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Agent-based simulation of passenger-centric disruption management for multimodal airport access

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Abstract

Efficient and seamless airport access is a critical yet often overlooked process of airport operations. Strong connectivity, especially during disruption periods, significantly reduces passenger delays and potential revenue losses. Tackling these challenges demands coordinated disruption management strategies. To that end, we model coordination in a system comprising two traffic orchestrators, each responsible for managing their respective domains: airside and landside. The airside orchestrator can implement tactical flight delays, while the landside orchestrator can apply rerouting to assist passengers at-risk of missing their flights. Through negotiation between these orchestrators, the approach aims to minimize missed flights and passenger delays, while also exploring a fair distribution of costs. The negotiation process is structured using a game-theoretic framework, and an agent-based simulation is used to evaluate the effects on airport operations. A case study demonstrates the effectiveness of these measures in enhancing airport operations while balancing costs.

Keywords: Coordination; Multi-Agent Systems; Simulation; Multimodal transport; Disruption management

1. Introduction

Effective coordination among transport stakeholders is essential for the success of advanced multimodal transport systems. Achieving seamless multimodal transport solutions requires removing administrative barriers and adopting flexible management structures (European Commission, 2016). Particularly for the aviation sector, this push for seamlessness is especially critical. The European Commission has set a target for 90% of travelers within Europe to complete their door-to-door journey within 4 hours by 2050 (European Commission, 2011), which highlights the need for efficient airport access. Achieving this goal requires the coordination of all transport modes involved (Colovic et al., 2022). In response, airlines have begun offering multimodal options that emphasize seamless connections, such as Lufthansa's ticketing partnership with Deutsche Bahn (Lufthansa, 2019). However, a key challenge remains: securing consensus and collaboration among transport operators.

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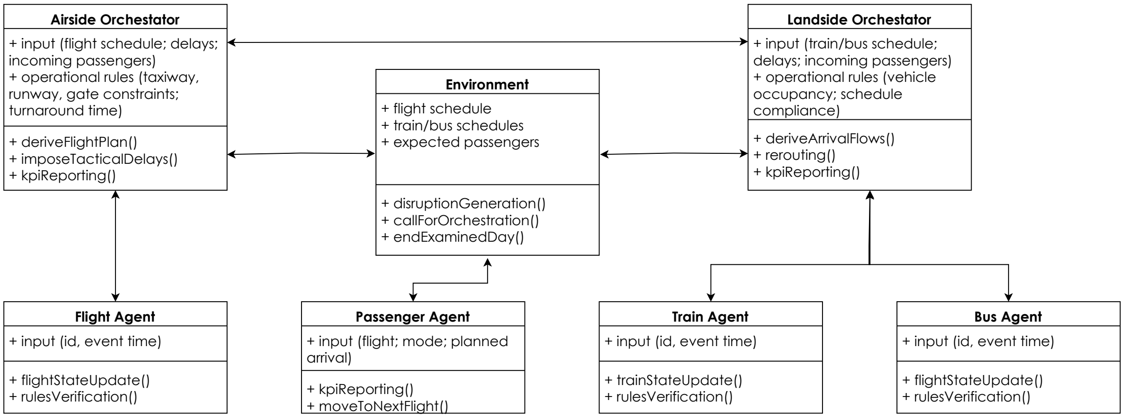

Fig. 1: Schematic representation of the agent-based simulation model.

Collaboration in multimodal transport is especially challenging during disruptions, which demand effective coordination across modes. Seamless integration of air and public transport can help minimize delays by enabling passengers to adapt quickly. A measure of seamless integration that has been proposed to address airport access disruptions is tactical flight rescheduling (Scozzaro et al., 2022). This involves strategically delaying certain passengers to accommodate disrupted ones, an approach that may lead to cumulative passenger delay minimization when considering rebooking related delays. Other proposed approaches focus on flexible trajectory updates such as the integration of rerouting models into public transport disruption management by Cebecauer et al. (2021). Particularly for airport connections, Parmaksizoglou et al. (2023) introduced a demand-responsive service leveraging urban taxi infrastructure to improve access in underserved areas via rerouting.

This study seeks to enhance disruption management for multimodal airport access by improving coordination among stakeholders in passenger airport access, under landside disruptions. To achieve this, we distinguish the problem into two distinct domains and propose a framework that incorporates traffic orchestrators for each domain, as outlined by Stav et al. (2024). A traffic orchestrator is considered responsible for traffic management within a well defined transport domain. The framework includes an airside and landside orchestrator, each capable of applying corrective measures to serve passengers during periods of disruptions. Assuming an integrated ticketing solution for train-accessing passengers, this study specifically explores the implementation of tactical flight delays as a corrective measure applied by the airside orchestrator, and the deployment of rerouting strategies, such as directing passengers to other transportation options like buses, by the landside orchestrator.

An agent-based simulation environment is developed mapping operations related to flight departures, passenger arrivals, transit network updates, and security screening. When a flight is identified as having passengers at-risk of missing their flights due to a disruption, corrective measures are established under a game-theoretic framework, where orchestrators negotiate to reach a consensus on the application of measures. Multi-agent negotiation across stakeholders in the aviation sector has been previously explored as a way to evaluate performance based on decision-making levels and coordination capabilities (Bouarfa et al., 2021). In our approach, orchestrators engage in iterative one-to-one negotiations to minimize their costs and the impact of different strategies is assessed through an experimental evaluation, focusing on the optimization of costs and their effects on airport performance.

2. Agent-based Simulation

Given the system under consideration consists of multiple autonomous, coordinating entities, the multi-agent system modeling and simulation paradigm is well-suited for representing and analyzing its dynamics. The proposed agent-based model is illustrated in Figure 1, with a detailed breakdown of all associated agents provided in the following sections.

Table 1: Modal share during different time periods.

Time Period	Bus	Car	Taxi	Train
Peak Hours	15%	45%	10%	30%
Shoulder Hours	10%	60%	10%	20%
Off-Peak Hours	10%	60%	20%	10%

Table 2: Expected safety margin prior to flight departure.

Carrier	Domestic	Schengen	Other
Legacy	2 hr	2 hr	3 hr
Low-Cost	1.5 hr	1.5 hr	2 hr
Leisure	1.5 hr	1.5 hr	2 hr

2.1. Environment

To model the operations of the examined airport, inputs are required on passenger behavior, flight schedule, airport conditions, and the transit network serving the airport. All modeling decisions regarding the simulated processes were made in consultation with the examined airport's accessibility managers (ORCHESTRA, 2021). Establishing modal splits for incoming passengers is a main environmental input. These vary depending on the time of day, as detailed in Table 1. Peak hours (7:00–9:00, 16:00–19:00) correspond to the highest arrival activity, shoulder hours to moderate activity between peak periods, and off-peak hours to lower activity. Transit schedules for buses and trains are integrated using publicly available General Transit Feed Specification (GTFS) data for the examined date (Transit.Land, 2025). Passenger arrival is also contingent on carrier and destination type, as they influence the expected safety margin for a passenger, which indicates how early we expect a passenger to arrive in the airport, compared to their scheduled departure time, as listed in Table 2.

Data on carriers, arrivals/destinations, aircraft types, and scheduled departure/arrival times for the examined date are collected from publicly available flight records (Flightera, 2025). Passenger volumes for specific flights were provided by the airport. Additionally, airport capacity limits are set as operational constraints. A maximum of 77 aircraft can be accommodated at the gates, with a two-runway configuration and a taxiway capacity of 15 aircraft. Finally, the airport is equipped with 20 X-ray machines, though not all are operational at all times. Their availability varies by period: 20 during peak hours, 10 during shoulder hours, and 5 during off-peak hours.

2.2. Passenger agents

In the absence of real-world data, approximation methods are used to generate the arrival times of passenger agents. Each passenger agent is assigned a mode and a flight as part of its characteristics, which influences their arrival time. We consider that passenger arrivals for a specific flight follow a normal distribution, with the mean centered around the flight departure time minus the arrival safety margin (as listed in Table 2), and a standard deviation of 30 minutes. This aligns with recent examples of existing literature (Brause et al., 2020) and consultations with the airport. Transfer passengers are treated as departing passengers, with their arrival time matching their flight's arrival time. For passengers arriving via a public transit mode, generated agent arrival times, are also linked to the airport's transit network, ensuring that their arrival corresponds to an available service line.

After arrival, passenger agent's processing time and waiting in security queues are approximated using the stationary backlog carryover approach (Stolletz, 2011). Once screened, an agent's state changes to either "safe" or "at-risk". Non-Schengen passengers are safe if they have 45+ minutes before departure, and others are safe with 30+ minutes. Passenger agents with an at-risk classification due to a disruption, may trigger corrective measures by the orchestrator agents.

2.3. Bus & Train agents

Passenger agents traveling by bus or train update the capacity of the corresponding line of a Train or Bus agent servicing their connection to the airport. These agents fall under the domain of the landside orchestrator and are sensitive to updates related to changes in the GTFS input (e.g., due to a disruption), based on interactions with the landside orchestrator. Operationally, a train line has a maximum capacity of 230 passengers, while a bus line has a maximum capacity of 55 passengers. As passengers are simulated, both bus and train agents update their capacity to ensure compliance with these limits. If a passenger attempts to board a line at maximum capacity, the bus or train agent will reschedule them to the next available service.

2.4. Flight agents

These agents fall under the domain of the airside orchestrator. Flight agents are activated according to the schedule of the examined environment and are continuously updated to reflect real-time changes in airport operations. The flight agent's state transitions through various phases such as waiting, taxiing, takeoff/landing, and arrived/departed, while interacting with airport infrastructure to ensure compliance with operational constraints for gate, taxiway, and runway utilization set by the environment. The two-runway configuration also requires a 2-minute separation between consecutive aircraft, with one runway dedicated exclusively to departures and the other to arrivals. Taxiing time is dynamically adjusted based on congestion, ranging from a minimum of 5 minutes on an empty taxiway to a maximum of 15 minutes under full congestion. Any flight agent that may violate these conditions is delayed. Additionally, turnaround time constraints are imposed mandating a minimum gap of 45 minutes between a flight's arrival and departure; if this is violated, the agent is delayed.

2.5. Orchestrator agents

Orchestrators oversee the activation of agents within their domain, ensuring compliance with operational constraints and reporting KPIs, such as delays. They are primarily responsible for implementing corrective measures during disruption than can lead to the adjustment of other agents' conditions. An airside orchestrator can directly impact the flight schedule of all flight agents by imposing tactical delays on individual flights, while a landside orchestrator can alter the capacity conditions of bus and train agents by rerouting passengers. Each orchestrator has its own objective function guiding its decision-making, which may consider multiple aspects. Orchestrators do not have explicit knowledge of each other's objective functions. The selection of appropriate measures is achieved by orchestrators trying to optimize their objectives through coordination between them.

3. Coordination

During the simulation, when a flight is identified as having at-risk passenger agents due to a disruption, orchestrator imposed measures are explored. In the examined framework, a disruption may involve a sudden cancellation of multiple train lines to the airport, leading to increased congestion and a supply-demand imbalance for this mode of transport. To determine which measures can be applied to mitigate disruption issues, we develop the "orchestrator game". In this game, the airside orchestrator can take actions related to tactical flight delays, while the landside orchestrator takes actions on multimodal rerouting. Effects of each action are highly correlated. For example, rerouting certain number of passengers may not be possible without a specific tactical delay applied, or a tactical delay may make rerouting of passengers redundant, as the passenger agents' would not be classified as at-risk. This has a direct effect on costs of orchestrators.

We associate costs for the airside orchestrators with the cost of unpunctuality. These are the implied revenue losses for an airline resulting from a departure delay. Monetary values used to estimate these costs, are based on aircraft type, delay duration, and the number of affected passengers (Cook et al., 2021). Regardless of cost, tactical delays must remain limited to avoid adverse effects, particularly on transfer passengers. Thus, the maximum tactical delay is capped at 30 minutes.

During a disruption, the landside orchestrator seeks to identify rerouting opportunities for at-risk passengers. Selecting passengers to reroute is also contingent on the state of the simulation, ensuring that potential options are not at capacity. Naturally, rerouting incurs a cost equivalent to the fare of the alternative mode of transport, set at 15€ for this simulation. As the amount of passengers that need to be rerouted is contingent on the applied tactical delay as well, we use an iterative approach with a five-minute step starting from 0 to 30 minutes to create a cost matrix for these measures.

Finally, there is the cost of rebooking passengers that missed their flights. Under the proposed integrated ticketing solution, orchestrators are assumed to share responsibility for this, to boost seamlessness of the door-to-door journey experience. We also make use of the Cook et al. (2021) report to associate costs of rebooking a passenger based on flight type (short-haul, mid-haul, or long-haul). To determine cost-sharing for rebooking costs during a network disruption, an ad-hoc mechanism is introduced. If the airside orchestrator takes no action, the costs are shared equally. Since the disruption originates on the landside, it is deemed unfair to allocate more than 50% of the cost to the airside, even in the absence of any intervention. However, for each tactical delay applied by the airside orchestrator, its share of rebooking costs is progressively reduced. Once a tactical delay of 15 or more minutes is imposed, the airside's cost share is reduced to zero.

4. Negotiation

We use the "orchestrator game" to reach decisions through negotiation between orchestrators. The goal is to develop solutions that enhance system performance but also ensure fairness. The negotiation **domain** involves orchestrators exchanging proposals to determine whether corrective measures should be applied individually or jointly, and to what extent. A heuristic-based framework simulating an alternate-offer **protocol** (described in Algorithm 1) is employed, enabling cost-bargaining while allowing orchestrators to retain autonomy in their decisions. Each orchestrator's **preferences** are represented through aspirations linked to their incurred costs as explained in Section 3.

For each flight f with at-risk passengers, a cost matrix $cost_f$ is created to represent the orchestrator game. The actions that minimize each orchestrator's objective functions are computed (Algorithm 1, Line 3) and serve as their initial aspirations. Objective functions can take various forms, and in this study, two approaches are explored: the independent approach, where an orchestrator always suggests the optimal measure from their own perspective, and the cooperative approach, which considers the other orchestrator's costs in their objective function as well. In the cooperative approach, the objective functions include the cost of the other orchestrator weighted by parameters w_A and w_L for airside and landside orchestrator, which represent the extent of concession each orchestrator might make.

Algorithm 1: Alternate offer protocol between orchestrators

Input: R, w_A, w_L, $cost_f$, $step$
1 Initialize $r_A \leftarrow 0$, $r_L \leftarrow 0$, $c_A \leftarrow 0$, $c_L \leftarrow 0$
2 **for** each flight f with at-risk disrupted passengers **do**
3   Determine orchestrator game cost matrix ($cost_f$) and extract $best_A$, $best_L$
4   Set $a_A \leftarrow best_A$, $a_L \leftarrow best_L$, $negotiated\_action \leftarrow \emptyset$
5   **while** $negotiated\_action = \emptyset$ **do**
6   **for** $r = 1$ *to* R **do**
7   Compute $step_A \leftarrow step \cdot w_A$, $step_L \leftarrow step \cdot w_L$
8   Find best $valid\_pair$ for minimizing $cost_A$ related to airside objective function
9   **if** $cost_L \leq a_L$ **then**
10                 $negotiated\_action \leftarrow valid\_pair$
11   **break**
12   Find best $valid\_pair$ for minimizing $cost_L$ related to landside objective function
13   **if** $cost_A \leq a_A$ **then**
14                 $negotiated\_action \leftarrow valid\_pair$
15   **break**
16   Update $a_A \leftarrow a_A + step_A$, $a_L \leftarrow a_L + step_L$
17   **if** $negotiated\_action = \emptyset$ **then**
18   Increase $step$
19   Update $r_A \leftarrow r_A + cost_A - best_A$, $c_A \leftarrow c_A + cost_A$, w_A
20   Update $r_L \leftarrow r_L + cost_L - best_L$, $c_L \leftarrow c_L + cost_L$, w_L
21 **return** r_A, r_L, c_A, c_L

Negotiations take place over a fixed number of rounds R, during which orchestrators alternate making offers based on their objective functions. In each round, an orchestrator can either accept the offer or propose a counter-offer, continuing until an orchestrator's acceptance condition is met. If a proposal results in a cost that is less or equal to the other orchestrator's aspiration, an agreement is reached, and negotiation concludes. If no agreement is reached within a round, aspirations are increased based on the current step of each orchestrator (Algorithm 1, Line 16). Acceptance conditions are closely tied to the orchestrators' concession parameters (w_A,w_L), as these directly influence how aspirations increase over successive rounds (Algorithm 1, Line 7). If an agreement is not reached within R rounds, the parameter $step$ is updated and the process is restarted (Algorithm 1, Line 18).

Parameters w_A and w_L may be updated to ensure that the outcomes of previous negotiations influence subsequent rounds. In a setting where agents do not use information over past outcomes, the parameters w_A and w_L simply remain equal. However, we also explore the case where these parameters are adjusted based on orchestrator's regret (r_A, r_L). Regret of each orchestrator is the additional cost over their best choice and is updated in the end of each game, along with the total cost (Algorithm 1, Lines 19-20). Specifically, we consider two options: setting w_A and w_L to 0.5 (based on the former case), or updating the values based on the percentile cumulative regret over the examined games.

5. Experimental Evaluation

We generate a case study for Malpensa International Airport (MXP) for June 2022 to test the proposed measures in managing disruptions to the access network. We simulate a series of disruptions on the weekend of 18/6/2022-19/6/2022, which is the busiest weekend of the month. The disruptions occur during the morning peak (7:00-10:00) or afternoon peak (16:00-19:00). During these periods, we generate either a 50% reduction of service on the most used train line to the airport, or a 30% reduction of service on all train lines servicing the airport. Agent-based simulation is implemented in Python using the Mesa library (Hoeven et al., 2025). We analyzed the impact of applying corrective measures under four strategies: (i) no measures, (ii) **independent**, where agents optimize their own cost without using past information and update their aspirations based on fixed weights (w_A=w_L=0.5), (iii) **cooperative**, where each orchestrator is optimizing their own cost plus half the other agent's cost (w_A=w_L=0.5), and (iv) **adaptive**, a modified version of (iii) where weights w_A and w_L are not fixed, but are updated according to the agent's regret from past games ($w_A = 1 - \dfrac{r_A}{r_A + r_L}$, $w_L = 1 - w_A$).

Table 3 presents the mean value metrics from the application of different strategies during negotiation after five simulation runs for each disruption. The table reports the costs incurred by both the airside and landside orchestrators, as well as the percentage of missed flights (i.e., the passenger agents that remained at-risk after application of measures), total delay incurred by passengers, and located Nash equilbria. In general, we observe that compared to the application of no measures, any negotiation strategy leads to similar results for missed flights and total delay. In the most disruptive case (D8), a decrease of up to 1.4 % in missed flights is reported, equating to more than 5000 passengers who were able to catch their flights as a result of the corrective measures. Decreases in total delay can also be significant, reaching up to 8 minutes.

Table 3: Comparison of different strategies across various instances. Optimal Egalitarian social welfare is highlighted in bold.

	No measures					**Independent**					**Cooperative**					**Adaptive**				
Instance	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash	Airside (€)	Landside (€)	Missed Fl. (%)	TD (min.)	Nash
D1	35825	35825	0.3	14.7	12.8	10693	16256	0.1	13.8	30.4	11839	**12378**	0.1	13.8	28.4	13862	11652	0.1	13.8	28.4
D2	72015	72015	0.6	16.5	13.8	12452	19159	0.1	14.7	44	12999	17392	0.1	14.7	43.6	14886	**16541**	0.1	14.7	41.2
D3	26545	26545	0.3	14.4	12.2	17999	22035	0.3	14.4	20.4	**19122**	17585	0.3	14.4	19.4	20064	17075	0.3	14.4	18.8
D4	154710	154710	1.6	25.6	11.2	28216	48782	0.4	16.5	63.8	30312	40184	0.4	16.6	62	33514	**38189**	0.4	16.6	59.4
D5	112890	112890	1.1	17.2	8	18356	23214	0.2	13.9	47.6	17754	**20752**	0.2	13.9	46.8	17938	21563	0.2	13.9	46.8
D6	124210	124210	0.9	17.9	12.6	16577	26981	0.2	14.9	52.2	17314	21047	0.2	14.8	53.2	18967	**19734**	0.2	14.9	53
D7	44705	44705	0.5	15.7	13.8	25713	37256	0.5	15.4	30	27515	**28745**	0.5	15.4	27	35127	22535	0.5	15.4	26.2
D8	149715	149715	1.9	26	16.2	66417	57146	0.6	18.3	50.8	**47371**	45833	0.5	17.7	49.4	52337	44330	0.5	17.7	49.2

In evaluating the performance of the selected strategies, two key metrics come into play: Utilitarian and Egalitarian social welfare. Utilitarian social welfare seeks to maximize the total sum of costs across all agents, which, in this case, refers to the combined Airside and Landside costs. In contrast, Egalitarian social welfare prioritizes fairness, focusing on the utility of the agent who is worst off. The cooperative strategy performs the best in terms of Utilitarian social welfare, which was expected as it strives to minimize both costs. The adaptive strategy is significantly aligned with the cooperative strategy, showing an average discrepancy of just 3%, whereas the independent strategy exhibits a slightly higher average discrepancy of 12%. When considering Egalitarian social welfare, the cooperative strategy continues to outperform the others in 5 out of the 8 disruption cases and the adaptive strategy performs the best in the remaining three. The discrepancy from the Egalitarian social welfare remains within 2% of the best observed by the cooperative strategy, increases slightly to 7% in the adaptive strategy, and rises significantly to 26% in the independent strategy. Although the independent strategy exhibits a higher discrepancy from the Egalitarian social welfare, it is more effective in prioritizing solutions that align with Nash equilibria. The differences between strategies in terms of Nash equilibria are minimal however, typically varying by just one to three equilibria.

6. Conclusions

This study demonstrates how corrective measures, such as tactical flight delays and passenger rerouting, can mitigate disruptions to maintain a seamless passenger experience. The developed agent-based simulation underscored the importance of balanced and adaptive interventions in enhancing airport operational efficiency through the use of negotiation within a traffic orchestrator framework to achieve this. Building on these findings, future research could explore extensions such as assessing multi-airport network effects, and incorporating more complex airline and passenger behavioral responses. Additionally, expanding the framework to other transport modes could provide insights into multimodal resilience strategies. By improving coordination among orchestrators, this study provides a basis for more adaptive, integrated disruption management in airport operations.

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