TRB Annual Meeting

A Hybrid Machine Learning and Microsimulation Framework for Simulating Metro Station Evacuation

--Manuscript Draft--

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ABSTRACT

The Mass Rapid Transit (MRT) is recognized as an efficient transportation mode globally. However, MRT stations are the place of large-scale pedestrian activities and are consequently susceptible to a multitude of potential risks and hazards, which may trigger small to large scale evacuations of the stations. This study develops a pedestrian evacuation microsimulation modeling framework that considers a wide spectrum of pedestrian behavior revealing different levels of panic during a metro station evacuation. The combined Latin Hypercube Sampling technique and Random Forest modeling are employed to generate pedestrian behavior parameter combinations, which are used for calibrating the simulation model and simulating panic evacuation conditions. The simulation model is calibrated using a Genetic Algorithm and validated through Geoffrey E. Havers statistics utilizing the CCTV data. Results suggest that the average speed fluctuates in the case of low panic evacuations, whereas it stays stable for medium and high panic scenarios. In low panic, most pedestrians evacuate in the latter half of the evacuation time. In medium panic, evacuations are spread out, and in high panic, peaks occur in the first and last thirds of the total evacuation time. Additionally, at the peak hour of the MRT station with 540 people, the total clearance time in low panic, medium panic, and high panic scenario was found to be 5.25-6.47 minutes, 5.12-5.25 minutes, and 4.90-5.07 minutes, respectively. The results of this study are vital for designing countermeasures to evacuate the MRT stations safely and efficiently during emergencies.

Keywords: Evacuation, Panic, Metro rail transit, Microsimulation, Random Forest, Advanced sampling, Pedestrian

1 INTRODUCTION

The Mass Rapid Transit (MRT) system has been recognized as an efficient transportation mode globally due to its large transportation capacity, high speed, eco-friendliness, and low energy consumption (*1*). The continuous population growth in megacities has led to a significant and consistent increase in travel demand for metro systems, making the metro stations heavily-crowded with pedestrians waiting for, boarding and alighting from the metro transit (*2*). Metro stations are the place of large-scale pedestrian activities and are consequently vulnerable to many potential risks and hazards such as fire, train failure and terrorist attacks (*3*). The occurrence of these events may trigger large-scale evacuation of the station. London Kings Cross station fire (*4*) and the 1995 Metro Baku fire are two exemplary metro station disasters that caused the deaths of more than 300 people (*5*). Additionally, more than 365 individuals were injured, suffering from burns, smoke inhalation, and other injuries sustained during the panic and evacuation (*6*). Post-accident reports of metro or subway disasters consistently revealed shortcomings in pedestrian evacuation planning and strategies. For instance, the tragic events at Daegu subway (*7*), where a fire originating in one train extended to another halted on the platform, resulted in a substantial loss of life and extensive damage. Given the nature of an emergency, the potential for injuries and casualties could be exceptionally severe. Thus, safe emergency evacuation in metro stations is a critical concern in the overall safety of passengers and the metro rail system (*8*).

The way passengers react in emergencies such as their speed, direction and decision-making under panic significantly influences the overall effectiveness of an emergency evacuation. The current body of literature accounts for panic behavior, psychological aspects, and crowd density to understand the intricacies around pedestrian evacuations during an emergency (*9*). However, these studies are deterministic in nature that define a condition with static measures of behavioral parameters and falls short in fully elucidating the extent of panic despite the great implications the wide levels of panic may have on evacuation process and time (*10*). A full-scale exploration of pedestrian behavior, particularly within and across different levels of panic, would aid in understanding evacuation dynamics, particularly for metro stations with high presence of pedestrian traffic. Additionally, there is a clear gap in extensive calibration and validation of the pedestrian simulation model due to the lack of data availability hindering the application of the state-of-the-art methods, including machine learning and optimization approaches for calibration purposes.

The objective of this study is to develop a pedestrian evacuation modelling framework considering a wide-ranging pedestrian behavior revealing different levels of panic conditions during a metro station evacuation. The study develops a pedestrian simulation model that implements the Social Force model (SFM) (*11*) to articulate pedestrian behavior during contrasting evacuation conditions. This research employs machine learning and advanced optimization and sampling techniques to calibrate and validate the simulation model and evaluate evacuation scenarios for a comprehensive analysis of the impacts of panic of different extremes on overall evacuation performances. Additionally, this study provides insights into the evacuation dynamics during evacuation in the light of results on evacuation flow and time across different panic scenarios which complements the increasing call for the analysis of pedestrian dynamics (*12*).

2 LITERATURE REVIEW

This literature review is primarily divided into two parts. The first one focuses on research related to pedestrian behavior during emergency evacuation scenarios. Past emergency events in MRT stations, such as the 2021 Manila MRT-3 fire, the 1995 Metro Baku fire, the 2000 Kaprun railroad tunnel fire, and the 2003 Daegu subway fire highlight the importance of efficient passengers evacuation (*13*). A study proposed an optimization approach for passenger evacuation from multi-exit subway stations by dividing station into four regions to ensure partitioned evacuation and implementing railings to reduce congestion (*14*). Meanwhile, another study introduced a guidance scheme aimed at enhancing evacuation in metro stations through the integration of an improved empirical formula (*15*). Their approach integrated pedestrian characteristics to evaluate the influence of pedestrian behaviors on evacuation efficiency. The findings of these studies emphasize improvement strategies while they fail to articulate differences in pedestrian movement behaviors (e.g., pushing, cooperation) in various conditions, including panic. Due to the confined spaces and overcrowding in MRT stations, emergencies can easily trigger panic among the people (*16*), which may further influence pedestrian speed and pushing behavior and impact the overall evacuation time.

Studies have recently started focusing on panic behavior in evacuation simulation modeling. A research simulated the evacuation and sheltering processes to conduct risk assessments of crowd congestion based on factors related to seismic risk in MRT systems using a spatial evacuation risk model (*17*). This study incorporated pre-evacuation response times of 30 to 60 seconds to account for potential panic behavior and then panic behavior was simulated in Pathfinder in steering mode. Another study proposed a framework integrating Random Forest (RF) and Non-dominated Sorting Genetic Algorithm III (NSGA-III) for evaluating and optimizing evacuations at metro stations, considering scenarios based on passenger volume and panic level (*9*). The evaluation criteria include evacuation time, density, and cost, while inputs are passenger volume, walking speed, herding behavior rate, number of fare gates, exits, and obstacles. The average passenger walking speed and herding behavior rate were used to represent the panic level in the study. However, the abovementioned studies articulated panic in an ad-hoc fashion and/or through one point specification of behavioral parameters. While a level of panic can be demonstrated over a range of change in criteria specifications (e.g., a speed range for low panic) *(18)*. This approach does not capture the full spectrum of panic behaviors that might emerge in real-world scenarios. In another study, a hybrid approach that integrates Building Information Modeling (BIM), Anylogic, and machine learning to simulate evacuation events and implement proactive evacuation strategies (*19*). Panic levels are addressed in the study by correlating it with congestion. A time period-based over-density rate rule is proposed to evaluate evacuations and determine if more congestion occurs due to existing congestion. However, defining panic based on congestion without the consideration of wide-ranging pedestrian behavior may not fully unfold their decision-making under stress *(20)*. Similarly, another study employed the ripple effect principle to simulate the spread and acquisition of information in a panic in the metro stations (*21*). Their model integrated panic-driven information dissemination and simulated decision-making through herd behavior to predict self-evacuation. Another study examined evacuation dynamics in subway stations, classifying pedestrians into three categories based on distinct force models, where one of the categories is panic pedestrians (*22*). The panic pedestrians are characterized by their attempts to overtake others and seek the shortest route to exits. A microsimulation modeling study examined pedestrians' social and physiological behaviors during airport evacuations, particularly focusing on how these behaviors vary across panic levels, where panic was defined by a rigid set of parameter combinations (*23*).

The second part of the review examines best practices in simulating and optimizing evacuation dynamics. Micro-simulation allows for detailed modeling of individual pedestrian movements, providing insights into peoples' behavior in different scenarios. These analyses employ different mathematical models, for instance the SFM model (*24*), Space-Syntax based agent simulation (*25*), Cellular Automata models or the PedGo model. Among these, the SFM was initially proposed in (*11*) and is a widely-used crowd model that's applied by many simulation software packages (*26*). It simulates crowd behavior by considering interactions between pedestrians based on physical forces. However, as traditional SFM fails to capture the complexity of diverse crowd scenarios effectively, many studies either modified social-force model or used it in combination with other algorithms to increase efficiency. For example, integration of the SFM with an exit choice model was used to analyze the influencing factors (pedestrian density, distance from pedestrian to exits, and exit width) of different pedestrian categories in the multiple-exit scenario (*27*). Another study combined SFM with fire dynamics model, to find out the safe design parameters of metro stations, considering pedestrians' impatience and psychology (*2*). In another research, the collision avoidance mechanism of the classical SFM was improved to avoid the overlap between people or between people and walls (*28*). Combination of the SFM with deep learning models for pedestrian detection in crowd evacuation at subways, demonstrated superior realism compared to traditional simulation models (*29*).

Similar to the study of (*9*), other studies used various data and feature analysis methods along with SFM and simulation tools to eliminate redundant information from the dataset to derive an optimal subset of features (*30*). Random Forest (RF) is another popular feature analysis tool that involves growing multiple decision trees and combining their outputs to make predictions and optimizations in evacuation dynamics. In evacuation studies, the RF algorithm has been used to predict and identify significant factors affecting household evacuation time using demographic and behavioral variables (*31*) and to delineate evacuation zones (*32*). However, they have been limitedly used to determine pedestrian panic behavior and calibration purposes. Moreover, a tendency exists to conduct calibration and validation of the pedestrian simulation model together based only on count data, which can resemble the observed counts with or without representative values of important simulation parameters *(33)*. This necessitates distinct calibration and validation processes for different criteria. The calibration of simulation model involves a large volume of data and parameter combinations that requires optimization processes to identify the best combinations of pedestrian behavior parameters to resemble the pedestrian behavior within the simulation model.

The contribution of this study is that it develops a methodological framework of evacuation modeling accounting for a wide-ranging pedestrian behavior to analyze the impacts of various panic levels on evacuation performances. A simulation model is developed, calibrated following a Genetic Algorithm (GA) and validated in terms of Geoffrey E. Havers (GEH) statistic. The Latin hypercube sampling (LHS) method is used to generate a distribution of plausible scenarios by systematically sampling from the input variables' ranges and then RF algorithm is used on gathered dataset to determine key behavioral parameters. Results from the LHS and RF are then used to simulate evacuation scenarios of different panic levels. Finally, simulation results are analyzed to provide insight into crowd dynamics in contrasting conditions.

3 STUDY AREA

The Dhaka Metro Rail is a rapid transit system that operates in Dhaka, the capital and largest city of Bangladesh. Since its launch, ridership has been continuously increasing, growing from just over 100,000 in 2023 to 290,000 in 2024. With this rising number of passengers, the demands for crowd management within the Dhaka Metro have become critical. Thus, this research focuses on one of the busiest metro stations in Dhaka, Agargaon to explore the evacuation scenarios. Agargaon station as shown in **Figure 1** is an elevated one, situated centrally along the line that connects Motijheel and Uttara. The station is surrounded by numerous shopping malls, bus interchanges, hospitals, and a central passport office. It also houses the central offices for metro operations. The station features two levels: the concourse on level 1 and the platforms on level 2. The station regularly experiences significant passenger volume, particularly during peak hours. This underscores the urgent need to assess and optimize the safety measures for evacuating Agargaon station during high traffic scenario.

(a) **(b)**

Figure 1 (a) and (b): Agargaon Metro Station, Dhaka

4 METHODOLOGY

The methodology of this study consists of three steps: (i) Development of a pedestrian microsimulation model employing SFM walking behavior parameters, (ii) Generation of behavioral parameter combinations through combined LHS and RF Regression Feature Importance techniques, (iii) derivation of panic evacuations and analysis. The overall framework of this study is illustrated in a flow-chart showcased in **Figure 2**.

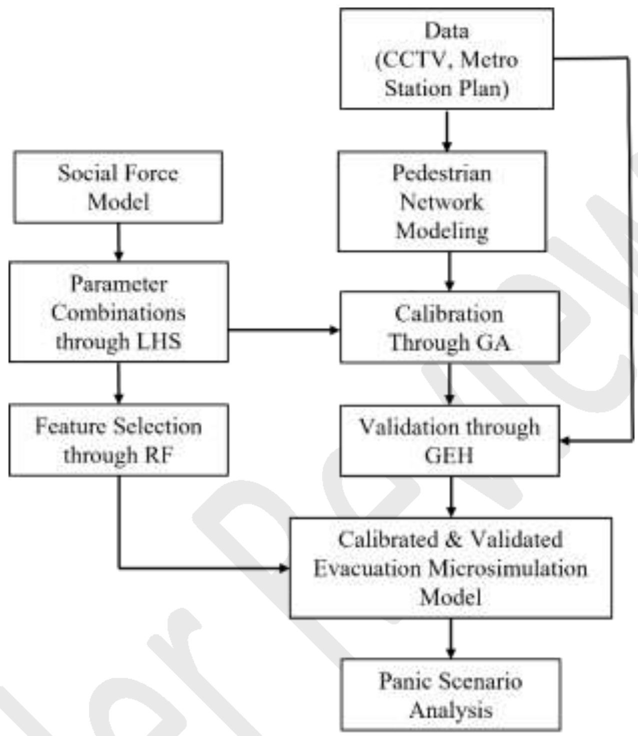

Figure 2 Methodology Flow-chart

Initially, a pedestrian simulation model is developed utilizing multiple datasets, including CCTV footage, and metro station plans. Using the SFM parameters, LHS combinations of parameters were generated which were utilized for: (i) the Genetic Algorithm (GA) in calibration process, and (ii) the RF Feature Importance Analysis. CCTV data is used, and GEH (Geoffrey E. Havers) statistics are developed to validate the simulation model. Then the evacuation scenarios are generated and simulated based on the criteria derived from the RF modeling. LHS is re-applied on the RF-identified features to generate feature combinations representing a set of evacuation scenarios for simulations. The calibrated values of the features of the base model that are not identified as influential in the RF modeling stage are retained for evacuation scenario analysis. Panic evacuations are derived from the simulations of evacuation scenarios and analyzed accordingly. In depth description of all the steps are given in the following sections.

4.1 Development of Pedestrian Microsimulation Model

Pedestrian Network Coding

The Agargaon station was replicated within the VISWALK simulation platform encompassing two levels, occupying a 180 x 26 meters area with four exit stairways located near the four corners of the station on the second level. The third floor has two tracks in the middle and platforms on both sides. The second floor has ticket counters, ticket vending machines, control unit, stairs and multiple restricted portions coded as "Blockage". Elevators are also considered blockages, as they are assumed to be shut down in accordance with standard emergency procedures. The simulation model is showcased in **Figure 3 & 4**. All the necessary data including CCTV footage for pedestrian flow count and average speed along with the station floor plan was collected from Dhaka Mass Transit Company Limited (DMTCL). From the 12-hour video footage of a typical working day, the peak hour was identified to be from 5 PM to 6 PM and the passenger flow in that hour was 3189. The average speed during the peak hour in different areas (Entry/Exitways, stairs, etc.) was used for base model calibration and the total passenger flow within that time was used for validation.

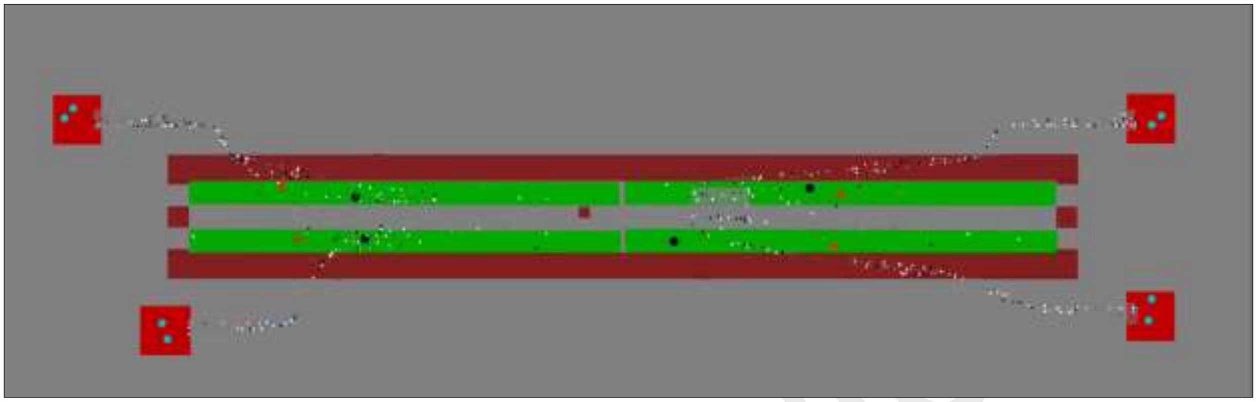

Figure 3 Base Model (Top View)

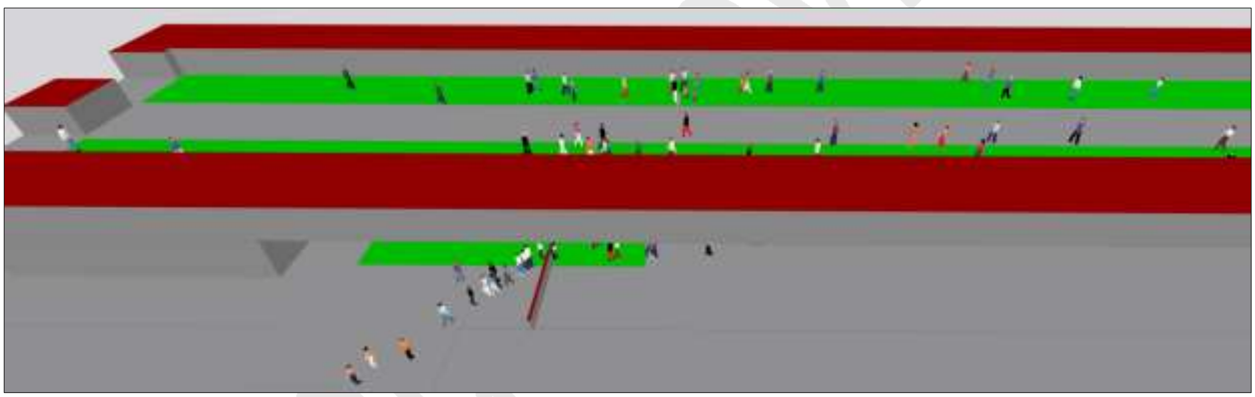

Figure 4 Base Model (3D View)

For the evacuation model, after calibrating the SFM walking behavior parameter values to impart panic amongst passengers, the pedestrian routes were altered with an assumption that the passengers will always choose the nearest exist during emergency. The highest number of occupants at a single moment of the MRT station was calculated to be 528 and the pedestrian inputs for the evacuation model was adjusted accordingly.

4.2 Pedestrian Behavior Parameters: Social Force Model

Social forces in SFM consider interactions among pedestrians, involving repulsion to avoid collisions, attraction toward desired destinations, and other factors influencing personal space. According to (11), pedestrian motion can be conceptualized as the outcome of individuals being influenced by various forces. Physical forces account for the impact of obstacles like walls. Psychological factors, such as urgency and comfort, also influence how individuals navigate through a crowd. Pedestrians in behavioral models have specific goals, and the forces are iteratively calculated to guide their movements, ensuring collision avoidance and maintaining personal space. Force *F*, which prompts pedestrians to either decelerate or accelerate can be calculated by **Equation 1**.

$$F = F_{\text{driving}} + F_{\text{social}} + F_{\text{noise}} \quad (1)$$

In the context of the SFM as applied in VISWALK, the forces influencing pedestrian behavior are directly related to the parameters described in **Table 1** (*34*). The parameter "Side preference" was not utilized in this study as it was found to be indifferent for the study area.

TABLE 1 SFM Parameters in Pedestrian Simulation

Parameter	**Description**	**Standard Values**
Tau (τ)	Represents the reaction time of pedestrians. In conjunction with the desired velocity and current velocity, tau determines the driving force, $F_{driving}$. Reducing tau increases both acceleration and the driving force. Consequently, decreasing tau can shorten the throughput time in narrow passages.	0–1
Lamda (λ)	Accounts for the reduced influence of people and events behind a pedestrian compared to those ahead. It affects the social force, F_{social}.	0–1
ReactToN	Determines the maximum number of pedestrians considered when calculating the social force, F_{social}.	≥0
VD	Considers the relative velocities of pedestrians and contributes to the social force, F_{social}. Increasing VD causes pedestrians to evade each other earlier when passing or meeting.	≥0
ASocIso & BSocIso	Governs the direction-dependent force between pedestrians.	ASocIso = 2.72 BSocIso = 0.2
ASocMean & BSocMean	Typically associated with the repulsive forces that govern the interactions between pedestrians	ASocIso = 2.1 BSocIso = 0.3
Noise	Determines the strength of the random force term, F_{noise}. This term is added after all other forces have been calculated, but only if a pedestrian is slower than their desired speed for a certain time.	0–2

4.3 Latin Hypercube Sampling of SFM Parameters

LHS, introduced in (*35*), is a statistical approach for creating a quasi-random sample of parameter values from a multidimensional distribution. In this method, a Latin hypercube generalizes the concept to an arbitrary number of dimensions, ensuring that each sample stands alone in each axis-aligned hyperplane containing it.

For *X* parameter with range *[a, b]*. The range is divided into *n* intervals showcased in **Equation 2**:

$$\Delta x = \frac{b-a}{n} \quad (2)$$

Each interval I_i for *I = 1, 2 ,..., n* is defined as shown in **Equation 3**:

$$I_i = a + (i - 1)\Delta x, a + i\Delta x) \quad (3)$$

For each interval I_i, a sample point x_i is chosen uniformly at random as **Equation 4**:

$$x_i = a + (i - 1)\Delta x + U_i \Delta x \quad (4)$$

Here, U_i is a random number drawn from the uniform distribution *U(0, 1)*.
For *k* be the number of parameters. For each parameter x_i where *j = 1, 2, …, k*, an $n \times k$ sample matrix *S* is constructed as shown in **Equation 5**:

$$S = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \quad (5)$$

Here, x_{ij} is the sample from the *i*-th interval of the *j*-th parameter.

For this study, LHS was utilized to generate parameter combinations. Initially, the standard values and ranges of the 9 SFM parameters were sampled using LHS to generate 100 combinations in which there was no repetition of a single value for a particular parameter to avoid clustering. Instructions were provided to not generate more than 3 decimal places due to the input restrictions in VISWALK. These 100 combinations were used firstly as inputs in the GA for base model calibration and secondly as the dataset for RF Feature Importance analysis. Another 500 combinations were generated after obtaining the results from the RF analysis but this time only the identified important parameters were sampled. The outputs from these 500 combinations were used to divide panic levels and conduct comparative analysis.

4.4 Base Model Calibration

The calibration of the simulation model is crucial for accurately simulating pedestrian dynamics and behaviors in various environments. By fine-tuning model parameters, calibration ensures that the simulation results are reliable, thereby enhancing the predictive accuracy of the model. For this study, the average speed of pedestrians across four different areas were gathered from CCTV footage and on-site analysis. To match the simulation average speeds with the observed values, a GA was utilized. GAs are search and optimization algorithms based on the principles of natural evolution, which were first introduced by john Holland (*36*). These implement optimization strategies by simulating evolution of species through natural selections. It is generally composed of two processes. First process is selection of individual for the production of next generation and second process is manipulation of the selected individual to form the next generation by crossover and mutation techniques (*37*). A fitness function is typically used to score the accuracy of a set of provided training examples. This study utilized the Mean Absolute Percentage Error (MAPE) as the fitness function to calibrate the VISWALK model as it has proved to be reliable in similar endeavors (*38*). MAPE can be defined as shown in **Equation 6.**

$$f = \frac{1}{N}\sum_{i=1}^{n} \left| \frac{V_{obs} - V_{sim}}{V_{obs}} \right| \times 100 \quad (6)$$

The fitness value of the average pedestrian speed gathered from the first 100 set of LHS combinations were used as the initial population for the GA. As there were only 9 parameters to calibrate, with a high initial population, within 20 generations the fitness value reached saturation point. The changes of the fitness value across generations for different areas are showcased in **Figure 5**.

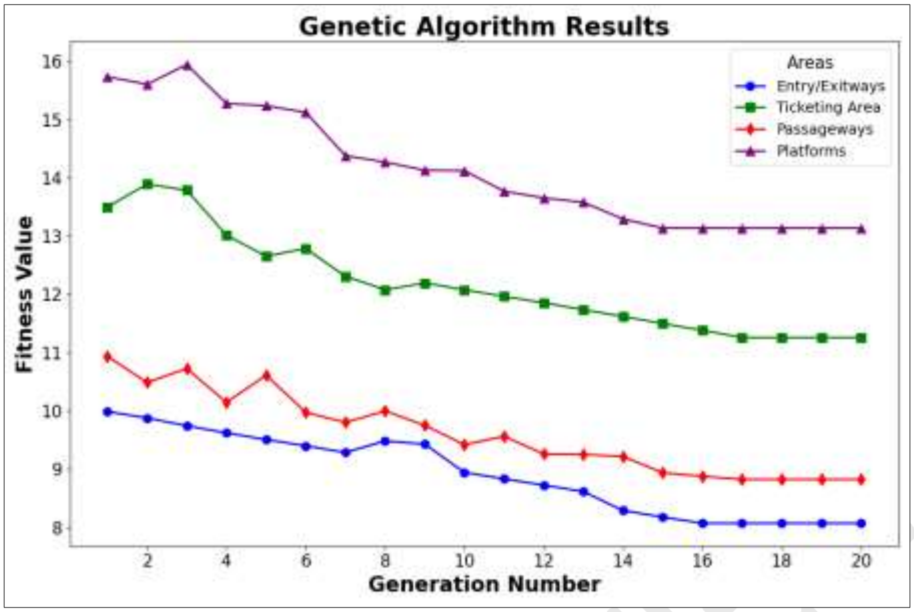

Figure 5 Fitness Value vs Generation Number

The results from the GA with fairly acceptable fitness values helped in determining the calibrated set of parameters for the different areas of the simulation model as shown in **Table 2**.

TABLE 2 Calibrated Parameters

Areas	Tau	ReacTon	ASocIso	BSocIso	Lamda	ASocMean	BSocMean	VD	Noise
Entry/Exit ways	0.5	3	2.467	0.2	0.042	1.723	1.851	3	1.2
Ticketing Area	0.9	6	2.281	0.28	0.055	1.539	2.19	2	1.5
Passageway	0.4	3	2.605	0.18	0.037	1.812	1.754	3	1
Platforms	0.8	4	2.3	0.25	0.048	1.636	1.98	2	1.3

4.5 Base Model Validation

In assessing the simulation model's validity, GEH is a valuable tool. GEH is able to provide a numerical score that quantifies model performance and is a reliable goodness check in validating simulation models (*39*). A lower GEH value indicates a better match between the simulated data and the observed data, while a higher value suggests a larger discrepancy. GEH can be defined according to **Equation 7** (*40*).

$$\mathrm{GEH} = \sqrt{\frac{2(x-y)^2}{x+y}} \qquad (7)$$

Here, x is observed flow and y is simulated flow.

In this study, the GEH values are calculated in all 4 entry/exit points. The entry pedestrians are considered to be the ones that entered the station and reached the platform to enter the trains, and the exit pedestrians are the ones that started from the trains and reached the exit. For the calibrated parameters, the GEH values for the entry passenger flow is given in **Figure 6** and for the exit passenger flow in **Figure 7**. This rigorous validation ensures the accuracy and reliability of the simulation model in replicating actual pedestrian behavior.

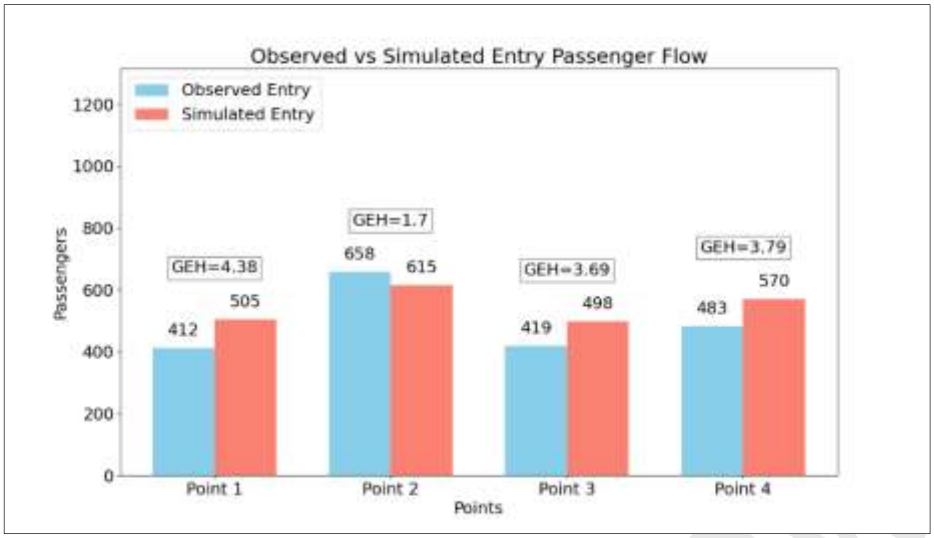

Figure 6 Base Model Validation (Entry Points)

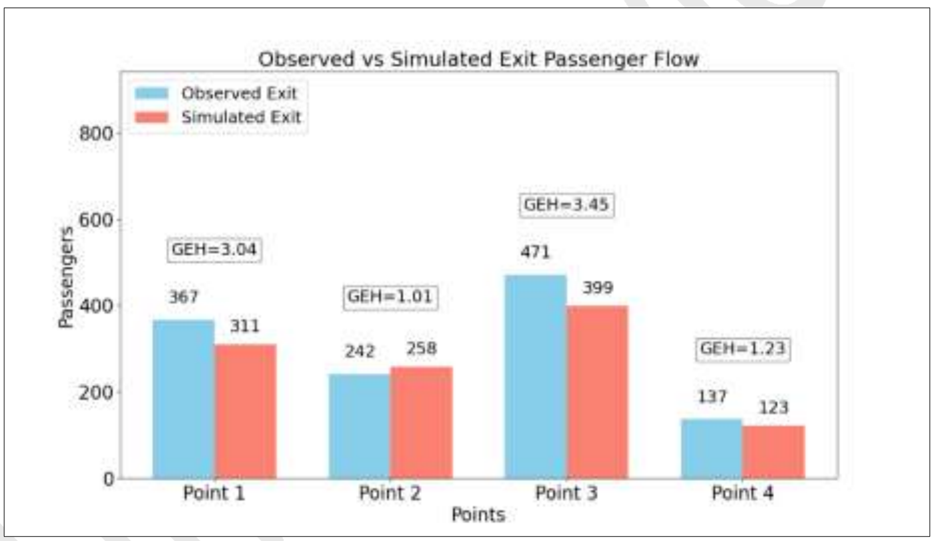

Figure 7 Base Model Validation (Exit Points)

5 Evacuation Scenario Generation and Simulation

As all SFM parameters are not associated with panic behavior, sampling all 9 parameters would not provide the level of exploration aimed in this study. To identify the key parameters affecting the average speed of pedestrians (a surrogate measure of panic behavior), RF Feature Importance technique was utilized. Existing research has shown the feature selection using RF to be reliable (*41*). RF determines feature importance by evaluating the contribution of each feature in predicting the target variable across multiple decision trees. During the training process, the algorithm measures the reduction in impurity (e.g., Gini impurity, entropy or Variance) brought about by each feature when making decisions. Impurity measures are used to assess the quality of splits at each node in the decision trees. Due to the type of data in this study, RF Regression has to be utilized which uses Mean Squared Error (MSE) as the criterion for splitting nodes. The feature importance is calculated based on the total decrease in MSE (or variance) that the feature contributes across all trees in the forest. The method of calculating Variance is given in **Equation 8**.

$$\text{Variance}(t) = \frac{1}{N_i}\sum_{i=1}^{N_i}(y_i - \bar{y})^2 \tag{8}$$

Here, N_i is the number of samples in node t, y_i is the value of the i-th sample, and $\bar{y}$ is the mean value of samples in node t.

In this study, the initially generated LHS combinations were used as the dataset for feature importance analysis where the 9 SFM parameters are the independent variables, and the average speed of pedestrians is the dependent variable. The influential parameters identified by the RF modeling are then used in the generation of evacuation scenarios through LHS processes. All the combinations of key features representing a set of evacuation scenarios are simulated and panic levels are explored accordingly.

6 RESULTS & ANALYSIS

6.1 Analysis of Feature Selection Results

The Feature Importance analysis on SFM parameters suggested 'Tau' to be the most sensitive parameter in altering the average speed of pedestrians with an importance factor of 0.4506. Among the other parameters, BSocMean, ReacToN, ASocMean, and Lamda exert the most substantial influence on pedestrian behavior with importance factors of 0.1624, 0.0893, 0.0872, and 0.0701 respectively. The importance ranking of all these parameters according to their importance factor is showcased in **Figure 8**. In contrast, the remaining four parameters exhibit comparatively lower significance in shaping the observed behavioral patterns.

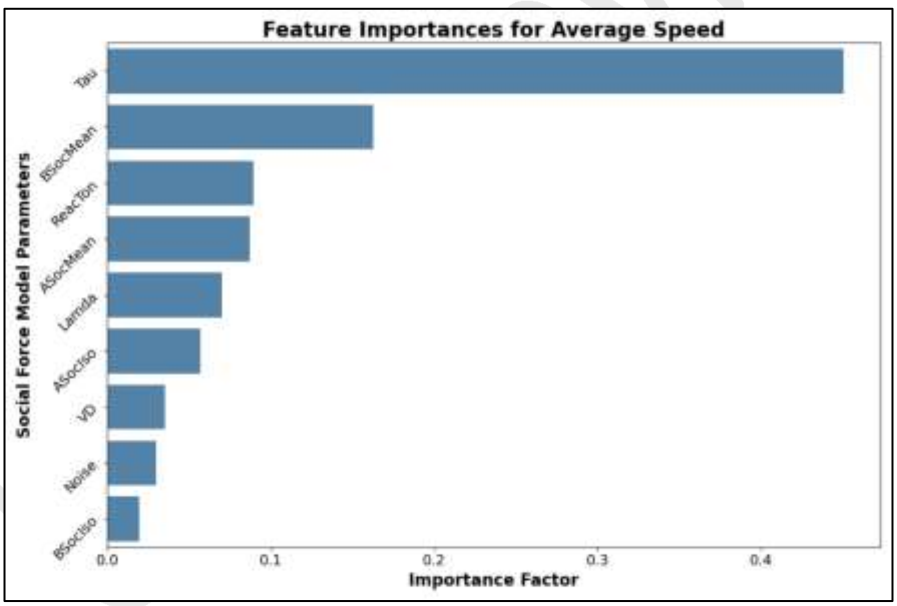

Figure 8 Feature Importance Ranking

6.2 Exploration of Panic Evacuations

The evacuation environment is categorized into three distinct levels: Low Panic, Medium Panic, and High Panic. The differentiation is based on the velocity of pedestrians, assuming a correlation between panic intensity and speed (*23*,*42*) . In this case, an ascending order of simulation numbers was orchestrated based on the average pedestrian speeds in each of the 500 simulations to form a graphical representation illustrated in **Figure 9**.

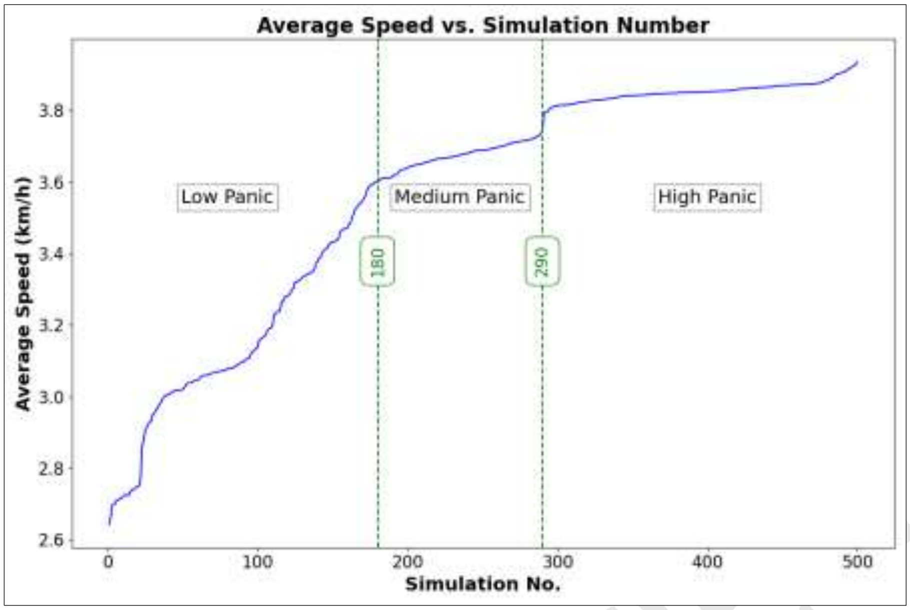

Figure 9 Panic Evacuation Exploration

This plot facilitated an assessment to finally depict three different panic levels through examination of the gradual increase of average speed. The initial sharp increase of the average speed until the start of a slight decline in the curve slope was determined to be Low Panic which consisted of the first 180 simulations and a highest average speed of 3.60 km/h. The range where the declination of the slope continued up until a sudden jump in average speed from 3.74 km/h in the 291th simulation was declared Medium Panic and the rest increasing average speed simulations were considered to be High Panic with an average speed range of 3.79 km/h to 3.93 km/h.

6.3 Analysis of Evacuation Performance

The overall evacuation performance of all the simulations under three levels of panic conditions is presented in **Table 3.** The total clearance time is recorded from the start of the evacuation procedure to the time of the last pedestrian leaving the MRT station. The average individual evacuation time is the average travel time of all the pedestrians in the simulation network. From **Table 3**, it is apparent that the total clearance time is the longest, with significant variation between lowest and highest times. The clearance times are shorter in Medium Panic conditions and the shortest in High Panic as supported by previous studies (*43*). In Low Panic, across the simulations, the variation between the lowest and highest value suggests non-uniform behavior amongst pedestrians as typically in less-urgency situations, pedestrians experience comparatively relaxed environments and have the freedom to choose their paths. But in Medium Panic and High Panic, the pedestrians exhibit homogenous response to the urgency of the situation and that leads to uniform behavior. A similar observation can be made from the variation of average individual evacuation times in different levels of panic. The average speed in Low Panic situation also varies across simulations as the SFM parameters are set to reflect stronger individual preferences and interactions. In Medium and High Panic, these parameters might be adjusted to reflect stronger forces towards evacuation, reducing variability.

TABLE 3 Pedestrian Network Performance

Panic Levels	Measures	Total Clearance Time (s)	Average Individual Evacuation Time (s)	Average Speed (km/h)
Low Panic	**Lowest**	315	86.35	2.6429
	Average	342	100.20	3.1714
	Highest	388	116.63	3.6023
Medium Panic	**Lowest**	307	82.38	3.6033
	Average	312	84.19	3.6686
	Highest	315	86.27	3.7439
High Panic	**Lowest**	294	78.16	3.7928
	Average	298	79.94	3.8592
	Highest	304	81.41	3.9348

Across the simulations, under different levels of panic, the Interquartile range was found to be 0.3292 for Low Panic, 0.0500 for Medium Panic, and 0.0296 for High Panic. It is evident that the variability in pedestrian speeds significantly decreases as panic levels increase. In the Low Panic scenario, the wide IQR indicates substantial variability in walking speeds whereas the much smaller IQRs for Medium and High Panic scenarios signify a marked reduction in speed variability. The decreasing IQR values highlight how increased stress and urgency lead to more uniform pedestrian responses, with less variation in speed as individuals prioritize urgent evacuation. Related box plots of the average speed among all the segmented simulations are showcased in **Figure 10**.

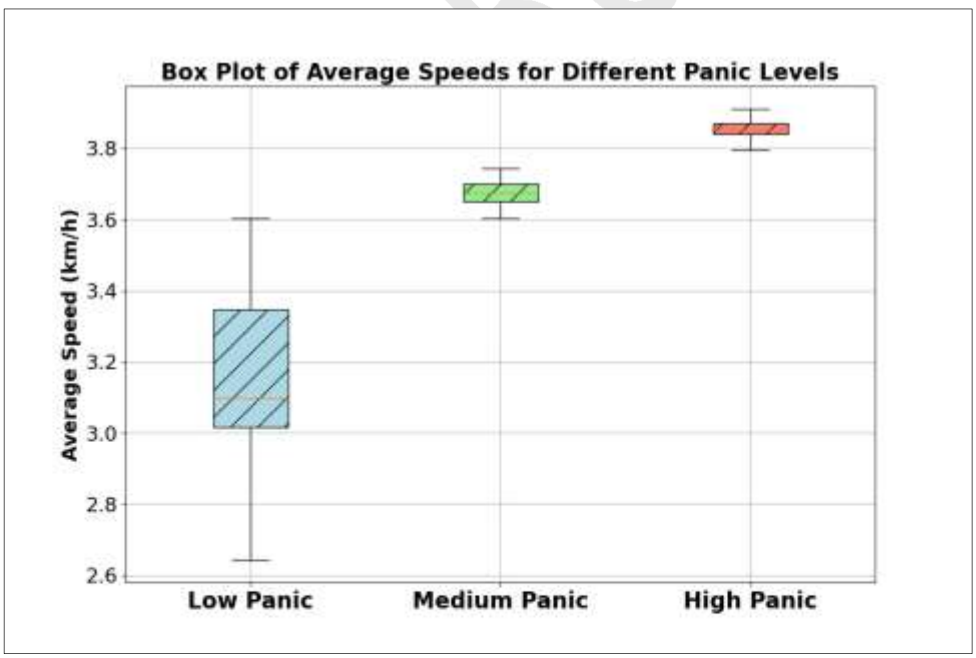

Figure 10: Box Plots of Average Speeds for Different Panic Levels

Now to understand the variability of the average speed across the evacuation time in a single evacuation simulation, **Figure 11** was plotted to compare the different levels of panic as distinct patterns emerge in average speeds over time. In this case, for each panic level, the simulation that represented the average of all the average speeds across simulations was selected to be analyzed. In the Low Panic scenario, average speeds initially rise significantly as pedestrians react to the situation, but then gradually decrease,

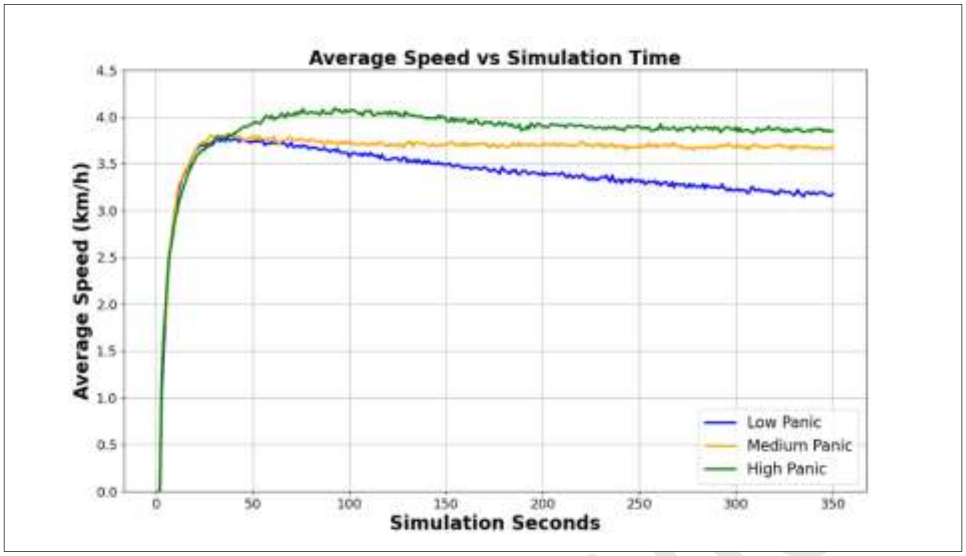

Figure 11 Average Speed Variation across Simulations

indicating a lack of sustained urgency and emergence of bottlenecks in critical points. The initial sharp rise of average speed in Low Panic demonstrates high variation which may be due to co-operation amidst evacuees and the significant differences in their rushed behavior across individuals (*23*). In the Medium Panic scenario, speeds rise and then stabilize, reflecting a moderate, consistent pace as pedestrians maintain a manageable and efficient speed throughout the evacuation. In contrast, the High Panic scenario shows a sharp initial increase in speed to over 4 km/h, driven by high urgency (44), followed by a decrease to 3.85 km/h as the initial rapid pace becomes unsustainable.

To understand the rate of consolidation of exited passengers over simulation time in the same single simulations for each panic level, frequency distribution graphs were generated as shown in **Figure 12, 13 & 14**.

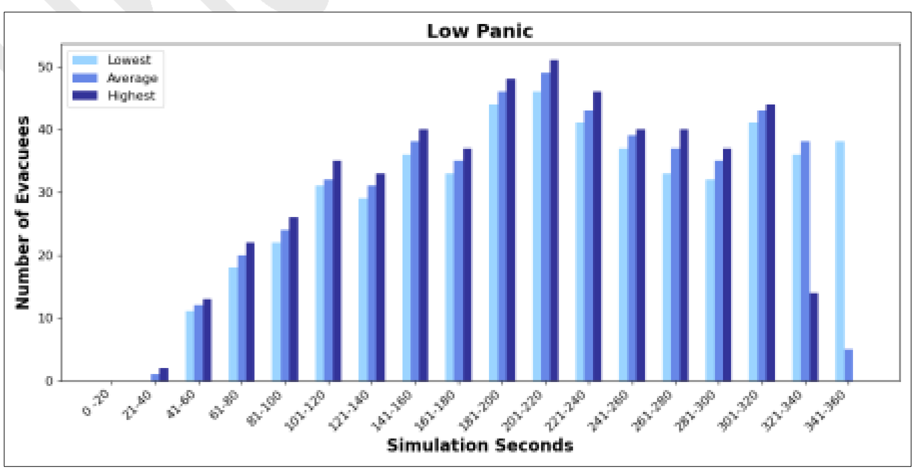

Figure 12 Distribution of Low Panic Evacuation Completion

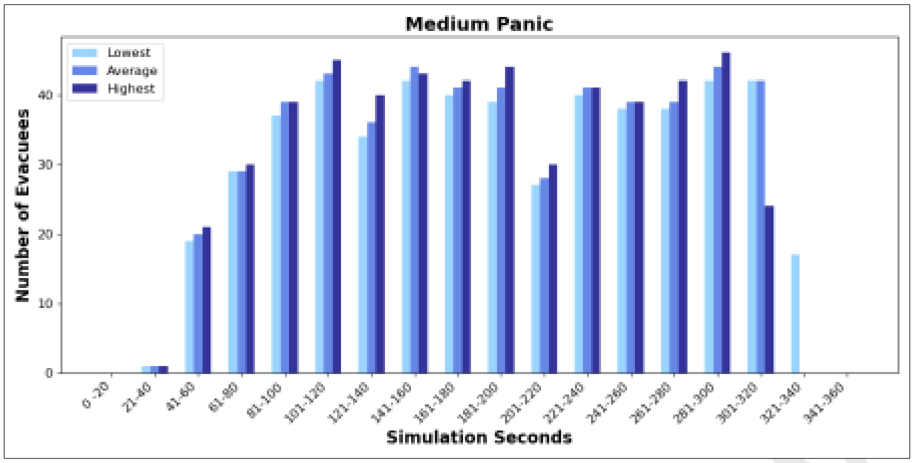

Figure 13 Distribution of Medium Panic Evacuation Completion

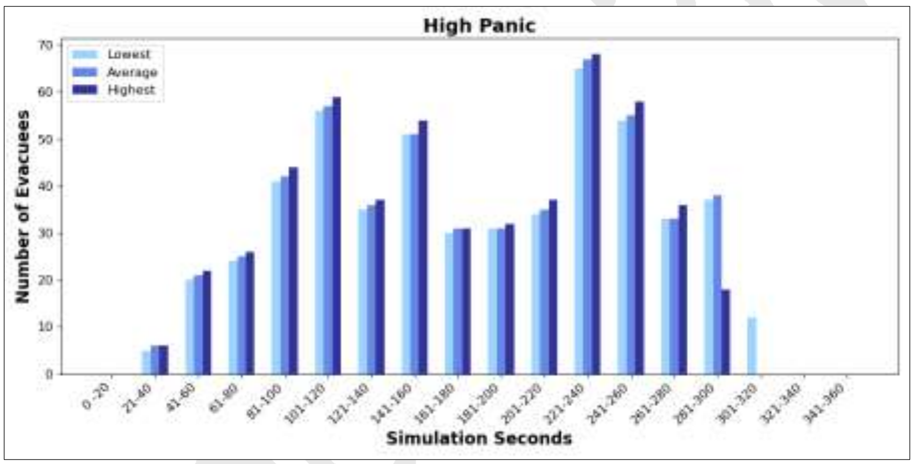

Figure 14 Distribution of High Panic Evacuation Completion

For this plot, in each panic level, three bar graphs are generated for the simulations in which the average speed of pedestrians was lowest, average and highest. **Figure 12** shows that in Low Panic scenario, the number of evacuees starts small and increases steadily over time. As time progresses, the evacuation rate picks up significantly, reaching a peak around 200-220 seconds, indicating a buildup in the number of evacuees. The examination of this graph reveals that in low panic, the larger share of evacuees is likely to exit the MRT station during the latter half of the evacuation time. For Medium Panic in **Figure 13**, the bar graph shows a more consistent increase in evacuees over time compared to the Low Panic scenario. The number of evacuees rises steadily with less fluctuation between "Lowest," "Average," and "Highest" values. The minimal change in bars suggests that people evacuate at a relatively uniform rate once the panic level increases, with fewer variations in individual evacuation times. For the High Panic scenario, **Figure 14** shows a sharp initial rise in the number of evacuees, reflecting a high level of urgency that drives rapid movement toward the exit. The number of evacuees quickly increases, peaking early in the time frame, and then gradually declines. This declination is due to a large crowd reaching the exit points from all over the MRT at a very fast pace creating congestion & bottlenecks, also understandable from **Figure 11**. This decline is followed by another rise in evacuees as congestion cleared up in the exit points allowing the rest of the passengers to evacuate swiftly. The evacuation behavior can also be examined in typical simulations showcased in **Figure 15, 16 & 17**.

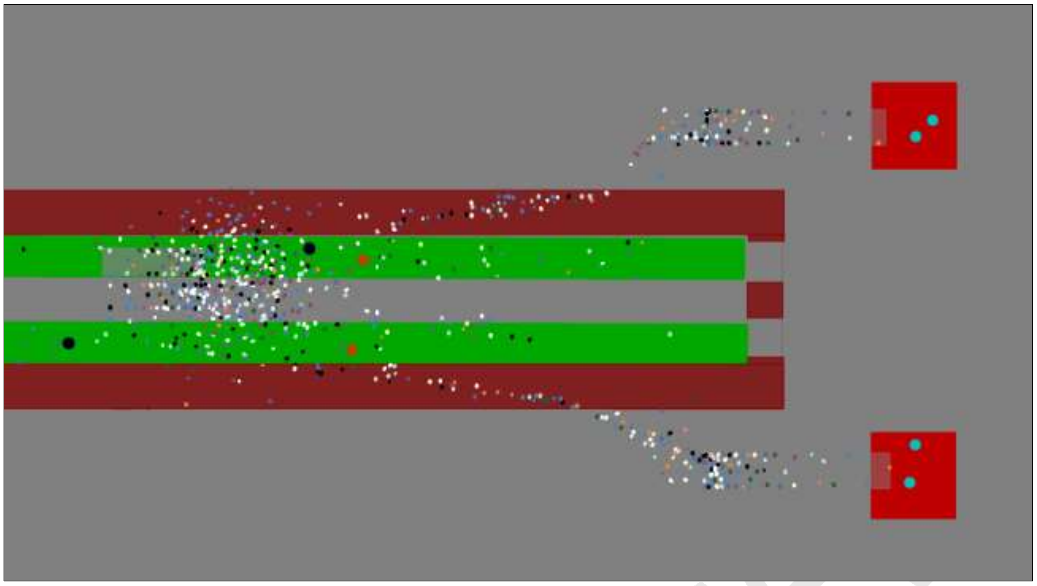

Figure 15 Low Panic Evacuation

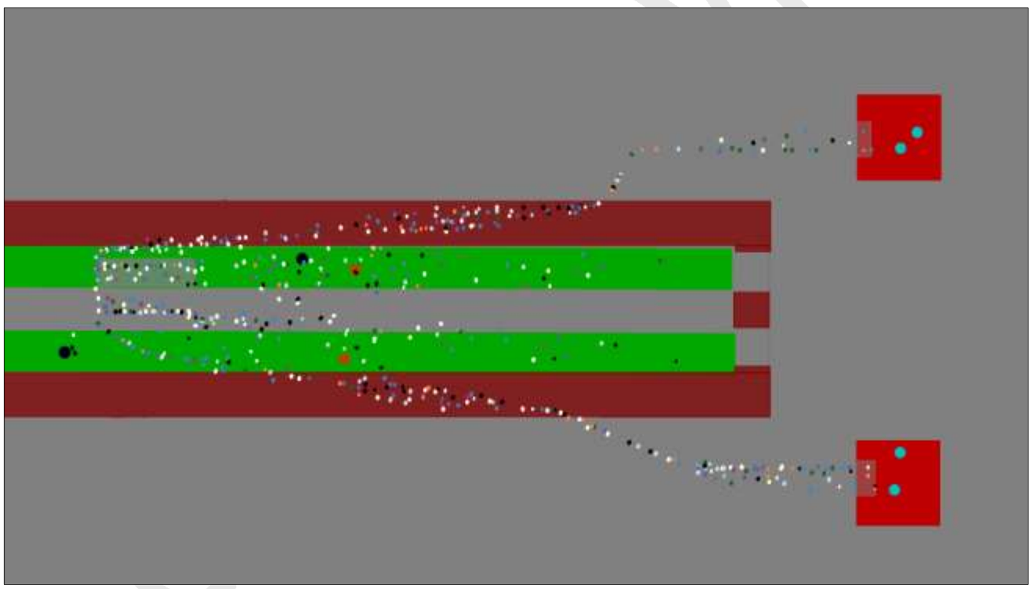

Figure 16 Medium Panic Evacuation

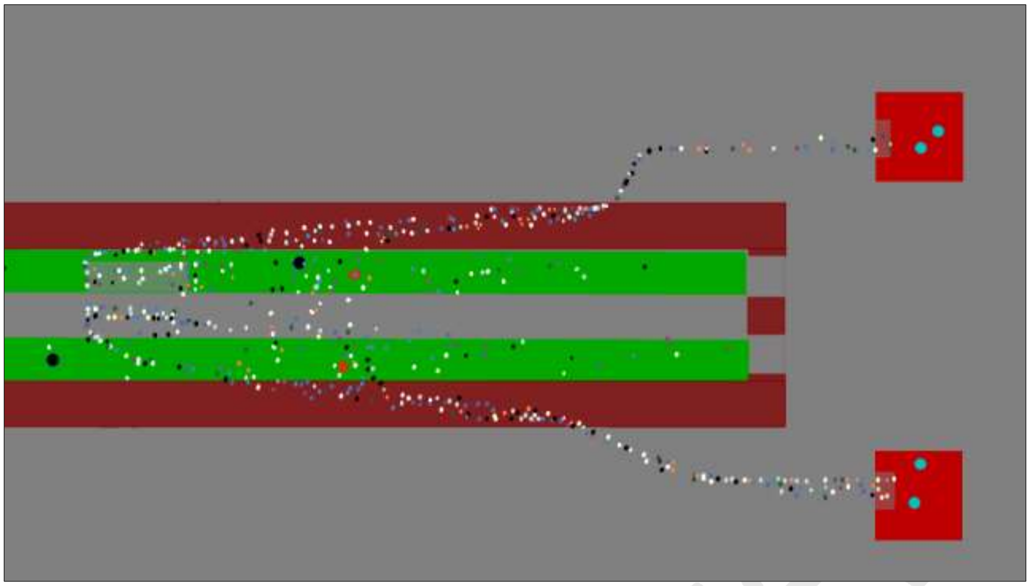

Figure 17 High Panic Evacuation

Research has showcased that in panic situations, pedestrians crowd together and the evacuation efficiency becomes lower (*45*). That resonates in this study as shown in **Figure 15** for low panic conditions. But **Figure 16** and **Figure 17** demonstrate that as the panic level goes higher, the increased average speed refrains the model from creating congestion all throughout the evacuation. In Medium Panic, the low variance in average speed causes no consistent significant congestion to be formed at the exit points all throughout the evacuation period. In High Panic, despite the propensity of forming congestion around the middle of the evacuation period, evacuees exit swiftly with high speed through the shortest path.

7 CONCLUSIONS

This study has outlined a framework to impart panic conditions in a pedestrian simulation platform and explore the crowd dynamics in an evacuation scenario. Behavioral parameters that influence pedestrian movement have been examined and key parameters have been identified. The categorization of panic levels into Low, Medium, and High, based on pedestrian speed, effectively illustrated how different levels of urgency influence evacuation patterns. The results show that in Low Panic scenarios, pedestrian speeds exhibit considerable variability due to relaxed behavior and individual preferences, leading to less uniform evacuation. In contrast, Medium and High Panic conditions result in more uniform speeds and quicker evacuation times, as increased urgency compels pedestrians to move more consistently and swiftly. The analysis of evacuation dynamics revealed that total clearance times are longer under Low Panic conditions due to variability in pedestrian behavior, while Medium and High Panic scenarios demonstrate more efficient and rapid evacuations. Box plots of average speeds and frequency distribution graphs further illustrate the decreased variability in pedestrian speeds as panic levels increase. The High Panic scenario, despite initially creating congestion, ultimately leads to a more rapid evacuation as congestion is cleared quickly. The Medium Panic scenario showcases such a behavior that does not compel any significant congestion to be formed through the evacuation. Conversely, Low Panic conditions show a slower buildup and peak of evacuees, reflecting the less urgent nature of the evacuation.

This study also indicates some limitations to be addressed in future research. For example, reaction delay to emergencies amongst pedestrians have not been introduced in this study. Furthermore, evacuation modeling for persons with mobility needs was not integrated as a part of this study. Density analysis of the study areas could also identify critical points consisting of a risk of impeding evacuation. It would also be interesting to explore the movement of people on the curbside, interaction with vehicles as well as accident and stampede events.

Nevertheless, this study advances pedestrian evacuation modeling framework by integrating both social-physiological behaviors and varying levels of panic into the assessment of MRT station evacuations as well as identifies key influential behavioral parameters and showcases complex crowd dynamics. The results of this study can be utilized in optimizing MRT station design as well as other similar public infrastructure as the methodology is adaptable, flexible and applicable in other scenarios.

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AUTHOR CONTRIBUTIONS

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