Crowd Behaviour in Canadian Football Stadia
- Part 2-
Modelling

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Abstract

In Part 1, a novel data collection exercise of a Canadian Stadium was conducted. Demographic distribution, pedestrian speed, exit and route choice, and areas of congestion were quantified using high resolution cameras. Herein, a numerical model space is built to simulate these observations in conventional software while exemplifying proper techniques. The simulations showed that using real-world behavioural data can significantly improve the accuracy of the model. When using lowest cost inputs rather than behavioural inputs, the maximum percent difference between the model and the observed egress was 15% higher. Parametric simulations showed that individual walking speeds impact overall egress time. This is in addition to crowd density also being a factor that further reduced speed. In simulations with only the fastest and slowest demographics, the maximum percent difference was 9%. Further parametric simulations increased the amount of two directional flow by 10%, which (non-linearly) increased the total egress time.

Key words: Egress, Evacuation modelling, Stadium design, Crowd behaviour

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1. Introduction and Objectives

Delivering crowd safety should begin in the design phase and adopt an approach that integrates management (Rowe and Ancliffe 2008). Practitioners will often use computational movement models to aid in the design of these stadia as it enables them to create simulations predicting movement in normal and emergency evacuation. This highlights potential queuing areas where unacceptable densities of populations may occur. A survey study completed by Lovreglio et al. showed that arenas and stadia are the third most frequent building type where pedestrian evacuation models are used. In addition, aiding and analyzing the design of new or existing structures are the second and third most common usages of these models (the first being codes/standard compliance) (Lovreglio et al. 2020).

Part 1 presented three filmed trials that were analyzed to understand how individuals' behaviour affects the egress of the entire population. In Part 1, the demographic distribution, pedestrian speed, exit and route choice, and areas of congestion were observed using high resolution cameras. Behaviourally, pedestrians exited the stadium where they entered which created high levels of cross flow and density. It was observed that contemporary walking speed profiles for stadia will differentiate from classical profiles, especially with reflection of demographic distribution. Individual walking speeds, while highly variable, impacted overall egress time despite crowd density. Overall, the aim of Part 2 of this study is to create accurate models and demonstrate good modelling practices in simulations by enforcing correct behavioural attributes within models using observed behaviour and data from Part 1. This provides confidence for simulated crowd models.

2. International Studies and Validation Modelling

In addition to Canadian studies presented in Part 1, studies regarding human behaviour in large populations outside of Canada were reviewed, particularly in relation to whether modelling efforts were made. Table 1 illustrates provisional literature regarding human behaviour in stadia or large gatherings (festivals). The second study in Table 1 was a data collection completed in the Netherlands in 1999 regarding the impact of motivation on egress speeds when on stairs. However, no model was created for this study (Graat et al. 1999). The studies from 2016 were closely related as the first was a guide for how to model a fictional music festival, and the second used the same scenario to model human behaviour in relation to the presence of toxic gas. Neither study had data collection (Lovreglio et al. 2016; Ronchi et al. 2016). The most recent study was performed by Larsson et al. in which three different events (rugby, soccer and concerts) held at the same stadium in the UK were recorded and analyzed (Larsson et al. 2020). That study highlights the complexity of human behaviour as it found different demographics attended each event and presented different behaviours. For example, the soccer game mainly had individuals whose ages ranged from 50 to 69 years. The population was mostly men, a smaller portion of families with children and an even smaller portion of couples. On the contrary, the female artist's concert was populated mainly by teenage girls who stayed in groups of two to five and young couples.

Table 1. Review of Large Gathering Studies outside of Canada

Title	Year	Authors	Country	Primary Focus	Modelling?
Safety in football stadia: a method of assessment (Poyner et al. 1972)	1972	B. Poyner	United Kingdom	Filmed and photographed crowd and egress behaviour at 15 football matches at 11 stadia to provide data for the "Green Guide"	No
Complex evacuation; effects of motivation level and slope of stairs on emergency egress time in a sports stadium (Graat. et al. 1999)	1999	E. Graat, C. Midden, P. Bockholts	Netherlands	A data collection on pedestrian egress movement on stairs in stadia and how their egress times vary with different motivation scenarios	No
A proposed pedestrian waiting-time model for improving space-time use efficiency in stadium 0evacuation scenarios (Fang et al. 2011)	2011	Z. Fang, Q. Li, Q. Li, L. D. Han, D. Wang	China	Maximizing the space usage and time efficiency of evacuations in stadia and apply this in a new model which attempts to prevent bottlenecking	Yes
Modelling large-scale evacuation of music festivals (Ronchi et al. 2016)	2016	E. Ronchi, F. Nieto Uriz, X. Criel, P. Reilly	N/A	A general guide on how to model a large-scale evacuation at a fictional music festival	Yes
A dynamic approach for the impact of a toxic gas dispersion hazard considering human behaviour and dispersion modelling (Lovreglio et al. 2016)	2016	R. Lovreglio, E Ronchi, G. Maragkos, T. Beji, B. Merci	N/A	A methodology to create models which simulate the impact of toxic gas on people in open spaces in large gatherings such as a fictional music festival	Yes
Pedestrian movement simulation for stadiums design (Kirik et al. 2018)	2018	E. Kirik, A. Malyshev, T. Vitova, E. Popel, E. Kharlamov	N/A	The importance of pedestrian movement modelling for stadium design	Yes
The impact of crowd composition on egress performance (Larsson et al. 2020)	2021	A. Larsson, E. Ranudd, E. Ronchi, A. Hunt, S. Gwynne	United Kingdom	Changes in movement in stadia depending on the crowd composition	Yes

It is evident there is little recent information on human behaviour in stadia or large gatherings even internationally. According to Gwynne et al., to accurately implement human behaviour into egress models, data collection of an egress needs to be followed by a model which can then be validated. Once validation has occurred, then other models can be created (Gwynne et al. 2016). This literature indicates that other than the most recent study, none consisted of both data collection and then modelling of that data.

3. Validating Pedestrian Modelling for Stadia and Discussion

The model space of the stadium was built within a Trimble Sketch-up Environment then imported into the MassMotion evacuation modelling software to run validation scenarios followed by preliminary predictive egress simulations (Kinsey 2015). The stadium's model geometry was determined using a combination of satellite imagery, drone footage and on-site field surveying. The as-built model can be seen in Figure 1.

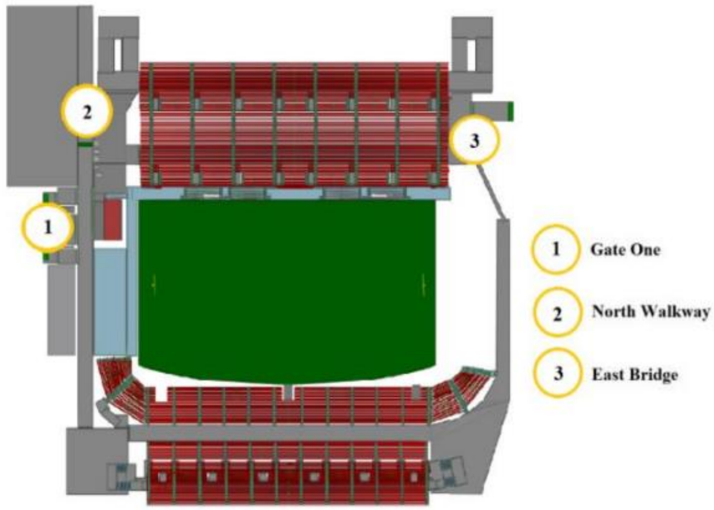

Figure 1. Stadium Model Space

MassMotion 10.6 was chosen as the software as it is the latest version and one of the most used for design by practitioners in Canada and worldwide (ARUP 2021; SimWell 2021; Lovreglio et al. 2020; Quiquero et al. 2018). It is therefore utilized for similar stadia. MassMotion is built utilising a social-forces movement framework, in which agents are automatically programmed to avoid collisions by maintaining a certain distance from other objects. The framework is further discussed in Section 3.1; however, it will allow modelling insights to be relatable to other software which utilises similar computational movement frameworks. Validation runs were calibrated to the experimental trials and the predictive scenarios modelled varying demographic distributions and gate configurations. In the modelled stadium featured, each row of stands received a single portal to represent the entire row's seats. In cases where the rows split to accommodate corridor entrances, the rows were split and each segment from this split received its own portal. The capacity of each row and corresponding share of the population was approximated based on the number of seats in each row or segment. Drone footage was used to count seats in each section's row, and the sum of section seats was taken to generate the row capacity. Rows with fewer seats were accounted for with separate counts. The row capacity was divided against the total stand capacity to determine a percent capacity for each row. This was done separately for the north and south stands, allowing for easy population distribution changes between the two locations.

Verification is the testing of the model to determine whether it meets the specifications or requirements as determined by building codes, literature or other models, whereas validation is the testing of the model to determine whether it addresses real-life observations (Ronchi 2021). As this paper compares directly to real observed data, we use the terminology of validation. This is a necessary step for the study herein because the movement profiles needed to align with the observed evacuation, as well, so that the movement profiles could be applied to predictive simulations (Gwynne et al. 2016). These validation simulations start by using all default inputs of MassMotion and increase in complexity by implementing observed behaviours from the trials. The results from these simulations were compared to the observed egress to determine the amount of uncertainty that came with varying levels of input parameters. The evolving complexity of the simulations aims to understand how uncertainty in simulations can be lowered by implementing accurate input parameters, as well as how necessary it is for the practitioner to consider these parameters properly. These predictive simulations were designed to demonstrate the effect that exit choices and demographics can have on modelling results. Most of the predictive trials in Section 4 are not meant to represent real-world conditions; they illustrate extremes to highlight the importance of considering these aspects when constructing models (e.g. the importance of considering the demographics specific to an event), and the uses of more accurate data for reducing uncertainty in the model.

3.1 Agent Profiles Utilised

Within MassMotion, all agents are assigned a preferred speed, representing the average, minimum and maximum speeds an agent will walk during a simulation. The agent speeds can move slower than their preferred walker speed due to local crowd density, agent deceleration and the adapted social forces model. The default agent radius is 0.25 m in width for all agents (0.5 m in diameter). The model herein was populated using a new movement profile derived from the walking speeds observed in the first preliminary event. The demographics were accommodated using a percent-based chance distribution which was applied to all agents as they spawned. An Origin-Destination matrix was used to assign the starting stand populations to their target exits, ensuring the traffic demand in the model reflected observations precisely.

Initially, all scenarios were simulated using the default agent profile for MassMotion, from Fruin (Fruin 1971). It is noted that Fruin, along with other authors of earlier datasets, have suggested that their data not be included in the more recent versions of the SFPE handbook, potentially to avoid being used in engineering calculations (Society of Fire Protection Engineering, 2016). There are limitations to this profile, as it collected homogeneous movement data on commuters in a 1970s transit terminal, not a modern stadium. Considering that the movement of modern stadium attendees may be different, the authors developed tailored agent profiles in Part 1 to more accurately represent modern demographics. These developed agent profiles were then implemented into the simulations, reducing uncertainty and demonstrating the importance of considering tailored agent profiles. These agent profiles as well as the proportion of each demographic observed during the trials were used to forecast the events observed in the trials to validate the model. MassMotion automatically applies a Level-of-Service (LOS) based speed-density relationship for congestion beyond unobstructed levels (Oasys n.d.), thus only the unobstructed data was used at this time. Future research should consider assessing the speed reduction algorithms for accuracy when more dense observations can be made.

3.2 Pre-Movement Times

A situation specific set of pre-movement times was defined by reviewing the footage. Of the spectators still seated when the final game buzzer sounded, it was found that people began to exit from the range of five seconds to seventy seconds. All premovement times observed from those who left are outlined in Table 2. Spectators that had no intention of egressing and remained in their seats for postgame activities on premise were not assigned a pre-movement time. These pre-movement times were modelled in MassMotion as a normal distribution. The calculated weighted average of the data set was found to be 36 seconds, which aligns with the behaviour observed in the footage as most people moved around this time frame. Standard deviation of the data calculated and used in MassMotion was 19 seconds. [v]

Table 2. Observed Pre-movement Times

Percent of Spectators that had started Egress	Time (s)
Minimum	5
10%	10
30%	17
50%	26
70%	38
90%	57
Maximum	70

3.3 Validation Simulations

Two validation scenarios were simulated using MassMotion (Table 3). Each simulation used both the default Fruin speeds, and the new profile created from the speeds observed in the trials. MassMotion does not currently have the option to input stair speeds. Instead, they are automatically calculated based on the rise/run input parameters using the MassMotion engine. The walking speed is reduced to between 42% and 38% for agents climbing stairs and between 57% and 50% for agents descending stairs (Oasys 2021). Simulation 1 was calibrated to represent Trial One with all exits open, applied the observed demographic distribution, and populated with the actual number of spectators still seated at the final game buzzer. Simulation 2 was calibrated to represent Trial Two with the East Bridge closed, observed demographic distributions, and populated with the actual number of spectators still seated at the final game buzzer. In both simulations, behavioural aspects, such as route and exit choice, were implemented as it was determined these have a significant impact on egress. The exit use in comparison to individuals' seats was determined from the video footage as seen in Table 3. Because those who left early were not included in this study, only a fraction of the total population counted was used. These numbers were determined by using time to find the number of people leaving through each exit based on their seats while excluding those who left the event early. Using both methods, the number of people egressing to each exit from their seat location after the end of the game was determined (Table 4). This data was used in both simulations to assign agents to an exit based on where they were located. Simulation 1 and 2 results were compared against the observed trials to validate the model, which was necessary before using the model for further simulation applications.

Table 3. MassMotion Model Validation Simulations

Simulation Number	Agent Speeds Applied	Demographics	Simulation Description	Exits Open or Closed
1a	Fruin	Default	Trial One event actual number of spectators left in stadium at end of game	All open
1b	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	Trial One event actual number of spectators left in stadium at end of game	All open
1c	Fruin (Lowest Cost)	Default	Trial One event actual number of spectators left in stadium at end of game	All open
2a	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	Trial Two event actual number of spectators left in stadium at end of game	East bridge closed
2b	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	Trial Two actual number of spectators left in stadium at end of game with tripled premovement time	East bridge closed

Table 4. Adjusted Exit Choice in Comparison to Seating for Trials One and Two

Trial 1	North Exit	Main Exit	East Bridge
North Stands	5472	936	0
Souths Stands	869	2893	1066
Trial 2	**North Exit**	**Main Exit**	**East Bridge**
North Stands	2126	4544	0
Souths Stands	1078	4611	0

A qualitative comparison between the simulations and the footage from Trials One and Two was done to ensure alignment of expected congestion and egress route utilization. The authors compared the usage of Gate One and the North Walkway in Simulation 2 to that in Trial Two. It was verified that the same points in the stadium architecture were subject to congestion. The exit and route choices of individuals were analyzed by colour coding agents based on their seating location and their exit. This allowed a qualitative analysis on the abundance of cross flow, as well as the accuracy of the proportion of agents using each exit based on the stand they were located. One issue observed when comparing the simulations to the trials was deadlocking, which was caused by agents heading to Gate One getting caught in dense cross flow traffic heading to the North Walkway. In the original model, agents exiting using Gate One would be pushed beyond their desired path and attempt to backtrack, going against the flow of traffic and eventually bringing the entire model to a halt. To resolve this, the entrance of cross flow traffic was split into two channels, this can be seen in Figure 2; Channel One is located closer to the North Walkway and was set up to only allow agents bound to the North Walkway through. Channel Two was located further south and allowed for anyone to pass through. Agents heading to Gate One would enter the cross flow traffic at a location with sufficient space and time to move across the crowds.

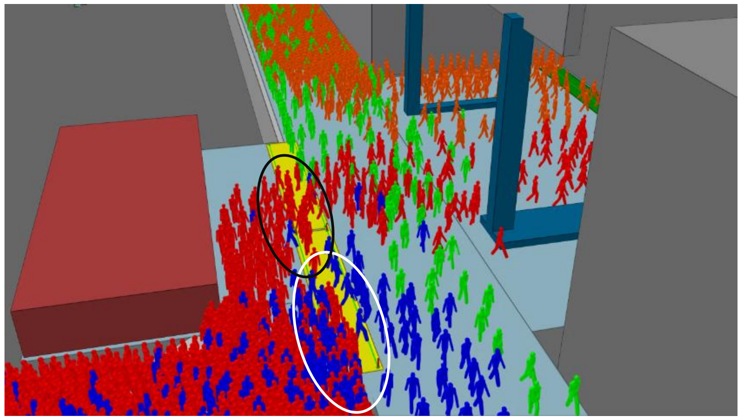

Figure 2. MassMotion Simulation During Egress at Gate One and North Walkway (Channel One: white circle, Channel Two: black circle)

Next, quantitative analysis of the stadium model was carried out. Figure 3 and Figure 4 represent the population count of the model stadium over time for Simulation 1 and Simulation 2 respectively. Comparing the simulated total post-game egress times to that of the observed trials, it can be noted that the simulation egress using both the Fruin profile (Simulation 1a) and the new profile (Simulation 1b) were more similar in overall egress time and in maximum percent difference in remaining population when transposed to begin at an earlier time. The cause of this transposition is likely due to the counting and data collection methodology. During the event, the data collection started by counting people at the exit right after the event ended. However, these individuals were at different indeterminable locations within the corridors instead of in the stands at the start of recordings. They were therefore captured in the count but not in the model. Thus, the simulations were transposed such that the first agents exit while the first people were observed to exit, which resulted in a significant improvement to the model's accuracy. The maximum percent difference decreased by 12% to 6% for Simulations 1a and 1b when transposed, as illustrated in Figure 3. Regardless, both models have similar egress times, with the new profile (1b) appearing to align closely to the default Fruin profile. Considering that the average of all the custom profiles is similar to that of Fruin, the result is not unexpected. However, the distinct demographic profiles still have an impact as illustrated by a higher egress in the early part of the simulation indicating faster walking demographics followed by lower egress indicating the slower walking demographics. With changing demographics at other events, egress times could show a greater difference from the Fruin profile, and these effects are expanded upon in Section 4, with Simulations 3a through 3d illustrating the effects of the different demographic profiles as well as using different demographic profile compositions. Using the default input parameters in Simulation 1c (Fruin, lowest cost) severely underestimates the egress time. The maximum percent difference in the percent of the population remaining between the observed data and Simulation 1c is 21%, and the overall egress times differ by approximately five minutes. When implementing behavioural aspects by assigning exits, both the new profile and the Fruin profile simulations more accurately represent the observed egress, thus emphasizing the importance of exit use. During Trial Two, the exit use was assigned as well, however, the overall egress times were not as accurate as Trial One. While some stadia may choose to explicitly assign entrance and exit gates based on seat location, this was not the case in the stadium being analyzed. This implies that the audience will self-select if exits are not explicitly assigned, considering more factors than just shortest distance to exit. Further behavioural studies to determine and analyze these factors may be useful in modelling the demand for each exit and resulting crowd volumes. The simulation was transposed and showed significant improvement as the maximum percent difference between the observed data and the simulation was 13%, a little over half of the maximum percent difference seen without transposing the data. However, the overall egress time was still shorter than the observed time, so the pre-movement time was tripled experimentally (Simulation 2b). While this simulation was more accurate than Simulation 2a, the transposed simulation was the closest in representing the observed egress. Overall, the transposed times are within reasonable range to consider the model calibration representative of the trials, however it is evident there are other influencing factors at play which account for the degree of variability.

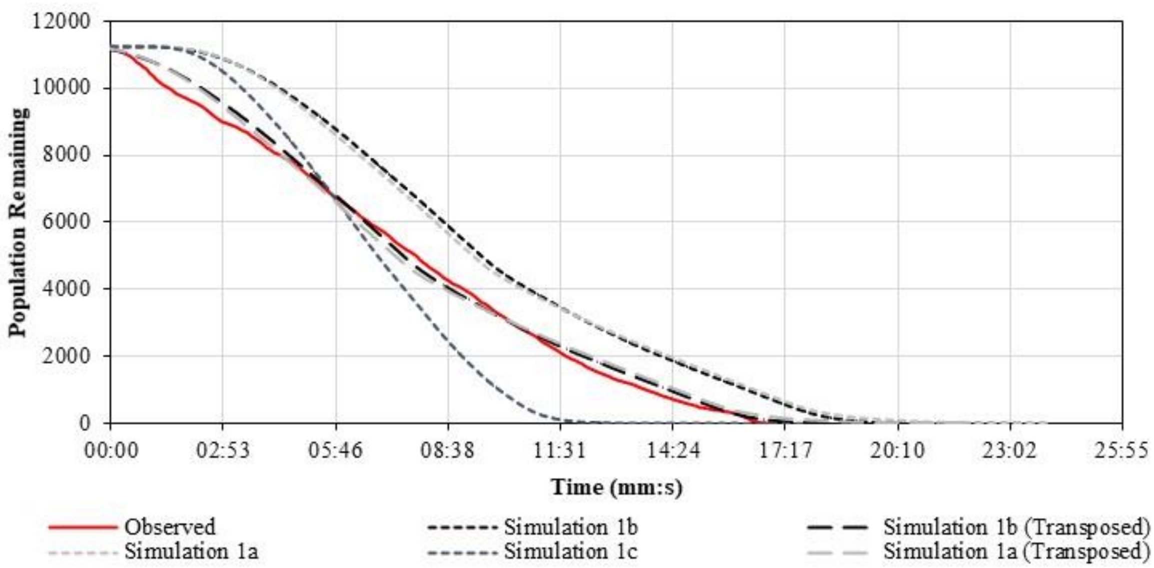

Figure 3. Simulation 1, Population Remaining over time in Trial One

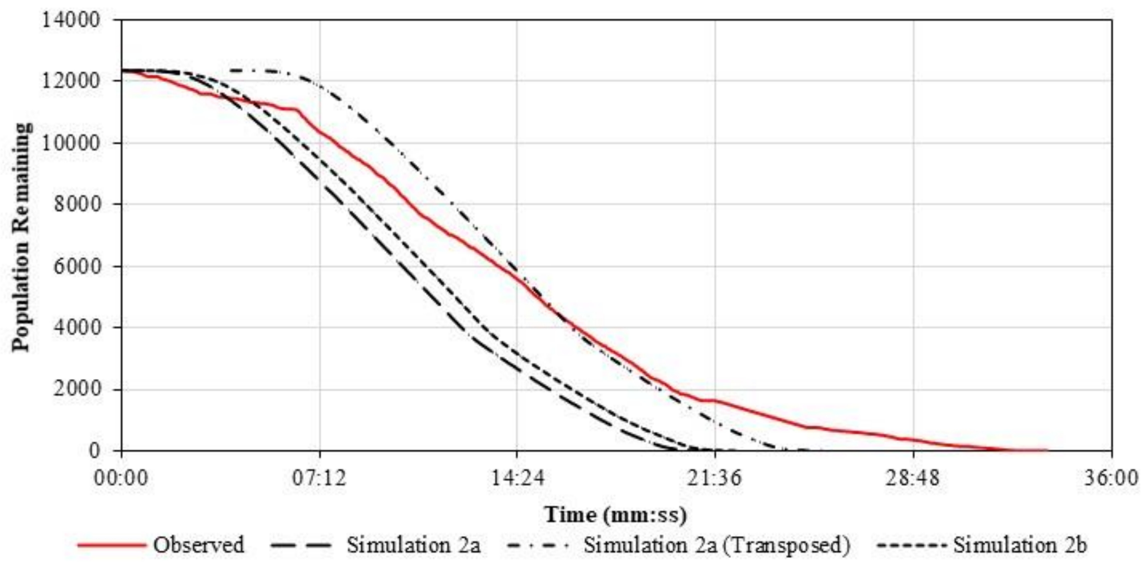

Figure 4. Simulation 2, Population Remaining over time in Trial Two

It appeared assigning agents exits positively impacted the accuracy of the simulations, so exit use was examined further. As seen in Figures 5 and 6, the egress time for each exit was graphed and the results of the Fruin lowest cost model as well as the new movement profile while assigning exit choices were compared to the observed times in the trials. Figure 5 shows the Simulation 1 exit count, and it is seen that the Fruin lowest cost default parameters overestimated the time of egress at the East Bridge and Gate One, but underestimates at the North Walkway exit. On the contrary, the new movement profile (Simulation 1b) shows egress very similar to the observed times with the curves. The default parameters can be seen to overestimate the egress at Gate One but underestimate the egress at the North Walkway in Simulation 2 (Figure 6). The new profile (Simulation 2a) is more accurate than the tripled pre-movement simulation (Simulation 2b) with the North Walkway egress more accurate than Gate One.

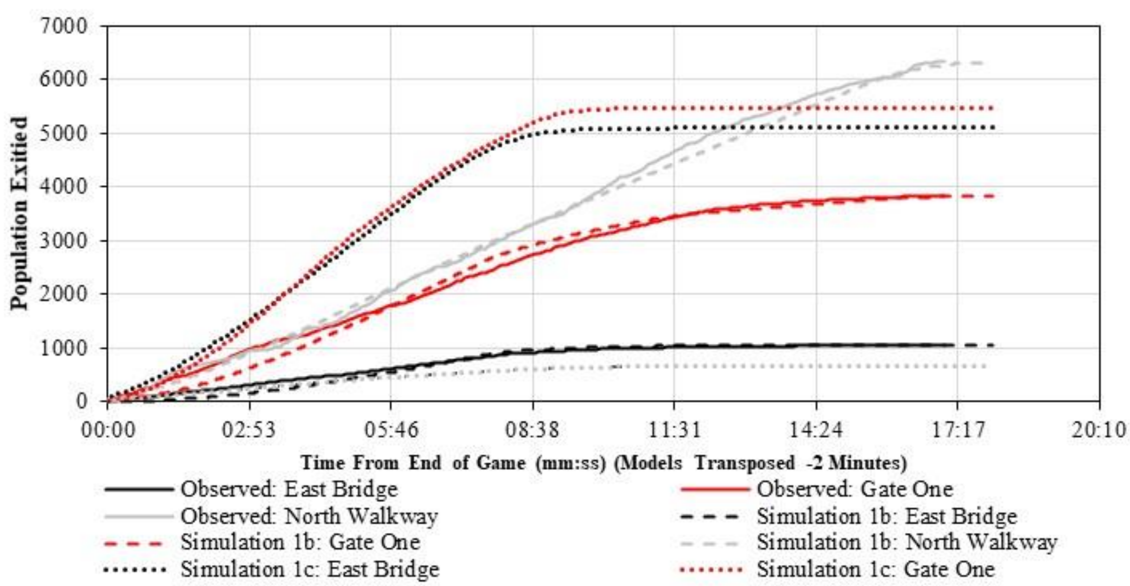

Figure 5. Simulation 1 Exit Count

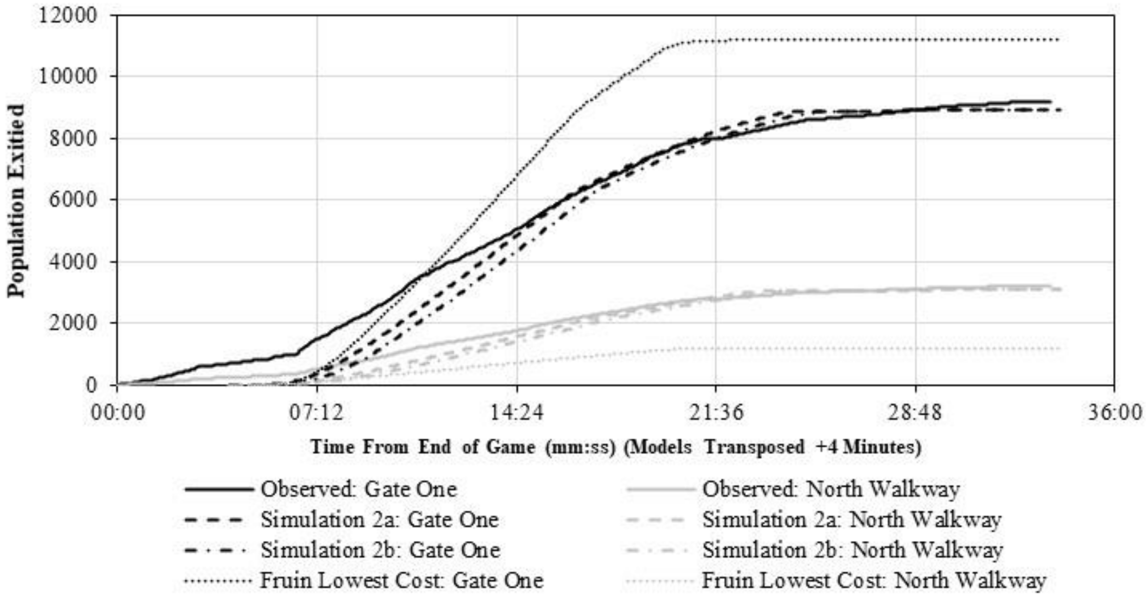

Figure 6. Simulation 2 Exit Count

All the simulations in this study (1 to 4) were run ten times and averaged to find the mean total egress time for the given scenario. The maximum variance in agent count in 10 runs of each simulation (less 4f) was less than 40. While this does not follow the methodology to ensure second-specific convergence and minimization of standard deviations (see Smedberg et al. 2021), these specific results are not to advise the design of this structure; instead, they are used to illustrate and highlight differences which occur based on changes to the walking speed and that exit choice variables are of concern. More runs may be performed to ensure that all variations are taken into account, but for the purposes of general comparison this level of detail was beyond the scope of the paper.

4. Predictive Modelling Implications and Discussion

To assess which factors in stadia influence the egress results, simulations (Table 5) were run with the objective of testing the egress performance of the stadium at full capacity and the impact of varying demographic distributions in attendance, as well as the impact of increasing the amount of cross flow. Simulation 3 tested the stadium with all exits open at three various demographic distributions: one trial with the actual demographics observed at the event, one trial with the majority of spectators as young adults, and one trial with the majority of spectators as elderly. The Fruin profile was also compared with the new profile and the varying demographics. All the movement profiles in Simulation 3 used lowest cost behaviour. Simulation 4 tested the stadium at full capacity with the demographics observed at the trials. These simulations started with no cross flow and increased cross flow for both sides equally by 10% up to 50% cross flow. Since the East bridge was closed in the simulation, cross flow only occurred between Gate One and the North Walkway.

Table 5. Summary of Predictive MassMotion Simulations Tested at Full Stadium Capacity

Simulation Name	Profile Used	Demographic Distribution	North Stand to Gate One	North Stand to North Walkway	South Stand to Gate One	South Stand to North Walkway	East Bridge
3a	Fruin	Default	N/A	N/A	N/A	N/A	Open
3b	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	N/A	N/A	N/A	N/A	Open
3c	New Profile	Fastest Profile (Young Adult)	N/A	N/A	N/A	N/A	Open
3d	New Profile	Slowest Profile (Elderly)	N/A	N/A	N/A	N/A	Open
4a	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	0%	100%	100%	0%	Closed
4b	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	10%	90%	10%	90%	Closed
4c	New Profile	As observed at events: 6% children, 29% young adult, 53% adult, 12% elderly	20%	80%	20%	80%	Closed
4d	New Profile	As observed: 6% children, 29% young adult, 53% adult, 12% elderly	30%	70%	30%	70%	Closed
4e	New Profile	As observed: 6% children, 29% young adult, 53% adult, 12% elderly	40%	60%	40%	60%	Closed
4f	New Profile	As observed: 6% children, 29% young adult, 53% adult, 12% elderly	50%	50%	50%	50%	Closed

As seen in Figure 7, Simulation 3 illustrates the total egress simulated using four different inputs. Simulations 3a and 3b show similar results. This is because when determining the overall speed of the crowd using the percentages of each demographic present, the speed is approximately 1.24 m/s. This is very close to the Fruin speed of 1.35 m/s. However, the impact of walking speeds can be seen in Simulations 3c and 3d. As expected, the slowest movement profile with a high population of elderly individuals (Simulation 3d) had the longest average egress time while the fastest movement profile with mainly young adults (Simulation 3c) had the shortest average egress time. The percent difference where there is the maximum difference in population remaining between Simulations 3c and 3d is 9.15%. Overall, the deviation between Simulations 3c and 3d show that demographic distribution, and therefore walking speeds, do have an impact on overall egress times, however, the percent difference illustrates there is not a large difference in population remaining during egress. Despite this, when designing stadia, knowing the intended use, including the types of events that will be hosted and what demographics those events may attract, are important considerations for egress planning.

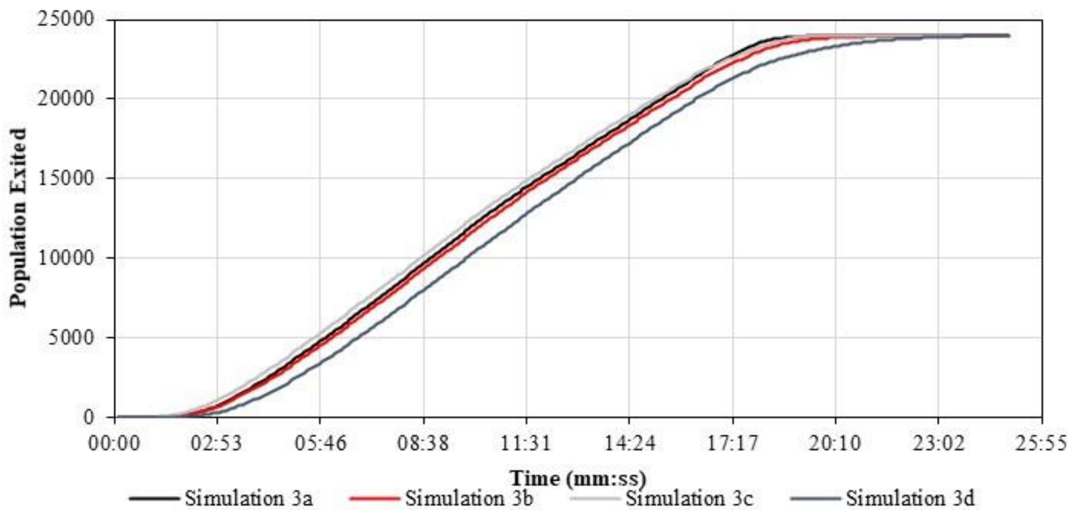

Figure 7. Simulation 3, Total Population Egressing

Simulation 4 specifically focused on the impact of cross flow. Figure 8 details that cross flow does have an impact on egress times by as much as six minutes additional time for 40% cross flow in comparison to Simulation 4a with no cross flow. However, the differences in additional time did not scale linearly; the differences between 0 to 10% and 30% to 40% cross flow saw smaller time differences than 10% to 20%. All the scenarios in Simulation 4 converged with the exception of Simulation 4f which showed significantly different results. While the other simulations had complete egress, Simulation 4f with 50% cross flow did not. When the simulation terminated 31.2% of the population remained. This was because the crossflow intersection between Gate One and the North Walkway became so dense the flow of agents egressing was severely or completely obstructed. This obstruction resulted in Simulation 4f not converging under the number of runs considered.

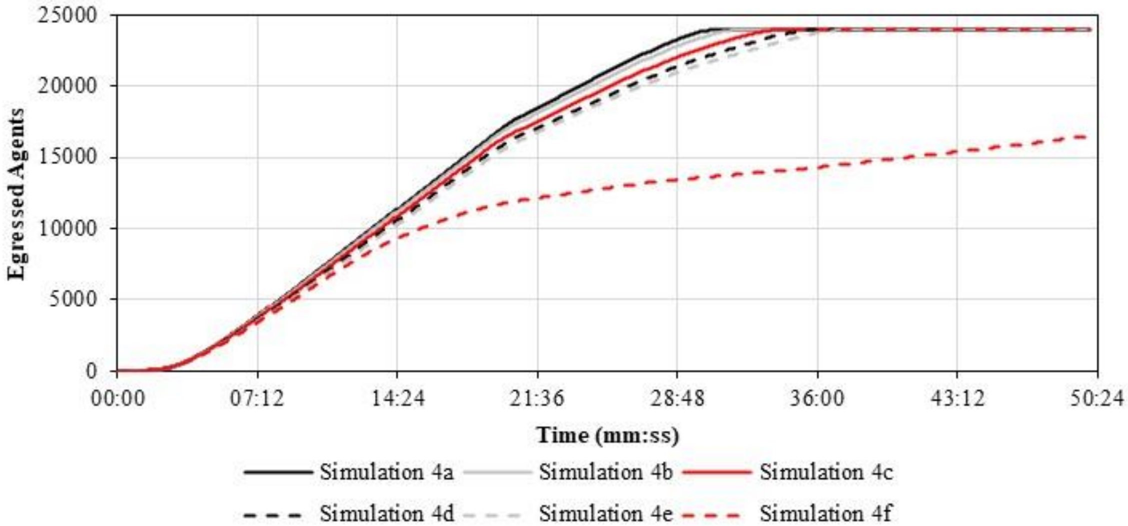

Figure 8. Simulation 4, Total Population Egress Time with Cross Flow

Overall, Simulation 3 indicates that individual walking speeds do impact overall egress times, though crowd density is the dominant governing factor for egress times. In other words, an increase of 10% in the walking speeds of agents in a simulation did not directly translate to a decrease of that magnitude in terms of total egress time in the simulation. This was a trend discovered in all simulations runs, concluding that crowd density had the largest impact on egress times for this case study. Note that crowd density is often formed due to the crossflow effect which is caused by route and exit choice. Implementing the observed behaviours from the trials into the model had a greater effect on the accuracy of the simulations compared to inputting the observed demographic distribution and their movement speeds. Simulation 4 shows that increasing cross flow increases overall egress time, however the relationship between egress time and increasing cross flow is not linear. Future work will include more runs and a complete statistically significant set of simulations to ensure convergence of average egress times, and a closer investigation of upper limits on cross flow and the effects when reaching this limit, specifically for Simulation 4f.

When comparing egress times for the trials of Simulation 3 vs Simulation 4, it becomes apparent that the East bridge being open does allow for faster egress times. However, it is noted that the bridge is narrow as it spans the field access road and was perhaps not intended for high volumes of pedestrian traffic. As such, the bridge acts as a bottleneck when used and/or assigned as an exit for agents in the South Stands. This demonstrates the utility of pedestrian simulation, as the models imply that if the bridge is to be used frequently as access for crowds in the South Stands, it should be widened. Alternatively, the model could be used to test different exit assignment strategies, but this is beyond the scope of this paper.

5. Conclusions and Future Research

The observations and analysis from Part 1 were implemented into the model to validate the new movement profile as well as the importance of inputting behaviours such as route and exit choice.

Two sets of validation simulations were completed. The first was a comparison of the simulation to Trial One, and the second compared the simulation to Trial Two. When transposing the graphs for Simulation 1, the new profile and Fruin profile in comparison to the observed trials had a maximum percent difference of 6%. Simulation 1c (Fruin lowest cost model) had a significantly larger maximum percent difference of 21% and underestimated the total egress time by approximately five minutes. This enforced the understanding that it is necessary to implement behaviours such as route and exit choice to create accurate simulations. During Simulation 2, the transposed simulation and observed Trial Two had a maximum percent difference of 13%. Overall, these numbers were reasonable and validated the new movement profile as well as the importance of implementing the behavioural aspects observed during the trials.

Once the validation simulations were completed, two sets of parametric simulations were completed. The first compared the impact of using the Fruin movement profile and the new movement profile. Results showed that although the new movement profile contained data for varying demographics, the Fruin profile and the new movement profile simulations were very similar. In addition, modelling various demographic distributions showed walking speed did have an impact on egress times though not proportionally. The maximum percent difference between Simulation 3c through 3d was 9%. In Simulation 4, the second set of parametric simulations analyzed the impact of the crossflow effect seen during the Trials. These simulations showed that increasing the amount of cross flow will increase the overall egress time, however, the increase will not be linear.

The social forces model is challenged to accurately represent group behaviour since individuals who are familiar with each other may behave differently. For example, family or friends will group together with a much smaller distance between themselves in comparison to strangers. The model used herein demonstrates difficulty representing group walking speeds. In general, it is known that walking speeds decrease linearly as group size increases (Moussaïd et al. 2010). Therefore, group behaviour tends to increase overall egress times, however this was not simulated, instead agents speed was also further dependent on crowd density.

Furthermore, the presence of vendors and post-game activities on the field encourages spectators to spend time inside the stadium after the event, making egress not their immediate priority. In contrast, each spectator in the model had evacuating the stadium as their primary task, ultimately reducing the total time required to vacate the grounds. In addition, more complex movement profiles such as those with accessibility needs were not considered in this study. The movement speeds of these individuals are likely to be much slower than the speed presented by the Fruin movement profile as well.

The research herein begins to address the gaps identified within the SFPE Research Roadmap for Fire Safety Engineering (SFPE 2018) through data collection of movement for demographics and consideration of large populations. It lays the foundation for continuing studies in the authors' SFPE foundation study where these profiles and observed egress data may be used for validation of software. Although this study can be used as a baseline indicator for egress performance during any evacuation, there is still a lack of research and understanding on the specific behaviours of individuals during emergency situations such as fire. Additional studies will be required to be carried out regarding the egress behaviours of individuals in emergencies.

Ethics Procedure

Ethics clearance for data collection was granted by the university on the basis of an internal university TD1/ TD2 process (Thesis and Dissertation Proposal by student researchers and Human Participants Research Protocol) that specified: filming permission from the stadium was granted, that standard information notices to patrons indicating that they will be filmed was performed, that ticketing indicated filming in progress, and that individuals were not readily identifiable in films or photos that would be published (hence image quality is downgraded for publication herein and altered to obscure facial reference), and filming archives were to be stored externally.

Data Availability

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Statement of Authorship

All persons who have meet authorship criteria in this manuscript are listed as authors. These authors certify that they have participated sufficiently in the work to take public responsibility for this manuscript's content, including the participation in the concept, design, analysis, writing, and revision of this manuscript. Those that do not meet these criterion are listed in the acknowledgements

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