operational rules. To validate the framework's efficacy, a case study of a theatre evacuation is conducted. In essence, this research establishes a robust simulation framework for crisis management, with a particular emphasis on modelling pedestrians during emergency evacuations. The framework generates prescriptive analytics to aid authorities in executing rescue and evacuation operations effectively.

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CCS Concepts: • **Computing methodologies → Modeling methodologies;**

Additional Key Words and Phrases: Modelling & simulation, conscious movement model, crisis management, emergency evacuation, predictive simulation, prescriptive analytics

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1 INTRODUCTION

Emergency evacuation and rescue planning pose significant challenges due to the unpredictable nature of human behaviour in fast-paced and escalating danger situations [8]. Traditional modelling and simulation techniques have been instrumental in studying crowded areas to formulate effective evacuation plans for crises like fires, bomb threats, or riots. However, simulating human behaviour under the influence of evolving danger remains a key challenge. To address this challenge, concepts from social sciences, such as **BDI (*beliefs, desires, intent*)** aspects [31], are integrated into Multi-Agent Systems [38], where each agent represents individuals involved in the simulation with unique characteristics and behaviour.

Other approaches, such as modelling human behaviour based on fluid dynamics [14] and adjusting urgency through observational studies [17, 21], have also been proposed to enhance the realism of emergency evacuations. Recognizing the importance of early preparation for rescue and evacuation operations, this research acknowledges that advance plans are often generic and may not address the ongoing crises well. These plans can only serve as guidelines for authorities on the ground, who must make critical decisions as dangers escalate. Delays can lead to higher casualties, emphasizing the need for symbiotic simulations [25] and digital twins [3]. These systems digitally replicate physical systems and utilize the **internet-of-things (IoT)** [2], incorporating smart devices and live CCTV footage for highly realistic simulations. While current state-of-the-art systems offer a plethora of crisis event simulations to improve emergency evacuation operations, challenges persist. The dependability of digital twins may decline in the face of device destruction during an ongoing disaster. Additionally, generic behavioural models may lack applicability globally, given the diversity of customs and reactions to danger among people. As a result, there is an increasing interest in highly accurate predictive simulation [19, 45], utilizing the predictive capabilities of machine learning models.

Machine learning has seen major advancements due to the recent availability of cheap and powerful **Graphical Processing Units (GPU)** that can speed up matrix computations rapidly, bringing down the overall performance time by a drastic measure [37]. This acceleration has propelled research in data-driven models for various human tasks, achieving close to real-time performance with remarkable accuracy in visual imagery (GoogLeNet [40], Inception-ResNet [39]) and image classification [16], as well as text classification [20], speech recognition [34], and more. While we may not have a model that replicates the entirety of human thinking, these successes showcase the potential of training computational models to "think like a human" for specific tasks, opening avenues for automation in diverse fields.

Recent work to capture human behaviour from video [41] and enhancing realism in simulation [29] with the aid of machine learning techniques have shown that it is possible produce realistic reactions in simulation [27, 28]. The higher level of realism introduced will allow for a more accurate analysis of strategies to overcome or mitigate different what-if scenarios for the area of concern. Hence, knowing what data-driven learning models can do today, it is pertinent to leverage the power it offers by investigating how such realism can be achieved to simulate realistic human behaviour in different emotional states and physical environments.

In our efforts to tackle the issue of realistic simulation of human behaviour in emergencies so as to prescribe effective strategies for evacuation, this research introduces an architecture to integrate the **Conscious Movement Model (CMM)** [26] into a simulation framework. The trained CMM's emergency behaviour can be assessed through real-life case studies involving evacuation from enclosed spaces. The simulation framework is extended with prescriptive analytics for crisis management, contributing to a functional utility for simulating emergency evacuation with a trained behavioural model. This work builds upon a prior publication [30], which covered the integration of CMM and evaluation in a small classroom case study. The expansion includes further evaluation on a larger theatre case study and an extension for prescriptive analytics.

The next section will briefly cover key concepts of the Conscious Movement Model (CMM) and explain why it stands as the state-of-the-art method for modelling human behaviour in emergencies. Subsequently, Section 2 will also delve into related work for emergency evacuations and prescriptive simulation. In Section 3, the methods and design for integrating the trained behavioural model into a simulation framework for simulating emergency evacuations will be delineated along with the techniques employed to integrate existing optimization methods for prescriptive analytics. Finally, Section 4 will detail the experiments and evaluation for our proposed methods, before concluding with recommendations for future work in Section 5.

2 RELATED WORK

This section will elucidate key concepts integral to the methods and design contributions presented in this paper. Firstly, we will provide a succinct overview of the foundational principles of the Conscious Movement Model (CMM) based on our earlier work. Subsequently, we will delve into the background and state-of-the-art methods related to emergency evacuation simulation. To enrich our understanding and enhance our proposed framework, we will explore existing works on prescriptive simulation that can offer valuable insights.

2.1 The Conscious Movement Model

The proposed Conscious Movement Model (CMM) [26] is capable of dynamic transitions between normal and evacuating states to reflect realistic behavioural reactions during emergencies. Within the CMM, we also introduced attention and memory mechanisms, called the **Conscious Movement Memory-Attention (CMMA)** model, to capture characteristics of human behaviour from real-life video data. The trained CMMA can then be attached to the CMM for each agent spawned into a simulation. As such, each agent will behave realistically based on its individual experiences. The proposed CMM equation to compute a pedestrian's conscious movement $\overrightarrow{CM}$ at time t can be written as follows:

$$\overrightarrow{CM}(t) = f\left(g\left(\overrightarrow{A}_t, \sum \overrightarrow{R}_t\right), \overrightarrow{CM}_{t-1}\right) \times (M_t/\rho_t) \tag{1}$$

where the result of memory function, f, on the direction of motion, both attractive $\overrightarrow{A}_t$, and repulsive $\overrightarrow{R}_t$, with attention g, and the previous conscious movement $\overrightarrow{CM}_{t-1}$, is multiplied by the force of motion M_t at a rate proportional to the level of calmness ρ_t. The elaborate derivation of the calmness term, explained in [26], is computed based an individual's perceived level of risk according to their own encounters at each time-step. In an evacuative state, the calmness term $F(t)_i$ for agent i at time step t, is given by:

$$F(t)_i = \rho_i^{t-1} + \log(d_t/s_t)\alpha \tag{2}$$

where d_t is the agent's current distance from the actual threat, s_t is the safety distance from threat at that point in time (to avoid injuries), and α is the relative weight of influence on an agent's calmness. ρ_i^0 will start at 1 (total calmness) in normal state and fluctuates over each time step as threat is introduced and danger escalates. The attractive directions, $\overrightarrow{A}_t$, include the attraction to goal $\overrightarrow{G}_t$, attraction to empty space $\overrightarrow{S}_t$, and attraction to distractions $\overrightarrow{D}_t$. For clarity, the CMMA model represents the first part of Equation (2) as such:

$$\text{CMMA}(\vec{G}_t, \vec{S}_t, \vec{D}_t, \vec{R}_t) = f\left(g\left(\overrightarrow{A}_t, \sum \overrightarrow{R}_t\right), \overrightarrow{CM}_{t-1}\right) \tag{3}$$

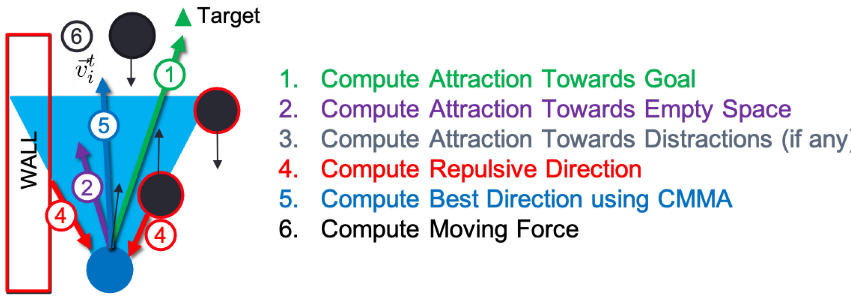


Fig. 1. Forces of the CMM model *(Image from [26])*.

The CMMA takes in all the possible directions of motion, $\vec{G}_t, \vec{S}_t, \vec{D}_t, \vec{R}_t$, and outputs a "rational" direction of motion, $\vec{B}_t$, based on attention and memory trained from historical trajectories of real-life pedestrian movements. Figure 1, taken from [26], shows an overview of how each of the forces in the CMM comes into play.

In Figure 1, all the possible directions of motion will present as options that an agent can take as we pass them through a memory-attention mechanism, the CMMA, as features to produce the best direction to take, instead of summing them all up like the Social Force Model and many of its variants. It differs such that an agent will reflect similar movement behaviour to pedestrian movements learned from the same scene (e.g., area, space, location). With the equations proposed, the CMM can reflect movement behaviour based on as individual's level of calmness and a memory-attention mechanism, the CMMA model given by $f(\vec{G}_t, \vec{S}_t, \vec{D}_t, \vec{R}_t)$, that will influence the direction of motion based on its surroundings and previous movements.

The CMMA model is trained on real-life crowd video data to capture realistic decision-making processes in response to various directional influences. At each time step, the CMM calculates the directional forces for each agent, passing them through the CMMA model. The resulting evaluation, considering individual calmness levels, guides the force of motion toward the desired direction. Notably, experiments in [26] underscore the CMMA model's transferability, showcasing its commendable performance across different scenes.

In contrast to related works in a similar domain, most fail to consider social factors influencing individual directional decisions or motion speed, as the CMM does. For instance, Yi et al. [44] leverage **Convolutional Neural Network (CNN)** for image processing, predicting trajectory paths only based on historical patterns. Heter-Sim [32] incorporates social influences such as velocity continuity, collision avoidance, attraction, and direction control, yet overlooks the impact of varying attention to surroundings that may also influence an agent's decision to choose a trajectory path. Similarly, the Proactive Crowd [22] model accounts for gap-seeking influences, akin to the CMM's attraction to empty spaces. However, like many other crowd modelling techniques [5, 23, 49], these models lack the learning capability inherent in the CMM with its CMMA model.

To the best of our knowledge, the CMM stands out as the sole behavioural model with built-in learning capabilities, consistently producing realistic behavioural reactions at each simulation time step. The experiments and evaluations presented in [26] demonstrate that the proposed CMM surpasses existing methods in terms of realism and dynamic responses to evolving environmental situations.

2.2 Emergency Evacuation Simulation

Our main goal is to realistically reflect human behaviour in the simulation of evacuations and explore methods to influence the level of urgency in emergency situations. To achieve this, we will review related works for modelling crowd dynamics and individual pedestrian dynamics in emergency evacuation simulations.

Noteworthy contributions in the field of crowd evacuation modelling [13] have been made to date. A flow-based modelling approach proposed by Almeida et al. [1] uses cellular automata within a **Multi-Agent System (MAS)** to simulate evacuations in crowded buildings or spaces. The proposed model integrates BDI techniques (Beliefs, Desires, Intentions) from social sciences, where agents are driven by Desires (the goals), according to certain Beliefs (set of knowledge of the world) and Intentions (actions) to fulfil the Desires. Zhong et al. [48] on the other hand, proposed an automatic model construction of human crowd dynamics, formulated as a symbolic regression problem solved by using self-learning gene expression programming. It is capable of describing the crowd dynamics in different and unseen scenarios based on a set of behavioural rules.

In another work, Chen et al. [4] addressed the limitation of discrete crowd distribution data by employing density estimation and optical flow. Density-based particle assignment is done to identify crowds rather than individuals. Using Machine Learning, a regression model is trained to match extracted features at each pixel of the crowd to find the corresponding density distribution. This density distribution can then estimate the number of persons in the crowd for inputs to a crowd simulation model. In order to track the movements of the crowd, Optical Flow-based Displacement Tracking is employed. The author matches the simulated location with particle allocation by using a matching algorithm to associate simulated locations of particles obtained from the optical flow with the locations of particles directly calculated from the density map. Another approach, using an **Artificial Neural Network (ANN)** classifier [47], focuses on learning different clusters of human behaviour. During a simulation, the initial state is fed to the classifier to predict the cluster it falls under, and then examples from that cluster are collected from a hierarchical example database. One example is then selected for the actions to be copied in the simulation.

These works indicate that, with more crowd data, machine learning frameworks can build accurate crowd-moving patterns and behavioural models, facilitating risk analysis and decision-making. However, modelling crowd dynamics only allow for an abstract study from a macroscopic view, often overlooking the impact of collective individual behaviour on overall crowd dynamics. Several works have sought to simulate different crisis conditions and how to efficiently evacuate the scene with the lowest number of casualties. In order to achieve this, the behavioural dynamics of individual evacuees have to be realistic and accurate. General cases of reaction to danger or other environmental cues can lead to dire circumstances. For example, while evacuating a burning building, it is common to observe a “follow-the-leader” pattern where everyone will simply follow the person in front of them. During such situations, panic or visual clarity can affect a person’s decision to find another exit. Such unanticipated conditions may result in different outcomes. These “special cases” can be just one out of many due to the number of possible behavioural reactions. Hence, it is important to factor in realistic behavioural reactions of individuals to different possible environmental, physical, or emotional influences.

In an effort to comprehensively model human evacuation characteristics, Lovreglio et al. [21] introduced an **Evacuation Decision Model (EDM)** that predicts the pre-evacuation state of an evacuee among three possible states: Normal, Investigating, Evacuating. Considering the perceived risk for an evacuation scenario, a person may transition from normal to investigating the situation, to finally transitioning into evacuating state where they will search for the nearest exits. Gelenbe and Wu [10] aimed to enhance human outcomes in emergencies through symbiotic simulation and various tools, proposing a comprehensive approach involving physical sensors, communication strategies, path-finding algorithms, simulation, and decision tools for large-scale evacuations. Additionally, some emergency evacuation simulation studies [36, 46] have focused on the role of working personnel in expediting evacuations. These aspects are also just as important and have been heavily covered in numerous research work and practical applications today [1].

However, despite the progress in various aspects of emergency evacuation simulations, our analysis identifies the modelling of human behaviour as a critical yet underdeveloped aspect in recent years. Simulating emergency evacuations in enclosed spaces remains crucial, especially with large numbers of civilians passing through daily, due to the probability of undesirable outcomes when an emergency strikes. The motive of such simulations is to improve evacuation time and reduce casualties in the event of such disasters. Hence, ongoing research aims to enhance methods and strategy prescriptions to minimize casualties during disasters and emergencies.

2.3 Prescriptive Simulation

An emergency evacuation simulation aims to improve the evacuation process by understanding the system better. For a typical emergency evacuation system, minimizing the total evacuation time will typically result in fewer casualties as the threat escalates over time. As such, several cost-minimization methods have been proposed in attempts to achieve optimal flow for evacuation that can supplement preparation and planning for crisis events [35].

A **Partially Observable Markov Decision Process (POMDP)** model with the belief-desire-intention (BDI) framework, was proposed by Rens and Moodley [33] to leverage the reward-maximizing ability of POMDP and multi-goal management from BDI theory. Achieving better results than standard POMDP architecture and previous works for both processing speed and effectiveness, this approach can generate optimal plans for real-life applications. The **min-cost flow (MCF)** network model is another popular method used in several works [6, 7] due to its simplistic nature and optimal results. Using the MCF, the evacuation routes are viewed as a graph where the nodes represent checkpoints towards the goal/exit. An objective function to measure the cost, typically the total evacuation time is then applied to edges in the graph to ultimately derive the minimum cost flow. The resulting paths will then represent the optimal evacuation route. The simplicity of this model allows its use for several problems although the speed performance may grow exponentially as the nodes or graph space increases. For more complex problems, other works [24] apply multi-objective optimization (also known as Pareto optimization) to deal with problems that necessitate the simultaneous optimization of multiple objective functions.

Prescriptive simulations can be viewed as an optimization problem, and there are already several competitive methods available today that have been evaluated and tested with rigour. The key issue when using these optimizers is that we assume the measured output from a simulation that we are trying to minimize are realistic and accurate. No matter how good the optimizer is, unrealistic inputs yield unrealistic results. Thus, it all points back to the realism of behavioural models to simulate an area under study. With an effectively trained Conscious Movement Model (CMM), the realistic output results can utilize any suitable optimizer for useful prescriptive analytics.

3 METHODS & DESIGN

We will first present the simulation framework designed for emergency evacuations, outlining our proposed methods to harness the realism of the Conscious Movement Model (CMM). Subsequently, we will detail our approach to generate prescriptive analytics within the proposed simulation framework.

3.1 Emergency Evacuation Simulation Framework

Building upon the foundation laid in our prior work [30], we expand the scope by simulating a larger area with increased exit choices. Additionally, we introduce prescriptive analytics to optimize evacuation strategies. This section elucidates how the trained Conscious Movement

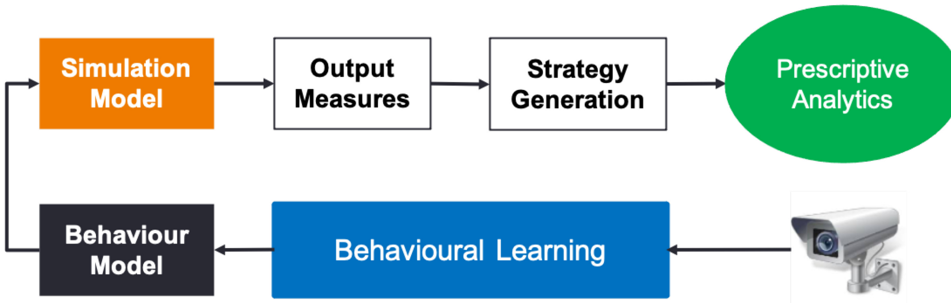


Fig. 2. Overview of simulation framework with prescriptive analytics *(image from [30])*.

Model (CMM) [26] is employed to infuse realistic human behaviour into emergency evacuation simulations [30], aiming for more accurate outputs that enhance effective analysis.

In the following, we will present one among several methodologies available in the literature to generate prescriptive strategy recommendations. Leveraging multiple simulation runs and a predefined objective function, we autonomously prescribe optimal strategies for execution during emergency evacuations. The realism of this proposed utility will be rigorously evaluated to ascertain its feasibility in real-life applications, particularly in optimizing emergency evacuation operations. To provide context, Figure 2, taken from [30], presents an overview of the entire system and demonstrates how this utility contributes to assisting relevant authorities in managing emergency evacuations.

We incorporated the CMM's behavioural learning architecture into our simulation framework, which allows us to run simulations with realistic behavioural characteristics based on the scene under study. The framework then simulates several what-if scenarios and generates strategic options for optimizing evacuation plans. Based on the output measures chosen, the framework will prescribe ideal strategies to adopt for different case scenarios. The integration of a realistic behavioural model learned from real-life CCTV footage of pedestrian movements in a specific scene to prescribe more effective strategies is the unique factor in this contribution.

In a typical simulation model for emergency evacuation of a particular area, we have static and dynamic data where we can observe how dynamic data changes in different scenarios with respect to static data. Static data (things that do not change) includes the area of space, exits, and static objects. As for dynamic data, we have humans with different roles (e.g., evacuees, staff, rescuers) and threats (e.g., fire, bombs, riots) that may change their positions or severity over time. Based on these data, we can run several simulations with different scenarios and measure critical metrics such as evacuation time or the number of casualties. Some of the things we can change to optimize these metrics may be static, such as the number of exits, or dynamic, such as the number of staff tasked to lead people to safety. The primary requirement for using our proposed framework is to have the necessary static data available. Hence, we will assume at this point that we already have static data such as distribution of arrivals, desired speeds, and positions of static obstacles. All that is left will be to introduce an intelligent behavioural model into each agent spawned into the simulation.

In our proposed Multi-Agent System, each agent will be able to process anything they see or encounter in the simulation environment and react appropriately based on forces acting around them, prior knowledge (memory), and their attention to the surroundings. These evacuees will need to transition from a normal state to an evacuating state at the start of the simulation. The CMM's computation of calmness handles this by assessing each agent's perceived level of risk and dynamically transitioning the state for each of them accordingly. The goal for each evacuee will simply be to reach an exit. To this end, the CMM can directly be used for regular evacuees navigating a scene and evacuating to the nearest or safest exit when a threat is encountered, or emergency evacuation procedure commences.

As for staff or security personnel tasked to usher evacuees to safety, we can also think of them as regular pedestrians with fear of danger but with a different goal. While ensuring their safety by keeping a safe distance from the threat, the goal of these ushers will be to reach as many people as they can and guide them to safety. As such, we can apply the same behavioural model set with a different (more appropriate) goal for such agents, if any were to be spawned into the simulation. For rescuers coming into a place of crisis, they also need to portray realistic human behaviour as well.

Therefore, for all three different roles, the computation of calmness based on an individual's perceived level of risk can still be applied to reflect the change in calmness over time as danger escalates. The main difference is the calmness threshold for the different roles since rescuers tend to have a higher threshold when handling threats. Thus, the goal for these rescuers will be to eliminate the threat and guide evacuees to safety. To achieve this, we can replace the requirement to keep a safe distance from the threat with the ability to reduce the severity of the threat. Assuming rescuers will have tools to handle the threat, such as a water hose for fires, we can imply that their presence can gradually reduce the threat over time. The severity of the threat can then be reduced accordingly based on realistic timings recorded by authorities, such as fire departments. Before rescuers arrive, we can also proportionally increase the severity of the threat over time, based on records of similar crisis events. These parameters can be set before running the simulation and considered as static data required before running simulations. Therefore, we can adopt the CMM for all three different typical roles by setting the appropriate goals for each of them as follows:

(1) Evacuees
- Goal is to reach the nearest and safest exit as quickly as possible.

(2) Staff/Security Ushers
- Goal is to get to as many people as possible, directing them to the best evacuation route while maintaining personal safety.

(3) Rescuers
- Goal is to reduce threat and guide evacuees to safety.

Realistically, each evacuee may consider changing their goals in order to avoid injury and evacuate faster, either by rushing to the nearest exit or looking for the safest exit. This decision-making process can be viewed as a game of balancing risks and rewards. As such, we devised a Panic Game to help each evacuee decide whether or not to update their goal. The algorithm for the Panic Game is shown in Algorithm 1.

The Panic Game will continue for each evacuee as long as they are still in the scene and have not reached any exit. During the simulation, evacuees may encounter ushers or rescuers who will point them in the right direction or assist them in getting to safety. The algorithm will then account for the consideration to change their goal. As such, no changes to the CMM are necessary to differentiate the various roles mentioned. Algorithm 1 is intended to reflect humans' realistic tendency to revise their goals based on what they believe will be most beneficial in achieving their desired outcome. When it comes to evacuation, the goal is to get out as quickly and safely as possible. Hence, when confronted with a threat or evacuation warnings such as directions from ushers/rescuers or exit signs, an agent will seek the nearest exit. If an agent is having difficulty getting through their current exit, they may change their goal and find another exit that may be faster to get through. Thus, in Line 4, an agent will scan its surroundings for threats or evacuation warnings communicated by other agents. If the condition is met, it will update its goal to the

ALGORITHM 1: Panic Game

```
   Require: τ ← speed threshold ;
   Require: τ′ ← wait threshold ;
1  EC ← [target]                                   ▷ list of possible destinations ;
2  wait = 0 ;
3  Function: findNearestExit();                    ▷ searches EC for nearest exit w/o passing threat;
4  if encountered a Threat/Evacuation warning then
5  |  Update self_goal ← findNearestExit() ;
6  if ||self_velocity|| < τ then
7  |  wait += 1                                    ▷ path is blocked - clogging/jams
8  else
9  |  wait = 0                                     ▷ no jams, reset wait
10 end
11 if wait > τ′ then
12 |  Remove current goal from EC ;
13 |  update = false ;
14 |  foreach agent ∈ self's angle of sight do
15 |  |  if agent_goal ≠ self_goal & agent_velocity > self_velocity then
16 |  |  |  add agent_goal to EC if not already in  ▷ neighbour is moving faster ;
17 |  |  |  update = true ;
18 |  end
19 |  if update then
20 |  |  Update self_goal ← findNearestExit()
```

nearest and safest exit without passing through the threat. Line 6 examines the agent's current velocity and increments the wait counter only if it falls below a predefined speed threshold τ. The wait counter is reset whenever an agent returns to an acceptable moving speed, as shown in Line 9.

Following that, we check to see if the wait counter has surpassed a predefined waiting threshold τ', in Line 11. This only happens when there is a bottleneck at an exit and the rate of egress is too slow. An agent will then look around to see if there are any better options and will only stay on if there are none. If the condition in Line 11 is satisfied, Line 12 will first remove the agent's current goal from the list of possible exits, implying that this agent is probably quite far back in the bottleneck.

This will force the consideration for a change of goal. Line 14 then scans its surrounding agents to see if any of them have a different goal (possibly relayed through other agents or ushers) and can move faster. In this case, it will include that goal into a list of potential exits. In Line 20, it will then update its goal to the nearest and safest exit based on the new list of possible exits, only if one or more options are available. All agents will eventually follow through to reach the best exit based on their own encounters. When all evacuees have been removed from the scene, the simulation will come to an end. The flowchart for the Panic Game was presented in [30].

Having detailed the methodologies for integrating the Conscious Movement Model (CMM) into a simulation model, it is essential to underline that this research exclusively concentrates on emergency evacuations within enclosed spaces. Our proposed methods are applied to gauge the resulting outputs, providing a basis for validating the accuracy of our model. The subsequent step involves a thorough evaluation of the model's capability to realistically simulate these emergency evacuation events.

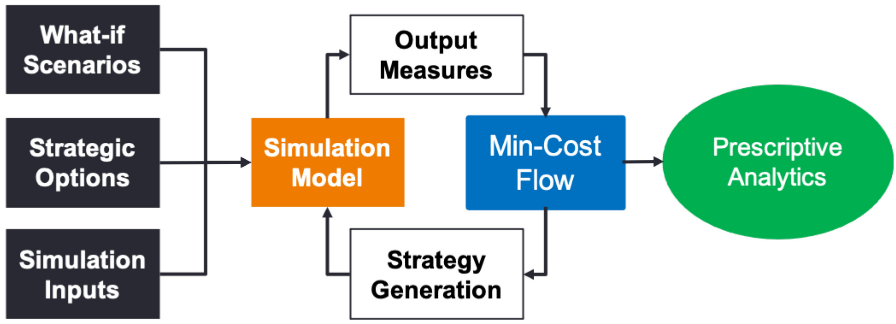


Fig. 3. Prescriptive analytics: Strategy prescription method.

3.2 Prescriptive Analytics for Emergency Evacuation Simulation

Building on the results obtained from our proposed evacuation simulation framework, we introduce a technique to automate the simulation of strategies and recommend the best course of action based on a predefined objective function. It will allow users to input a range of possible "what-if" scenarios, along with the metrics or measures to optimize. Additionally, users also need to provide options or strategies to minimize or maximize measures through an objective function. The framework is designed to automatically expand these scenarios into numerous possible combinations of provided options, evaluating their outputs through the objective function to derive candidate solutions.

Our methods employ the min-cost flow (MCF) network model, utilizing it to generate optimal paths and facilitate the automatic generation of robust strategies. The overview of deriving prescriptive analytics using our proposed simulation framework and the MCF network model is illustrated in Figure 3.

The method begins with the user setting inputs for the simulation, including what-if scenarios and strategic options (e.g., number/size of exits, number of control staff) they wish to study. The simulation model will then initiate the simulation for each scenario and compute user-specified measures based on a given objective function. This process is described in Algorithm 2.

Since each replication may produce slightly different behaviour, different strategies may be generated. Hence, at least n new strategies will be generated for each strategy simulated. From the new n strategies, only unique sets of strategy options will be added into the strategy list for the next run unless the terminating condition is already met. Line 5 can include a simple check to only run strategies that have yet been assigned scores so we will not run the same strategy twice. Generating strategies in Line 10 of Algorithm 2 uses the min-cost flow network to find optimal flows and generate different combinations of strategic options to simulate again. These strategic options will be deployed at points with min-cost paths in order to distribute the flow of evacuation in an effort to minimize the output measure. The range of options is the minimum and the maximum number of each specified strategic option available to deploy. The algorithm will then distribute these options accordingly based on how the resulting measures improve after the simulation. Each individual's path towards their exit is recorded and their speeds at key aisles are associated to the corresponding edges in the flow network. The min-cost path in this case would suggest slow moving traffic. As such, new strategies generated will give more attention to these paths that were identified. This cycle continues until either the min-cost flow model can no longer generate better combinations or the output measures have met a user-specified threshold. At the end of the run, the framework can then prescribe a list of best strategy combinations for each scenario based on the resulting output measures.

ALGORITHM 2: Prescriptive Analytics

```
strategyList = initial list                          ▹ at least one initial strategy ;
while terminating condition not met do
    strategies = empty list ;
    foreach strategy ∈ strategyList do
        i = 0 ;
        while i < n do
            output ← runSimulation(strategy) ;
            build min-cost flow network with output measures ;
            identify high-cost paths ;
            objective function → generate new strategy ;
            strategies ← add new strategy ;
            i += 1                                   ▹ run n replications
        end
        compute average results from output ;
        record scores for this strategy
    end
    add all unique strategy in strategies to strategyList ;
    update terminating condition
end
return recorded scores for all strategies → sorted
```

This method, coupled with our proposed simulation framework integrated with realistic human behaviour produces a novel utility contribution that can extend from predictive simulation to prescriptive strategy recommendation. However, it may not be an ideal solution for real-time applications due to its high time complexity in predicting pedestrians' trajectory at each time step as well as the exhaustive search for the optimal strategy. We will discuss possible enhancements to these limitations in our further work.

4 EXPERIMENTS & EVALUATION

The work done in [30] experimented the framework on a small setting of a classroom. We will extend the evaluation of the simulation framework against a bigger case study of real-life evacuation in a theatre. Then, we will show experiments on the theatre case study model to derive prescriptive analytics with the methods proposed.

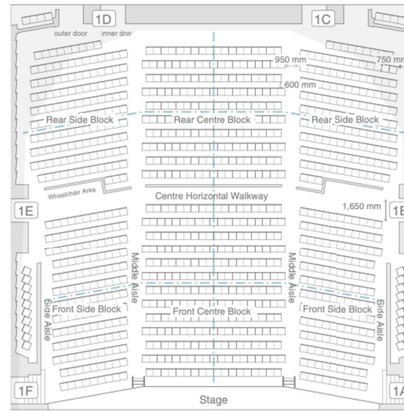
4.1 Theatre Case Study

In this study, we evaluated the framework on a larger scale. An enclosed theatre with multiple exits and larger capacity can result in a much higher fatality rate if a threat occurs and evacuation plans are not executed well. Therefore, Imanishi and Sano [15] carried out an elaborate study to analyse evacuation drills in a theatre. The study ultimately produced and captured useful data for evacuation and rescue planning. The input and output data for this case study were provided based on real-life simulations. Hence, we can prove the realism of our simulation framework by validating that the input-output transformation between them is consistent. Figure 4 shows a snapshot of the theatre, and Figure 5 shows its schematic representation used to build the 3D model.

The desired speeds for the agents were fixed at a normal distribution, as in [15], with a mean of $\mu = 0.8$ m/s and a standard deviation of $\sigma = 0.2$. We conducted simulations for the evacuation according to the experiment parameters, across three distinct scenarios involving varying numbers

Source: Image from [15]

Fig. 4. Theatre snapshot.



Source: Image from [15]

Fig. 5. Theatre schematic.

Table 1. Details of Theatre Evacuation Experiments

Scenario	**No. of Evacuees**	**No. of Control Staff**	**Avg. Exit Flow** (persons/s)
1	398	13	0.54
2	540	7	0.60
3	476	2	0.59

of evacuees and control staff guiding them to safety. While the presence of evacuees with reduced mobility could potentially impact total evacuation time [11, 18], the setup outlined by Imanishi and Sano [15] included only two wheelchair users for the first and second runs and none for the third run. The results indicated no significant effects from the wheelchair users, given their small numbers and the availability of helpers prepared to assist these evacuees.

Hence, for the sake of simplicity, our simulation excludes evacuees with reduced mobility. Table 1 presents our findings, evaluating whether our model can produce exit flow rates similar to those reported by Imanishi and Sano for each scenario.

Due to the larger area and multiple numbers of exits, we have control staff to usher the evacuees towards the best exit in order to achieve the most efficient exit flow rate. A higher exit flow rate will also reduce the total evacuation time proportionally to the total number of evacuees. Hence, we simulated these scenarios and observed the resulting flow rate to validate the accuracy of our simulation framework in representing a real-world evacuation.

4.1.1 Verification & Validation. We designed the space of the theatre in Unity 3D to proportional scale based on the experiments in the case study. We used the provided bridge in Unity to access the trained CMMA model written in Python. The CMM model was written within Unity in C#. For the 3D model, the theatre has a capacity of 925 folding seats and eight wheelchair seats. The chairs are fixed to the ground and cannot be pushed away. The width between the seats of each row is 60cm. The side aisles are 75cm wide, while the middle aisle is 95cm wide.

There are a total of eight doors with similar inner widths of 165cm. In order to verify that we have built the model correctly, we will need to check that the following requirements are met:

— Space and exits are built to scale in the simulation environment.
— The locations of evacuees and staff at the start of the simulation are the same.

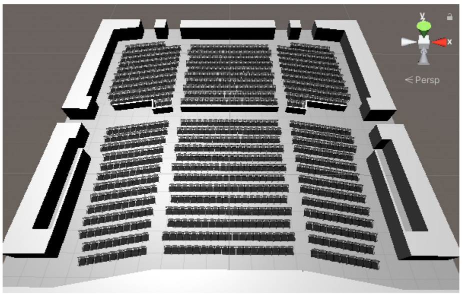


Fig. 6. Theatre model 3D.

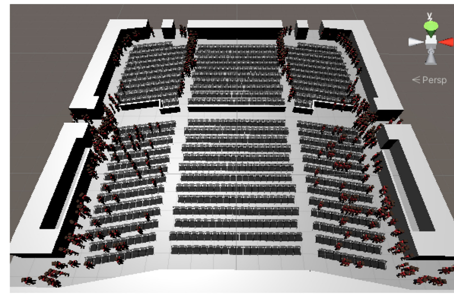


Fig. 7. Theatre evacuation 3D.

Table 2. Experiments for Theatre Exit Flow Rate (Persons/s)

Scenario	1^{st} Run	2^{nd} Run	3^{rd} Run	4^{th} Run	5^{th} Run	6^{th} Run
1	0.76	0.33	0.56	0.67	0.64	0.39
2	0.59	0.62	0.55	0.54	0.65	0.57
3	0.45	0.67	0.33	0.58	0.72	0.64

— Events and agent behaviours are represented correctly.
— The mathematical formulae and relationships we used in the simulation are valid.

Hence, for this case study, every agent is fully aware of the eight exits located around the theatre. Each agent then simply makes its way to the best exit (nearest and least congested) and may change its goal accordingly with the changing environment. Control staff are placed in between aisles and at exits without blocking the way while informing nearby evacuees of the direction towards an exit. The system then records the number of evacuees crossing the exit every second and computes the average to compare with the real system. Figure 6 shows the 3D simulation model of the theatre, while Figure 7 shows a snapshot of an evacuation being carried out in the theatre model.

Through simulations and observations, we can verify the correctness of events represented and the logical flow of our model. Next, we validate the correctness of the simulation being carried out. To do that, we evaluated its ability to behave and produce similar results to a real-life evacuation or mock drills. We ensured that the model we have built has high face validity and the model, as well as its structural assumptions, follow the experiments specified in [15]. In order to conduct the t-test, we computed the required number of replications (R) from the inequality equation below:

$$R \geq \frac{Z^2_{\alpha/2, R-1} S^2_0}{\epsilon^2} \tag{4}$$

We retrieved the population variance S_0^2 from an initial sample for each scenario and computed R with a confidence interval $\alpha = 0.1$ and a pre-specified accuracy ϵ. It was concluded that no fewer than six replications are required. Therefore, a total of six replications (runs) were executed for each scenario, s. The average exit flow for six independent runs for each scenario is reported in Table 2.

The **mean absolute errors (MAE)** of the simulation results were compared against the real-world results in Table 1. For each scenario, the MAE scores for each replication is shown in Figure 8. The average MAE across all three scenarios over six independent replications is only 0.096, with the highest error reaching no more than 0.26.

From the six independent replications (runs) for each of the scenarios, we computed the mean and standard deviation. For this hypothesis test, we evaluated whether the resulting exit flow,

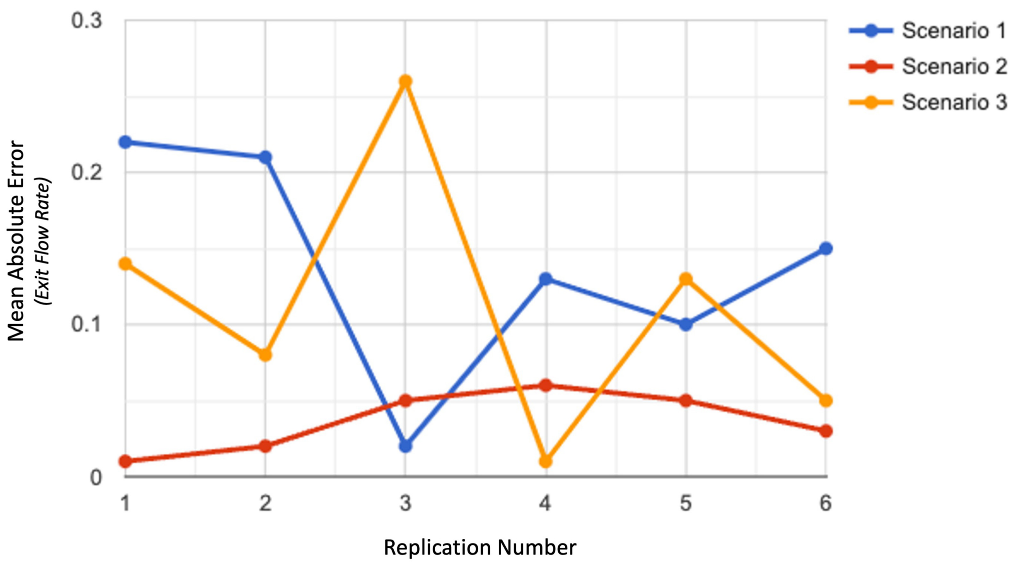


Fig. 8. Simulation vs real-world MAE scores.

Table 3. Theatre Hypothesis Test t-score

Scenario	$E(Z_i)$	Mean (μ)	Standard Deviation (σ)	t_0	Accept/Reject
1	0.54	0.56	0.17	0.29	Accept
2	0.60	0.58	0.04	1.22	Accept
3	0.59	0.57	0.15	0.33	Accept

given by function E, from the simulation, Y, and the real system, Z, are the same. We derived the null hypothesis H_0 and the alternate hypothesis H_1 as follows:

Hypothesis $\mathbf{H_0}$. : $E(Y_i) = E(Z_i)$ *seconds*

Hypothesis $\mathbf{H_1}$. : $E(Y_i) \neq E(Z_i)$ *seconds*

With a level of significance of $\alpha = 0.05$, and sample size ($n = 6$), we computed the t-score t_0 for each scenario s with the mean μ_y^s and standard deviation σ_y^s against the true value $E(Z_i)$, with Equation (5) and reported the results in Table 3.

$$t_0^s = \left| \frac{\mu_y^s - E(Z_i)}{\sigma_y^s / \sqrt{n}} \right| \tag{5}$$

The critical value for a 2-sided test was $t_{critical} = 2.571$. Table 3 showed that all the t-values are lower than the critical value. Hence, we can safely accept the null hypothesis H_0 proving that the average exit flow for each scenario from our simulation is similar to the output results from real-life evacuations. Regardless of the size of evacuees, the average flow rate at the exits does not vary significantly, which makes sense since the door sizes do not change. Through this input-output transformation, we confirmed the model's ability to correctly simulate an emergency evacuation, in this scenario of a theatre, realistically. We were also able to observe realistic changes in the resulting output when the input data was modified accordingly.

4.1.2 Simulation Experiments & Discussion. We evaluated the emergency movement behaviour of the CMM for this scenario by observing the changes in speed. State-of-the-art methods in

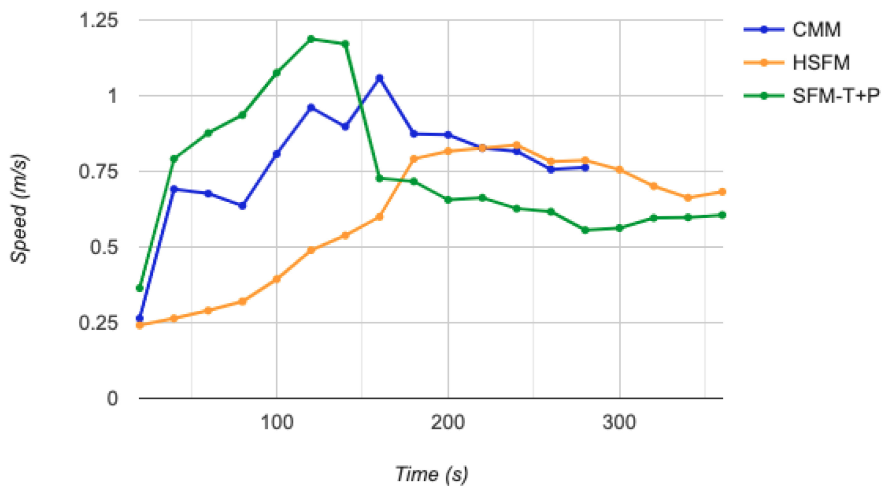


Fig. 9. Theatre: Speed changes.

trajectory prediction was shown to be less than ideal for such evacuation simulations in [30]. Thus, we will evaluate the experiments on the popular **Headed Social Force Model (HSFM)** [9] and the **Social Force Model with Tolerance** [42] and **Panic** [12] **(SFM-T+P)**. Figure 9 show the speed changes between the three different models based on six independent replications. We simulated Scenario 1 on all three behaviour models to observe the changes in speed. The simulation parameters were set up accordingly as in Table 2.

We can observe similar issues through this analysis. The changes in speed show how the HSFM was unable to display any phenomena of urgency in emergency evacuations. Even when there is more space to pick up speed towards the exit, the HSFM would comfortably increase its speed to the desired pace and eventually pass through the exits with minimal arching and clogging at bottlenecks. As we have learnt from social science theories and observational studies [17], such phenomena are common in emergency evacuations. Due to the absence of any influential variable that can reflect appropriate urgency in evacuation for the HSFM, this behavioural model is not ideal for such critical simulations. As for the SFM-T+P, it showed a quick increase in speed before a sudden drop when most agents have reached an exit. The average speed then continues to drop as the repulsive forces come into play, causing agents to bounce off one another before sliding past the exit. As a result, the total evacuation time was much higher than the results from the real-life case study on average. Again, the CMM was able to reflect a much smoother change in speed that showed an initial surge as agents begin to evacuate, and then slow down when approaching the exits to allow efficient egress. We show in Figure 10 a closer study on the changes in speed of the CMM against the development of calmness over time.

Since the HSFM has no urgency term, while the SFM-T+P only has a fixed panic threshold that influences urgency, we cannot measure the development of emergency behaviour in these two models. However, for the CMM, the computation of calmness based on an individual's perceived level of risk allows us to quantitatively analyse the development of calmness and its effects on the average speed of egress. We found that in a large setting such as a theatre, the level of calmness drops more gradually as compared to a smaller space such as a classroom [30]. We can also see the average speed increasing as the level of calmness drops. However, the average speed begins dropping at a period where everyone was already at the exit area waiting for the exits to unclog. At this point, the level of calmness continues to drop. As more evacuees leave the scene, we can see

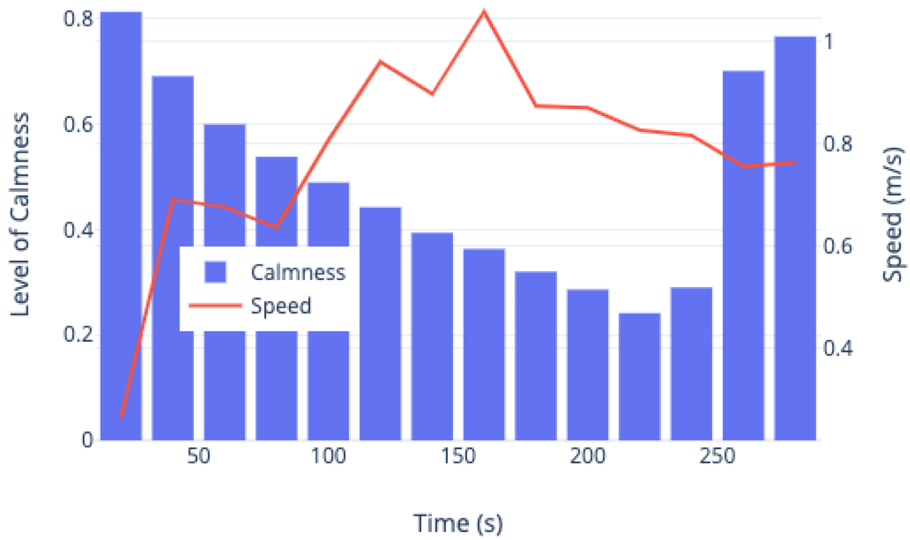


Fig. 10. Theatre: Development of calmness vs average speed over time (CMM).

Table 4. Categories of Moving Speed

Category	Slow Walk	Fast Walk	Jogging	Running
Speed Range (m/s)	1.21 - 1.75	1.76 - 2.21	2.22 - 2.68	2.69 - 2.97

the level of calmness begins restoring to normal, and the average speed becomes more regulated. This logic can also be expected in a real-life scenario.

Having shown the performance of the CMM against other recent behavioural models and its realism in reflecting emergency behaviour, we can now use the proposed simulation framework to simulate different scenarios and observe different metrics for effective analysis. For a larger simulation such as this case study, there are a number of things that can be considered for optimization such as the size of doorways, the number of doors, the spaces between aisles, the number of control staff to facilitate evacuation, and how different numbers of evacuees and speeds can affect evacuation time. For this evaluation, we will focus on an average capacity of 470 evacuees evacuating through eight 1.65m exits at different categories of walking speed listed in Table 4 [43]. We can then observe how control staff placed at strategic points may affect the overall exit flow rate.

Although control staff were set as a scenario parameter for verifying the similarity of our simulations to the real-life evacuation drill, we strategically place the control staff in our experiments to assist in the distribution of traffic flow so as to improve the resulting evacuation time. As such, the placement of control staff is now a strategy parameter in our optimization experiments. Assuming the theatre is an existing site where we cannot change the size of aisles and doors, or the number of exits, the resulting egress rate based on occupancy and speed can still be optimized through strategic placements of control staff to facilitate evacuation effectively. Hence, we will study the effects on the exit rate with different numbers of control staff deployed at different placements. For both scenarios, we experimented on the exit flow rate with 0 to 8 control staff randomly placed at strategic spots in the theatre. Figure 11 shows the possible placements of control staff at exits, while Figure 12 shows possible placements of control staff at major aisles.

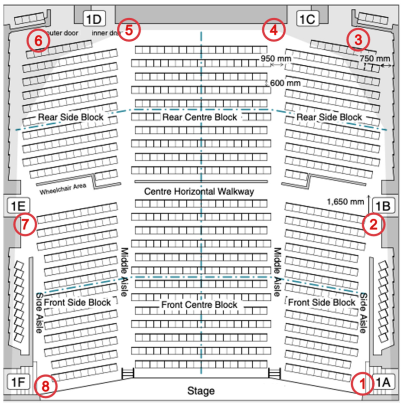


Fig. 11. Staff placements at exits.

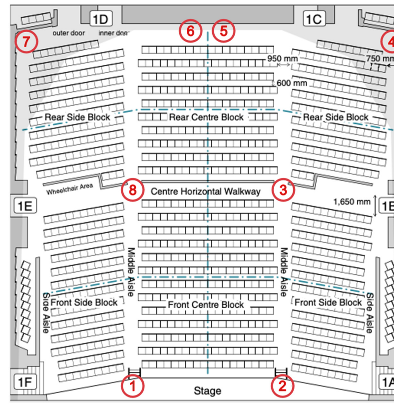


Fig. 12. Staff placements at aisles.

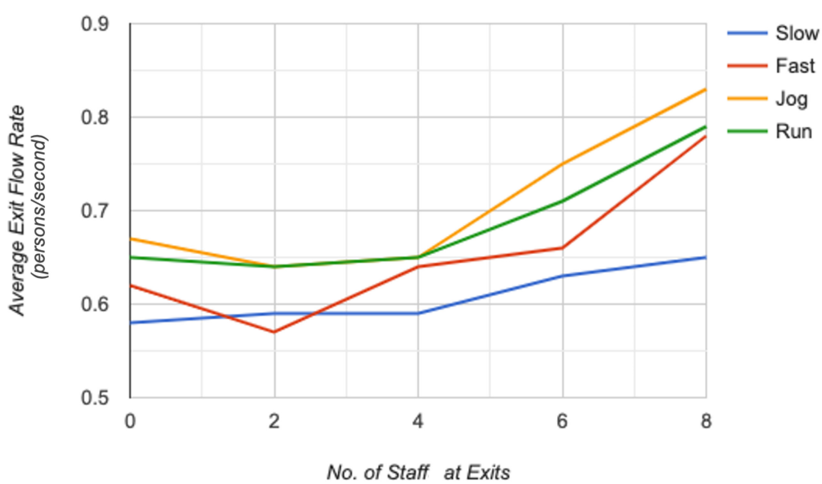


Fig. 13. Case study II: Exit rate with staff at exits.

Figure 13 shows the exit rate for Scenario 1 with control staff at exits, while Figure 14 shows the exit rate for Scenario 2 with control staff at major aisles. They show how different speeds may change the exit flow rate and how different numbers of control staff were able to regulate the flow of exit as well.

Based on the graphs, we can see that placing staff at aisles can regulate the flow much better as compared to placing them at exits. This is possibly due to the clogging happening at exits. Placing a staff there may block the exit or produce no results since evacuees coming to that exit must have already made the decision to use that exit. On the other hand, staff placed at aisles were able to give evacuees advanced information on which is the best exit they should take and regulate their speed earlier before clogging at the exits starts to form.

The regulation of speed is crucial since we can see how running speed usually results in a much lower exit rate as compared to jogging speed. The results also showed that placing a few control staff (2 - 4) made almost no difference. We deduced that just a few staff is not sufficient to make a significant impact in large areas such as this theatre. Although we can see some significant effects in the average exit flow with more control staff (6 - 8), our goal is to reduce casualties

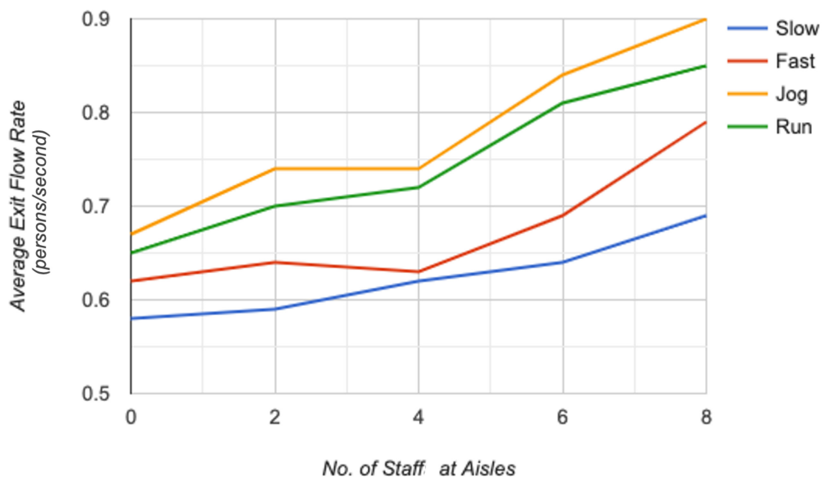


Fig. 14. Case study II: Exit rate with staff at aisles.

without adding more people that could end up as casualties themselves. Thus, finding the optimal configuration for effective egress is pertinent.

4.2 Prescriptive Analytics

The theatre case study we have evaluated is of a bigger area than the classroom case study done in [30], with many strategic options available to improve the average evacuation time. Hence, we will use this case study and apply the proposed prescriptive analytics method to derive optimal strategies to adopt in an emergency evacuation. The proposed methods can allow for automated simulation runs for each of the strategies generated for every fire evacuation scenario that a user wishes to study. Through the simulation runs, the user-defined measures will be recorded for output analysis to determine the best strategies to adopt. The strategic options we can supply to the strategy generation algorithm may include, but are not limited to, the following:

— Number of doors: for high evacuation time
— Size of doors: for congested doorways
— Number of control staff: for heavy traffic flows

To simplify this experiment, we will study a single evacuation scenario and seek to find the best combination for the number and placement of control staff facilitating the evacuation. The number of doors, size of exits, and the width of aisles, will remain the same in order to focus on improving the regulation of evacuation flow. The measure we will optimize is the total evacuation time. The experiment was set up with 470 evacuees, evacuating through eight 1.65m exits at a normal distribution of speeds between 1.21 - 2.97 m/s, with mean $\mu = 2.09$ and standard deviation $\sigma = 0.29$. The initial simulation will provide the following strategic options with a range of 4 to 16 available resources to deploy:

— Control staff at exits: for congested doorways
— Control staff at aisles: for heavy traffic flows

The simulation framework with prescriptive analytics should then help us find the optimal placement and number of control staff to deploy in this theatre evacuation scenario. Figure 15 shows the traffic flow with control staff only at exits, while Figure 16 shows the traffic flow with control staff only at aisles.

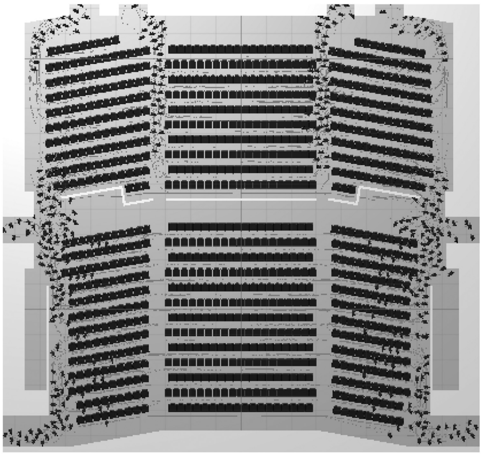


Fig. 15. Traffic flow: Staff at exits.

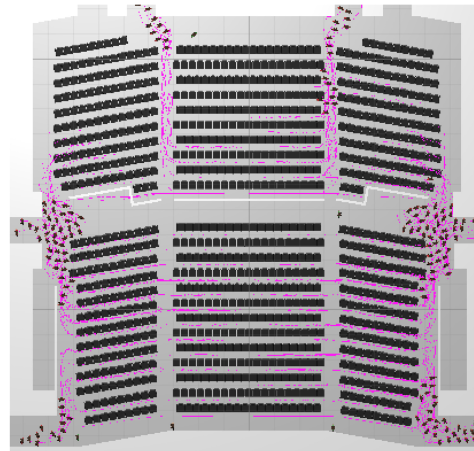


Fig. 16. Traffic flow: Staff at aisles.

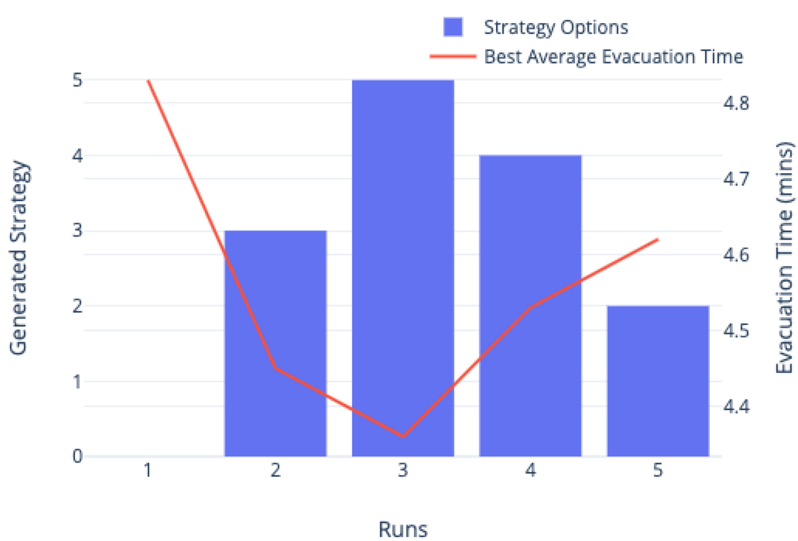


Fig. 17. Optimization for prescriptive analytics.

After the first simulation run, Algorithm 2 will then redeploy the control staff at positions with high traffic flow accordingly with the knowledge of minimum cost paths to guide the evacuees. We can see from Figure 15 that the flow of traffic is quite distributed among all the exits when there are control staff placed only at exits. In Figure 16, when control staff are only placed at aisles, we found that the flow of traffic is heavily congested at the middle exits while the exits at the top are quite empty. However, experiments in Section 4.1.2 suggest that placing control staff at aisles resulted in a much better overall exit flow rate. This is due to the regulation of speed from the control staff at the aisles that are not blocking the exits. Hence, we see how there is a need to combine both the placements at exits and aisles to derive an optimal solution.

Figure 17 shows the optimization process from Algorithm 2. For each run, we plotted the number of strategies generated and the best average evacuation time among all strategies for that run. Each strategy is simulated over 10 replications. We started with no strategies at all (0 staff at aisles and 0

Table 5. Prescriptive Analytics Report

Rank	Placement at Aisles	Placement at Exits	Average Evacuation Time
1	2	4	4.36 mins
2	4	2	4.39 mins
3	6	8	4.45 mins
4	4	4	4.53 mins
5	4	6	4.60 mins

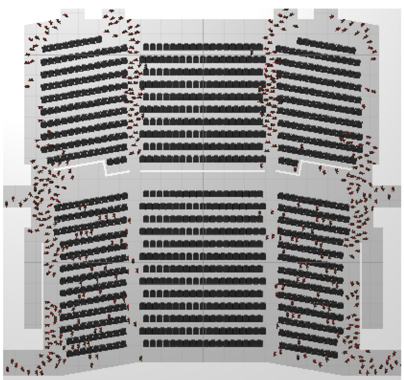


Fig. 18. Evacuation at 1-minute.

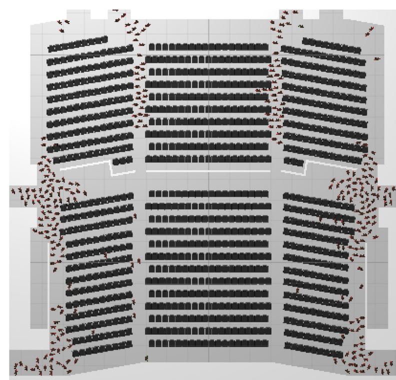


Fig. 19. Evacuation at 2-minutes.

staff at exits). Referring to Algorithm 2, the first run will generate 10 strategies based on the MCF network. Out of the 10 strategies, only 3 were unique. As such, the second simulation run would simulate 3 different strategies over 10 replications each, generating 30 strategies of which only 5 were unique. This is reasonable considering for each strategy, the min-cost paths through several replications would usually be about the same, thus producing the same strategy result.

With reference to Figure 17, the first run reported over 4.8 minutes for the best average evacuation time. The optimization then generated three strategy combinations (strategy options) to be executed in the second run. The process repeats until no better average evacuation time was found after two consecutive runs. Finally, we recommend the top strategies to adopt based on the best average evacuation time found. Table 5 presents the top 5 combinations with their corresponding average evacuation time.

The report shows ideal combinations, which otherwise would have been difficult to derive manually or by trial and error. From the original case study of real-life evacuations, the average evacuation time is about 4.83 minutes, with a few different combinations of control staff deployed around the theatre. In our simulation for finding the ideal number and placement of control staff to be deployed, we found a maximum of up to 5.42 minutes of average evacuation time as the worst combination. Ultimately, we found that the ideal combination is to have 2 control staff to regulate traffic at the aisles and 4 of them placed at exits to guide evacuees and maximize the available exits. Figures 18–21 show the progression of the simulated evacuation (with no strategies employed) at 1 minute, 2 minutes, 3 minutes, and 4 minutes, respectively.

In this proof-of-concept, we have demonstrated a single-objective optimization utilizing min-cost flow to recommend optimal staff placement configurations, enhancing the efficiency of the evacuation process. The flexibility inherent in the framework extends to the ability to switch optimizers and objective functions, facilitating the utilization of Pareto methods for

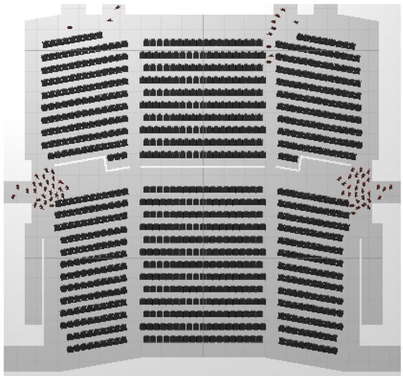


Fig. 20. Evacuation at 3-minutes.

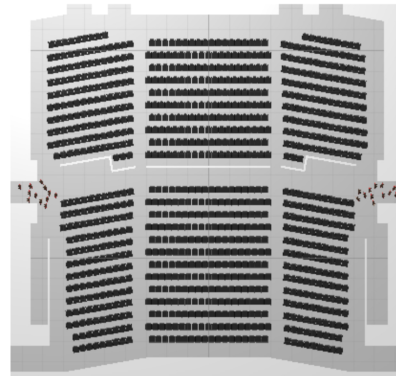


Fig. 21. Evacuation at 4-minutes.

multi-objective optimization. With the implementation of our proposed framework, we have established a more effective approach for examining evacuation systems that incorporates realistic behavioural reactions, thereby enhancing the capabilities for prescriptive analytics.

5 CONCLUSIONS

We introduced a simulation framework for integrating intelligent agents trained from real-life video, enabling realistic responses to emergencies. This framework, driven by predefined output measures, autonomously generates strategies and optimal solutions for diverse case scenarios. Our findings have been shown to advance the current state of the art in related fields. The focus on emergency evacuations addresses a crucial real-world problem, offering a comprehensive study given the range of potential crisis events worldwide. However, any influences from various types of crises will necessitate careful investigation and integration with our proposed methods. To that end, we achieved our goals of enhancing the realism of emergency evacuation simulations through high-accuracy behavioural modelling and designing a simulation framework with prescriptive analytics to recommend ideal strategies for authorities to adopt.

In summary, we utilized a recent novel solution, the Conscious Movement Model (CMM), that learns pedestrian dynamics from video through the Conscious Movement Memory-Attention (CMMA) model. We thoroughly evaluated the CMM on its emergency behaviour by analysing how urgency develops throughout the evacuation. A realistic simulation can result in a better and timely strategic response for several disaster events occurring all around the world. The contributions made through this research can see the possibility of its application into real-world systems such as traffic or crisis management. Its successful application in the real world can lead to lives being saved or rescued in disaster situations. Such potential impact will certainly push the boundaries of several research areas surrounding this work.

5.1 Recommendations for Future Research

Our research presents a novel approach to simulating emergency evacuations, incorporating realistic human behaviour and offering strategy recommendations for real-world evacuation operations. This advancement enhances the authenticity of critical simulations, particularly in crisis management, with potential global benefits. To further advance this research, we emphasize the need for improved optimizations and the introduction of distributed parallel architectures to enhance performance speed.

For future work, addressing the speed performance of proposed methods is crucial. Exploring the integration of additional functionalities for advanced simulation systems and incorporating efficient parallel and distributed architectures, such as leveraging GPUs for training the CMMA model, can significantly enhance processing speed. Developing a distributed architecture for the simulation framework could optimize strategy options and scenario outputs, improving overall efficiency for authorities during unprecedented crisis events.

Furthermore, collaborative efforts with relevant authorities to obtain actual crisis data can be instrumental in refining and evaluating the emergency behaviour of the proposed behavioural model. In conclusion, this work establishes a robust foundation for advancing realistic behavioural modelling in crisis simulation, paving the way for future significant contributions in the field.

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