

A PARTICLE SWARM OPTIMIZATION MODEL OF EMERGENCY AIRPLANE EVACUATIONS WITH EMOTION

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ABSTRACT. Recent incidents such as the Asiana Flight 214 crash in San Francisco on July 6, 2013 have brought attention to the need for safer aircraft evacuation plans. In this paper we propose an emergency aircraft evacuation model inspired by Particle Swarm Optimization (PSO). By introducing an attraction-repulsion force from swarm modeling we considered realistic behaviors such as feeling push-back from physical obstacles as well as reducing gaps between passengers near emergency exits. We also incorporate a scaled emotion quantity to simulate passengers experiencing fear or panic. In our model elevating emotion increases the velocity of most passengers and decreases the effect of forces exerted by nearby passengers. We also allow a small percentage of passengers to experience a sense of panic that slows their motion. Our first simulations model a Boeing 737-800 with a single class of seats that are distributed uniformly throughout the aircraft. We also simulate the evacuation of a Boeing 777-200ER with multiple service classes. We observed that increasing emotion causes most passengers to move more quickly to the exits, but that passengers experiencing panic can slow down the evacuation. Our simulations also suggest that blocking exits in locations with high seat density significantly delays the evacuation.

1. Introduction. On July 6, 2013, Asiana Airlines Flight 214 crashed at San Francisco International Airport, which resulted in three deaths and 181 injures. [17] According to the European Transport Safety Council in 1996, there are approximately 1500 people who die each year in air transport accidents. About 270 of them die “due to the effects of smoke, toxic fumes, heat and resulting evacuation problems” instead of the direct result of impact.[12] This report exposed the need to redesign aircraft for improved passenger safety.

Researchers have been looking into this issue since as early as the 1960s. A regulation referred to as the “90-second rule” was published by the Federal Aviation Administration to provide criteria on the egress time of safety evacuation to airplane manufacturers. The regulation requires a demonstration be conducted with only illumination of the exit path and slides with a specific mix of participants. During the demonstration “all passengers and crew must be evacuated from the aircraft to the ground within 90 seconds” and not more than 50 percent of the emergency exits may be used.[4] To meet these strict standards, researchers have conducted studies to gauge whether airplane designs are qualified, ranging from

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recruiting volunteers to participate in full-scale evacuation certification demonstrations to the development of computer simulations in recent years.[4] In 1993, The Office of Technology Assessment (OTA) estimated that running a single real-sized airplane evacuation costs more than one million dollars.[4] In addition, an average of 6% of the participants suffer injuries, such as bone fractures and paralysis during the demonstrations.[4] Moreover, to ensure the accuracy of the result, repetition is required, but the real-life demonstrations are unlikely to be repeated under the exact same conditions. Since a complete version of a human airplane evacuation experiment is difficult to implement both in economic and social aspects, using computer models to simulate the behaviors of passengers offers a better solution.

The current models of emergency building and airplane evacuations can be categorized as two basic types: a macroscopic approach and a microscopic approach. The macroscopic approach treats evacuees as a fluid and focuses more on the general movements over a large population. These fluid-dynamic models offer better predictions of a large crowd's behavior, since "at medium and high densities, the motion of pedestrian crowds shows some striking analogies with the motion of fluids and granular flows." [10] One example is the network flow model developed by Cova et al. in [2] for lane-based evacuation routing to solve traffic delay at intersections by minimizing the cost of each node along the flow. Another example is the General Purpose Simulation System (GPSS), which controls the passenger flow rates by statistical information from experimental data to simulate aircraft emergency evacuations.[8]

On the other hand, the microscopic approach tracks the behavior of each passenger as they move toward the exits. Multiple microscopic models have been proposed that emphasize different elements that can affect the egress time. Many of these models discretize the space into cells or nodes that can represent open spaces and obstacles, such as seats and aisles in an airplane. One of the most widely used egress models, EXODUS, was developed to help individuals avoid fire hazards, heat, and toxic gases by assigning different costs to the nodes along the path and minimizing a cost function.[6, 7] Sharma et al. proposed a multi-agent system based on AvatarSim. It uses a combination of three models (social force model, geometric model and fuzzy logic-based model) to incorporate the influence of the environment and the interactions between agents.[20] Liu et al. developed a cellular automata model that takes passengers' physical characteristics such as waist size, gender, age, and disabilities into account and allows evacuees to identify and choose the least crowded and shortest route on a discrete node map.[13] As for the continuous domain, Particle Swarm Optimization was introduced to simulate pedestrian evacuation by minimizing a fitness function which represents "the sum of the distances between each pedestrian and the set of exits." [11, 22] In addition to these factors, the emotion of passengers such as fear and panic could play a significant role in airplane emergency evacuation. Miyoshi et al. incorporated emotion into their model and quantified the panic level by calculating the remaining time, frequency of waiting and the difficulty of finding an exit as agent moves from cell to cell on a discrete grid.[16] In [21], Tsai et. al. developed a simulation tool called ESCAPES to model the effect of emotional interactions during airport evacuations.

In this paper, we propose an aircraft evacuation simulation that is inspired by elements of Particle Swarm Optimization (PSO), but also incorporates the spread of emotion based on the interactions between agents. Different from the models that utilize nodes or cells, PSO uses a continuous domain which allows passengers

to infringe on each others' space and more accurately simulate an evacuation. In addition, the nature of the PSO algorithm allows randomness in the model in order to produce more realistic movements of the agents. For our model, we designed an aircraft potential function to represent a more complicated terrain that consists of chairs and seats rather than simply using a fitness function that computes the sum of the distances between agents and exits as in the pedestrian evacuation models. Also, by incorporating different states of swarm behavior, our model factors in the attraction and repulsion between agents.[1, 3] Based on these simulations, we will present a comparison of performances of passengers evacuating from different exit locations with or without the influence of emotion. The goal of this paper is to study how this emotion impacts individuals and the entire group as they attempt to exit the aircraft. We hope that our models will lead to increased understanding of how panicked crowds behave in evacuation situations which could lead to better, safer evacuation procedures.

2. Particle Swarm Optimization. The development of swarm modeling is motivated by examples in nature in which organisms congregate in large numbers such as flocks of birds, schools of fish or crowds of people. These large populations are comprised of individuals who are influenced by the group motion as well as their individual will. Over the years, researchers have been interested in modeling various swarm behaviors. For example, in 2007, Cucker and Smale offered a model for both continuous and discrete time to justify that “the state of the flock converges to one in which all birds fly with the same velocity.”[3] In the same year, Chuang et al. further developed individual-based and continuum swarm models and analyzed their linear stabilities focusing on the swarming problems over generations.[1] Particle Swarm Optimization (PSO) is also an effective method to model swarm intelligence. The PSO algorithm describes how populations adapt to their environment and share information with each other. PSO is “a method for optimization of continuous nonlinear functions” that was first introduced by Eberhart and Kennedy and can be used for simulating social behaviors.[5]

PSO is widely used to simulate how an initial swarm propagates in the design space toward the optimal solution over a number of iterations (moves). The main feature of this algorithm that has inspired our model is that each individual incorporates information about both the local and global landscape that is assimilated and shared by all members of the swarm to determine their direction of motion. We begin by describing a sample PSO algorithm as outlined in [9]. After initial position and velocities are specified, the position x_k^i and velocities v_k^i are updated at each iteration, where k is the number of iterations and i is the index of particle.

The velocity of each particle is affected by three factors, namely inertia, particle memory, and swarm influence. The first part of the velocity update equation includes an inertia term to describe the tendency that a particle would continue to move with the same speed and in the same direction as previous iteration. The particle memory factor describes how each particle records its optimal position along its individual trajectory and the tendency to move to its personal best position. Finally, when updating the swarm influence term, the personal best positions of the entire swarm are compared at each iteration, and the optimal one among them is stored as the global best position. All the particles share knowledge of this global best point and are attracted to it. These three main factors are present in the velocity and corresponding position updates from [9],

$$\begin{aligned}\mathbf{x}_{k+1}^i &= \mathbf{x}_k^i + \mathbf{v}_{k+1}^i \Delta t \\ \mathbf{v}_{k+1}^i &= w \mathbf{v}_k^i + c_1 U_k^1 (\mathbf{p}^i - \mathbf{x}_k^i) + c_2 U_k^2 (\mathbf{p}_k^g - \mathbf{x}_k^i).\end{aligned}\tag{1}$$

Here, w is the inertia factor and c_1 and c_2 are the strengths of the self-confidence and swarm confidence terms respectively. The term \mathbf{p}^i represents the best position of particle i over all previous moves and \mathbf{p}_k^g represent the global best position at the current move k . U_k^1 and U_k^2 are uniform random variables on $[0, 1]$ that allow for variability in choice between following individual will versus the swarm influence.

We note that with larger w , particles are more likely to maintain their current velocity even if better fitness values are discovered. Thus, greater w values are more suitable for searching a larger portion of the domain because particles are less likely to be trapped by local extremes. On the contrary, smaller w values correspond to a smaller probability of finding the global best position because particles are more likely to be attracted to the current best position. This behavior is favored when local search is preferred. By increasing c_1 , particles are more likely to trust their own knowledge and move toward their personal best positions as opposed to paying attention to the entire swarm's movement. A larger c_2 corresponds to a larger opportunity for the swarm to find the local/global optimal position.

3. Modified PSO for airplane evacuation. The Particle Swarm Optimization (PSO) algorithm as described in [9] models the position and velocity of agents moving toward a specific goal. Each agent then moves according to its knowledge of its own previous best position and the group's current best position. To better fit real-life scenarios such as the Asiana plane crash, we modified the PSO algorithm. The main differences between this revised version and the original PSO algorithm are reflected in the individual particle local search term, the global search term, and the attraction-repulsion term.

The goal of each individual is to move toward one of the optimal locations as soon as possible, in this case, the airplane emergency exits. In our model, each agent's position is compared to a fitness function that describes the current environment. The static environment is modeled by a potential function that describes the layout of the airplane that includes the exits and physical barriers such as the seats. The seats and other physical barriers are represented by large values in the fitness function to prevent individuals from moving through them. Any dangerous regions are designated as global maximums and exits are represented as global minimums. The seating areas are tilted downward toward the aisle which represents the natural inclination of passengers to leave their seats and move into the aisle. The aisles are sloped downward toward the nearest exit, which represents the emergency lights that guide passengers to the exit rows. Finally the exit rows are sloped downward toward the exits. We first modeled a Southwest Airlines Boeing 737-800 due to its uniform seat arrangements. This aided us in designing more complex aircraft such as the Boeing 777-200ER used in Asiana Flight 214. Figure 1 shows a section of the potential function that describes a Boeing 737.

In this way, it is intuitive for the particles to choose their paths. The local search for each particle is calculated by finding the gradient of the potential function at its position. The gradient of the potential function from Figure 1 is pictured in Figure 2. We scale the gradient by the hill function

$$h(\nabla f) = \frac{\nabla f}{h_0 + |\nabla f|},\tag{2}$$

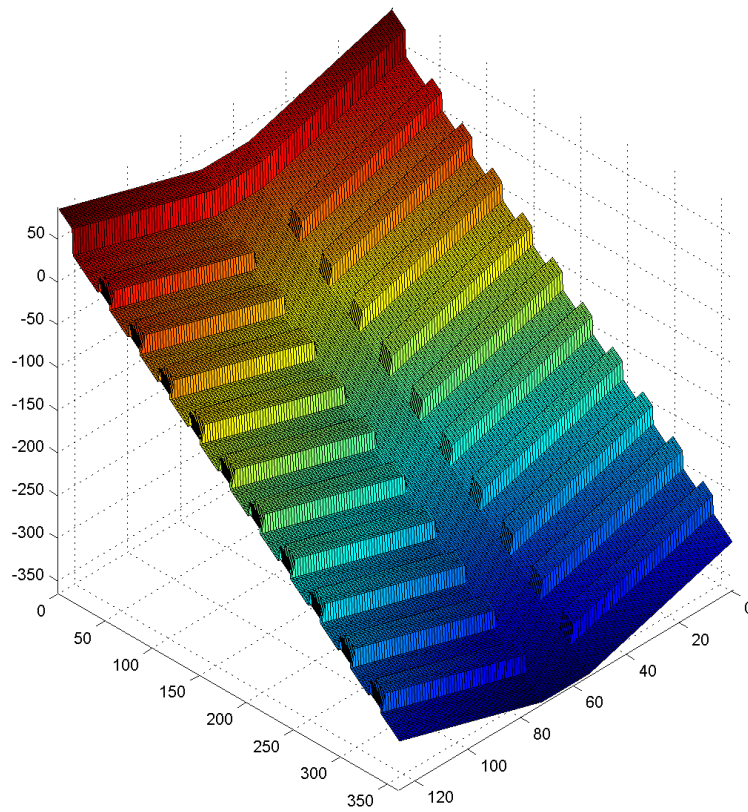


FIGURE 1. The potential function for a section of a Boeing 737 measured in inches.

where ∇f is the gradient of the plane potential function and h_0 is the value of $|\nabla f|$ so that h attains half of its maximum value.[14, 15] This helps prevent extreme values that would cause particles to move at an unreasonable velocity.

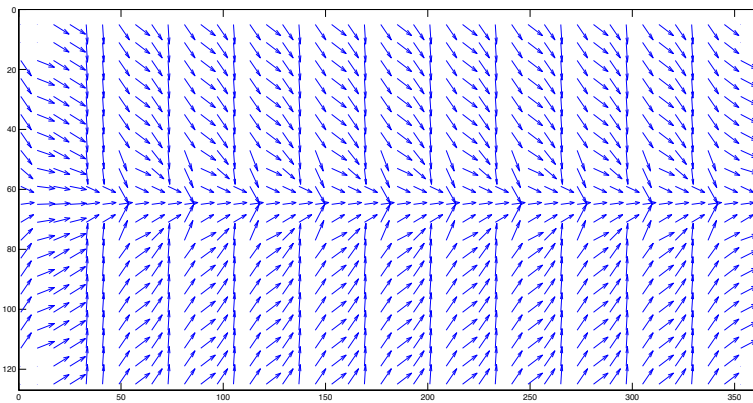


FIGURE 2. Gradient field corresponding to the potential function in Figure 1.

The global best position is also calculated differently from the previous PSO algorithm. In the original PSO algorithm, the particles explore the designed region, compare with a fitness function, and share the location of the individual with the best position with the entire swarm at each iteration. An airplane contains multiple exits which can serve as the global best position. Therefore in our model, passengers are attracted to the closest emergency exit instead of the position of the passenger at the global minimum. In this way, agents do not have to detect the global best positions themselves and could avoid moving toward a global minimum point that is further away from them. We believe global knowledge of the exit locations is reasonable since they are clearly marked throughout the airplane and on safety information cards that are available to the passengers upon boarding the aircraft. We can reduce visibility or knowledge of the exit locations by reducing the influence of the global fitness term. To prevent extreme values, the global best term is also scaled by a hill function

$$h(\mathbf{u}) = \frac{\mathbf{u}}{c_0 + |\mathbf{u}|} \quad (3)$$

where $\mathbf{u} = \mathbf{p}_k^g - \mathbf{x}_k^i$ and c_0 is the value of $|\mathbf{u}|$ so that h attains half of its maximum value.

In the original PSO model particles converge very quickly and tend to cluster together, but in airplane evacuations, people tend to stay close but cannot occupy the same space. Therefore, instead of only considering the current motion, particle memory influence, and swarm influence when updating the velocities, we also incorporated a particle attraction-repulsion force between agents. Specifically, we adapted the D'Orsogna-Bertozzi model with self-propulsion for attraction and repulsion from [1]. The attraction-repulsion force that each agent i feels is given by

$$\mathbf{u}_i = \sum_{j=1}^{N_i} \left(C_A e^{-\frac{|\mathbf{r}_{ij}|}{L_A}} - C_R e^{-\frac{|\mathbf{r}_{ij}|}{L_R}} \right) \frac{\mathbf{r}_{ij}}{|\mathbf{r}_{ij}|}. \quad (4)$$

where \mathbf{r}_{ij} is the displacement from agent i to agent j and N_i is the number of neighboring agents to i .

In this way, the attraction force helps fill in the gaps between evacuees and the repulsion force prevents agents from occupying the same space. Agents in our model are particles with a fixed radius. The attraction length L_A is designed to be 48 in, which suggests that agents start attracting one another when they are within the distance about the diameter of two agents. The repulsion length L_R is set as 24 in; when two agents are about half the diameter of an agent apart from each other, they begin to repel. The balance between C_A and C_R is 1:6.

The equations that model the discrete movements of individual agents in our modified PSO algorithm are given below. The position and velocity of the k th iteration of the i th particle are denoted \mathbf{x}_k^i and \mathbf{v}_k^i respectively.

$$\begin{aligned} \mathbf{x}_{k+1}^i &= \mathbf{x}_k^i + \mathbf{v}_{k+1}^i \Delta t \\ \mathbf{v}_{k+1}^i &= w \mathbf{v}_k^i + c_1 U_k^1 h(\nabla f(\mathbf{x}_k^i)) + c_2 U_k^2 h(\mathbf{p}_k^g - \mathbf{x}_k^i) \\ &\quad - c_3 \sum_{j=1}^{N_i} \left(C_A e^{-\frac{|\mathbf{r}_{ij}|}{L_A}} - C_R e^{-\frac{|\mathbf{r}_{ij}|}{L_R}} \right) \frac{\mathbf{r}_{ij}}{|\mathbf{r}_{ij}|}. \end{aligned} \quad (5)$$

The constant c_3 controls the strength of the attraction-repulsion term.

3.1. Boeing 737 simulations. The Boeing 737-800 has only a single Economy Class that consists of 175 standard seats with 17 inch width and 32 inch pitch and eight emergency exits located at the front (two exits), middle (four exits) and back (two exits). There are 28 rows and most commonly each row has six seats with three on each side of an aisle in the middle as shown in Figure 3. Our first evacuation model assumes that each seat is filled and that all exits are available. Using a $\Delta t = 0.05$ seconds, the passengers move at a walking speed of approximately 4 ft/s when unimpeded. We display still frames from our simulation in Figure 4.

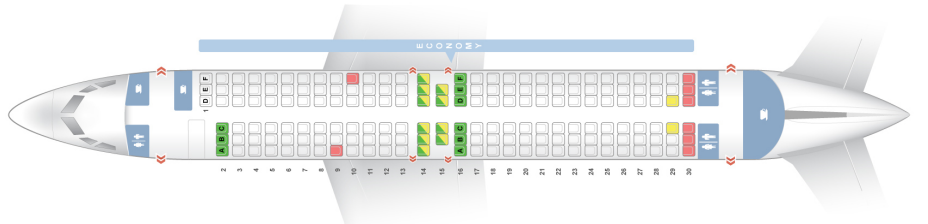


FIGURE 3. Seating arrangement for Boeing 737-800.[18]

In this simulation particles successfully avoid the seats and the repulsion force effectively prevents the particles from crashing into each other. All of the agents escape from the plane within 54 seconds with 95% exiting within 47 seconds and 90% within 42 seconds. From the data we have seen that the last five percent of agents consume more time to exit. This could be attributed to the fact that agents are attracted to each other and the remaining agents feel a smaller attractive force when agents exit the aircraft and their locations are deleted from the simulation. During the simulation we observed that the agents seated in rows 7 and 8 as well as rows 21 and 22 have to make a choice whether to go to the front or the back exits. Also, when agents arrive at the front, middle or back of the plane, it takes some time for them to decide whether to move to the port or starboard exits depending on the distance between their locations and the exits. The last agents to exit the plane are the ones seated in the window seats at the last rows before the exits, rows 2, 14, 16 and 28. These agents are attracted to the global minimum, the emergency exit, but must follow the local gradient in the opposite direction to exit the row of seats and then proceed to the emergency exit. The passengers in the window seats also experience the repulsion force from passengers that are already in the aisle which keeps them in the seating area until there is a clear path.

4. Revised PSO model with emotion. The final component we included in our model is spread of emotion such as fear throughout the group of passengers on the plane. As previously mentioned, researchers such as Miyoshi et al. have delved into the development of models with emotional factors. In [16], Miyoshi et al. used an autonomous agent and multi-agent model (AAMAS) as the fundamental basis and added emotion parameter L that depends on the remaining time t , frequency of waiting q and difficulty of finding an exit s . They assumed that when L reaches threshold crisis level L_0 , the passengers would exhibit non-adaptive behaviors, such as forcing themselves into an occupied cell. The D'Orsogna-Bertozzi model with self-propulsion for attraction and repulsion in [1] and the Cucker-Smale model for alignment in [3] offer us great insights into updating the emotion factor and deciding

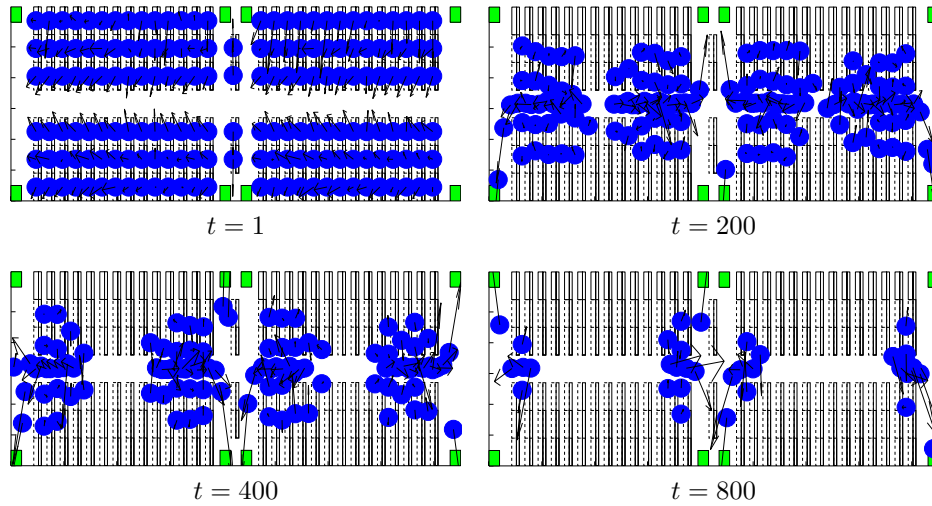


FIGURE 4. Snapshots of the Boeing 737 simulation with no emotion at $t = 1, 200, 400$ and 800 iterations.

how the emotion affects agent mobility. To that end we added a variable q^i that stores the amount of emotion an individual feels during the simulation. The value of q^i ranges from 0 (calm) to 1 (extreme fear) and is updated according to the agents' surroundings. We assumed when an agent encounters a source of danger, their emotion level is elevated to 1. Also, we assumed that agents would adjust their emotions to conform with their neighbors' and in the absence of emotional stimuli, q^i gradually decays to zero over time. To update a passenger's emotion level we first considered adapting the Cucker-Smale alignment model in [3] so that

$$q_{k+1}^i = \gamma q_i + \frac{1}{N_i} \sum_{j=1}^N \left(\frac{1}{1 + |\mathbf{r}_{ij}|^2} \right)^\alpha (q_i - q_j) \quad (6)$$

where N_i is the number of neighboring agents to agent i . Ultimately, we considered a simpler model,

$$q_{k+1}^i = \frac{1}{N_i} \sum_{j=1}^N g(q_i - q_j), \quad (7)$$

where

$$g(q) = \begin{cases} \beta q & q > 0 \\ \frac{1}{2}\beta q & q < 0 \end{cases} \quad (8)$$

and β is a constant that controls how rapidly emotion spreads. In this way, a difference in emotion with nearby agents will influence an individual's emotional state and thus emotion will spread throughout a crowd.

In our model, the level of emotion affects the behavior of an agent in two ways. First we assume that an increase in fear will increase the velocity of an agent. We also assume that an increase in fear in an agent will increase the force exerted on other agents and decrease the repulsion from partial obstacles such as airplane seats.

Our updated model to include emotion appears below.

$$\begin{aligned}
 \mathbf{x}_{k+1}^i &= \mathbf{x}_k^i + \mathbf{v}_{k+1}^i \Delta t \\
 \mathbf{v}_{k+1}^i &= w \mathbf{v}_k^i + c_1 U_k^1 h(\nabla f(\mathbf{x}_k^i)) + c_2 U_k^2 h(\mathbf{p}_k^g - \mathbf{x}_k^i) \\
 &\quad - c_3 \sum_{j=1}^{N_i} \frac{C_A e^{-\frac{|r_{ij}|}{L_A}} - C_R e^{-\frac{|r_{ij}|}{L_R}}}{1 + q_i - q_j} \frac{\mathbf{r}_{ij}}{|\mathbf{r}_{ij}|} \\
 q_{k+1}^i &= \frac{1}{N_i} \sum_{j=1}^{N_i} g(q_i - q_j).
 \end{aligned} \tag{9}$$

4.1. Boeing 737 simulations with emotion. In order to provide stimulus for an emotional response by the passengers, we assumed that there is a fire that blocks the two middle exits on one side of the aircraft. The fire spreads slowly into the exit row in the middle of the plane. The agents closest to that fire change color from blue to pink indicating their emotional response to the danger. The color changes from blue to dark pink to light pink as the q value increases from values close to 0 to values close to 1. Compared to particles’ behaviors from the non-emotional PSO model, particles near the spreading fire in the emotional PSO simulation significantly increase their speed and rush directly to the global fitness point. We observed that agents with a high emotion factor move faster and the space between agents decreases. On average it takes 50 seconds for all of the passengers to evacuate the aircraft with 95% exiting within 42 seconds and 90% within 36 seconds. With the last 5% of agents being relatively far from the source of danger, the emotion factor has a less significant effect on agent’s motion, leaving them “wandering” out of the airplane. Overall, we have observed that given the same aircraft and corresponding potential function, agents in simulations with emotion exit the aircraft more quickly than agents in simulations without emotion. Figure 5 shows the still frames from this simulation. The fire is represented by the red area in the figure which spreads over time.

5. Asiana flight 214 case study. In this section, we take a closer look at Asiana Flight 214 in particular, and hope to use this model as a template that we can apply to other airplane models in the future. Compared to the Boeing 737 model, this aircraft consists of multiple classes, business and economy, with a larger number of rows and aisles. For the Boeing 777 model, we implemented simulations both with and without an emotion factor using the same revised PSO algorithm.

5.1. Boeing 777 simulation without emotion. We designed the potential function for the simulations according to the layout of a Boeing 777-200ER C which was used for Flight 214. A diagram of the aircraft is displayed in Figure 6. That flight carried a total of 291 passengers (19 business class and 272 economy class). In the front business class, there are four rows and each row has seven seats (two each on the side and three seats in the middle) and two aisles. Each seat in business class is 20.2 inches wide and has a 62 inch pitch.[19] The economy class consists of two parts, the first and second economy classes. The first economy class has 18 rows, and each row has nine seats (three groups of three seats separated by two aisles) with the exception of the first and last rows (eight seats and six seats respectively). The second economy class has 14 rows with the same seating arrangement as the 1st economy class except for the first and last two rows (three seats, seven seats

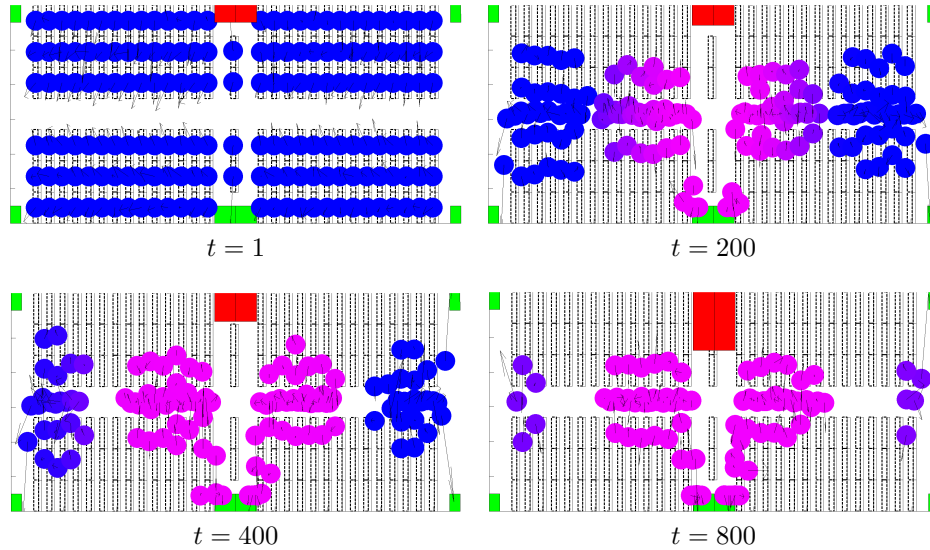


FIGURE 5. Snapshots of the Boeing 737 simulation with emotion at $t = 1, 200, 400$ and 800 iterations. The passenger color changes from blue to light pink as the emotion value increases from 0 to 1.

and five seats respectively). Each seat in economy class is 18 inches wide and has a 33 inch pitch.[19] There are eight exits altogether, located in the front, between business and first economy classes, between first and second economy classes and the back of the plane. The complexity of the potential function that describes the plane adds more difficulty for the agents to move around. As a result, we decreased the global search parameter c_2 to prevent agents from getting stuck in the seating area or aisles.

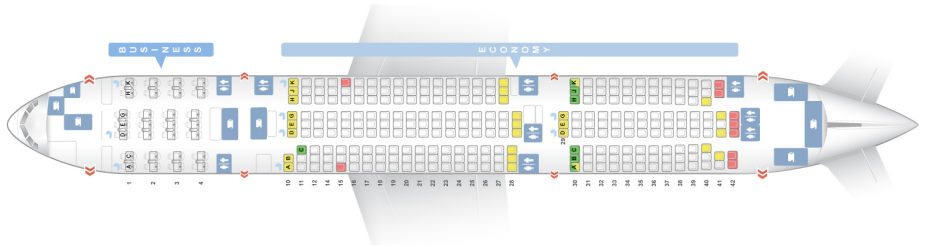


FIGURE 6. Seating arrangement for Boeing 777-200ER.[19]

Besides the previously mentioned lag time for agents seated in the middle rows of each class to decide between front exits and back exits, and for agents to choose between the port exits and starboard exits, we also observe that the evacuees seated in the middle seats of each row take time to choose from taking the port aisle or the starboard aisle. The agents in the middle rows are equidistant to the port and starboard exits, and in case of a tie between the closest exits, choose a side randomly. The total evacuation time for simulations without emotion is on average

72 seconds for the entire swarm to exit, 54 seconds for 95%, and 48 seconds for 90%. The last agents to exit the plane are initially located in the window seats in the last rows before the emergency exits for the same reasons as described in the previous Boeing 737 simulations. The only exception is at the very front of the plane where the density of passengers is lower and the window passengers did not have to wait behind as large a number of passengers in the aisle. The still frames from this simulation are in Figure 7.

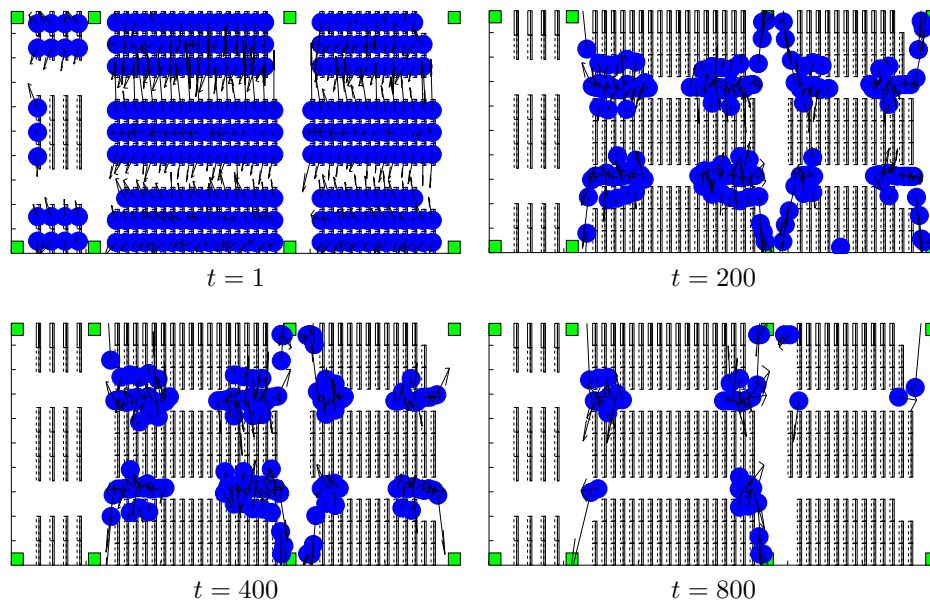


FIGURE 7. Snapshots of the Boeing 777 simulation without emotion at $t = 1, 200, 400$ and 800 iterations.

5.2. Boeing 777 simulation with emotion. Based on the same potential airplane function, we created a simulation where one of the exits between first and second economy classes is blocked and on fire. The fire then spreads along the aisle, driving the agents who would normally take that blocked exit to the exit on the opposite side of the aircraft. As with the Boeing 737 simulation with emotion, the agents with higher emotion level move faster and more aggressively. On average, all of the passengers exit within 63 seconds. Within 49 seconds 95% evacuate and 90% evacuate within 42 seconds. The agents near the blocked exit take the longest to escape since they have to travel extra distance to the other side of the plane to find an open emergency exit. The still frames from this simulation are shown in Figure 8. The fire is represented by the red area in the figure which spreads over time.

6. Evacuation simulations with blocked exits. In some cases, not all of the exits are available to the agents in emergency evacuations. Reasons could range from the exits being physically blocked by obstacles to the exit doors being damaged and unable to open. Therefore, it is necessary for us to consider the cases where not all of the exits are accessible. We will consider simulations where either one or both exits in a particular row are blocked for both the Boeing 737 and 777 configurations.

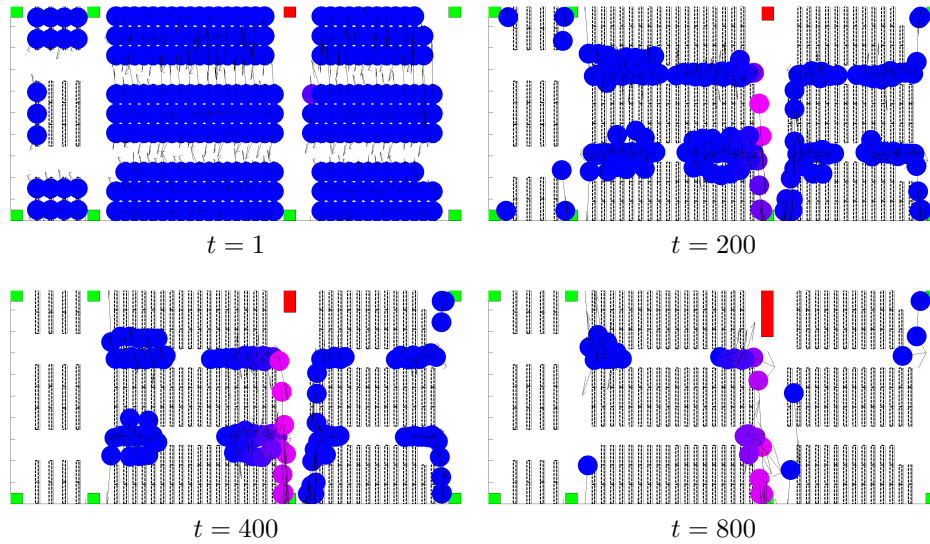


FIGURE 8. Snapshots of the Boeing 777 simulation with emotion at $t = 1, 200, 400$ and 800 iterations. The passenger color changes from blue to light pink as the emotion value increases from 0 to 1.

Tables 1 and 2 display the average evacuation times for the Boeing 737 with various configurations of blocked exits both with and without emotion. Because the Boeing 737 is symmetric, for both the simulations with and without emotion, blocking the front or the back exit essentially yields the same result. From the data we can see that by blocking the middle exits it takes slightly more time for all of the agents to evacuate. This reflects that the middle exits are utilized more than the front or the back exits. If one of the middle exits is blocked, agents have to travel to other exits to escape which causes more congestion in the middle of the plane and slows down the egress process. The evacuation times for the Boeing 737 simulations with emotion are more robust and it takes less time to achieve full evacuation. The average maximum velocity increases by 5-15% and the average time for all passengers to escape with a single exit blocked decreases from 55 to 50 seconds. The data again suggest that the middle exits have a larger effect on overall egress time. The decrease in evacuation time is also less significant when exits are blocked on both sides of the aircraft.

As for the Boeing 777 model, the complexity of the travel classes makes the analysis of blocking different exits more significant. Tables 3 and 4 display the average evacuation times for the Boeing 737 with various configurations of blocked exits both with and without emotion. The front exit or back exit being blocked creates less lag time compared to the others, because only some of passengers seated in the business class or second economy class take these exits. Both the second exit and third exit are used more heavily; hence, blocking either of them slows the evacuation. In particular, if the second pair of exits is blocked, more passengers are directed toward the third exit which has the highest density of passengers and the evacuation time is the longest. Similar to the Boeing 737 model, the evacuation times with emotion are slightly less and the maximum velocity of passengers is up to 5% faster.

Exits Blocked	Evacuation Time (s)			Maximum Velocity (ft/s)
	90%	95%	100%	
None	42.8	47.6	53.9	7.8
Single Front Exit	42.8	47.7	54.7	7.6
Single Rear Exit	43.4	47.9	54.4	7.7
Pair of Wing Exits	44.5	50.9	57.0	7.7
Both Front Exits	65.3	75.5	92.9	7.7
Both Rear Exits	63.7	74.8	91.9	7.8
All Wing Exits	77.3	81.1	94.6	7.8

TABLE 1. Average evacuation times for Boeing 737 without emotion.

Exits Blocked	Evacuation Time (s)			Maximum Velocity (ft/s)
	90%	95%	100%	
Single Front Exit	38.2	42.1	47.7	8.2
Single Rear Exit	39.15	44.25	51.5	8.3
Pair of Wing Exits	36.4	41.7	49.6	9.1
Both Front Exits	61.1	71.2	86.8	8.7
Both Rear Exits	61.9	71.2	91.1	8.3
All Wing Exits	75	80.2	92	9.1

TABLE 2. Average evacuation times for Boeing 737 with emotion.

Exits Blocked	Evacuation Time (s)			Maximum Velocity (ft/s)
	90%	95%	100%	
None	43.4	49.9	64.7	7.9
Single Front Exit	44.2	50.8	65.1	7.7
Single Second Exit	44.2	50.8	65.1	7.7
Single Third Exit	44.8	50.5	66.0	7.8
Single Rear Exit	44.4	50.7	65.5	7.8
Both Front Exits	45.1	59.7	72.7	7.6
Both Second Exits	77.3	93.2	121.7	7.6
Both Third Exits	78.5	88.4	116	7.8
Both Rear Exits	53.8	64.4	87.6	7.8

TABLE 3. Average evacuation times for Boeing 777 without emotion.

7. Variable responses to emotion. In our model we assumed that emotion would increase the velocity of passengers and increase the force exerted on other passengers. While fear may motivate some passengers to speed up and become more pushy, other passengers may feel a sense of panic which causes them to slow their motion and become more passive. To recreate this effect we randomly assigned a small percentage of passengers to become susceptible to a panic response. If the emotion factor increases above a certain threshold, say $q = 0.5$, the panic response causes these passengers to slow down and exert a smaller force on nearby passengers. This panic response continues until the emotion factor returns to a level below the threshold.

Exits Blocked	Evacuation Time (s)			Maximum Velocity (ft/s)
	90%	95%	100%	
Single Front Exit	42.9	47.6	60.1	8.0
Single Second Exit	43.1	48.9	62.9	8.0
Single Third Exit	41.5	48.6	62.8	7.6
Single Rear Exit	39.6	47.0	62.1	7.5
Both Front Exits	41.4	47.1	61.7	8.1
Both Second Exits	76.5	91.1	118.8	8.3
Both Third Exits	76.3	87.8	111.9	7.8
Both Rear Exits	49.4	57	80.5	7.7

TABLE 4. Average evacuation times for Boeing 777 with emotion.

We observed in simulations that passengers who experience a panic response move more slowly and block passengers from moving into the aisles and progressing toward the emergency exits. Tables 5 and 6 show average evacuation times for 95% of passengers from both the Boeing 737 and 777 aircraft with various configurations of blocked exits and 5%, 10% and 20% of passengers susceptible to a panic response for $q \geq 0.5$. For both plane configurations the egress time is increased as the percentage of passengers that are susceptible to panic increases. For many of the configurations of blocked exits for the Boeing 737 and 777 the evacuation times are comparable to the simulations without emotion when only 5% of passengers are susceptible to a panic response.

Exits Blocked	95% Evacuation Time (s)		
	5% Panic	10% Panic	20% Panic
Single Front Exit	44.1	51.8	68.4
Single Rear Exit	45.2	53.4	66.4
Pair of Wing Exits	43.5	64.3	83.5
Both Front Exits	75.0	89.5	98.3
Both Rear Exits	90.6	101.1	105.4
All Wing Exits	73.5	82.8	92.3

TABLE 5. Average evacuation times for 95% of passengers from a Boeing 737 with 5%, 10% and 20% of passengers susceptible to a panic response for $q \geq 0.5$.

8. Conclusions. In summary, we have adapted features of the particle swarm optimization (PSO) algorithm to model emergency aircraft evacuations. The flexibility of our code has allowed us to consider models of both a Boeing 737 and Boeing 777 aircraft. We considered different configurations of blocked exits and discovered that blocking exits in high density areas of the aircraft slowed evacuation times considerably. This suggests that passengers in the first economy class of a Boeing 777 should be directed to prefer exits at the front of the aircraft where the passenger density is much lower. Also, our simulations suggest that in order to expedite evacuations, future aircraft designs should consider the arrangement of emergency exits relative to the density of passengers. By adding an emotional component, we modeled the response of passengers to both external stimuli and other emotionally charged passengers which increased the speed of evacuation. Our simulations also showed that

Exits Blocked	95% Evacuation Time (s)		
	5% Panic	10% Panic	20% Panic
Single Front Exit	49.9	52.5	55.8
Single Second Exit	50.4	65.4	74.0
Single Third Exit	51.5	57.75	69.4
Single Rear Exit	47.5	59.2	65.1
Both Front Exits	48.1	52.3	54.3
Both Second Exits	89.1	90.7	118.15
Both Third Exits	89.8	92.2	59.1
Both Rear Exits	57.6	59.1	63

TABLE 6. Average evacuation times for 95% of passengers from a Boeing 737 with 5%, 10% and 20% of passengers susceptible to a panic response for $q \geq 0.5$.

passengers who experience a panic response that slows their motion will extend the time it takes to complete an emergency evacuation. In the future we would like to consider adding passenger characteristics such as varying passenger radius or the rate and severity of response to emotional stimuli. All of these modifications to our PSO model would be helpful in creating more realistic simulations that can inform evacuation plans and aircraft designs.

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REFERENCES

- [1] Y. Chuang, M. R. D'orsogna, D. C. Marthaler, A. L. Bertozzi and L. S. Chayes, [State transitions and the continuum limit for a 2D interacting, self-propelled particle system](#), *Physica D*, **232** (2007), 33–47.
- [2] T. J. Cova and J. P. Johnson, [A network flow model for lane-based evacuation routing](#), *Transportation Research Part A: Policy and Practice*, **37** (2003), 579–604.
- [3] F. Cucker and S. Smale, [Emergent behavior in flocks](#), *IEEE Transactions on Automatic Control*, **52** (2007), 852–862.
- [4] K. Depart, et al., *Aircraft evacuation testing: Research and technology issues*, Office of Technology Assessment, Congress of the United States, 1–51.
- [5] R. Eberhart and J. Kennedy, [A new optimizer using particle swarm theory](#), in *Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, 1995, 39–43.
- [6] E. Galea and J. P. Galparsoro, [A computer-based simulation model for the prediction of evacuation from mass-transport vehicles](#), *Fire Safety Journal*, **22** (1994), 341–366.
- [7] E. Galea and J. Galparsoro, *Exodus: An Evacuation Model for Mass Transport Vehicles*, Papers, Civil Aviation Authority, 1993.
- [8] J. Garner, R. F. Chandler and E. Cook, *GPSS Computer Simulation of Aircraft Passenger Emergency Evacuations*, U.S. Department of Transportation, Federal Aviation Administration, Office of Aviation Medicine, 1978.
- [9] R. Hassan, B. Cohanin, O. De Weck and G. Venter, [A comparison of particle swarm optimization and the genetic algorithm](#), in *46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, 2005, 1–13.

- [10] D. Helbing, I. Farkas, P. Molnár and T. Vicsek, Simulation of pedestrian crowds in normal and evacuation situations, in *Pedestrian and Evacuation Dynamics* (eds. M. Schreckenberg and S. D. Sharma), Springer, Berlin, 2002, 21–58.
- [11] J. Izquierdo, I. Montalvo, R. Pérez and V. Fuertes, [Forecasting pedestrian evacuation times by using swarm intelligence](#), *Physica A: Statistical Mechanics and its Applications*, **388** (2009), 1213–1220.
- [12] P. Jorna, et al., Increasing the survival rate in aircraft accidents: Impact protection, fire survivability and evacuation, *European Transport Safety Council*, 1–48.
- [13] Y. Liu, W. Wang, H.-Z. Huang, Y. Li and Y. Yang, [A new simulation model for assessing aircraft emergency evacuation considering passenger physical characteristics](#), *Reliability Engineering & System Safety*, **121** (2014), 187–197.
- [14] T. A. Lucas, [Operator splitting for an immunology model using reaction-diffusion equations with stochastic source terms](#), *SIAM J. Numer. Anal.*, **46** (2008), 3113–3135.
- [15] T. A. Lucas, [Maximum-norm estimates for an immunology model using reaction-diffusion equations with stochastic source terms](#), *SIAM J. Numer. Anal.*, **49** (2011), 2256–2276.
- [16] T. Miyoshi, H. Nakayasu, Y. Ueno and P. Patterson, [An emergency aircraft evacuation simulation considering passenger emotions](#), in *Computers & Industrial Engineering*, Soft Computing for Management Systems, Vol. 62, 2012, 746–754.
- [17] B. Peterson, What we’ve learned so far from the Asiana Flight 214 investigation, Popular Mechanics, <http://www.popularmechanics.com/technology/aviation/crashes/what-weve-learned-so-far-from-the-asiana-flight-214-investigation-16264162>".
- [18] SeatGuru by TripAdvisor, http://www.seatguru.com/airlines/Southwest_Airlines/Southwest_Airlines_Boeing_737-800_new.php.
- [19] SeatGuru by TripAdvisor, http://www.seatguru.com/airlines/Asiana/Asiana_Boeing_777-200_ER_C.php.
- [20] S. Sharma, H. Singh and A. Prakash, [Multi-agent modeling and simulation of human behavior in aircraft evacuations](#), in *Aerospace and Electronic Systems, IEEE Transactions on*, Vol. 44, 2008, 1477–1488.
- [21] J. Tsai, et al., ESCAPES: Evacuation simulation with children, authorities, parents, emotions, and social comparison, in *The 10th International Conference on Autonomous Agents and Multiagent Systems*, AAMAS ’11, International Foundation for Autonomous Agents and Multiagent Systems, 2, Richland, SC, 2011, 457–464.
- [22] Y. Zheng, J. Chen, J. Wei and X. Guo, [Modeling of pedestrian evacuation based on the particle swarm optimization algorithm](#), *Physica A: Statistical Mechanics and its Applications*, **391** (2012), 4225–4233.

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