Investigating Resilience in Passenger Handling Systems:

a detailed agent-based simulation study in airport terminals

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ABSTRACT

Airport terminals have little buffer capacity for potential disturbances, and resilience, i.e., the ability of a system to absorb disturbances and return to its initial state in the shortest possible time, is an important goal in this context. Our goal in this work is to investigate resilience to disturbances in the context of passenger handling systems in airport terminals. To this end, we develop a general disturbance agent-based simulation model for an airport passenger processing system. We extend an event-based model in such a system developed in a previous study, and use detailed attributes for processing times and distributions, especially for the security checkpoint, as inputs and variables to model the agents and their interactions in the terminal. We outline different scenarios and associated relevant parameters for the simulations and explore different countermeasures and mitigation strategies to address the identified problems. By incorporating detailed processing steps into the agent-based simulation model, we can observe how disruptions affect the results of the model at the passenger level. This provides valuable insights into different parameters and strategies that can be used to mitigate the effects of disruptions and maximize the effectiveness of these countermeasures. By taking a passenger-specific view of the input data and selected parameters, the complexity of an airport terminal system and its resilience to disruptions can be understood. Such effects can be predicted and measured, not only when implementing innovative technologies in airport terminals, but also in overall operations.

Keywords: Resilience, Passenger Processing, Airport Terminal, Agent-based Modeling, Simulation.

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1. INTRODUCTION

Airport terminals are part of the critical infrastructure of metropolitan areas, and like other such infrastructures, they face many challenges today. In addition to sustainability, cost-effectiveness and increasing passenger volumes, there is a clear technological trend for future systems. These infrastructures have little buffer capacity for potential problems that could lead to lasting effects in the form of supply shortages, significant disruptions to public safety, and other major consequences. (Mattsson & Jenelius, 2015)

Most of the developments by designers and operators to find mitigation strategies focus on the need to thoroughly investigate an appropriate framework for airport operations to deal with issues such as instrument failure, staff strikes, unlawful acts, or prolonged disruptions such as a pandemic, and their impact on the system. (Gudmundsson et al., 2021) In this context, resilience, i.e. the ability of a system to absorb disturbances and return to its initial state in the shortest possible time, is also an important objective. (Hosseini et al., 2016) Thus, our goal in this work is to investigate resilience against disturbances in the context of passenger handling systems in airport terminals.

There are numerous performance studies that focus on the different processing steps that a passenger has to go through in an airport terminal (e.g., Zhao et al., 2020; Zain Elabedeen et al., 2023; Inama et al., 2023). However, most of them focus on an event-based approach and do not use specific processing times and distributions. However, some critical processing steps, such as security control, require more detail in the models. This approach takes into account the complexity and allows the evaluation of the impact this process may have on the overall performance in a passenger-specific manner. (Alers et al., 2013)

To address this gap, we develop a general disturbance agent-based simulation model for an airport passenger processing system, considering detailed times and distributions for departing passengers, especially the several steps included in the security checkpoint phase, as inputs and variables to model agents in the terminal. We outline different scenarios and associated relevant parameters for the simulations and explore different countermeasures and mitigation strategies to address the identified problems. By incorporating detailed processing steps into the agent-based simulation model, we expect our results to allow the observation of how disruptions affect the results of the model at the passenger level.

2. PASSENGER PROCESSING MODELS

An airport terminal is the interface between the necessary ground processes for passengers and is required to be operationally efficient and economically profitable, while providing passengers with an effortless and uncomplicated travel experience. Departing passengers enter the airport terminal from landside and exit via airside. They use the terminal building for access, check-in, security, immigration, customs, and boarding. (Horonjeff et al., 2010)

In a complex system such as passenger processing in airport terminals, trying different scenarios is usually too expensive, too dangerous, or not possible, and in this case, modeling is a valuable resource for management in this industry. (Alodhaibi et al., 2017; Manataki and Zografos, 2010; Grigoryev, 2022) Simulations are particularly useful because the models reproduce complex interactions as a function of time at the right level of abstraction. In the case of disruptions, for example, this is remarkably effective: simulations can predict not only the effects of disruptions (Metzner, 2020a; 2020b), but also the possible outcomes related to countermeasures from a management perspective (Zain et al., 2023; Inama et al., 2023).

When the interaction of passengers with different characteristics is the goal, agent-based models come into play. State dynamics are represented in terms of probabilistic functions that govern agent behavior. Once validated, these simulation models can predict the individual behavior of real users. (Garifullin et al., 2007) In our simulation

model of the airport terminal, we draw attributes from the literature for passenger behavior.

3. RESILIENCE

While simulations provide performance metrics, sensitivity studies evaluate the impact of different scenarios. In the case of disruptions, where it's necessary to observe the state of the system over a period of time and, for example, evaluate its recovery qualities, resilience studies are more useful. (Li and Lence, 2007)

Nan et al. (2014; 2017) define three system properties to characterize resilience: absorptive capacity, adaptive capacity, and restorative capacity. Figure 1 shows the differences between these three properties and the phases of a system's response to a disturbance.

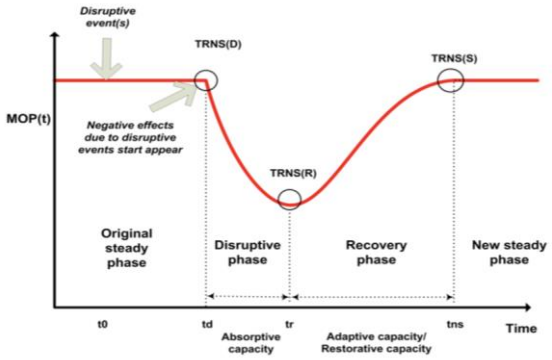


Figure 1 Resilience properties and phases. (Nan et al., 2014)

Initially, there is a disruption of the system, described by the time t_0. As soon as the first performance drop of the system becomes noticeable (t_d), the disruptive phase begins. The course of this phase is characterized by the *absorptive capacity*. The higher the absorptive capacity, the lower the performance drops. The point in time at which the system's performance slowly begins to increase again (t_r) can be seen in the graph as the lowest point and represents the end of the disruptive phase. This is followed by the recovery phase, which lasts until the point in time at which the system again exhibits a constant performance (t_{ns}). In the recovery phase, the system approaches a constant performance level with (*restorative capacity*) or without external influence (*adaptive capacity*). Here, the higher the adaptive and restorative capacity, the faster the recovery phase is completed again, and the new constant performance state is reached. (Nan et al., 2014)

If a system cannot return to its normal state after a disruption, it is said to be a non-resilient system, in which case the system performance deteriorates, leading to a possible collapse of the system. On the other hand, if a system takes a long time to recover and has difficulty reaching the normal state, it is a low resilient system. Highly resilient systems react less intensively to the disturbance and reach the initial state again after a short time. An adaptive system can even achieve an improvement in system performance after the disruption has occurred, as the weakness can be addressed as the system recovers. (Hosseini et al., 2016)

According to Metzner (2020b), in an airport terminal, resilience is the ability to react robustly and quickly to an internal or external disturbance. This means, for example, that when a terminal closure occurs at an airport, passenger throughput recovers to their original levels as soon as possible after the closure is over. This capacity can be described in three different parameters: robustness, recovery speed, and accumulated performance loss. These parameters are calculated according to Equations 1-3 and, in a simulation study, they refer to the system time as a measurement of performance. A combination of the three parameters provides a general resilience indicator, as calculated by Equation 4.

$$R^{t1-} = \frac{p_0}{p_{max}} \tag{1}$$

$$R^{t2} = \frac{t_{disturbance}}{t_{disturbance} + t_{recovery}} = \frac{t_{s,end} - t_{s,start}}{t_0 - t_{s,start}} \tag{2}$$

$$R^{t3-} = \frac{\int_{t_0}^{t_{end}} p_0 \, dt}{\int_{t_0}^{t_{end}} p(t) \, dt} \tag{3}$$

$$R^{t-} = R^{t1-} \, R^{t2} \, R^{t3-} \tag{4}$$

For robustness R^{t1}, system is highly resilient, it does not experience more than a doubling of the performance parameter because of the disturbance ($R^{t1} \geq 0.5$). A system is low resilient if the performance indicator is reduced by a factor of more than 10

because of the disturbance ($R^{t1} < 0.1$). If the resilience parameter lies between these two values, it exhibits medium resilience ($0{,}1 \leq R^{t1} < 0.5$). In addition, the system is said to be non-resilient in the dimension of robustness if the R^{t1} ratio equals 0. Speed R^{t2} and performance loss R^{t3} follow the same principle and the same boundary values. Deriving these values for the resilience indicator R^{t}, the boundary values amount to 0.125 and 0.001. (Metzner, 2020a)

These resilience parameters and limits can be used to evaluate the results of the system times of the simulations according to different disruptive scenarios.

4. TERMINAL CLOSURES

A disturbance or disruption can be defined as an internal or external event that stresses the system and alters system performance. (Gluchshenko and Foerster, 2013). In airport terminals, this can mean a myriad of different possibilities. In addition to indirect disruptions (e.g., weather-related restrictions), the most common events at major German airports, for example, are related to strikes, terminal clearing, IT problems, and handling interruptions. On average, a strike incident lasts 16.57 hours and a terminal evacuation 2.45 hours. (Metzner, 2020a)

A terminal must be closed and evacuated when there is a mix of passengers and baggage that have already passed through security and passengers and baggage that have not yet been screened (i.e., screened and unscreened flows). Such a scenario can occur if, for example, passengers use emergency doors without authorization or if there are errors in the processing of passengers or baggage. In the event of a terminal closure, all passengers who are in the security area or boarding process at the time of the incident must leave the secured area.

The affected area of the terminal is then searched for unauthorized individuals or dangerous items and released upon completion of the search. The duration of such an incident varies depending on the size of the airport and the impact of the disruption. After the screening is complete, all passengers must go through security again. Terminal closures can lead to flight delays and cancellations, even days after the incident, affecting numerous flights and possibly thousands of passengers (Metzner, 2020a; Schubert, 2022).

For our resilience study, we chose terminal closures as the main simulated disruption because airport operators have less time to adjust schedules and take countermeasures compared to strikes, which are usually announced days before they occur. As a result, our simulation study can be constrained to a specific timeframe and the impact of the incident can be depicted in realistic disruption and management scenarios.

5. SIMULATION MODEL

Given the goal of this work, we developed a generic two-method model consisting of discrete event simulation and agent-based simulation following the steps proposed by Enciso et al. (2016): selection of input variables, development of the generic simulation environment, implementation of agents, attributes, and functions, and validation of the model.

Due to the detailed focus in this work on input data to highlight passenger-specific characteristics and behaviors, especially during security screening, attributes are structured according to their impact on behavior, decisions, and time for processing and movement. These attributes either influence the decisions of the passengers, thus creating a realistic simulation, or influence the time spent in the terminal and thus the resilience metric.

We distinguish between basic and extended attributes according to Ma et al. (2011, 2012) and Bueker et al. (2010). Basic attributes are known to the passenger or are specified when the ticket is purchased, while extended attributes are not known to the passenger directly or are specified later.

Basic attributes include: amount of checked and carry-on baggage per passenger; class of travel; use of online check-in; mobility issues and wheelchairs; traveling in groups; companions and visitors. Extended attributes include: random selection for extra security screening; health status; liquids in carry-on baggage; travel experience and purpose &

frequency of travel; drunk & disorderly behavior; technology affinity. Each attribute added or subtracted a few seconds or percentage points from the various processing times, movement speeds, and distributions along the processing steps for these passengers in the terminal.

Table 1 summarizes the proportion attributes used for passengers in this work. Table 2 shows the processing times used for the simulation of the security checkpoint process as an example. Detailed information on all input data can be found in Wiebringhaus (2023).

Table 1 Summary of Passenger attributes

	attribute	expression	distribution
Basic attributes	Luggage definitions (give away)	0 1 2	33% 39% 28%
	Grouping	yes no	50% 50%
	Luggage definitions (hand luggage)	1 2 3 4 5	3% 36% 44% 16% 1%
	Online Check-In	yes no	40% 60%
	Booking Class	Economy Business/First	86% 14%
	Wheelchair	yes no	2% 98%
	Meet and Greeters	yes no	15% 85%
Extended attributes	Alarm	yes no	13% 87%
	Hand luggage liquids	yes no	28% 72%
	PAX health	good poor	93% 7%
	Travel experience	experienced unexperienced	38.50% 61.50%
	Travel purpose	business leisure	38.50% 61.50%
	Behavior	rude drunken	$1{,}92*10^{-5}$% $3{,}84*10^{-5}$%
	Random selection	yes no	10% 90%

Table 2 Summary of Passenger processing times at the security checkpoint

process	attribute	distribution	duration (s)
Place hand luggage on conveyor belt		triangular	(10; 23,16; 39)
	Hand luggage liquids	constant	+20
	Travel experienced	constant	-5
	Travel unexperienced	constant	+20
Control time hand luggage		triangular	(1; 6,06; 20)
	Amount hand luggage		*amount hand luggage
Remove hand luggage from belt		triangular	(12,5; 28,83; 39)
Secondary control			
	Alarm/Random selection	triangular	(60; 199,4; 240)
Other passenger attributes			
	Drunken behavior	uniform	+(100; 200)
	Rude behavior	uniform	+(100; 200)
	Sits in wheelchair	constant	+300

Figure 2 summarizes this model, and each node represents a decision-making process based on the different attributes for each individual agent in the model.

For our model, we considered a generic international hub airport terminal operating a real flight schedule from Frankfurt Airport (FRA) and considering an IATA Busy Day with a night flight ban from 23:00 to 05:00. Passengers arrive at the terminal according to their scheduled flights in generic profiles, adjusted to the airline recommendations and the terminal model. (IATA, 2016; Metzner, 2020a).

The number of processing stations along each step followed the analytical method proposed by IATA (2016) and was adjusted interactively through simulations to meet an optimal level of service. The distances between stations were determined by an average in terminals at major hub airports around the world (i.e., FRA, IST, LHR) and translated into a fictitious airport terminal, as shown in Figure 3.

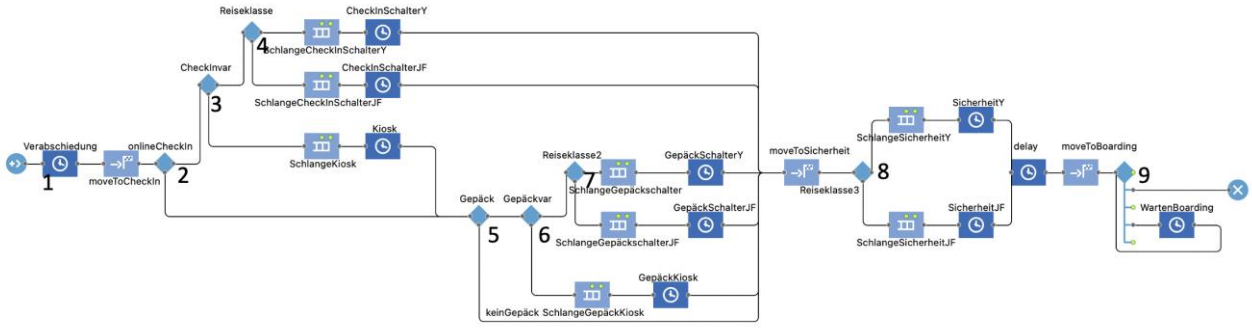


Figure 2 Decision making process in the model.

No other activities, such as restrooms or food and beverage facilities, are included in the model, and the passenger moves from one process station to the next. Due to the stochastic variability associated with the model, we conducted ten simulation runs for each scenario.

To ensure the validity of the model, we followed the steps suggested by Law (2010). First, we selected the passenger attributes according to the objective, and then we collected the available data on these parameters. After comparing their values and checking for outliers, the input data were implemented with different probability distributions. We then developed and validated the model for visual correctness, compared the input data with the data used in the model runs, and performed several sensitivity analyses. Figures 4 and 5 show the observations for the sensitivity analysis for different possible proportions of travel classes and walking speed, respectively , as these were found to have a greater impact on the output. Finally, we implemented the disturbances in the model and documented the results with the resilience estimates.

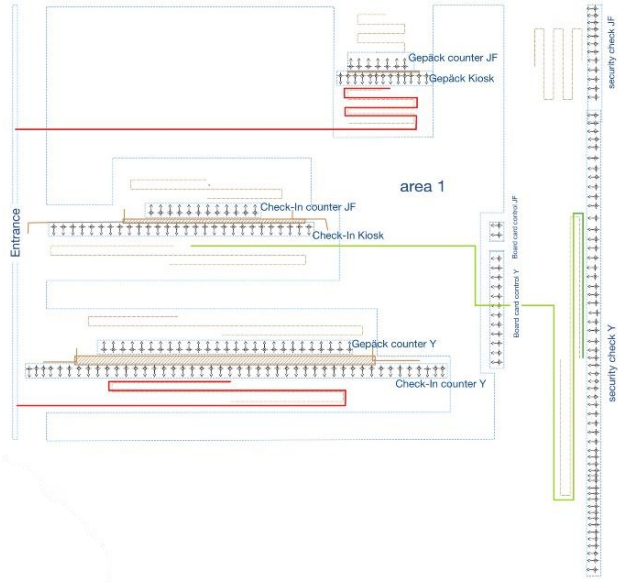


Figure 3 Representation of fictional general airport terminal for an international hub airport.

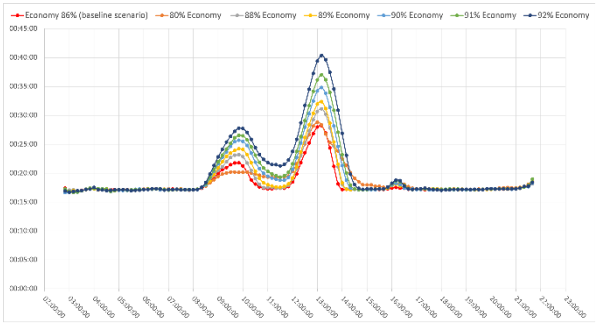


Figure 4 Sensitivity analysis of system times according to travel classes.

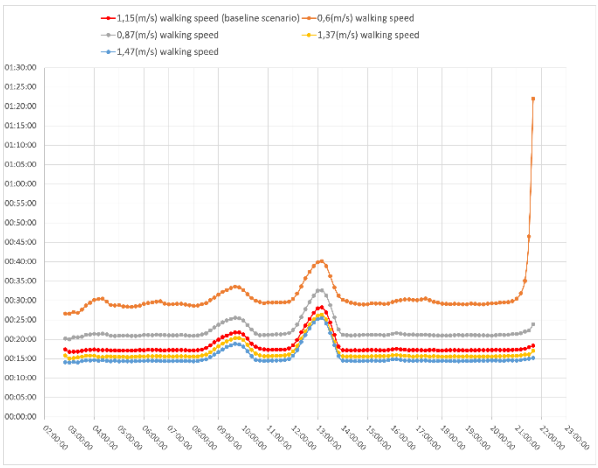


Figure 5 Sensitivity analysis of system times according to average walking speed.

6. DIRUPTIVE SCENARIOS

A terminal closure lasts between 45 minutes and 5 hours, with an average duration of 2 hours (Metzner, 2020a). To account for this variability, we simulated scenarios of terminal closures lasting 1.5, 2, and 2.5 hours. Due to peak patterns in the flight schedule, we simulated these disruptions at 9:00 AM, 12:00 PM, and 4:00 PM, resulting in nine disruption scenarios that were added to the baseline scenario for comparison.

Figures 6 and 7 show the throughput times of passengers and system quality, respectively, compared to their terminal entry time in 10-minute intervals, both for the baseline scenario and for a 1.5 hour terminal closure starting at 9:00 am. In Figure 5, the base scenario is the benchmark for 100% system quality.

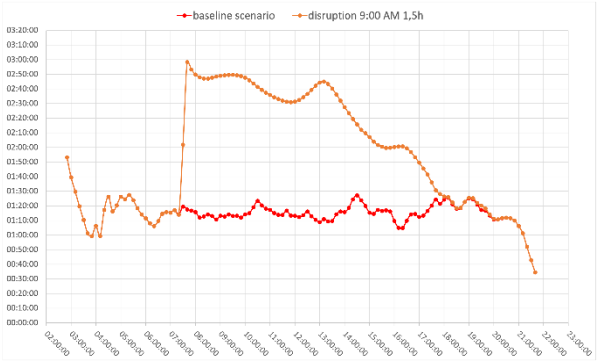


Figure 6 Average throughput times per terminal entrance time in basis and disturbed scenario

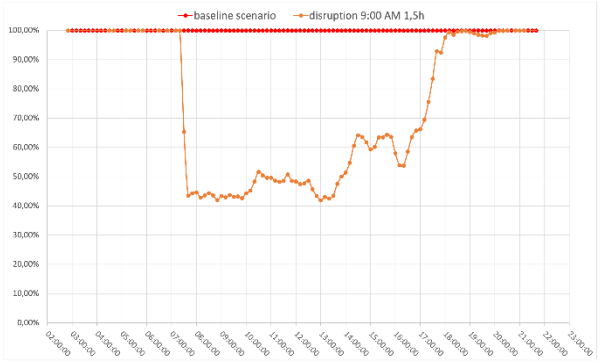


Figure 7 Average system performance per terminal entrance time in basis and disturbed scenario

The two curves first diverge around 7:30 a.m., which can be attributed to the implemented disruption, as there is a jump in throughput times in the disruption scenario (yellow). After the spike in turnaround times, system performance slowly returns to the baseline scenario due to the resulting congestion at the security checkpoint.

Table 2 shows the results of the resilience measures in both numerical values (percentages) and categories (colors).

Robustness (R^{t1}) and accumulated performance loss (R^{t3}) are, in general, on the higher resilience range, except for longer disturbances (i.e. 2.5 hours duration). Recovery speed (R^{t2}), on the other hand, exhibits, in general, rather low or no resilience.

In most scenarios, the system is unable to return to baseline quality within the simulated time frame (i.e., by the end of the day), either because the disruption occurs later in the day, too close to a peak hour, or for too long. We observed that the resilience performance for robustness tends to depend primarily on the duration of the disruption, while for recovery speed and performance loss, the timing of the disruption tends to be just as critical.

7. DISRUPTION MANAGEMENT

As proposed in Inama et al. (2023), we also evaluate two possible countermeasures in the face of terminal closures: increasing the number of security counters in the short term or diverting part of the passenger flow to another terminal.

Increasing the number of security lanes in the short term is a cost-effective measure (IATA, 2016). We modeled a 15% increase in capacity for a period of 5 hours, as shorter durations have little impact on system resilience (Inama et al., 2023). In the case of a decentralized security screening system, passengers are no longer processed at a single security checkpoint, but can choose between two possible security checkpoints implemented as different terminals. For this to happen, passengers must be able to change terminals after passing through the security checkpoint without leaving the secured area (IATA, 2016).

Table 1 Resilience results among disruptive scenarios

Moment:	**9:00 AM**			**12:00 PM**			**4:00 PM**		
Duration:	**1,5h**	**2h**	**2,5h**	**1,5h**	**2h**	**2,5h**	**1,5h**	**2h**	**2,5h**
R^{t1}	62.9%	54.0%	47.4%	62.1%	53.5%	46.9%	61.1%	52.7%	46.3%
R^{t2}	13.4%	16.5%	0.0%	16.9%	0.0%	0.0%	0.0%	0.0%	0.0%
R^{t3}	59.1%	50.8%	43.8%	64.8%	56.7%	49.6%	79.0%	71.3%	64.6%
R^{t}	5.0%	4.5%	0.0%	6.8%	0.0%	0.0%	0.0%	0.0%	0.0%

very high	high	mid	low	very low	none

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Like Inama et al. (2023) results, speed (R^{t2}) and performance loss (R^{t3}) tends to improve with a temporary increase of counters, while robustness (R^{t1}) shows no impact, as it primarily on the duration of the disturbance. Adopting a decentralized security system, on the other hand, tends to improve robustness (R^{t1}) and especially performance loss (R^{t3}), while speed (R^{t2}), doesn't show the same level of improvement across all scenarios.

In general, our results agree with Inama et al. (2023): unlike increasing the capacity temporarily in some cases, a decentralized security system can absorb the negative consequences of a terminal closure given the correct circumstances. Our robustness (R^{t1}) in our model presents slightly better values, while performance loss (R^{t3}) has slightly worse values. Recovery speed (R^{t2}), or the time taken for recovery of the system was higher in our findings than in the event-based model developed in Inama et al. (2023). This deviation is probably because of our further characterization of passenger behavior into detailed times and variations. Both models can be considered comparable, and this equivalence indicates that our detailed approach can produce similar results.

9. OUTLOOK

In this work, we explored the agent-based modeling of an airport terminal and the determination of resilience in passenger processing using attributes embedded in the model agents. Our modeling focused on the main bottleneck of the airport terminal, especially during a closure event (Alers et al., 2013), the security checkpoint.

We extend the event-based model proposed in Inama et al. (2023), and use detailed processing times and distributions as inputs and variables to model the agents and their interactions in the terminal. Given the limited availability of data, we conducted an extensive literature review on the myriad of attributes used as inputs in the model. (Appel et al., 2011) For example, we found that the presence of wheelchair users, the purpose of the trip, and the general walking speed of the users can have a significant impact on the average system time.

We developed a model where individual passengers behave differently based on their unique attributes, thus inducing individual system times. By incorporating detailed processing steps into the agent-based simulation model, we can observe how perturbations affect the results of the model at the passenger level.

This model can later be enhanced to represent a very realistic behavior of passengers in the terminal. In doing so, we provide valuable insight into various parameters and strategies that can be used to mitigate the effects of disruptions and maximize the effectiveness of these countermeasures. Future work may explore different variations of such attributes, e.g., related to the implementation of new

technologies and procedures, or in the overall operations at the terminal according to new observations.

Our next step is to implement specific decision patterns in the model to simulate the emergence of disruptive scenarios through these attributes. By using resilience attributes, we expect our model to properly capture the impact of disruptions faced by the terminal system, especially during the disruption and subsequent recovery phases.

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