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Ped-Air: a simulator for loading, unloading, and evacuating aircraft

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Abstract

We present Ped-Air, a pedestrian simulation system to model the loading, unloading, and evacuation of commercial aircraft. We address the challenge of simulating passenger movement in constrained spaces (e.g., aisles and rows), along with complex, coordinating behaviors between the passengers. Ped-Air models different categories of passengers and flight crew, capturing their unique behaviors and complex interactions. We exhibit Ped-Airs capabilities by simulating passenger movements on two representative aircraft: a single-aisle Boeing 737, and a double-aisle Boeing 777. We are able to simulate the following behaviors: stress, luggage placement, flight staff assisting passengers, obstructed exits for evacuation.

Keywords: behavior finite state machines; global planning; local navigation; reciprocal velocity obstacles; evacuation

1. Introduction

Air travel is an integral part of transportation infrastructure. Over 2.8 billion passengers traveled by airplane in 2013, and that number is expected to double over the next fifteen years[1]. Balancing passenger safety, passenger comfort, and airline profitability is a challenging, evolving task. One factor in coping with expanding volumes of flights and passengers is reducing the amount of time a plane stays on the ground at an airport (turning time); it allows fewer aircraft to service more passengers and makes the experience more pleasant by reducing delays and layovers. Reducing loading and unloading times can improve turning time, but airlines need the ability to experiment with boarding orders, seating arrangements, and overhead layouts without interrupting commercial service. Simulation is one way to achieve this.

For the certification of any aircraft designed to carry more than forty-four passengers, US federal law requires a live demonstration of the aircraft being safely evacuated in under 90 seconds (14 C.F.R.25.803 (1990)). The flight is certified for commercial use only upon a successful demonstration. Failed demonstrations require costly mitigation

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efforts before a new attempt can be made. The ability to perform test evacuations in a simulated environment, before engaging in live testing or, possibly, in lieu of a live test, would be extremely useful for aircraft designers and manufacturers; it would save time and and money by reducing the cost of design evaluation.

We propose the use of agent-based simulation to model passenger behaviors in loading, unloading, and evacuating commercial aircraft. We have constructed a framework (Ped-Air), which not only addresses the navigation issues in these scenarios, but incorporates the behavior and characteristics of and interactions between passengers aboard an aircraft. We highlight the performance of Ped-Air across different scenarios.

The rest of the paper is organized as follows. We briefly relate work on pedestrian simulation and evacuation in Section 2. We highlight some major challenges in simulating passenger behaviors on an aircraft and present our agent-based simulation framework in Section 3. Finally, we detail our results, and offer conclusions and future direction.

2. Related Work

2.1. Pedestrian Simulation

In agent-based simulations, each pedestrian is modeled as a discrete entity, capable of planning and acting on its own. Ped-Air implements a particular abstraction of agent-based simulation. This abstraction is based on a coupled global and local navigation mechanism connected by a *preferred velocity*. The preferred velocity, sometimes called *desired velocity* is the velocity an agent would take if not affected by local dynamic conditions (Van den Berg et al. (2008); Helbing et al. (2000); Zanlungo et al. (2011)). Agents plan a path with respect to the fixed environment, continuously adapting that plan to avoid dynamic hazards.

2.2. Global Navigation

The global navigation mechanism devises a plan for optimally progressing towards a goal while avoiding collisions with the static environment. This plan serves as the basis for computing an instantaneous preferred velocity for the agent. The preferred velocity is the "optimal" velocity for the agent to realize the navigation plan, considering the agent's current position and state. Its optimality can be defined according to arbitrary criteria based on the static environment (Latombe (1991); Snook (2000); Geraerts et al. (2008)).

Many techniques exist to determine the preferred velocity. Some involve discretizing the traversable space into connected components on a graph and using graph search algorithms (e.g. A*). This type of techniques includes roadmaps (Latombe (1991)), navigation meshes (Snook (2000)), and corridor maps (Geraerts et al. (2008)). Other techniques, such as potential fields, do not explicitly compute a path but rather discretize the space into a field that is the gradient of some cost function (Khatib (1986)). The preferred velocity in this case is the value of the field at the agent's location.

2.3. Local Navigation

Because global navigation only considers the static environment, it may be insufficient when the scene is populated with dynamic elements (such as other agents). Local navigation algorithms are used to adapt the preferred velocity computed by the global navigation algorithm to a feasible velocity which respects local, dynamic conditions. Local navigation is also referred to as "pedestrian model,“ "steering algorithm," or "collision avoidance" (Reynolds (1999); Van den Berg et al. (2008); Helbing and Molnár (1995)).

Different methods and paradigms have been proposed for local navigation. One class of local navigation algorithms is force-based models (Helbing and Molnár (1995); Johansson et al. (2007); Zanlungo et al. (2011); Chraibi et al. (2010)). These algorithms treat agents as mass-particles. The preferred velocity is achieved through a driving force which accelerates the agent towards the preferred velocity as necessary. The actual velocity taken by the agent is computed through the application of the driving force, as well as repulsive and attractive forces depending on local conditions.

Another commonly used approach is velocity-space based techniques (Van den Berg et al. (2008); Paris et al. (2007); van den Berg et al. (2011)). These approaches use geometric optimization to compute a collision-free, feasible velocity directly in velocity space. Nearby agents and obstacles serve as constraints on an agent's velocity. A velocity is selected from the available velocity space, based on an optimization criteria.

2.4. Behavior Modeling

Ped-Air uses a Behavioral Finite State Machine (BFSM) to represent the mental state (including such factors as immediate goals and mood) of agents in the simulation. FSMs are well-studied in crowd and pedestrian simulation (Ulicny and Thalmann (2002); Bandini et al. (2006)) and animation, and provide an effective mechanism for establishing time-dependent behaviors and goals for agents to accomplish.

2.5. Evacuation

Evacuations and panic modeling have been studied by researchers in many fields. Helbing et al. (2000) studied the effect of panic on evacuations in simulation. Burghardt et al. (2012) performed stadium exit experiments with human subjects. Kim et al. (2013) modeled physical interactions between dense crowds. Nilsson and Johansson (2009) studied evacuation experiments performed in a cinema theater. Studies on mass transit evacuation have been performed as well. Galea et al. (2011) performed experiments in the proposed blended wing body aircraft. Galea et al. (2012) examined evacuations on large sea vessels and Liu et al. (2012) performed simulations of evacuating a train tunnel.

3. Ped-Air: Simulating Loading, Unloading, and Evacuations

In this section, we highlight the advantages of agent-based methods for behavioral simulation in aircraft, and highlight some of the goals and challenges in terms of the design of Ped-Air. We present the architecture of Ped-Air and techniques used to model different behaviors.

3.1. Agent-Based Simulation

Agent-based simulation is not the only paradigm which could be applied to simulating passengers on an airplane. Continuum crowds (Narain et al. (2009)), or event-based simulations could also be used. However, agent-based simulation provides unique advantages. First, agent-based models inherently support modeling heterogeneity of agent goals, behaviors, and characteristics. This is important because every passenger in the aircraft has unique goals and targets (e.g., luggage or seat location). Passengers also display a wide range of personal characteristics, including moving at different speeds, and response to stress.

Agent-based methods also naturally support modeling complex interactions and relationships. During unloading, flight staff will assist infirm passengers. During loading, passengers will temporarily move out of the aisle seat to allow another passenger to sit in a neighboring seat. In each case, these actions affect how passengers respond to others. Agent-based simulation uniquely captures not only the behavioral coordination, but the physical coordination that takes place between passengers.

Agent-based methods additionally can be parallelized on current commodity CPUs and GPUs. As the behavioral complexity and simulation domain expand, it will be important to have a simulator which supports many independent entities as well as individual actions and plans. Additionally, efficient simulation techniques would allow safety engineers the ability to test many possible emergency situations in rapid succession or parallel. Because of the nature of agent-based simulations to provide both the intentions of the agent (e.g., getting a bag, waiting for the isle to clear, evacuating) and the trajectory, they provide a strong foundation for behavioral analysis.

3.2. Challenges in Simulating Passenger Behavior and Navigation

Simulating passengers in an aircraft provides some unique challenges. One of these challenges arises from the sensitivity to preferred velocity computation. Many global planning mechanisms involve discretization of the traversable space and can introduce small errors in preferred velocity which lead the agent into collision with an obstacle. The

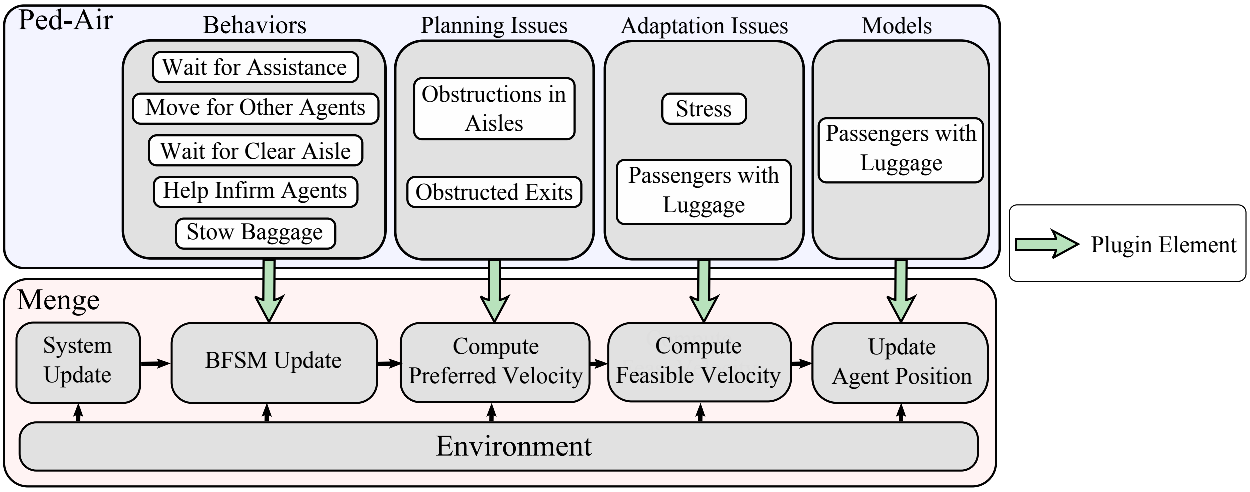


Fig. 1. The architecture of Ped-Air and how it is built on top of Menge (Curtis et al. (2014). We highlight different behaviors modeled in Ped-Air.

preferred velocity does not necessarily point directly into an obstacle, but rather leads the agent on a path with insufficient clearance. In cases with few nearby agents to consider and a relatively large amount of traversable space, we find the local planner is able to correct these errors. However, we observe in the aircraft that these issues lead to the agents failing to find a collision-free, non-zero velocity. Agents stuck in these conditions become obstructions for others, often causing a cascade effect and a deadlock in the simulation.

A further challenge in this environment is the transient nature of preferred velocities. Agents change preferred velocities often, turning corners or changing direction completely to return to their seats. Agent-based models tend to use simple extrapolation on current velocities to make predictions and plan for future states. These assumptions become particularly problematic as agents seek to move into the aisles of the aircraft, where agents can reach a stalemate waiting for one another to turn a corner.

Pedestrian models tend to assume symmetric relationship between pedestrians; both pedestrians experience a deviation from preferred velocity to avoid collision. However, the social conventions of passengers aboard aircraft suggest that, in some occasions, one passenger yields to another. It is important to model these types of *asymmetric* relationships in simulation. Passengers also engage in cooperative and sometimes counter-intuitive behaviors which are difficult to capture, but are necessary in order to successfully load and unload the aircraft. For example, a seated passenger will rise and leave their row to allow others to enter. Other passengers not involved with the exchange respect the motion and wait until the aisle clears to resume moving. Also, passengers moving against the flow of the aircraft slide into an unoccupied seat to allow others to pass.

3.3. Ped-Air Architecture

Ped-Air is built on the Menge crowd simulation framework (Curtis et al. (2014)). Menge is a modular, agent-based framework for research in crowd and multi-agent simulation. Menge models the work of simulating crowds in complex environments as the composition of various computational elements (e.g., global navigation algorithms, spatial query structures, etc.) While the framework provides default implementations of all of the element types, it provides a plug-in architecture to allow for arbitrary element implementations. Ped-Air exploits this plug-in architecture and introduces novel elements, designed specifically to bring about agent behaviors deemed consistent with actual passenger behaviors (see Fig. 1).

3.4. Behavior Modeling

We have modeled several behaviors and phenomena typical of airline loading and unloading in our simulations. These behaviors include:

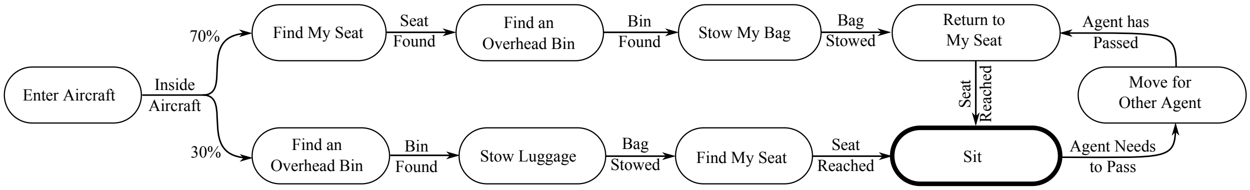


Fig. 2. An example BFSM for aircraft loading. Agents enter the aircraft, and are split into two groups based on a distribution. Agents either find their seat first, or place their bag first, and proceed to sit. Should another agent need the seated agent to move, the agent can stand and leave their row, returning to their seat once the other agent has passed. The "Sit" state is a final state; once all agents reach this state, the simulation ends.

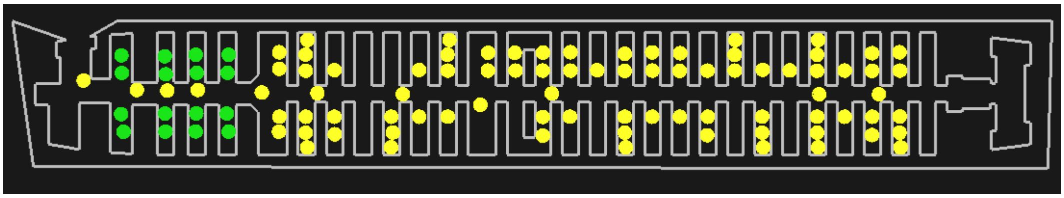
- *Waiting*: Some passengers wait until the space around them and the aisle is clear to exit the plane. The agents only advance from their waiting state to an exiting state when a region forward of the passenger is clear.
- *Infirm*: Passengers wait until a flight attendant comes to assist them off the plane. Flight attendants wait until the aisles clear, then move through the plane assisting infirm passengers. When the attendant reaches an infirm passenger, both agents move into a state which causes them to move together toward the exit – the flight attendant "assisting" the passenger.
- *Bin Searching*: Passengers stow their carry-on luggage in the overhead bins. However, the bin directly overhead may not be available and the passenger must find an alternative location to stow their bag. Bin selection mechanisms such as nearest, farthest, and nearest behind accomplish the search. Each bin has a certain capacity, and each agent's carry-on luggage is assigned a size value. The agent must find a bin that can hold their luggage.
- *Physical Carry-on*: Carry-on luggage is attached to the agent and takes up space in the aisles. The luggage is modeled using a proxy-agent. The agent attaches to its owner and follows them like a normal agent. The agent and proxy are exempt from colliding with one-another. However, other agents must avoid the luggage.
- *Evacuation Stress*: Evacuations cause stress and increased stress affects how efficiently the passengers can evacuate the plane. We model stress by modifying navigation parameters of the agents over time as stress increases.
- *Aisle Obstructions*: Exits on the plane and aisles can be obstructed increasing evacuation complexity. Obstructions are treated like other obstacles in the simulation; agents must plan and navigate around them.
- *Physiological Variance*: Agents in the aircraft vary in characteristics, reflecting models of gender and age. Agents are assigned a "profile" which determines their simulation characteristics (preferred speed, max neighbors, etc.). By crafting these profiles according to parameter research (Zheng et al. (2013)), we can model various types of passenger.
- *Loading Order Variation*: The aircraft can be loaded front to back, back to front, randomly, and by zones. Each agent is assigned a seat according to which strategy is employed, and new strategies can be implemented in the framework.

We illustrate several behaviors realized in the simulator in Fig. 4. Fig. 2 shows an example set of BFSM states and transitions for loading the aircraft. For more details on how these elements fit into Menge, we refer the reader to Curtis et al. (2014).

3.5. Coordination and Navigation

Ped-Air employs a navigation mesh for global navigation. The navigation mesh decomposes the traversable space into connected, convex polygons. We found this representation to be more amenable to consistently producing error-free preferred velocity, virtually eliminating the observed deadlocks discussed in Section 3.2. While it is certainly possible to use other methods (e.g., roadmaps or guidance fields), we found that these approaches required excessive engineering effort and/or computation resources to achieve a comparable quality in preferred velocity.

Guidance fields implicitly define paths from any location to a single goal. In the aircraft, each seat is a goal and would therefore require its own guidance field. Furthermore, each guidance field must be computed with a very small cell size to robustly sample the traversable space.



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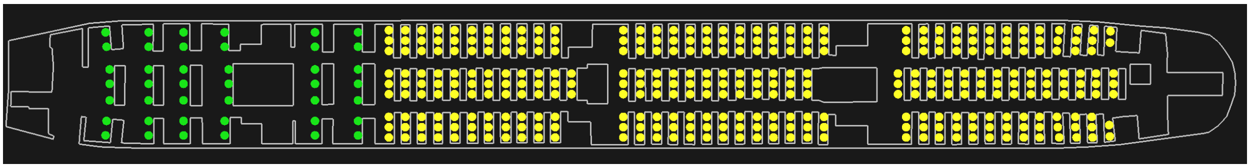

(*b*)

Fig. 3. The simulated aircraft layouts in a loading and unloading scenario. Business class passengers are modeled in green and coach passengers in yellow. (*a*) Agents load onto the 737 aircraft model in random order. (*b*) 376 agents ready to disembark the Boeing 777-300.

In contrast, roadmaps provide a mechanism to plan paths from any point to any other point. However, roadmaps represent the traversable space as a graph in which the vertices are discrete *samples* of free space. Two samples are connected iff there is a straight, collision-free path between them. The planning is largely constrained to paths along the graph and is therefore sensitive to the number and quality of the samples. This sensitivity requires extensive effort in producing a high quality roadmap. Furthermore, we found that typical techniques for producing *smooth* trajectories from the piecewise-linear paths implied by the graph failed in the aircraft's narrow passages.

While the underlying framework supports a number of local navigation algorithms, we constrained our exploration to two specific models, a simple, representative social-force-based model from Helbing et al. (2000), and ORCA, a velocity-space based model proposed by van den Berg et al. (2011). Using typical simulation parameters, both models suffered from severe simulation artifacts; often agents remain on the aircraft indefinitely as evidenced in Table 1.

The force based method suffered from deadlocks when unloading the aircraft. The obstacle forces tend to cause oscillation in the narrow rows. As agents reach the aisles, the repulsive forces from nearby agents can cancel the driving force, keeping the agents in the rows indefinitely or deadlocked with the agents across the aisle. In simulations where we lowered force distances sufficiently to prevent this, we had difficulty preventing inter-penetration between agents.

The velocity-space based method suffers from deadlocks as well. When two agents arrive at the aisle from opposite rows, they tend to meet exactly in the center of the aisle without sufficient room for either to advance. This also occurs when agents turn into occupied rows. Agents tend to stop at the boundary of the row because of the local navigation constraints.

In order to successfully unload the aircraft and prevent deadlocks, we use the symmetry breaking algorithm proposed by Curtis et al. (2012). Right of Way shifts the burden of avoiding collision from being evenly shared between agents, to being unevenly distributed. The mechanism allows us to capture asymmetric relationships among the passengers. We assign priority to agents near the front of the plane, and agents who have arrived at the aisle, causing those in the row to yield. For example, while fetching luggage from an overhead bin, an agent is given higher priority; this allows them to largely ignore nearby neighbors, relying on the neighbors to take responsibility for avoiding collisions. This mechanism also gives us the ability to force agents to yield to flight staff, modeling the deference to authority in tense situations and the crew's ability to push through the crowd. We apply a small noise in the base priority values of agents in the aircraft to generate the desired tendency for agents meeting head-on to resolve the deadlock; one agent yields to the other, allowing for progress.

4. Results

Below we highlight some results and experiments performed using Ped-Air.

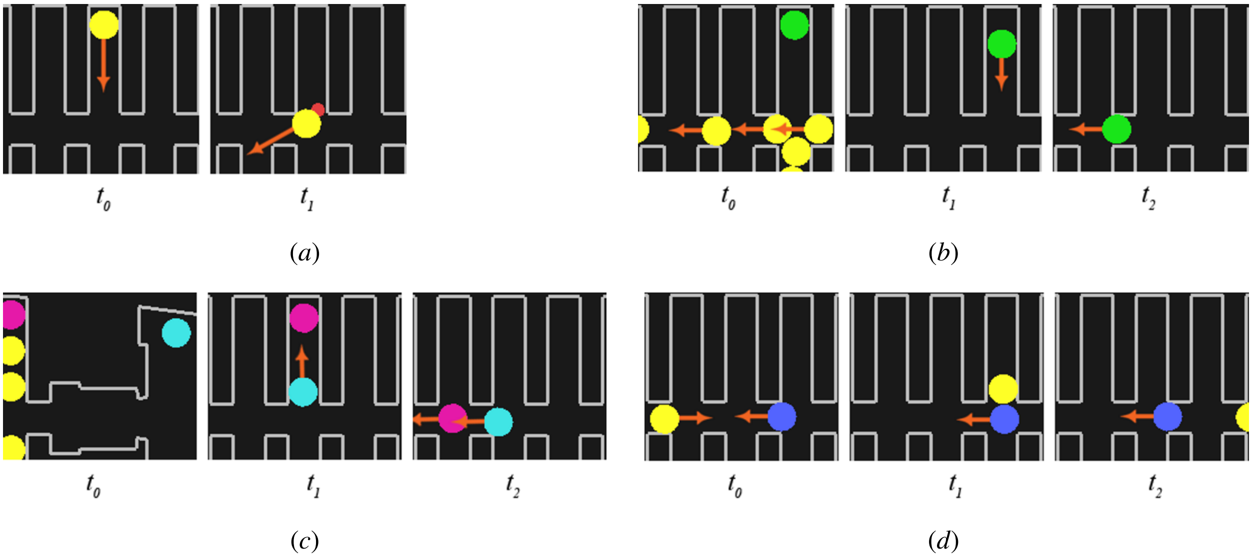

Fig. 4. Several behaviors displayed in Ped-Air (shown at elapsed time t). (a) Typical agents exiting a plane leave their seat (t_0), collect their luggage from the overhead (t_1) and exit. (b) Waiting agents wait until the space around them is clear (t_0) before leaving their seat (t_1), collecting their luggage, and exiting (t_2). (c) Flight attendants (cyan) wait for the aisles to clear (t_0), then move through the plane, and assist infirm agents out of the aircraft (t_1 & t_2). (d) Particularly in loading, agents meet head-on in the aisles (t_0). Ped-Air forces one agent to yield to the other (t_1), allowing both to proceed through the aircraft (t_2).

4.1. Modeled Aircraft

We have applied Ped-Air to simulating single aisle and dual aisle aircraft, but its techniques can be applied to any model. Fig. 3 illustrates the models we used, based on reconstructions of two Boeing Commercial aircraft. The space between seat rows has been increased to accommodate the circular agents typically found in agent-based simulation.

4.2. Experimental Timings

Table 1. Baseline timing for unloading 158 passengers from the single aisle aircraft (averaged over 10 iterations). Results for ORCA (van den Berg et al. (2011)), Social-Forces (Helbing and Molnár (1995)), and ORCA + Right of Way (Curtis et al. (2012)). In this baseline scenario, there are no passengers who need assistance and no carry-ons. As discussed in Section 3.5, without symmetry-breaking techniques, both local navigation methods suffer from deadlocks and agents getting stuck. The max simulation time for this experiment was 600 seconds. Neither local navigation method was able to complete the unloading in this time frame. By contrast, with Right of Way, ORCA is able to unload the plane in 481.94 seconds.

Model	Agents unloaded after 60 seconds (t)	After 180 seconds	after 300 seconds	Total Unload Time (t)
ORCA	8	28	41	-
SF	52	52	52	-
ORCA + Right of Way	29	70	107	481.94

Federal regulations require the following distribution of passengers in a simulated evacuation: 40% must be female, 35% must be over 50 years of age, 15% must be both female and over 50 years of age. Additionally, half of all usable exits must be blocked or unused during evacuation (no more than one exit from each pair) (14 C.F.R.25 Appendix J (2004)). Using Zheng et al. (2013)'s model of physiological heterogeneity, we are able to produce an evacuation simulation corresponding to this distribution of passengers. Fig. 5 illustrates the evacuation, and Table 2 highlights the results from our simulator.

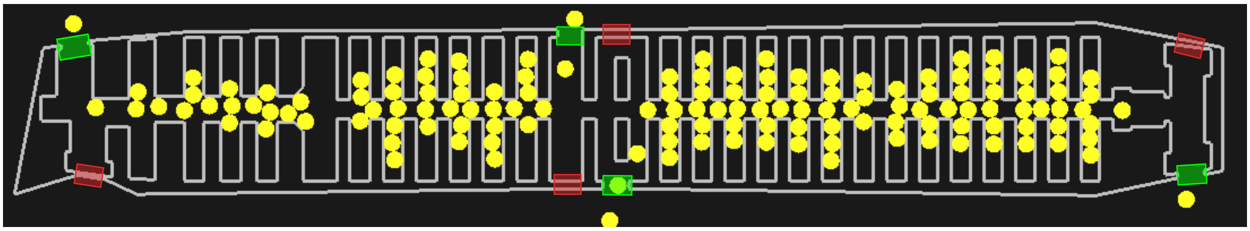

Fig. 5. A simulation of an evacuation of the 737-800 with 50% of the exits obstructed. Available exits are highlighted in green. Obstructed or unavailable exits are highlighted in red. This evacuation simulation took 89.89 seconds in Ped-Air.

Table 2. Baseline timing for an evacuation of 158 passengers from the single aisle aircraft (averaged over 10 iterations). Results shown for ORCA, Social Forces, ORCA + Right of Way, and ORCA + Right of Way + GAS (Kim et al. (2012)), a stress model. The max time given to these simulations was 120 seconds. Similar to the results in Table 1, without the use of symmetry-breaking techniques, we were unable to evacuate the aircraft in the full 120 seconds. With the application of Right of Way, agents are nearly able to evacuate in the time alloted by regulation. Modeling of stress in the aircraft, based on Kim et al. (2012), generates the impetus to evacuate in under regulated time. As stress builds, agents move more quickly and are less concentrated on collision avoidance.

Model	Agents evacuated after 30 seconds (t)	after 60 seconds	after 90 seconds	Total Evacuation Time (t)
ORCA	20	20	20	-
SF	57	57	57	-
ORCA + Right of Way	78	125	155	92.65
ORCA + Right of Way + GAS	78	90	158	89.89

5. Conclusion

We have presented the challenges of agent-based simulation in aircraft and motivation for why agent-based simulation is a suitable method for exploring this domain. We have additionally presented Ped-Air, a framework capable of addressing these challenges and generating meaningful simulations of aircraft loading, unloading, and evacuation. We describe the architecture of Ped-Air and highlight different passenger behaviors that can be simulated.

5.1. Limitations

At present, Ped-Air lacks some important behaviors and categories of passengers needed for a complete simulation. Groups, children, and passengers in a hurry are not modeled in the current simulator. In addition, our framework only admits the BFSM for behavioral modeling. We do not currently support other methods for representing passenger behavior.

5.2. Future Work

In addition to the constraints we placed on evacuation simulation, federal regulation requires partial aisle obstructions and four passengers to be carrying simulated infants. Further study would be required to appropriately model how the presence of infants affects behavior of the carrying adult and those around the infant. We would also like to include techniques for partial aisle obstruction.

Ped-Air is currently based on intuition and observation. It would be useful to validate its performance by comparing with some real-world loading and unloading data. Additionally, the air travel experience extends beyond simulations in the aircraft; the simulator provides a foundation for modeling entire airport terminals. Extending the simulations to include more aircraft and airport terminals would extend the usefulness of the simulation beyond safety and design considerations of aircraft and would provide a cohesive modeling framework for the design of efficient infrastructure, leading to and a more pleasant and safer overall travel experience.

5.3. Acknowledgments

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