Crowd Behavior

Modeling the Mechanics of Fleeing with the Individual Agent Model

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Abstract

In order to better understand how particular individual behaviors, particularly reaction times and propensity to travel against the flow of people, affect the ability of a crowd to evacuate a given location, an individual agent model was developed to simulate the movements of thousands of sprites in a given location. Baseline simulations involving random motion suggest that increasing the rate of dispersion dramatically increases evacuation rates. In a more complex simulation, where agents seek to minimize their distance to the exit, the sensitivity of the crowd to agents' reaction times and tendencies to move against the crowd was explored. The results provide evidence that increasing the variance of reaction times diminishes the negative effects of crowds with slow mean reaction times. Additionally, agents moving counter to the general flow of people can hasten evacuation beneath a certain threshold, beyond which evacuation times are inhibited and escape routes are severely distorted.

1 Introduction and Background

According to the United Nations Population Fund, approximately half of the world's population currently lives in cities, with the number of urban residents expected to swell to 5 billion by the year 2030. With an increasing amount of stress being put on current city infrastructure and the unfortunate possibility that these public places fall victim to an accident or attack, the ability to understand how people move through these spaces becomes incredibly important. Many public areas are built with the intention of accommodating thousands, if not millions, of people; however, it is crucial that these locations provide people with adequate evacuation routes.

Much research has been dedicated to understanding how individuals will react and think during an emergency and how these individual behaviors will affect the group as a whole. Some evacuation simulations attempt to mimic sociological factors by implementing factors such as herding tendencies, where people follow the people in front of them, and the Yerkes-Dodson Law, which describes the correlation between stress and performance. Other models, however, build on the rational behaviors of people and implement methods that minimize agent effort or allow them to seek alternate routes. Despite these various methods, the quest to best understand evacuation behaviors remains an open and improving field.

Understanding human behavior and the most important characteristics of individuals in the event of an evacuation should help shed light on how to best manage crowds. While the complexity of human intelligence is nearly impossible to capture, a simplistic model can, at the very least, provide us with a rudimentary understanding of how crowds may operate.

2 Individual Agent Model

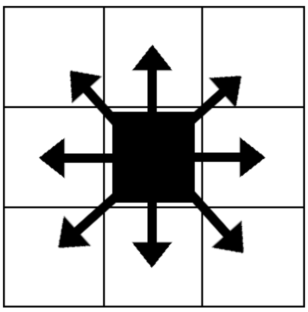
In order to best simulate the various behaviors of crowds evacuating a small enclosure, individual agent models were employed for their ability to guide the interactions of thousands of sprites based on a set of predetermined rules. Each model contained the following parameters:

Parameters:

- Width and height of the grid in which the simulation would take place
- Perimeter and wall locations that will block the agents
- Exit location that delineates that location of the exit in the grid
- Number of people that the simulation should control and some basic information about their individual behavior
- Duration of the simulation

Essentially the individual agent model consisted of an array of agents with a predetermined set of characteristics who are placed into a grid with demarcated exits and perimeters. As the simulation progresses, the model iterates over each individual and based on the guidelines set forth in the simulation, each person receives a 'turn' during which they will determine the direction in which they travel. For the purposes of this simulation, a person can choose from 8 or 9 positions (including the horizontal, vertical, and diagonal directions) that are 1 unit of the grid away.

The legal moves are illustrated below:



Several different individual agent models were created to model different behaviors, as outlined in the next several sections.

2.1 Random Escape Model

The first model constructed, to be used as a baseline, is the Random Escape Model. Under this model, each agent randomly selects one of the 8 possible directions that it can travel in based on a uniform distribution. After picking a direction that the person desires to travel, the person will attempt to move in that direction. If the location is already occupied, the agent will remain in its current position. This model essentially simulates extremely unaware agents with a lack of flexibility in their movements, due to the fact that the agents have no knowledge of the exit and they choose a direction to move in even if that space is already occupied. In a real scenario, this model could represent the behaviors of a crowd of incredibly disoriented people.

The essential probability guiding this behavior for a given direction D and the position it leads to $D_{position}$ is as follows:

$P(\text{selecting } D) = P(\text{selecting } D \mid D_{position} \text{ is occupied}) = \frac{1}{8}$.

While this model could potentially be very useful for basic crowd behavior, there are other random characteristics that can be implemented in additional models.

2.2 Adaptive Random Escape Model

Building off the Random Escape Model, another baseline could prove more accurate and useful by allowing an agent to randomly select a direction from only the set of possible positions that are available. For example, if moving to the left is blocked by another agent, then the individual will have a 0% chance of selecting that direction.

In relation to the Random Escape Model, the essential probability guiding this behavior for a given direction D and the position it leads to $D_{position}$ is as follows:

$P(\text{selecting } D) \neq P(\text{selecting } D \mid D_{position} \text{ is occupied})$

More generally:

$P(\text{selecting } D \mid D_{position} \text{ is not occupied}) = \frac{1}{\text{number of possible positions}}$

$P(\text{selecting } D \mid D_{position} \text{ is occupied}) = 0$

2.3 Shortest Distance Escape Model

The most robust, and most likely the most accurate, underlying model is the Shortest Distance Escape Model. This model forces an individual to calculate the distance between all possible new positions and each point of exit. The individual will select the move that minimizes his distance to an exit. If multiple moves are equivalent, he will randomly select from those options with each having an equal probability of being selected. Additionally, unlike the previous models, an agent can decide to remain at its location if all possible options bring it farther away from the exits. The distance is calculated using simple trigonometry.

The probabilities of this model given direction D and the position it leads to $D_{position}$ are as follows:

$P(\text{selecting } D \mid D_{position} \text{ is not occupied}) = \frac{1}{\text{number of equivalent positions}}$

$P(\text{selecting } D \mid D_{position} \text{ is occupied}) = 0$

2.4 Shortest Distance Escape with Reaction Model

To further build on the Shortest Distance Escape Model, in the Shortest Distance Escape with Reaction Model each individual agent is given a reaction time, after which they will proceed to implement the Shortest Distance Escape. Before this reaction time, however, an individual will remain unmoved under the Stationary Reaction Model or move in random directions under the Random Reaction Model. Both seem to be viable models, as in some circumstances individuals will be immobile for a certain amount of time and in other circumstances individuals will flee chaotically based on impulse.

Some important probabilities for the Stationary Reaction model are as follows:

$P(\text{selecting } D \mid \text{current time} < \text{reaction threshold}) = 0$

$P(\text{selecting } D \mid \text{current time} > \text{reaction threshold AND } D_{position} \text{ is not occupied}) = \frac{1}{\text{number of equivalent positions}}$

$P(\text{selecting } D \mid \text{current time} > \text{reaction threshold AND } D_{position} \text{ is occupied}) = 0$

Some important probabilities for the Random Reaction Model are as follows:

$P(\text{selecting } D \mid \text{current time} < \text{reaction threshold AND } D_{position} \text{ is available}) = \frac{1}{\text{number of possible positions}}$

$P(\text{selecting } D \mid \text{current time} < \text{reaction threshold AND } D_{position} \text{ is not available}) = 0$

$P(\text{selecting } D \mid \text{current time} > \text{reaction threshold AND } D_{position} \text{ is not occupied}) = \frac{1}{\text{number of equivalent positions}}$

$P(\text{selecting } D \mid \text{current time} > \text{reaction threshold AND } D_{position} \text{ is occupied}) = 0$

2.5 Shortest Distance Escape with Counter Flow Model

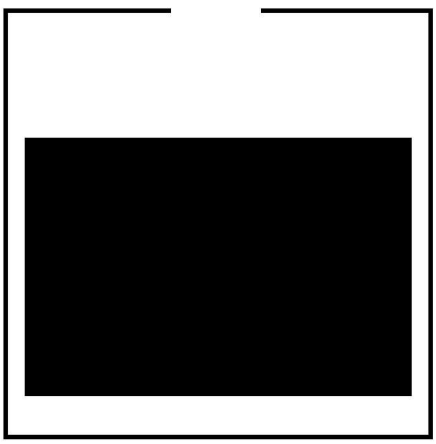
Lastly, building even further off the Shortest Distance Escape Model and the Reaction Dependent Model, an additional variable was added that mimics the behavior of people travelling opposite the exit to a predetermined location. These people can be thought of as emergency responders or other critical personnel. In this model, a percentage of people exhibit this behavior and will seek to minimize the distance between them and a given location (i.e. a somewhat inverted version of the shortest distance escape). The probabilities for this model are generally identical to the models described above.

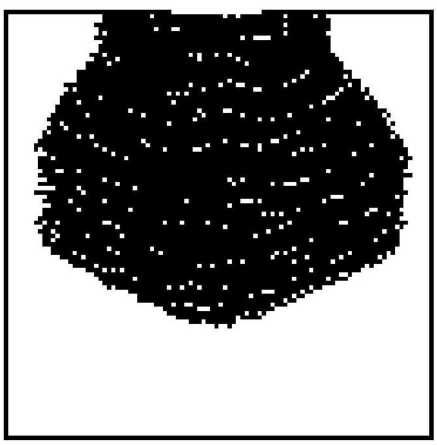
Essentially this model pits two groups of people going against each other, whereby each group follows the Shortest Distance Model but with different destinations. So, a counter flow agent will follow the same methods as the other agents, but will be minimizing its distance with another point, generally on the side opposite the exit. Frequently, in the event of an emergency, a particular group of people will approach the source of danger in order to help or assist other people. As Fred Rogers, a famous American TV personality, once said, ”Look for the helpers. You will always find people who are helping.”

3 Analysis of Models

3.1 Conditions

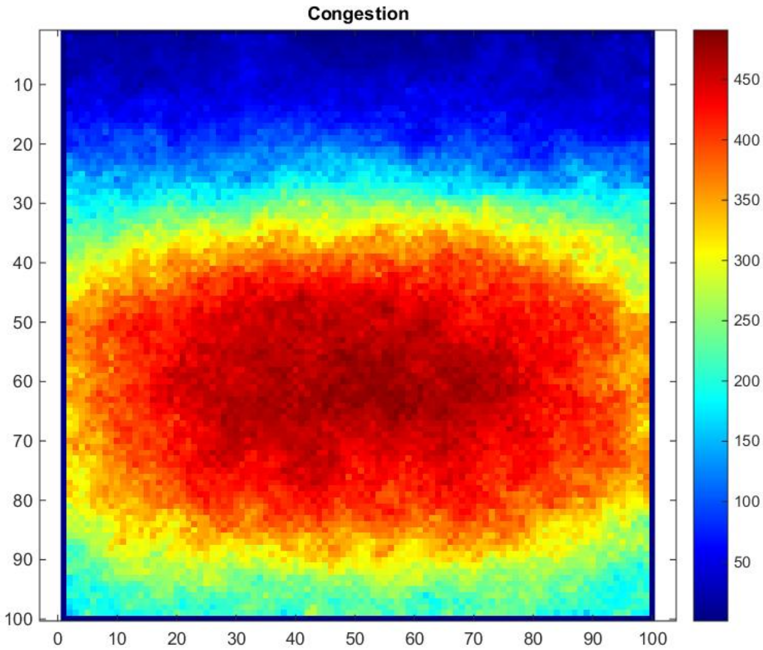
For the purpose of this report, a particular set of constants are implemented so as to make comparison and analysis easier. The setup consists of a 100 by 100 grid, with the edges serving as walls. On the top wall, an exit of 20 units is created. Each simulation consisted of 5400 people organized into 60 rows of 90 people each toward the bottom of the grid. The goal of such a simulate is to as accurately as possible recreate a small concert venue or club. A representative setup is recreated below, with the first image depicting the starting positions of the 5400 people, and the next image portraying a sample simulation partway through. The black lines along the edges are walls, and the black squares in the middle are individual people.



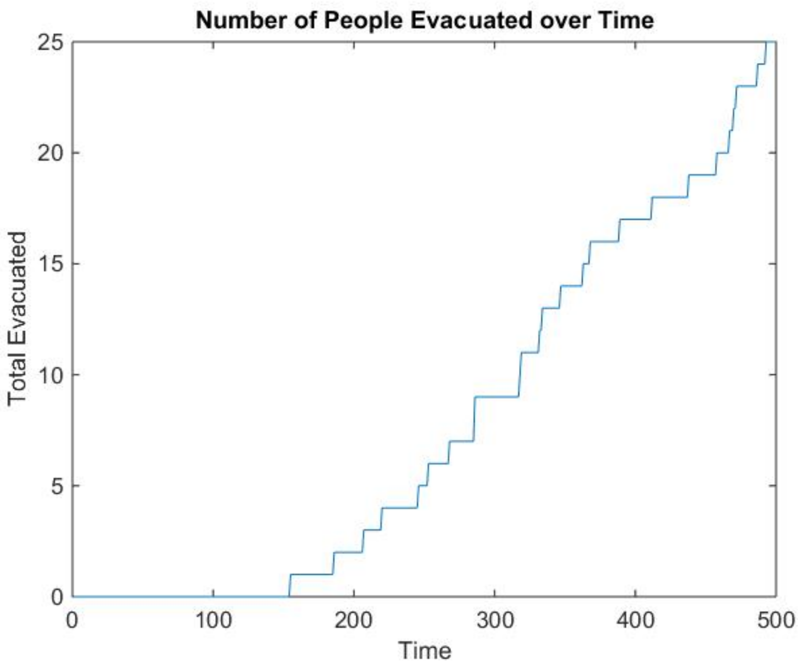


3.2 Random Escape Model

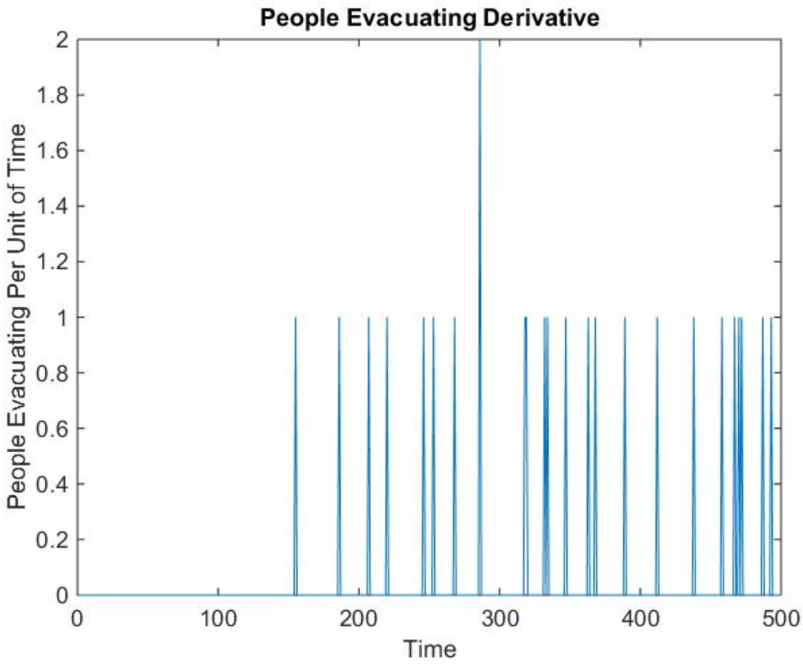
To begin the analysis, the Random Escape Model was run with the parameters and constants described above. Below is a heat map of the evacuation process, where each space is colored according to how frequently that space was occupied.



The second graph produced plotted the total number of people evacuated as a function of time.

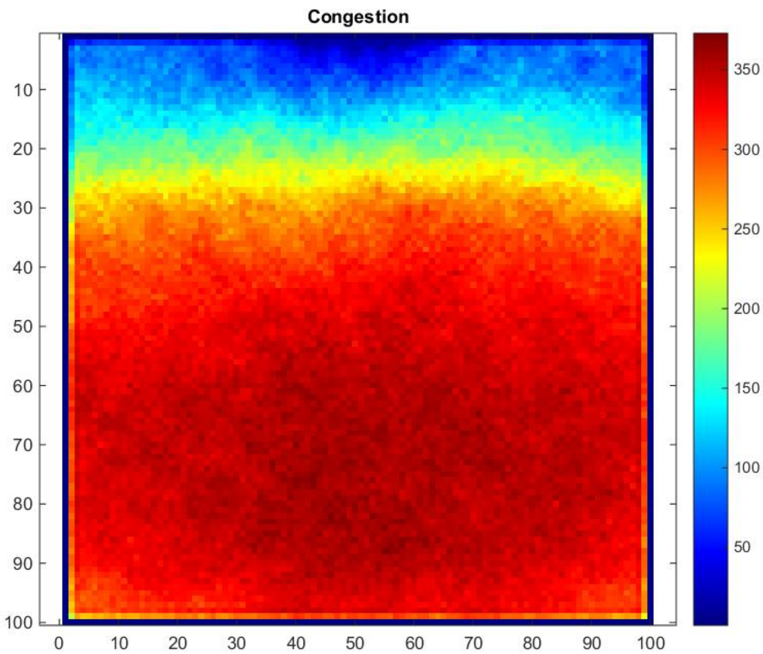


Lastly, the next graph shows the rate of evacuation as a function of time.

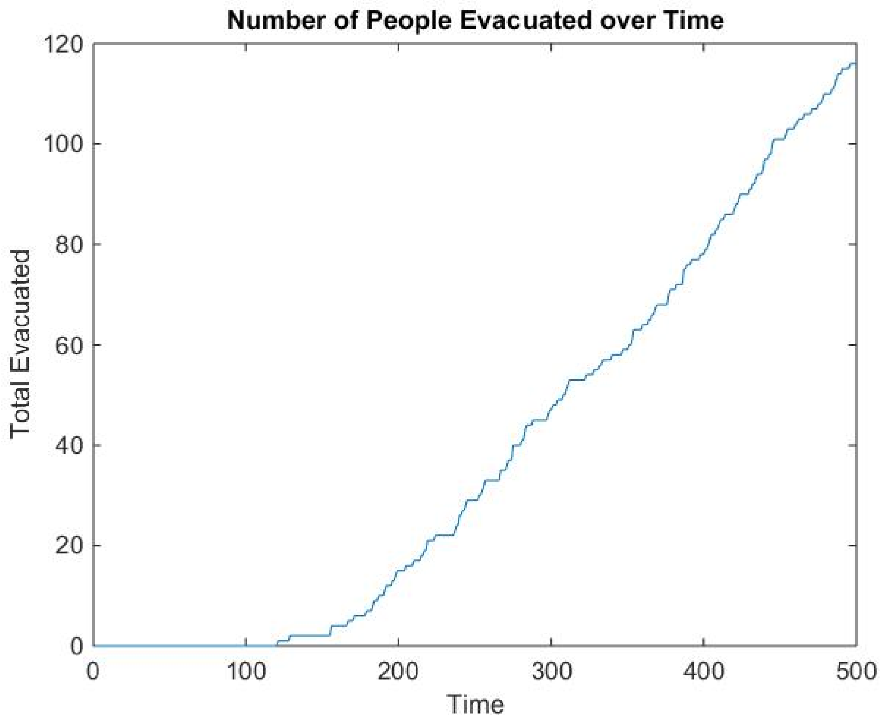


3.3 Adaptive Random Escape Model

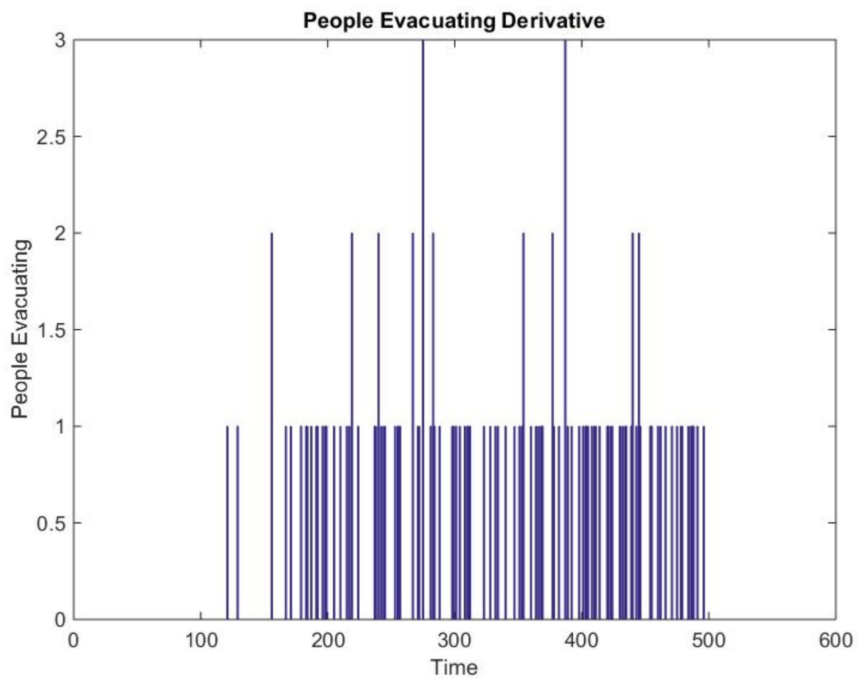
Similar to the process for the Random Escape Model, the Adaptive Random Escape Model was simulated under the same conditions. First a heat map was produced, revealing a large swath of space that was occupied for more than 50% of the simulation.



Next, the number of people evacuated over time was graphed, revealing a period of approximately 120 units of time before an agent escaped. Additionally, the graph follows a generally linear trend, resulting in approximately 116 people being evacuated after 500 units of time.

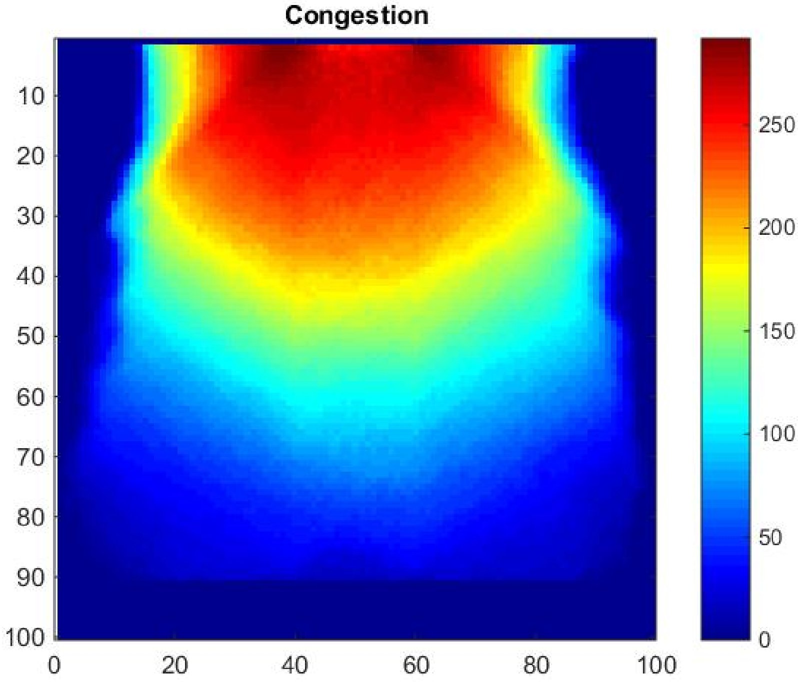


Additionally, the rate of evacuation reveals that during the first 500 units of time, the majority of agents were escaping alone at a given point in time. The highest rate only reached 3 escapees per unit of time.

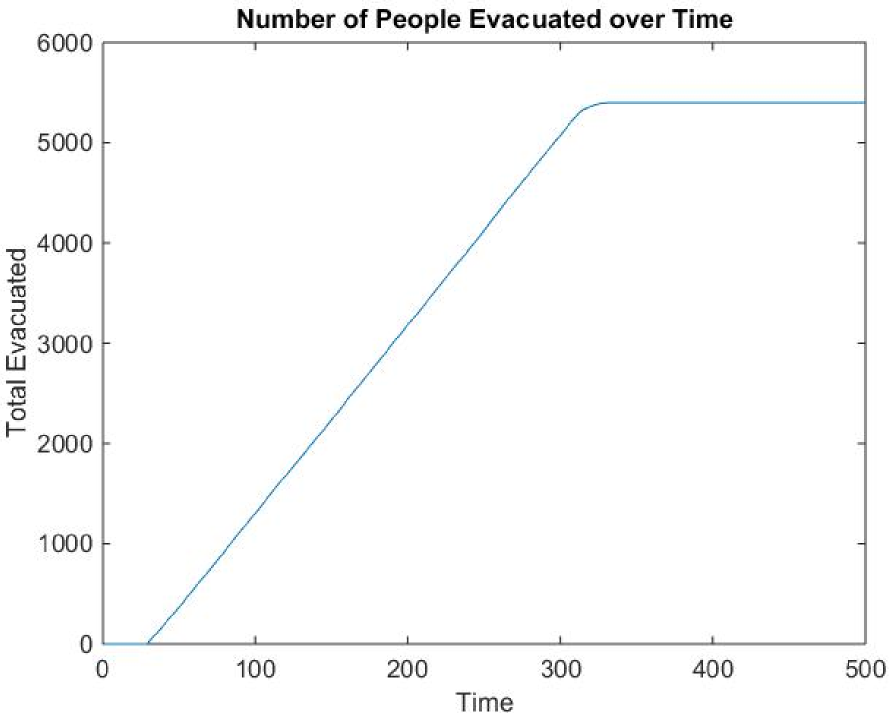


3.4 Shortest Distance Escape Model

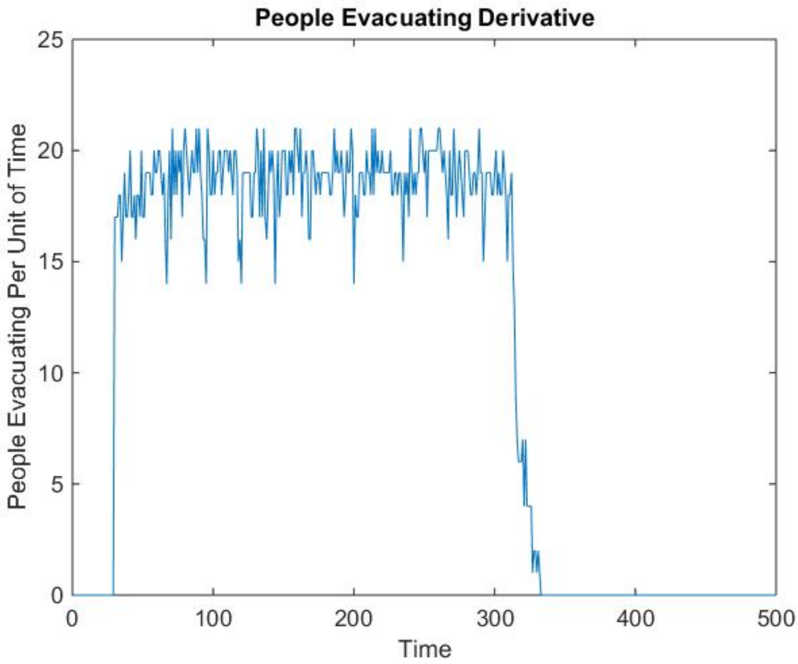
For the Shortest Distance Escape Model, a heat map was produced as well, revealing a gradual increase in the likelihood of a space having been occupied as one nears the exit. Note that the highest level of congestion was no greater than 300 times during the simulation of 500 units of time.



In the plot below comparing the total number of people evacuated over time, we can see a linear trend beginning at 30 units of time and continuing until 315 units of time, at which point all people have been evacuated and the function reaches an equilibrium.



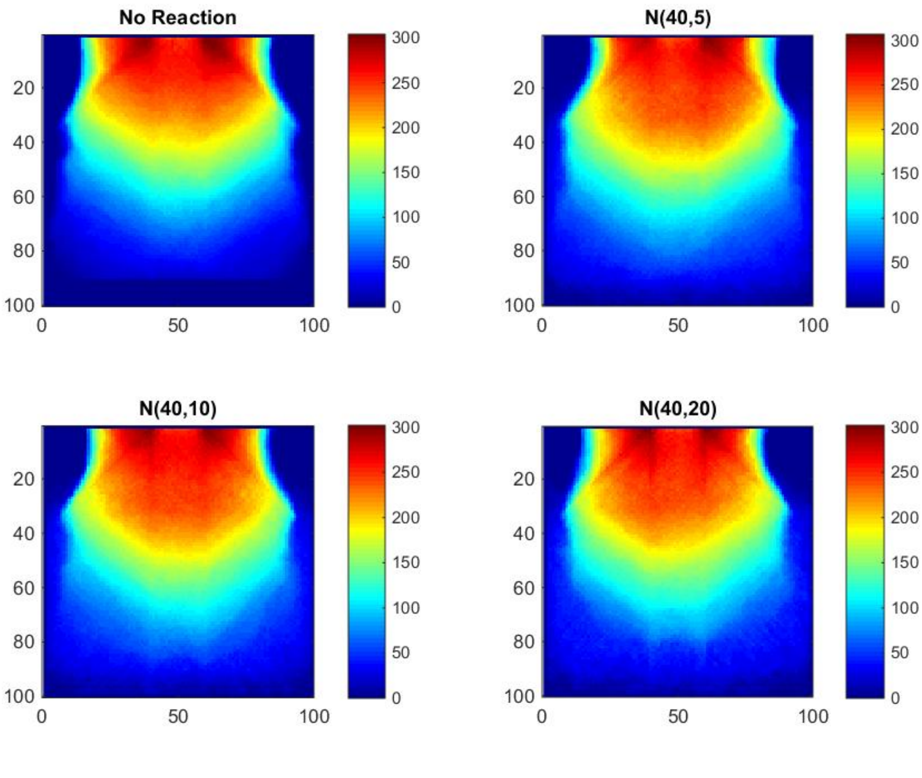
The rate of evacuation under the Shortest Distance Escape Model shows an interesting pattern, where the rate quickly spikes to 17 evacuated agents per unit of time and the proceeds to hover in the 16-20 range until approximately 300 units of time. Near the end, the rate dips significantly, briefly stays in single digits, and then plummets to 0 as all people have evacuated.



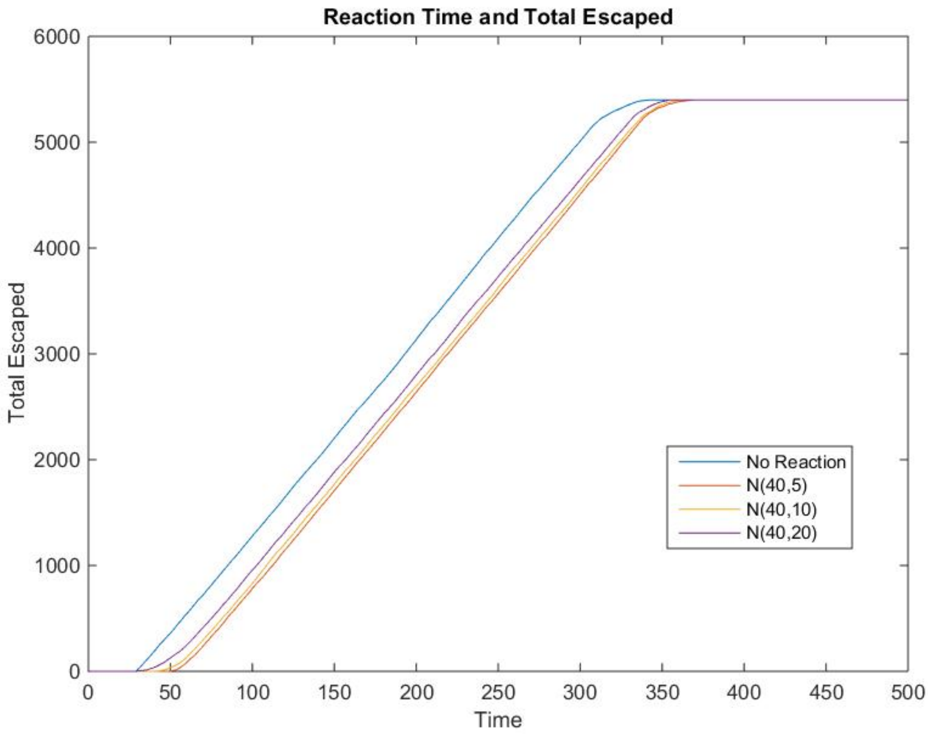
3.5 Shortest Distance Escape with Random Reaction Model

In order to test the sensitivity of the Shortest Distance Escape Model to different reaction behaviors, a set of 4 different parameters was used. The first implementation had agents with immediate reactions (labeled either 'No Reaction' or 'Immediate Reaction' below) in the graphs below, which will serve as a baseline. The next three implementations assigned each agent a reaction time from a normal distribution with a mean of 40. The key difference, however, is that in these normal distributions one simulation had a standard deviation of 5, another a standard deviation of 10, and the last had a standard deviation of 20. The purpose of the exploration below is to understand not just how a slow reaction influences evacuation times, but also how the variance in people's ability to find the exit can influence the crowd as a whole.

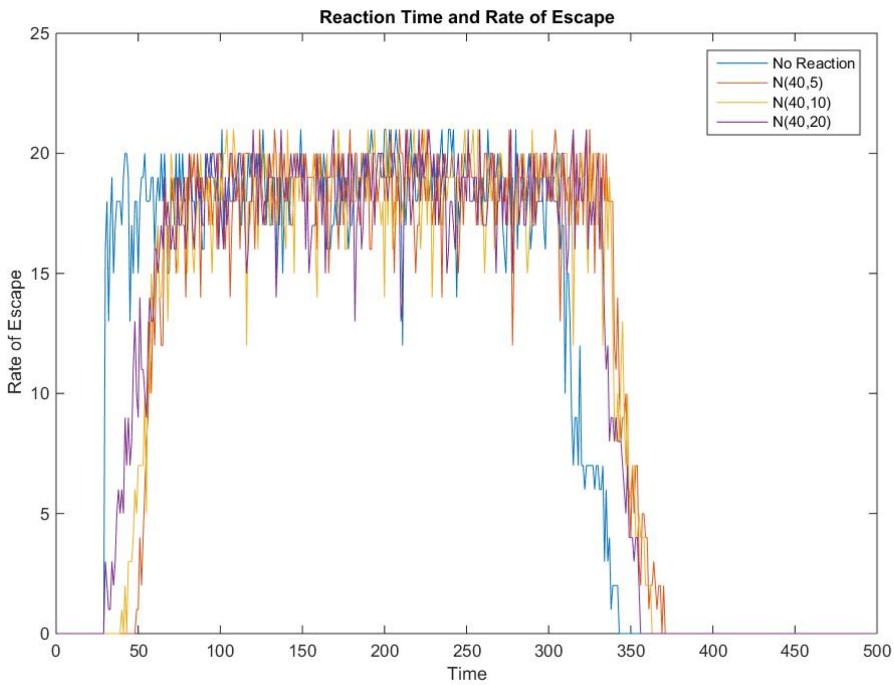
First we can look at the model in which people move around randomly before they head for the exit. The heat maps look surprisingly similar for the different standard deviations, although there appear to be minute differences in the edges of the exit.



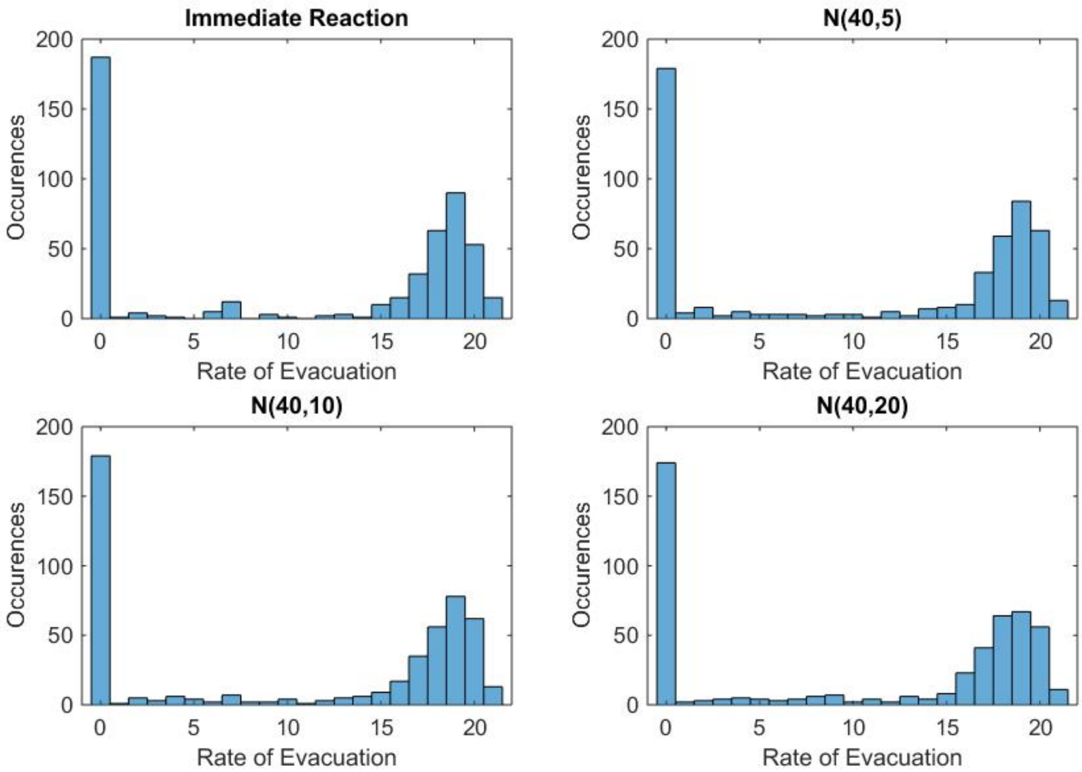
Analyzing the total number of people evacuated over time reveals that having an immediate reaction is most effective at clearing the room, while the higher the variance, the faster the grid is evacuated. The simulation with the immediate reaction evacuates its first agent after 30 units of time and clears the grid after 342 units of time. The simulation with the highest standard deviation in reaction time (20) evacuates its first agent after 30 units of time as well and evacuates all agents in 355 units of time. The simulation with the next highest standard deviation in reaction time (10) evacuates its first agent after 40 units of time and evacuates all agents in 362 units of time. The simulation with the lowest standard deviation in reaction time (5) evacuates its first agent after 49 units of time and evacuates all agents in 370 units of time.



If we look at information about the derivatives, all of the models follow a similar trend, although the simulations with the reaction times are delayed by a certain amount of time.

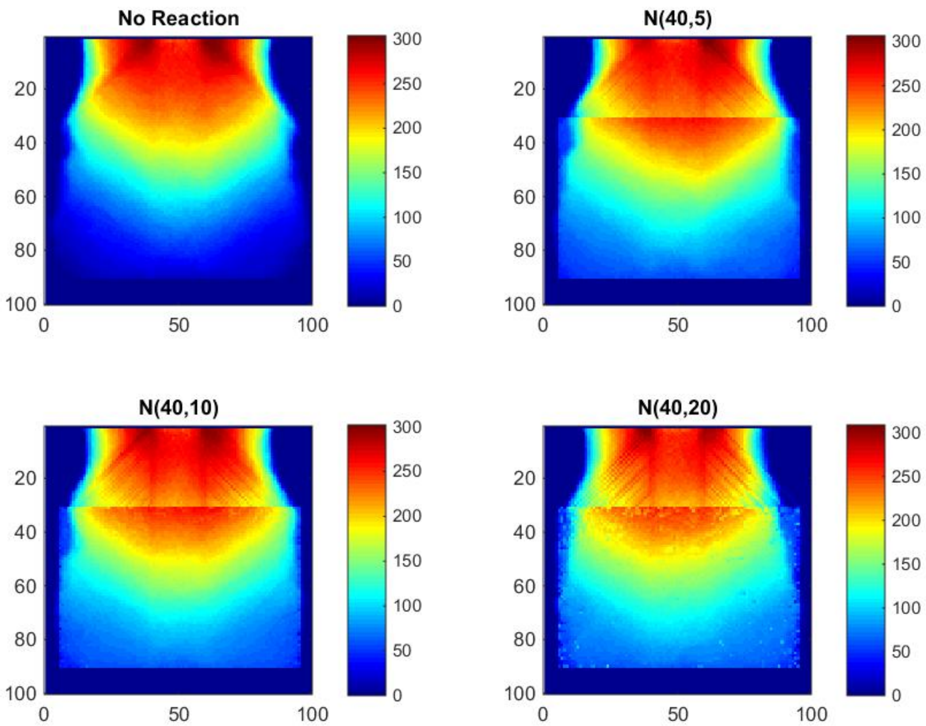


However, the frequency of the rates of evacuation shed more light on the effects of different reaction time distributions.

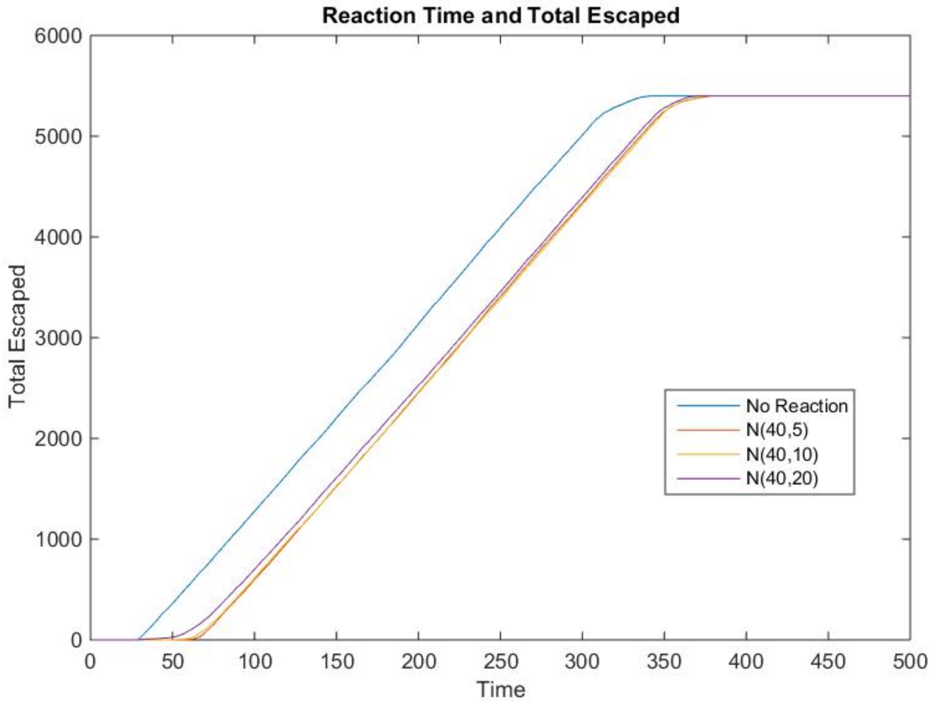


3.6 Shortest Distance Escape with Stationary Reaction Model

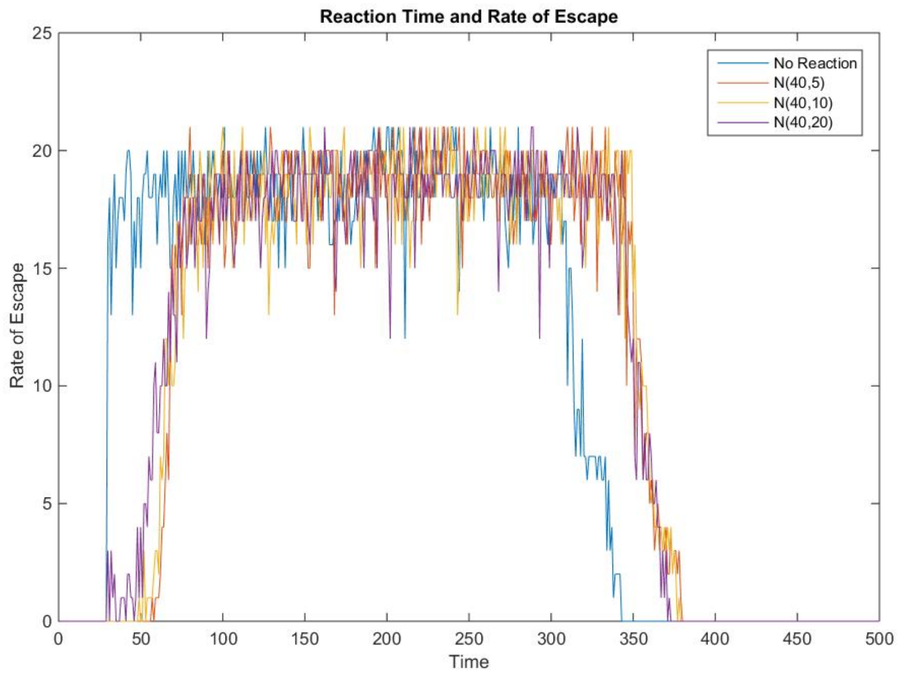
For the Stationary Reaction Model, simulations were run with the same distributions used in the Random Reaction Models. Similar graphs were produced, starting with the heat maps.



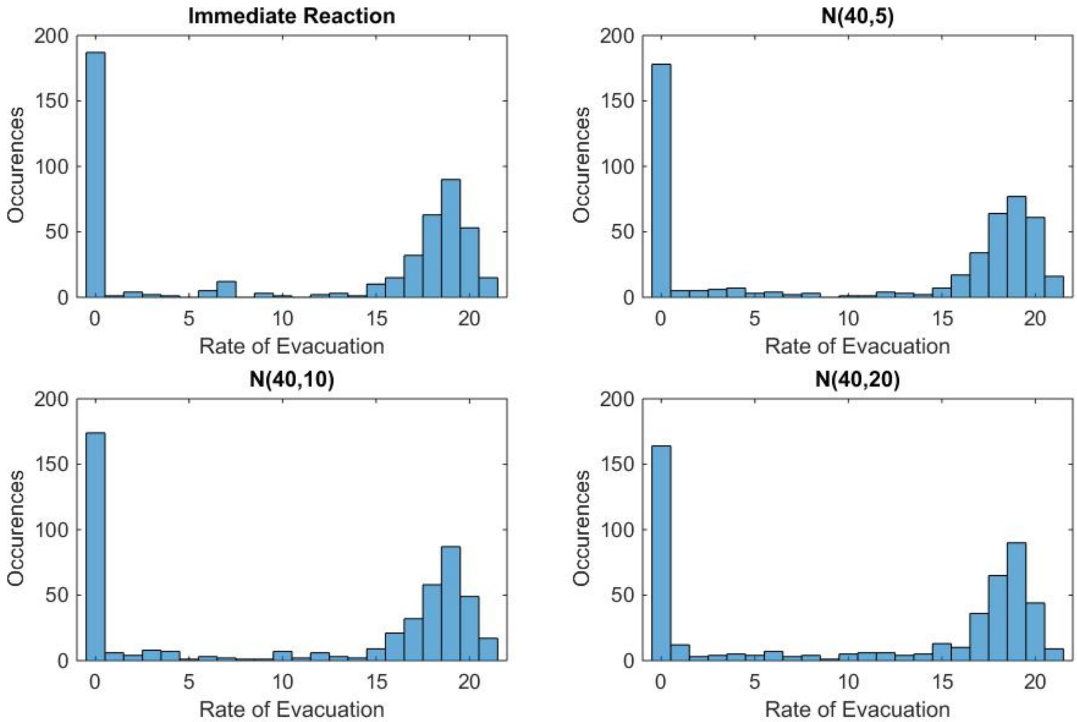
The simulation with the immediate reaction evacuates its first agent after 30 units of time and clears the grid after 342 units of time. The simulation with the highest standard deviation in reaction time (20) evacuates its first agent after 30 units of time as well and evacuates all agents in 372 units of time. The simulation with the next highest standard deviation in reaction time (10) evacuates its first agent after 49 units of time and evacuates all agents in 378 units of time. The simulation with the lowest standard deviation in reaction time (5) evacuates its first agent after 58 units of time and evacuates all agents in 379 units of time.



If we look at information about the derivatives, all of the models follow a similar trend, although the simulations with the reaction times are delayed by a certain amount of time.

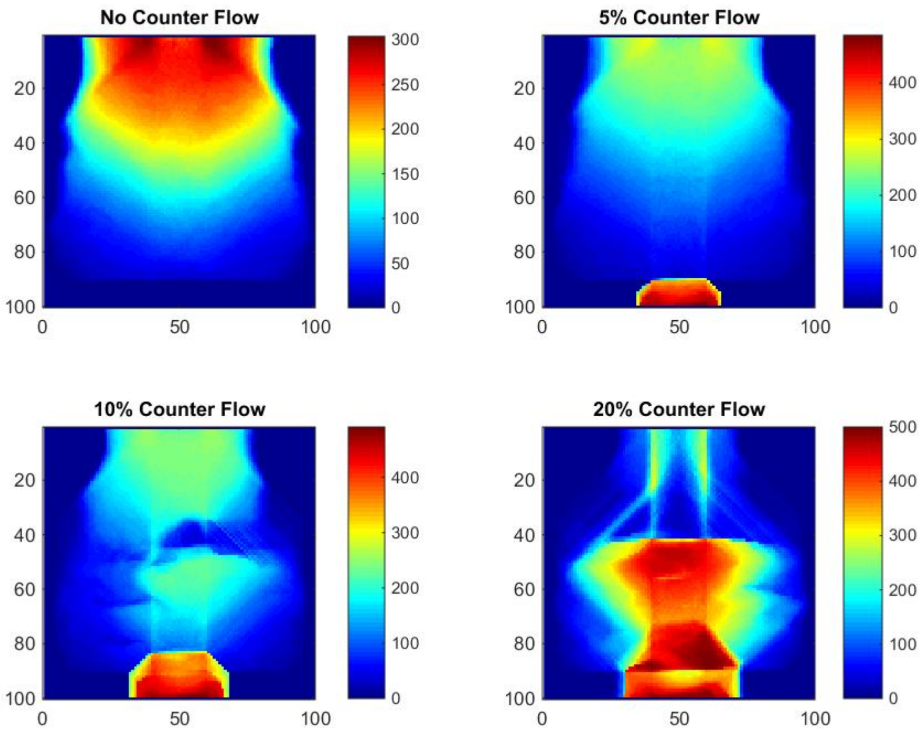


However, the frequency of the rates of evacuation shed more light on the effects of different reaction time distributions.

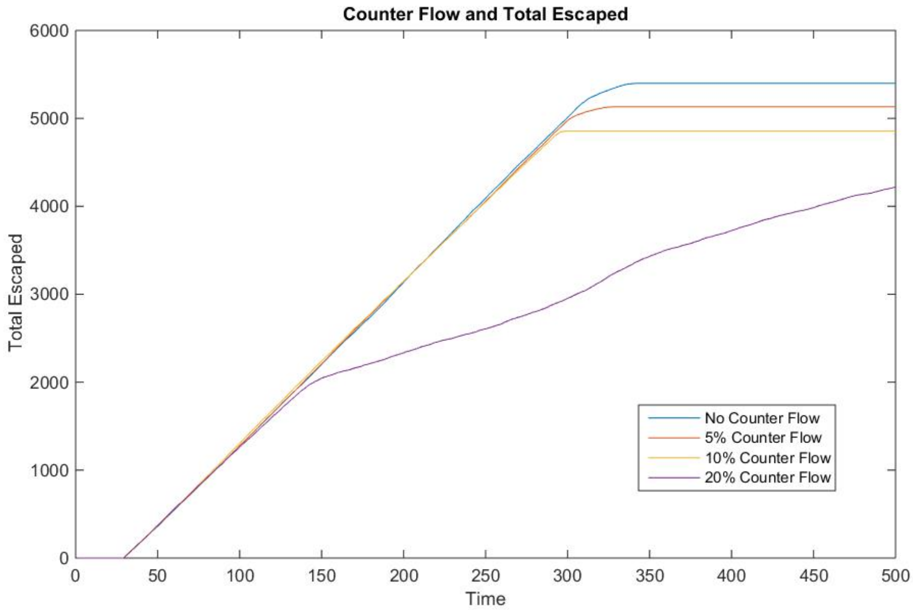


3.7 Shortest Distance Escape with Counter Flow Model

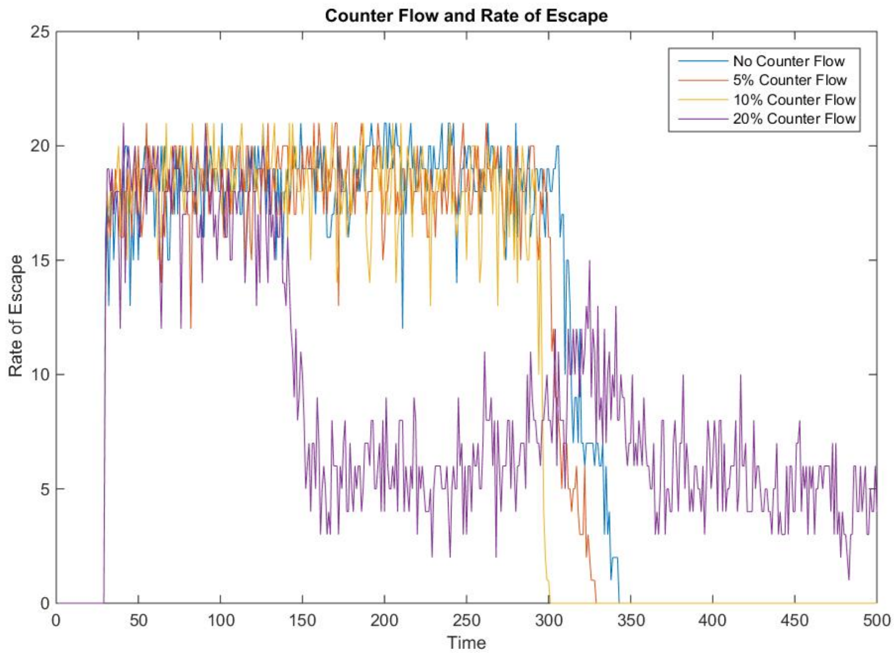
Lastly, simulations were run to see the effects of having a certain subset of the population travel in the direction opposite the exit. These agents are attempting to reach a set of points that are exactly opposite the exit. Four different simulations were run with different parameters: the baseline had no people moving counter flow, one simulation had 5%, the next had 10%, and the last had 20%.



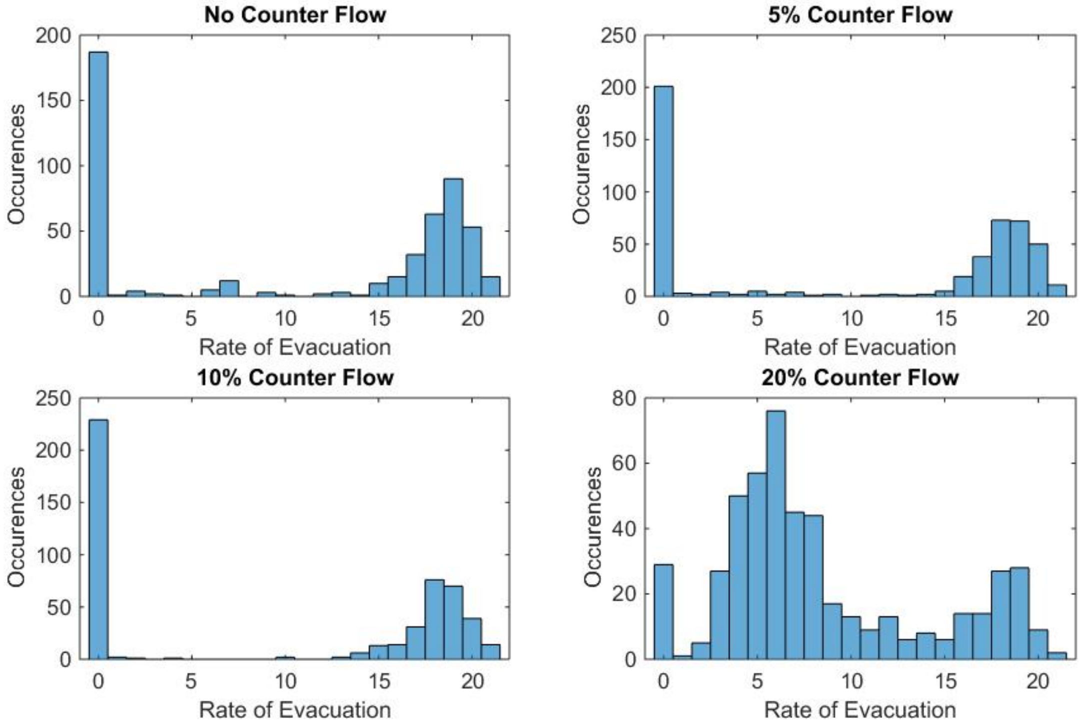
The simulation without counter flow evacuates its first agent after 30 units of time and clears the grid after 342 units of time. The simulation with 5% counter flow evacuates its first agent after 30 units of time as well and evacuates all agents in 328 units of time. The simulation with 10% counter flow evacuates its first agent after 30 units of time and evacuates all agents in 300 units of time. The simulation with 20% counter flow evacuates its first agent after 30 units of time and evacuates about 98% eligible people after 500 units of time.



The derivative of the total evacuated people as a function of time reveals information about the behavior of crowds with varying counter flow percentages.



The frequency of the rates of evacuation also shed more light on the effects of different amounts of counter flow.



4 Discussion of Results

4.1 Random Escape Model

From the heat map for the Random Escape model, it is evident that the failure to move when given the opportunity severely restricts the ability for a crowd to evacuate a given location. The heat map shows a lack of dispersal throughout the grid and the total number of evacuated people reveals a rather depressing reality. In a span of 500 units of time, only 25 people managed to stumble across the exit, with generally only 1 or 2 people exiting at a time in a way that does not fully utilize all available exit positions.

4.2 Adaptive Random Escape Model

Compared to the Random Escape Model, the Adaptive Random Escape Model offers drastic improvement in evacuating the grid. Evident in the heat map is the increased rate of dispersion throughout the grid, which thereby increased the crowds probability of coming across the exit. In 500 units of time, nearly 120 agents were evacuated, although the derivative again reveals a lack of full utilization of the exit.

From the two random models, it seems that increasing the rate of dispersion has a multiplicative effect, in that not only does it increase one's own probability of finding an exit, but also one's movement frees up additional space for other individuals in the crowd. The data seems to suggest that constantly moving to find an exit helps others in the crowd find an exit as well.

4.3 Shortest Distance Escape Model

Unlike the previous random models, the Shortest Distance Model reveals a more promising method of evacuating, as shown by the highest concentrations of occupied positions near the exits in the heat map. The Shortest Distance Model also gave the agents behaviors that allowed the entirety of the crowd to evacuate. Interestingly, the derivative is fairly consistent and shows a near maximum utilization of the exit.

4.4 Shortest Distance Escape with Random Reaction Model

The heat maps of this model are strikingly similar, implying that the initial period of random reaction does not dramatically alter the paths of the individual agents. As the variance increases, however, the heat maps reveal small streaks near the corners of the exits and a more expansive region of high occupancy. Intuitively, it seems that the agents with the quick reactions are forced to move around the agents with the slow reactions. Interestingly, however, the effects of the reaction time do not lead to an equal delay in evacuating the entire crowd. In the total number of people escaped over time, a crowd with an average reaction of 40 units of time and a small variance only took an additional 28 units of time to evacuate all agents. After looking at the frequency of the rate of change in total agents evacuated, it becomes evident that the higher variance leads to a greater spread in this derivative (i.e. the exit is not jammed at all times). With a greater variance, the exit is used more often but on average for less people at any given moment in time.

4.5 Shortest Distance Escape with Stationary Reaction Model

Analysis of the heat maps for a crowd that does not move before reacting reveals an even greater level of distortion to the paths that evacuating agents take to the exit. As the variance in reaction times grows, the paths bow towards the edges and form noticeable streaks toward the exit. The total number of people evacuated over time reveals that the variance has less of an effect in diminishing the total time to evacuate all agents as it does in the Shortest Distance Escape with Random Reaction Model. Doubling the standard deviation from 5 to 10 barely improves the evacuation time. A further doubling to 20 makes a much smaller difference than it did for the previous model. The graphs for the derivatives reveal that there is less of an effect on the variance in the derivative as was seen in the random reaction model. A possible reason for this behavior is that stationary people cause significant backlogs that are more difficult to overcome because the agents blocking important pathways refuse to move. In conclusion, the preferred reaction behavior is to disperse, rather than remain in a single position.

4.6 Shortest Distance Escape with Counter Flow Model

The heat map for the counter flow model reveals an incredible amount of distortion to the paths that people take in exiting the grid. With no counter flow and 5% counter flow, the distribution of agents throughout the grid was fairly uniform and gradual. However, once the counter flow percentage reached 10% and 20%, pockets of agents formed and the heat map becomes much more jagged. Looking at the total number of people evacuated over time reveals that with a counter flow of 10% or less, all agents were able to evacuate. From these initial data points, it seems that increasing counter flow (1) decreases the stress on the exit as less people are exiting and (2) allows the agents to reach the exit more quickly. However, once that percentage jumps to 20%, the consequences begin to outweigh the benefits, as the number of people evacuating drops off significantly. The simulation with 20% counter flow never evacuates all its agents (we can reason that its possible some are trapped in the grid) and from its rate of evacuation per unit of time we can deduce that agents are struggling to reach the exit. This model had a significant number of times when only a few people were exiting at a time, suggesting an inefficiency in how the crowd was evacuating. So, while a few number of 'helpers' provides no significant consequences, too many 'helpers' can actually harm the performance of the crowd as a whole.

4.7 Assumptions and Limitations

The models used in this report are, by their nature, incredibly simplistic when compared to how crowds actually function. There are a significant number of modifications that could be made to make the models more accurate, including everything from stress-induced decisions to imitation to aggression.

For the purposes of this simple model, I will outline the most notable assumptions and limitations:

- Uniform speed: In a true population of people, running and walking speeds will vary greatly between people, who are also very likely to utilize their full range of speeds in the event of an evacuation.
- Grid system: The gridded format of the simulation simplified the motions of people to a very particular set of possible positions, eliminating the possibility of nuanced responses to external stimuli. Additionally, the gridded system assumes each person has an equal and constant amount of personal space.
- Normal distribution for reaction time: Although normal distributions are generally useful in modeling population features, making the assumption that reaction times would follow a normal distribution was crucial to the simulation.
- Location of counter flow agents: Agents that were poised to move against the flow of people were randomly distributed throughout the initial setup, which may or may not accurately reflect true crowd behavior.
- Random assignment of people to matrix: The method of assigning people to an index in a matrix of people could influence the results. Additionally, counter flow agents were randomly assigned an index, which may or may not reflect how crowds actually operate.

4.8 Future Exploration

Because of the incredibly complex nature of crowd behavior, there are a vast number of future directions for modeling evacuations. Each new characteristic that is given to the individual agents can make the simulation more realistic. Further exploration would fit into two general categories:

1. Individual Agent Characteristics: Adding behaviors to the individual agents, such as speed, aggression, imitation, stress, and many others, would make the model much more realistic. People are guided by both rational and irrational thoughts that allow them to interact with both their environment and the rest of the crowd.

2. Environment Complexity: Increasing the complexity of the environment by increasing the fineness of the grid or providing the agents with additional stimuli would help strengthen the model. New obstacles, variable lighting, and different exit shapes would be interesting areas to explore.

5 Summary

From the exploration in this report, we can make several conclusions about crowd behavior.

1. First, an increase in the dispersion of people helps to facilitate evacuation. If people are unsure where the exits are located, then according to the models simulated above, they are better of moving around until they find the exit. Such increased dispersion increases the performance of both the individual and the crowd as a whole.

2. Second, if the average reaction time of a crowd is fairly slow, increasing the variance of reaction times can significantly diminish the overall negative effects of these slow reactions. A higher variance allows faster people to exit and clear more space for slower people to exit. Intuitively, one may assume that a crowd with an average reaction time of x units of time will evacuate a room x units of time slower than a crowd with no reaction time; however, this is not true, as a higher variance will diminish the effects of the reaction time.

3. Third, a low percentage of 'helpers' that go against the flow of people exiting the building can yield increased evacuation performance. By removing stress from the exit and cutting through the crowd, the people going against the crowd can hasten the evacuation of others. However, too large of a percentage of counter-flow people can prove to negatively effect evacuation performance.

6 Appendix of Matlab Code

6.1 re.m, re_trials.m

Implements Random Escape Model

6.2 are.m, are_trials.m

Implements the Adaptive Random Escape Model

6.3 sdem.m, sdem_trials.m

Implements the Shortest Distance Escape Model

6.4 sdercf.m, sdercf_trials.m

Implements the Shortest Distance Escape Model with both Random Reaction and Counter Flow Models

6.5 sdercf2.m, sdercf2_trials.m

Implements the Shortest Distance Escape Model with both Stationary Reaction and Counter Flow Models

7 References

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