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Optimization of airport operations during access mode disruptions to improve passengers experience

Geoffrey Scozzaro

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Geoffrey Scozzaro. Optimization of airport operations during access mode disruptions to improve passengers experience. Optimization and Control [math.OC]. Université de Toulouse, 2024. English. NNT : 2024TLSES009 . tel-04609246

HAL Id: tel-04609246

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THÈSE

En vue de l'obtention du
DOCTORAT DE L'UNIVERSITÉ DE TOULOUSE
Délivré par l'Université Toulouse 3 - Paul Sabatier

Présentée et soutenue par
Geoffrey SCOZZARO

Le 2 février 2024

**Optimisation des opérations aéroportuaires en cas de
perturbation des modes d'accès afin d'améliorer l'expérience
passager**

Ecole doctorale : **AA - Aéronautique, Astronautique**

Spécialité : **Mathématiques et Applications**

Unité de recherche :
ENAC-LAB - Laboratoire de Recherche ENAC

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Remerciements

First and foremost, I would like to express my deepest gratitude to Pr. Yasemin Arda and Pr. Michael Schultz for their invaluable guidance and support throughout the review and evaluation of my thesis. Special thanks to Pr. Schultz for his unparalleled expertise in airport operations, which helped me to refine and expand my research. Pr. Arda's meticulous evaluation and proofreading of the manuscript significantly improved its overall quality. I also thank Catya Zuniga, Luis Delgado and Marie-Pierre for accepting to be experts during my defence and for their thorough evaluation and insightful feedback.

I also want to thank other researchers and students who helped me during my work. Maji, thank you for her help during the beginning of the thesis and her collaboration on works for rescheduling flight. Thanks to Miguel Mujica Mota for the visiting in Amsterdam and for all his kindness in involving me in research committees, reviewing process, and for our collaborative work. Merci Clara pour la co-rédaction de deux papiers de recherche et pour toutes ses heures passées à travailler sur le projet TRANSIT. Merci à Florian à l'équipe data de CDG, et à Anne Bonneton pour leur collaboration et le partage de données. Je souhaite aussi remercier Paul Landais pour sa vision opérationnelle sur mes travaux de recherche et pour son aide afin de rendre plus réaliste le cas d'étude autour de CDG. Je souhaite également exprimer ma gratitude envers Philippe sans qui ma thèse n'aurait sûrement pas vu le jour et pour son aide dans le début de celle-ci.

Je souhaite ensuite remercier mes trois encadrants pour m'avoir accompagné et guidé pendant ces trois années. Daniel, merci pour m'avoir donné le goût de la recherche avec cette première expérience en Floride, et merci pour m'avoir offert cette opportunité de thèse lorsque j'étais face au mur au début de la pandémie. Je te remercie aussi pour cette balade en montagne avec Adan qui m'a permis de déconnecter pendant la rédaction. Eric, merci pour ton ouverture d'esprit qui m'a permis d'appréhender la recherche sous un autre angle, en me rendant compte de l'importance réaliser mes projets de manière passionnée. Merci aussi d'avoir pris le temps d'apprendre à me connaître et d'avoir pu m'épauler quand cela allait moins fort. Enfin Catherine, merci sincèrement pour tout le temps que tu m'as accordée afin de m'accompagner, aussi bien dans la relecture des modèles mathématiques, que lors de la rédaction du manuscrit, ou encore de la préparation de l'oral. Merci pour cette aide précieuse, et pour ces quatre soutenances blanches, qui m'ont permis d'être fier de mon manuscrit et de ma présentation finale.

Je tiens aussi à remercier l'ensemble de mes collègues (et amis) doctorants sans lesquels cette aventure n'aurait pas été aussi belle.

Alexis Brun, merci pour ta bonne humeur et pour ces discussions autour de la Carbonara et du Guanciaie. Alexis Bregeon et Adrien, merci d'avoir supporté nos pitreries avec Andréas et Clara. Céline, merci pour ces expressions de la langue française oubliées que je pourrais ressortir lors des repas de Noël. Julien, merci pour ces soirées

au Biergarten pendant la rédaction, tu as été un super compagnon de levé de coude!

Jean-Claude, merci de respecter la tradition et la cuisine italienne, c'est rare de rencontrer quelqu'un qui l'apprécie autant! Manu, merci pour ces repas à Santosha et pour cette fameuse soirée où "on a fini à Montpellier". Rémi P, merci pour m'avoir appris l'écriture du mot "dilemme" et merci pour ces innombrables imitations lors de la pause café. Bastien, merci pour cet atelier 2 tonnes et pour ces performances de voltige de dosettes à café. Thomas (ou plutôt Thomaev), merci pour ton soutien pendant toute la rédaction, ta résilience à toute épreuve aura été une vraie source de motivation ! Eliot, merci pour m'avoir toujours tenu informé sur les mouvements sociaux, et pour ces échanges autour de recettes de cuisine et de l'Italie. Zahraa, merci pour ces délicieuses pâtisseries Libanaises ! Rémi C, merci pour ta bonne humeur et pour ces discussions autour de recettes de cuisines. Antoine, merci pour ces moments sympas passés à ICRAT (on se souviendra de la pool party et de la soirée pina colada), je te laisse mon bureau prends en soin ! Andréas, merci pour avoir partagé ces chimneys cake à Budapest et merci pour ces discussions autour du vin. Sans oublier cette fameuse soirée à la Tantina qui, j'espère, t'aura donné envie de recommander des Long Island ! Denis, merci pour ces soirées burgers et pour ces apremis pétanque (on retiendra la partie avec Lukman et la soirée ayant fini au Nabuchodonosor).

Enfin, Clara, merci pour m'avoir supporté pendant ces trois années, pour ces fous rires (Julien Leperce, Mira la naranja, C'est claaaaasse) qui resteront gravés en ma mémoire ! D'autres souvenirs tels que ce magnifique repas sous un pont à Zurich ou encore cette course en taxi à Séville resteront inoubliables.

Je remercie aussi tous mes amis qui m'ont soutenu pendant ces trois années. Merci Ravel et Enzo pour toutes vos relectures. Merci Lucas, Lisa et Charlotte pour ces escapades en Espagne et pour ces soirées à la maison qui m'ont permis de me rendre compte que je n'étais jamais seul !

Enfin, je souhaite remercier ma famille et mes proches. Maman et Martial, merci pour les cours d'anglais qui auront finalement bien servi. Papa, merci sincèrement de m'avoir toujours poussé à aller au bout des choses. C'est bon, je suis arrivé au bac +8, on peut s'arrêter là je crois ! Aurore, merci pour toute l'organisation du pot de thèse !

Résumé

Dans un contexte de crise climatique et de régulations du transport aérien, les transports publics ou les trains sont amenés à remplacer les véhicules privés et les vols court-courriers pour accéder aux aéroports. Afin de garantir aux passagers des trajets porte-à-porte fiables, il est alors nécessaire d'assurer une coordination entre les modes de transport aérien et terrestre. Cette intégration est essentielle notamment en cas de perturbations, telles qu'une panne de métro ou de train, induisant un risque pour les passagers d'arriver en retard à l'aéroport et éventuellement de manquer leur vol. Dans le cadre du projet européen TRANSIT, dédié au développement de mécanismes de coordination entre acteurs du transport aérien et terrestre basés sur le partage d'informations, nous proposons dans cette thèse des solutions pouvant être mises en œuvre au niveau de l'aéroport pour limiter l'impact de perturbations sur l'accès de l'aéroport pour les passagers. Supposant un échange d'informations en temps réel entre les opérateurs de transport aérien et terrestre, nous proposons des ajustements tactiques des opérations aéroportuaires afin d'améliorer l'expérience globale du passager.

Cette thèse présente différentes contributions. Tout d'abord, nous avons développé un cadre de modélisation d'un aéroport et de son flux de passagers associé. Nous y présentons également une distribution de probabilité paramétrique appropriée pour modéliser le profil d'arrivée des passagers d'un vol en fonction de ses caractéristiques, permettant de reconstruire le flux d'arrivée des passagers à un aéroport à partir d'un planning de vol. Dans un deuxième temps, nous proposons deux stratégies pour les opérateurs aéroportuaires afin d'atténuer l'impact des perturbations sur les passagers. Ces deux stratégies sont basées sur des méthodes de Recherche Opérationnelle, faisant appel à des modèles mathématiques et des résolutions algorithmiques pour aider à la prise de décision. La première stratégie consiste en une réaffectation tactique des équipes de sécurité afin de réduire les temps d'attente des passagers aux points de contrôles de sûreté. Nous proposons deux formulations du problème, incluant ou non une ségrégation des flux de passagers pour traiter les passagers impactés par la perturbation dans une file d'attente séparée. La seconde stratégie consiste en une replanification tactique des vols pour attendre les passagers retardés tout en tenant compte des contraintes opérationnelles côté piste et des passagers en correspondance. Plusieurs approches de résolutions sont mises en place et comparées pour résoudre les différents problèmes d'optimisation. Ces méthodes reposent sur de la PLNE, un recuit simulé ou encore des heuristiques gloutonnes. Nous proposons également une approche par fenêtre de temps glissante pour mettre en œuvre ces stratégies en tenant compte des aspects opérationnels et de la disponibilité des données passagers. Nous testons les deux stratégies sur différents scénarios de perturbation afin de mieux comprendre et d'évaluer les bénéfices de ces solutions pour les passagers. Enfin, nous proposons une validation et extension des deux stratégies. Premièrement, nous proposons une intégration de la stratégie de réaffectation des équipes de sûreté avec de la simulation à événement

discret pour fournir une évaluation plus réaliste et établir la base d'un système d'aide à la décision pour les opérateurs aéroportuaires. Nous élargissons également le champ d'application de la replanification des vols au niveau du réseau air-rail, permettant une prise en compte de la propagation des retards et de son impact sur l'ensemble du réseau de transport. Cette extension permet une évaluation des retards des passagers à leur destination finale et l'évaluation de la pertinence d'une replanification tactique des vols pour les passagers.

Abstract

In light of the climate crisis and air transportation regulations, there is a growing interest in using public transportation or trains to replace cars and short-haul flights to access hub airports. In order to ensure passengers with reliable door-to-door journeys, seamless integration between air and ground transport modes is required. This integration is essential, especially during disruptions such as train or subway shutdowns, which significantly increase the risk of passengers arriving late and missing their flights. As part of the European TRANSIT project, dedicated to developing coordination mechanisms between air and ground transport operations based on information sharing, we propose solutions that can be implemented at the airport level to deal with airport access mode disruptions. Assuming real-time information sharing between air and ground transport stakeholders, our approach involves tactical adjustments in airport operations to enhance the overall passenger experience.

Our work presents different contributions. Firstly, we propose a comprehensive framework for airport and passenger flow modelling. We also present the finding of a suitable parametric distribution for modelling the passenger arrival profile of a flight based on its characteristics, allowing for a reconstruction of passenger arrival flow at the airport entrance based on a flight schedule. Secondly, we propose two recovery strategies for airport operators to mitigate the impact of disruptions on passengers. Both strategies are grounded in Operations Research, employing mathematical modelling and algorithmic solution approaches to help decision-making. The first strategy is a tactical reallocation of security teams to reduce passenger waiting times at security screening checkpoints. We propose two problem formulations: whether or not to consider passenger flow segregation to handle disrupted passengers in a dedicated fast-track lane. The second recovery strategy is a tactical flight rescheduling to wait for delayed passengers while considering airside operational constraints and air-connecting passengers. We propose different approaches for solving the related optimisation problems, through direct solution with ILP commercial solver, simulated annealing and greedy heuristic approaches and compare their effectiveness. We also propose a sliding-time window approach to implement such recovery strategies when dealing with operational aspects and data availability. We test both recovery strategies on a benchmark of disruption scenarios to gain insights and evaluate the benefits of such disruption management solutions for passengers. Finally, we propose a validation and an extension of both recovery strategies. First, we combine the security team reallocation strategy with discrete simulation tools to provide realistic assessments and the basis of a decision support system for airport operators. Secondly, we broaden the scope of flight rescheduling to the air-rail network level, capturing delay propagation and its impact on the overall transportation network. This extension allows for a comprehensive evaluation of passenger delays at their final destinations and an assessment of the benefits obtained for passengers through a tactical flight rescheduling adjustment.

Contents

Introduction	3
I From flight-oriented to passenger-oriented airport management: a new paradigm	5
1 Airport management and passenger experience	9
1.1 Introduction	9
1.2 Airport management	9
1.2.1 Passenger and aircraft operations within the airport	10
1.2.2 Management of airport operations	11
1.3 Principles of Operations Research	13
1.3.1 Definition of Operations Research	13
1.3.2 Mathematical optimisation modelling	15
1.3.3 Optimisation methods	16
1.3.3.1 Exact methods	17
1.3.3.2 Heuristic	18
1.3.3.3 Simulation	19
1.4 Operations Research applied to airport management	20
1.4.1 Check-in counter Allocation Problem	21
1.4.2 Baggage Carousel Assignment Problem	21
1.4.3 Security/Border control shift scheduling problem	22
1.4.4 Passenger boarding/disembarkation problem	22
1.4.5 Gate Assignment Problem	23
1.4.6 Ground Movement Problem	23
1.4.7 Runway Sequencing Problem	24
1.5 Tactical handling of airport operations and passenger recovery	25
1.5.1 Disruption management at the airport level	25
1.5.2 Airline disruption management and passenger recovery	26
1.5.3 Handling transportation disruptions through passenger-oriented metrics	26
1.6 Proposition of passenger-oriented optimisation problems	27

1.6.1	Security staff rescheduling problem	28
1.6.2	Passenger-oriented flight rescheduling problem	29
1.7	Conclusion	30
2	A data-driven methodology to model passenger flows at Paris-Charles de Gaulle airport	31
2.1	Introduction	31
2.2	Presentation of the datasets	31
2.3	Modelling outbound passenger arrival flow at the airport	35
2.3.1	Selection of suitable probabilistic distribution	36
2.3.2	Model validation	43
2.4	Modelling access mode disruption impact on passengers	45
2.4.1	Assigning transportation modes to outbound passengers	45
2.4.2	Modelling high-frequency mode disruptions	46
2.4.3	Modelling low-frequency mode disruptions	46
2.5	Modelling air connecting passengers	47
2.6	Airport landside modelling	48
2.6.1	Modelling airport security screening system	49
2.6.2	Modelling passenger transfers from security checkpoints to the gate	51
2.7	Conclusion	53
II	Recovery strategies to improve passenger experience during airport access mode disruptions	57
3	Security Screening Resources Allocation Problem (SSRAP)	61
3.1	Tactical reallocation of airport resources: a literature review	62
3.2	Security resources management at CDG airport	64
3.2.1	Interview with Paris-Charles de Gaulle airport (CDG) airport operators	64
3.2.2	Initial security team allocation	66
3.2.3	Illustration of security team reallocation relevance	67
3.3	Classical-Security Screening Resources Allocation Problem (C-SSRAP)	68
3.3.1	Problem description	68
3.3.2	Mixed Integer Linear Programming (MILP) model C-SSRAP	71
3.3.3	Solution approaches	75
3.3.4	Performance analyses	77
3.4	Priority-Security Screening Resources Allocation Problem (P-SSRAP)	81
3.4.1	Problem description	81
3.4.2	Optimisation model P-SSRAP	82
3.4.3	Solution approach	88

CONTENTS

3.4.4	Performance analyses	89
3.5	Conclusion	91
4	Passenger-oriented Flight ReScheduling Problem (PFRSP)	93
4.1	Literature Review	94
4.2	Problem description	96
4.2.1	Assumptions for a tactical flight rescheduling strategy and integration with ATC tool	96
4.2.2	Airside resources modelling	96
4.2.3	Time horizon	98
4.2.4	PFRSP formulation	99
4.3	Mathematical Modelling	100
4.3.1	Data	100
4.3.2	Decision variables	102
4.3.3	Constraints	103
4.3.4	Objective function	105
4.4	Solution approaches	107
4.5	Computational results	109
4.5.1	Heuristic vs ILP solution approach	109
4.5.2	Maximum off-block time delay sensitivity analysis	111
4.6	Conclusion	112
5	Practical insights: a case study for recovery strategies implementation	113
5.1	Communication links and online data handling	113
5.1.1	Communication links	113
5.1.2	Online data handling	114
5.2	Case study description	116
5.3	Results and analyses	117
5.3.1	SSRAP results	117
5.3.1.1	Staff shortage analysis	118
5.3.1.2	C-SSRAP results in scenario R60	119
5.3.1.3	Security team allocation performance analysis: classical vs. priority reallocation	122
5.3.2	PFRSP results	124
5.3.2.1	Operational insights in scenario S45	124
5.3.2.2	Comparison of the different disruptive scenarios	128
5.4	Conclusion	130

III Validation and extension: Advanced airport disruption recovery strategies	135
6 Simulation-Optimisation framework for tactical security team reallocation strategy	139
6.1 Introduction	139
6.2 Literature Review	140
6.3 SIM-OPT architecture framework	141
6.4 Optimisation problem description	142
6.5 Simulation and case study description	143
6.5.1 Terminal 2 of Mexico City Airport	144
6.5.2 System Description	144
6.5.3 Experimental set up	146
6.6 Discussion	149
6.6.1 Experimental results	149
6.6.2 Practical application of the proposed framework	151
6.7 Conclusion	152
7 Extending the flight rescheduling strategy to an air-rail network: The Air-Rail Delay Management Problem	153
7.1 Introduction	153
7.2 Literature Review	154
7.3 Problem description	155
7.3.1 Total passenger delay	155
7.3.2 ARDMP description	156
7.4 ARDMP model	157
7.5 Western Europe case study	161
7.5.1 Network characteristics and data	161
7.5.2 Modelling passenger transfers	162
7.5.3 Passenger reallocation procedure	163
7.6 Results	164
7.6.1 Passengers gain	164
7.6.2 Operator cost	166
7.7 Conclusion	169
Conclusion and perspectives	173
Bibliography	181

List of Figures

1.1	Generic configuration of an airport. The main airport components on the airside, terminal processes and passenger access modes are displayed. . . .	10
1.2	An optimisation methods overview.	16
1.3	Simulation-optimisation framework. The simulation is used to evaluate the solution provided by the optimisation algorithm. The performance evaluated is then given as input to the optimisation algorithm to drive the search. . .	21
2.1	Scheme of Paris-Charles de Gaulle airport.	32
2.2	Distribution of passenger arrival times at the airport security checkpoint. In this graph, the time before flight departure is the difference between the scheduled departure time and the passenger timestamp recorded at the security checkpoint. The three months of records are aggregated here (June 2019, December 2019, June 2020).	38
2.3	Comparison of fitting probabilistic distribution on distribution of earliness passenger arrival at the security screening system. Each distribution has been fitted through the maximum likelihood method.	40
2.4	Passenger arrival time distribution at security, before their flight departure time, aggregated on June 2019 and grouped by features (Schengen/Non-schengen; period of the day). Each graph is associated with a couple of features. An Exponentially Modified Gaussian distribution has been fitted for each graph with actual passenger arrival times at security (represented through red curves).	42
2.5	Comparison of actual and simulated passenger volumes at the T2F terminal security checkpoint in April 2019. The top figure shows the simulated passenger volume with flight clustering (i.e., an Exponentially Modified Gaussian (EMG) distribution fitted to each cluster), while the bottom figure shows the passenger volume without clustering.	44
2.6	Passenger delay modelling depending on the ground transportation mode under disruption. Example of a disruption starting at 6 am, ending at 2 pm, with an average airport access time of two hours and a start delay of 60 minutes.	47
2.7	Sequence of airport processes that outbound passengers go through.	48

LIST OF FIGURES

2.8	General appearance of an airport security checkpoint.	50
2.9	Illustration of a cumulative diagram. The top diagram illustrates the cumulative demand and service through red and blue curves. The red area between both curves represents the total waiting time. Based on the cumulative diagram, the bottom diagram represents the passenger waiting time evaluated by measuring the horizontal distance between the red and the blue curves.	51
2.10	Passenger flow modelling methodology.	52
3.1	Illustration of the number of lanes required for one security checkpoint. The number of passengers per hour is displayed in blue, the service rate per hour in orange, and the number of opened lanes providing the required service rate is shown above the orange bars.	66
3.2	Illustration of passenger arrival profile at two security checkpoints, without and with subway disruption, in blue and orange, respectively.	68
3.3	Scheme of an airport security system with finite resources and a single market (classical version). It consists of a set of security checkpoints, and a finite number of security teams to operate them. Each checkpoint has a finite number of lanes and a common queuing line.	69
3.4	Queuing line model retained for the security area. The figure displays for a time t how auxiliary variables representing demand ($d_{s,t}$), queue ($q_{s,t}$) and service ($y_{s,t}$) are updated for a common queuing line of a security area s	70
3.5	Cumulative diagram used to compute passenger waiting time at a common security area s . The red dotted curve represents the cumulative passenger arrival profile at the security area while the blue curve represents the cumulative number of passengers served. The red zone in the diagram highlights the time when a queuing line is formed. The number of passengers arrived at t and served at t' is noted $p_{s,t,t'}$. In this example, three-time steps are required to process the total number of passengers arriving at t	70
3.6	Simulated Annealing neighbour generation process C-SSRAP.	77
3.7	Scheme of a single market airport security system with finite resources and fast-track lanes. It is composed of a set of security checkpoints. Each checkpoint has a finite number of common lanes, a common queuing line, one fast-track lane and its associated queuing line displayed in red. Passengers are routed either to the common or the fast track lane depending on their status (regular/priority) and depending if the priority lane is open.	81
3.8	Simulated Annealing neighbour generation process P-SSRAP.	89
4.1	Airport macroscopic model.	97

LIST OF FIGURES

4.2	Illustration of maximum T2E capacity calibration. The blue curve represents the scheduled initial occupancy. The red dotted line translates the maximum capacity by hour.	98
4.3	Illustration of the different flight statuses for one optimisation window. . .	99
4.4	Flow chart of the proposed heuristic.	108
4.5	Values of different criteria obtained after ILP solution approach on a 4-hour time window. Each graph corresponds to a criterion, and each point to one pair of weight parameters (α, β) . α is associated with the total flight delay, while β is associated with the number of flights delayed by 15 minutes or more. The larger these parameters are, the less the algorithm assigns flight delays. The red lines correspond to the best value obtained with the heuristic approach for each criterion among the set of ϵ parameters tested.	110
4.6	Evolution of the relative number of stranded passengers as a function of the maximum off-block delay allowed. The relative number of stranded passengers is computed by comparing the number of stranded passengers before and after flight rescheduling.	111
5.1	Illustration of communication links between stakeholders.	114
5.2	Evolution of the average passenger waiting time and proportion of passengers successfully board as a function of the percentage of staff reduction (initial allocation in scenario R60).	118
5.3	Distribution of passenger waiting times before and after optimisation in scenario R60.	119
5.4	Maximum waiting time and average waiting time before and after optimisation in scenario R60, in blue and orange, respectively. (top figure: maximum waiting time, bottom, average waiting time).	120
5.5	Cumulative number of stranded passengers over the day before and after optimisation in scenario R60, in blue and orange respectively.	121
5.6	Evolution in the number of stranded passengers and the average aircraft delay assigned during the disruption. The blue and orange bars on the top figure represent the number of stranded passengers per hour before and after rescheduling, respectively. The bottom figure represents the average delay assigned to the arrival and departure flights per hour in red and green, respectively.	125
5.7	Number of flights depending on the assigned delay after rescheduling. A distinction is made between departing flights (in blue) and arriving flights (in orange).	126
5.8	Evolution of runway throughput over the day. Maximum throughputs are represented through dotted red lines. Blue and orange curves represent throughput before and after rescheduling, respectively.	126

LIST OF FIGURES

5.9	Evolution of occupancy on terminal T2E and T2F and taxi network over the day. Resource capacities are represented through dotted red lines. Blue and orange curves represent occupancy levels before and after rescheduling, respectively.	127
5.10	Comparison of buffer time for connecting passengers before and after rescheduling, in red and blue respectively.	128
6.1	Architecture of the Simulation-Optimisation Decision Support System. . .	142
6.2	Illustration of Mexico City airport. Security areas are circled in red.	145
6.3	Illustration of security areas in Mexico City airport (displayed in yellow). .	146
6.4	Standard path followed by passengers within the airport. A distinction is made between companions (in blue), regular passengers (in black) and priority ones (in red).	147
6.5	Arrival profiles of passengers with and without disruption (in orange and blue respectively).	148
6.6	Average number of passengers missing their flights depending on the security allocation strategy (unexpected disruption Scenario).	149
6.7	Illustration of decision-making time window approach. Once a new update of the passenger arrival profile at the airport is obtained, the airport operation centre will launch the Decision Support System (DSS) to implement the management action plan and know how to reallocate airport security teams.	151
7.1	Illustration of flights operated on December 4, 2019, over the Western European air network (source:Buire et al. (2023)).	163
7.2	Distribution of passenger transfer buffer times before and after rescheduling. Buffer times are calculated by subtracting the minimum connecting time from the actual passenger transfer time. A negative buffer time indicates that passengers do not have enough time to transfer, caused by a delay on their first leg. This graph only shows passengers who could recover their initial flights thanks to the rescheduling (i.e. missing their flights by 30 minutes or less before rescheduling).	165
7.3	Total passenger delays before and after rescheduling, stacked by passenger types (<i>on-time passengers</i> , <i>reallocated passengers</i> and <i>stranded passengers</i>).	166
7.4	Distribution of total vehicle delays per hour. Flight and train delays are displayed in blue and orange, respectively. The hatched bars represent propagated delays.	167
7.5	Visualisation of post-rescheduling flight delays. The linewidth and the colour-coding system indicate the delay magnitude and the departure time of the day, respectively. Dotted lines correspond to flights departing from CDG airport, plain lines to other flights.	168

List of Tables

2.1	Characteristics of one row of the flight data set.	32
2.2	Example of one row of the passenger timestamps data set.	33
2.3	Transfer time from security system to the gate (in minutes).	33
2.4	Connecting passenger share between terminals. Each departure terminal is associated with one column, and each arrival one to a row. For instance, 30% of connecting passengers departing from T2E arrived from T2F.	34
2.5	Minimum transfer time for connecting passengers between terminals (in minutes). Each departure terminal is assigned to a column and each arrival terminal to a row. The transfer time is set to 0 minute if there is no connecting passenger between a pair of terminals.	34
2.6	Share of connecting passengers for each departure terminal. It represents the average number of connecting passengers per departure flight.	34
2.7	Average taxi time for each couple (terminal, runway) in seconds.	35
2.8	Share of passengers using different ground transportation modes to access Paris-Charles de Gaulle airport (CDG).	35
2.9	Comparison of different performance criteria obtained by fitting the passenger arrival distribution with several probability density distributions. GMM-x refers to the Gaussian Mixture Model with x-components. The best and worst values are highlighted in green and red, respectively. For each metric, the lower the value, the better the fit.	40
3.1	Example of Greedy Lane Allocation.	77
3.2	Performance obtained by the proposed solution approaches (Initial, Heuristic, Mixed Integer Linear Programming (MILP), or Simulated Annealing (SA)) for solving the Classical Security Screening Resource Allocation Problem (C-SSRAP) over different time windows on scenario R60 (described in Table 5.1). \mathbf{W} , $\bar{\mathbf{w}}$, and \mathbf{t} refer to the maximal waiting time, average waiting time, and computational time, respectively. A time limit has been set to 600 seconds for the Mixed Integer Linear Programming (MILP) solution approach. Minimum waiting times are highlighted in green and maximum waiting times over the maximum acceptable ones are highlighted in red.	79

3.3	Performance obtained by the proposed solution approaches (Initial, Heuristic, Mixed Integer Linear Programming (MILP), or SA) for solving the 4-hour C-SSRAP with model parameter changes in scenario R60 (described in Table 5.1). \mathbf{W} , \bar{z} , and \mathbf{t} refer to the maximal waiting time, average waiting time, and computational time, respectively. A time limit has been set to 600 seconds for the Mixed Integer Linear Programming (MILP) solution approach. Minimum waiting times are highlighted in green and maximum waiting times over the maximum acceptable ones are highlighted in red.	80
3.4	Performance obtained by the proposed solution approaches (Initial, SA) for solving the Priority Security Screening Resource Allocation Problem (P-SSRAP) over different instances in scenario R60 (described in Table 5.1). \mathbf{W} , \bar{z} , and \mathbf{t} refer to the maximal waiting time, number of stranded passengers, and computational time, respectively. Columns titled ‘ $\mathbf{x-h TW}$ ’ refer to instances where the optimisation time window duration is changed. The ‘ $\mathbf{5min TS}$ ’ and ‘ $\mathbf{30min D}$ ’ columns correspond to instances where the discretisation time step is reduced from 10 to 5 minutes, and the time interval duration used to reallocate security teams is reduced from 60 to 30 minutes, respectively. The last column titled ‘ $\mathbf{All-SC}$ ’ represents an instance where teams are authorised to be reallocated over the entire airport (i.e. removal of market flow segregation constraint).	90
4.1	Criteria values after rescheduling with the heuristic approach depending on the score parameter ϵ (see Equation (4.34)). This parameter penalises the score of a decision ‘Assign delay d to flight f ’ as a function of the delay d . A high ϵ will reduce the score of decisions, implying large flight delays. The best values are highlighted in bold.	109
5.1	Characteristics of the different disruptive scenarios.	116
5.2	Results obtained before and after redistributing the security teams across the different scenarios. For each scenario, the performance of the initial allocation (denoted \mathbf{init}), the reallocation after Classical Security Screening Resource Allocation Problem (C-SSRAP) resolution (denoted \mathbf{C}) and the one after Priority Security Screening Resource Allocation Problem (P-SSRAP) resolution (denoted \mathbf{P}) are compared. \mathbf{W} , \bar{w} , \mathbf{z} and $\mathbf{p10}$ refer to the maximum waiting time, the average waiting time, the number of stranded passengers and the proportion of passengers waiting more than 10 minutes.	122
5.3	Results obtained in the different scenarios through the direct ILP solution approach.	130
6.1	Optimisation problem characteristics and solution approach features.	143
6.2	Modelling assumptions.	147

LIST OF TABLES

7.1	Case study characteristics	162
7.2	Number of connecting passengers per airport. A distinction is made between train-air connections and air-air connections.	164
7.3	Actual flight delay on December 4 th 2023 (in minutes) (source: Eurocontrol). 168	

Acronyms

A-CDM Airport-Collaborative Decision Making

AIBT Actual In Block Time

ALT Actual Landing Time

AMAN Arrival Manager

AOBT Actual Off Block Time

AOC Airport Operation Centre

APOC Airport Operation Centre

ARDMP Air Rail Delay Management Problem

ATC Air Traffic Control

ATFM Air Traffic Flow Management

ATM Air Traffic Management

ATOT Actual Take-Off Time

BCAP Baggage Carousel Assignment Problem

C-SSRAP Classical Security Screening Resource Allocation Problem

CAP Check-in counter Allocation Problem

CDG Paris-Charles de Gaulle airport

CDM Collaborative Decision Making

DES Discrete Event Simulation

DGAC French Civil Aviation Authority

LIST OF ACRONYMS

DM	Delay Management
DMAN	Departure Manager
DSS	Decision Support System
E-AMAN	Extended Arrival Manager
EMG	Exponentially Modified Gaussian
FAA	Federal Aviation Agency
FIFO	First-In-First-Out
GAP	Gate Assignment Problem
GMP	Ground Movement Problem
GTFS	General Transit Feed Specification
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
ILP	Integer Linear Programming
KPI	Key Performance Indicator
LOS	Level of Service
LP	Linear Programming
MAE	Mean Absolute Error
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MRAE	Mean Relative Absolute Error
OBT	Off Block Time
OR	Operations Research
OTP	On-Time Performance
P-SSRAP	Priority Security Screening Resource Allocation Problem
PFRSP	Passenger-oriented Flight ReScheduling Problem

RMSE Root Mean Square Error
RSP Runway Sequencing Problem
SA Simulated Annealing
SC Security Checkpoint
SIBT Scheduled In Block Time
SID Standard Instrument Departure
SL Security Lane
SMAN Surface Manager
SNCF Société Nationale des Chemins de fer Français
SOBT Scheduled Off Block Time
SSP Shift Scheduling Problem
SSRAP Security Screening Resource Allocation Problem
STAR Standard Terminal Arrival Route
TAM Total Airport Management
TMA Terminal Manoeuvring Area

Introduction

During their 77th Annual General Meeting, International Air Transport Association (IATA) members passed a resolution committing the aviation industry to achieve net-zero emissions by 2050 (IATA, 2021). Four key drivers were identified to reach this ambitious goal: bringing sustainable aviation fuels to market, improving air traffic management and airspace infrastructure, producing more efficient aircraft engine technologies, and providing the necessary sustainable aviation fuel infrastructure at airports. However, Sacchi et al. (2023) show that ‘a European climate-neutral aviation will fly if air traffic is reduced to limit the scale of the climate impacts to mitigate’. Therefore, limiting air transportation movements has been at the centre of public debate, as the Fligskam movement in Sweden (Wolrath Söderberg and Wormbs, 2019). Legislative measures have already been taken, e.g. France banned short-haul flights for which there is an efficient transportation alternative (Legifrance, 2023). Such measures, combined with passenger environmental awareness, have led to an increasing use of public transportation and trains to access the airport, replacing private cars and domestic flights.

At the same time, the European Commission has set the ambitious goal for 2050 that ‘90% of travellers within Europe are able to complete their journey, door-to-door, within 4 hours’ (European Commission, 2011). With this new perspective in mind, the lack of integration and coordination between ground and air transportation modes could lead to inefficiencies, compromising the reachability of such a target. In particular, delays in one transportation mode can impact passenger multimodal travels, leading, in the worst case, to missed connections and jeopardising their door-to-door journey. The European Commission has launched various research projects to address this challenge. For instance, Paul (2022) in the MODUS project aims to assess the role of air transportation in an integrated intermodal transportation system. Mujica Mota et al. (2020) develop a concept of operations that enables real-time collaboration between airports and ground transportation operators through the IMHOTEP project. Bagamanova et al. (2022) study the integration of Air Traffic Management (ATM) in a multimodal transportation system, considering currently available modes and the emerging ones for the next decades within the X-D2D project. Bueno et al. (2022), through the TRANSIT project, develop and evaluate new coordination mechanisms

between air and ground transportation stakeholders, based on information sharing, to offer passengers seamless and reliable door-to-door journeys.

In this context, we propose to enhance airport operations from a passenger perspective, assuming active collaboration between transportation stakeholders. Indeed, airports play a key role in multimodal transportation networks, acting as the interface between ground and air transportation systems, and could serve as an interface for information sharing as well.

This work focuses on the tactical management of airport operations, i.e. day-to-day operations ([Niarchakou and Cech, 2019](#)), to handle passenger late arrivals due to disruptions on their journey toward the airport.

The main contributions of this thesis are the following:

- We introduce an innovative airport and passenger modelling framework, enabling the evaluation of tactical airport management solutions for addressing disruptions during the airport access phase of a passenger’s journey. The framework incorporates parametric distributions to model passenger arrival patterns and reconstructs passenger flow at airport entrances based on flight schedules;
- We develop two recovery strategies for airport operators to mitigate the impact of disruptions. The first strategy is a tactical reallocation of security teams to reduce passenger waiting time at the security screening system. The second strategy is a tactical flight rescheduling to wait for delayed passengers by applying small deviations to the original flight schedule, considering airside operational constraints and connecting passengers. For both strategies, we propose mathematical optimisation models and Operations Research (OR) solution methods, such as Integer Linear Programming (ILP), Simulated Annealing (SA) and greedy heuristics;
- We propose a validation and an extension of both recovery strategies. Firstly, we combine the security team reallocation strategy with a discrete simulation tool to provide realistic performance assessments and the basis of a decision support system for airport operators. Secondly, we broaden the scope of flight rescheduling strategies to the network level, capturing delay propagation and its impact on the overall air traffic network. This extension also evaluates door-to-door passenger delays, allowing benefit assessment of such rescheduling strategies for passengers.

The thesis is structured into three parts. The first part presents the contextual background and an airport and passenger modelling framework. The second part describes two recovery strategies to handle delayed passengers during airport access mode disruptions. Each strategy is studied as a static optimisation problem, and a sliding-time window framework is proposed for real-life implementation. The third part validates and extends both recovery strategies, using a simulation-optimisation framework for reallocating security teams and applying the flight rescheduling strategy to an air-rail network.

Part I

From flight-oriented to passenger-oriented airport management: a new paradigm

The European Commission highlights in its Flightpath 2050 report that passengers must be the clear focus of the transportation sector in which aviation is a key player (European Commission, 2011). However, flight-oriented metrics, such as On-Time Performance (OTP), have assessed the performance of the air transportation system for decades. This metric quantifies the percentage of flights that depart or arrive more than 15 minutes behind schedule. It is the first Key Performance Indicator (KPI) highlighted in the Global Air Navigation Plan of the International Civil Aviation Organization (ICAO) (ICAO, 2021). As explained by Ball et al. (2010), flight-oriented metrics do not capture the actual delays experienced by passengers (e.g. due to flight cancellations or missed connections). They only consider a part of the passenger’s door-to-door journey and, therefore, fail to measure the quality of the overall transportation network. As a result, a paradigm shift has been taking place since 2010.

First, passengers have become the focus for measuring the efficiency of a transportation system. Bratu and Barnhart (2005) analyse the delays experienced by passengers travelling on US airlines. They estimate that if stranded passengers represent only 3% of the total number of delayed passengers, their delays represent 39% of the total passenger delay, with a total delay at their final destination of 303 minutes. Cook et al. (2012) develop a passenger-centred framework and simulation model for air transportation as part of the European project called POEM. Monmousseau et al. (2019) emphasise the importance of considering the entire transportation system, i.e. including the modes used to access and egress the airport, to measure the performance of the air transportation system. They take a data-driven approach, collecting Uber data to measure passenger door-to-door travel times between Paris and Amsterdam, using either rail or air as the primary mode of transport. Marzuoli et al. (2018) and Burrieza-Galán et al. (2022) use mobile phone data to characterise passenger door-to-door travel and assess overall transportation system performance.

Second, various incentives have emerged to create a multimodal long-distance transportation network in which trains and planes were previously seen as competitors (Chiamaretto and Decker, 2012; Li et al., 2018; Song et al., 2018). AIRail (Frankfurt Airport Services Worldwide, 2023), stands out as one of the best examples of intermodal cooperation between an airline (Lufthansa) and a railway operator (Deutsche Bahn) at Frankfurt airport, where passengers can check in their luggage directly at the railway station. Other partnerships exist, such as that between Air France and SNCF, or Rail & Fly in Germany, involving Deutsche Bahn and several airlines such as TAP Air Portugal, Lufthansa, or Singapore Airlines (Air Portugal, 2023; Lufthansa, 2023; Singapore Airlines, 2023). Laplace et al. (2014) present the META-CDM project, which aims to extend the concept of airport Collaborative Decision Making (CDM) by involving ground transportation stakeholders to improve passenger door-to-door journeys. In this context, Dray et al. (2015) and Marzuoli et al. (2015) investigate how multimodal recovery solutions in the event of massive disruptions, such as the closure of an airport due to volcanic ash, would help to reduce the delay experienced by passengers at their

final destination. Another benefit of air-rail collaboration is reducing the increasing airport congestion at major European airport hubs and reducing passengers' carbon footprint, which is crucial in the context of the climate crisis. In this context, France has banned short-haul flights for which there is an alternative train service of less than 2h30 with sufficient frequency ([Legifrance, 2023](#)).

Finally, the European Commission launched several research projects under the Horizon 2020 research and innovation program to support the development of air-ground system integration, such as MODUS ([Paul, 2022](#)), IMHOTEP ([Mujica Mota et al., 2020](#)), X-D2D ([Bagamanova et al., 2022](#)), and TRANSIT ([Bueno et al., 2022](#)). The latter project aims to improve coordination between air and ground transportation systems through information sharing, to offer passengers a reliable and seamless door-to-door journey.

This thesis focuses on a similar collaborative environment as investigated in the TRANSIT project. We consider a futuristic scenario where information sharing and active cooperation between air and ground transportation stakeholders is already implemented, allowing perfect knowledge of the actual status of the air-rail network. We assume that transportation suppliers have access to passengers' information related to their door-to-door journey, and their current situation during disruptive events. In addition, we consider a high level of air-rail integration, where transportation operators would share the costs of re-accommodating stranded passengers, incentivising them to minimise delays. In this context, we propose to develop OR approaches to assist airport operators in their decision-making process to respond to airport access mode disruptions.

This first part comprises two chapters. The first draws a current picture of how airports are currently managed and how OR has been used in the literature to solve airport operational problems. The chapter concludes by proposing two recovery strategies to enhance passenger experience during airport access mode disruptions in a multimodal collaborative environment. In the second chapter, we propose a framework for airport and passenger flow modelling, including a suitable probability distribution to model passenger arrivals at the airport. This framework serves later as an experimental platform for testing the proposed recovery strategies.

Chapter 1

Airport management and passenger experience

1.1 Introduction

In this chapter, we look at airport systems from the perspective of both, a passenger and an operations researcher. Airports are complex transportation hubs for passengers. When airport operations are managed efficiently, passengers can enjoy a seamless journey within the airport. However, when poorly managed, they can result in a chaotic experience. OR has historically played a critical role in optimising resource use, balancing capacity and demand or handling disruptions in airport management. Here, we propose to consider an intermodal collaborative environment that leads to new operational problems to be solved. We go beyond the traditional problems, such as check-in counter allocation problem ([Mujica Mota, 2015](#)) or runway sequencing problem ([Ikli et al., 2021](#)), and explore new prospects that information sharing between air and ground transportation modalities would present for improving passenger door-to-door journeys. Beginning with a comprehensive overview of airport operations and the basic principles of OR, we explore the existing airport optimisation problems in the literature. Looking ahead, we propose passenger-centric optimisation problems that could be tackled by OR methods in a futuristic context of information sharing between air and ground transportation stakeholders to improve the passenger experience.

1.2 Airport management

This section provides a general overview of how an airport operates. First, we describe a passenger's journey from entering the airport to boarding their departing flight. We also provide an overview of the aircraft journey from its stand to the en-route sector. Lastly, we discuss the current real-time handling of airport operations.

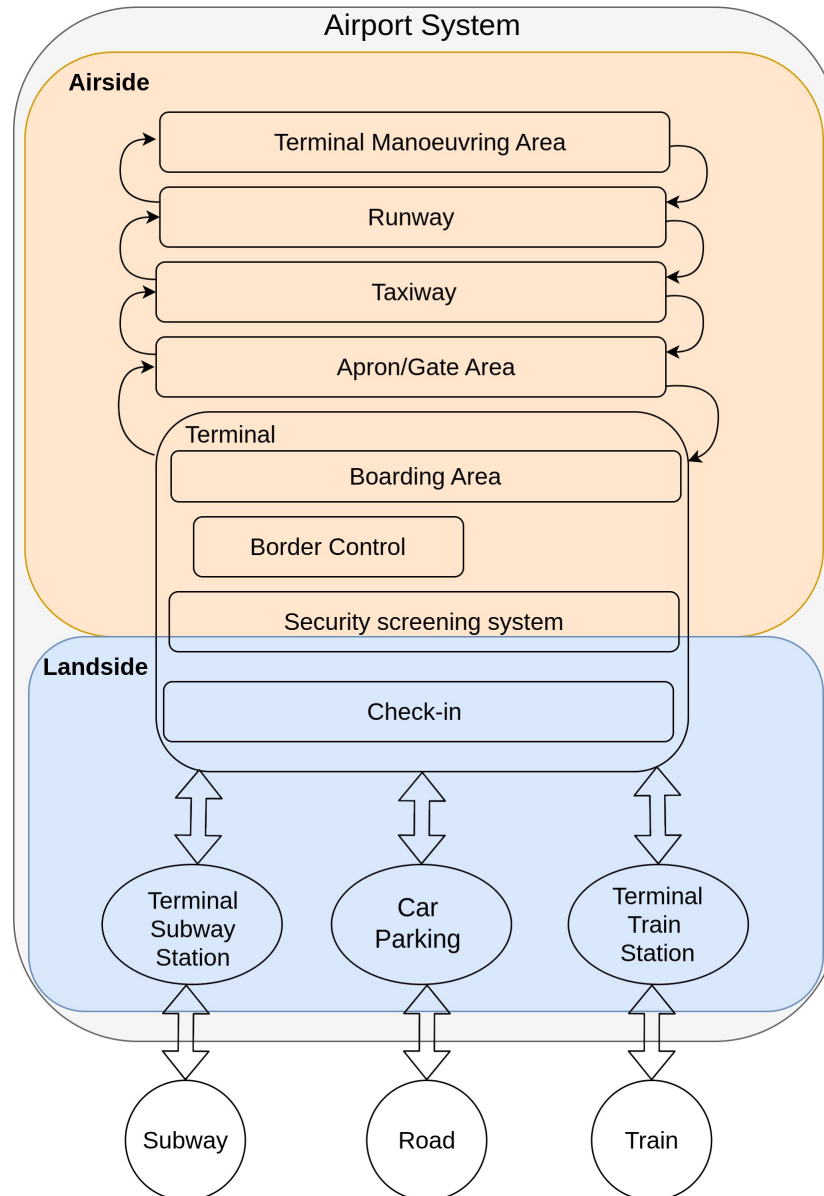


Figure 1.1: Generic configuration of an airport. The main airport components on the airside, terminal processes and passenger access modes are displayed.

1.2.1 Passenger and aircraft operations within the airport

Airport operations for aircraft and passengers are illustrated in [Figure 1.1](#). Airports are often partitioned into landside and airside. The airport landside is open to the general public, even for people without flight tickets, who may be accompanying departing or arriving passengers, attend business meetings, or other. Passengers can access the

landside with a ground access mode such as a subway, a train, a bus, a taxi or by using their own cars. The landside includes facilities such as restaurants, shops and information stations. The check-in facility is one of the primary airport operations on the landside. In this facility, passengers can print their flight tickets and check their luggage to be loaded in the aircraft cargo bay later on. It is worth noting that the airport has a complex process for routing baggage from check-in to the different aircraft. However, this topic is not covered here. For more information on the baggage handling process, the reader can refer to Chapter 7 of (Ashford et al., 2013). The security screening system allows passengers to access the airport airside. This facility performs passenger and carry-on luggage screening of hazardous and forbidden items. After passing the security screening system, passengers may have to go through a border control process depending on the destination of their flights. These operations (check-in, security screening, border control) can be time-consuming and directly affect passenger experience and their door-to-door travel time. Past this set of control operations, passengers are often required to pass through a commercial/shopping area. They can finally reach the boarding area associated with their flight and process the boarding.

Regarding the aircraft movement area, departing aircraft are waiting in a ramp, directly at the gate or in an advanced position called an apron. In the latter case, a shuttle brings departing passengers from the terminal to the aircraft. Once passengers have boarded and luggage has been loaded, the aircraft follows a path on a road system named a taxiway to reach the runway threshold. It finally takes off, entering the Terminal Manoeuvring Area (TMA) and follows a Standard Instrument Departure (SID) to exit the TMA and reach the en-route airspace¹. An arriving flight follows the reverse procedure. It enters the TMA, follows a Standard Terminal Arrival Route (STAR), lands on a runway, and uses the taxi network to reach its stand. Since multiple aircraft use simultaneously the different components of the airport airside, rules need to be considered to organise the air traffic. Airports use a centralised approach, where air traffic controllers provide directions to pilots to authorise aircraft to safely move and sequence the take-offs and landings at the runway.

Arriving passengers then disembark, and luggage is unloaded. Passengers can connect with another flight or start the airport exit process. In the latter case, they may need to go through border control depending on the origin of their flight. They finally exit the airside area and can get back their checked luggage in the baggage carousels assigned to their flight.

1.2.2 Management of airport operations

De Neufville et al. (2013a) provide guidelines on how to build efficiently and manage an airport. They present operational problems considered during airport operation. They

¹Part of the airspace where the climb, cruise and descent phases of the flight are performed.

also present the idea of the CDM process that emerged during the mid 1990 in the US (Vail et al., 2015). It consisted firstly of collaboration between flight operators and the Federal Aviation Agency (FAA), the governmental body of the United States in charge of regulating and promoting civil aviation there. Prior to CDM in air transportation, operational decisions were made independently by stakeholders with little consideration for other stakeholder decisions. As each decision made by one operator could potentially affect the operations of other stakeholders, this approach led to suboptimal performance of airport operations. Implementing strong communication links between stakeholders allowed them to understand the consequences of each decision taken by one stakeholder on another. For instance, when an airline operator chooses to change the departure time of one flight, this decision can affect the sequence of departing flights at the runway, induce conflict with the next flight at the gate or even increase air traffic controller overload for a specific air sector. The early communication of this decision makes it possible for each stakeholder to update their initial decisions and improve the global efficiency of the air transportation system. This concept has been extended to other air traffic stakeholders, such as airport operators, through ground surface surveillance to improve operational efficiency (Pujet et al., 1999). Eurocontrol published its Airport-Collaborative Decision Making (A-CDM) Implementation Manual in 2005 to help airports implement this concept. The fifth version of this manual is available since 2017 (EUROCONTROL, 2017).

Paris-Charles de Gaulle airport (CDG) is one of the first European airports to implement the A-CDM in 2005 (Groupe ADP, 2023). CDG reports improvement in quality of service, air traffic predictability, traffic flow, punctuality, and even the reduction of the air transportation environmental footprint. Groupe ADP (2022) explains how CDG manages their airport operations in 2022. This airport has implemented the Airport Operation Centre (APOC) concept, which is used to monitor day-to-day airport operations collaboratively. While A-CDM is mainly a set of procedures used to optimise airport airside operations in real-time, the APOC consists of a dedicated location that brings together stakeholders involved in different airport processes. This location is a large workspace with various control screens to monitor real-time airport operations. Such a concept is useful for incident management to reduce the airport reactive response time and enable a collaborative response. The A-CDM and APOC concepts make it possible to improve the management of airport operations by involving all stakeholders. It is a step towards the final stage that CDG operators want to reach, called Total Airport Management (TAM). At this stage, the best decisions are made by anticipation, on both the landside and airside.

Operational management of the airport involves making many decisions in a limited time. The number of possibilities for such decisions can be huge, especially in the case of large airports. Consequently, a Decision Support System (DSS) is needed to select the optimal decisions for the airport. Nowadays, DSSs help the management of airport activities. For instance, air traffic control tools regulate flights according to demand

and capacity. This process involves the Surface Manager (SMAN), the Departure Manager (DMAN) and the Arrival Manager (AMAN) or its enhanced version, the Extended Arrival Manager (E-AMAN). SMAN optimises surface movements, enhance safety, and reduce the risk of conflicts during taxiing. DMAN allocates runways and departure delays based on runway pressure and slots allocated by the *network manager*². Similarly, AMAN/E-AMAN organises the sequence of arriving flights.

This work considers a scenario where enhanced passenger information is available to airport operators. Such information could be obtained by involving ground transportation stakeholders in the APOC. Based on this, efficient communication links could be established to mitigate the impact of airport access mode disruptions on passengers. We propose to improve the current handling of access mode disruptions by properly defining the operational problems encountered in such a case. Based on this, we propose to use modelling techniques and optimisation algorithms to solve these problems. Such a problem-solving framework could form the basis of a DSS that could be implemented, for example, in the APOC, thus contributing to the extension of the TAM concept to the ground transportation side. We use OR to develop such algorithms, a discipline widely known for solving complex industrial problems. It provides analytical methods to support the decision-making process. The following section introduces such a discipline.

1.3 Operations Research: a valuable discipline to improve decision-making

First, we present a brief history and definition of OR. Then, we detail two basic notions in OR: mathematical optimisation modelling and optimisation solving techniques. The following content is based on the following two books: (Hillier and Lieberman, 2001) and (Bierlaire, 2018).

1.3.1 Definition of Operations Research

The Institute for Operations Research and the Management Sciences (INFORMS) website provides the following definition of the OR: “Operations research (O.R.) is defined as the scientific process of transforming data into insights to making better decisions” (INFORMS, 2023). It is a discipline that has seen growing interest since the Second World War. It grew through the need to improve the allocation of scarce resources to various military operations. This led to applied *research* on (military) *operations*. The

²In the domain of air traffic management, a network manager is a central entity responsible for coordinating and optimizing the use of airspace and airport resources. It plays a key role in ensuring efficient and safe air traffic operations by managing the flow of aircraft, coordinating with different air traffic control units, and addressing potential disruptions to the air traffic network.

efficiency of the techniques developed during the war led to their continued use in an industrial context, where similar resource optimisation problems were often encountered.

Two main factors contributed to the increased popularity of OR after the war. First, there was significant progress in improving OR techniques, with scientists motivated by post-war developments and significant advancements, such as George Dantzig's simplex method in 1947 (Dantzig, 2002). Standard tools like linear programming, dynamic programming, queueing theory, and inventory theory were well-developed by the 1950s. Second, the computer revolution significantly accelerated OR growth. Electronic digital computers, capable of performing complex computations much faster than humans, were crucial. In the 1980s, powerful personal computers and user-friendly software further expanded OR's accessibility, enabling millions of individuals to use OR software on various computing devices, from mainframes to laptops.

OR discipline is aimed at practical problem-solving to coordinate or improve organisational activities (i.e. activities operations). It is based on three main steps:

- Define the problem to be solved;
- Formulate the problem through mathematical modelling;
- Developing a computer-based procedure (i.e. algorithm) to find a solution to the mathematical model.

The first step consists of discussions with the operators to define the needs and the problem to be solved. This step is crucial to understand the constraints related to the problem (e.g. limited resources), the decisions to be made and the evaluation method to test the efficiency of the proposed decisions. The latter can be done by defining an 'objective function' to measure the overall performance of selected decisions. Given the operational constraints, the final problem is based on either minimising or maximising the objective function.

The second step is to reformulate the problem using mathematical modelling, i.e., writing equations that characterise the problem. Different mathematical models can be used to represent the same problem. Note that a mathematical model is an idealised representation of the real problem in which approximations are made. Therefore, finding the optimal solution of a mathematical model does not guarantee to find the best solution for the real problem. We must, therefore, ensure that the model remains a sufficiently good representation of the actual system before solving it. Even if a model isn't exact, a sufficiently similar model allows comparison and classification of decisions to choose the best one. The challenge is to define a model that still gives a sufficiently valid representation of the actual system while still being tractable.

The last step relies on deciding a computational-based procedure to solve the mathematical problem formulation. Depending on the nature of the problem, solving strategies may be applicable and more relevant than others. For instance, if the problem

is governed by linear constraints, a linear objective function, and continuous decision variables, then the theory of Linear Programming can be applied. The solving strategy is usually defined by an algorithm that has to be implemented and executed by a computer to solve large size instances of the problem.

Today, OR is a discipline widely used in industry to optimise resource management and improve system efficiency. In particular, it helps solving task scheduling, team allocation, facility location or network optimisation problems. These problems can be encountered in airport operations, making OR a powerful decision support tool, especially for large airports. Since OR relies on mathematical models and optimisation algorithms, we provide a more detailed overview of both notions below.

1.3.2 Mathematical optimisation modelling

Mathematical optimisation or mathematical programming is a field of applied Mathematics research that involves solving optimisation problems. Such problems consist of searching for the best solution in a defined space regarding an objective function that needs to be minimised or maximised and subject to constraints. An optimisation problem can be presented through the following generic formulation:

Objective:

$$\min f(\vec{X})$$

Subject to:

$$g_i(\vec{X}) \leq 0, \forall i \in \mathcal{I}$$

Decision variables:

$$\vec{X} \in \Omega$$

where f is the objective function, \vec{X} the decision variable vector, g_i the constraints, \mathcal{I} the index set of constraints, and Ω the search space. Ω is characterized by a set of unrelaxable constraints, which are integral to the nature of the problem. These constraints, such as the positivity of the logarithm function, must be satisfied for any valid solution. In contrast, there are other constraints represented by g_i that may be relaxed during the search for a solution. For instance, constraints related to cost budgets might be temporarily relaxed to explore a wider solution space, with the final solution ensuring adherence to these constraints.

An optimisation problem can be formulated using different mathematical models, and depending on the characteristics of the model, different solution strategies can be applied. In particular, the nature of the decision variables, either continuous or discrete, is important in choosing a relevant solution technique. For example, if the

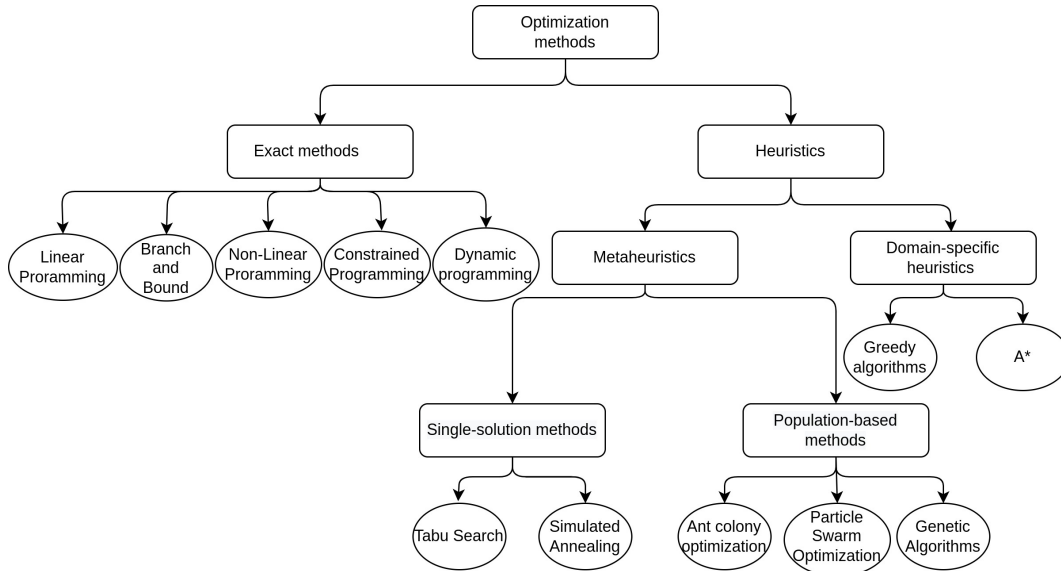


Figure 1.2: An optimisation methods overview.

decision variables are continuous and the objective function is differentiable, gradient descent techniques can be applied. If the problem consists of integer decision variables, such as knapsack, assignment and matching, or even set-covering problems, integer and combinatorial optimisation techniques are relevant. The reader can refer to (Wolsey and Nemhauser, 1999) for a description of well-known combinatorial optimisation techniques.

Problem modelling is a crucial step when trying to solve an operational problem. The closer the model is to the actual system, the more likely the optimal solution of the model will be close to the real one. Different model types exist, such as deterministic, stochastic, or microscopic-simulation models. Depending on the granularity of the model, the search for the best solution can be more or less time-consuming. The choice of the solving strategy is crucial for guaranteeing the effectiveness of an OR approach to tackle the operational problem. This choice must be made depending on the mathematical model characteristics, e.g. the number of constraints and decision variables, the types of variables (continuous or not), or the type of constraints (e.g. linear, convex, etc.). We present below a taxonomy of the different optimisation methods used in OR.

1.3.3 Optimisation methods

For each type of problem, different optimisation methods can be found in the literature. Figure 1.2 displays a non-exhaustive overview of these methods. We can divide optimisation methods into two types: exact methods and heuristics. The former finds the optimal solution to a problem. However, they can be time-consuming and intractable

for complex problems, such as NP-hard problems applied to large instances. Heuristics can also be used to find a good solution to problems in a limited amount of time. However, heuristics do not guarantee the optimality of the solution obtained. A brief explanation of the different methods shown in [Figure 1.2](#) is proposed below.

1.3.3.1 Exact methods

One of the most famous exact optimisation methods is Linear Programming (LP). LP is a powerful tool that emerged after World War II to solve industrial problems and help the decision-making process in the industry. The name comes from Koopmans and Dantzig ([Dantzig, 2002](#)), who actively contributed to developing and spreading the Linear Programming technique. However, the first studies on solving linear inequalities are also present in Joseph Fourier's work in 1823. Linear Programming aims to minimise or maximise a linear objective function under a set of linear equalities and inequalities. Dantzig was the first to introduce the notion of objective function to be optimised. He also proposed the Simplex method to solve linear problems. This method enables finding the optimal solution in a short computation time compared to the previously used brute force methods. Additionally, the Simplex method is tractable for problems with large search space. One geometric interpretation of this algorithm relies on the exploration along the edges and the extreme points of a polyhedron (called polytope) defined by the set of linear constraints. Indeed, it can be demonstrated that if the problem is bounded, the optimal value is observed at least on one extreme point of the polytope.

Such a method requires decision variables to be continuous. However, many industrial problems require decisions to be integer, e.g. the number of production lines in a factory. Therefore, ILP techniques emerged. A naive algorithm to solve such a problem is to relax the constraints related to integer variables, solve the associated LP problem and round the solution variables. However, this rounding can significantly degrade the solution. The development of branch and bound techniques emerged to solve such problems. These techniques obtain bounds on the solution by breaking down the initial problem into sub-problems and fixing the value of several variables. These bounds help to reduce the search space and avoid exploring solutions that are guaranteed to be worse than those already found during exploration.

Other exact methods exist, such as Constraint Programming ([Apt, 2003](#)) or Dynamic programming ([Bellman, 1966](#)). The first is powerful to solve highly constrained problems where it is difficult to find a feasible solution. The second is often used for optimal control problems and relies on decomposing a problem into a series of recursive sub-problems. The limitation of exact methods is due to their algorithmic complexity, which can make them unable to cope with large-size real problems.

Finally, Non Linear Programming ([Bertsekas, 1997](#)) is essential for solving models with nonlinear objective functions or constraints. In such cases, gradient methods or

other descent algorithms are used to iteratively adjust decision variables to minimise or maximise the objective function. By introducing penalty terms to the objective function, Lagrangian multipliers can also be employed when dealing with constraints.

1.3.3.2 Heuristic

Heuristics are widely used to solve industrial or academic NP-hard problems. Such methods enable the exploration of large search spaces and finding quasi-optimal solutions in a limited computation time. There are two main classes: domain-specific heuristics and metaheuristics. The former are problem-dependent and rely on an exploration strategy that depends on the nature of the problem. Greedy and A* algorithms belong to this first class. Metaheuristics are generic heuristics applicable to various problems. An analogy with natural phenomena generally drives these methods. For instance, evolutionary algorithms are inspired by an analogy with Darwin's theory (Charles, 2009), while particle swarm optimisation is based on a metaphor of social behaviour observable during the motion of bird flocks and schooling fish (Kennedy and Eberhart, 1995). There are two types of metaheuristics: single-solution and population-based. The second class generates a group of solutions which explore, at each iteration, the state space. Genetic algorithm (Holland et al., 1992), particle swarm optimisation (Kennedy and Eberhart, 1995), and ant colony optimisation (Dorigo et al., 2006) belong to this class. These methods explore more the state space than single-solution approaches. However, they tend to use more memory allocation and can be time-inefficient with limited resources. Conversely, Simulated Annealing (SA) and Tabu Search are two examples of single-solution methods (Kirkpatrick et al., 1983; Glover and Laguna, 1998). Each method requires less memory allocation and quickly generates good solutions for NP-Hard problems.

Especially, SA has already been proven to work well on NP-Hard problems in the air transportation field: strategic aircraft deconfliction (Courchelle et al., 2019), airport TMA decongestion (Ma et al., 2016) or even to design optimal strategies for baggage screening at airport (Candalino Jr et al., 2004). We focus on SA below. For a more detailed description of other metaheuristics, the reader can refer to (Siarry, 2014).

1.3.3.2.1 Simulated Annealing

Kirkpatrick, Gelatt, and Vecchi introduced the concept of optimisation by Simulated Annealing in 1983 (Kirkpatrick et al., 1983). The same method has been found independently by Cerny in 1985 (Černý, 1985). An analogy of annealing in metallurgy inspired this method, which consists of finding a metal's minimal energy configuration. The metal starts from a melting state and is cooled down. When the cooling down is too fast, asymmetric arrangements of atoms are reached, and the minimum energy configuration is not found. A sufficiently slow cooling is required to find a crystal configuration with minimum energy configuration. When a sub-optimal arrangement is found, the

metal is heated and then cooled down again to reach a lower energy configuration. This process is repeated until it reaches the lowest energy configuration. This method is based on the Metropolis criteria (Metropolis et al., 1953), a Monte Carlo method to estimate probability distributions. Algorithm 1 provided by (Delahaye et al., 2019) describes the SA optimisation method.

Algorithm 1 Simulated annealing algorithm

Initialisation $i := i_{\text{start}}, k := 0, c_k = c_0, L_k := L_0$
repeat
 for $l = 0$ **to** L_k **do**
 Generate a solution j from the neighborhood S_i of the current solution i
 if $f(j) < f(i)$ **then**
 $i := j$ { j becomes the current solution}
 else
 j becomes the current solution with probability $e^{\left(\frac{f(i)-f(j)}{c_k}\right)}$
 end if
 end for
 $k := k + 1$
 Compute(L_k, c_k)
until $c_k \approx 0$

In this pseudo-code, c_k refers to the temperature at iteration k and L_k to the number of transitions at iteration k . The process is initialised with a high temperature c_0 to accept a degradation of the criteria and thus enable exploration of the state space. As the temperature c_k decreases, the algorithm becomes more selective until accepting only better solutions when the temperature has sufficiently decreased and thus intensifies the research around promising solutions. The parametrisation of the algorithm is crucial to converge to a good solution and often requires some experience. However, some guidelines exist to calibrate some parameters. For instance, a heating process enables the initial temperature calibration. This process defines an initial temperature based on an acceptance criterion. Regarding the decrease of the temperature, this process needs to be slow and a geometrical decrease with a decay temperature parameter $\alpha > 0.99$ is often used in the literature.

1.3.3.3 Simulation

Simulation is a powerful, flexible, and intuitive tool that has become increasingly popular for decision-making. It is particularly useful for analysing stochastic systems where analytical approaches have failed to model them or have become irreducible. An advantage of detailed simulation is that it represents the real system with a high-fidelity model. As explained by Law et al. (2007), most real-world systems are too complex to

allow realistic models to be evaluated analytically, and these models must be studied by means of simulation. This is particularly true when considering a whole airport system, which is a highly complex system with various intricate and interconnected system components.

Detailed simulation allows operators to work with high-fidelity models and test experiments before implementing them on real systems. This can be a significant cost saving. For example, considering an aircraft, using a simulation to test different designs would be far less expensive than testing the different designs by developing a new aircraft at each iteration. Additionally, compared to real tests, simulations save significant time since they can cover a large time-period and still being executed in just a few seconds. For these various reasons, simulation techniques are being used more and more to guide the decision-making process of operators in the industry.

We can divide simulation into two categories: Discrete Event Simulation (DES) and continuous simulation. The former can be used to model a series of discrete events, such as passengers arriving at an airport, while the latter can be used to model the evolution of a system over time, e.g. an aircraft operating a flight. In the latter case, differential equations are generally used to describe the evolution of continuous state variables.

One drawback of simulation is the intensive computational time it can require due to the granularity of the modelling. The high level of fidelity generally leads to a high computational cost for evaluating one set of decision variables. Consequently, the search for an ‘optimal’ solution in this sense may be unrealistic when the number of possible decisions is large. However, simulation can be combined with optimisation techniques to improve the current solution ([Andradóttir, 1998](#)). These range from gradient-based approaches for continuous simulation to random search and hybridisation with heuristics. [Figure 1.3](#) shows the general way to integrate simulation with optimisation. In this case, simulation enables evaluating the solution’s quality (i.e. plays the role of the objective function).

1.4 Operations Research applied to airport management

OR is widely used in the literature to address complex airport decision-management challenges. This section provides a review of OR problems related to different airport operation handling. This review highlights a significant gap in the current literature: the lack of research on optimising airport operations for the benefits of passengers, particularly in the event of disruptions occurring in the multimodal environment surrounding the airport.

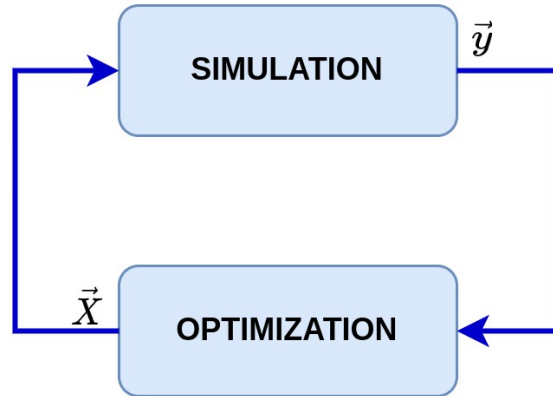


Figure 1.3: Simulation-optimisation framework. The simulation is used to evaluate the solution provided by the optimisation algorithm. The performance evaluated is then given as input to the optimisation algorithm to drive the search.

1.4.1 Check-in counter Allocation Problem

Check-in counters are a limited airport resource that must be shared by different airlines to allow passengers to check in for their flights. The Check-in counter Allocation Problem (CAP) is the problem of deciding which counter to allocate to which airline. A check-in counter can be dedicated to a single flight or shared by a group of flights scheduled simultaneously. In addition, the problem generally imposes an adjacency constraint when several check-in counters are open for the same flight. The objective of this problem is usually to minimise either the passenger walking time, the passenger waiting time in the queuing system, or the number of open desks. [Park and Ahn \(2003\)](#) optimise the staffing of check-in counters based on the airport access behaviour of passengers. [Yan et al. \(2004\)](#) propose a heuristic method by decomposing the initial problem into three heuristic models and succeeds in reducing the total walking distance of passengers. [Araujo and Repolho \(2015\)](#) use a sequential approach to solve the CAP, combining ILP optimisation and simulation. [Mujica Mota \(2015\)](#) proposes an evolutionary algorithm to solve the CAP and a simulation tool to evaluate the service level of the new allocation.

1.4.2 Baggage Carousel Assignment Problem

Solving the Baggage Carousel Assignment Problem (BCAP) consists of assigning a baggage claim carousel at the arrival airport to each flight. Constraints such as time separability between two flights assigned to the same carousel, balance of use between carousels, or capacity of the baggage claim area are considered. The objective may be to minimise the average walking time from the gate to the baggage claim area or to assign flights to carousels close to the airline's handling agents for lost baggage

(Pisinger and Scatamacchia, 2021). Barth and Pisinger (2021) present a Mixed Integer Programming (MIP) model to solve the BCAP. Frey et al. (2017) propose a MIP model that incorporates constraints related to transporting baggage from the aircraft to the baggage carousels. Pisinger and Scatamacchia (2021) use a branch-and-price algorithm to solve the BCAP. Their algorithm outperforms the commercial solver CPLEX tested on the ILP formulation of the problem.

1.4.3 Security/Border control shift scheduling problem

The operation of an airport security and border control system involves defining how many lanes should be open throughout the operating day and defining a workforce schedule to meet this requirement. This problem has been studied in the literature under the name of Shift Scheduling Problem (SSP). Edie (1954) was the first to raise this problem to plan the workforce to operate toll booths. The problem relies on creating a shift schedule that covers the expected demand. In other words, the SSP aims to find a workforce schedule that operates the required toll booths for each hour. Dantzig (1954) was the first to propose a mathematical formulation of the SSP. He shows that it can be formulated as a set coverage problem. In general, there is a cost associated with each shift and the objective function of the problem is to minimise the total shift cost. Bechtold and Jacobs (1990) and Aykin (1996) propose other formulations by assigning decision variables to break times, allowing a large reduction of decision variables. Thompson (1995) proposes an implicit formulation of the problem, which reduces the computation time compared to the previous formulation. When considering large instances, exact methods generally fail to solve SSP. In this case, other strategies based on column generation (Demasse et al., 2006; Restrepo et al., 2012), large neighbourhood search (Quimper and Rousseau, 2010) or implicit models (Côté et al., 2011; Dahmen et al., 2018) have been proposed in the literature.

1.4.4 Passenger boarding/disembarkation problem

As explained by Schultz (2018b), the passenger boarding process significantly impacts aircraft departure times. Inefficient boarding can lead to additional time and potential flight delays. Similarly, inefficient disembarkation affects turnaround time and subsequent flights. The passenger boarding problem aims to find an optimal passenger seat assignment and an optimal passenger sequence for boarding. The passenger disembarkation problem is based on finding the optimal disembarkation sequence. The problem generally considers passenger characteristics, such as the number of carry-on items. The primary objective function minimised for this problem is the total boarding/disembarking time.

Schultz (2018a) proposes a stochastic aircraft boarding model to test different strategies for passenger boarding sequences. While back-to-front and block strategies achieve

small benefits (compared to random boarding), the combination of aircraft rear door and individual boarding policy achieves the highest benefits. Other studies propose optimisation strategies for boarding and disembarking in the context of the Covid-19 pandemic. [Schultz and Soolaki \(2021\)](#) presents an optimisation model for passenger group seat allocation and boarding sequence to minimise the risk of virus transmission. [Schultz and Soolaki \(2022\)](#) consider a multi-objective function to find a trade-off between minimising total disembarkation time and transmission risk. [Schultz et al. \(2023\)](#) propose a simulation-optimisation framework to solve the passenger seat allocation and boarding sequence.

1.4.5 Gate Assignment Problem

The Gate Assignment Problem (GAP) aims to assign a set of gates to a set of flights. The set of gates is usually smaller than the set of flights. The problem usually considers constraints regarding minimum turnaround time and compatibility between gates and aircraft types. Regarding the possible objective functions of this problem, they can be either airline/airport-oriented or passenger-oriented. The former objective benefits the airport and airline stakeholders, while the latter improves the passenger's door-to-door journey. [Kim et al. \(2013\)](#) proposed to address the GAP by minimising passenger transit time and aircraft taxi time. [Kim and Feron \(2017\)](#) solved the robust GAP to minimise gate conflicts due to stochastic aircraft delays. [Kim et al. \(2017\)](#) propose to find a trade-off between the passenger transit time through the airport, the aircraft taxi time and the robustness of the gate assignment. They apply a tabu search and succeed in improving each criterion. [Dell'Orco et al. \(2017\)](#) tried to minimise the total passenger walking time, i.e. considering departing, arriving and connecting passengers.

1.4.6 Ground Movement Problem

The Ground Movement Problem (GMP) involves optimising conflict-free routes for aircraft between runways and stands, combining routing and scheduling. Inputs include flight origin, destination (runway and gate), departure time and optional arrival time. Primary constraints prevent conflicts between flights by incorporating separation rules and route-aircraft compatibility. Timing constraints ensure compliance with Air Traffic Flow Management (ATFM) slots and gate availability. The primary objective is to minimise taxiing congestion and reduce the number of flights waiting at the runway threshold to improve the environmental efficiency of the airport. [Ravizza et al. \(2013\)](#) propose an approach to tackle this problem through a graph-based approach and a multi-objective function, considering taxi time and fuel consumption. [Burgain et al. \(2013\)](#) demonstrate that surface monitoring can improve decisions by holding aircraft at the gate when taxiing is congested and waiting time is expected at the runway threshold. [Ravizza et al. \(2014\)](#) extend the work presented in ([Ravizza et al., 2013](#))

with gate-holding strategies. This approach reduces fuel consumption by shifting the waiting time at the runway threshold to the gate. [Stergianos et al. \(2015\)](#) highlight the importance of pushback modelling to assess the total delay in ground movement at airports. They show that modelling without consideration of the pushback process and its associated constraints can lead to a significant underestimation of the delay for several aircraft.

1.4.7 Runway Sequencing Problem

The Runway Sequencing Problem (RSP) is one of the main problems known in the literature regarding airside operations. [Bennell et al. \(2011\)](#) propose a survey of methods to solve this problem until 2011, and [Ikli et al. \(2021\)](#) complete this survey with new techniques implemented until 2021. The solving of the RSP aims to find a sequence of arriving and departing aircraft at the runway. The average flight delay, the airport's environmental impact or even the air traffic controllers' workload are potential objective functions to be minimised. The first approaches in the literature focused on sequencing only arrivals or departures. Subsequently, other studies considered the sequencing of both arrivals and departures. In the latter case, runway crossing constraints and the use of runways in mixed mode are usually considered. The RSP primarily considers two key constraints: wake turbulence separation between aircraft and adherence to assigned slot times. Aircraft generate turbulence during flight, which affects neighbouring flights. Safety requires a minimum separation between arriving flights and also between departing flights, determined by aircraft wake turbulence categories. In addition, several flights must respect 15-minute slot windows assigned by the network manager. Several optimisation techniques can solve such problems. [Atkin et al. \(2007\)](#) proposed a hybrid metaheuristic to reduce the average delay for departing aircraft at London Heathrow. [Kim et al. \(2010\)](#) used a mixed integer linear model to find a sequence for both arrivals and departures to minimise the CO₂ emissions of aircraft within the TMA. [Anagnostakis and Clarke \(2003\)](#) proposed a two-stage level heuristic to maximise runway throughput while incorporating runway crossing. The first stage aims to find the optimal sequence of departure class slots and runway crossing slots, while the second stage relies on assigning aircraft to these slots through integer programming.

Conclusion

Understanding how an airport is operated is essential before proposing a potential strategy to improve passenger door-to-door journeys. We presented different airport management problems that have been successfully addressed through OR techniques. The different problems refer to airport management at the strategic or tactical levels. In airport management, the strategic level involves long-term planning, policy development and high-level decision-making, while the tactical level focuses on intermediate

planning, resource allocation and day-to-day operational decisions. CAP, GAP or SSP refer to decisions taken at the strategic level. GMP problem and RSP can be solved at the strategic level but can also be considered at the tactical level when dealing with unexpected events on the day of operations.

As the main focus of this work is to address unexpected disruptions that occur during airport access, the next section focuses on tactical airport handling. We review the works related to the tactical handling of airport management and how air transportation stakeholders currently manage passenger recovery during disruptive events.

1.5 Tactical handling of airport operations and passenger recovery

This section focuses on past works dealing with managing airport operations at the tactical level. First, we present the tactical management of airside operations. Second, we discuss the management of disruptions from the airline's point of view and the recovery of passengers. Last, we review previous works related to managing airport access mode disruptions.

1.5.1 Disruption management at the airport level

[Pujet \(1999\)](#) was one of the first to propose a virtual queuing system that allowed the waiting time at the runway threshold to be shifted directly to the gate. Such an approach improved airport efficiency by reducing fuel consumption and, thus, the airport's carbon footprint. Later, [Bohme et al. \(2007\)](#) studied the integration of departure and arrival runway scheduling problems to improve the overall airport efficiency. [Kjenstad et al. \(2013\)](#) tries to improve runway scheduling with the surface management problem at Arlanda Airport. [Khadilkar and Balakrishnan \(2015\)](#) extend the integration by also considering the management of flights in the TMA, which is the airspace surrounding an airport, through dynamic programming. [Ma et al. \(2019\)](#) also propose an integrated approach to optimise airport operations from the terminal to the TMA. They consider resource capacity constraints and flight conflict resolution in the TMA by using SA to reschedule flights. [Guimarans and Padrón \(2022\)](#) use a simulation approach to airport ground resource scheduling. Their approach increases schedule robustness with aircraft turnarounds mostly on time in all scenarios. [Ma et al. \(2021\)](#) optimise the departure runway scheduling at CDG considering the arrival runway crossing by proposing two ILP models and a SA. [Ahmadian and Salehipour \(2022\)](#) presents a mathematical algorithm for the aircraft landing problem. This algorithm is mainly based on iterative changes of aircraft landing subsequences. Its approach finds optimal schedules for small instances (up to 50 aircraft) and best-known solutions for large instances (500 aircraft) in less than a minute of computation time. [Evler et al. \(2021\)](#) highlights how an inte-

grated decision support system for schedule recovery would help the APOC to handle ground operations under uncertain arrival times. Using a study case around Frankfurt Airport, they demonstrate the robustness of their solution by considering 20 aircraft during a morning peak.

1.5.2 Airline disruption management and passenger recovery

Airline disruption management, including passenger recovery, is an active area of research. Different approaches propose an integrated recovery that considers both aircraft re-routing and passengers (Jozefowicz et al., 2013; Hu et al., 2016). Delgado et al. (2016) combine two strategies for airlines to recover delays in a hub strategy. The first strategy relies on dynamic cost indexing, which allows aircraft to be accelerated to recover delays, while the other relies on delaying departing aircraft to wait for connecting passengers. Santos et al. (2017) propose an ILP solution approach to decide whether connecting flights should be delayed to wait for late passengers, considering airport capacity constraints. The problem aims to minimise passenger delay costs and possible related fuel costs. Montlaur and Delgado (2017) optimise flight and passenger delay at tactical and pre-tactical levels. Optimisation at the pre-tactical level limits propagated delays and reduces the number of passengers missing their connections. Bouarfa et al. (2018) use a multi-agent system to propose a disruption management policy for an airport operations centre. Delgado et al. (2021) propose an agent-based model for handling air traffic delays through 4D trajectory adjustment to reduce costs and delays for connecting passengers. De La Vega et al. (2022) proposes to solve a short-term flight rescheduling problem to recover flight delays in the context where employees of a gas and oil company need to be transported to maritime units.

1.5.3 Handling transportation disruptions through passenger-oriented metrics

When a multimodal transportation system is considered, a disruption occurring in one mode could be mitigated by using alternative modes to re-route disrupted passengers. Marzuoli et al. (2013) propose extending the CDM concept to involve ground transportation stakeholders. They highlight how collaboration between air and ground transportation stakeholders can help passengers during crisis, e.g. airport closure. Dray et al. (2015) present a quantitative analysis on how multimodal passenger re-accommodation would help to fasten a disruption recovery. Marzuoli et al. (2015) study the impact of the Asiana crash in San Francisco on the transportation network. They highlight how multimodal collaboration would help to provide passengers with resilient door-to-door journeys. However, these studies only focus on massive disruptions that must re-route passenger flow. They do not study how disruptions occurring in airport access mode affect passengers and airport operations. Although such events are less severe than

snowstorms or volcanic ash hazards, they are frequent. For instance, in 2022, more than 20% of regional trains used to access CDG were delayed ([Ile de France mobilités, 2023](#)).

Only a few studies have been led to mitigate airport access mode disruption. [Rahimi et al. \(2021\)](#) use an agent-based simulation to evaluate the benefits of multimodal management action to mitigate the impact of a disruption on passengers. They show that informing passengers about the disruption at its starting time is as efficient as proposing management actions such as increasing vehicle frequency or capacity. [Bagamanova et al. \(2022\)](#) study the integration of ATM in a multimodal transportation system, considering currently available modes and the emerging ones for the next decades. They consider different disruption scenarios on airport access mode and evaluate their impact on business travellers in 2025 and 2035. [Rothe et al. \(2022\)](#) evaluate the impact of a road and a subway disruption on airport passenger arrival flow through two case studies, focusing on London City Airport and Palma de Mallorca Airport. They proposed a management action plan, which relies on either opening a fast-track line at security for delayed passengers or advising them to arrive earlier at the airport. However, there was no consideration of actual resource limitation constraints (e.g., the number of security teams available) to implement such management plans.

Conclusion

We have presented various incentives for handling disruption management in air transportation systems, from both the airport and airline sides. However, most of the studies in the literature have only considered the air transportation system, neglecting the airport surroundings and their intrinsic connection with other modes of transportation. The few works that do consider this multimodal environment generally lack optimisation techniques for finding the best recovery strategy, as well as proper problem formulation for optimisation. To address this, we propose two new optimisation problems focused on passenger recovery. They aim to offer original recovery strategies for airport operators when a disruption occurs on a passenger's journey towards the airport.

1.6 Proposition of passenger-oriented optimisation problems

We have seen various classic problems considered in the literature on airport management. We have also seen how transportation service providers react when faced with delays to mitigate the impact of a disruption on passengers. We propose to merge the two concepts by proposing two operational problems that could be addressed at the airport level to improve the passenger experience during access mode disruptions. Such problems could only be addressed thanks to real-time information-sharing be-

tween ground and air transportation stakeholders. As in the European project TRANSIT (Bueno et al., 2022), we assume that this collaborative multimodal environment is implemented and allows the airport operators to optimise their operations at the tactical level to improve passenger door-to-door journeys. We assume that information sharing between ground and air transportation stakeholders could be used to update passenger airport arrival time forecasts. Based on this, the airport could decide to delay flights or allocate more resources to the security screening system to help delayed passengers reach their gates before their flight departs. In the following, we present two optimisation problems related to tactical airport operation management. The first one is a tactical security staff reallocation problem, and the second is a tactical flight rescheduling problem. Both problems are briefly presented below and Part II details their mathematical formulation and the methods we develop to tackle them.

1.6.1 Security staff rescheduling problem

Airport security systems are key components for passenger processing time at the airport. A poor handling of security resources could lead to excessive passenger waiting times and thus threaten the whole passenger journey. Airport operators estimate the number of security teams required at the strategic level, based on a forecast of the passenger arrival profile at airport security. However, if actual passenger flows differ from the forecast, e.g. if there is a disruption to a train or metro that is used to access the airport, the capacity of the security system may not match the actual passenger demand. Nikoue et al. (2015) highlight how irregular passenger flows can affect the level of service of airport queuing systems. For example, an unexpected wave of delayed passengers arriving at the airport security checkpoint can cause congestion and increase passenger waiting time. Therefore, a disruption in the airport access mode directly impacts the airport security screening system. Without pre-emptive measures taken by airport operations, the airport's level of service is likely to be degraded, which could eventually lead to more passengers missing their flights.

Our proposal aims to alleviate congestion in airport security screening systems by reallocating security teams at the tactical level. We assume a finite resource, i.e. a fixed number of security teams, and a resource pooling assumption that allows teams to be moved to different security positions during the day. In the event of a disruption to the airport access mode, passenger arrival profile forecasts for airport security can be dynamically updated during the day thanks to information sharing between transportation stakeholders. These new passenger arrival profiles can be analysed to detect potential imbalances between demand and capacity at different security checkpoints during the following operating hours. To achieve this, we propose to solve an optimisation problem of security team reallocation to smooth the flow of passengers at different security checkpoints in the airport. We propose to consider different strategies, such as using a single queue lane or opening a fast lane for passengers affected by the disruption

and likely to miss their flights. Both strategies would be further described in [Chapter 3](#).

1.6.2 Passenger-oriented flight rescheduling problem

Airline and rail operators have entered into few bilateral partnerships, such as Air France-SNCF or Lufthansa-Deutsche Bahn partnerships. However, there is a lack of global coordination at the airport level. Additionally, most existing air-rail collaborations do not include the coordination of transportation means in case of delays occurring on the initial leg. This lack of coordination may cause missed connections and stranded passengers. If such a situation arises, transportation suppliers must rebook passengers on a new flight or train. This solution is not efficient for both stranded passengers and transportation providers, as it may lead to significant delays and additional costs.

According to CDG operators, when significant disruptions occur on the ground side, such as bomb threats or major road traffic accidents, a strict waiting policy may be implemented to minimise the number of passengers missing their flights. This policy delays all departing flights at the gate to accommodate delayed passengers. However, such a program can lead to substantial congestion at the airport and disrupt the overall air traffic flow management. Combining a ground delay program with this waiting policy can alleviate congestion by directly delaying arriving flights at their departure airports.

In case of airport access disruption, such as train or subway shutdown, we suggest a compromise between no coordination and strict waiting policies. To achieve this, we propose a new passenger-oriented flight rescheduling problem that balances between waiting for delayed passengers and sticking to the original flight schedule. Here, we consider a collaboration based on information sharing between ground and air transportation stakeholders. When disruptions occur in one of the airport access modes, several outbound passengers will probably miss their flights. Assuming that a passenger information service allows passengers to declare themselves as delayed, the APOC could then know which passengers are affected by the disruption. With this information, the APOC could decide to delay specific flights to assist passengers affected by the disruption in catching their flights. Nevertheless, holding multiple aircraft at the gate could lead to congestion on the airport's airside. Therefore, it becomes necessary to regulate arriving flights to alleviate airport congestion. Having information about air passengers is crucial to avoid causing missed air connections while managing the flow of arriving aircraft. Therefore, we propose to solve an optimisation problem based on flight rescheduling at the tactical level to minimise the number of passengers missing their flights while satisfying airport operational constraints. Airport resource constraints, such as terminal capacity or maximum runway throughput, and flight- and aircraft-related constraints, such as minimum turnaround constraint or minimum transfer time for connecting passengers, are considered in the rescheduling. This problem and its associated Integer Linear Programming formulation are detailed in [Chapter 4](#).

1.7 Conclusion

This chapter has presented the current method of managing airport operations, which has limitations when providing passengers with a seamless experience during airport access mode disruptions. We have proposed new recovery strategies to improve passenger experience by creating a multimodal collaborative environment with real-time information sharing. We have presented the scenario envisioned in this thesis and supported by the European project called TRANSIT, where ground and air transportation systems collaborate to provide reliable multimodal passenger door-to-door journeys. This new paradigm could allow tactical airport operation management strategies to be implemented to limit the impact of disruptions occurring on passenger journeys towards the airport.

We also have introduced the OR concept and its value throughout our work. This discipline can be used to model operational problems and propose mathematical and computer-based approaches to solve them. We have highlighted how OR has already been successfully used to improve current airport operations handling, especially in the case of airside disruption management.

Based on this background, we have proposed two passenger-oriented problems that could be solved through OR techniques and in a multimodal collaborative environment, where passenger information enhancement could help the airport to reallocate security screening teams and reschedule flights tactically. The next chapter presents a passenger flow modelling framework within CDG required for studying these new optimisation problems. Then, [Part II](#) is dedicated to their modelling and solving.

Chapter 2

A data-driven methodology to model passenger flows at Paris-Charles de Gaulle airport

2.1 Introduction

In this chapter, we describe the experimental framework we built to test new recovery strategies implementable by airport operators. Thanks to various datasets and statistics provided by CDG airport, we have been able to develop and calibrate realistic models for passenger flow at different stages of their transit through the airport, from their arrival to the boarding gate.

The remainder of this chapter is structured as follows. First, we present the datasets and statistics provided by CDG. Then, we describe the data-driven methodology we use to model the flow of passenger arrivals at the airport with an accurate parametric distribution (Buire et al., 2021). Next, we explain how we simulate disruptions in the airport access mode for passengers and the way we model connecting passengers. Finally, the modelling of the passenger flows in the airport landside is presented.

2.2 Presentation of the datasets

A schematic of CDG is provided in [Figure 2.1](#). This airport comprises three main terminals (T1, T2, T3). Terminal T2 is broken down into a subset of terminals, with two main ones (T2E and T2F) and five others (T2A, T2B, T2C, T2D, and T2G). Four runways are available. In West configuration¹, runways 27R and 26L are dedicated to arrivals flights (external runways), while 27L and 26R are dedicated to departure flights.

¹A runway can be used in two configurations depending on the wind direction.



Figure 2.1: Scheme of Paris-Charles de Gaulle airport.

Characteristics	Values
Day	2019/06/26
SOBT/SIBT	16:15
AOBT/AIBT	16:16
ATOT/ALT	16:37
Type	Departure
Callsign	EZY7420
Terminal	T2D
Room	C2D-D62
Airport	SEN
Tail Number	GUZHS
Runway	09L
Passengers carried	148

Table 2.1: Characteristics of one row of the flight data set.

Different data sets provided by various units at CDG support this study. The first data set is historic flight schedules from 2017 up to 2021. [Table 2.1](#) provides an example of the values and characteristics of one flight in this data set. For each departure (respect. arrival) flight, the date, the Scheduled Off Block Time (SOBT)(respect. Scheduled In Block Time (SIBT)), the Actual Off Block Time (AOBT) (respect. Actual In Block Time (AIBT)), the Actual Take-Off Time (ATOT) (respect. Actual Landing Time (ALT)), the type of movement (Departure or Arrival), the callsign, the terminal,

Characteristics	Values
Date	2019/06/26
10-min interval	14:20
Callsign	EZY7420
Terminal	T2D
Boarding room	C2D-D62
Number of passengers tracked	3

Table 2.2: Example of one row of the passenger timestamps data set.

T1	T2A	T2B	T2C	T2D	T2E	T2F	T2G	T3
10	10	5	10	10	5	5	5	10

Table 2.3: Transfer time from security system to the gate (in minutes).

the boarding room, the tail number, the origin (respect. arrival) airport, the departure (respect. arrival) runway, and the number of carried passengers are given. SOBT and SIBT are the scheduled times when an aircraft should depart from and arrive at the gate, respectively.

The second data set contains passenger arrival timestamps at security screening locations for three months (June 2019, December 2019 and June 2020) as shown in [Table 2.2](#). Each entry records the number of passengers for a given flight going through the security checkpoints over successive 10-minute periods. The two previous data sets can be combined to infer when passengers go through security screening relative to their flight SOBT. Indeed, the two entries displayed in [Tables 2.1](#) and [2.2](#) provide information for the same flight. Combined, we can infer that three passengers for flight EZY7420 went through security checkpoints 115 minutes before their flight SOBT.

CDG has provided other statistics to model passenger flow within the airport:

- for each terminal, the minimum transfer time by walk from security to the gate is displayed in [Table 2.3](#);
- for each pair of terminals, the share of connecting passengers is available in [Table 2.4](#);
- for each pair of terminals, the minimum transfer time is provided in [Table 2.5](#);
- for each terminal, the share of departure passengers in connection is reported in [Table 2.6](#).

Finally, the flight schedule data set is used to compute the average taxi time between pairs (terminal, runway), and results are available in [Table 2.7](#). Regarding airport access modes, General Transit Feed Specification (GTFS) data related to high-speed

TO \ FROM	T1	T2A	T2B	T2C	T2D	T2E	T2F	T2G	T3
T1	0.93	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.0
T2A	0.01	0.93	0.01	0.01	0.01	0.01	0.01	0.01	0.0
T2B	0.01	0.01	0.93	0.01	0.01	0.01	0.01	0.01	0.0
T2C	0.01	0.01	0.01	0.93	0.01	0.01	0.01	0.01	0.0
T2D	0.01	0.01	0.01	0.01	0.93	0.01	0.01	0.01	0.0
T2E	0.01	0.01	0.01	0.01	0.01	0.60	0.60	0.60	0.0
T2F	0.01	0.01	0.01	0.01	0.01	0.30	0.30	0.30	0.0
T2G	0.01	0.01	0.01	0.01	0.01	0.05	0.05	0.05	0.0
T3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Table 2.4: Connecting passenger share between terminals. Each departure terminal is associated with one column, and each arrival one to a row. For instance, 30% of connecting passengers departing from T2E arrived from T2F.

TO \ FROM	T1	T2A	T2B	T2C	T2D	T2E	T2F	T2G	T3
T1	40	65	60	65	70	65	60	75	0
T2A	60	25	30	25	60	50	50	70	0
T2B	80	50	20	50	40	45	45	60	0
T2C	60	25	30	25	60	50	50	70	0
T2D	55	60	20	60	10	50	35	45	0
T2E	85	55	55	55	85	35	50	60	0
T2F	55	45	45	45	40	30	10	20	0
T2G	75	60	60	60	50	50	25	10	0
T3	0	0	0	0	0	0	0	0	15

Table 2.5: Minimum transfer time for connecting passengers between terminals (in minutes). Each departure terminal is assigned to a column and each arrival terminal to a row. The transfer time is set to 0 minute if there is no connecting passenger between a pair of terminals.

T1	T2A	T2B	T2C	T2D	T2E	T2F	T2G	T3
0.03	0.05	0.02	0.05	0.02	0.5	0.5	0.5	0.03

Table 2.6: Share of connecting passengers for each departure terminal. It represents the average number of connecting passengers per departure flight.

	27R	26L	26R	27L
T1	523	956	987	827
T2A	803	653	764	1128
T2B	734	657	696	774
T2C	956	590	777	1269
T2D	713	657	738	987
T2E	783	522	908	1261
T2F	560	528	841	868
T2G	709	352	885	1318
T3	447	795	786	812

Table 2.7: Average taxi time for each couple (terminal, runway) in seconds.

Train	Subway	Road
11%	26%	63%

Table 2.8: Share of passengers using different ground transportation modes to access CDG.

rail schedules have been collected for one day in 2019. Such data are regularly updated and available on the website of the Société Nationale des Chemins de fer Français (SNCF) (SNCF, 2023). This data set has been processed to extract train arrival times at CDG station. Finally, Table 2.8 displays the modal shares of transportation modes passengers use to access CDG, according to a survey conducted by the French Civil Aviation Authority (DGAC).

2.3 Modelling outbound passenger arrival flow at the airport

This section presents the methodology developed to capture the outbound passenger arrival process during regular days of operations. In the following, we use the term ‘outbound passenger’ for the ones who arrive at the airport from the ground. The term ‘nominal day’ refers to a regular day of operations where no airport access mode disruption occurs. The modelling of a realistic nominal passenger flow at the airport is crucial for a valid model to measure the airport’s level of service. Then, based on this baseline, a disrupted passenger flow is generated to see the impact of an access mode disruption on airport operational performance. We present below a suitable parametric distribution, called Exponentially Modified Gaussian (EMG) distribution, to model the passenger arrival process at the airport security screening system. This work has been published in (Buire et al., 2021) and is detailed below.

We use the data sets presented in [Section 2.2](#) to infer how long outbound passengers arrive at security screening before their flight departure time. We propose to fit a probabilistic distribution on these data sets to simulate passenger arrival times at airport security checkpoints for each flight. We justify the choice of simulating flow instead of directly working with raw data of one historical day for the following two reasons:

1. Firstly, inferring passenger arrival time distributions provides a generic way to simulate a passenger population for any application without requiring access to raw data. As CDG data management policies consider raw passenger data to be sensitive, such a dataset is not publicly available. However, it is possible to provide aggregated data, such as the parameters of a probabilistic distribution fitted to the data, thus contributing to reproducible research.
2. Secondly, scanning the datasets has revealed discrepancies, such as missing passengers. According to CDG operators, such discrepancies are due to hardware dysfunction at the security, leading to manual verification of passenger flight tickets and, consequently, missing records. Aggregating data over the month is a solution to reduce the error and limit the impact of discrepancies.

Thanks to the flight schedule data set, the actual number of passengers carried per aircraft is known. If this information is unavailable, it can be estimated by considering the number of seats and assuming an 80% load factor per aircraft.

2.3.1 Selection of suitable probabilistic distribution

In the literature, two different methods exist to model the outbound passenger arrival profile at the airport entrance. The first one directly estimates passenger inter-arrival rates at the airport entrance, calibrated thanks to data collection. Studies using simulation software to model passenger flows within the airport often used this method ([Guizzi et al., 2009](#); [Ju et al., 2007](#)). The inter-arrival rate is dynamic throughout the day, depending on the hour of the day and the expected passenger throughput. Generally, a distinction is made between high and low passenger throughput hours, called peak and off-peak hours, respectively. The other method creates a passenger arrival profile according to the flight schedule ([Mujica Mota, 2015](#); [Postorino et al., 2019](#)). This method infers a passenger arrival profile at the airport entrance for each flight. The passenger arrivals are then aggregated to obtain the total passenger flow at the airport entrance. The second method has the advantage of being dynamic, depending on the characteristics of the flight schedule. It also allows the direct assignment of passengers to flights, which is not the case with the first method. Therefore, we choose the second method and propose to build a realistic model of passenger arrival at the airport for each flight.

Only a few works in the literature studied the definition of a suitable probability distribution to model passenger arrival profiles for a flight. [Postorino et al. \(2019\)](#) tries to find a suitable probability distribution to model how long passengers arrive at the airport before flight departure. They collected passenger time stamp records from the security screening system at Bologna airport. After testing several parametric distributions, they propose a Weibull distribution to model the passenger early arrival process.

Here, we propose a similar work by finding a parametric continuous distribution suitable to model passengers' arrival time before their flight. We choose to use parametric distributions instead of non-parametric distributions for reproducibility. Indeed, parametric distributions have the advantage of aggregating information, and anyone with access to the parameter values can quickly reproduce the arrival profile. To find a suitable distribution, we select different candidate distributions and different performance metrics to choose the best one. In the following, we perform a preliminary study to identify potential parametric distributions to model the passenger earliness arrival process. Then, the methodology used to perform the fit and the performance metrics to evaluate the quality of the fit are presented.

Identification of probability distribution candidates for passenger earliness arrival process

We use the records of passenger time stamps collected at the security screening system and the historical flight schedules described in [Section 2.2](#). Thanks to both datasets, we infer, for each flight, how long passengers arrive at the security checkpoint before their flight departure time. We then aggregate these values for each departure flight of the three months of records (June 2019, December 2019, June 2020). [Figure 2.2](#) displayed the passenger arrival distribution obtained. This distribution is asymmetric, with a tail on the left side of the distribution. More than 40% of passengers arrive at the security screening system between 100 min and 60 min before their flights, while 6% of more conservative passengers arrive between four and seven hours before departure.

The candidates often used in the literature to model arrival processes are the exponential, log-normal, gamma and Weibull distributions, all of which have their support on \mathbb{R}^+ . Indeed, we want to model how early passengers arrive at the security checkpoint before the flight departure time. In all likelihood, we assume that passengers go through security before their flight departure time. However, if we look closely at [Figure 2.2](#), we can see that passengers arrive up to 20 minutes before the scheduled departure time in the raw data. We generate the distribution using the scheduled off-block time, not the actual one. Therefore, passengers may have passed through security with their delayed flight later than the initial SOBT of their flight.

We also investigate other distributions that have their support in \mathbb{R} instead of \mathbb{R}^+ . The mixed Gaussian distribution is the first candidate to model an asymmetric distri-

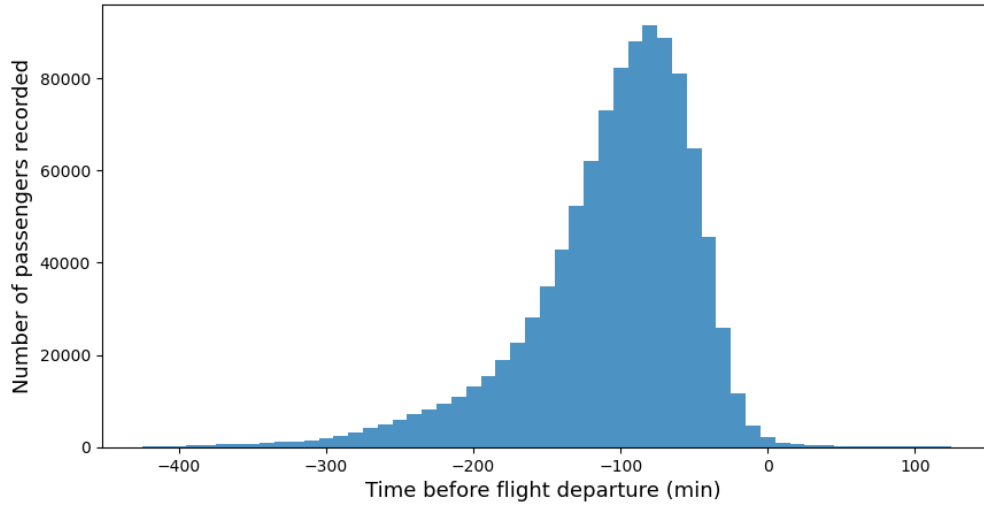


Figure 2.2: Distribution of passenger arrival times at the airport security checkpoint. In this graph, the time before flight departure is the difference between the scheduled departure time and the passenger timestamp recorded at the security checkpoint. The three months of records are aggregated here (June 2019, December 2019, June 2020).

bution. A linear combination of independent random variables that follow Gaussian distributions characterise this distribution.

A closer look at the distribution in [Figure 2.2](#) leads to considering another parametric distribution based on a combination of an exponential and a Gaussian distribution. A normal distribution captures most of the passengers arriving around 90 minutes before their flights, while a ‘reversed’ exponential distribution seems better suited to model the left tail of the distribution. This type of distribution can be found in the literature under the name of EMG distribution. The probability density function of the EMG is a convolution between a Gaussian and an exponential distribution ([Haney and Kam, 2011](#)). It is characterised by three parameters (μ, σ, λ) (two parameters from the Gaussian distribution and one from the exponential distribution). EMG distribution is used, for instance, in biomedical science ([Golubev, 2017](#)) or even to model visual reaction time ([Palmer et al., 2011](#)). The probability density function of such a distribution is

$$f_{\text{emg}}(x; \mu, \sigma, \lambda) = \frac{\lambda}{2} e^{\frac{\lambda}{2}(2\mu + \lambda\sigma^2 - 2x)} \operatorname{erfc}\left(\frac{\mu + \lambda\sigma^2 - x}{\sqrt{2}\sigma}\right),$$

where

$$\operatorname{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-t^2} dt.$$

Fitting methodology and performance metrics

The parameters of each probability distribution can be estimated to fit the data using the maximum likelihood method. Given the set of observations $S = \{s_1, s_2, \dots, s_n\}$ (i.e., passenger arrivals), this method consists of finding the set of parameters $(\theta_1, \theta_2, \dots, \theta_N)$ that maximises the following expression:

$$L(S; \theta_1, \theta_2, \dots, \theta_N) = \prod_{i=1}^n f(s_i; \theta_1, \theta_2, \dots, \theta_N),$$

where f is the probability density function of the distribution under consideration.

Different criteria can be used to test the quality of the fit. Here, we selected three performance indicators:

- the Mean Absolute Error (MAE);
- the Mean Relative Absolute Error (MRAE);
- the Root Mean Square Error (RMSE).

Let us denote $Z = \{z_1, z_2, \dots, z_n\}$ and $Y = \{y_1, y_2, \dots, y_n\}$, the predicted and observed values respectively, and \bar{y} the average observed value. Each of these metrics is calculated by Equations (2.1), (2.2) and (2.3) respectively.

$$\text{MAE}(Z, Y) = \frac{\sum_{i=1}^n |z_i - y_i|}{n} \quad (2.1)$$

$$\text{MRAE}(Z, Y) = \sum_{i=1}^n \frac{|z_i - y_i|}{|z_i - \bar{y}|} \quad (2.2)$$

$$\text{RMSE}(Z, Y) = \sqrt{\frac{\sum_{i=1}^n (z_i - y_i)^2}{n}} \quad (2.3)$$

The MAE compares the absolute difference between the actual and predicted values for each histogram bar after fitting. The MRAE is similar but gives a relative error, which can be more informative. It provides a measure of the error percentage associated with the fit. The RMSE takes the root square instead of the absolute value, which tends to penalise stronger significant errors. For each metric, the lower the value, the better the fit .

As all candidate parametric distributions have a right tail instead of a left tail, we fit them to the opposite distribution to the one shown in [Figure 2.2](#) (i.e., we consider the distribution with an inverted x-axis). In addition, since several of the distributions tested have their support in \mathbb{R}_+ , we artificially shift the distribution to have only positive values during the fit. This shift ensures that passengers arriving later than the departure time observed in the dataset are also captured.

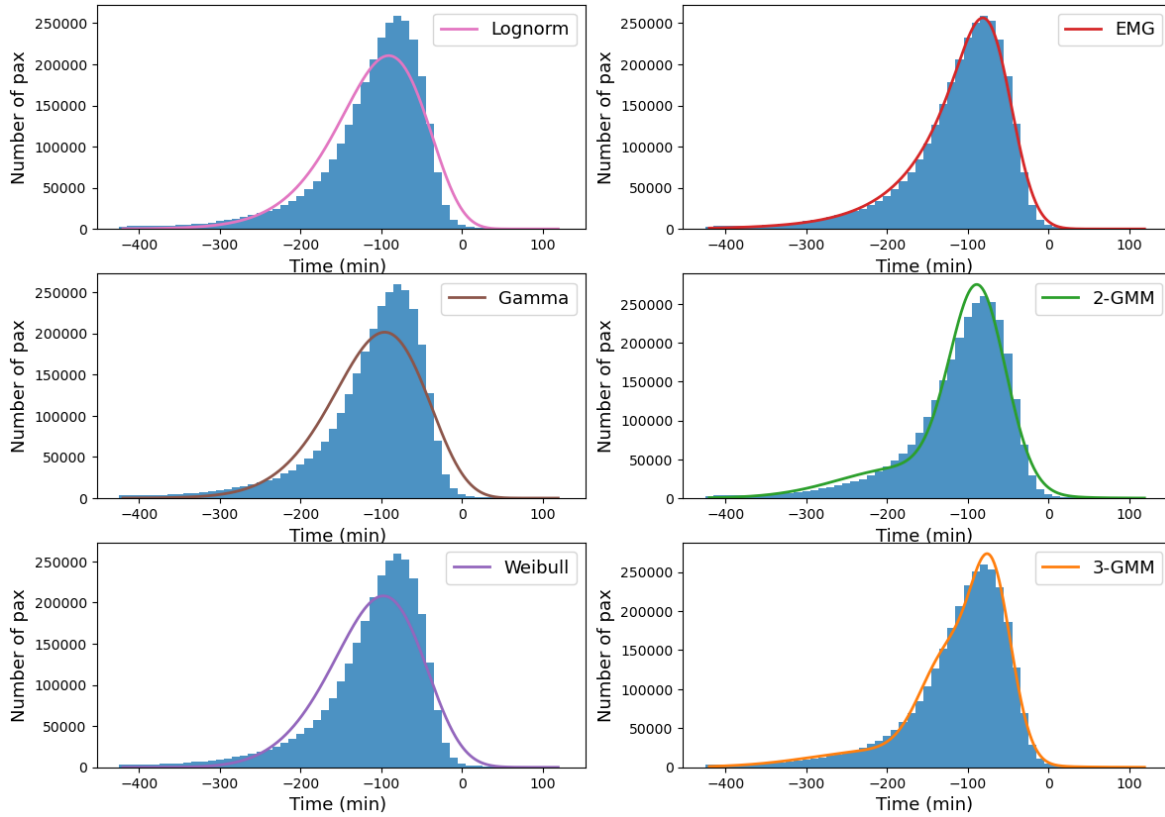


Figure 2.3: Comparison of fitting probabilistic distribution on distribution of earliness passenger arrival at the security screening system. Each distribution has been fitted through the maximum likelihood method.

Fitting Results

The curve fits associated with each parametric distribution is shown in [Figure 2.3](#).

	PDF	LogNormal	Gamma	Weibull	EMG	GMM-2	GMM3
Metric							
MAE		12421	15346	15417	3080	7396	3479
MRAE		0.436	0.538	0.550	0.126	0.211	0.101
RMSE		19558	23986	23814	4882	11529	5352

Table 2.9: Comparison of different performance criteria obtained by fitting the passenger arrival distribution with several probability density distributions. GMM-x refers to the Gaussian Mixture Model with x-components. The best and worst values are highlighted in green and red, respectively. For each metric, the lower the value, the better the fit.

According to this figure, the EMG distribution seems to be the one that best fits the observed distribution. It accurately captures the peak of arrivals 90 minutes before the flight’s departure time while also capturing the left tail of the distribution. The 3-GMM and 2-GMM (Gaussian mixture model with three and two components, respectively) do not fit as well but still capture the general shape of the distribution. The fits of other parametric distributions (log-normal, gamma, Weibull) on the left side of the figure are too spread out and fail to capture the true shape of the distribution. This observation is confirmed by evaluating the performance metrics reported in [Table 2.9](#). The Gamma and Weibull distributions are the least accurate, with the former achieving two of the three worst scores and the latter achieving one regarding the three metrics considered. The EMG distribution fitting outperforms the other probability distribution fittings for two out of three metrics. The 3-GMM outperforms the other method for the MRAE. The EMG distribution is characterised by only three parameters (two characterising the Gaussian distribution and one the Exponential distribution). In contrast, the 3-GMM requires nine parameters (two describing each Gaussian distribution and one weight for each Gaussian distribution). Consequently, we keep the EMG distribution to model the arrival of passengers at the security checkpoint for each flight in the following.

Clustering and refinement

As explained by [Postorino et al. \(2019\)](#), the passenger arrival profile can change depending on the flight characteristics. For instance, passengers on international flights are likely to arrive earlier than passengers on domestic flights. This fact is supported by the CDG website ([Paris Aéroport, 2023](#)) that advises passengers to arrive two hours before their flight if it is a short-haul flight and three hours if it is a long-haul flight. Similarly, the time of the day may influence the passenger arrival profile as suggested in ([Postorino et al., 2019](#); [Rauch and Kljajić, 2006](#)).

Therefore, we propose to refine the model by clustering the data according to flight characteristics. First, we distinguish whether the flight is operated within the Schengen area or not. The Schengen area is a group of 26 European countries that have abolished border controls at their mutual borders. A second distinction is made according to the departure time of the flight. Passengers taking a flight at 6 am are more likely to arrive closer to the boarding closure time than those taking a flight at 11 am. Consequently, we group flights into eight classes, differentiated by destination airport - Schengen vs. non-Schengen - and by time of day. An EMG distribution is fitted with data recorded in June 2019. The buffer time between passenger arrival time at security and SOBT is calculated for each flight. The results of such fits are shown in [Figure 2.4](#).

The values of the characteristic parameters obtained after fitting are given in the legend of each sub-figure. The μ and σ parameters belong to the Gaussian distribution, while the λ parameter comes from the exponential distribution. The variation of each parameter of the function f_{emg} can be interpreted as follows:

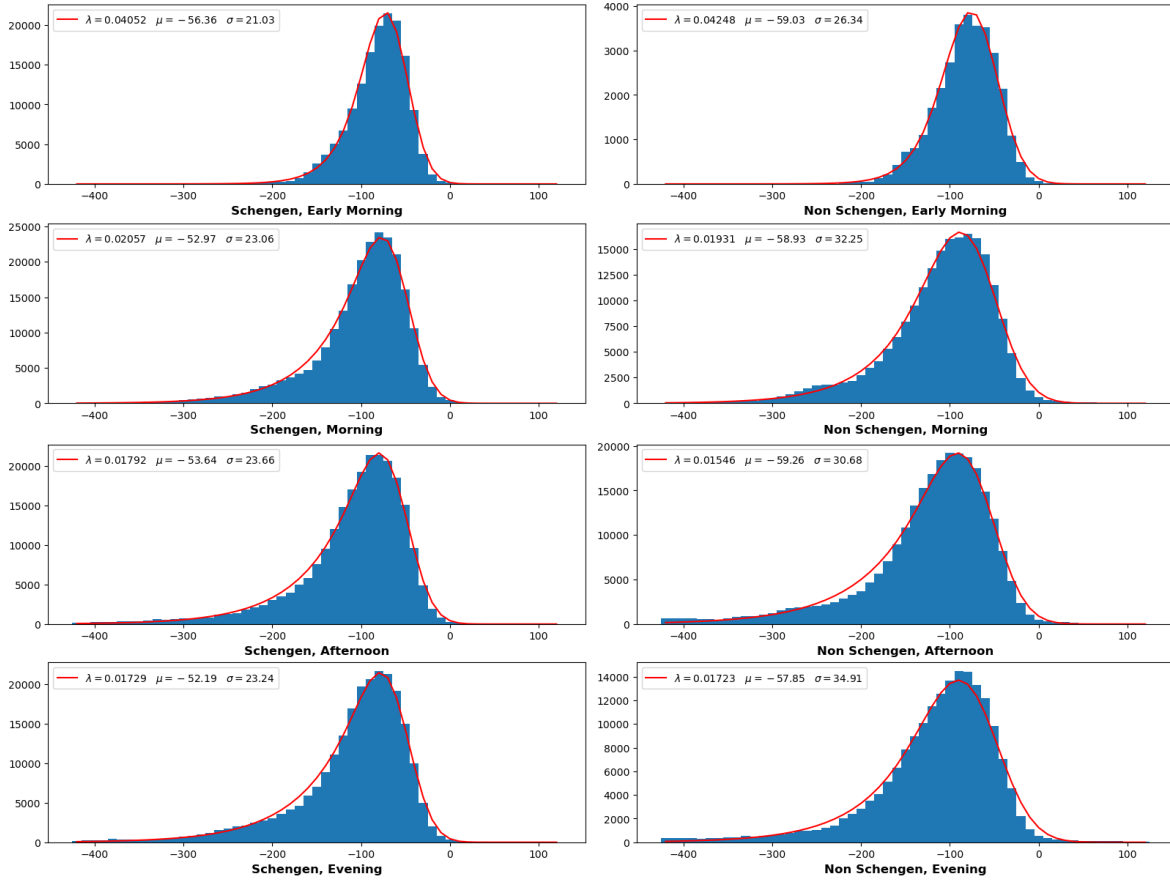


Figure 2.4: Passenger arrival time distribution at security, before their flight departure time, aggregated on June 2019 and grouped by features (Schengen/Non-schengen; period of the day). Each graph is associated with a couple of features. An Exponentially Modified Gaussian distribution has been fitted for each graph with actual passenger arrival times at security (represented through red curves).

1. as the value of μ increases, passengers tend to arrive later at the airport (note that μ is negative),
2. as the value of σ increases, passenger arrivals are more spread out over time,
3. as the value of λ increases, the exponential decay that defines the left tail of the distribution also increases. This increase reduces the distribution's left tail, meaning fewer conservative passengers arriving very early before their flight.

A higher μ parameter is observed for distributions fitted on non-Schengen flights (shown to the right of Figure 2.4) compared to those fitted on Schengen flights (shown to the left of Figure 2.4). This increase confirms the assumption that passengers tend

to arrive earlier on long-haul flights. Non-Schengen passenger arrivals are also more spread out in time, as the σ parameter is higher for these distributions. Finally, the λ parameter is higher for the distribution fitted to early morning arrivals (shown at the top of [Figure 2.4](#)), resulting in a smaller tail distribution and, thus, fewer early passenger arrivals.

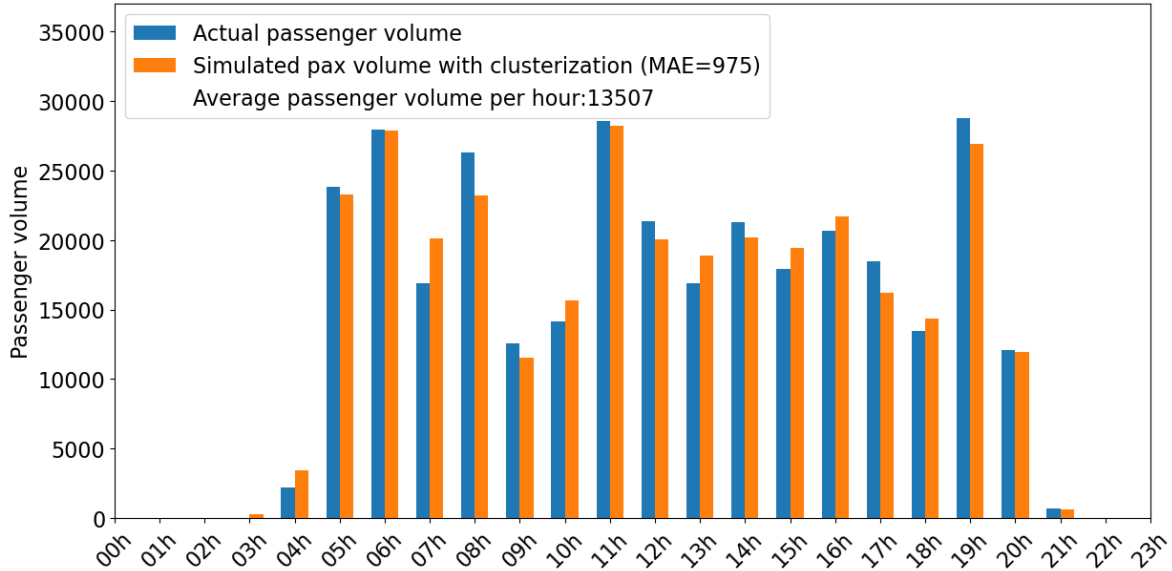
2.3.2 Model validation

To validate the EMG distribution as a suitable probability distribution for modelling passenger arrivals, we compare the actual passenger volume at the airport security screening system (obtained through the passenger scan dataset) with the one obtained through the use of the flight schedule and the fitted EMG distributions. CDG provided an extra month of passenger arrival scan at the airport security screening (April 2019). We applied the previously outlined methodology to simulate the passenger arrival profile at security checkpoints on the T2F terminal, one of the main terminals at CDG. We fitted the EMG distribution to the initial 3-month dataset for this terminal. We tested the fitting either with or without the clustering of flight characteristics. The count of passengers scanned from the new dataset (April 2019) was the only feature used to determine the number of outbound passengers per flight. Finally, passenger arrival profiles at security checkpoints of all the flights of April 2019 were then aggregated for each terminal and compared to the actual passenger volume obtained through the reading of the new dataset. [Figure 2.5](#) displayed the results obtained.

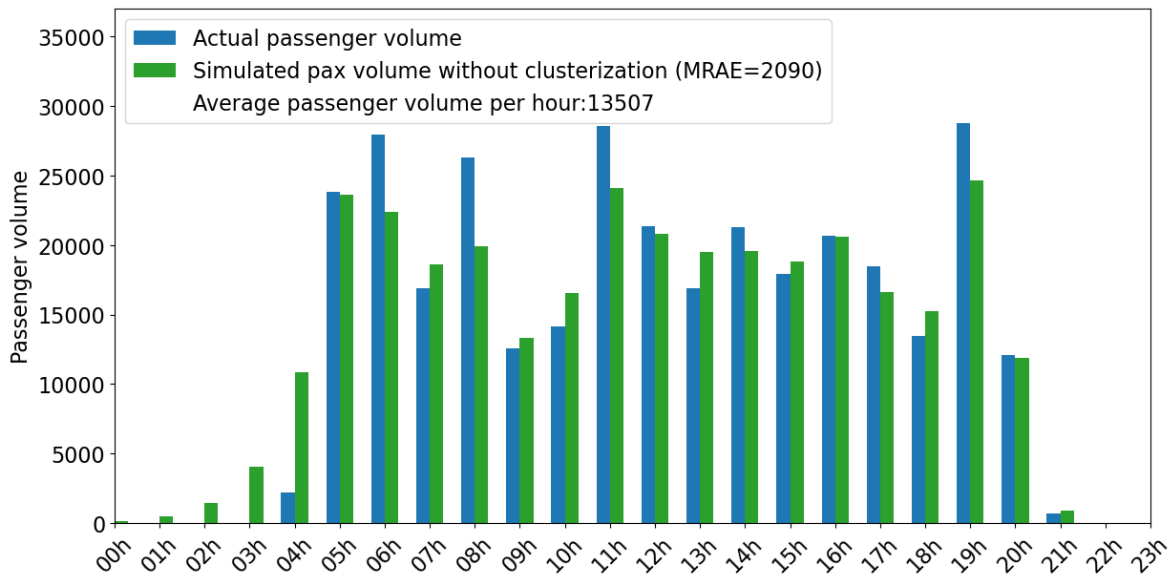
This figure shows that the simulated passenger volume at the T2F security checkpoint is very close to the actual one. The MAE has been calculated and gives a value of 975. Considering that the average observed number of passengers at the T2F security checkpoint is 13507 per hour, the average relative error is around 7%.

This result validates the appropriateness of the EMG distribution to represent the dynamics of passenger arrivals within the CDG security system. In addition, we compare the simulated passenger arrival profile obtained using clustering for data fitting and the one obtained without clustering. In the latter approach, a global EMG distribution is applied to all flights without differentiation based on whether they operate under the Schengen agreement or the time of the day. Under this alternative scenario, the arrival profile of the simulation results in an MAE of 2090, which is twice as high as the value obtained with clustering. This significant difference underlines the importance of performing clustering before distribution fitting.

We use these distributions to model nominal passenger arrivals at security checkpoints, i.e., without airport access mode disruption. Depending on the flight's characteristics, one of the eight proposed distributions generates samples of random passenger arrival. The following section presents the modelling retained to model outbound passenger flow during airport access mode disruptions.



(a) Passenger volume simulated at airport security checkpoints with flight clustering.



(b) Passenger volume simulated at airport security checkpoints without flight clustering.

Figure 2.5: Comparison of actual and simulated passenger volumes at the T2F terminal security checkpoint in April 2019. The top figure shows the simulated passenger volume with flight clustering (i.e., an EMG distribution fitted to each cluster), while the bottom figure shows the passenger volume without clustering.

2.4 Modelling access mode disruption impact on passengers

Simulation tools can be used to model the impact of a disruption on the distribution of passenger arrivals. For example, [Leng et al. \(2018\)](#) and [\(Leng and Corman, 2020\)](#) use MATSim, an agent-based simulation tool ([W Axhausen et al., 2016](#)), to evaluate the impact of a disruption on passenger travel times. Since we can access passenger timestamps at security checkpoints, we do not simulate passenger routing to the airport. However, the passenger timestamp dataset does not provide information on passenger delay status, i.e. if passengers have been affected by a disruption on their journey toward the airport. We assume that the EMG distribution fitted to this dataset modelled passengers during the nominal operating day. In the following, we propose a methodology to model the passenger arrival distribution during an airport access mode disruption. First, we propose a procedure to match passengers with airport access mode based on modal shares provided in [Table 2.8](#). Then, we distinguish whether the disturbance occurs on a high-frequency mode, such as the subway or the road, or on a low-frequency mode, such as the train. In the first case, the flow of passengers can be approximated by a continuous flow of arrivals. In contrast, discrete modelling is more appropriate in the second case since passengers arrive in waves.

2.4.1 Assigning transportation modes to outbound passengers

The dataset containing passenger timestamps lacks information on transportation modes used by passengers to reach the airport. To address this gap, we developed a straightforward method for assigning each passenger to a specific mode of transportation. Firstly, we determine passenger arrival times for each flight using the fitted EMG distribution. Next, we estimate the number of passengers using trains, roads, or subways based on the modal shares outlined in [Table 2.8](#). To introduce variability, we add a 10% noise factor to the modal share for each flight, thus altering the proportions of passengers using different modes for each flight.

To match the expected number of passengers using trains, we utilise the GTFS dataset containing train schedules. We assume that passengers can use any train arriving between one to four hours before the departure time to access the airport. If such trains are available, we randomly select a specific number of passengers and assign them to one of these trains until the expected passenger count for train usage is met.

In cases where no trains are scheduled within this timeframe, we infer that road access is the sole viable option for these passengers. Consequently, the proportion of passengers using roads is increased. The remaining passengers are then randomly divided and assigned to the subway or road access based on the respective modal shares

for subways and roads.

2.4.2 Modelling high-frequency mode disruptions

To model the impact of a subway or a road access mode disruption on passenger arrival distribution at the airport, we implement the following methodology:

1. Randomly assign each passenger to a ground access mode depending on modal shares provided by the DGAC survey;
2. Select a ground access mode to be disrupted;
3. Fix the starting time T_S and the ending time T_E of the disruption;
4. Define an average access time Δ_A representing the buffer time between the start of the disruption and its impact on passenger arrival flow at the security screening system. For instance, if a mode shuts down at 10 am, passengers who were supposed to arrive via this mode at the security system at 10 am + Δ_A are delayed. This parameter is arbitrarily fixed to 60 minutes;
5. Determine a maximum passenger delay D_{MAX} that is assigned to the first passengers facing the disruption;
6. For passengers who initially relied on the disrupted mode to access the airport and who were supposed to arrive at the security system between $T_S + \Delta_A$ and $T_E + \Delta_A$, delay them by a linear penalty, equals to D_{MAX} at $T_S + \Delta_A$ and decreasing down to 0 at $T_E + \Delta_A$. As passengers become more aware of the disruption throughout the day, we assume passenger delay duration decreases. We assume that the likelihood of a passenger learning about the disruption increases over time, which leads to better routing decisions and reduced delays when accessing the airport.

This linear decrease models passenger reactivity to disruptions across time. For instance, passengers can choose a re-routing option or even can choose to take additional buffer time to arrive on time at the airport. Indeed, [Paulsen et al. \(2021\)](#) highlights that the more a passenger receives information on the disruption and the traffic situation, the more he can improve his routing decisions and reduce delay. [Leng and Corman \(2020\)](#) also show through different simulated scenarios that higher passenger delays are observed at the beginning of a mode disruption during unexpected disruptions.

2.4.3 Modelling low-frequency mode disruptions

Passengers relying on a train to access the airport generally live far away from Paris' city centre and thus have fewer re-routing options during train disruptions. In this

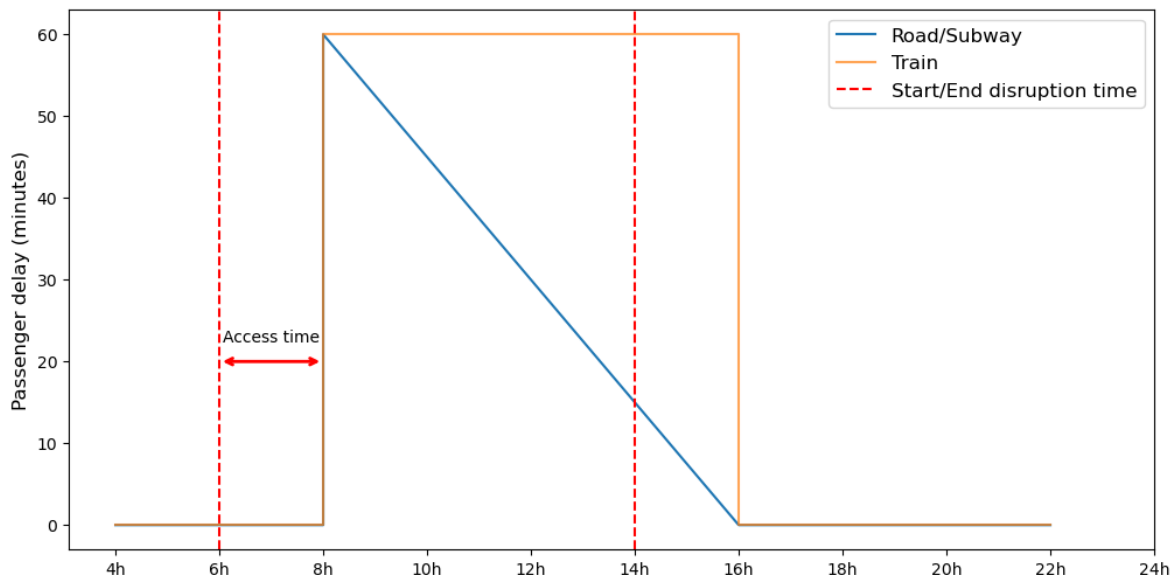


Figure 2.6: Passenger delay modelling depending on the ground transportation mode under disruption. Example of a disruption starting at 6 am, ending at 2 pm, with an average airport access time of two hours and a start delay of 60 minutes.

case, when a train experiences a delay, passengers who were relying on this train are likely to share the same delay. Consequently, we propose to model train disruption as constant delays. Figure 2.6 illustrates the assumptions retained to simulate the impact of an airport access mode disruption on passengers.

2.5 Modelling air connecting passengers

The information regarding connecting passengers is usually owned by the airlines and is not available to the airport operators. Thus, we propose a methodology to generate data on connecting passengers. The historical flight schedule and the statistical data presented in Section 2.2 support the implementation of this methodology.

Consider a pair of arrival and departure flights (f_a, f_d) . We assume that they can have connecting passengers if the passenger transfer time (i.e. the difference between the scheduled off-block time of f_d and the scheduled in-block time of f_a) is greater than the Minimum Connecting Time (MCT) and less than a Maximum Acceptable Connecting Time (MACT). We arbitrarily set $MACT = MCT + 2h$. The MCT depends on the minimum transfer time between the terminals associated with flights f_a and f_d . We consider only relevant flight pairs to generate potential connecting passengers. For instance, flights arriving from a French airport origin have been connected to international flights and vice versa. The fraction of connecting passengers per flight

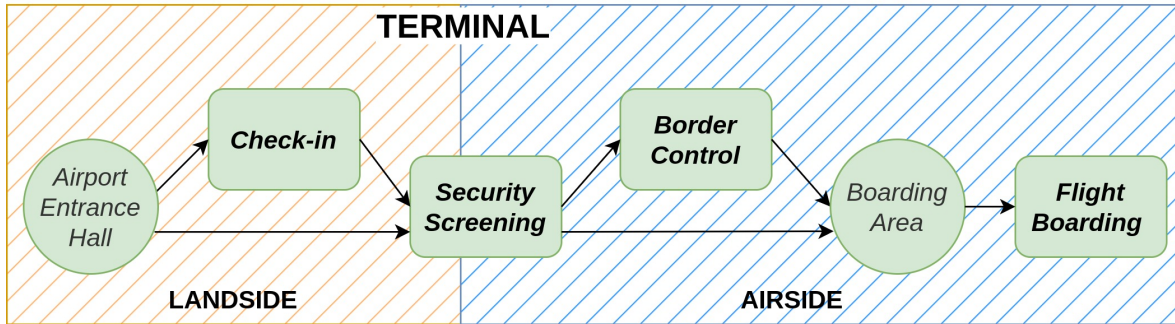


Figure 2.7: Sequence of airport processes that outbound passengers go through.

is estimated using statistics provided by CDG. These statistics inform on the average share of connecting passengers per departing terminal and the average percentage of connections between terminals.

2.6 Airport landside modelling

One of the main challenges encountered during this work is to model the airport passenger arrival process at the gate during nominal operations and during disruptive events. [Figure 2.7](#) presents the successive steps that, taken together, make the passenger door-to-gate journey. First, passengers go from home to the airport using their private car, a taxi, a bus, a subway, or a train. They can go to the check-in facilities to drop off their luggage and obtain their boarding pass. If passengers have no checked baggage, they can go directly to the security checkpoint and access the airport airside. Passengers travelling to a destination outside of Schengen area are subject to passport control, while those travelling to a Schengen airport can proceed directly to their departure gate. If passengers have extra time, they can spend it on facilities such as shops or restaurants on both the airport landside and airside.

Several papers have modelled the passenger journey through the airport. Various studies used discrete event simulation to model passenger behaviour in complex systems such as airports ([Mujica Mota, 2015](#); [Alodhaibi et al., 2017](#); [Kierzkowski and Kisiel, 2017](#)). Other works use agent-based modelling to simulate passenger journeys ([Schultz and Fricke, 2011](#); [Ma et al., 2011](#)). The first model focuses on the flow and sequence of events in each process part of the system. In contrast, the second focuses on individual agents and their interactions with other agents. It enables a microscopic modelling of passenger flows that can capture passenger behaviours. Discrete event simulation can provide a mesoscopic representation, focusing only on the flow of passengers rather than on each passenger. Both types of methods can be implemented thanks to commercial solvers such as AnyLogic ([Borshchev, 2014](#)), ARENA ([Kelton et al., 2002](#)) or SIMIO

(Pegden, 2008).

Microscopic modelling captures detailed passenger behaviour and complex interactions between processes. In this sense, it enables a more realistic approach than analytical approaches using macroscopic models. However, due to the high granularity, optimisation on these models is generally challenging due to the extensive computational time it can take to perform a single run. Several works have focused on integration frameworks for simulation and optimisation; this will be discussed in [Chapter 6](#).

Finally, machine learning and statistical approaches have been used with the collection of data from Wi-Fi, Bluetooth sensors or even personal mobile devices to characterise the passenger journey within the airport terminal ([Nikoue et al., 2015](#); [Schauer et al., 2014](#); [Mujica Mota et al., 2020](#)). [Schultz et al. \(2009\)](#), through data collection with Dresden Airport’s video surveillance system, reveal that passenger speed is notably impacted by gender, travel purpose (business/leisure), group size, and carry-on baggage details. In the current study, however, we only access anonymised passenger timestamps at airport security screening. We are therefore unable to carry out such kind of analyses.

We propose a deterministic model that only considers passenger flows and transfers based on statistics provided by CDG. This study assumes that passengers go directly to their departure gate and do not spend extra time in other facilities such as restaurants or shops. Moreover, due to the type of collected data (i.e. passenger timestamps at the security screening system), the work presented here does not consider passenger check-in. Instead, the passenger journey is captured from security screening onwards. We describe below the modelling retained for the security screening system process.

2.6.1 Modelling airport security screening system

Security checkpoints are a key element of airports. These facilities scan passengers and carry-on luggage to detect threats and ensure safe flights. An illustration of a generic Security Checkpoint (SC) is provided in [Figure 2.8](#). A SC comprises a set of security lanes and a common queuing line. A security team of five or six agents can operate each security lane. For the sake of simplicity, we do not model priority lanes or specific facilities that could be dedicated to a specific type of passenger (e.g. business passengers or even passengers with reduced mobility). An airport can be composed of several SC. For instance, between 16 and 18 SCs are operated at CDG airport. Some specific SCs are also dedicated to connecting passengers. However, since we do not have information on connecting passengers and do not know which connecting passengers have to go through SC, we do not model connecting SCs in this study. Each SC is associated with a boarding room. Passengers go through the queuing line and wait until they are assigned to a security lane to be screened. In this model, we assume several security lanes are operated each hour on each SC based on the passenger volume forecast. This number can evolve during the day, depending on the expected number of passengers.

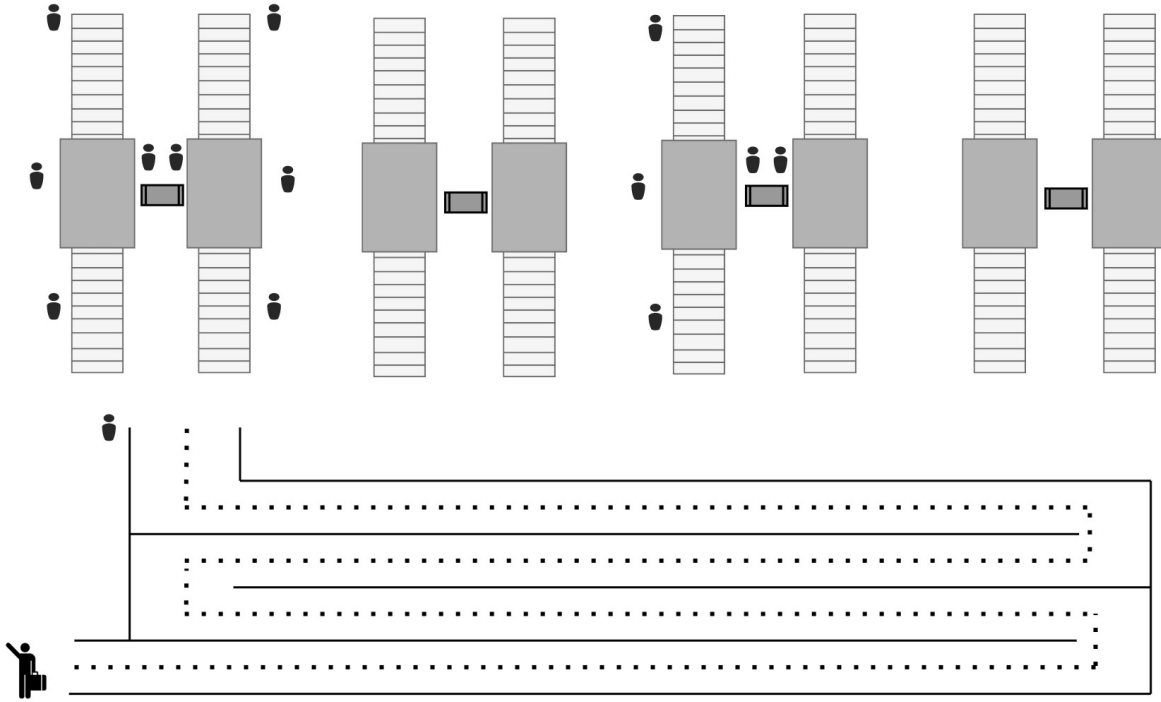


Figure 2.8: General appearance of an airport security checkpoint.

Each open security position is assumed to provide a constant service rate, and the queuing line follows a First-In-First-Out (FIFO) model. This assumption means that security checkpoints serve passengers according to their arrival order. Furthermore, since we consider a multimodal collaborative environment with real-time information sharing, passenger arrival profiles predicted at the tactical level are assumed sufficiently reliable to model the process in a deterministic context.

Under these assumptions, passenger waiting times can be computed thanks to cumulative diagrams as explained by [De Neufville et al. \(2013b\)](#). [Figure 2.9](#) provides an example of this type of diagram. Depending on the number of open security lanes and the passenger demand, passenger throughput and queuing time can be computed.

We consider an alternative scenario that involves opening a priority lane for passengers with ‘priority’ status. This status may be granted to delayed passengers due to an access mode disruption. Such information could be obtained through information sharing with ground transportation operators or a dedicated passenger service application. In this case, we propose considering a fast-track queue for each security checkpoint linked to a security lane where only priority passengers could be processed.

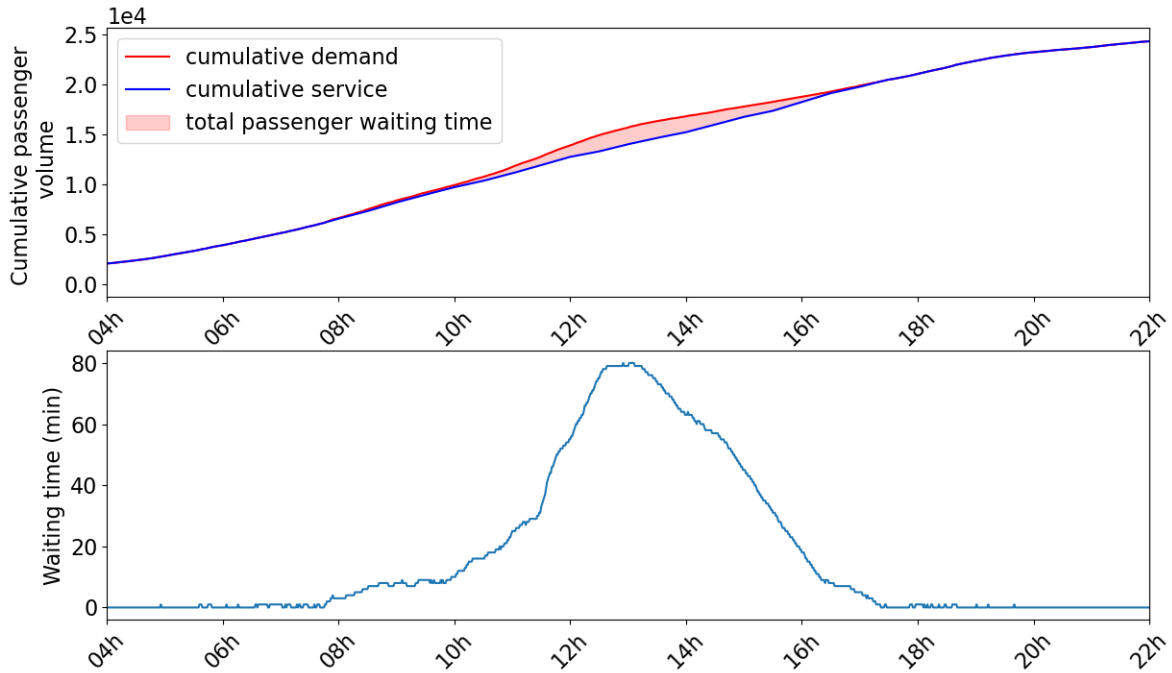


Figure 2.9: Illustration of a cumulative diagram. The top diagram illustrates the cumulative demand and service through red and blue curves. The red area between both curves represents the total waiting time. Based on the cumulative diagram, the bottom diagram represents the passenger waiting time evaluated by measuring the horizontal distance between the red and the blue curves.

2.6.2 Modelling passenger transfers from security checkpoints to the gate

Once passengers go through the security screening system, they can either directly proceed to the boarding area or need to cross a border control. We do not model this process in this study due to a lack of data, but we should consider it in future work. We assume non-Schengen passengers spend some time at the border control, unlike those travelling within the Schengen area. This time is assumed to be constant and equal to ten minutes, accounting for queuing effects. Finally, we model the transfer time from security to the gate through a constant walking time, depending on the terminal. Values are available in [Table 2.3](#).

[Figure 2.10](#) summarises the global procedure to model passenger trajectory throughout the airport.

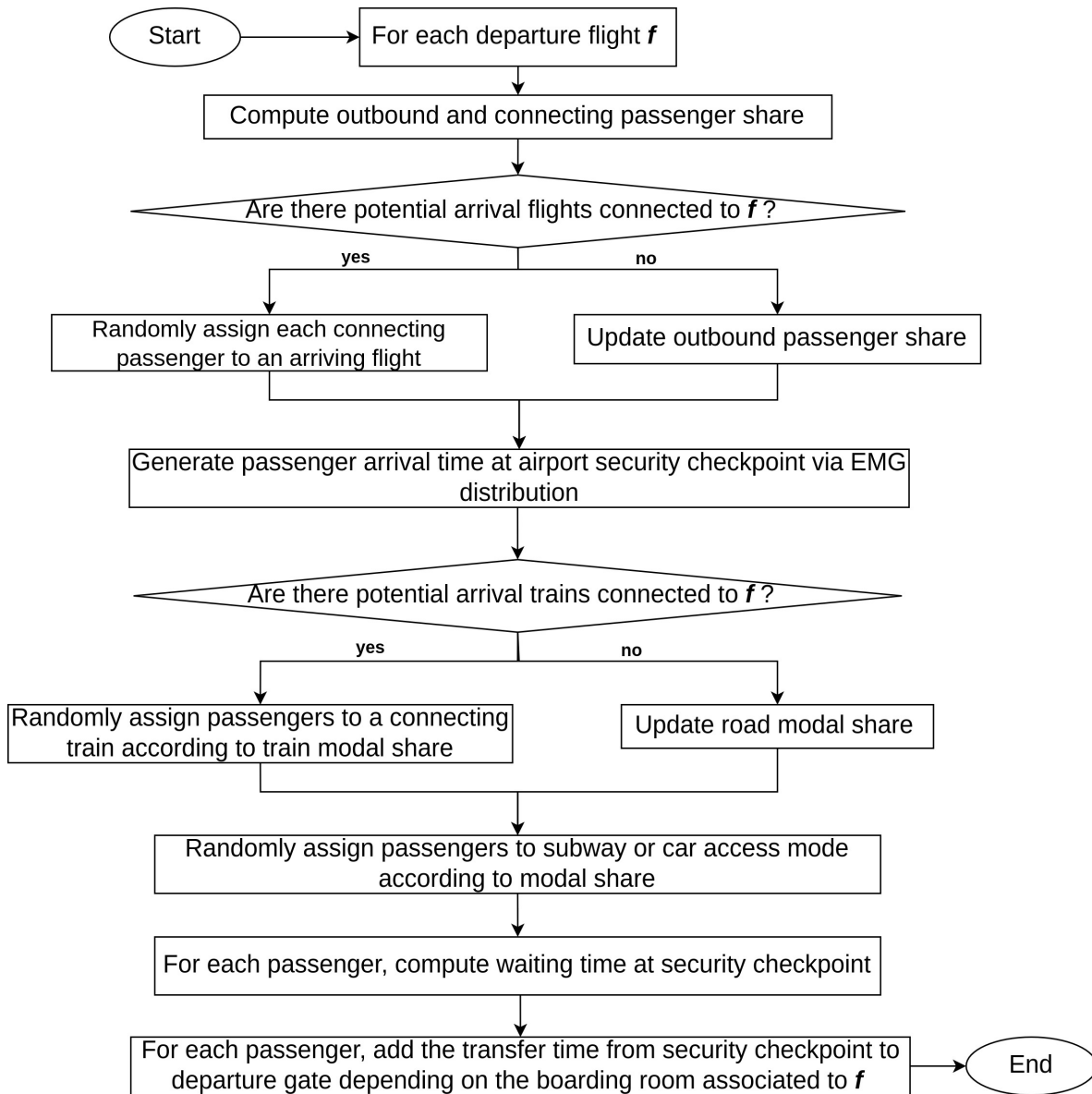


Figure 2.10: Passenger flow modelling methodology.

2.7 Conclusion

This chapter has provided the basis for modelling passenger flows within the airport before considering airport operations optimisation. We have constructed an airport modelling framework that serves as a strong foundation for our proposed optimisation models and methods. First, we have introduced datasets supporting our analysis, laying the groundwork for data-driven approaches. Secondly, we have presented a framework to create an accurate model of the passenger arrival process at the airport. We have demonstrated the suitability of using the EMG distribution to simulate such a process (Buire et al., 2021). Additionally, we have proposed modelling passenger trajectory through the airport, focusing on the journey towards the security screening system. Using queuing models, the model can generate estimations of passenger waiting times at this facility, which will be required when evaluating the benefits of optimising security team allocation later. The complete methodology has been detailed to provide a reproducible framework, with aggregated data available via the following link: <http://data.recherche.enac.fr/scozzaro/pfrsp/>.

Part I conclusion

This first part has provided an exploration of airport systems, examining them from the perspective of both a passenger and an operations researcher. In [Chapter 2](#), we have illustrated the current management of airport operations, with a particular focus on tactical disruption management strategies. We have looked at the basic principles of OR, a powerful discipline that has shown promising results in improving decision-making processes for complex systems such as hub airports. After analysing existing incentives to improve passenger door-to-door journeys and integrate different modes of transport, we have explored the tactical management of airport operations within a novel paradigm.

In the context of the European project TRANSIT ([Bueno et al., 2022](#)), we consider a futuristic scenario where we envision a seamless collaboration between air and ground transportation stakeholders, providing airport operators with a holistic view of passenger door-to-door journeys and potential delays resulting from disruptions in airport access modes. Our literature review reveals a gap in efficiently accounting for ground transportation disruptions affecting airport operations. We have identified the need for recovery strategies based on optimisation techniques that could significantly enhance airport operators' ability to improve the passenger experience. We have concluded [Chapter 1](#) by proposing two optimisation problems to mitigate the impact of such disruptions on passengers.

To test our models and solution approaches for these problems, [Chapter 2](#) has introduced a data-driven macroscopic methodology for modelling passenger flows and the airport landside. We have shown that the EMG is a suitable parametric distribution to capture how long passengers arrive before their departing flights. The entire modelling framework has been made publicly available for reproducibility, accessible via the following link: <http://data.recherche.enac.fr/scozzaro/pfrsp/>.

In [Part II](#), we study the two passenger-oriented optimisation problems formulated to address airport access mode disruptions. We present models and solving methods for both problems, followed by an extensive case study on CDG. This study includes various access mode disruption scenarios and generates diverse problem instances for analysis. By solving these instances, we aim to evaluate the ability of the solution we propose to provide efficient recovery strategies for airport operators.

Part II

Recovery strategies to improve passenger experience during airport access mode disruptions

Airport access mode disruptions can threaten the resilience of passenger door-to-door journeys. In [Part I](#), we have explored how airports can react to these disruptions, emphasising the need for collaboration between air and ground transportation stakeholders. In this second part, we develop innovative recovery strategies introduced in [Section 1.6](#), in order to manage these disruptions and reduce their impact on passenger journeys.

This part is divided into three chapters. [Chapter 3](#) presents the first recovery strategy based on a tactical reallocation of airport security screening resources. By dynamically reallocating the security teams, we aim to optimise the passenger flow in the airport security screening system. To achieve this, we define two optimisation problems that differ in their consideration of segregating the passenger flow to prioritise the passengers affected by the disruption. This chapter provides a detailed description of both optimisation problems, outlining their associated mathematical models, the solution strategy adopted, and performance tests of the different proposed solution algorithms.

[Chapter 4](#) details the second recovery strategy, which consists of rescheduling departing and arriving flights at the tactical level, specifically to accommodate delayed passengers. This complex task involves striking a balance between waiting for delayed passengers, complying with operational constraints, and considering the transfer time requirements of connecting passengers. The problem is defined, and a linear mathematical formulation is proposed. Two solution approaches are suggested and their performances, depending on problem and instance characteristics, are discussed in detail.

Finally, [Chapter 5](#) explores the practical implementation of these recovery strategies at the airport level. Unlike the previous chapters, which focus on mathematical problem definitions and algorithmic solutions, in this chapter, we aim to study the practical implications and feasibility of implementing these recovery strategies within a real airport system. We highlight the communication links required between stakeholders to regularly update the airport's passenger arrival profile forecast in the event of an access mode disruption. The online aspect of this data flow, arriving throughout the day, led us to consider a dynamic approach to implement the proposed recovery strategies. Therefore, we propose a sliding window approach to optimise airport operations along the day of operation, allowing the handling of real-time passenger information arriving along the considered day. In order to bridge the gap between theoretical solutions and practical applicability, a case study is developed, based on a historical operating day, and several disruption scenarios are simulated and investigated. The analyses identify the differential impact of each strategy, providing valuable insight into the effectiveness of such recovery mechanisms at the operational level.

Chapter 3

Security Screening Resources Allocation Problem (SSRAP)

Security screening systems are a critical part of the passenger journey through the airport. They are essential for detecting potential objects that could pose a threat during flights. Initially, the security screening process was straightforward for passengers. However, various terrorist attacks led to the emergence of a more complex system, increasing passenger screening time. These events include:

- 9/11 Attacks (2001): the 9/11 attacks led to the creation of the TSA in the U.S. and global security enhancements ([Blalock et al., 2007](#));
- Underwear Bomber Attempt (2009): this incident prompted the use of full-body scanners ([Stewart and Mueller, 2011](#));
- Transatlantic Bomb Plot (2006): restrictions on liquids in carry-on luggage resulted from this foiled plot ([Seidenstat and Splane, 2009](#));
- Lockerbie Bombing (1988): baggage screening and security measures improved after this tragedy ([Hainmüller and Lemnitzer, 2003](#)).

A key challenge for airports is to strike a delicate balance between strict security protocols and ensuring a seamless experience for travellers. To ensure a smooth flow of passengers through airport security, operators must determine the optimal number of security teams to be deployed in the security screening system. The greater the number of security teams, the greater the passenger processing capacity. However, hiring additional teams yields a direct cost for the airport. Consequently, any unused excess capacity represents an undesirable additional cost to the airport. The objective is therefore to match demand with capacity to minimise overall operating costs for airport operators while maintaining a high level of service for passengers. This level of

service can be assessed using performance indicators, such as average passenger waiting times or average queue lengths.

In this chapter, we focus on the impact on the airport security system of a disruption in passenger flow due to an unexpected event on a ground transportation mode. Such events directly impact the passenger arrival profile and can lead to a mismatch between airport capacity and passenger demand. This mismatch can lead to exceeded capacity, resulting in longer passenger waiting times. In such scenarios, since some passengers are already late due to delays on their way to the airport, long waiting times could cause them to miss their departure flights, thus jeopardising their entire door-to-door journey. Therefore, we propose a strategy to improve the passenger experience in security during disruptive events (Scozzaro et al., 2022). In the following, we assume that the disrupted passenger arrival profile can be anticipated thanks to an active communication exchange between air and ground transportation actors and passengers. Thanks to this, we propose to reallocate airport security teams at the tactical level to match demand and capacity in order to improve passenger flow at security checkpoints. Two problem versions are investigated. The first version is based on reallocating security teams under the assumption of finite resources, to match capacity and demand at the tactical level, without segregating passenger flow. The second strategy proposes an extension to the problem by considering the opening of a dedicated fast-track security lane for passengers affected by the disruption.

The remainder of the chapter is structured as follows: [Section 3.1](#) presents a literature review on tactical reallocation of airport resources. Then, the allocation of human resources at CDG airport is presented in [Section 3.2](#). [Section 3.3](#) and [Section 3.4](#) present the security reallocation problem without and with passenger flow segregation. For each problem version, a problem description, a mathematical model, solving methods and computational performance tests are presented.

3.1 Tactical reallocation of airport resources: a literature review

Different works have been led to improve airport queuing systems and resource allocation. [Alodhaibi et al. \(2020\)](#) uses a simulation optimisation strategy to propose a dynamic allocation of security staff across the airport. Security staff can be reallocated to inbound and outbound passenger flow depending on the queue lengths observed at the security screening processes.

Queues are often observed in airport operations, either airside (such as aircraft waiting at the runway threshold) or in terminals (such as passengers waiting at check-in counters, border control, or even security checkpoints). [De Neufville et al. \(2013b\)](#) highlight that queuing theory can be powerful in improving the handling of airport operations. This approach, which makes several assumptions about demand, provides

analytical results that can be used to design optimal control strategies. Queuing theory is part of stochastic modelling and takes into account the variability of the demand rate and/or the service rate (Harchol-Balter, 2013). This variability can cause queues to form even if the service rate (i.e. the number of passengers that can be served within a given time interval) is higher than the demand rate (i.e. the number of passengers that enter the queuing system in a given time). If a large number of passengers enter the system at the same time, a queue will form. Queuing theory is, therefore, particularly useful for designing control policies at the strategic level, when the demand rate can be highly variable. On the airside, Pujet et al. (1999) implement a virtual queue to control the departure process and avoid aircraft waiting at the runway threshold. Jacquillat and Odoni (2015) combine an arrival and departure service rate control strategy with a stochastic and dynamic queuing model to estimate airport delays as a function of a flight schedule or airport capacity. On the terminal side, Zhang (2009) designs a staffing policy at border crossing stations by adjusting the number of servers depending on the expected queue length of the system. However, such criteria do not always prevent passengers from experiencing long delays. A major drawback of using queuing theory to design optimal control strategies is that it relies on assumptions about the demand distribution. For example, suppose the demand distribution does not follow a Poisson distribution (as is the case for passenger arrivals at an airport). In that case, analytical results are much more difficult to obtain, especially for large-scale problems.

To address this problem, discrete event simulation models are often used to design control policies for queuing systems. Kierzkowski and Kisiel (2017) develop a simulation model to control the operation of the security system at Wrocław Airport. They highlight the potential cost benefits of allowing queue formation in the scheduling phase while maintaining an acceptable Level of Service (LOS). They use the maximum queue length as a criterion to be minimised. The control strategy is dynamic and defines the number of lanes to open or close depending on the queue length observed during the simulation. Mujica Mota et al. (2021b) partition passengers according to characteristics that influence their speed in the security screening process (such as business passengers, families or passengers with reduced mobility). They show that this distinction helps to improve security line policies by adapting the system to these different categories. They highlight that by designing an appropriate category in combination with new technology, capacity could be increased by up to 20% in a study case around Mexico City airport. Mujica Mota et al. (2021c) use simulation to study the impact of ‘smart passengers’ on the flow of departing passengers at airports. This new category of passengers, who share live information with airport stakeholders, can reduce their time spent in airport queuing systems by using new specific processes or facilities. Pérez et al. (2021) use a simulation approach to study the dynamic allocation of security screening resources at Phoenix Sky Harbor International Airport. They minimise either the passenger waiting time or the queue length under staff resource constraints per 15-minute interval. The allocation is optimised using feedback from the simulation

model.

The main weakness of simulation-based control strategies is that they generally require many iterations to find an efficient control policy. This often leads to high computational time, especially for large problem instances. Furthermore, such strategies are not guaranteed to be optimal.

In this chapter, we propose to model and solve the SSRAP using linear programming. This exact method is often used to solve resource allocation problems (Panik, 2018). We assume that thanks to the exchange of information at the tactical level with passengers and ground transportation operators, the airport would have accurate forecasts of the demand of arriving passengers. Therefore, we propose to work in a deterministic context. Consequently, our approach does not consider stochastic delays and focuses only on minimising congestion delays. The next section presents how the CDG airport operators currently allocate security teams to the airport's security screening system.

3.2 Security resources management at CDG airport

This section explains how CDG operators allocate teams to the airport's security screening system. First, we present the main outcomes obtained from an interview with the person responsible for allocating security resources at CDG airport. We then describe the methodology used to calculate the initial number of security teams based on the interview outcomes.

3.2.1 Interview with CDG airport operators

On May 24th, 2022, we conducted an interview with A. Bonneton, responsible for allocating security teams at security screening resources at CDG. This interview allowed us to gain insights into how CDG manages its airport security teams, allowing us to model the security team reallocation problem and align it with the actual operational characteristics and constraints of the airport.

Subcontracting and market allocation

At CDG, airport security operations are outsourced to three different companies, each of which is assigned to specific areas of the airport known as markets, with each market comprising one or more CDG terminals. These security companies are integrated into the APOC. The segregation of markets is useful to increase operational resilience during workers' strikes. If the personnel of one company goes on strike, the other two can cover the market managed by the striking company, ensuring uninterrupted security services.

However, in most cases, each company operates exclusively within its designated market and there is no inter-market transfer of security officers.

Demand forecasting and resource allocation

CDG undertakes the responsibility of providing passenger traffic forecasts for each security checkpoint to the contracted security companies. Based on these forecasts, the security companies determine the number of security teams required to meet the forecast demand.

A structured timeline governs this process: an initial passenger arrival forecast is communicated to the security companies 45 days before the day of operations. This forecast undergoes an update 20 days before the operational day. Since the COVID-19 pandemic, a revised passenger forecast is sent seven days before operations, ensuring adaptability in response to evolving situations.

Airport level of service measurement

CDG employs different strategies to evaluate the level of service of its airport security system:

- compliance with airport security procedures: ensures adherence to established security protocols;
- fluidity (passenger waiting time): compute the share of passengers waiting less than 10 minutes;
- anonymous passenger surveys: used to evaluate overall passenger satisfaction.

Order of magnitudes

CDG operators provided different order of magnitude regarding security system characteristics:

- Each security checkpoint comprises between 8 and 15 lanes;
- Each lane is staffed by five to six agents, including personnel for pre-X-ray screening, pre-screening, and full-body searches. Notably, when two lanes are opened concurrently, the need for duplicate full-body search agents is eliminated;
- Each open security lane provides a throughput of 120-130 passengers per hour;
- As of June 2022, CDG employed 474 agents for Terminal 2E, 548 for Terminal 2F, 55 for Terminal G, and 305 for Terminals A/B/C/D. These figures account

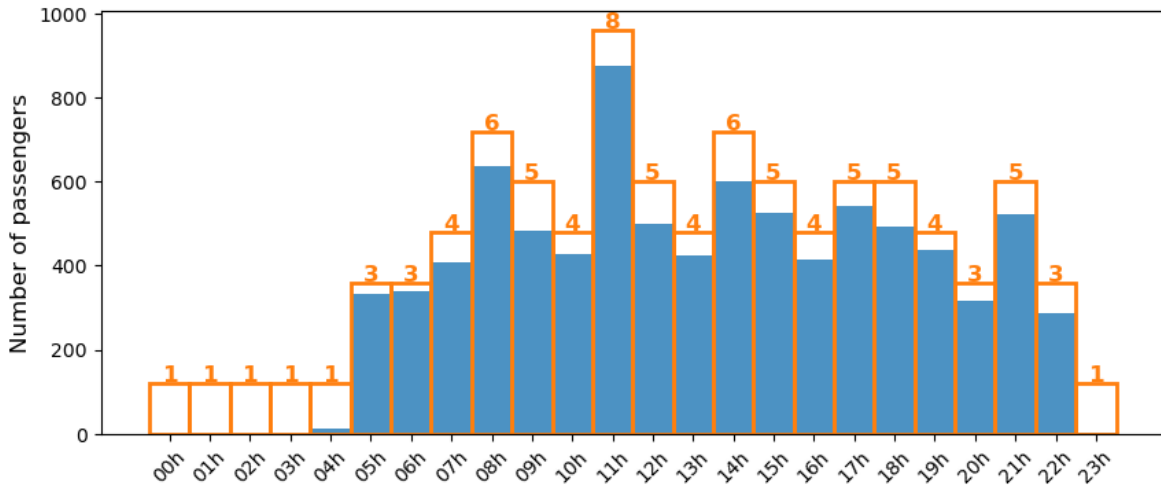


Figure 3.1: Illustration of the number of lanes required for one security checkpoint. The number of passengers per hour is displayed in blue, the service rate per hour in orange, and the number of opened lanes providing the required service rate is shown above the orange bars.

for various employment arrangements, including part-time work and partial un-employment. Terminals 1 and 3 were still closed in the context of the COVID-19 pandemic;

- CDG has set itself one target: 90% of passengers should experience queuing times of less than 10 minutes, and any passenger queuing for more than 30 minutes is considered to be unacceptable, although such delays occur sometimes in practice.

Time and passenger screening system configuration

Each boarding area, and therefore each gate, is equipped with a security system for departing passengers. There is currently no priority line based on departure time, except for a dedicated fast-track lane for business passengers. Departing passengers can pass through the security system at any time during the departure day, giving travellers the flexibility to reach their boarding gate at any time.

This comprehensive overview sheds light on the complex management of security resources at CDG and provides a basis for our subsequent analysis and modelling work.

3.2.2 Initial security team allocation

In order to allocate security teams effectively, it is essential to know the actual available resources. Unfortunately, the exact number of lanes operating at CDG on specific days was not available. To estimate this, we used a method that takes into account

the predicted flow of passengers per hour at each security checkpoint. Each open line was assumed to handle 120 passengers per hour, and the number of lanes was determined by opening the minimum number of lanes necessary to exceed the number of passengers in that hour. In addition, at least one lane was open each hour at each checkpoint. [Figure 3.1](#) illustrates this approach for a single security checkpoint, where blue bars represent the number of passengers per hour and orange rectangles represent the maximum service rate. The number of open lanes leading to such a service rate is shown above each bar.

3.2.3 Illustration of security team reallocation relevance

Our proposal to reallocate security screening teams is based on the statement that disruptions in passenger flows can create imbalances between demand and capacity in airport security screening systems. We illustrate this statement through a simplified example below.

[Figure 3.2](#) shows the effect of a disruption on the passenger arrival time distribution at two security checkpoints. The blue curve represents the normal passenger arrival profile, while the orange curve illustrates the disrupted flow due to a subway disruption. Note that the impact of the disruption varies between security checkpoints. For example, at 10am there is a simultaneous increase and decrease in passengers at checkpoints C2F-F1 and CT1-B, respectively. This is due to potential imbalances in access mode shares, where more passengers associated with one security checkpoint may be affected than those at another checkpoint. In this case, transferring resources between them could be beneficial. Consequently, one security lane should be closed at C2F-F1 and one lane should be open at CT1-B.

Conversely, at 11am, the situation is reversed: one lane should be open at C2F-F1 and one lane should be closed at CT1-B. Understanding the impact of disruptions guides the strategic redeployment of security teams, ensuring efficient use of resources in response to dynamic passenger patterns.

To this end, we propose a tactical reallocation of security teams when access mode disruptions occur. We present two different versions of the security resource allocation problem: the first one, with a common queue for all passengers under the FIFO assumption, is called the Classical Security Screening Resource Allocation Problem (C-SSRAP). The second one, which allows passenger flow segregation to process those affected by the disruption in a fast-track lane, is called the Priority Security Screening Resource Allocation Problem (P-SSRAP).

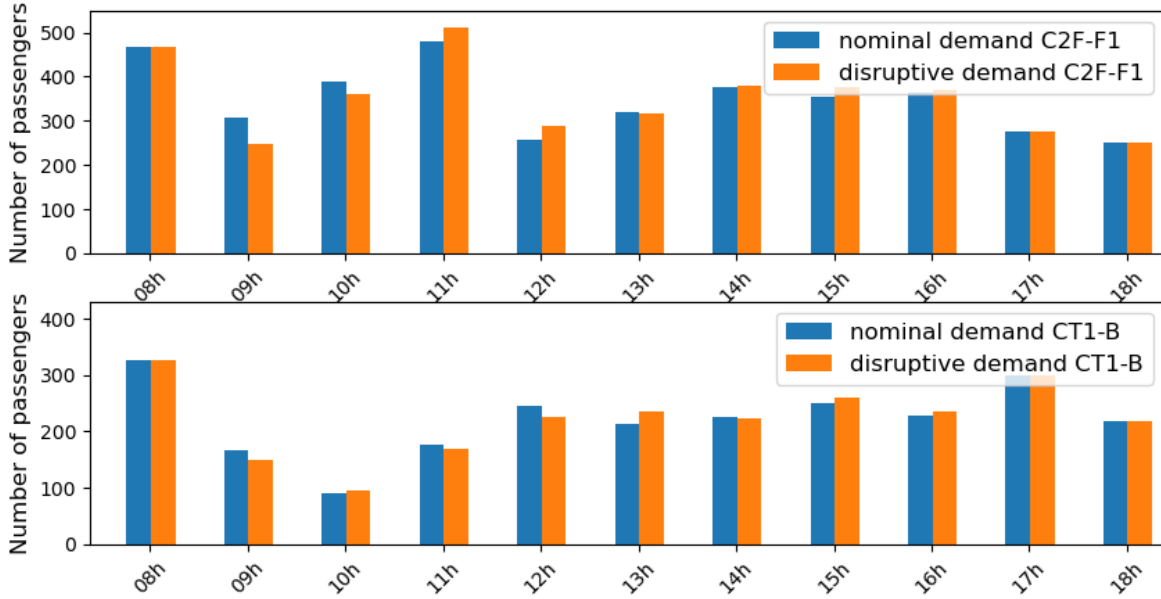


Figure 3.2: Illustration of passenger arrival profile at two security checkpoints, without and with subway disruption, in blue and orange, respectively.

3.3 Classical-Security Screening Resources Allocation Problem (C-SSRAP)

3.3.1 Problem description

We assume that CDG airport is divided into three markets, each operated by a specific security company. Each market is associated with a specific area of the airport. Therefore, we assume that each security team works in a specific area. It can work at the various security checkpoints in that area, but not in the areas of the other markets. Consequently, the reallocation problem can be considered for each single market, each problem being independent from the other ones. We therefore describe the C-SSRAP for only one market.

The only decisions that need to be made are how to allocate the different teams to the different checkpoints during the day. The optimisation problem consists of finding a number of lines to be opened, for each security checkpoint, for each hour, under the finite resource constraint to improve the airport LOS. Several criteria can be used to optimise the allocation, such as minimising the maximum passenger waiting time, the average waiting time or even the queue length. The first one favours fairness among passengers, unlike the second and third ones, which do not prevent long waiting times for several passengers. In terms of magnitude, the CDG operators consider an allocation resulting in a waiting time of more than 30 minutes to be unacceptable. In addition,

90% of passengers should wait less than ten minutes. In the following, we choose to keep the first two criteria in order to design an objective function to be minimised. We aim to minimise the average waiting time of the passenger and penalise large delays (by activating a penalty if the maximum waiting time of the passenger is higher than 30 minutes). The mathematical model of this optimisation problem is presented in Section 3.3.2.

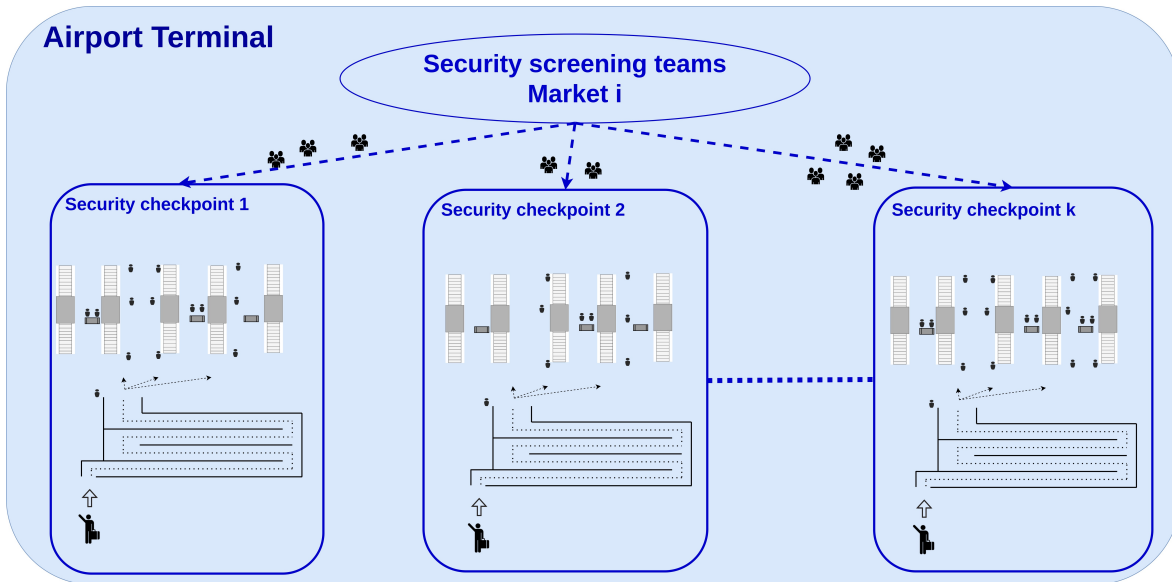


Figure 3.3: Scheme of an airport security system with finite resources and a single market (classical version). It consists of a set of security checkpoints, and a finite number of security teams to operate them. Each checkpoint has a finite number of lanes and a common queuing line.

We consider FIFO assumption to model security checkpoint queuing systems. Each open lane is assumed to maintain a constant throughput of 120 passengers per hour, as estimated by CDG operators. We consider a deterministic context to evaluate passenger waiting time and use cumulative services and cumulative demand metrics to compute them, as previously explained in Section 2.6. An illustration in Figure 3.3 provides a summary of the problem being considered for one market and one hour.

Queuing model and waiting time computation

We consider a discrete-time horizon denoted T and a set of security checkpoints denoted S . A specific time window during the day is considered. This means that an initial queue can be formed at each security checkpoint. For each time step t and each security checkpoint s , a number of arriving passengers $d_{s,t}$ is expected. We introduce the variables $q_{s,t}$ and $y_{s,t}$ as the length of the queue and the number of passengers served

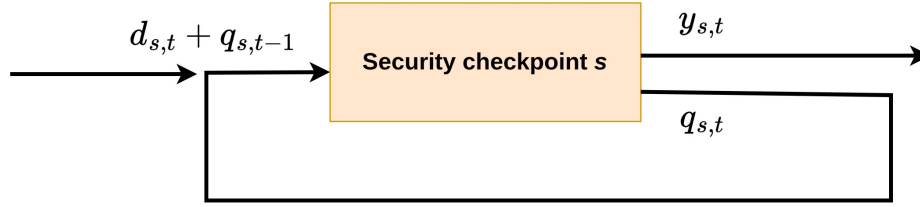


Figure 3.4: Queuing line model retained for the security area. The figure displays for a time t how auxiliary variables representing demand ($d_{s,t}$), queue ($q_{s,t}$) and service ($y_{s,t}$) are updated for a common queuing line of a security area s .

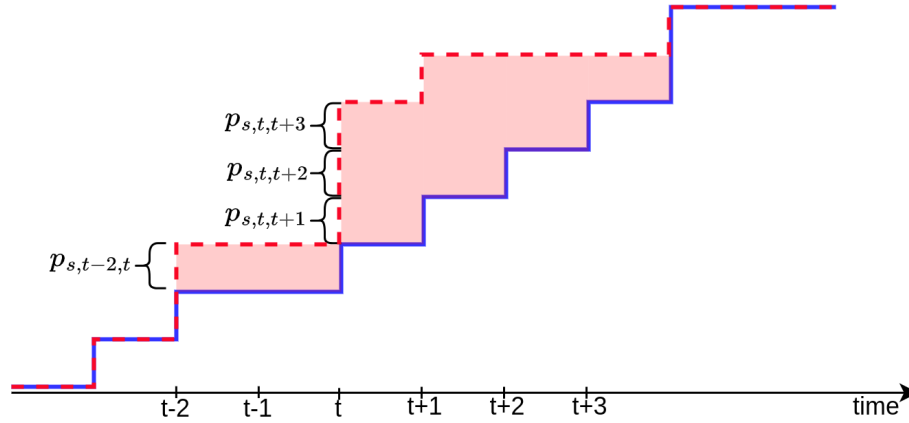


Figure 3.5: Cumulative diagram used to compute passenger waiting time at a common security area s . The red dotted curve represents the cumulative passenger arrival profile at the security area while the blue curve represents the cumulative number of passengers served. The red zone in the diagram highlights the time when a queuing line is formed. The number of passengers arrived at t and served at t' is noted $p_{s,t,t'}$. In this example, three-time steps are required to process the total number of passengers arriving at t .

at time t at security checkpoint s . More precisely, $q_{s,t}$ is the length of the queue after processing $y_{s,t}$ passengers. The dynamics linking the different variables is illustrated by [Figure 3.4](#).

Since we consider a discrete-time horizon, the methodology for computing waiting time is slightly different from the one using continuous cumulative diagram, presented by [De Neufville et al. \(2013a\)](#). This results in cumulative demand and service curves being represented by step functions. Consequently, passengers arriving at different time steps may experience different waiting times. Let \mathcal{S} be the set of security checkpoints and \mathcal{T} be the set of discrete times. We introduce the notation $u_{s,t,t'}$ with $s \in \mathcal{S}$ and $(t, t') \in \mathcal{T}^2$ such as $t \leq t'$ to quantify the number of passengers waiting at security checkpoint s at t and served at t' . Similarly, we introduce $p_{s,t,t'}$ as the number of

passengers arriving at security checkpoint s at t and served at t' . The waiting time at security checkpoint s at t is computed by calculating the average waiting time of passengers $p_{s,t,t'}$ for all $t' \geq t$. An illustration of such modelling is given in [Figure 3.5](#). In this example, the average waiting time of passengers arriving at t is equal to two time steps. Note that the number of passengers arrived at t and served at $t+1$ ($p_{s,t,t+1}$) is equal to the number of passengers initially queuing at $t+1$ and served after $t+1$ ($u_{s,t+1,t+1}$).

3.3.2 Mixed Integer Linear Programming (MILP) model C-SSRAP

This section proposes a linear mathematical formulation of the C-SSRAP, for one market and over one time window. In order to present the mathematical model related to this problem, we detail the data, decision variables, objective function and constraints below.

Data

δt	time step (usually 5 minutes)
\mathcal{S}	set of security areas
$\mathcal{T} = \{1, \dots, \mathcal{T} \}$	set of discrete times indices. Each consecutive times are separated by δt .
$\mathcal{H} = \{1, \dots, \mathcal{H} \}$	set of time interval indices where security lane openings are decided. Each time interval lasts an exact number of time steps δt (usually 60-minute duration)
$\forall s \in \mathcal{S}, t \in \mathcal{T} : D_{s,t}$	number of passengers expected to arrive at t in security checkpoint s
θ	service rate per time step for one security lane
$\forall h \in \mathcal{H} : L_h$	maximum number of security lanes that can be operated during interval h
$\forall s \in \mathcal{S} : L_s$	maximum number of security lanes that can be operated in security checkpoint s
$\forall t \in \mathcal{T} : H_t$	time interval included in \mathcal{H} that covers t
$\forall s \in \mathcal{S} : Q_s$	initial number of passengers waiting in queuing line of security checkpoint s
W_{\max}	maximum acceptable passenger waiting time in security system

Decision variables**Main decision variables**

$\forall s \in \mathcal{S}, h \in \mathcal{H} : x_{s,h}$	number of security lanes open in security check-point s during time interval h
--	--

Auxiliary decision variables

$\forall s \in \mathcal{S}, t \in \mathcal{T} : y_{s,t}$	number of passengers served in security check-point s at t
$\forall s \in \mathcal{S}, t \in \mathcal{T} : q_{s,t}$	number of passengers that are still waiting in queuing line after passengers served at t
$\forall s \in \mathcal{S}, t \in \mathcal{T} : w_{s,t}$	average waiting time experienced by passengers entered in queuing system of s at t
$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : p_{s,t,t'}$	number of passengers arrived at security check-point s at t and served at t'
$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : u_{s,t,t'}$	number of passengers in queuing line at t and served at t'
$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : o_{s,t,t'}$	$= \begin{cases} 1 & \text{if at least one passenger queuing at } t \text{ on } s \text{ is still unserved at } t' \\ 0 & \text{otherwise} \end{cases}$
$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : r_{s,t,t'}$	$= \begin{cases} 1 & \text{if at least one passenger arrived at } t \text{ on } s \text{ is served at } t' \text{ or later} \\ 0 & \text{otherwise} \end{cases}$
$\forall s \in \mathcal{S}, t \in \mathcal{T} : l_{s,t}$	number of passengers arrived at t in s and queuing at the end of the optimisation time window
\bar{w}	maximum passenger waiting time allowed
k	penalty for maximum waiting time over \bar{w}

Objective function

The objective function to be minimised is the average passenger waiting time and is computed as follows:

$$\min \frac{\sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} (w_{s,t} \cdot D_{s,t})}{\sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} D_{s,t}} + \alpha \cdot k \quad (3.1)$$

where α is a coefficient such that a penalty $\alpha \cdot k$ is activated when the maximum waiting time exceeds W_{\max} . The penalty coefficient α is chosen large enough to favour solutions where passengers wait less than 30 minutes and, secondly, to favour the reduction of the average waiting time.

Constraints

The constraints are presented below.

$$x_{s,h} \leq L_s \quad h \in \mathcal{H}, s \in \mathcal{S} \quad (3.2)$$

$$\sum_{s \in \mathcal{S}} x_{s,h} \leq L_h \quad h \in \mathcal{H} \quad (3.3)$$

$$q_{s,t} = D_{s,t} + q_{s,t-1} - y_{s,t} \quad s \in \mathcal{S}, 2 \leq t \in \mathcal{T} \quad (3.4)$$

$$q_{s,1} = D_{s,1} + Q_s - y_{s,1} \quad s \in \mathcal{S} \quad (3.5)$$

$$y_{s,t} \leq \theta \cdot x_{s,H_t}, \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.6)$$

$$\sum_{t'=t}^{\mathcal{T}} u_{s,t,t'} \leq q_{s,t-1} \quad s \in \mathcal{S}, 2 \leq t \in \mathcal{T} \quad (3.7)$$

$$o_{s,t,t'} \geq \frac{1}{Q_s + \sum_{i=1}^{t'} D_{s,i}} \cdot (q_{s,t-1} - \sum_{i=t}^{t'} u_{s,t,i}) \quad s \in \mathcal{S}, (2 \leq t \leq t') \in \mathcal{T}^2 \quad (3.8)$$

$$p_{s,t,t'} \leq D_{s,t} \cdot (1 - o_{s,t,t'}) \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.9)$$

$$p_{s,t,t'} \leq y_{s,t'} - u_{s,t,t'} \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.10)$$

$$l_{s,t} = D_{s,t} - \sum_{i=t}^{|\mathcal{T}|} p_{s,t,i} \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.11)$$

$$w_{s,t} = \frac{1}{\max(1, D_{s,t})} \cdot \left(\sum_{t'=t}^{|\mathcal{T}|} (t' - t) \cdot p_{s,t,t'} + (|\mathcal{T}| - t) \cdot l_{s,t} \right) \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.12)$$

$$r_{s,t,t'} \geq \frac{p_{s,t,t'}}{\max(1, D_{s,t})} \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.13)$$

$$r_{s,t,|\mathcal{T}|} \geq \frac{l_{s,t}}{\max(1, D_{s,t})} \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.14)$$

$$\bar{w} \geq (t' - t) \cdot r_{s,t,t'} \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.15)$$

$$k \geq \bar{w} - W_{max} \quad (3.16)$$

$$x_{s,h} \in \mathbb{N} \quad s \in \mathcal{S}, h \in \mathcal{H} \quad (3.17)$$

$$k \geq 0, \bar{w} \geq 0 \quad (3.18)$$

$$q_{s,t} \in \mathbb{N}, w_{s,t} \in \mathbb{R}^+, l_{s,t} \in \mathbb{N} \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.19)$$

$$p_{s,t,t'} \in \{0, 1\}, s_{s,t,t'} \in \{0, 1\}, \quad s \in \mathcal{S}, t \in \mathcal{T}, t' \in \mathcal{T} \quad (3.20)$$

$$o_{s,t,t'} \in \mathbb{N}, r_{s,t,t'} \in \mathbb{N}, \quad s \in \mathcal{S}, t \in \mathcal{T}, t' \in \mathcal{T} \quad (3.21)$$

Constraint (3.2) limits the number of security teams allocated to each security checkpoint at each time interval. Similarly, Constraint (3.3) restricts the total number of security staff allocated across the airport during each time interval h . Constraints (3.4) and (3.5) govern the queue length, accounting for passenger arrivals, previous queue lengths, and passengers being screened. Constraint (3.6) regulates passenger service, ensuring they are served by the available security staff at each time slot. Constraints (3.7) and (3.8) maintain the queue service and compute waiting queue length. Constraints (3.9) and (3.10) fix the number of passengers arrived at t and served at t' . Constraint (3.11) computes the remaining number of passengers still queuing at the end of the optimisation time window considered. The waiting time for each passenger is calculated using Constraint (3.12). The maximum waiting times is set through Constraints (3.13), (3.14), and (3.15). The penalty variable k is fixed by Constraint (3.16). Constraint (3.17) imposes decision variables $x_{s,h}$ to be non-negative integers, while variables k and \bar{w} are ensured to be non-negative through Constraint (3.18). Queue lengths, waiting times, and passengers not served are non-negative integers, as specified in Constraint (3.19).

3.3.3 Solution approaches

Three solution approaches are considered to tackle the C-SSRAP. The model described in Section 3.3.2 is a MILP model, with continuous variables (average waiting time variables) and integer variables (e.g., security lane opening variables). A direct solving approach through Integer Programming is proposed, using the commercial solver Gurobi [Gurobi Optimization, LLC \(2023\)](#). Then, a greedy heuristic method is implemented, which is assumed to mimic what airport operators might decide during crisis management. Finally, a Simulated Annealing is proposed to solve this model. The greedy heuristic and simulated annealing are described in detail below.

Greedy Heuristic

Below, we propose a heuristic for allocating security teams to checkpoints. This heuristic relies on a greedy algorithm to reallocate security teams based on new passenger arrival profiles. The number of security teams assigned to each checkpoint for each hour is proportional to the number of passengers expected to arrive there. This greedy heuristic is similar to the strategy used by CDG operators for initially sizing the number of teams required per hour (as a reminder, CDG operators open a number of lanes proportional to the expected demand per hour on each checkpoint). The main steps of this heuristic are presented in [Algorithm 2](#), and an illustrative example is provided in [Table 3.1](#).

Algorithm 2 Greedy heuristic algorithm

```

1: for each hour-long interval do
2:   for each security checkpoint do
3:     Count the number of passengers expected over the interval time plus those
       already in the queue.
4:   end for
5:   Compute the proportion of passengers per security checkpoint.
6:   for each security checkpoint do
7:     Assign a (real) number of lanes proportional to the number of passengers.
8:     Truncate the decimal part of the number of lanes to get an integer number of
       open lanes.
9:   end for
10:  Compute the total number of lanes open throughout the airport security system.

11:  if the total number of allocated lanes is smaller than the total number of available
    lanes then
12:    Order the security checkpoints by the decimal parts of their fractional number
    of lanes in descending order. In the case of an equal decimal part, order by the
    lower integer part.
13:    for each security checkpoint do
14:      Open one lane and update the total number of open lanes.
15:      if the total number of open lanes equals the total number of available ones
        then
16:        break
17:      end if
18:    end for
19:  end if
20: end for

```

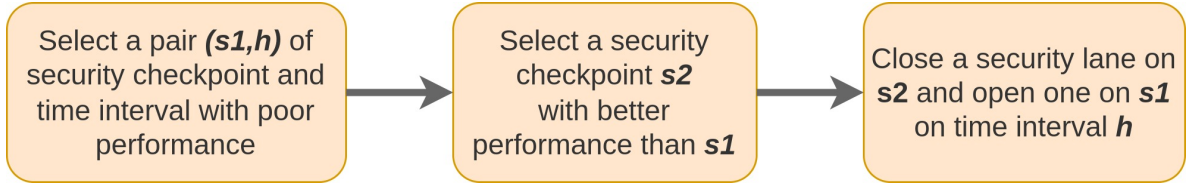
Simulated Annealing

SA is a metaheuristic known for solving complex problems, previously introduced in [Section 1.3](#). This method is a framework in which a neighbourhood generation process and an initial solution must be defined.

The initial allocation is estimated following the methodology presented in [Section 3.2](#), where a number of lanes are open depending on the forecast passenger arrival profile. Passenger arrival profile forecasts before the disruption are considered to generate this initial allocation. A neighbour of the current solution is selected by choosing a time interval h , during which decisions are made on opening lanes. Two security checkpoints are selected, and a team is moved from one checkpoint to the other during h by closing one lane at one checkpoint and opening another at the other. The selection

Table 3.1: Example of Greedy Lane Allocation.

Characteristics	Values
Hour considered	9 AM
Number of available teams	8
Security checkpoints	S1, S2, S3
Passengers arriving per checkpoint	S1: 700, S2: 100, S3: 200
Probability assigned to each checkpoint	S1: 0.7, S2: 0.1, S3: 0.2
(Real) number of open lanes per checkpoint	S1: 5.6, S2: 0.8, S3: 1.6
(Integer) number of open lanes per checkpoint	S1: 5, S2: 0, S3: 1
Order of checkpoints for additional lane opening	S2, S3, S1
Final allocation	S1: 5, S2: 1, S3: 2

**Figure 3.6:** Simulated Annealing neighbour generation process C-SSRAP.

is based on a performance indicator associated with each security checkpoint. The performance of each checkpoint is calculated by evaluating its contribution to the objective function. Since we consider a minimisation problem, the higher the contribution, the worse the performance. Checkpoints with worse performance are more likely to have a new security lane open, while those with better performance are more likely to have a lane closure. The neighbour generation is summarised in [Figure 3.6](#). In order to parameterise the simulated annealing process, a heat-up process is used to fix the initial acceptance rate of the new solution at 80%. The temperature-decreasing parameter is set to 0.999 and 2000 transitions are performed for each temperature step.

3.3.4 Performance analyses

This section compares the different solution approaches and tests their performances depending on the characteristics of the C-SSRAP model. The tests are conducted on a single test scenario that simulates a disruption on the road access to the airport, and the security team reallocation is operated just after the beginning of the disruption on a single security market. Here, only algorithmic performances are compared to assess the solution approach performances. The best solution approach is used later to test the method on other disruptive scenarios, gaining operational insights regarding resource allocation benefits for passengers and airport level of service in [Chapter 5](#).

We refer to the different solution strategies by the following terms:

- Greedy: solving the C-SSRAP model with the greedy algorithm;
- MILP: solving the C-SSRAP model with the MIP solver Gurobi 9.5.0 ([Gurobi Optimization, LLC, 2023](#));
- SA: solving the C-SSRAP model with the simulated annealing algorithm.

The tests are performed on an AMD Ryzen 5 4500U processor, Radeon GPU and 16 GB of RAM. The MILP-model is solved using the commercial solver Gurobi 9.5.0 solver.

First, we compare the results of different solution approaches, taking into account both objective function values and computation times. To do so, we generate different C-SSRAP instances by varying the time window duration for the security team reallocation. The larger the duration of the time window, the larger the model size (in terms of decision variables and constraints), and the more challenging it becomes to solve. We conduct sensitivity analyses by changing several parameters of the model, such as the time step duration used to discretised the model, the duration of time intervals where security teams are reallocated, or even by authorising the teams to be reallocated over the entire airport (i.e. removal market segregation constraint). These tests allow us to investigate the effects of model parameters on the different problem-solving strategies.

[Table 3.2](#) provides a comprehensive overview of the analyses and performances of the chosen solution methods applied to the C-SSRAP problem. It outlines the results for different time windows (2-hour, 4-hour, 6-hour, 8-hour, 10-hour, and 12-hour) through different key performance indicators (KPI) including the maximal waiting time (\mathbf{W}), average waiting time ($\overline{\mathbf{w}}$), and computational time (\mathbf{t}). The MILP-solution approach had a time limit of 600 seconds for each instance.

For the 2-hour time window, MILP solution approach achieved the optimal waiting time. The average passenger waiting time was reduced from 5.36 to 3.28 minutes, illustrating its effectiveness in reallocating security teams. The computation time for MILP was 2.6s, which is operationally low enough to support tactical disruption management actions by airport operators. The computation time for the SA and the greedy heuristic is 0.474s and 0.163s, respectively, slightly faster than the MILP solution approach. The SA also performs well, finding a solution within 0.6% of the optimal one. It is five times faster than the MILP solution approach and, with more computation time budget, may find the optimal solution. The greedy heuristic already improves the initial allocation but is still far from the optimal one.

Different trends can be observed for other time windows (4 hours, 6 hours, 8 hours, 10 hours and 12 hours). In each case, the greedy heuristic and SA methods consistently outperformed the MILP method regarding computational efficiency. The MILP model quickly becomes intractable on large instances, reaching the time limit for problems with time windows of 6 hours or more. The greedy heuristic improves the initial allocation in each case and runs in less than 1s, making it a simple but useful tool to

Table 3.2: Performance obtained by the proposed solution approaches (Initial, Heuristic, MILP, or SA) for solving the C-SSRAP over different time windows on scenario R60 (described in Table 5.1). \mathbf{W} , $\overline{\mathbf{w}}$, and \mathbf{t} refer to the maximal waiting time, average waiting time, and computational time, respectively. A time limit has been set to 600 seconds for the MILP solution approach. Minimum waiting times are highlighted in green and maximum waiting times over the maximum acceptable ones are highlighted in red.

TW duration	KPI	Initial	Greedy	MILP	SA
2-hour	\mathbf{W} (min)	30	20	20	20
	$\overline{\mathbf{w}}$ (min)	5.36	4.4	3.28	3.30
	\mathbf{t} (s)	-	0.163	2.616	0.474
4-hour	\mathbf{W} (min)	30	30	20	20
	$\overline{\mathbf{w}}$ (min)	7.52	5.66	3.99	3.99
	\mathbf{t} (s)	-	0.163	261.7	0.58
6-hour	\mathbf{W} (min)	30	30	20	20
	$\overline{\mathbf{w}}$ (min)	6.29	4.87	3.42	3.22
	\mathbf{t} (s)	0.0	0.162	600	6.04
8-hour	\mathbf{W} (min)	30	30	30	30
	$\overline{\mathbf{w}}$ (min)	5.69	4.58	3.28	3.31
	\mathbf{t} (s)	-	0.164	600	9.77
10-hour	\mathbf{W} (min)	30	30	30	20
	$\overline{\mathbf{w}}$ (min)	6.04	4.89	2.98	2.95
	\mathbf{t} (s)	-	0.165	600	13.80
12-hour	\mathbf{W} (min)	80	40	30	20
	$\overline{\mathbf{w}}$ (min)	6.86	5.32	2.68	2.67
	\mathbf{t} (s)	-	0.168	600	12.72

help operators at the tactical level. The SA found the best solution compared with the other methods, with a computation time still lower than 15 seconds. This illustrates its robustness and effectiveness in solving the C-SSRAP problem. In summary, the results presented in Table 3.2 highlight the performance of the MILP and SA solution approaches when considering small problem instances. However, when the instance becomes larger, SA becomes a more suitable approach to solve the C-SSRAP, allowing a significant reduction of the average waiting time with a computational time compatible with tactical decisions.

Tests are also conducted to see the influence of model parameter variations on the different solution strategies in terms of performance and computation time. We set the duration of the time window to four hours. The following parameter changes are tested:

Table 3.3: Performance obtained by the proposed solution approaches (Initial, Heuristic, MILP, or SA) for solving the 4-hour C-SSRAP with model parameter changes in scenario R60 (described in Table 5.1). \mathbf{W} , $\bar{\mathbf{z}}$, and \mathbf{t} refer to the maximal waiting time, average waiting time, and computational time, respectively. A time limit has been set to 600 seconds for the MILP solution approach. Minimum waiting times are highlighted in green and maximum waiting times over the maximum acceptable ones are highlighted in red.

Instance	KPI	Initial	Greedy	MILP	SA
5min timestep	\mathbf{W} (min)	30	30	15	15
	$\bar{\mathbf{w}}$ min	7.67	4.93	4.02	4.02
	\mathbf{t} (s)	0	0.595	600	8.92
30min duty	\mathbf{W} (min)	40	40	20	20
	$\bar{\mathbf{w}}$ min	5.89	8.64	2.80	2.81
	\mathbf{t} (s)	0	0.164	600	7.61
All SC	\mathbf{W} (min)	40	80	20	20
	$\bar{\mathbf{w}}$ min	6.29	5.65	2.64	2.64
	\mathbf{t} (s)	0	1.016	600	48.85

- Time step duration: the time step duration is reduced from 10 minutes to 5 minutes;
- Lane opening duration: the time interval for deciding when to open security lanes is reduced from 60 minutes to 30 minutes;
- Number of security checkpoints: the number of security checkpoints is increased by authorising the transfer of security teams between all CDG security checkpoints (instead of considering three separate markets).

Table 3.3 presents the results obtained for the different scenarios. While providing fast solutions, the greedy heuristic does not always perform well regarding objective function reduction. It increases the average waiting time in the 30-minute duty instance compared with the initial allocation, and leads to a maximum waiting time of 80 minutes on this instance, considering all security checkpoints. Conversely, the MILP solution approach, despite its high computational demand, achieves the best results regarding objective function reduction. The time limit is reached for the three instances considered. Therefore, the MILP approach does not guarantee optimality in this case. SA consistently produces competitive results when compared with MILP solution approach, providing a solution in less than one minute for each instance. The greedy heuristic, while it is fast, tends to fall short of meeting the maximum waiting time requirements, making it less preferable in scenarios where precision and efficiency are

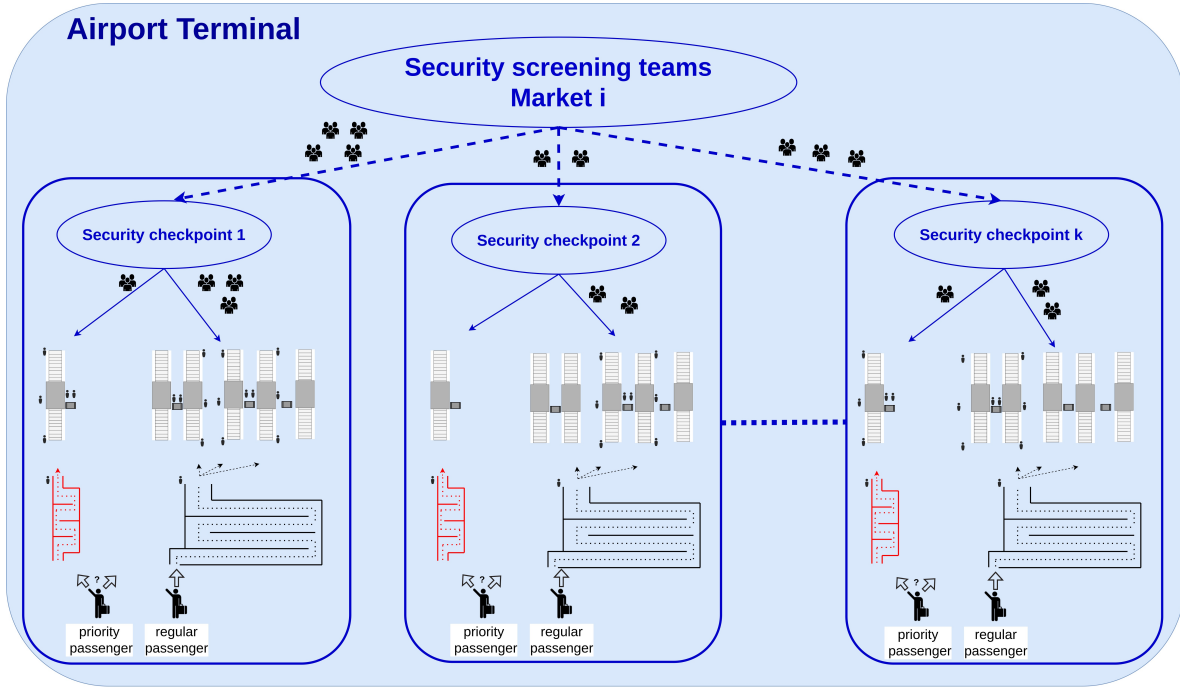


Figure 3.7: Scheme of a single market airport security system with finite resources and fast-track lanes. It is composed of a set of security checkpoints. Each checkpoint has a finite number of common lanes, a common queuing line, one fast-track lane and its associated queuing line displayed in red. Passengers are routed either to the common or the fast track lane depending on their status (regular/priority) and depending if the priority lane is open.

paramount. These outcomes underscore that SA solution approach could be a valuable tool for efficient and effective decision-making to help airport operators.

3.4 Priority-Security Screening Resources Allocation Problem (P-SSRAP)

3.4.1 Problem description

In the following, we present a second version of the Security Screening Resource Allocation Problem (SSRAP), specifically designed to deal with late passenger arrival scenarios that can cause stranded passengers. In this version, a security checkpoint consists of a set of security lanes, a common queuing line, plus a fast-track lane and its associated queue. Figure 3.7 gives a visual representation of this system. Passengers are divided into two categories: regular and priority. The priority status is assigned

to passengers who arrive late at security due to access mode disruption. They can be identified either by an app tracking their journey or through a single ticketing system informing the airport about the access mode used by the passengers. In this new problem version, we allow the segregation of passenger flow at the security screening system by serving priority passengers in a fast-track system, which comprises its dedicated queuing line. In order to perform this passenger flow segregation, a security team has to operate the fast track lane.

We assume a constant service rate for each common lane and a 50% higher rate for the fast-track lane. This represents priority passenger behaviour who are in a hurry and tend to be quicker at security. Priority passengers use the fast-track queuing system when the fast-track lane is operational. The opening of this lane does not incur additional costs on the airport's side. It just requires closing a regular lane to operate it, and therefore, is relevant only if enough priority passengers are expected during a time interval. Otherwise, they follow the standard security procedure. The optimisation problem consists of determining the optimal number of security lanes, including the fast-track lane, to operate during each time interval at each security checkpoint. We consider a finite resource constraint that specifies a maximum number of security teams available for each time interval. This constraint directly limits the number of open lanes and fast-track lanes at each time interval. The objective function considers two criteria to be minimised. The first is the number of passengers missing their flights, while the second is a penalty that is triggered if the maximum acceptable waiting time is exceeded.

3.4.2 Optimisation model P-SSRAP

In order to present the mathematical model related to this problem, we detail the data, decision variables, objective function and constraints below. The model is close to the C-SSRAP model presented in [Section 3.3.2](#). Most constraints have been duplicated to compute the queuing time of common and fast-track queuing systems. The new model considers passenger boarding times to evaluate if they miss their flights. Also, new decision variables and constraints regarding passenger flow segregation have been added. The main changes compared to the C-SSRAP model have been highlighted in red to facilitate the reading.

Data

δt	time step (usually 5min)
\mathcal{S}	set of security areas
$\mathcal{T} = \{1, 2, \dots, \mathcal{T} \}$	set of discrete times indices. Each consecutive times are separated by δt .
$\mathcal{H} = \{1, 2, \dots, \mathcal{H} \}$	set of time interval indices where security lane openings are decided. Each time interval lasts an exact number of time steps δt (usually 30-min duration)
\mathcal{F}	set of departing flights
$\forall s \in \mathcal{S}, t \in \mathcal{T} : D_{s,t}^{R/P}$	number of regular/priority passengers expected to arrive at t on security area s (information extracted from simulation)
$\theta_{C/F}$	service rate per time step for one common/fast security lane
$\forall h \in \mathcal{H} : L_h$	maximum number of security lanes that can be open during time interval h
$\forall s \in \mathcal{S} : L_s^C$	maximum number of common security lanes that can be operated on security area s
$\forall t \in \mathcal{T} : H_t$	time interval included in \mathcal{H} that covers t
$\forall s \in \mathcal{S} : Q_s^{C/F}$	initial number of passengers waiting on common/fast queuing line of security area s
W_{\max}	maximum acceptable passenger waiting time in security system
$\forall f \in \mathcal{F} : T_f^c$	boarding closure time of flight f .
$\forall f \in \mathcal{F} : \Delta T_f$	transfer time from the security area to the gate assigned to flight f .
$\forall f \in \mathcal{F} : S_f$	security checkpoint associated to the boarding room of flight f
$\forall f \in \mathcal{F}, t \in \mathcal{T} : N_{f,t}^{R/P}$	number of regular/priority passengers arriving at security area S_f at time step t

Decision variables

Main decision variables

$\forall s \in \mathcal{S}, h \in \mathcal{H} : x_{s,h}^C$	number of common security lanes open on security area s during time interval h
$\forall s \in \mathcal{S}, h \in \mathcal{H} : x_{s,h}^F = \begin{cases} 1 \\ 0 \end{cases}$	$\begin{cases} \text{if fast lane } s \text{ is open during time interval } h \\ \text{otherwise} \end{cases}$

Auxiliary decision variables

$\forall s \in \mathcal{S}, t \in \mathcal{T} : y_{s,t}^C/y_{s,t}^F$	number of passengers served on common/fast security lanes of area s between t and $t + 1$
$\forall s \in \mathcal{S}, t \in \mathcal{T} : d_{s,t}^C/d_{s,t}^F$	number of passengers that arrive on common/fast security area s at t
$\forall s \in \mathcal{S}, t \in \mathcal{T} : q_{s,t}^C/q_{s,t}^F$	number of passengers that are still waiting in common/fast queuing line after passengers served at t

$\forall s \in \mathcal{S}, t \in \mathcal{T} : w_{s,t}^C/w_{s,t}^F$: average waiting time experienced by passengers entered in common/fast queuing system of s at t

$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : p_{s,t,t'}^{C/F}$: number of passengers arrived at common/fast security area s at t and served at t'

$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : u_{s,t,t'}^{C/F}$: number of passengers in common/priority queuing line at t and served at t'

\bar{w} : maximum passenger waiting time

$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : o_{s,t,t'}^{C/F} := \begin{cases} 1 & \text{if at least a passenger queuing in common/priority line at } t \text{ on } s \text{ is still unserved at } t' \\ 0 & \text{otherwise} \end{cases}$

$\forall s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 : r_{s,t,t'} := \begin{cases} 1 & \text{if at least a passenger arrived at } t \text{ on } s \text{ is served at } t' \text{ or later} \\ 0 & \text{otherwise} \end{cases}$

$\forall s \in \mathcal{S}, t \in \mathcal{T} : l_{s,t}^{C/F}$: number of passengers arrived at t on s and queuing at $|\mathcal{T}|$

$\forall f \in \mathcal{F}, t \in \mathcal{T}_f : z_{f,t}^{R/P} = \begin{cases} 1 & \text{if regular/priority passengers arrived at } t \text{ are stranded} \\ 0 & \text{otherwise} \end{cases}$

$\forall s \in \mathcal{S}, t \in \mathcal{T} : \delta_{s,t} = \begin{cases} 1 & \text{if } x_{s,H_t}^F = 0 \text{ and } q_{s,t}^F > 0 \\ 0 & \text{otherwise} \end{cases}$

Objective function

We consider the minimisation of a bi-criteria objective. The first criterion is the number of passengers missing their flights. It is computed by summing the number of regular and priority passengers that miss their flights, equal to $N_{f,t}^R \cdot z_{f,t}^R$ and $N_{f,t}^P \cdot z_{f,t}^P$ respectively. The second criterion is a penalty activated if the maximum passenger waiting time is above the maximum acceptable waiting time. Thus the objective function is formulated as the following linear combination:

$$\min \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} \left(N_{f,t}^R \cdot z_{f,t}^R + N_{f,t}^P \cdot z_{f,t}^P \right) + \alpha \cdot k \quad (3.22)$$

where α is the coefficient of the maximum waiting time penalty for which the value is set high enough to favour, firstly, solutions where passengers wait less than 30 minutes and, secondly, to favour the reduction of the number of passengers missing their flights.

Constraints

The different constraints set to fix main and auxiliary variables are listed below:

$$x_{s,h}^C \leq L_s^C \quad h \in \mathcal{H}, s \in \mathcal{S} \quad (3.23)$$

$$\sum_{s \in \mathcal{S}} \left(x_{s,h}^C + x_{s,h}^F \right) \leq L_h \quad h \in \mathcal{H} \quad (3.24)$$

$$d_{s,t}^C = D_{s,t}^R + \left(1 - x_{s,H_t}^F \right) \cdot D_{s,t}^P \quad s \in \mathcal{S} \quad (3.25)$$

$$d_{s,t}^F = x_{s,t}^F \cdot D_{s,t}^P \quad s \in \mathcal{S} \quad (3.26)$$

$$q_{s,1}^C = D_{s,1}^C + Q_s^C - y_{s,1}^C \quad s \in \mathcal{S} \quad (3.27)$$

$$q_{s,1}^F = D_{s,1}^F + Q_s^F - y_{s,1}^F \quad s \in \mathcal{S} \quad (3.28)$$

$$q_{s,t}^C = d_{s,t}^C + q_{s,t-1}^C - y_{s,t}^C \quad s \in \mathcal{S}, 2 \leq t \in \mathcal{T} \quad (3.29)$$

$$q_{s,t}^F = d_{s,t}^F + q_{s,t-1}^F - y_{s,t}^F \quad s \in \mathcal{S}, 2 \leq t \in \mathcal{T} \quad (3.30)$$

$$\delta_{s,t} = (1 - x_{s,t}^F) \cdot \frac{q_{s,t}^F}{\max(1, q_{s,t}^F)} \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.31)$$

$$y_{s,t}^C \leq \theta_C \cdot (x_{s,H_t}^C - \delta_{s,t}) \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.32)$$

$$y_{s,t}^F \leq \theta_F \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.33)$$

$$\sum_{t'=t}^{|\mathcal{T}|} u_{s,t,t'}^C \leq q_{s,t-1}^C \quad s \in \mathcal{S}, 2 \leq t \in \mathcal{T} \quad (3.34)$$

$$\sum_{i=t}^{|\mathcal{T}|} u_{s,t,t'}^F \leq q_{s,t-1}^F \quad s \in \mathcal{S}, 2 \leq t \in \mathcal{T} \quad (3.35)$$

$$o_{s,t,t'}^C \geq \frac{1}{Q_s^C + \sum_{i=1}^{t'} (D_{s,i}^R + D_{s,i}^P)} \cdot (q_{s,t-1}^C - \sum_{i=t}^{t'} u_{s,t,i}^C) \quad s \in \mathcal{S}, (2 \leq t \leq t') \in \mathcal{T}^2 \quad (3.36)$$

$$o_{s,t,t'}^F \geq \frac{1}{Q_s^F + \sum_{i=1}^{t'} D_{s,i}^P} \cdot (q_{s,t-1}^F - \sum_{i=t}^{t'} u_{s,t,i}^F) \quad s \in \mathcal{S}, (2 \leq t \leq t') \in \mathcal{T}^2 \quad (3.37)$$

$$p_{s,t,t'}^C \leq d_{s,t}^C \cdot (1 - o_{s,t,t'}^C) \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.38)$$

$$p_{s,t,t'}^F \leq d_{s,t}^F \cdot (1 - o_{s,t,t'}^F) \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.39)$$

$$p_{s,t,t'}^C \leq y_{s,t'}^C - u_{s,t,t'}^C \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.40)$$

$$p_{s,t,t'}^F \leq y_{s,t'}^F - u_{s,t,t'}^F \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.41)$$

$$l_{s,t}^C = d_{s,t}^C - \sum_{i=t}^{|\mathcal{T}|} p_{s,t,i}^C \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.42)$$

$$l_{s,t}^F = d_{s,t}^F - \sum_{i=t}^{|\mathcal{T}|} p_{s,t,i}^F \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.43)$$

$$w_{s,t}^C = \frac{1}{\max(1, d_{s,t}^C)} \cdot \sum_{t'=t}^{|\mathcal{T}|} (t' - t) \cdot p_{s,t,t'}^C \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.44)$$

$$w_{s,t}^F = \frac{1}{\max(1, d_{s,t}^F)} \cdot \sum_{t'=t}^{|\mathcal{T}|} (t' - t) \cdot p_{s,t,t'}^F \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.45)$$

$$r_{s,t,t'} \geq \frac{p_{s,t,t'}^C + p_{s,t,t'}^F}{\max(1, D_{s,t}^R + D_{s,t}^P)} \quad s \in \mathcal{S}, (t \leq t') \in \mathcal{T}^2 \quad (3.46)$$

$$r_{s,t,|\mathcal{T}|} \geq \frac{l_{s,t}^C + l_{s,t}^F}{\max(1, D_{s,t}^R + D_{s,t}^P)} \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.47)$$

$$\bar{w} \geq (t' - t) \cdot r_{s,t,t'} \quad s \in \mathcal{S}, t \in \mathcal{T} \quad (3.48)$$

$$z_{f,t}^R \geq \frac{1}{|\mathcal{T}|} \left(t + w_{s_f,t}^C + \Delta T_f - T_f^c \right) \quad f \in \mathcal{F}, t \in \mathcal{T} \quad (3.49)$$

$$z_{f,t}^P \geq \frac{1}{|\mathcal{T}|} \left(t + x_{s,H_t}^F \cdot w_{s_f,t}^F + (1 - x_{s,H_t}^F) \cdot w_{s_f,t}^C + \Delta T_f - T_f^c \right) \quad f \in \mathcal{F}, t \in \mathcal{T} \quad (3.50)$$

$$k \geq \bar{w} - W_{max} \quad (3.51)$$

$$x_{s,h}^C \in \mathbb{N} \quad s \in \mathcal{S}, h \in \mathcal{H} \quad (3.52)$$

$$x_{s,h}^F \in \{0; 1\} \quad f \in \mathcal{F}, h \in \mathcal{H} \quad (3.53)$$

Constraint (3.23) limits the number of security staff assigned to each common lane at each time slot depending on security checkpoint capacity. Constraint (3.24) ensures

the total number of staffs allocated to security checkpoints in each time slot does not exceed the total number of teams available. Constraints (3.25) and (3.26) determine the common and fast lane demand, taking into account the potential opening of the fast-track lane. Constraints (3.27) and (3.28) fix the initial queue lengths for the common lane and the fast-track lane. Constraints (3.29) and (3.30) govern the queue length evolution of the common and fast queues depending on passenger demand and passengers served. Penalty $\delta_{s,t}$, taking into account for the under-utilisation of the common lanes due to passengers still queuing in the fast service, is fixed through Constraint (3.31). Constraints (3.32) and (3.33) ensure the common and fast service do not exceed the available resources. Constraints (3.34) and (3.35) enforce the number of served queuing passengers to be lower than the queue lengths. Constraints (3.36), (3.37), (3.38) and (3.39) impose that passengers queuing at t are served before the ones arrived at t . Constraints (3.40), (3.41), (3.42) and (3.43) determine served and unserved passengers for both common and fast lanes, taking into account allocated resources and passenger demand. Average waiting times are calculated for both lanes through Constraints (3.44) and (3.45). Constraints (3.46), (3.47) and (3.48) compute the maximum waiting time.

Additionally, Constraints (3.49) and (3.50) account for regular and priority passengers who miss their flights. Penalty k is activated when waiting times exceed the maximum allowed one through Constraint (3.51). Finally, decision variables for opening common lanes are constrained to be non-negative integers through Constraint (3.52), while Constraint (3.53) imposes the fast-track lane opening decision variable to be binary.

3.4.3 Solution approach

The mathematical model associated to the P-SSRAP is non-linear due to the segregation of passenger flow, which leads to demand at common and fast-track queuing systems being auxiliary decision variables. This results in Constraints (3.31), (3.38), (3.39), (3.44), (3.45), (3.50) being non-linear. As a result, solving the problem directly using a linear solver is not possible. Additional work could be done to reformulate the problem in a linear formulation. However, since the SA algorithm performs efficiently on the C-SSRAP, we propose using a similar approach to solve the P-SSRAP.

As previously explained, SA implementation requires the definition of an initial solution and a neighbour selection process. The initial solution is the initial allocation that would have been operated if no airport access mode disruption happened. For each security checkpoint, five regular security lines are initially open. The neighbourhood generation process is detailed in Figure 3.8. A neighbour of the solution is generated by closing a fast or a regular security line on a security checkpoint and by opening a new one. The selection of the lines that are open and closed is based on a performance computed for each security checkpoint. The lower the performance, the higher the chance a new security line will be open and vice versa. The process is randomised to

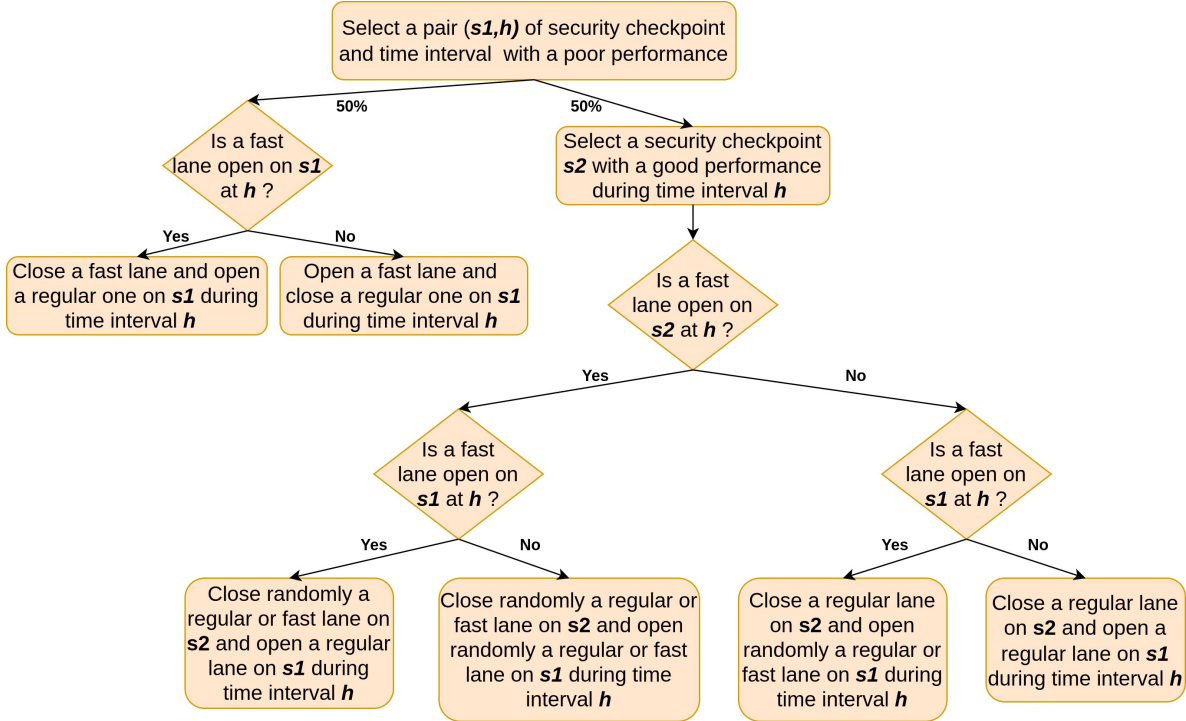


Figure 3.8: Simulated Annealing neighbour generation process P-SSRAP.

favour the exploration of new solutions. The initial acceptance rate of the new solution is set to 80% using a heating process, similar to the approach used in C-SSRAP. The temperature decay parameter is set to 0.999. Due to the passenger flow segregation, the assessment of the P-SSRAP solution is more time-consuming than the assessment of the C-SSRAP solution. In order to keep a total computation time suitable for the tactical implementation of the proposed recovery strategy, the number of transitions per temperature step is reduced from 2000 to 400.

3.4.4 Performance analyses

Different performance analyses are conducted to see the influence of different parameters on the P-SSRAP solving in terms of solution quality and computation time. As previously done, we propose considering the influence of the time window duration, the time step, the duty duration or even the number of security checkpoints to challenge the solution approach. We consider the same scenario as in [Section 3.3.4](#), which simulates a road access mode disruption, and we perform the reallocation on a single security market. We assign priority status to passengers affected by the disruption who arrive at the airport with less than an hour left before their scheduled departure time. The tests are performed on an AMD Ryzen 5 4500U processor, Radeon GPU and 16 GB of

Table 3.4: Performance obtained by the proposed solution approaches (Initial, SA) for solving the P-SSRAP over different instances in scenario R60 (described in Table 5.1). \mathbf{W} , \mathbf{z} , and \mathbf{t} refer to the maximal waiting time, number of stranded passengers, and computational time, respectively. Columns titled ‘ $\mathbf{x-h TW}$ ’ refer to instances where the optimisation time window duration is changed. The ‘**5min TS**’ and ‘**30min D**’ columns correspond to instances where the discretisation time step is reduced from 10 to 5 minutes, and the time interval duration used to reallocate security teams is reduced from 60 to 30 minutes, respectively. The last column titled ‘**All-SC**’ represents an instance where teams are authorised to be reallocated over the entire airport (i.e. removal of market flow segregation constraint).

	KPI	2h	4h	6h	8h	10h	12h	5min	30min	All
		TW	TW	TW	TW	TW	TW	TS	D	SC
Init	$\mathbf{W}(\text{min})$	30	30	30	30	30	80	30	40	40
	\mathbf{z}	325	679	747	833	976	1277	706	675	1525
	\mathbf{t} (s)	0	0	0	0	0	0	0	0	0
SA	$\mathbf{W}(\text{min})$	30	30	30	30	30	30	30	30	30
	\mathbf{z}	207	418	473	564	625	674	431	334	968
	\mathbf{t} (s)	12.21	23.70	31.46	40.70	37.78	46.91	29.68	22.63	35.42

RAM.

Table 3.4 presents the different results obtained. Each column corresponds to a P-SSRAP instance, and for each instance, the initial security team allocation is compared to the one obtained thanks to the SA solution approach.

The solving time for different instances is lower than 50 seconds, making it viable for tactical-level usage. The solving time ranges from 12 seconds for the 2-hour time window instance up to 47 seconds for the 12-hour time window duration instance. The reallocation of resources helps to reduce the maximum waiting time to 30 minutes for all tested instances. Interestingly, the reallocation approach does not yield a solution with a maximum waiting time lower than 30 minutes, which is not the case for the allocation obtained after solving the C-SSRAP. This observation can be explained by the change in the objective function in the P-SSRAP. Here, the minimisation of the number of passengers who miss their flights is prioritised while also penalising waiting times exceeding 30 minutes. Therefore, the algorithm prioritises reducing the number of stranded passengers instead of reducing passenger waiting times. Therefore, the solving approach might tend to open a fast-track lane for priority passengers even if it increases waiting times for non-priority passengers.

The reallocation approach significantly reduces the number of stranded passengers, with a reduction ranging from 32% up to 50% over the different instances. The reduction is around 35% for instances where the time window is changed, and the best reduction is achieved for the instance where the duty duration is reduced to 30 minutes. In this

instance, a fast-track lane can be open for only 30 minutes, allowing an allocation that better adapts to passenger demand and waves of priority passengers.

3.5 Conclusion

This chapter has detailed a recovery strategy based on reallocating airport security resources when an access mode disruption occurs. We have studied two versions of the problem, with and without passenger flow segregation. The classical version of the security resource allocation problem (C-SSRAP) has been formulated through an ILP model, which allows a direct solution approach through an ILP commercial solver. Performance tests on the different solving approaches lead to the conclusion that although the ILP solution approach is efficient on small instances, the solving approach using SA seems almost as good and significantly reduces the computation time while being robust to parameter sensitivity. The second version of the problem, which considers the potential opening of a fast-track lane for passengers affected by the disruption and likely to miss their flight (P-SSRAP), has been modelled using a non-linear model. Again, the SA solution approach proposed for solving this model is efficient and appears to be a valuable tool to help the airport decision-making process at the tactical level, significantly improving the initial allocation in an acceptable computational time for tactical decision management.

The next chapter introduces the second recovery strategy, based on flight rescheduling to minimise the number of stranded passengers. Then, [Chapter 5](#) presents how such recovery strategies could be adapted to deal with real-life disruptive events, proposing a sliding time window approach for online data handling and data reliability. A case study and different disruption scenarios are designed to test the different rescheduling strategies and provide insights into how such recovery mechanisms could improve airport decision-making in an operational context.

Chapter 4

Passenger-oriented Flight ReScheduling Problem (PFRSP)

The previous chapter shows that reassigning security staff can effectively reduce passenger waiting times, resulting in fewer passengers missing their flights, especially when passengers arrive late at the airport. In this chapter, we propose a second-stage strategy by investigating a 'wait-passenger' policy applied to departing flights. This strategy consists of tactically rescheduling departures to wait for passengers delayed due to an airport access mode disruption (Scozzaro et al., 2023b). We also consider arrival flight rescheduling to mitigate airport congestion and deal with airport resource capacities. Therefore, we define an optimisation problem, referred to as the Passenger-oriented Flight ReScheduling Problem (PFRSP), firstly introduced in Section 1.6. In the following, we propose a formulation of the PFRSP that aims at rescheduling flights at the tactical level based on information provided by ground transportation service providers. The objective is to find a balance between minimising the number of passengers missing their flights and limiting the total deviation from the original schedule, taking into account airport constraints. A linear programming formulation is proposed that allows an exact solution approach using a commercial ILP solver. A heuristic, based on a procedure that could be followed by airport operators, is also developed to reschedule flights and to evaluate the relevance of an exact solution approach.

The remainder of this section is structured as follows. Section 4.1 presents previous related works. A description of the problem is provided in Section 4.2. The ILP formulation of the PFRSP is presented in Section 4.3. The ILP solution approach and the alternative heuristic are detailed in Section 4.4. Finally, Section 4.5 presents computational tests to evaluate the performance of the different solution approaches.

4.1 Literature Review

We consider in this chapter a tactical flight rescheduling at an airport, through passenger-oriented metrics, during ground transportation disturbances. Therefore, this work involves three topics vastly studied in the literature: tactical handling of airside operations, optimisation of transportation systems through passenger-oriented metrics and disruption effects on an intermodal transportation network. The first topic has been mostly studied through optimisation methods focusing on flight-oriented metrics. Most passenger-oriented methods have been led at the strategic level. The final topic has been studied through analytical studies, generally lacking in optimisation methods to propose recovery solutions. A literature review associated with each subject is proposed below.

Tactical handling of airside operations

Several studies have been led to improve airport operations efficiency on the airside. [Pujet \(1999\)](#) is one of the first to propose a virtual queuing system to shift waiting times at the runway threshold directly to the gate. This improved airport efficiency by reducing fuel consumption and, therefore, airport carbon footprint. Later, [Bohme et al. \(2007\)](#) study the integration of departure and arrival runway scheduling problems to improve the overall airport efficiency. [Kjenstad et al. \(2013\)](#) integrate arrival and departure runway scheduling problems with the surface management problem at Arlanda airport. [Khadilkar and Balakrishnan \(2015\)](#) extend the integration by also considering the management of the flights in the Terminal Manoeuvring Area (TMA), which is the airspace surrounding an airport, through dynamic programming. [Ma et al. \(2019\)](#) also propose an integrated approach to optimise airport operations from terminals to the TMA. They consider resource capacity constraints and air conflict resolution in the TMA using a SA to reschedule flights. [Guimarans and Padrón \(2022\)](#) use a simulation approach for airport ground resource scheduling. Their approach increases schedule robustness with aircraft turnaround mostly on time in all scenarios. [Ma et al. \(2021\)](#) propose two ILP models and a SA to optimise the departure runway scheduling at CDG while considering arrival runway crossing. [Ahmadian and Salehipour \(2022\)](#) present a matheuristics for the aircraft landing problem. This algorithm relies mainly on an iterative destruction of aircraft landing sub-sequences. Their approach enables to obtain optimal schedules for instances up to 50 aircraft and best-known solutions for instances up to 500 aircraft in less than a minute of computation time. [Evler et al. \(2021\)](#) highlight how an integrated decision support system for schedule recovery would help the Airport Operator Centre (AOC) for ground operation handling under uncertain arrival times. Through a study case around Frankfurt airport, they show the robustness of their solution with the consideration of 20 aircraft during a morning peak.

Finally, several works have also been carried out regarding airline disruption management, including passenger recovery, as presented in [Section 1.5.2](#).

Transportation service optimisation through passenger-oriented metric

Most passenger-oriented optimisation works have been led with a clear distinction between air and ground transportation systems. Regarding the airport side, [Dell’Orco et al. \(2017\)](#) propose a fuzzy bee colony optimisation to minimise the total passenger walking time by optimising gate allocation to flights. [Kim et al. \(2017\)](#) optimise gate/flight allocation with a trade-off between the passenger transit time through the airport, the aircraft taxi time and the robustness of gate assignment. [Biolini et al. \(2023\)](#) proposes a change of paradigm for optimising slot allocation through passenger-oriented metrics. [Buire et al. \(2022\)](#) propose a strategic synchronisation to coordinate train and flight timetables based on passenger transfer time at CDG airport. On the ground transportation level, [Guajardo and Rönnqvist \(2016\)](#) report over 40 cost allocation methods retained in collaborative transport. Their work can be seen as a baseline for implementing collaborative decision-making processes and achieve single ticketing. On the ground side, [Rahimi Mazrae Shahi et al. \(2016\)](#) optimise subway headways to minimise passenger travel time while having appropriate train load factors. They combine a discrete-event simulation and a response surface methodology to optimise the train schedule with limited simulation runs. [Yu et al. \(2021\)](#) study routing optimisation in a multimodal context for passengers. They propose a mixed integer programming model and a heuristic to find optimal routing with a combined use of ride-sharing and public transport. They highlight that passengers using both combinations could reduce up to 7% and 8% the total vehicle travel distance and the vehicle travel time, respectively. Finally, [Filippi et al. \(2023\)](#) proposes a literature review on passenger transportation optimisation at an urban scale.

Effect of disruptions on a multimodal transportation network

[Dray et al. \(2015\)](#) and [Marzuoli et al. \(2015\)](#) analyse disruptive events on multimodal networks. Both highlight how multimodal recovery solutions should help in improving passenger-door-to-door journeys. [Liu et al. \(2021\)](#) present a review on public transportation coordination at the tactical level. [Siegrist and Corman \(2020\)](#) study the direct and indirect effects of a disruption in a public transportation network. They highlight the impact of different information dissemination strategies in passenger delays through a simulation-based evaluation using MATSim tool ([W Axhausen et al., 2016](#)). They highlight that informing passengers about the disruption at the latest moment induces large passenger delays, mainly at the disrupted station. On the contrary, a beforehand dissemination induces more indirect effects spread over the entire network and a higher number of small delays for passengers indirectly affected by the disruption. [Rothe et al. \(2022\)](#) evaluate the impact of passenger delays and multimodal airport operations on two case studies.

There is still a gap in the literature in studying how airports could react to access mode disruption. Here, we propose the definition of the PFRSP through an ILP

formulation, enabling an optimal solution approach.

4.2 Problem description

This section describes the Passenger-oriented Flight ReScheduling Problem (PFRSP). First, we introduce the general concept of rescheduling and its integration into the current airport environment with tools used by airport operations to handle departing and operating flights at the tactical level. Then, we present the airside modelling approach retained for this study. Finally, we propose a formulation for the PFRSP in terms of decisions, constraints and optimisation criteria.

4.2.1 Assumptions for a tactical flight rescheduling strategy and integration with ATC tool

In the context of this thesis, we assume the Airport Operation Centre (AOC) receives regular updates on passenger arrival time forecasts. Based on these forecasts, the AOC can identify flights that need to be delayed to reduce the number of passengers stranded at the airport. Since an airport has a limited capacity, delaying only departure flights may induce airport congestion. Thus, we consider the possibility to reschedule both departure and arrival flights to limit the impact of an access mode disruption while mitigating airport congestion. From an operational perspective, airport aircraft flow is managed by Air Traffic Control (ATC) tools that regulate flights according to demand and capacity. This process involves the DMAN and the AMAN or its extended version, E-AMAN. DMAN allocates runways and departure delays based on runway pressure and slots allocated by the Network Manager. Similarly, AMAN/E-AMAN organises the sequence of arriving flights. As we propose rescheduling flights at the tactical level, i.e. a few hours before the operations, such a rescheduling tool should be interfaced with DMAN and AMAN/E-AMAN.

4.2.2 Airside resources modelling

We consider a macroscopic view of the airport as shown in [Figure 4.1](#). Passengers can access the airport by various ground transportation modes (e.g. road, subway, train). The airside of the airport is characterised by a set of terminals, a taxi network and a set of runways. In this model, we assume that each runway is dedicated to either arrivals or departures, as is the case at CDG. The taxi network connects the different runways to the terminals. A departure flight starts its journey from the stand (or gate). Two types of stands exist: those close to the terminal, connected with a jet bridge, and those in a remote area called the apron. In the latter case, passengers must take a shuttle from the airport to reach the aircraft. This study does not consider the last type of stand. The

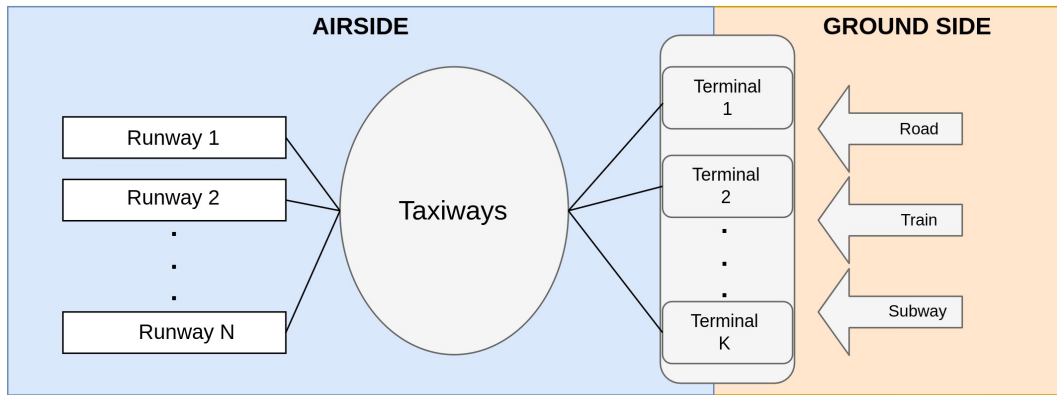


Figure 4.1: Airport macroscopic model.

departing flight leaves its stand and passes over taxiways, part of the taxiway network, to reach the runway threshold assigned to the flight by ATC. When cleared by ATC, the flight can take off, enter the TMA (i.e. the airspace surrounding the airport) and follow a SID route to leave the TMA. An arrival flight does the opposite, entering the TMA and following a STAR route. If the runway is unavailable, it may have to use a holding pattern (i.e. an aerial racetrack for holding) before receiving ATC clearance and authorisation to land. Once the aircraft has landed, it follows a path in the taxiing network to reach its assigned stand.

In the following, we focus on the airport components up to the runway and do not consider the TMA part. Each airport component, such as terminals, the taxiways network, and runways, is considered as a resource with a limited capacity. For example, the maximum number of flights operated on a terminal or taxi network is limited. A maximum throughput also limits the number of movements per runway. These capacities can fluctuate during the day as they are a function of the available workforce, such as the number of ground handling crews or air traffic controllers. However, we did not have access to such type of data and have to define a methodology to estimate these capacities. Using the flight schedule, we infer the airport's capacity for each resource and hour based on the maximum occupancy observed. This constraint would also help in the acceptance of the new flight schedule by air transportation stakeholders, as we propose to maintain the same occupancy level per hour before and after the rescheduling. [Figure 4.2](#) illustrates this principle to estimate the capacity of terminal T2E. The time it takes for a plane to move on the ground before takeoff, known as taxiing time, is assumed to be constant. It only depends on the terminal and runway assigned to the flight. Finally, we do not consider waiting time at the runway threshold and assume an aircraft can take off as soon as it reaches it.

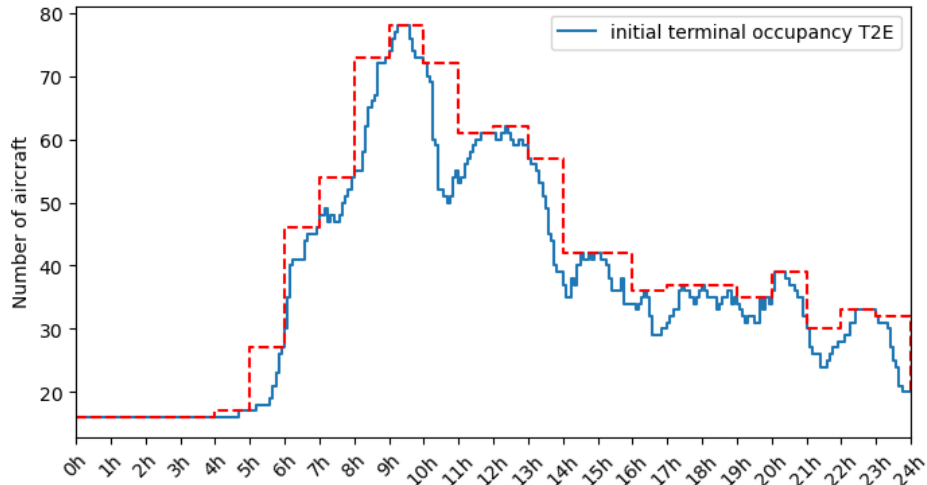


Figure 4.2: Illustration of maximum T2E capacity calibration. The blue curve represents the scheduled initial occupancy. The red dotted line translates the maximum capacity by hour.

4.2.3 Time horizon

In an operational context, a flight rescheduling tool would be launched when the access mode disruption occurs. It would be relaunched regularly during the day to reschedule the next flights, for instance when passenger arrival time forecasts would have been updated. Based on the assumption that forecast updates would occur on discrete time intervals, we define the PFRSP as a static problem on a specific time window for which we consider the following data are known:

- passenger arrival time forecasts;
- available airside resources, as presented in [Section 4.2.2](#);
- aircraft movements, before, during and after the time window, that could impact the airport resource occupancy.

To describe these airport aircraft movements, we use the methodology proposed by ([Ma et al., 2019](#)) that assigns a status to each flight for a specific optimisation time window. Four statuses are considered (completed, on-going, active and planned), based on the scheduled departure or arrival time of flights. The first and second statuses refer to flights that have already been operated during the day, but the on-going ones can still occupy airport resources, e.g. a flight taxiing from its stand to the runway. Active flights are those for which decision variables are taken during the time window. The planned status concerns flights that will be operated after the time window. [Figure 4.3](#) illustrates the four statuses for a specific time window. On-going and planned flights

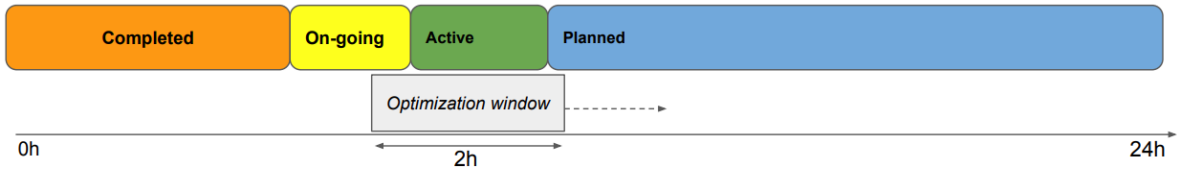


Figure 4.3: Illustration of the different flight statuses for one optimisation window.

can induce occupancy variation on airport resources.

4.2.4 PFRSP formulation

Considering a specific time window as previously defined, the PFRSP consists in making two types of decisions for each flight. A new off-block time and a new departure runway must be assigned to each departure flight. Similarly, a new landing time and a new arrival runway must be assigned to each arrival flight.

The objective function of the PFRSP includes three criteria to be minimised:

- the total number of stranded passengers;
- the total time deviation from the initial schedule;
- the total number of flights delayed by 15 minutes or more.

The last criterion relates to the OTP metric, which is widely used to measure airline punctuality ([OAG Aviation Worldwide, 2023](#)). According to this criterion, a flight is considered to be delayed if its actual delay is equal to or greater than 15 minutes.

Three sets of constraints are considered: aircraft and flight-related, flight pair, and airport resource constraints.

The first ones constrain the maximum delay that can be applied to each flight. Departures can only be delayed as it is rare for a flight to depart earlier than scheduled. However, an arriving flight can be accelerated in the air to arrive earlier. Therefore, we assume that arrivals can be slightly advanced or delayed. In addition, priority status is given to departures that must be on time regarding the OTP metric, i.e. delayed by 10 minutes or less. In the following, the maximum assignable departure delay is set to 20 minutes, and arrival flight times can be deviated from -5 minutes up to +15 minutes.

The second set of constraints imposes a minimum time between landing and departing times of several flight pairs. For instance, when an aircraft operates consecutively an arrival flight and a departure one, a minimum turnaround time constraint is considered. Similarly, a minimum transfer time is imposed between arrivals and departures that share connecting passengers.

The last set of constraints is defined for each airport resource. Each terminal and the taxi network have a maximum capacity, translated into a maximum occupancy

level for on-going flights, active flights and planned flights, as defined in [Section 4.2.3](#). These capacities reflect limitations in the number of aircraft that can be handled by aircraft operators, such as air traffic controllers or ground handling teams, or due to physical resource limitations, e.g., the number of stands or taxiways. Since the number of airport operators is dynamic during the day of operations, a dynamic maximum capacity for each resource is considered. The capacity of each resource is set for each hour as explained in [Section 4.2.2](#). The taxi network is assumed to be a common resource shared by both departure and arriving flights. Each runway is also assumed to be constrained by a maximum throughput per time step.

The following section details the ILP model developed to solve the PFRSP over one time window. A sliding-time window approach to solve a series of PFRSP and reschedule flights over a full day of operations is presented later in [Chapter 5](#).

4.3 Mathematical Modelling

Data, decision variables, constraints and the objective function are detailed below. Departure and arrival flight sets are defined for flights with the ‘active’ status. Non ‘active’ flights linked by a constraint to an active one are also considered.

4.3.1 Data

We define the following sets and parameters :

Sets and subsets

\mathcal{D}	set of departing flights
\mathcal{A}	set of arriving flights
$\mathcal{F} = \mathcal{D} \cup \mathcal{A}$	set of flights
$\mathcal{D}^{\text{priority}} \subset \mathcal{D}$	set of departing flights that need to be on time regarding the OTP metric
\mathcal{K}	set of terminals
$\forall k \in \mathcal{K}, \mathcal{F}^k = \mathcal{D}^k \cup \mathcal{A}^k$	departing and arriving flights assigned to terminal k
\mathcal{R}^{l}	set of landing runways
\mathcal{R}^{to}	set of takeoff runways
$\mathcal{T} = \{t_{\text{start}}, t_{\text{start}} + \delta t, \dots, t_{\text{end}}\}$	set of discrete times on the time window considered (with δt the time step retained for the time discretisation, equals to 5 minutes in the following)
$\mathcal{H}_{\mathcal{T}}$	set of hours considered in \mathcal{T} (used to set hourly capacities of each resource)

Sets and subsets (2)

$\mathcal{AD} = \mathcal{AD}^{\text{cog-a}} \cup \mathcal{AD}^{\text{a-a}} \cup \mathcal{AD}^{\text{a-p}}$	subset of arrival/departure pairs that are operated by the same aircraft. It is composed of three subsets depending on the status of each flight (completed/ongoing-active, active-active, active-planned)
$\mathcal{CF} = \mathcal{CF}^{\text{cog-a}} \cup \mathcal{CF}^{\text{a-a}} \cup \mathcal{CF}^{\text{a-p}}$	set of flight pairs having at least one connecting passenger (composed of three subsets: completed/ongoing-active, active-active, active-planned)
$\forall f \in \mathcal{A}, \mathcal{T}_A^f$	subset of time steps when f can land
$\forall f \in \mathcal{D}, \mathcal{T}_D^f$	subset of time steps when f can depart from its gate
$\forall t \in \mathcal{T}, \mathcal{A}^t = \{f \in \mathcal{A} \mid t \in \mathcal{T}_A^f\}$	subset of arriving flights that can land during time step t
$\forall t \in \mathcal{T}, \mathcal{D}^t = \{f \in \mathcal{D} \mid t \in \mathcal{T}_D^f\}$	subset of departing flights that can depart from the gate during time step t

Parameters (1)

$\forall f \in \mathcal{A}, T_f^{\text{l/in}}$	initial landing time/in-block time of flight f
$\forall f \in \mathcal{D}, T_f^{\text{out/to}}$	initial off-block time/takeoff time of flight f
$\forall f \in \mathcal{D}, T_f^{\text{to}}$	initial takeoff time of flight f
$\forall f \in \mathcal{F}, k_f$	terminal associated to f
$\forall k \in \mathcal{K}, \forall r \in \mathcal{R}^1, \delta t_{k,r}^{\text{in}}$	average taxi time from runway r to terminal k
$\forall k \in \mathcal{K}, \forall r \in \mathcal{R}^{\text{to}}, \delta t_{k,r}^{\text{out}}$	average taxi time from terminal k to runway r
$\forall (k_1, k_2) \in \mathcal{K}^2, \delta w_{k_1, k_2}$	minimum passenger transfer time from terminal k_1 to k_2
$\forall (f_1, f_2) \in \mathcal{AD}, \lambda_{f_1, f_2}$	minimum turnaround time for aircraft operating flights f_1 and f_2
$\forall t \in \mathcal{T}, h_t$	hour that t belongs to
$\forall k \in \mathcal{K}, N_k^{\text{init}}$	initial occupancy of terminal k at t_{start}
$\forall k \in \mathcal{K}, \forall h \in \mathcal{H}_{\mathcal{T}}, C_h^k$	maximum capacity of terminal k at h
$\forall r \in \mathcal{R}, \forall h \in \mathcal{H}_{\mathcal{T}}, \Phi_{r,h}^{\text{max}}$	maximum throughput of runway r on hour h
$\forall h \in \mathcal{H}_{\mathcal{T}}, C_h^{\text{TN}}$	maximum capacity of the taxi network at h
$\Delta t^{\text{l+/-}}$	maximum/minimum landing delay that can be applied to a flight (= -5minutes /+15minutes)
$\Delta t^{\text{out+}}$	maximum off-block time delay that can be applied to a flight (=20 minutes)

Parameters (2)

$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, \Delta_{k,t}^{\text{OGP}}$	occupancy variation of terminal k at t due to on-going flights and planned flights
$\forall t \in \mathcal{T}, \Delta_{TN,t}^{\text{OGP}}$	occupancy variation of taxi network at t due to on-going and planned flights
$\forall r \in \mathcal{R}, \forall t \in \mathcal{T}, \Delta_{r,t}^{\text{OGP}}$ $\Delta t^{\text{on-time}}$	number of on-going or planned flights on runway r at t maximum takeoff deviation time without impacting the OTP metric
$\forall f \in \mathcal{D}, \forall t \in \mathcal{T}_D^f, g_{ft}$	number of stranded outbound passengers (i.e. non air-connecting passengers) if f departs from its gate at t

The sets \mathcal{T}_D^f and \mathcal{T}_A^f include constraints related to the maximum delay that can be assigned to a departing or an arriving flight f . Introducing such sets requires some data pre-processing but has the advantage of introducing fewer decision variables. As this time window problem does not involve any decisions on planned and on-going flights, they are considered as a constraint for the mathematical model. However, several flights with this status are partially operated during the considered time window. Consequently, such flights occupy airport resources (e.g. an on-going flight that is already taxiing at t_{start} will occupy the taxiing network at least at t_{start}). The parameters $\Delta_{k,t}^{\text{OGP}}$ and $\Delta_{r,t}^{\text{OGP}}$ sum the variation in occupancy due to planned and on-going flights for each airport resource and for each time step to update the actual airport resource occupancy.

4.3.2 Decision variables

The following main decision variables are introduced to reschedule flights:

$$\begin{aligned} \forall f \in \mathcal{A}, \forall t \in \mathcal{T}_A^f, \forall r \in \mathcal{R}^l, x_{f,t,r}^l = & \begin{cases} 1 & \text{if } f \text{ lands on runway } r \text{ during time step } t \\ 0 & \text{otherwise} \end{cases} \\ \forall f \in \mathcal{D}, \forall t \in \mathcal{T}_D^f, \forall r \in \mathcal{R}^{\text{to}}, x_{f,t,r}^{\text{out}} = & \begin{cases} 1 & \text{if } f \text{ leaves the gate during } t \text{ and takes off on } r \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

We introduce the following auxiliary decision variables to formulate the constraints properly:

$\forall k \in \mathcal{K}, \forall t \in \mathcal{T}, n_t^k$	number of aircraft occupying terminal k at t
$\forall t \in \mathcal{T}, n_t^{\text{TN}}$	number of aircraft occupying taxi network at t
$\forall f \in \mathcal{A}, t_f^l$	landing time of flight f
$\forall f \in \mathcal{A}, t_f^{\text{in}}$	in-block time of flight f
$\forall f \in \mathcal{D}, t_f^{\text{out}}$	off-block time of flight f
$\forall f \in \mathcal{D}, t_f^{\text{to}}$	takeoff time of flight f
$\forall f \in \mathcal{D}, y_f =$	$\begin{cases} 1 & \text{if } t^{\text{to}} - T_f^{\text{to}} > \Delta t^{\text{on-time}} \text{ (delayed flight regarding OTP metric)} \\ 0 & \text{otherwise (on-time flight regarding OTP metric)} \end{cases}$

4.3.3 Constraints

We formulate the following linear constraints:

$$\sum_{t \in \mathcal{T}_A^f} \sum_{r \in \mathcal{R}^l} x_{f,t,r}^l = 1 \quad \forall f \in \mathcal{A} \quad (4.1)$$

$$\sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{\text{to}}} x_{f,t,r}^{\text{out}} = 1 \quad \forall f \in \mathcal{D} \quad (4.2)$$

$$t_f^l = \sum_{t \in \mathcal{T}_A^f} \sum_{r \in \mathcal{R}^l} t \cdot x_{f,t,r}^l \quad \forall f \in \mathcal{A} \quad (4.3)$$

$$t_f^{\text{in}} = \sum_{t \in \mathcal{T}_A^f} \sum_{r \in \mathcal{R}^l} (t + \delta t_{r,k_f}^{\text{in}}) \cdot x_{f,t,r}^l \quad \forall f \in \mathcal{A} \quad (4.4)$$

$$t_f^{\text{out}} = \sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{\text{to}}} t \cdot x_{f,t,r}^{\text{out}} \quad \forall f \in \mathcal{D} \quad (4.5)$$

$$t_f^{\text{to}} = \sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{\text{to}}} (t + \delta t_{k_f,r}^{\text{to}}) \cdot x_{f,t,r}^{\text{out}} \quad \forall f \in \mathcal{D} \quad (4.6)$$

$$t_{f_2}^{\text{out}} - T_{f_1}^{\text{in}} \geq \lambda_{f_1,f_2}^{\text{min}} \quad \forall (f_1, f_2) \in \mathcal{AD}^{\text{cog-a}} \quad (4.7)$$

$$t_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \lambda_{f_1,f_2}^{\text{min}} \quad \forall (f_1, f_2) \in \mathcal{AD}^{\text{a-a}} \quad (4.8)$$

$$T_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \lambda_{f_1,f_2}^{\text{min}} \quad \forall (f_1, f_2) \in \mathcal{AD}^{\text{a-p}} \quad (4.9)$$

$$t_{f_2}^{\text{out}} - T_{f_1}^{\text{in}} \geq \delta w_{k_{f_1}, k_{f_2}} \quad \forall (f_1, f_2) \in \mathcal{CF}^{\text{cog-a}} \quad (4.10)$$

$$t_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \delta w_{k_{f_1}, k_{f_2}} \quad \forall (f_1, f_2) \in \mathcal{CF}^{\text{a-a}} \quad (4.11)$$

$$T_{f_2}^{\text{out}} - t_{f_1}^{\text{in}} \geq \delta w_{k_{f_1}, k_{f_2}} \quad \forall (f_1, f_2) \in \mathcal{CF}^{\text{a-p}} \quad (4.12)$$

$$y_f \geq \frac{t^{\text{to}} - T^{\text{to}} - \Delta t^{\text{on-time}}}{\Delta t_f^{\text{out}+} + \max_{r \in \mathcal{R}^{\text{out}}} \delta_{k_f, r}} \quad \forall f \in \mathcal{D} \quad (4.13)$$

$$y_f = 0 \quad \forall f \in \mathcal{D}^{\text{priority}} \quad (4.14)$$

$$n_{t_{\text{start}}}^k = N_k^{\text{init}} + \Delta_{k, t_{\text{start}}}^{\text{OGP}} \quad \forall k \in \mathcal{K} \quad (4.15)$$

$$n_{t+\delta t}^k = n_t^k + \sum_{r \in \mathcal{R}^1} \sum_{f \in \mathcal{A}^k \cap \mathcal{A}^{t'}} x_{f, t', r}^1 - \sum_{r \in \mathcal{R}^{\text{to}}} \sum_{f \in \mathcal{D}^k \cap \mathcal{D}^t} x_{f, t, r}^{\text{out}} + \Delta_{k, t+\delta t}^{\text{OGP}}, \quad \forall k \in \mathcal{K}, \forall t \in \mathcal{T} \setminus t_{\text{end}}$$

where $t' = t - \delta t_{k_f, r}^{\text{out}}$

$$(4.16)$$

$$n_t^k \leq C_{ht}^k \quad \forall t \in \mathcal{T}, \forall k \in \mathcal{K} \quad (4.17)$$

$$n_{t_{\text{start}}}^{\text{TN}} = \Delta_{\text{TN}, t_{\text{start}}}^{\text{OGP}} \quad \forall k \in \mathcal{K} \quad (4.18)$$

$$n_{t+\delta t}^{\text{TN}} = n_t^{\text{TN}} + \sum_{r \in \mathcal{R}^1} \left(\sum_{f \in \mathcal{A}^t} x_{f, t, r}^1 - \sum_{k \in \mathcal{K}} \sum_{f \in \mathcal{A}^{t'} \cap \mathcal{A}^k} x_{f, t', r}^1 \right) + \sum_{r \in \mathcal{R}^{\text{to}}} \left(\sum_{f \in \mathcal{D}^t} x_{f, t, r}^{\text{out}} - \sum_{f \in \mathcal{D}^{t''}} x_{f, t'', r}^{\text{out}} \right) + \Delta_{\text{TN}, t+\delta t}^{\text{OGP}}, \quad \forall t \in \mathcal{T} \setminus t_{\text{end}} \quad (4.19)$$

where $t' = t - \delta t_{r, k_f}^{\text{in}}$ and $t'' = t - \delta t_{k_f, r}^{\text{out}}$

$$n_t^{\text{TN}} \leq C_{ht}^{\text{TN}} \quad \forall t \in \mathcal{T} \quad (4.20)$$

$$\sum_{r \in \mathcal{R}^1} \sum_{f \in \mathcal{A}^t} x_{f, t, r}^1 + \Delta_{r, t}^{\text{OGP}} \leq \phi_{r, ht}^{\text{max}} \quad \forall r \in \mathcal{R}^1, \forall t \in \mathcal{T} \quad (4.21)$$

$$\sum_{r \in \mathcal{R}^{\text{to}}} \sum_{f \in \mathcal{D}^{t'}} x_{f, t', r}^{\text{out}} + \Delta_{r, t}^{\text{OGP}} \leq \phi_{r, ht}^{\text{max}}, \quad \text{where } t' = t - \delta t_{k_f, r}^{\text{out}} \quad \forall r \in \mathcal{R}^{\text{to}}, \forall t \in \mathcal{T} \quad (4.22)$$

$$x_{f, t, r}^1 \in \{0, 1\} \quad \forall f \in \mathcal{A}, \forall t \in \mathcal{T}_A^f, \forall r \in \mathcal{R}^1 \quad (4.23)$$

$$x_{f,t,r}^{\text{out}} \in \{0, 1\} \quad \forall f \in \mathcal{D}, \forall t \in \mathcal{T}_D^f, \forall r \in \mathcal{R}^{\text{to}} \quad (4.24)$$

$$y_f \in \{0, 1\} \quad \forall f \in \mathcal{D} \quad (4.25)$$

Constraint (4.1) (resp. (4.2)) refers to arrival (resp. departure) time and runway assignment constraint. Landing time, in-block time, off-block time and takeoff time intermediate variables are fixed thanks to constraints (4.3), (4.4), (4.5) and (4.6) respectively. Constraints (4.7), (4.8), (4.9) impose minimum turnaround time for flights operated by the same aircraft. Each one depends on the flight status of the pair considered. Similarly, constraints (4.10), (4.11), (4.12) express the minimum transfer time for flights having at least one connecting passenger. Constraint (4.13) fixes the value of the binary variable y_f that determines whether a flight f is delayed according to the OTP metric. Constraint (4.14) forces priority flights to be delayed by 10 minutes or less. Constraint (4.15) fixes the initial terminal occupancy. Constraint (4.16) establishes the next occupancy of each terminal depending on the current one at time step t . It is equal to the current occupancy plus flights arriving at the block at t minus the ones departing from the block at t and an occupancy variation term due to on-going or planned flights. Terminal capacity constraints are represented through (4.17). Analogous constraints are applied for the taxi network through (4.18), (4.19) and (4.20). Finally, throughput constraints related to arrival and departure runways are represented by (4.21) and (4.22) respectively.

4.3.4 Objective function

A multi-criteria function is considered and several terms need to be introduced:

- G that represents the total number of stranded outbound passengers:

$$G = \sum_{f \in \mathcal{D}} \sum_{t \in \mathcal{T}_D^f} \sum_{r \in \mathcal{R}^{\text{to}}} g_{f,t} \cdot x_{f,t,r}^{\text{out}} \quad (4.26)$$

- D that quantifies the total in-block time and take-off time deviation from the initial schedule:

$$D = \sum_{f \in \mathcal{A}} |t_f^{\text{in}} - T_f^{\text{in}}| + \sum_{f \in \mathcal{D}} |t_f^{\text{to}} - T_f^{\text{to}}| \quad (4.27)$$

- Y that is a measure of the total number of delayed flights regarding OTP metric:

$$Y = \sum_{f \in \mathcal{D}} y_f \quad (4.28)$$

The objective function to be minimised is the following one:

$$G + \alpha.D + \beta.Y, \quad \text{with } \alpha, \beta \geq 0. \quad (4.29)$$

α and β are parameters that can be adjusted by the airport operators depending on whether the rescheduling should favour a reduction of the total number of passengers missing their flights, the total deviation time from the schedule or the number of flights delayed by 15 minutes or more. For example, for $(\alpha, \beta) = (0.1, 1)$, a 20-minute flight delay has the same impact on the objective function as three passengers missing their flight.

At this stage, the objective function is not linear due to the absolute values. Thus, we introduce intermediate variables to represent the absolute in-block and takeoff time deviation:

- $\forall f \in \mathcal{A}$, δ_f^{in} : in-block time deviation of flight f
- $\forall f \in \mathcal{D}$, δ_f^{to} : takeoff time deviation of flight f

These variables are fixed through the following constraints:

$$\delta_f^{\text{in}} \geq t_f^{\text{in}} - T_f^{\text{in}} \quad \forall f \in \mathcal{A} \quad (4.30)$$

$$\delta_f^{\text{in}} \geq T_f^{\text{in}} - t_f^{\text{in}} \quad \forall f \in \mathcal{A} \quad (4.31)$$

$$\delta_f^{\text{to}} \geq t_f^{\text{to}} - T_f^{\text{to}} \quad \forall f \in \mathcal{A} \quad (4.32)$$

$$\delta_f^{\text{to}} \geq T_f^{\text{to}} - t_f^{\text{to}} \quad \forall f \in \mathcal{A} \quad (4.33)$$

The deviation criteria can finally be written through the following expression:

$$D = \sum_{f \in \mathcal{A}} \delta_f^{\text{in}} + \sum_{f \in \mathcal{D}} \delta_f^{\text{to}}$$

The choice to consider absolute values for the total deviation time criterion is questionable. It might have been preferred to consider a quadratic term, which exact solvers can also handle through quadratic programming. However, such a quadratic term tends to favour an equitable solution, i.e. where each flight is affected by a small deviation. Such a solution would increase the workload for air traffic controllers. On the other hand, the number of delayed flights could have been considered to favour parsimonious solutions. However, this could lead to larger delays and an increase in the number of flights delayed regarding the OTP metric. The absolute deviation seems to be a

trade-off between creating parsimonious solutions and limiting the assignment of large delays.

4.4 Solution approaches

Two approaches for solving the ILP model on a specific time window are presented. The ILP model proposed in [Section 4.3](#) can be optimally solved thanks to an ILP commercial solver in many cases (see [Section 4.5](#)). In order to tackle the largest instances in a short computing time, as well as to compare the model results to solutions that could be ‘manually’ designed by an airport operator, we also propose a simple greedy heuristic to solve the PFRSP.

The main idea of this algorithm is to reduce the number of stranded passengers by delaying priority flights that have the highest impact on this criterion. Therefore, the following score s for each pair of flight and delay (f, d) is computed:

$$s(f, d) = \frac{p_{f,d}}{1 + \epsilon \cdot d} \quad (4.34)$$

where $p_{f,d}$ corresponds to the number of ‘recovered’ passengers if the flight f is delayed by a delay d and ϵ a positive parameter. Here, the higher the score is, the more efficient the pair (f, d) is. If $\epsilon \ll 1$, a lexicographical order is used to rank score first by the number of recovered passengers and, in case of equality, by the smaller deviation from the initial schedule. Conversely, if ϵ is set to a high value, small delays are prioritised. For the sake of simplicity, the runway assignment for departure and arrival flights is not changed with this heuristic. [Figure 4.4](#) displays a flow chart representing the main steps of this heuristic. We can show that $\epsilon = 10^{-5}$ is suitable to priorities first the reduction in the number of stranded passengers then the delay.

In order to focus only on (flight, delay) pairs that are relevant, a pre-processing step is carried out. For instance, delays over 10 minutes are not tested with priority flights. These pairs are ordered by decreasing score values and stored in a stack S . Then, the first pair (f, d) of S is unstacked, and the delay d is tested on flight f . If the maximum runway throughput is exceeded, the next element of S is unstacked. Otherwise, the terminal capacity constraint is evaluated. If an overload is observed, a recovery mechanism is launched to test if an arrival flight can be delayed to mitigate terminal congestion. Finally, the taxi capacity constraint is checked. If this one is satisfied, the departure flight’s off-block time is updated, and, if necessary, the flight’s arrival time that mitigates terminal congestion is also updated. These flights are removed from consideration (i.e., all pairs (f, d) including flight f from S are removed, and the arrival flight is removed from the ones considered to alleviate airport congestion), and the next element of S is unstacked until this one is empty.

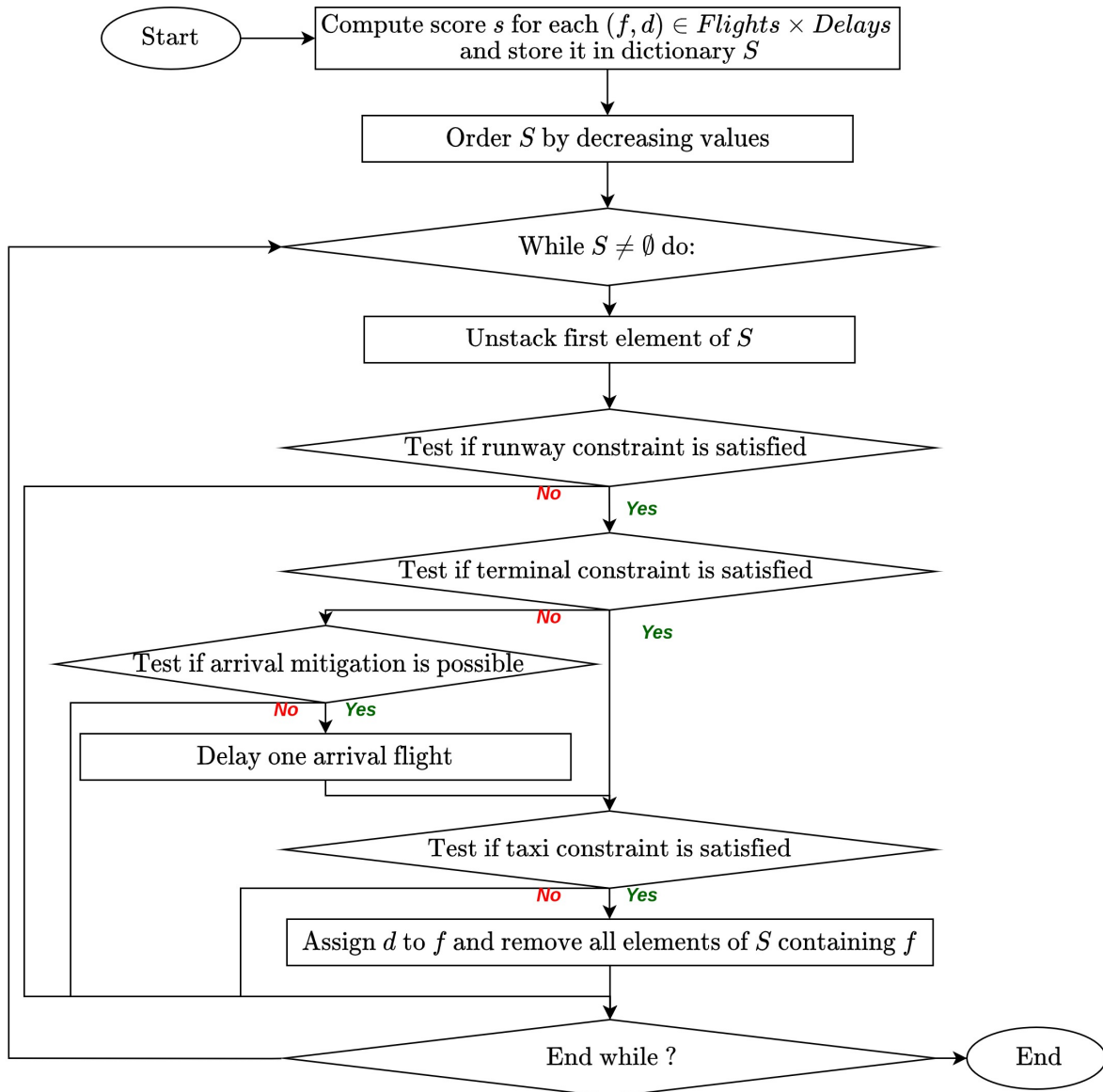


Figure 4.4: Flow chart of the proposed heuristic.

ϵ	10^{-3}	10^{-2}	10^{-1}	1	10^1	10^2	10^3
stranded passengers	113	107	107	122	125	141	158
total deviation (min)	895	990	990	870	875	785	690
Number of delays \geq 15min	33	37	37	26	24	24	17

Table 4.1: Criteria values after rescheduling with the heuristic approach depending on the score parameter ϵ (see Equation (4.34)). This parameter penalises the score of a decision ‘Assign delay d to flight f ’ as a function of the delay d . A high ϵ will reduce the score of decisions, implying large flight delays. The best values are highlighted in bold.

4.5 Computational results

This section presents tests and analyses to compare the different solution approaches. Exact and heuristic algorithms have been tested on a Ryzen AMD5 4500U with Radeon GPU and 16GB. The Gurobi 9.5.0 solver is used to solve the ILP model proposed in Section 4.3. The maximum off-block time (OBT) delay is set to 20 minutes, while the arrival delay is limited between -5 and +15 minutes. A 5-minute time step is used, meaning the Off Block Time (OBT) delay can equal 0, 5, 10, 15 or 20 minutes.

First, the optimal ILP model solution and the heuristic approach are compared. Then, the ILP performance is analysed depending on the time window duration and maximum OBT delay. The following tests are carried out on the S45 scenario, which models a scenario simulating a disruption occurring on the subway with passengers delayed up to 45 minutes.

4.5.1 Heuristic vs ILP solution approach

For this study, the time window length is set to four hours. Since the objective function of the ILP model is multi-criteria, several pairs (α, β) are tested to determine whether priorities one criterion or another. Similarly, the value of the score parameter ϵ used in the heuristic impacts the final solution. Figure 4.5 presents criteria values obtained with the ILP model depending on weight parameters (α, β) . The lowest value obtained through the heuristic on each criterion is also displayed in red. Results related to the heuristic problem solution approach in the function of ϵ are provided in Table 4.1.

The initial number of stranded passengers is equal to 249. The ILP solution approach reduces this number to 92 for $(\alpha, \beta) = (0.1, 0)$, representing a 63% improvement. This is 7% better than the best solution found by the heuristic. However, for this pair, the heuristic can perform better for the delay deviation and the OTP metric. The more the schedule deviation penalty increases, i.e. the higher α and β , the lower the reduction of the number of stranded passengers after optimal ILP rescheduling. If the

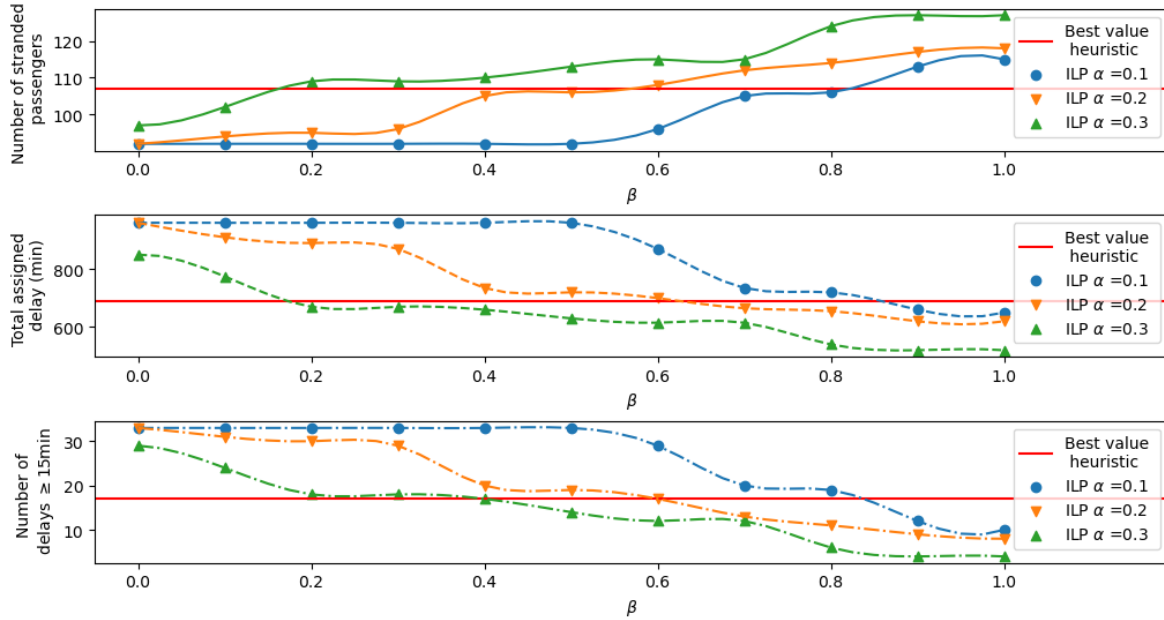


Figure 4.5: Values of different criteria obtained after ILP solution approach on a 4-hour time window. Each graph corresponds to a criterion, and each point to one pair of weight parameters (α, β) . α is associated with the total flight delay, while β is associated with the number of flights delayed by 15 minutes or more. The larger these parameters are, the less the algorithm assigns flight delays. The red lines correspond to the best value obtained with the heuristic approach for each criterion among the set of ϵ parameters tested.

penalty overcomes a threshold, the ILP solution approach provides a schedule with more stranded passengers than the heuristic approach. However, in parallel, a significant reduction of both other criteria is observed, and the ILP solution approach outperforms the heuristic approach on both criteria. Comparing Figure 4.5 and Table 4.1, when a similar value is obtained on one criterion with the heuristic and the ILP solution, the ILP one outperforms the heuristic one on the two other criteria. The heuristic can be efficient on one criterion but tends to degrade the two other ones. A trade-off between criteria can be found through ILP solution for pairs $(\alpha, \beta) = (0.3, 0, 3)$, or $(0.2, 0, 6)$ for instance, as illustrated in Figure 4.5, where the exact solution is almost as good as each best criterion value found by the heuristic depending on ϵ .

Table 4.1 shows test results for $0.001 \leq \epsilon \leq 10000$. Note that the solution no longer varies for epsilon lower than 0.0001 or higher than 10000. Interestingly, the highest reduction of the number of stranded passengers is not obtained with the lowest ϵ . A closer look at solutions obtained with $\epsilon = 10^{-3}$ and $\epsilon = 10^{-2}$ lets us see that fewer flights are delayed for the smaller parameter value. This observation can be explained

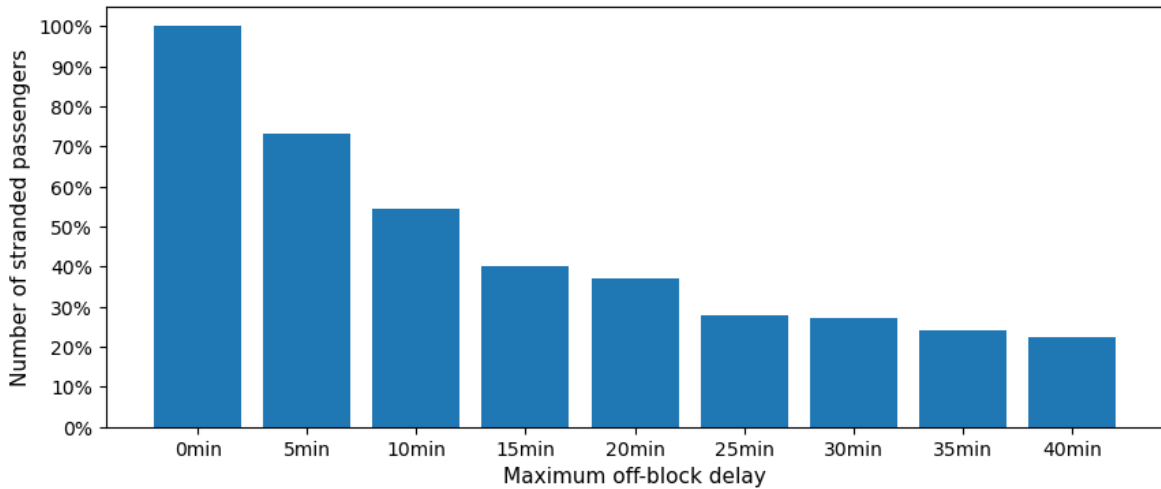


Figure 4.6: Evolution of the relative number of stranded passengers as a function of the maximum off-block delay allowed. The relative number of stranded passengers is computed by comparing the number of stranded passengers before and after flight rescheduling.

since reducing the deviation penalty tends to increase the score related to large delays. However, an aircraft experiencing a significant delay uses airport resources longer and could limit delay assignment for the next flights. Therefore, prioritising larger delays that save the highest number of passengers can lead to sub-optimal solutions regarding this criterion.

Finally, the average computation time of ILP and heuristic approaches are 0.6s and 0.02s, respectively. Therefore, the heuristic approach is 30 times faster than the ILP solution. However, the computation time of the ILP solution is still acceptable for tactical airport operations handling. The impact of the time window duration on the ILP computation time has also been investigated. The computation time increases when the time window is lengthened since more flights are considered and, thus, more decision variables are generated. It goes from 0.1s up to 1.74s for a 2-hour and a 12-hour time window duration, respectively. Therefore, solving the ILP with Gurobi is still efficient to reschedule flights planned over an entire day of operations. For the rest of the section, the presented results are obtained with the optimal ILP model solution approach.

4.5.2 Maximum off-block time delay sensitivity analysis

The impact of the maximum allowed OBT delay on the number of stranded passengers is investigated below. In other words, we conduct tests to measure if authorising larger delays would help reducing the number of stranded passengers. To evaluate this effect,

the schedule deviation penalty is removed by setting (α, β) to $(0,0)$. [Figure 4.6](#) displays the obtained results.

As expected, the number of stranded passengers decreases when the maximum allowed pushback time increases. The decrease goes from 25% if the maximum delay is set to 5 minutes and steadily increases up to 78%. Maximum OBT delays over 25 minutes induce smaller benefits due to resource capacity constraints. Indeed, when an aircraft is delayed, it uses a resource for a longer duration and, thus, is likely to induce congestion. Therefore, even for the solving with a maximum OBT delay set to 40 minutes, the average departure delay is lower than 18 minutes. Consequently, even after rescheduling flights while authorising large OBT delays, almost 20% of passengers who initially miss their flights remain stranded. This information could be provided to airlines to anticipate the need to reallocate these passengers on the next flights. Finally, increasing the maximum delay widens the search space and thus can lengthen the computational time. This one is around 0.35s for a 5-minute maximum OBT delay and increases up to 0.82s for a 40-minute one.

4.6 Conclusion

This chapter has presented a flight rescheduling strategy to mitigate the impact of airport access mode disruptions on passenger door-to-door journeys. We have defined the PFRSP, an optimisation problem which aims at rescheduling flights to minimise the number of passengers missing their flights, while limiting the total deviation from the original schedule and satisfying airport operational constraints. We have formulated this problem using a ILP model and have proposed a direct solution approach using ILP solver Gurobi and a greedy heuristic.

Our results illustrate the superiority of the ILP solution approach over the tested instances. The ILP solution approach provides an optimal rescheduling strategy in a short computational time and can be considered a valuable decision-support tool for flight rescheduling at the tactical level. We also have performed sensitivity analyses on different model parameters, such as prioritising one objective criterion over the other one, and on the solution performance approach depending on the maximum OBT allowed. We have seen that the ILP solution approach remains efficient in terms of computational time across the different tests performed. On the operational level, we saw that increasing the maximum OBT tends to reduce the number of stranded passengers, but reaches a limit due to resource constraints, leading to congestion of airport resources, which limits the maximum delays applicable to flights.

In summary, this chapter presents a second-stage recovery strategy to improve the resilience of passenger door-door journeys during airport access mode disruption. The next chapter proposes to test this recovery strategy and the one presented in [Chapter 3](#) on a realistic case study to get practical insights into their benefits for passengers.

Chapter 5

Practical insights: a case study for recovery strategies implementation

The previous chapters presented strategies for reallocating security teams and rescheduling flights in response to airport access disruptions. In this chapter, we propose to test the effectiveness of these strategies in an operational context through the study of realistic disruption scenarios. We have identified several examples of disruptions that can occur with ground transportation modes and test the recovery strategies on a historical operational day at CDG. We also present a methodology for implementing recovery algorithms at the tactical level to reschedule operations throughout the day. To do this, we identify the communication links required between transportation stakeholders to support the implementation of these recovery strategies. We also introduce a sliding time window framework to deal with the reliability of the data and the dynamic nature of the information flow established by the various communication links. This constrains the decisions that must be made dynamically throughout the operational day. We then describe the different disruption scenarios considered to perform the tests of both recovery strategies. Finally, we present and discuss the results obtained for each recovery strategy in order to gain operational insights and quantify the benefits of implementing such action plans at the airport level, both for airport stakeholders and passengers.

5.1 Communication links and online data handling

5.1.1 Communication links

When an airport access mode is disrupted, several passengers are likely to be delayed, and several may miss their flights. If the Airport Operation Centre (AOC) identifies these passengers early enough, their associated departure flights can be delayed to wait for them. Therefore, efficient communication links between transportation stakeholders are one key component to implement such a coordination mechanism. The successive

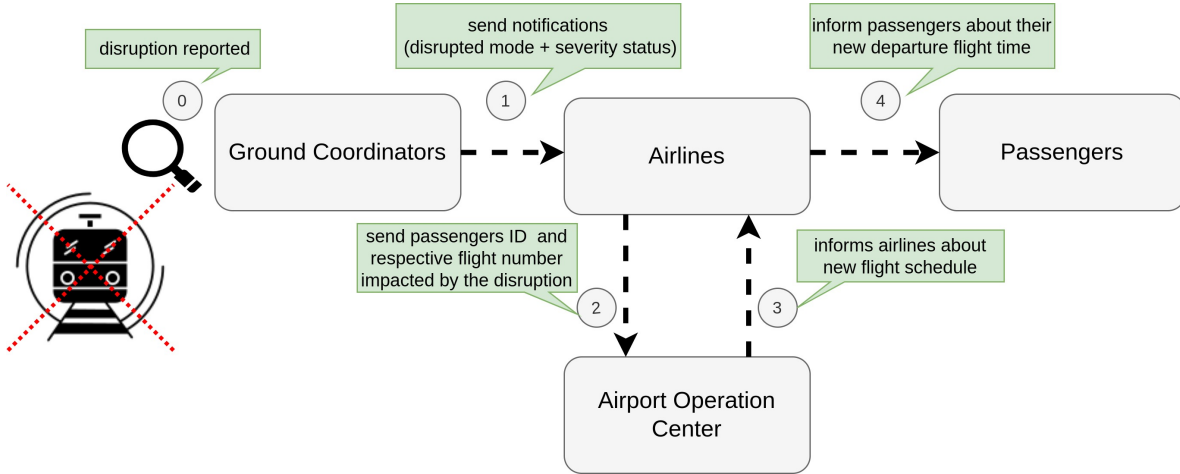


Figure 5.1: Illustration of communication links between stakeholders.

steps are illustrated in [Figure 5.1](#). We assume that the coordinator in charge of the transportation mode under disruption reports the incident and its severity level to airlines as soon as it occurs. Then, airlines can communicate with the AOC about passengers impacted by the disruption and their associated flights. The airport coordinator could estimate new passenger arrival times at the boarding gate and launch the flight rescheduling optimisation tool based on this information. A new flight schedule is finally obtained and transmitted to airlines that can inform passengers of the new flight departure time. In parallel, we assume that the information collected by the AOC could be used to forecast the new passenger arrival profile at security checkpoints and to reallocate security team resources based on this new forecast.

5.1.2 Online data handling

The recovery strategies proposed here aim at handling disruptive events, i.e. situations where actual passengers' arrival times are different from the forecasted one. Information provided by airlines and ground operators would help the AOC to update these forecasts, but only over a limited time horizon. For instance, when an access mode disruption occurs in the morning, forecasts related to passengers arriving in the evening are unreliable. Thus, reallocating security teams and rescheduling flights on a single time window lasting from morning until the end of the day is irrelevant. Therefore, we propose a sliding time window approach to reschedule airport operations over the day. We assume the AOC receives regular updates on passenger arrival times. In the following, this update is assumed to be done every 30 minutes. Security teams and flights planned over the next hours following the new update could be rescheduled. We propose to reschedule operations expected between one and three hours after the rescheduling decision. The selection of these bounds is motivated by the following considerations:

- Decisions on security teams and flights should be taken sufficiently early to inform the different stakeholders (e.g., security agents, air traffic controllers, pilots and other operators) about the new decisions and avoid poor operation handling. Indeed, if a delay is communicated to an arrival flight ten minutes before its initial landing time, the flight would probably use a holding pattern. Such an operation should be avoided since it increases the fuel burn. Conversely, if the delay is communicated between one to three hours in advance, speed regulation during the cruise phase or delay directly at the gate of the departure airport would be considered, limiting the extra-fuel consumption of aircraft. Similarly, it would not be realistic to tell a security team that they need to move to another security checkpoint within 10 minutes. Instead, an hour buffer would give them enough time to understand the new plan and make the move efficiently, without rushing;
- The upper boundary is set regarding the reliability of passenger arrival time forecast. Consider an airport access mode disruption happening at t_{start} . Since CDG advises passengers to arrive two and three hours before short-haul and long-haul flights respectively (Paris Aéroport (2023)), first passengers affected by the ground disruption would have their flight planned between $t_{\text{start}} + 120\text{min}$ and $t_{\text{start}} + 180\text{min}$. Therefore, we assume that passenger arrival time forecasts are reliable up to three hours in advance.

Algorithm 3 describes the proposed sliding time window process. The reassignment mechanism is launched for the first time at t_{start} to replan operations between $[t_{\text{start}} + 60\text{min}, t_{\text{start}} + 180\text{min}]$. Then, the reassignment is solved again on the next time window shifted by 30 minutes. This process is repeated until the end of the disruption plus, eventually, extra time to recover the initial schedule while accounting for possible domino effects.

Algorithm 3 SlidingTimeWindowManagement($tMin, tMax, x$)

```

tStart = tMin
tEnd = tMin +  $\Delta TW$ 
repeat
  x.windowInitialisation(tStart, tEnd)
  x.optimise(tStart, tEnd)
  tStart = tStart +  $\delta TS$ 
  tEnd = tEnd +  $\delta TS$ 
until tStart +  $\delta TS$   $\geq$  tMax

```

In this algorithm, x represents the decision variable vector, $tMin$ and $tMax$ the starting and ending time of the team reallocation or flight rescheduling, ΔTW the time window duration and δTS the time window shift. The function *windowInitialisation*()

Scenario name	Disrupted mode	Disruption starting time	Disruption ending time	Initial passenger delay
S45	Subway	8AM	3PM	45 minutes
R45	Road	8AM	3PM	45 minutes
T45	Train	8AM	3PM	45 minutes
S60	Subway	8AM	3PM	60 minutes
R60	Road	8AM	3PM	60 minutes
T60	Train	8AM	3PM	60 minutes
S90	Subway	8AM	3PM	90 minutes
R90	Road	8AM	3PM	90 minutes
T90	Train	8AM	3PM	90 minutes
T120	Train	8AM	3PM	120 minutes
S45_L	Subway	6AM	9PM	45 minutes

Table 5.1: Characteristics of the different disruptive scenarios.

updates the input data, such as resource availability or flight status, and the function *optimise()* represents the algorithm used to solve either the PFRSP or the SSRAP. As a reminder, a Simulated Annealing (SA) is used to solve the SSRAP, while a direct solution approach through ILP commercial solver is used to solve the PFRSP.

5.2 Case study description

We describe here the case study used to evaluate the effectiveness of the proposed recovery strategies in realistic disruption scenarios. This is based on a historical operational day at CDG. On this day, 1284 flights were operated, including 561 departures. Scheduled departure and arrival times are taken into account but actual flight delays are not considered below. The methodology used to model passengers presented in [Section 2.3](#) results in 100 000 departing passengers, including 35 000 connecting passengers.

In the following, we consider different access mode disruption scenarios. [Table 5.1](#) presents the different characteristics of each scenario. Each scenario name is composed of the first letter of the disrupted mode (S, T, R for Subway, Train and Road, respectively) and the maximum delay experienced by passengers in minutes. Therefore, S45 simulates a subway disruption with passengers experiencing an initial delay of 45 minutes at 8 am, linearly decreasing to 0 minute when the disruption ends at 3 pm. T45 simulates a train disruption with a constant passenger delay of 45 minutes. We design these scenarios to study how the severity of a disruption and the type of access mode impact outbound passengers. The first seven scenarios simulate a disruption lasting from 7 am to 3 pm. We select this time window to consider a disruption covering airport peak hours, which occur at 9 am and 12 pm. The severity of the disruption is

analysed by comparing 45-minute and 90-minute delay scenarios, respectively. We also introduce a scenario labelled ‘T120’, with train passengers delayed by 2 hours, in order to observe how the algorithm behaves when a large number of passengers arrive 20 minutes later than gate closure; i.e. passengers that are stranded in any case since we limit the maximum departure delay to 20 minutes. Finally, the last scenario’s analyses quantify the influence of a larger disruption lasting from early morning to evening.

The different instances related to each scenario are available via the following link: <http://data.recherche.enac.fr/scozzaro/pfrsp/>

5.3 Results and analyses

This section provides a detailed analysis of the recovery strategies applied to the different disruption scenarios simulated in the CDG case study. The different recovery strategies are applied independently, and we do not consider their integration. Firstly, we consider the reallocation of security teams in a scenario that does not include passenger flow segregation. We then compare the performance of the tactical team reallocation with and without allowing fast-track lane opening for each disruptive scenario introduced in Table 5.1. Secondly, we present analyses obtained from a disruptive scenario involving flight rescheduling. The results are then presented by testing the rescheduling on the different disruption scenarios described in Table 5.1.

The tests are performed on an AMD Ryzen 5 4500U processor, Radeon GPU, and 16 GB of RAM.

5.3.1 SSRAP results

We now present operational insights on security team reallocation recovery strategies in different disruption scenarios without considering the opening of fast-track lanes. A sliding time window approach is considered to reallocate teams throughout the day, solving a series of two-hour C-SSRAP models. This approach is designed to deal with the limited reliability of passenger arrival time data during the disruption. We perform the reallocation over the entire airport and constraint teams to be reallocated within their associated market.

On average, it takes 38 seconds to reallocate the security team over the day of operations without considering the fast-track lane opening and 120 seconds if considered. This represents an average computation time of 3s and 9s for solving the 2-hour C-SSRAP and P-SSRAP instances, respectively.

Firstly, we present an analysis of the initial security system performance as a function of staff shortage (before optimisation). Secondly, we present analyses of how the security team reallocation strategy, without passenger flow segregation, would affect passenger waiting time and the number of stranded passengers over the day. These

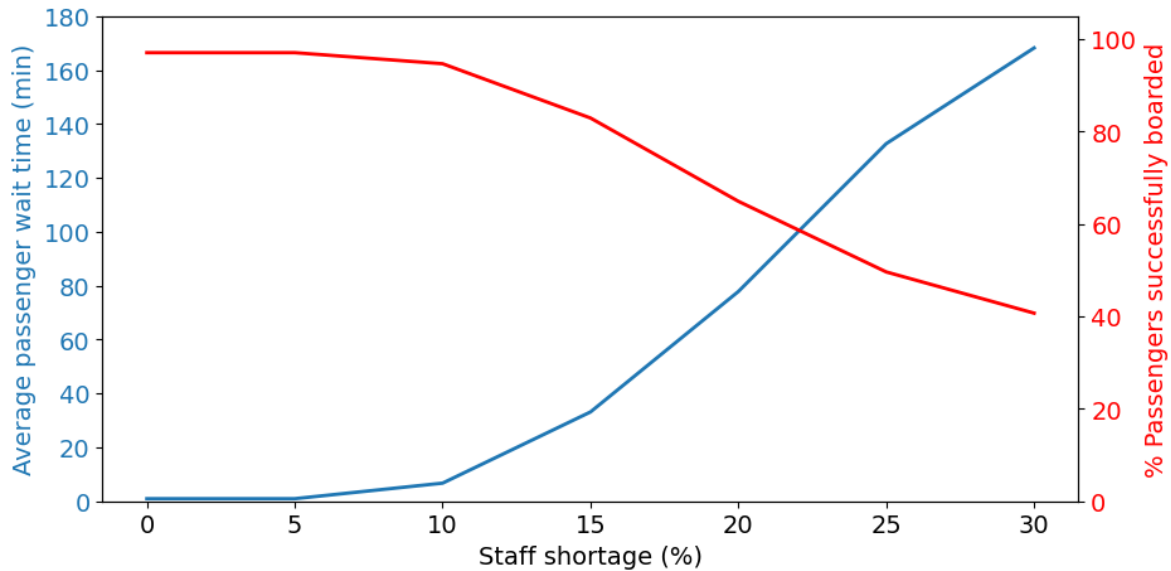


Figure 5.2: Evolution of the average passenger waiting time and proportion of passengers successfully board as a function of the percentage of staff reduction (initial allocation in scenario R60).

analyses are conducted in scenario R60, which simulates a road access disruption during the day with a passenger delay of up to 60 minutes. Finally, we test and compare the reallocation solution strategies with and without passenger flow segregation over the different disruptive scenarios presented in [Table 5.1](#).

5.3.1.1 Staff shortage analysis

Airport performance is directly related to the actual number of staff available. [Malandri et al. \(2019\)](#) highlight the correlation between airport LOS reduction and airport staff depletion. They estimate that a 50% reduction in available ground handling teams leads to a doubling of the average aircraft turnaround time. In order to assess airport LOS during nominal operations and under an access mode disruption scenario, we proposed in [Section 3.2](#) a methodology to estimate the number of security lanes that should be operated to provide a sufficient level of service. However, a staff shortage may occur during a ground transportation disruption as workers rely on these modes to access the airport. [Figure 5.2](#) quantifies the effect of a security staff shortage on the average passenger waiting time and the percentage of passengers arriving on time for boarding in scenario R60.

According to this Figure, the more security resources are reduced, the longer the passenger waiting time. The number of passengers arriving at the boarding gate on time is negatively correlated with the average passenger waiting time. This waiting time

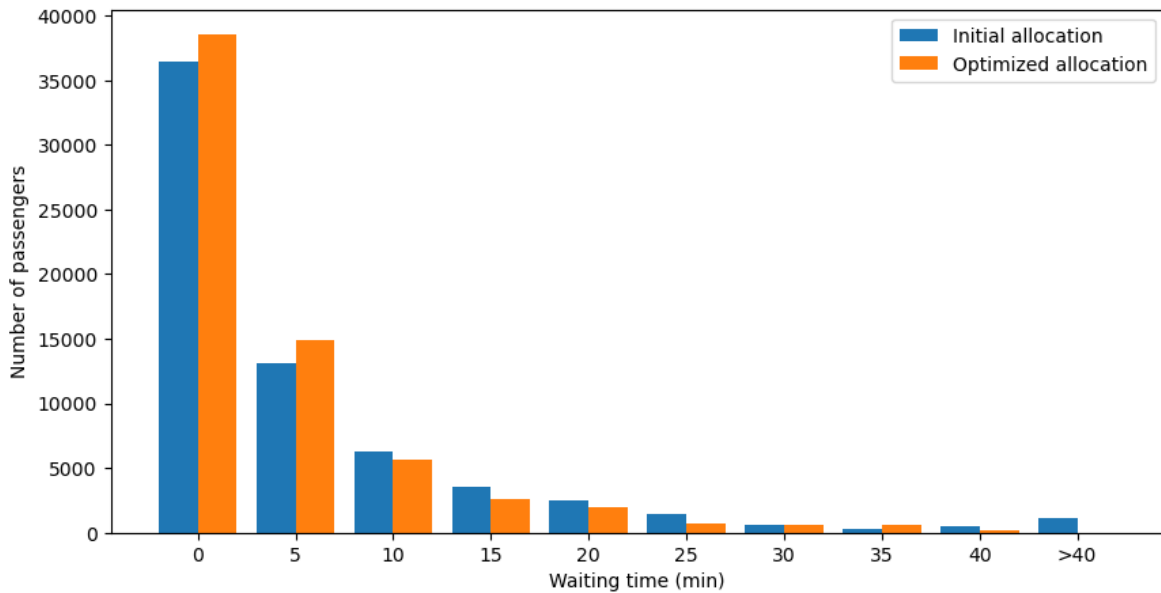


Figure 5.3: Distribution of passenger waiting times before and after optimisation in scenario R60.

increases from 1 minute to 40 minutes when the number of security teams is reduced by 15%. With this staff reduction, 17% of passengers miss their flights. The situation quickly becomes chaotic, with passengers waiting on average more than two hours if the staff shortage increases to 25%, causing half of the passengers to be stranded. In the following, we assume a 10% reduction in the number of security teams available during the airport access mode disruption.

5.3.1.2 C-SSRAP results in scenario R60

[Figure 5.3](#) shows the distribution of passenger waiting times before and after the security team reallocation. While most passengers wait less than 10 minutes at the security screening system before the reallocation, there are still 20% of passengers who wait 15 minutes or more. Reallocating teams increases the proportion of passengers waiting up to 10 minutes and reduces the proportion of passengers with long waits. We can observe that after the optimisation, no passengers are waiting more than 40 minutes.

In order to better understand the dynamics of the queues, [Figure 5.4](#) shows the evolution during the day of the maximum and average waiting time of the passengers before and after the reallocation of the security teams, aggregated for all the SC.

We can see that, before optimisation, two large peaks of maximum waiting time occur around 15:30 and 21:00. These peaks translate into an overburdened security screening system for at least one security checkpoint SC. The tactical reallocation

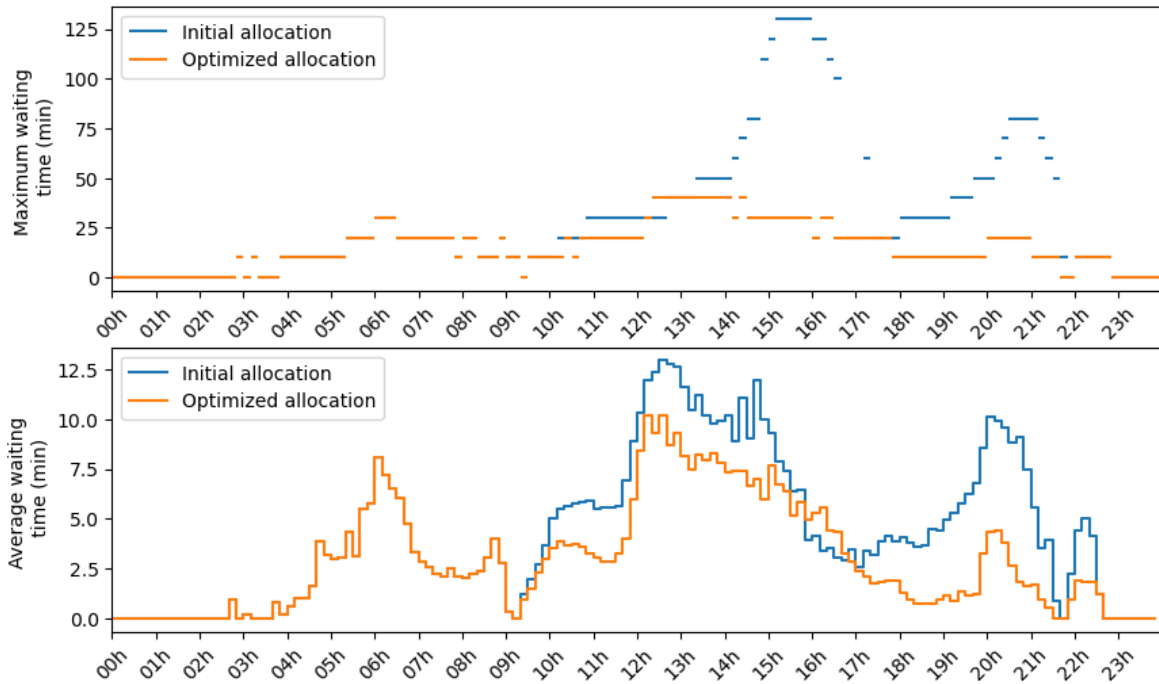


Figure 5.4: Maximum waiting time and average waiting time before and after optimization in scenario R60, in blue and orange, respectively. (top figure: maximum waiting time, bottom, average waiting time).

smooths the passenger flow at the security checkpoint, reducing the maximum waiting time from 130 to 40 minutes. Similarly, the resource reallocation allows the average waiting time to be reduced from 6.59 to 4.21 minutes. Note that the reallocation only starts when the first communication with the ground transportation side is established, i.e. just after the disruption. Since the disruption begins at 8 am and we take a 60-minute buffer between the reallocation decision and the actual operation, the average and maximum waiting times remain unchanged before 9 am.

Figure 5.5 displays the cumulative number of passengers who missed their flights before and after the security team reallocation. Initially, around 3500 passengers missed their flights by the end of the day. Following the reallocation, this number decreased by 23%. The effects of the reallocation vary throughout the day. For instance, from 10 am to 2 pm, the number of stranded passengers increases rapidly, both before and after reallocation. This period marks the beginning of disruptions, with several passengers arriving at the airport too late to reach the boarding area on time. As a result, even with security reallocation at this time, the number of stranded passengers only decreases by 15%. During the second part of the day, the initial number of stranded passengers increases sharply around 3 pm and just before 9 pm. These times correspond to the ones where significant waiting times have been observed in Figure 5.4. The stranded

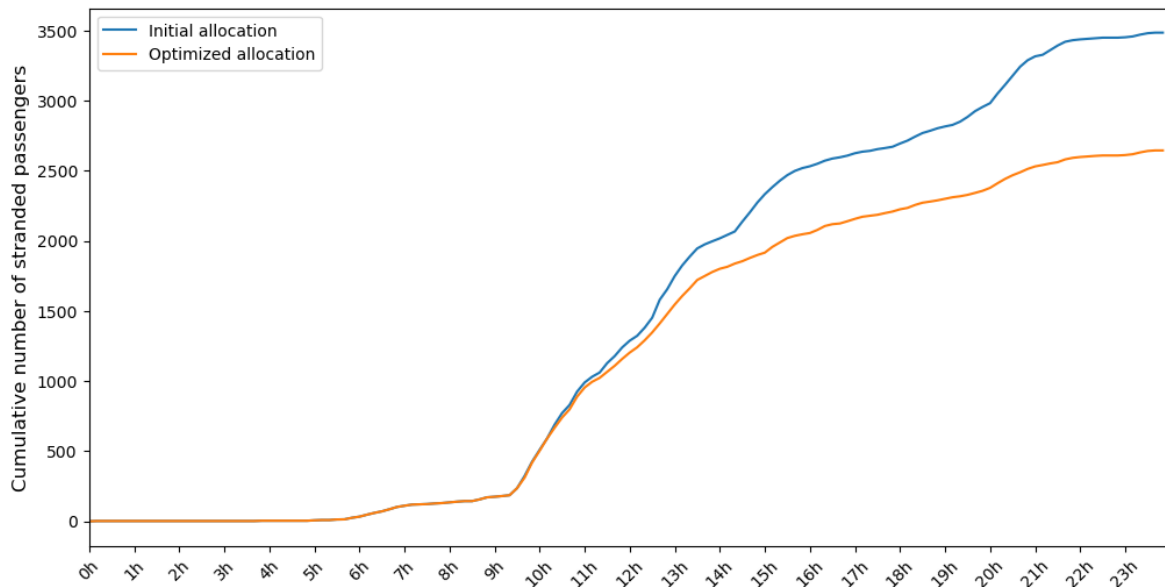


Figure 5.5: Cumulative number of stranded passengers over the day before and after optimisation in scenario R60, in blue and orange respectively.

passengers during this period are likely to be those who experience significantly long waiting times, which reach up to 130 minutes initially. Since the reassignment enables a significant reduction of the maximum passenger waiting time, it successfully allows passengers in the second part of the day to catch their flight on time, with a 35% reduction of the number of stranded passengers.

Since this scenario simulates a disruption ending at 3 pm, passengers arriving in the evening are not impacted by the disruption and should arrive on time at the entrance of the security screening system. Consequently, passengers missing their flight at the end of the day are indirectly affected by the disruption and miss their flights due to significant waiting time at security. Since the security team reallocation is more efficient during the second part of the day, it is particularly beneficial for passengers indirectly affected by the disruption. While it is still helpful for passengers directly affected by the disruption, its effectiveness is limited because a proportion of them is already too late to catch their flight, regardless of the security screening performance.

5.3.1.3 Security team allocation performance analysis: classical vs. priority reallocation

Table 5.2: Results obtained before and after redistributing the security teams across the different scenarios. For each scenario, the performance of the initial allocation (denoted *init*), the reallocation after C-SSRAP resolution (denoted *C*) and the one after P-SSRAP resolution (denoted *P*) are compared. \mathbf{W} , $\bar{\mathbf{w}}$, \mathbf{z} and $\mathbf{p10}$ refer to the maximum waiting time, the average waiting time, the number of stranded passengers and the proportion of passengers waiting more than 10 minutes.

	\mathbf{W} (min)			$\bar{\mathbf{w}}$ (min)			\mathbf{z}			$\mathbf{p10}$ (%)		
	<i>init</i>	<i>C</i>	<i>P</i>	<i>init</i>	<i>C</i>	<i>P</i>	<i>init</i>	<i>C</i>	<i>P</i>	<i>init</i>	<i>C</i>	<i>P</i>
S45	110	50	50	7.88	6.05	8.14	2755	2211	1788	28.4	20.3	30.64
S60	170	60	50	8.52	6.81	7.94	3247	2560	2074	27.7	17.8	28.07
S90	150	50	40	7.64	5.35	6.80	3338	2674	2149	24.6	15.2	24.43
R45	160	50	50	8.12	5.5	9.10	3222	2365	1879	25.0	15.0	30.75
R60	130	40	40	6.59	4.21	7.00	3355	2582	2341	21.5	13.2	24.04
R90	170	60	60	10.11	7.03	8.66	4804	4031	3226	29.4	18.5	30.13
T45	190	60	60	7.48	6.77	7.37	3786	3335	2886	20.1	18.8	24.69
T60	120	40	60	6.93	4.98	6.58	4513	3686	3420	21.5	16.8	20.93
T90	100	40	60	5.58	4.34	6.07	5503	5110	4900	22.1	16.6	21.0
T120	140	40	60	5.86	4.15	7.39	6550	6096	5863	16.0	14.0	25.53
S45L	140	50	60	8.64	5.8	8.57	3569	2495	2386	28.0	18.4	27.49

Table 5.2 displays the performance of different security team allocation strategies for various disruptive scenarios as explained in Table 5.1. For each scenario, we evaluate the initial allocation, the one obtained from solving the C-SSRAP and the one from P-SSRAP and denote them as ‘*init*’, ‘*C*’ and ‘*P*’, respectively. We compare the performance of the three allocations using several key metrics, including maximum waiting time, average waiting time, number of stranded passengers, and the proportion of passengers waiting 10 minutes or less.

We refer to the allocations obtained from solving the C-SSRAP and P-SSRAP as classical reallocation and priority reallocation, respectively. We also assume a 10% reduction in the number of security teams available for different disruptive scenarios.

The maximum waiting time before reallocating security teams ranges from 100 to 190 minutes for scenarios T90 and T45, respectively. The average waiting time varies from 5.58 to 10.11 minutes for scenarios T45 and R90, respectively. Therefore, the different disruptions do not affect the airport’s LOS similarly. The reduction in LOS, in terms of waiting time, does not seem to be correlated with passenger delay since passengers wait more in scenario S90 than in scenario S60, for instance. However, it

is correlated with the maximum waiting time or the proportion of passengers waiting more than 10 minutes. A high maximum waiting time translates to a congested security system, which results in higher waiting times and a higher number of passengers waiting more than 10 minutes. Finally, the higher the passenger delay, the more passengers miss their flights. Road disruptions also lead to more stranded passengers than subway disruptions since they affect a higher proportion of passengers.

As observed in the columns denoted ‘C’, the classical reallocation significantly reduces passenger waiting time. On average, the waiting time is reduced by 25%, ranging from 10% in scenario T45 to 36% for scenario R60. The reallocation also reduces the maximum passenger waiting time by at least 50% for all the disruption scenarios. However, the waiting time remains still high, equal to 60 minutes for the last six scenarios. This can be explained by the staff shortage assumption we took, with a 10%-reduction in the number of security screening teams available, strongly reducing airport LOS. The classical allocation also enables between 400 and 1100 passengers initially stranded to catch their flight on time. Regarding this criterion, the classical reallocation is the most performant in scenario S45L, which lasts longer than other disruptions with low passenger delays. It is less performant in train disruption scenarios where passengers are delayed due to a constant delay. This reduction highlights that minimising passenger waiting time, without consideration of priority passengers, is already a powerful strategy to reduce the number of passengers missing their flights.

Regarding the priority reallocation (columns denoted ‘P’ in [Table 5.2](#)), it achieves similar results in reducing the maximum passenger waiting time as the classical reallocation for road and subway disruption scenarios. The priority reallocation reduces the number of stranded passengers by 30% on average, outperforming the classical reallocation on this criterion for all scenarios. However, this reallocation strategy increases the average passenger waiting time, when compared to the initial allocation, for 6 out of 11 scenarios. For instance, it increases the initial average waiting time from 5.86min to 7.39min in scenario T120. The number of passengers that wait more than 10 minutes is increased by 10% on average after priority reallocation. These observations highlight an essential compromise that airport operators need to find. While the priority significantly reduces the number of passengers missing their flights, it is made at the expense of other passengers who arrived on time but experience larger delays. This is due to the finite resource constraint, where opening a fast-track lane requires closing a common lane, thus increasing waiting time for regular passengers.

A compromise could be found by changing the objective function of the P-SSRAP and considering a multi-criteria objective function, incorporating the average waiting time as another criterion to be minimised, and therefore limiting the side effects of such reallocation that would degrade airport LOS for regular passengers.

5.3.2 PFRSP results

We outline below the insights gained from rescheduling flights during various disruptive days. As previously detailed, our approach involved rescheduling flights within a 2-hour sliding time window, by solving the optimisation problem called PFRSP introduced in [Chapter 4](#). The rescheduling starts from the beginning of the disruption and it extended until the end of the day. To only focus on the flight rescheduling mechanism, we assume a constant passenger waiting time of ten minutes at security screening. This deliberate choice is made to isolate the effects of flight rescheduling from potential variations caused by the reallocation of the security team. By ensuring this consistency, we aimed to prevent any influence on rescheduling performances due to potential low performance in the upstream process.

We set the objective value parameters α and β to 0.2 and 1, respectively (see model in [Section 4.3](#)). With this parameterization, a 5-minute delay has the same impact on the objective function as one stranded passenger and a 15-minute delay has the same impact as four stranded passengers. The average computation time to reschedule flights over the day of operations is 6 seconds. This represents an average computation time of 0.5s per 2-hour PFRSP instance.

Firstly, the general results obtained for scenario S45 are presented. For this scenario, the performance in terms of reduction of stranded passengers and allocation of flight delays throughout the day is analysed. The impact on runway and terminal utilisation is also examined. A brief analysis is also carried out to examine the relevance of delaying arriving flights to reduce airport congestion. Finally, the impact of such rescheduling on connecting passengers is analysed. The rescheduling obtained for the scenarios described in [Table 5.1](#) is then compared.

5.3.2.1 Operational insights in scenario S45

[Figure 5.6](#) displays the evolution in the number of stranded passengers before and after rescheduling and the average aircraft delay assigned in scenario S45. One can observe that the number of stranded passengers is divided by two thanks to the rescheduling. A 1.5-minute and a 0.2-minute average delay are assigned to departure and arrival flights, respectively. By comparison, the actual average delay experienced by departing and arriving flights on this day of operations is equal to 20.5 minutes and 8.0 minutes, respectively. The average arrival delay is lower than the departure one since arrival delays are only assigned to mitigate airport congestion. Since arrival delays can be equal to -5, 0, 5, 10, or 15 minutes, an average delay of 0.2 minutes means that a small proportion of flights are delayed. [Figure 5.7](#) shows the number of delayed flights as a function of the assigned delay, with a distinction between departures and arrivals. Most arrivals are on time, with 5 flights delayed by 5 minutes and one by ten minutes. Three flights arrive earlier than expected to reduce airport resource overload. For departures, 80% of the flights meet their original OBT, and most of the delays attributed are less

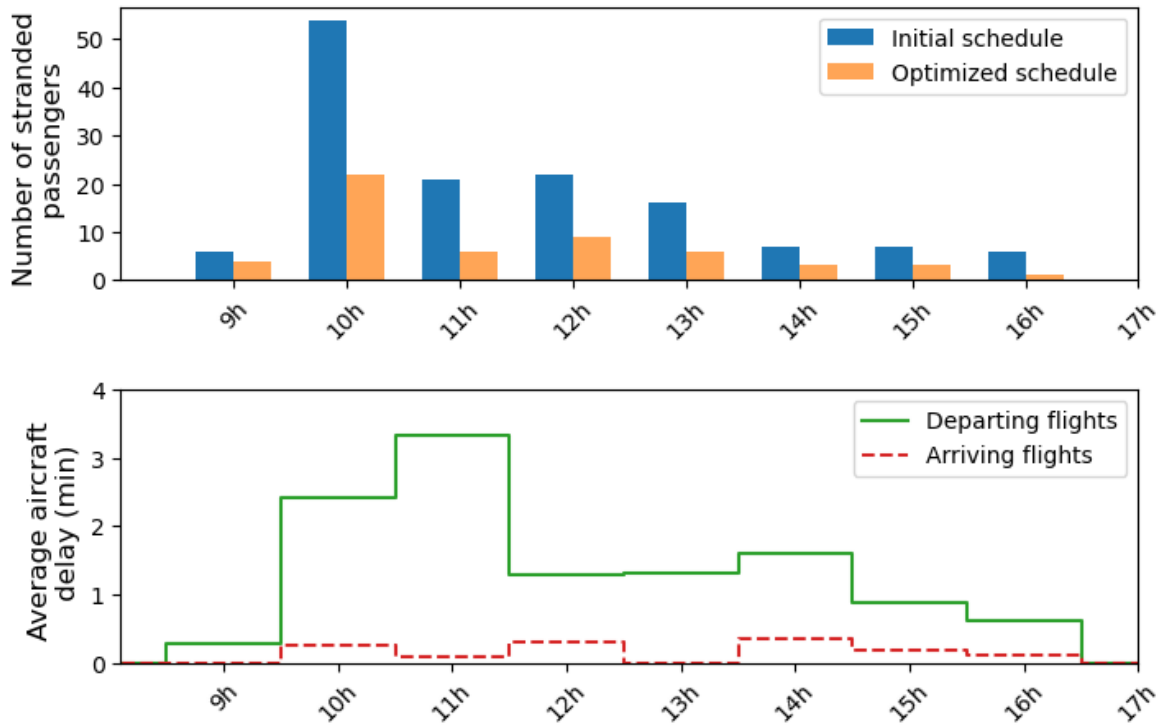


Figure 5.6: Evolution in the number of stranded passengers and the average aircraft delay assigned during the disruption. The blue and orange bars on the top figure represent the number of stranded passengers per hour before and after rescheduling, respectively. The bottom figure represents the average delay assigned to the arrival and departure flights per hour in red and green, respectively.

than 15 minutes. In this case, the flight rescheduling would have little impact on airlines' on-time performance, with only one flight considered as delayed. By comparison, the actual percentage of flights delayed by 15 minutes or more during this day of operations was 42.3%.

Resource constraint satisfaction

Figure 5.8 and Figure 5.9 depict runway throughput and terminal/taxi network occupancy before and after rescheduling. We only display the occupancy for the main terminals (T2E and T2F) and for the taxi network regarding space consideration.

One can observe that capacity constraints are respected for Terminals and the taxi network. Runways throughputs are also lower than the maximum ones, showing that the algorithm successfully reschedule flights over the day without violating these constraints, despite its sliding time window characteristics.

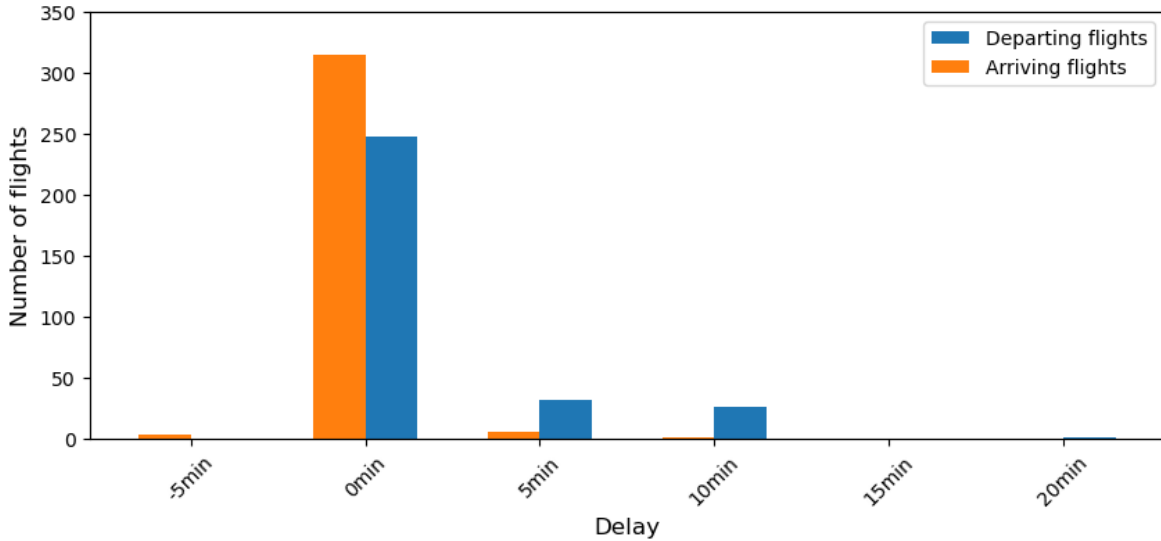


Figure 5.7: Number of flights depending on the assigned delay after rescheduling. A distinction is made between departing flights (in blue) and arriving flights (in orange).

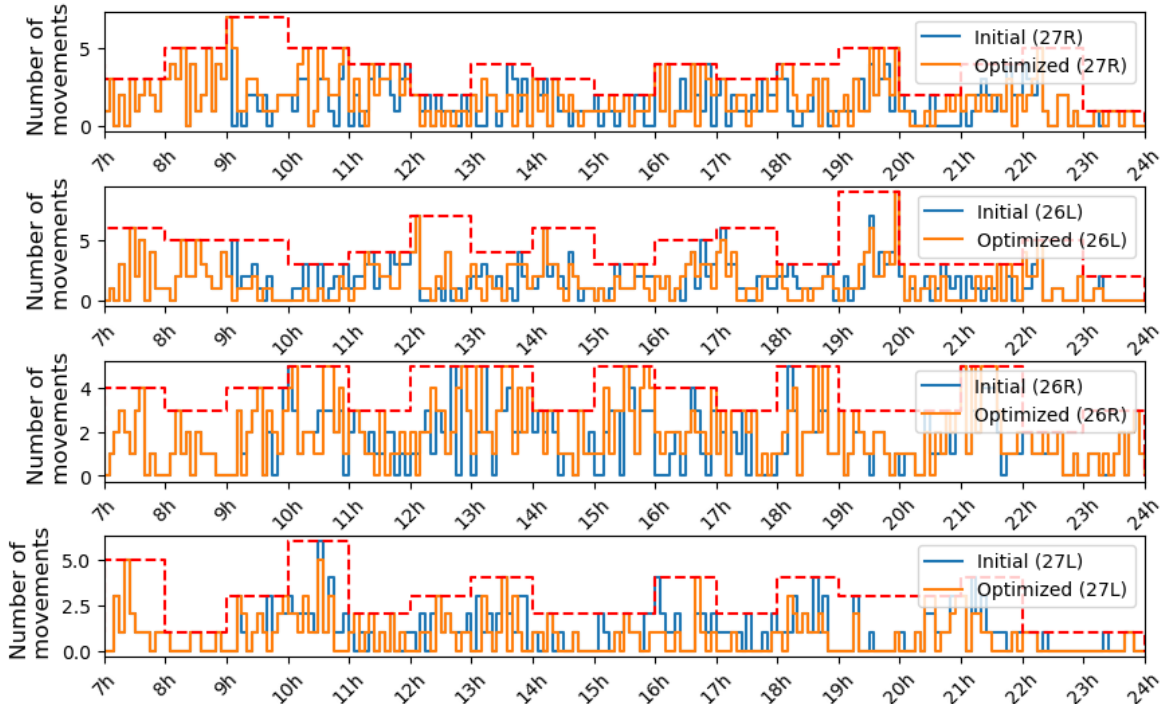


Figure 5.8: Evolution of runway throughput over the day. Maximum throughputs are represented through dotted red lines. Blue and orange curves represent throughput before and after rescheduling, respectively.

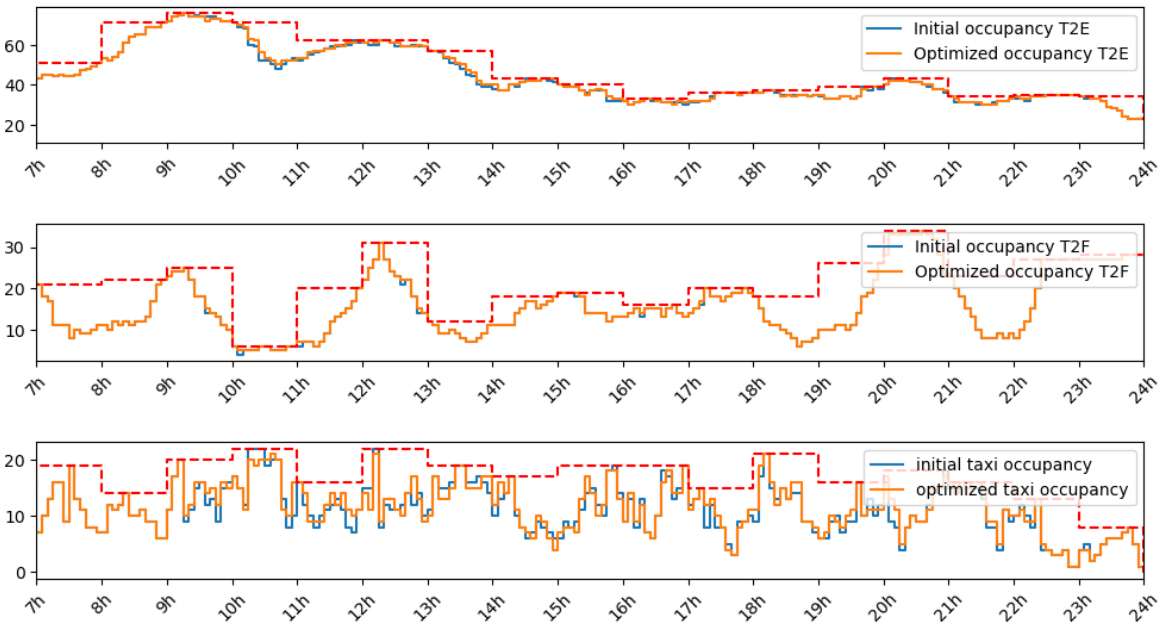


Figure 5.9: Evolution of occupancy on terminal T2E and T2F and taxi network over the day. Resource capacities are represented through dotted red lines. Blue and orange curves represent occupancy levels before and after rescheduling, respectively.

Effect of arrival delay constraints

As the average delay assigned to arrivals in scenario S45 is only 0.2 minutes on average, the relevance of delaying arrivals is questionable. Furthermore, at the tactical level, it is much more difficult to control the flow of arriving flights from the airport operations centre than to delay departing flights at the gate. Therefore, we run the algorithm by constraining arrivals to be on time. For scenario S45, 3% difference is observed in the relative reduction in the number of passengers missing their flights. For scenario R90, where a higher number of arrival delays were assigned after rescheduling, constraining arrival flights to stick to the initial schedule increase the final number of stranded passengers from 383 to 426. Such a difference is observed since we put pressure on CDG airport by constraining resource occupancy close to the scheduled one (see [Section 4.2.2](#)). If the algorithm were run in an airport with extra resource capacity, we can assume that the difference would be less significant.

Impact of the rescheduling on buffer time for connecting passengers

The rescheduling algorithm considers the transfer time of connecting passengers to ensure a minimum transfer time between flights. However, the closer the actual transfer time is to the minimum one, the greater the pressure on passengers. Therefore, we also examine the impact of flight rescheduling on the buffer times for passenger transfers, i.e.

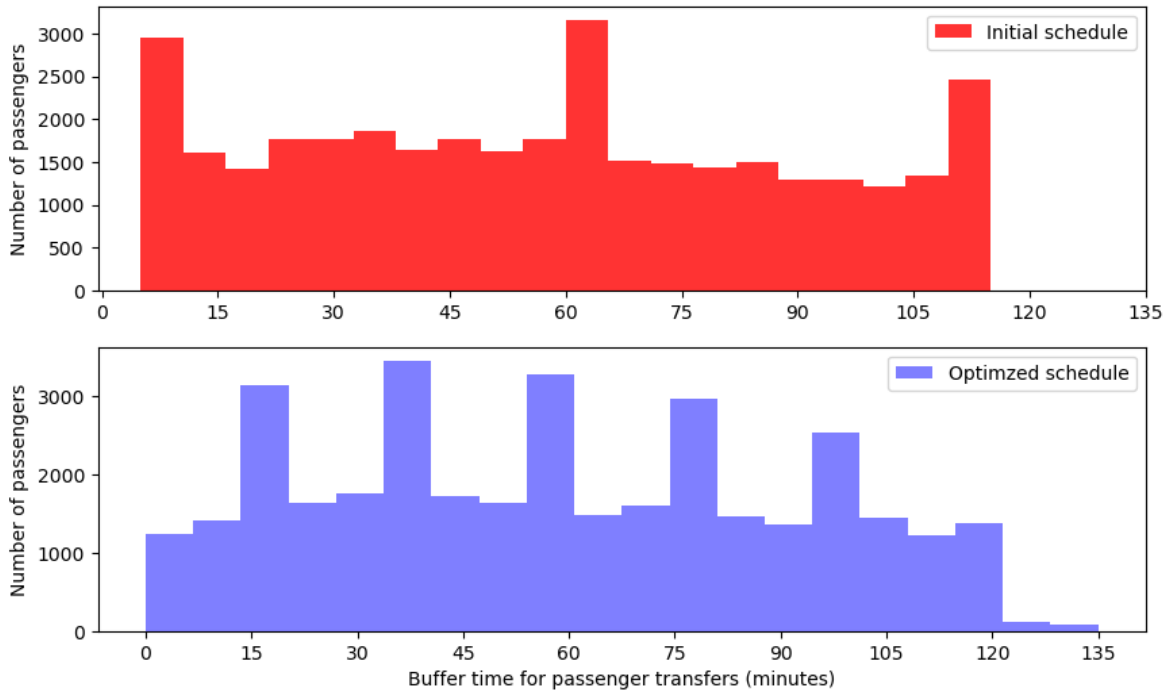


Figure 5.10: Comparison of buffer time for connecting passengers before and after rescheduling, in red and blue respectively.

the actual transfer time minus the minimum one. [Figure 5.10](#) shows the distribution of buffer times for passenger transfers before and after rescheduling.

As observed in this figure, the flight rescheduling has a limited impact on connecting passengers' buffer time. The average buffer time increases from 57 minutes to 59 minutes. The distribution of buffer times is more spread after the rescheduling. Initially, the minimum and maximum buffer times are 5 and 115 minutes, respectively. After rescheduling, 1200 passengers experienced transfers with no buffer time and about 200 passengers experienced buffers longer than 2 hours. This can be interpreted as a decrease in the level of service provided to air-connecting passengers. However, such degradation is offset by the reduction in the number of passengers missing their flights thanks to the rescheduling. Future work could explore trade-offs by imposing minimum or maximum buffer time constraints during the rescheduling.

5.3.2.2 Comparison of the different disruptive scenarios

The results for different disruption scenarios are presented in [Table 5.3](#). The severity of the disruption and the mode considered affect the initial number of stranded passengers, ranging from 139 up to 2605. Scenarios associated with a high delay, labelled as 'X90', generate more stranded passengers than 'small' and 'moderate' disruptions

associated with the same disrupted mode, labelled as ‘X45’ and ‘X60’, respectively. A road disruption induces more stranded passengers than a subway since the share of passengers using the first mode is higher. A train disruption has a greater impact than other modes of transportation because it simulates a constant passenger delay, equal to the highest one, instead of a decreasing passenger delay. As a reminder, the delay experienced by train passengers is equal to the ‘start delay’ throughout the day since, for this mode, we assume passengers have no re-routing options. Scenario S45_L generates 405 stranded passengers, which is higher than for S90, as the disruption lasts longer for this scenario and thus affects more passengers.

The rescheduling performance in reducing the number of stranded passengers is quite close for different scenarios, ranging from 45% to 61%, except for scenarios T90 and T120, where a 29% and 16% reduction are observed, respectively. Since a 90-minute and a 120-minute delay represent massive disruption, with passengers arriving at the airport much later, authorising a 20-minute deviation for departing flights might not be sufficient for waiting for most delayed passengers.

The departure delay assigned by the rescheduling tool increases with the severity of the disruption. For instance, in scenario S90, the average departure delay is 3.1 minutes, which is 50% higher than the delay in scenario S45. Similarly, the road disruption scenario has higher delays than the subway disruption scenario, with a delay of 5.6 minutes in the R90 scenario. This increase is due to a larger number of passengers using the last mode of transport, leading to more delays in mitigating the disruption and more passengers affected by the disruption.

However, there is an exception in scenario T120, where the delay is lower than in scenario T90. In this scenario, most stranded passengers arrive at the gate at least 20 minutes after the boarding time. As a result, the exact ILP solution assigns lower delays as these passengers would be stranded anyway.

A similar observation can be made for the last criterion, which quantifies the number of delayed flights with respect to the OTP metric. The higher the severity of the disruption, the more the ILP approach assigns large flight delays. Looking more closely at the new flight schedule, we can see that most of the large delays are assigned in the morning for the subway and road disruption scenario. Due to the disruption modelling retained, large passenger delays are observed at the beginning of the disruption. Therefore, flights in the morning should be delayed longer at the gate to wait for delayed passengers. For train disruption scenarios, large delays are evenly distributed throughout the whole rescheduling window. An exception is observed when most of the delayed passengers arrive at the gate 20 minutes after the original departure time, as in scenario T120. In this case, rescheduling assigns fewer large delays than for scenario T90.

The last column quantifies the propagated delay resulting from the rescheduling operations carried out during the disruption. A delay assigned to a flight operated after the disruption due to limited capacity of airport resources is defined here as a propagated delay. As can be seen, the impact on the rest of the timetable is quite limited. The

Scenario	Initial number of stranded passenger	Relative stranded passenger reduction	Average* ¹ delay		Number of delays \geq 15 minutes	Total propagate delay* ²
			per departure flight	per arrival flight		
S45	139	61.15%	1.5min	0.2min	1	30min
S60	234	52.14%	2.2min	0.1min	3	20min
S90	391	54.22%	3.1min	0.3min	14	5min
T45	456	47.15%	3.8min	0.2min	15	15min
T60	832	45.43%	5.6min	0.6min	39	40min
T90	1803	29.45%	7.4min	0.6min	57	10min
T120	2605	15.66%	6.4min	0.6min	51	50min
R45	353	56.94%	3.0min	0.2min	6	5min
R60	518	60.81%	4.2min	0.3min	21	0min
R90	921	58.41%	5.6min	0.6min	39	5min
S45_L	405	58.27%	2.2min	0.1min	9	5min

Table 5.3: Results obtained in the different scenarios through the direct ILP solution approach.

*1: Values have been computed only between the starting and ending time of the disruption. Thus, passengers stranded outside the disruption times are not considered here. *2: Propagate delays are the ones assigned to flights planned after the end of the disruption due to resource overload implying delay next arrival flights).

total propagated delay distributed over the entire flight schedule is generally less than 15 minutes. The most significant propagated delays are seen for T120, with a total delay of 50 minutes allocated to flights operating after the end of this disruption. In this scenario, rescheduling leads to significant delays for flights until the end of the disruption period, as train passengers experience a delay of 2 hours until the end of the disruption period. Consequently, flight delays are assigned until the end of the rescheduling. Therefore, more propagated delays are needed to alleviate the airport congestion caused by the rescheduling in this scenario.

5.4 Conclusion

This chapter has presented a methodology to implement the proposed tactical security screening and flight rescheduling strategies at the airport level. By considering disruption scenarios and proposing a sliding time window approach to effectively use the new information accessible through collaboration with the ground transportation side during a disruption, it has introduced an effective way of replanning airport operations at the tactical level. Various disruption scenarios have been considered to assess their

impact on airport operations and passengers. The recovery strategies proposed earlier in [Chapters 3](#) and [4](#) have been tested to see how they improve passenger journey resilience against access mode disruption.

Results show that reallocating security teams without passenger flow segregation, based on new passenger arrival time forecasts, significantly reduces passenger waiting times and the number of passengers missing their flights. Allowing a fast-track lane to be opened for passengers affected by the disruption further reduces the number of passengers missing their flights. However, a side effect has been noticed, where the fast-track lane opening strategy tends to increase the waiting time for regular passengers, potentially reducing their satisfaction. Therefore, a compromise should be found by also taking into account the average passenger waiting time when solving the P-SSRAP, for instance by considering a multi-criteria objective function.

Regarding the flight rescheduling strategy, it has been observed that slight delays at the tactical level can significantly reduce the number of passengers who miss their flights. With moderate changes made to the flight schedule, while respecting airside constraints, this approach is a powerful mechanism for recovering from disruptions, especially those that result in passengers arriving shortly after the original boarding time. However, in case of more severe disruptions, such as a train being delayed by two hours, and passengers arriving 20 minutes after boarding closure, tactical rescheduling with small delays may not be sufficient. In such cases, other recovery strategies should be implemented for these passengers.

Both recovery strategies have been studied independently without considering their respective impact. However, reallocating security teams changes the arrival time of passengers at the gate and, similarly, changing the departure time of flights impacts the buffer time passengers have at security before missing their flights. Therefore, the next step for this duty would be to consider both recovery strategies in an integrated approach. We also made several assumptions that need to be pointed out in order to mitigate the observations presented in this chapter. Firstly, we worked in a deterministic context where we assumed perfect knowledge of passenger arrival times. Secondly, we worked with aggregated passenger flows without a clear distinction on potential passenger behaviour depending on their characteristics, such as leisure, elderly or passengers with reduced mobility. Therefore, the performance of the proposed solution could be reduced in reality. The next step would be to include these aspects, either by considering stochasticity in the model or trying to validate it through a detailed simulation solver that handles this type of feature.

Part II conclusion

Airport access mode disruptions can impact the level of service provided by the airport leading to significant delays on passenger door-to-door journeys. To avoid such situations, we have suggested two recovery strategies for handling airport operations at the tactical level. The first one is based on a resource reallocation of security teams across the airport. To this end, we have formulated two optimisation problems, one considering a common single queuing line for passengers for each security checkpoint, and another allowing for a passenger flow separation to handle the priority passengers affected by the disruption. For each model, we have proposed different solution approaches, either based on a hand-crafted heuristic, an Integer Linear Programming (ILP) solution approach or a Simulated Annealing (SA). The test results and analysis show that the SA is a promising approach for the efficient reallocation of airport security teams in an acceptable computational time in terms of tactical operations management.

The second recovery strategy is based on tactical flight rescheduling to wait for delayed passengers due to airport access mode disruptions while limiting the total deviation applied to the original schedule. We have defined an optimisation problem that deals with flight rescheduling while satisfying airside operational constraints and dealing with air-connecting passengers. An ILP formulation of the problem has been proposed, which offers the possibility of a direct solution approach using an ILP commercial solver. The ILP solution approach gives promising results, rescheduling flights in a small computational time. The rescheduling approach succeeds in reducing the total number of stranded passengers by about 60%, while the average flight delay remains significantly low. In addition, most flights remain on time regarding the OTP metric.

In [Chapter 5](#), we have presented a sliding time window approach to effectively apply team reallocation and flight rescheduling strategies throughout a day of operations, considering regular updates on passenger arrival time from the ground transportation side during disruption. We conducted tests on various disruption scenarios to assess the performance of recovery strategies and their impact on passengers. Our results indicate that reallocating security teams helps reduce passenger waiting time and the number of stranded passengers. Additionally, opening a fast-track lane for late passengers may help reduce the number of stranded passengers but could increase the waiting time of other passengers. Rescheduling flights appears to be an efficient strategy to

help passengers recover their flights with limited aircraft delays compared to the ones observed in air transportation. However, this rescheduling strategy may not be sufficient for severe disruptions where passengers arrive significantly later than the boarding time at the gate.

Several research tracks could be explored. Firstly, a focus should be made on passengers still stranded after airport operation rescheduling, in order to see how these passengers can be accommodated on other flights. It would also be valuable to integrate the two recovery mechanisms through an integrated problem. Indeed, waiting times have a direct impact on the arrival time of passengers at the gate, and the re-allocation of security teams therefore has a direct impact on which flight should be delayed to wait for delayed passengers. Integrating both works could be considered to propose a global optimisation of both airport operations.

The next part presents a validation and extension of the two recovery strategies. We extend the team reallocation strategies through discrete event simulation on another airport, while the rescheduling strategy is extended to an air-rail network level to capture propagative delays.

Part III

Validation and extension: Advanced airport disruption recovery strategies

This third part widens the scope of recovery strategies presented in [Part II](#) by considering the environment surrounding airport operations, allowing for a better evaluation of their effectiveness. Indeed, security processes are intrinsically connected to other airport terminal processes, and rescheduling flights can have a propagative effect on the overall air transportation network. That is why we propose to study the underlying effect of such recovery strategies on their environment.

Collaborating with other researchers, we propose to integrate our proposals with simulation-optimisation frameworks and transportation network optimisation. This integration will help in providing a validation test for rescheduling flights and reallocating security teams to manage airport access mode disruptions. This will also help in a better evaluation of the benefits of the proposed solutions.

Firstly, in [Chapter 6](#), we present a simulation-optimisation framework that we developed in collaboration with Professor Mujica Mota ([Scozzaro et al., 2023c](#)). This framework is designed to reallocate airport security teams while considering the overall airport terminal environment. To achieve this, we develop a microscopic simulation model of passenger journeys through the airport and terminal configurations. We explore the optimisation problem of prioritising delayed passengers and test it on a case study of one terminal of Mexico City airport. This case study also provides an opportunity to see how relevant the security team reallocation strategy, previously presented in [Chapter 3](#), could be extended to another airport, accounting for its characteristics. Furthermore, this simulation-optimisation framework lays the groundwork for a decision support system for airport operators.

Secondly, [Chapter 7](#) explores a tactical coordination of flights and trains at a transportation network level. In collaboration with PhD student Clara Buire, a problem formulation has been proposed to extend the flight rescheduling strategy, previously presented in [Chapter 4](#), at the network level, taking into account propagative effects ([Scozzaro et al., 2023a](#)). We focus on air-rail connections and propose a delay management strategy to tactically synchronise rail and trains while taking operational constraints into consideration. We introduce a concept of total passenger delay and propose a strategy to decide whether a flight should wait for delayed passengers while ensuring compliance with airside and train-side constraints. We conduct a realistic case study using the Western European air-rail network to validate this delay management strategy. Our approach aims to reduce passenger delay during disruptions on multimodal journeys.

[Chapter 6](#) and [Chapter 7](#) provide a comprehensive exploration of the methodologies, results, and implications of the proposed recovery strategy extensions, paving the way for reliable passengers' door-to-door journeys.

Chapter 6

Simulation-Optimisation framework for tactical security team reallocation strategy

6.1 Introduction

Departing passengers go through several airport processes, including check-in, security screening, border control and finally, boarding. Each process can influence downstream processes, and not taking these effects into account may negatively impact overall airport performance. In this chapter, we aim to analyse the impact of our proposed tactical security team redeployment strategy on the airport security screening system environment. To gain a broader perspective, we propose to analyse how the proposed recovery strategy may benefit airport operators and whether it may adversely affect other terminal operations. To achieve this, we propose to test the recovery strategy through a detailed simulation model of an entire airport terminal, which captures the impact of security team redeployment on the overall airport operations and realistically assesses its actual benefits. Such simulation modelling also allows for differentiating different passenger categories, each having different behaviours and following different trajectories within the airport, as explained by [Schultz and Fricke \(2011\)](#). Therefore, such a tool acts as a validation tool to test our proposed recovery strategy by ensuring an adequate evaluation of the real benefits obtained by reallocating security teams. We collaborate with Prof. Miguel Mujica Mota, a simulation specialist who has developed a detailed model of the entire terminal building at Mexico City Airport.

The simulation model is also used to capture passenger behaviour from the airport entrance to the security screening area. It allows us to extract precise information and understand deviations in passenger arrival profiles at the security checkpoint from the standard profile based on the airport terminal configuration. Our approach illustrates how the management of resources in a complex system such as an airport at

the operational level can be improved through the simultaneous use of simulation and optimisation techniques. It could form a Decision Support System (DSS) for airport operators to manage security teams at the operational level effectively.

The rest of the chapter is structured as follows. Previous related work are presented in [Section 6.2](#). The SIM-OPT framework is presented in [Section 6.3](#). [Section 6.4](#) makes a reminder on the priority security screening resource allocation problem. [Section 6.5](#) describes the case study of Mexico City Airport and the simulation model. Finally, [Section 6.6](#) presents the results and discussion.

6.2 Literature Review

We present a literature review of simulation-optimisation studies that have been successful in improving airport operations planning.

Simulation techniques have played a key role in evaluating airport capacity and optimising resource allocation, especially at critical points such as check-in and security screening systems for large airports. The various previous works by Mota and colleagues are significant contributions to this field ([Mujica Mota, 2015](#); [Mujica Mota et al., 2021a,b,c](#)). Their research delved into various aspects of airport operations and provided valuable insights. They used an evolutionary algorithm coupled with a simulation model to address the check-in allocation problem. In the wake of the COVID-19 pandemic, they investigated the impact of new procedure restrictions on security checkpoint capacity. They also studied passenger segregation based on individual characteristics at security screening in order to improve the airport's level of service. In addition, they investigated the influence of a specific category of passengers. This group, willing to share personal information, could speed up their processing time at the airport by using a new type of facility.

Other studies have been led using simulation techniques to enhance airport performance. [Munasingha and Adikariwattage \(2020\)](#) employed SIMIO simulation tool to model passenger flow within airport terminals, aiding in bottleneck identification and decision-making for airport planners. [Kıyıldı and Karasahin \(2008\)](#) utilised fuzzy logic to assess the optimal number of counters for check-in, aiming to minimise queues. [AlKheder et al. \(2020\)](#) utilised simulation to evaluate the security screening system efficiency at Kuwait International Airport. Their study advocated for improving the airport's Level of Service by augmenting the number of security teams, challenging the assumption of finite resources.

These studies demonstrate the potential benefits of simulation tools for analysing the intricacies of airport operations and improving overall efficiency and passenger satisfaction. Integrating optimisation techniques with simulation makes it possible to use and allocate airport resources efficiently. Therefore, we propose to integrate simulation techniques with the optimised approach considered previously to reallocate security

screening teams. The following section presents the architecture framework of this integration.

6.3 SIM-OPT architecture framework

To improve the allocation of airport security screening resources, we proposed to solve the P-SSRAP introduced in [Section 3.4](#). However, evaluating the quality of the solution using aggregated passenger flow and deterministic assumptions may lead to an overestimation of the benefits of the proposed solution, as it does not consider the stochastic nature of the various processes involved. Furthermore, since airport security screening is not an independent process and the performance of each process affects the others, it is important to consider the whole airport terminal environment when evaluating performance. Therefore, we propose to model the entire airport and passenger journey within the airport to capture the interconnectedness of these processes and to obtain a realistic evaluation of airport operation performance.

We consider the use of a simulation framework, developed with a tool called SIMIO ([Simio, 2023](#)), in our approach. Its name derives from ‘Simulation Modeling framework based on Intelligent Objects’. This tool allows for fine-scale modelling, enabling the capture of highly complex systems behaviours. It can be used to build an accurate airport model and simulate passenger flow through different airport processes, as demonstrated in previous works ([Mujica Mota, 2015](#); [Mujica Mota et al., 2017](#); [Alrabghi, 2019](#)). Such simulation frameworks can capture the influences of different airport operations and their respective impacts by precisely modelling each operation and passenger trajectory from the airport entrance up to the gate. The simulation model can handle various characteristics such as arrival time, boarding time, category, and flight gate, among others. Stochastic elements can also be added to test different scenarios and evaluate the performance of airport operations with a higher degree of realism compared to deterministic models.

In our proposed architecture, the simulation serves two functions. The first function is to provide inputs to the optimisation model. Through the detailed modelling of airport operations, the simulation captures the entire passenger trajectory within the terminal. We leverage this characteristic to extract realistic passenger arrival profiles at the entrance of the security screening system, which are then used as inputs for the optimisation model. The second function of the simulation is to evaluate the quality of a security lane opening policy through a series of simulations, each differing from the others due to the stochastic features of airport processes. This evaluation helps assess the initial airport LOS and the one after the implementation of the management action plan, obtained through the P-SSRAP mathematical model solving. [Figure 6.1](#) summarises the integration of the SIM-OPT framework proposed in this study.

The simulation model is run once, prior to the reallocation of security teams during

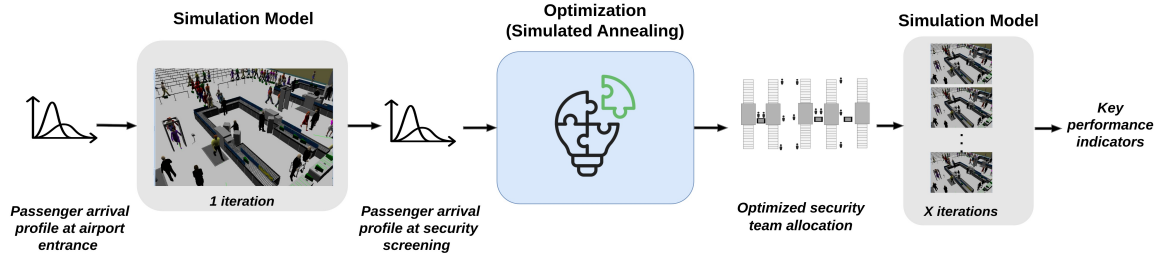


Figure 6.1: Architecture of the Simulation-Optimisation Decision Support System.

the day, to extract the arrival profiles of passengers at each security screening checkpoint. This information is fed to the optimisation algorithm to reallocate the security teams during the day of operations. The new allocation is then tested by running the simulation model 10 times, enabling an evaluation considering the system’s stochastic nature.

6.4 Optimisation problem description

In this work, we consider the optimisation problem introduced in [Section 3.4](#), namely the Priority-Security Screening ReAllocation Problem (P-SSRAP). We propose a brief reminder of the problem below.

The airport security screening system comprises several SC. Each SC includes a set of Security Lane (SL), a common queuing line, a fast-track lane and its dedicated queuing line. Each SL is a facility where security teams screen carry-on luggage and passengers. A security team of five or six agents is required to operate an open SL.

Every passenger entering the security system is characterised by an entering time at the SC, a status, and a boarding time. We categorise passengers into two categories, namely regular and priority. The passengers who identify as priority ones are not responsible for their hurry at the airport, as it occurs due to a disruption on their journey towards the airport. We assume a constant service rate for each SL, and a higher service rate for fast-track SL. When a fast-track SL is operated, priority passengers go through the fast-track queuing system. Otherwise, they go through the common security system.

We consider the passenger boarding time of each passenger to infer the maximum waiting time he/she can spend at security before missing his flight. The optimisation problem is to decide when and where passengers’ flow should be segregated by opening a fast-track lane for priority passengers. We consider a finite resource assumption, which implies that opening a fast-track lane leads to closing a shared SL. Due to the Mexico City terminal configuration, we do not allow security team transfers between checkpoints. We break down the day into 30-minute time intervals to provide enough flexibility and adaptability to the system as per the demand. Consequently, the problem

Table 6.1: Optimisation problem characteristics and solution approach features.

Optimisation model characteristics	
Service rate	120 pax/hour
Service rate priority	180 pax/hour
Working time interval duration	30 minutes
Number of Security Checkpoints (SC)	2
Number of segregated markets	2
Number of common security lanes per SC	5
Number of fast-track security lanes per SC	1
Maximum acceptable waiting time	30 minutes
Simulated Annealing features	
Initial solution acceptance rate	80%
Temperature decay parameter	0.999
Number of iterations per temperature step	2000

relies on deciding for each 30-minute interval if a priority lane should be opened (and a regular lane closed) for each security checkpoint.

The proposed reallocation aims to improve the airport security system's efficiency by minimising the total number of passengers missing their flights and the maximum passenger waiting time experienced among all passengers. A passenger is assumed to miss his flight if his arrival time at the boarding area is later than the closure boarding time of his flight. The maximum passenger waiting time is characterised by a penalty that is activated if a passenger experiences a queuing time higher than a waiting threshold noted as W_{\max} . We consider this penalty to favour fair solutions by avoiding significant passenger waiting times. The value of W_{\max} is 30 min.

The optimisation model related for this problem is presented in [Section 3.4.2](#). Regarding the solution approach, we use a Simulated Annealing (SA) as proposed in [Section 3.4.3](#). The problem characteristics and SA features are summarised in [Table 6.1](#).

6.5 Simulation and case study description

Simulation techniques has a high-level descriptive power compared to other techniques, such as mathematical programming or machine learning, solely based on observational data. Simulation offers the benefit of providing transparent causal relationships to the analyst, given that the model is descriptive enough. As such, we combined a detailed airport terminal model with optimisation to create a tool to help airport operators react in real-time to disruptions. This integrated tool also makes the consequences of decisions on one system element transparent, thus allowing us to predict the overall effect on passengers. In this particular case, the simulation-optimisation approach is

developed to minimise the number of passengers who miss their flights at the end of the day. To achieve this, we consider a complete model of one of the terminal buildings of an airport, which encompasses the different processes undertaken by any passenger, including check-in, waiting in departure halls, boarding pass control, security, and boarding gates. The level of detail in the model is critical as the airport's geometry and physical dimensions play an important role in determining the time consumed between processes. The following subsections describe the simulation aspect of the developed architecture.

6.5.1 Terminal 2 of Mexico City Airport

This work focuses on Terminal 2 of Mexico City Airport. The model encompasses the complete terminal building under study. We focus on the security checkpoints of the terminal, as security is the main hurdle for passengers arriving late due to disruptions in their surface access to the airport. The security screening system associated with this terminal comprises two security areas, each with five security lanes and an extra fast-track lane. Based on historical data, we considered the actual demand for the airport and simulated the demand under disrupted circumstances. The model is parameterised considering the different facilities' actual capacity and expected performance. It is verified and partially validated using historical data from 2019. The model is used to evaluate three different lane-opening strategies. The first scenario involves opening only common lanes while keeping the priority lane closed. In the second scenario, a priority lane is opened during the airport peak hour in each security area, reducing the number of open common lanes by one due to the limited number of teams assumption. Finally, in the third scenario, the allocation of security teams is made dynamically using the strategy obtained after solving the P-SSRAP. The main objective is to minimise the number of passengers missing their flights. By implementing this, we illustrate the benefit of having a DSS that can provide support when critical situations appear where human capacities are set up to the limit. Illustrations of the terminal model and the security areas under study are provided in Figures 6.2 and 6.3, respectively.

The Terminal 2 model comprises two security areas that are highlighted in red. Passengers access the terminal's departure area through three different entrances. They then proceed to check in, spend some time in the departure hall if they have time, go through security, and finally board their flight at the designated gates.

6.5.2 System Description

In this section, we provide a detailed description of the different elements that play a significant role in the problem. These elements are:

- Regular passengers: These are the most commonly found passengers at airport terminals;

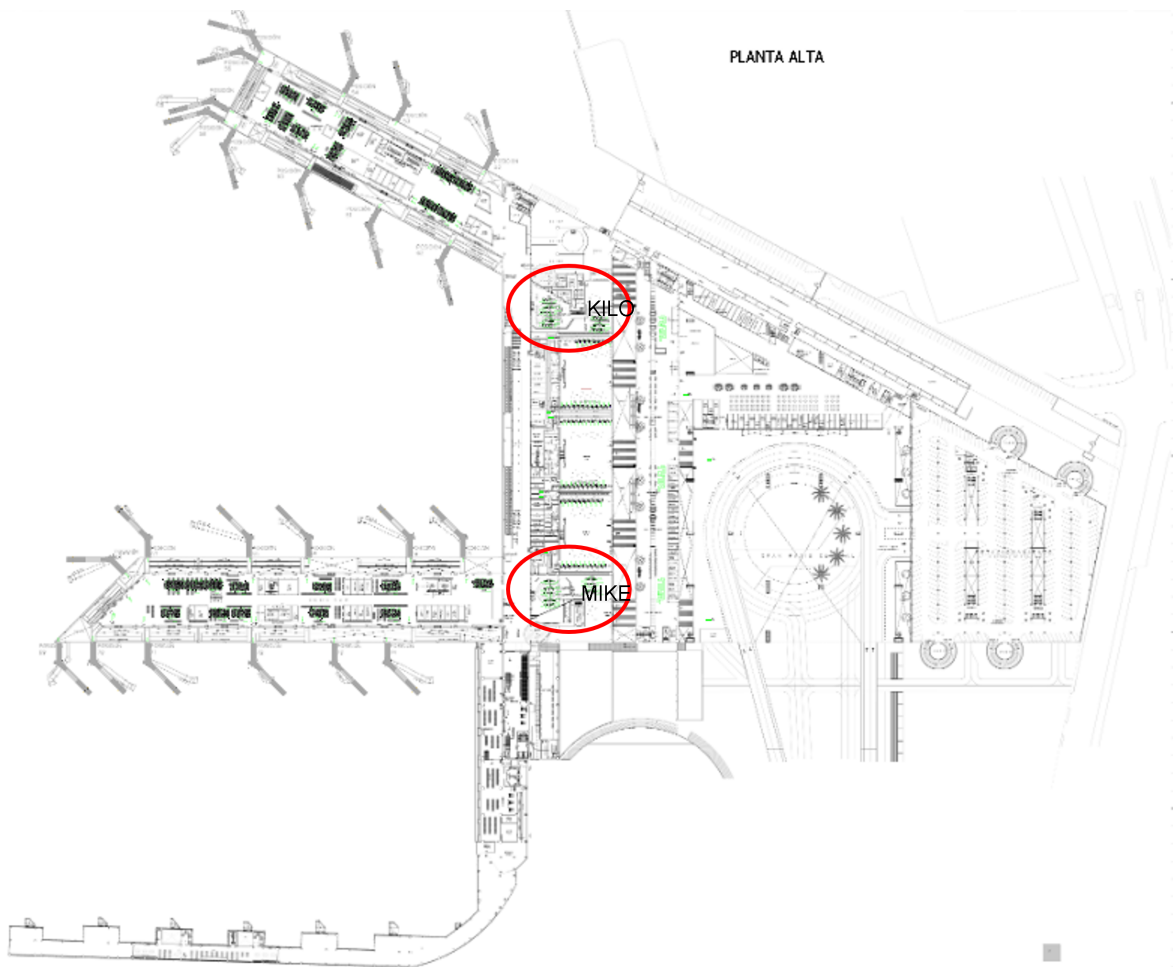


Figure 6.2: Illustration of Mexico City airport. Security areas are circled in red.

- Elderly passengers: These are passengers who typically move slower than regular passengers and may require special attention or support;
- Priority passengers: These passengers are in a hurry due to disruption and are at risk of missing their flight;
- Common queuing line: This is the security queuing line for all passengers, following the FIFO scheme. In this line, the three categories of passengers are mixed, which can cause slower passengers to obstruct the flow of other passengers;
- Fast-track queuing line: This is a segregated queuing line that is used in the alternative scenario. It is reserved for passengers with priority status, such as those severely impacted by the ground side or business.

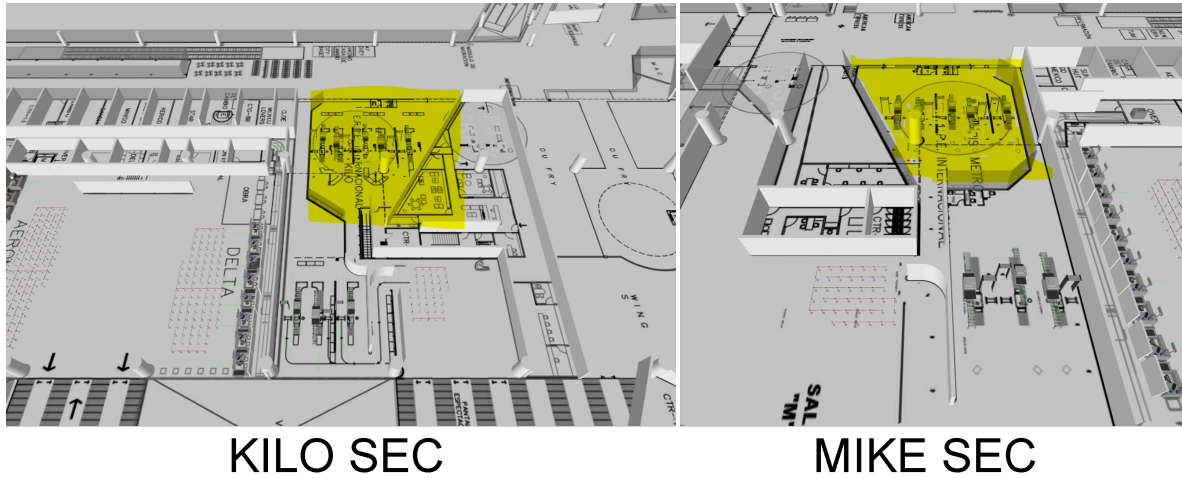


Figure 6.3: Illustration of security areas in Mexico City airport (displayed in yellow).

Each passenger is characterised by a service time at security screening that can vary (fast for priority, slow for elderly or common passengers) and the walking speed. Other elements that play a role in the model might be the following:

- Check-In areas: the three areas for check-in are considered in the model;
- Departure Hall: area where passengers and their companions spend time after check-in. Priority passengers skip those areas as they have very limited time;
- Security areas: areas within the terminal where the passengers are screened for metals or liquids;
- Boarding gates: rooms where the passengers spend their final time before boarding the aircraft;
- Physical dimensions: as the passengers spend time in the terminal while they move around it, the physical dimensions of the terminal should be considered for the model.

6.5.3 Experimental set up

The flow of passengers follows a sequential process as depicted in Figure 6.4. In the simulation model, the passenger enters with a companion who stays in the departure hall while the passenger performs his check-in. Once he finishes and if there is still time, they spend some time together, and after some minutes, the companion leaves the system, and the passenger goes to security. In the case of priority passengers, they walk faster and skip the departure hall. In the alternative scenarios, when priority

Table 6.2: Modelling assumptions.

Parameter	Value	Comment
Simulation Run	7 hrs	assumption
Peak Hour	1 hr (3rd hr)	assumption
Regular Pax Speed	1.1 m/s	assumption
Elderly Pax Speed	0.5 m/s	assumption
Priority Pax Speed	1.4 m/s	assumption
Distribution of arrivals	discrete distribution	assumption for priority and regular
Processing time	35 sec + variability	regular pax
Processing time	20 sec + variability	priority pax
Security lanes	10 lanes (5+5) and 2 optional ones for priority	finite number of personnel

passengers notice that a priority line is open, they take it to speed up the process. From the system description, we included the most relevant elements. We developed a base case scenario with the characteristics presented in Table 6.2.

We run a simulation representing a 7-hour period to generate the nominal passenger flow. The period covers one peak hour, and we simulate the complete passenger trajectory from entering the building until the gate is reached. From previous studies, we considered realistic processing time and variability sources, mainly on arrival times and processing times. To test the proposed management action, we model the disruption of the airport access mode by delaying the arrival time at the airport of a fraction of the passengers. Figure 6.5 shows the arrival profiles considered for all passengers. The graph shows how the disruption affects the passenger arrival profile and how the new arrival profile is considered in the simulation model. According to this figure, some passengers arrive at the airport with very little time before their boarding time and

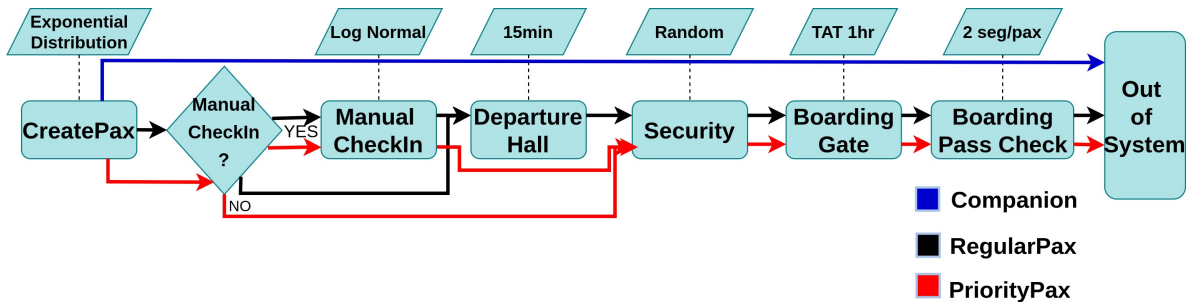


Figure 6.4: Standard path followed by passengers within the airport. A distinction is made between companions (in blue), regular passengers (in black) and priority ones (in red).

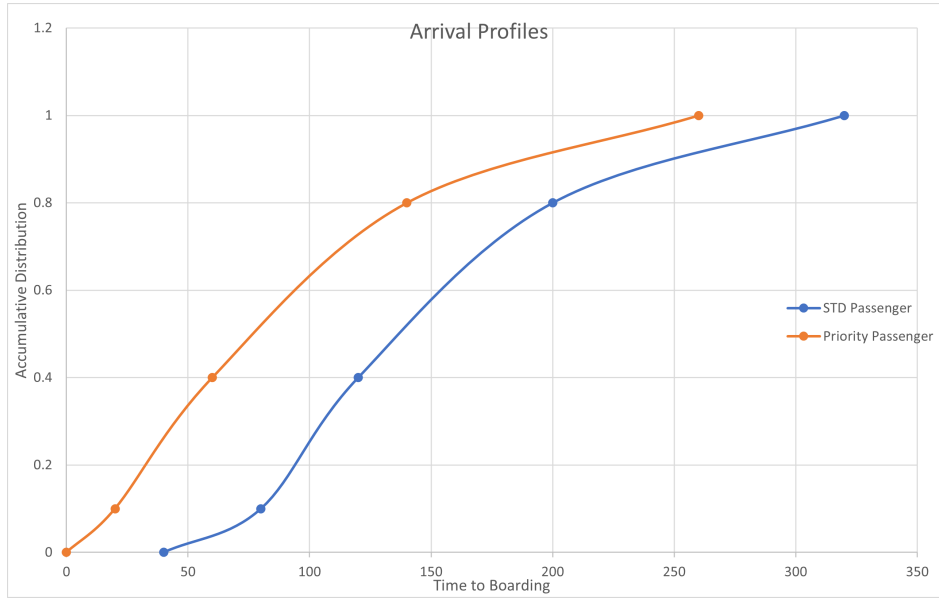


Figure 6.5: Arrival profiles of passengers with and without disruption (in orange and blue respectively).

need to be processed at security quickly to avoid missing their flights.

Finally, the share of elderly passengers is set at 7%. This number is chosen according to the 2015 survey led in France on air passengers (DGAC, 2015). This number should be adapted to the specific case under study for more realistic analysis.

We consider two disruptive scenarios to assess the impact of the management action plan during airport access disruptions. Each scenario is presented below:

- **Unexpected disruption Scenario:** In this scenario, we assume that an unexpected event occurs on one of the airport access modes, such as a metro shutdown or a last-minute train cancellation due to a bomb threat. As a result, many passengers have to make last-minute re-routing decisions. We have identified 20% of passengers as priority passengers who are at risk of missing their flight due to the disruption;
- **Planned disruption Scenario:** In this scenario, ground transportation service providers notify passengers of a service interruption days in advance. This information sharing allows passengers to change their routing decisions and reach the airport. However, we assume that some passengers may not pay attention to this communication and hence be affected by the disruption. In this case, we have set the proportion of priority passengers at 5%.

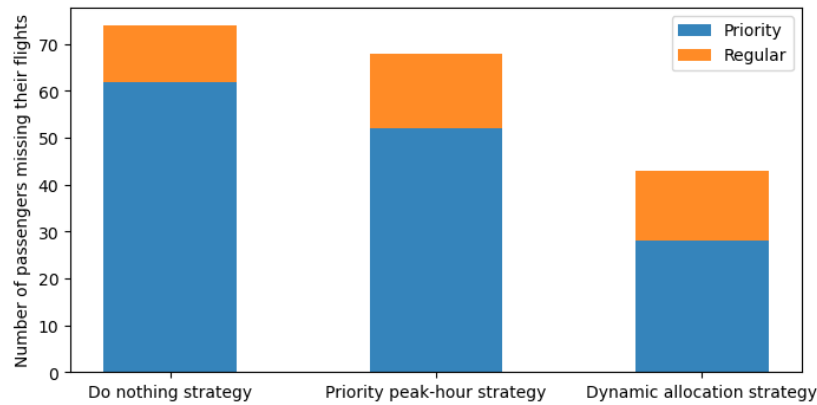


Figure 6.6: Average number of passengers missing their flights depending on the security allocation strategy (unexpected disruption Scenario).

6.6 Discussion

The following section presents the results for the disruptive scenarios described in Section 6.5.1. Then, we discuss how this optimisation framework could be used in a real airport system to assist operators at the tactical level. The tests are performed on an AMD Ryzen 5 4500U processor, Radeon GPU, and 16 GB of RAM.

6.6.1 Experimental results

For each scenario, we compare two strategies for managing airport security resources:

- **Do-nothing strategy:** passengers follow the trajectory already presented and use the system’s full capacity. Management action plan is not considered, i.e. no priority lane is opened for priority passengers. The modelling assumptions presented in Table 6.2 are retained, including the finite resource assumptions. We assume that five regular lanes are open at each security area throughout the simulation period;
- **Priority Peak-hour strategy:** we open a priority lane during the airport’s peak hour, when large numbers of passengers are expected, with potential queuing and long waiting times. The modelling assumptions presented in Table 6.2 are maintained. Based on the finite resource assumption, we assume that five regular lanes are open throughout the simulation, except during the peak hour when only four regular lanes are open;
- **Dynamic allocation strategy:** we use the proposed SIM-OPT approach to define a management action plan by dynamically opening priority lanes in time according to the expected number of passengers at both security checkpoints during the day.

The modelling assumptions presented in Table 6.2 are maintained. Based on the finite resource assumption, we decide whether to open a priority lane and close a regular lane for each 30-minute time interval.

Different performance indicators can be used for each scenario and strategy to measure the airport security screening LOS, such as average passenger waiting time and queue length. For this study, we consider the most critical one, namely the number of passengers missing their flights. This criterion determines whether the system can fulfill its main function of allowing passengers to board their aircraft on time. Figure 6.6 presents the average number of passengers who missed their flights, distinguishing between those who suffered a disruption (priority) and those who did not for the ‘unexpected disruption Scenario’.

For each scenario and strategy, different performance indicators can be used to measure the airport security screening Level of Service, such as the average passenger waiting time and queue length. However, for the purpose of this study, we consider the most critical one, namely the total number of passengers missing their flights. This criterion determines whether the system can fulfill its main function of allowing passengers to board their aircraft on time. Figure 6.6 presents the average number of passengers who missed their flights, distinguishing between those who suffered a disruption (priority) and those who did not for the ‘unexpected disruption Scenario’.

It is noticeable that the number of passengers missing their flights is reduced simply by closing a regular lane and opening a priority lane during the airport’s peak hours. Dynamic allocation is even more effective and shows the potential of the measures taken by the airport operator. Dynamic allocation allows the total number of passengers missing their flights to be reduced by 40%. The results show that separating the passenger flow at the right time is beneficial overall. However, this action cannot be easily managed by the airport operator on a daily basis, and a naive strategy such as the peak priority strategy is not optimal. Therefore, using a DSS such as the one proposed by our simulation-optimisation approach would be relevant. A slight increase in the number of regular passengers missing their flights is observed with the dynamic allocation strategy (15 instead of 12). This increase is due to the assumption of finite resources, where introducing a priority lane requires the closure of a regular lane, which subsequently affects the service throughput for regular passengers. It is important to emphasise that this model does not consider the dynamic status changes of passengers, notably the transition of a regular passenger to a priority passenger. This limitation is an area for future refinement.

Regarding the planned disruption scenario, a distinct observation arises. The dynamic allocation strategy yields to the ‘Do-nothing’ strategy. Indeed, it leads to not opening a priority lane throughout the simulated period. This outcome can be rationalised based on a combination of three factors:

- Within this particular case study, the Mexico City airport operates ten security

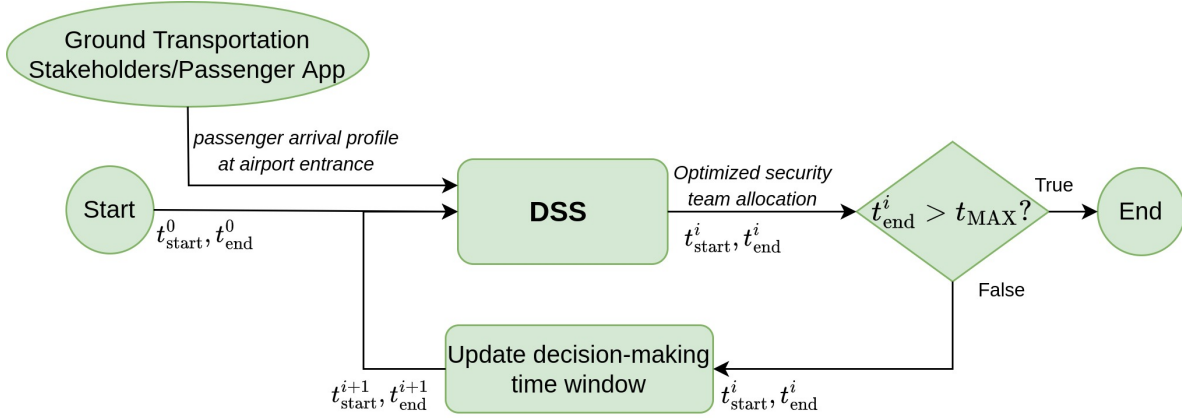


Figure 6.7: Illustration of decision-making time window approach. Once a new update of the passenger arrival profile at the airport is obtained, the airport operation centre will launch the DSS to implement the management action plan and know how to reallocate airport security teams.

lanes evenly distributed across two security areas. Assuming an even distribution of passenger load, each checkpoint should handle approximately 10% of the total passengers;

- The planned disruption scenario considers 5% of passengers with priority status;
- Adhering to the constraint of finite resources, a regular lane must be closed whenever a priority lane is opened.

From these various premises, we can infer that a threshold value must be reached to justify opening a dedicated lane for priority passengers. In this case, the proportion of priority passengers must be higher to justify opening a dedicated lane. Such an initiative could negatively impact regular passengers, outweighing the benefits for priority passengers.

6.6.2 Practical application of the proposed framework

This section discusses the practical implementation of the proposed optimisation framework in managing airport access mode disruptions. The airport's responsiveness is critical, as decisions must be made at the operational level for short-term planning. Determining when these decisions need to be made and the applicable time horizon is essential. Therefore, we propose to use such DSS through a sliding time window approach as proposed in Part II. This approach allows the reallocation tool to work with arrival passenger profiles that are still reliable due to the limited time horizon,

performing the security team's reallocation only during a period when the data fed into the DSS system is reliable.

The airport operations centre would reallocate security teams on a two-hour basis. We also consider a buffer of 30 minutes between the DSS decision and the actual reallocation to give the security teams enough time to become aware of the new plan and implement the new strategy. Therefore, in a practical system, the DSS should be activated every time the passenger arrival profile is updated (i.e. every 30 minutes). Calling this time t_{update} , the DSS would reallocate the security teams between $t_{update} + 30min$ and $t_{update} + 120min$. The process is summarised in Figure 6.7.

6.7 Conclusion

In this chapter, we have presented a simulation-optimisation framework that aims to improve the security lane opening policy in airport environments. The simulation incorporates stochastic elements and takes into account the complex interaction between passenger movement and terminal configurations. Such simulation-optimisation integration makes it possible to evaluate the fast-track lane opening strategy proposed in section [Section 3.4](#) realistically. We have applied this framework to one terminal of Mexico City airport and gained valuable insights.

This study highlights the effectiveness of dynamically opening a fast-track lane to separate passenger flow and manage disruptions without the need for additional security personnel. By categorising passengers and allowing flexibility in resource allocation, this recovery strategy optimises the use of limited resources throughout the day. During disruptions that affect a large number of passengers, the dynamic security allocation strategy would help to mitigate the impact. However, opening a fast-track lane for latecomers during disruptions involving only a small number of passengers may not be a worthwhile investment.

The next step would be to simulate larger airports such as CDG, where security teams can move between different checkpoints. This extension could provide valuable insights into improving the overall airport level of service. Investigating such scenarios could help refine and optimise security strategies on a broader scale, ultimately improving the passenger experience and airport efficiency.

Chapter 7

Extending the flight rescheduling strategy to an air-rail network: The Air-Rail Delay Management Problem

7.1 Introduction

In the context of climate change and increasing airport congestion, trains tend to replace short-haul flights to relieve airport congestion and reduce passengers' carbon footprint ([Givoni and Banister, 2006](#); [Givoni, 2007](#)). In such a case, coordination between trains and flights is necessary to maintain a high level of service for passengers.

When considering combined air-rail journeys, one of the key challenges is managing delays efficiently. Such events could cause passengers to miss their connections, resulting in significant delays at their final destination. To protect passengers, Regulation 261 ([European Parliament and Council, 2004](#)) imposes airlines to re-accommodate or compensate them in case of delay. However, there is no equivalent of such regulation for multimodal transportation services ([Official Journal of the European Union, 2023](#)). Such a service might, in practice, be one key lever to encourage people to use the train as a feeder mode, especially for non-frequent travellers ([Chiambaretto et al., 2013](#)).

In this chapter, we envision a scenario where airlines and rail service providers would cooperate and communicate actively. In this scenario, passengers travel using an air-rail integrated ticketing system, submitted to similar compensation laws defined in Regulation 261. This collaborative environment would enable transportation providers to be promptly notified if a train or a flight carrying connecting passengers is delayed. In addition, transportation operators would share the costs of re-accommodating stranded passengers, incentivising them to minimise delays. In this context, we present a tactical

rescheduling of flights and trains to limit the impact of delays on passengers. This work is an extension of the recovery strategy based on solving the PFRSP, introduced in [Chapter 4](#). Here, we consider a similar delay management strategy, focusing on air-rail passenger connections and taking into account an overall network of airports and railway stations. [Schöbel \(2001\)](#) was the first to introduce such a problem, with the aim of minimising the total delay experienced by passengers in a multimodal transportation network. This problem relies on deciding, in a transportation network, whether a connecting vehicle (e.g. train, bus, plane, etc.) should wait for connecting passengers who are delayed on their first leg. We propose an extension of the problem to include both airside and ground transportation side constraints. In addition, we use a data-driven approach to evaluate the passenger reallocation time in the case of a missed connection. In the following, we refer to this problem as the Air Rail Delay Management Problem (ARDMP). We address the ARDMP through the Western Europe air-rail network case study, with a model including 496 airports and 72 railway stations. We apply the proposed delay management strategy considering a disruption occurring on the rail network.

To our knowledge, this is the first study to address the delay management problem in a long-haul multimodal network, combining constraints on the air and ground sides. It is a joint collaboration with Clara Buire, PhD student at ENAC who works on synchronising air and rail timetables at the strategic level ([Buire et al., 2022](#)). We combine our works to propose tactical coordination between flights and trains when passengers experience delays.

This chapter is structured as follows. [Section 7.2](#) presents a state-of-the-art related to the delay management problem on the ground and air sides. [Section 7.3](#) and [Section 7.4](#) introduce the ARDMP and its mathematical model, respectively. [Section 7.5](#) describes the European case study considered, and [Section 7.6](#) presents the results.

7.2 Literature Review

Previous works have studied the Delay Management (DM) problem on the ground side. [Schöbel \(2001\)](#) is the first to formulate the problem of deciding whether or not to delay a vehicle in a public transportation system to wait for transferring passengers. She proposes a mixed-integer formulation to minimise the total delay of passengers at their final destination. She assumes that passengers' delay is equal to the delay of their train, if they catch it, or to a constant delay otherwise. [Gatto et al. \(2005\)](#) show that even restricted versions of this problem are NP-complete. Later, [Schöbel \(2009\)](#) considers track capacity constraints for a railway system. [Dollevoet et al. \(2012\)](#) propose integrating passenger rerouting into the DM process. The same authors consider station capacity constraints and track re-allocation ([Dollevoet et al., 2015](#)). For a review of DM problem handling, the reader can refer to [König \(2020\)](#). On the airside, several

works have been carried out on delay management strategies for airlines, as presented in [Section 1.5.2](#). In particular, [Santos et al. \(2017\)](#) propose a version of the DM problem for the airside, including airport capacity and passenger delay costs.

Collaboration between air and ground transportation systems received a growing interest these last years. [Li et al. \(2018\)](#) present an overview of actual collaboration between airlines and train service providers to create an integrated air-rail service for passengers. [Laplace et al. \(2014\)](#) propose a collaboration decision-making between air and ground transportation stakeholders to improve multimodal passenger journeys. Other studies on multimodal recovery solutions in case of massive disruptions show promising results in mitigating the impact of such events on passengers (see for instance [Dray et al. \(2015\)](#); [Marzuoli et al. \(2015, 2016\)](#)).

Regarding air-rail coordination mechanisms, [Buire et al. \(2022\)](#) suggest strategically synchronising air and rail timetables to ensure smooth passenger transfers. However, they do not consider delays and their impact on the passenger journey.

In [Chapter 4](#), we have proposed a flight rescheduling at the tactical level to mitigate the impact of airport access mode disruptions on passengers. We have considered airside constraints such as terminal capacity, maximum runway throughput or minimum passenger connecting time. We have focused on a single airport and have not considered propagated delay. Here, we propose a tactical delay management strategy at the network level, integrating the work presented in [Chapter 4](#) and the work of [Buire et al. \(2022\)](#). We extend the original version of the problem developed by [Schöbel \(2001\)](#). We take into account real operational constraints, such as airport and railway station capacities, ATFM slot adherence or even minimum aircraft turnaround time. We also consider the reallocation time for passengers who miss their connections.

7.3 Problem description

This section introduces the *total passenger delay* metric and then defines the ARDMP.

7.3.1 Total passenger delay

As explained by [Cook et al. \(2012\)](#), flight delays do not necessarily capture the actual delays experienced by passengers. The situation is similar for train delays, which can lead to missed connections and potentially late arrivals at the final destination. We therefore introduce the *total passenger delay* as the sum of the delays experienced by passengers when arriving at their final destination. To compute passenger delays, we define the following three groups of passengers:

- *on-time passengers*: passengers who catch their flight/train; their delay is equal to the delay of the flight/train;

- *reallocated passengers*: passengers who miss their connections due to a delay on the first leg, they are consequently reallocated to another flight/train going to the same destination within the same day;
- *stranded passengers*: passengers who miss their connections and without reallocation option (no seat available or no more flight/train going to the same destination within the day).

The delay of *reallocated passengers* is computed as follows. For each flight and train, we consider the direct alternative, enabling the passengers to arrive at their destination with the smallest possible delay. This alternative can be either a train or a flight, and, in this study, we only consider direct alternatives for the sake of simplicity. The delay of *reallocated passengers* corresponds to the difference between the arrival time of the new flight/train at the destination and the initial one. Regarding *stranded passengers*, we assume they will be re-accommodated to the same flight on the next day at the same departure time, thereby experiencing a 24-hour delay. The objective of the ARDMP is therefore to reschedule flights and trains at the tactical level to minimise the total passenger delay.

7.3.2 ARDMP description

To address the ARDMP problem, a one-day time window is considered. In the event of disruptions on the ground or air sides leading to train or flight delays, we assume that service providers are notified ahead of time about the affected vehicles and their expected delays for the remainder of the day. For instance, consider a power outage on a railway network between 6 am and 8 am, causing delays for several trains throughout the day due to a domino effect. We assume that the rescheduling of trains and flights can occur once operators anticipate delays caused by the incident, such as when power is restored at 8 am. The key challenge is deciding whether a vehicle should wait for connecting delayed passengers. For example, consider a flight of 100 passengers scheduled to leave at 9 am, with 10 passengers connecting from a previous train. Due to the disruption, these passengers arrive at the boarding gate 10 minutes after the scheduled boarding time. There are two options: depart on time or delay the flight. On one hand, if there is another flight to the same destination in three hours, departing on time will result in a total passenger delay of $3 \times 60 \times 10 = 1800$ minutes. On the other hand, if the flight waits for the delayed passengers, the total passenger delay will only be $100 \times 10 = 1000$ minutes. In this situation, the aircraft should wait for the connecting passengers. However, if only five passengers were connecting, it would be better to depart on time.

This study considers an air-rail transportation network covering a specific region. The time scope is discretised into h -minute time steps. Air and rail networks can be represented by graphs, where nodes correspond to airports and train stations, and links

model flight and train legs that are operated between stations. Each flight or train has expected departure and arrival times. Passengers' itineraries on this multimodal network are known, including possible transfers between modes. Assuming that delays arise on several trains or flights during the day, the ARDMP consists in assigning tactical delays to trains and flights so as to minimise the total passenger delay. The following operational constraints are taken into account:

1. the number of trains scheduled to stop at each train station cannot exceed the number of tracks at this station (train-station capacity constraint),
2. the number of airport departure and arrival movements, operated at each time step and at each hour is limited (airport capacity constraint),
3. a minimum turnaround time between two flights operated by the same aircraft is considered,
4. train dwell time at the station remains the same as in the initial schedule,
5. the train and flight travel times remain unchanged (the vehicle maintains its scheduled speed),
6. a Minimum Connection Time (MCT) is ensured for passengers who are not directly affected by the disruption (*i.e.* whose first leg is on time), to let them enough time to transfer between their first and second legs,
7. the departure time of flights subject to an ATFM slot must happen within a [-5,10]-minute time interval around the scheduled departure time (ATFM slot adherence),
8. a maximum tactical delay of 30 minutes can be assigned to flights or trains (except for flights under ATFM slot adherence).

7.4 ARDMP model

This section describes the optimisation model of the ARDMP. Data, decision variables, constraints and the objective function are detailed below.

Sets and Parameters

N^a/N^r	index set of airports/train stations
L	index set of flights and rail legs scheduled for the day of operation
L^{atfm}	index set of flights subject to the ATFM slot adherence constraint
\mathcal{S}	index set of slots
\mathcal{S}'	index subset of slots for which airport occupancy is computed
\mathcal{C}^p	index set of priority leg pairs for which passenger connections must be maintained.
\mathcal{C}_l	index set of legs with passengers connecting to leg l , $l \in L$
P^{air}	index set of flight leg pairs operated consecutively by the same aircraft
P^{rail}	index set of rail leg pairs operated consecutively by the same train
L_n^A	index set of legs scheduled to arrive at station n , $n \in N^a \cup N^r$
L_n^D	index set of legs scheduled to depart from station n , $n \in N^a \cup N^r$
W	index set of slot window duration on which the airport runway capacities are evaluated
h	discretisation time step
Δ	maximum pushback parameter, multiple of h
Δ_{atfm}	maximum pushback parameter for flights subject to the AFTM slot adherence constraint, multiple of h
o_n^{max}	number of tracks at train station n , $n \in N^r$
$y_n^{A,w}$	runway arrival capacity for a window of length w , $w \in W$, (<i>i.e.</i> , the maximum number of arrival flights that could be scheduled within the hw minutes window), $n \in N^{\text{air}}$
$y_n^{D,w}$	runway departure capacity for a window of length w , $w \in W$, $n \in N^{\text{air}}$.
$\text{MCT}_{l',l}$	minimum connection time to connect from leg l' to leg l , $l \in L, l' \in \mathcal{C}_l$

Input data

T_l^D	initial scheduled departure time of leg l , $l \in L$
T_l^A	initial scheduled arrival time of leg l , $l \in L$
o_n^0	the initial number of trains at train station n , $n \in N^r$
IVT_l	in-vehicle time of leg l , $l \in L$
TAT_{l_1,l_2}	minimum turnaround time between legs l_1 and l_2 , $(l_1, l_2) \in P^{\text{air}}$
dw_{l_1,l_2}	stop time between legs l_1 and l_2 , $(l_1, l_2) \in P^{\text{rail}}$
n_l^D	volume of passengers using l as a direct connection, $l \in L$
$n_{l',l}$	volume of passengers transferring from leg l' to leg l , $l \in L, l' \in \mathcal{C}_l$
r_l	reallocation delay for passenger missing their connection with leg l , $l \in L$

Main decision variables	
k_l^D	index of slot at which leg l is scheduled to depart, $l \in L$
Auxiliary decision variables	
k_l^A	index of slot at which leg l is scheduled to arrive $l \in L$
t_l^D	new scheduled departure time of l , $l \in L$
t_l^A	new scheduled arrival time of l , $l \in L$
d_l	delay associated to leg l , $l \in L$
$d_{l',l}$	delay experienced by passenger connecting from leg l to leg l' , $l \in L, l' \in \mathcal{C}_l$
$y_{l',l}$	binary, indicates whether the connection from leg l' to leg l is feasible or not, $l \in L, l' \in \mathcal{C}_l$
$x_{l,s}^D$	binary, indicates whether leg l is scheduled to depart after s , $s \in S$
$x_{l,s}^A$	binary, indicates whether leg l is scheduled to arrive after s , $s \in S$
$o_{n,s}$	the number of trains stopped at n at slot s , $n \in N^r$

The model, which aims to minimise the total passenger delay, therefore reads:

$$\min \sum_{l \in L} \left(n_l^D d_l + \sum_{l' \in \mathcal{C}_l} n_{l',l} d_{l',l} \right), \quad (7.1)$$

subject to:

$$t_l^D = h(k_l^D - 1) \quad l \in L \quad (7.1a)$$

$$t_l^A = t_l^D + IVT_l \quad l \in L \quad (7.1b)$$

$$k_l^A = k_l^D + \frac{IVT_l}{h} \quad l \in L \quad (7.1c)$$

$$k_l^D \leq s + Mx_{l,s}^D \quad l \in L, s \in S \quad (7.1d)$$

$$\sum_{s=0}^{N_s} x_{l,s}^D \leq k_l^D \quad l \in L \quad (7.1e)$$

$$k_l^A \leq s + Mx_{l,s}^A \quad l \in L, s \in S \quad (7.1f)$$

$$\sum_{s=0}^{N_s} x_{l,s}^A \leq k_l^A \quad l \in L \quad (7.1g)$$

$$t_l^D \leq t_l^{D,0} + \Delta \quad l \in L \quad (7.1h)$$

$$t_l^D \leq t_l^{D,0} + \Delta_{\text{atfm}} \quad l \in L^{\text{atfm}} \quad (7.1i)$$

$$t_l^D - t_l^{D,0} = d_l \quad l \in L \quad (7.1j)$$

$$t_{l_2}^D - t_{l_1}^A \geq TAT_{l_1, l_2} \quad (l_1, l_2) \in P^{\text{air}} \quad (7.1k)$$

$$t_{l_2}^D - t_{l_1}^A = dw_{l_1, l_2} \quad (l_1, l_2) \in P^{\text{rail}} \quad (7.1l)$$

$$o_{n,0} = o_n^0 \quad n \in N^r \quad (7.1m)$$

$$o_{n,s} = o_{n,s-1} + \sum_{l \in L_n^A} (x_{l,s-1}^A - x_{l,s}^A) + \sum_{l \in L_n^D} (x_{l,s-1}^D - x_{l,s}^D) \quad n \in N^r, s \in \mathcal{S} \quad (7.1n)$$

$$o_{n,s} \leq o_n^{\max} \quad n \in N^r, s \in \mathcal{S} \quad (7.1o)$$

$$\sum_{\tau=s}^{s+w-1} \sum_{l \in L_n^A} x_{l,\tau}^A - x_{l,\tau+1}^A \leq y_n^{A,w,s} \quad n \in N^a, w \in W, s \in \mathcal{S}' \quad (7.1p)$$

$$\sum_{\tau=s}^{s+w-1} \sum_{l \in L_n^D} x_{l,\tau}^D - x_{l,\tau+1}^D \leq y_n^{D,w,s} \quad n \in N^a, w \in W, s \in \mathcal{S}' \quad (7.1q)$$

$$t_{l'}^D - t_l^A \geq \text{MCT}_{l',l} \quad (l, l') \in \mathcal{C}_l^p \quad (7.1r)$$

$$t_{l'}^D - t_l^A + My_{l',l} \geq \text{MCT}_{l',l} \quad l \in L, l' \in \mathcal{C}_l \quad (7.1s)$$

$$d_{l',l} \geq y_{l',l} r_l \quad l \in L, l' \in \mathcal{C}_l \quad (7.1t)$$

$$d_{l',l} \geq d_l \quad l \in L, l' \in \mathcal{C}_l \quad (7.1u)$$

$$k_l^D, k_l^A \in S \quad l \in L \quad (7.1v)$$

$$t_l^D, t_l^A \in \{0, \dots, h(|S| - 1)\} \quad l \in L \quad (7.1w)$$

$$d_l \in \{0, h, \dots, \Delta\} \quad l \in L \quad (7.1x)$$

$$d_{l',l} \in \{0, h, \dots, r_l\} \quad l \in L, l' \in \mathcal{C}_l \quad (7.1y)$$

$$y_{l',l} \in \{0, 1\} \quad l \in L, l' \in \mathcal{C}_l \quad (7.1z)$$

$$x_{l,s}^A, x_{l,s}^D \in \{0, 1\} \quad l \in L, s \in \mathcal{S} \quad (7.1aa)$$

$$o_{n,s} \in \{0, \dots, o_{n,s}^{\max}\} \quad n \in N^r, s \in \mathcal{S} \quad (7.1ab)$$

Constraints (7.1a) and (7.1b) link the time slot to the actual auxiliary time variable for the departure and arrival time of leg l , respectively. Constraints (7.1c) calculate the arrival time slot of leg l based on its departure time slot. Constraints (7.1d) and (7.1e) fix the values of the binary variables $x_{l,s}^D$. Similarly, the constraints (7.1f) and (7.1g) fix the values of the binary variables $x_{l,s}^A$. Constraints (7.1h) limit the maximum departure delay for each leg l . Constraints (7.1i) ensure ATFM slot adherence. The actual delay is calculated by constraints (7.1j). The turnaround time constraints and the train dwell time constraints are given by (7.1k) and (7.1l), respectively. Constraints (7.1m) to (7.1o) fix the train station occupancy and ensure that it does not exceed the number of tracks

at each train station. The maximum arrival and departure flight movement per time window are limited with constraints (7.1p) and (7.1q), respectively. Constraints (7.1r) ensure that passenger minimum connecting times for priority flights are maintained. Constraints (7.1s) fix the value of variables $y_{l',l}$ that characterise if passengers connecting between legs l' and l miss their connection. Constraints (7.1t) and (7.1u) fix the reallocation delay between flights l' and l to d_l if passengers have their connection, and to the reallocation delay r_l , otherwise. Finally, constraints (7.1v)-(7.1ab) define the definition domain of the decision variables.

7.5 Western Europe case study

This section focuses on the Western European case study. It first outlines the data used and the assumptions made. The modelling approach for passenger transfers is then presented. Finally, it describes in detail the post-processing procedure for reallocating passengers, which is crucial for accurately assessing the total passenger delay.

7.5.1 Network characteristics and data

Table 7.1 presents the characteristics of the considered case study. This case study focuses on the historical day of December 4, 2019 when the SNCF went on strike. We gather initial flight schedules Eurocontrol (2023) from the 18 largest airports in France, Germany, and Spain, including three major hub airports: Frankfurt Airport (FRA), Madrid-Barajas Airport (MAD), and Paris-Charles de Gaulle Airport (CDG). Figure 7.1 illustrates the flights considered in this scenario. Throughout this day, 10,407 flights were operated, with 593 departures scheduled at CDG. We also consider the train schedules associated with each hub airport and their respective connecting airports, involving 646 train legs SNCF (2023); RENFE (2023); DeutscheBahn (2023). It is important to note that we could not access the actual train delay data or the number of train cancellations. Therefore, we simulate the disruption by randomly delaying 30% of trains arriving at CDG-High Speed Rail train station. The delay times were randomly selected using a uniform distribution ranging from a minimum delay, denoted as t_{\min} , to a maximum delay, denoted as t_{\max} .

ATFM delays were not considered here. Therefore, *delayed* flights are only those impacted by the proposed rescheduling algorithm. We assume that the maximum delay assignable to a flight is 30 minutes and that 25% of flights at each main hub airport were subject to ATFM slots and needed to adhere to them. This percentage is arbitrarily fixed and can be tuned by a final user, depending on airport characteristics. The maximum assignable delay for flights subject to ATFM slot adherence is set to 10 minutes.

Table 7.1: Case study characteristics

Case study description.	
Case Study	Western European Transportation Network
Number of airports	496
Number of train stations	72
Number of flights	10407 (593 from CDG)
Number of trains	646 (66 to CDG station)
Airports with limited capacity	18 largest airports in France, Germany, and Spain
Airport with connecting passengers	CDG, FRA, MAD
Train stations with limited capacity	3 stations, each associated with a hub
Train schedule data source	GTFS data
Flight schedule data source	OAG
Disruption scenario characteristics	
Date	4 December 2019
Considered events	French railway company on strike
Disruption duration	From 00:00 to 23:59
Train delay percentage	30% of trains are late at CDG
Train delay duration (min)	$X \sim \mathcal{U}(30, 90)$
Train cancellation	Not considered
Flight/Train travel time	Constant
Priority flights	25% of flights need to comply with their ATFM slots at main airport hubs
ATFM delays	Not considered
Maximum priority flight delay	10 min
Maximum flight delay	30 min
Minimum aircraft turnaround time (TAT)	45 min

Additionally, we allowed tactical rescheduling to ensure compliance with the maximum train station capacity, which may have been compromised due to the initial train delays and disruptions caused by the strike. Lastly, we assume that all information regarding train delays and connecting passengers is fully known before rescheduling. Therefore, we employ a one-iteration process to reschedule all legs operated from the morning until the end of the day.

7.5.2 Modelling passenger transfers

To model passenger transfers between modes, the same method proposed by [Buire et al. \(2023\)](#) is used. In a nutshell, the method consists in modelling intramodal (air-air)

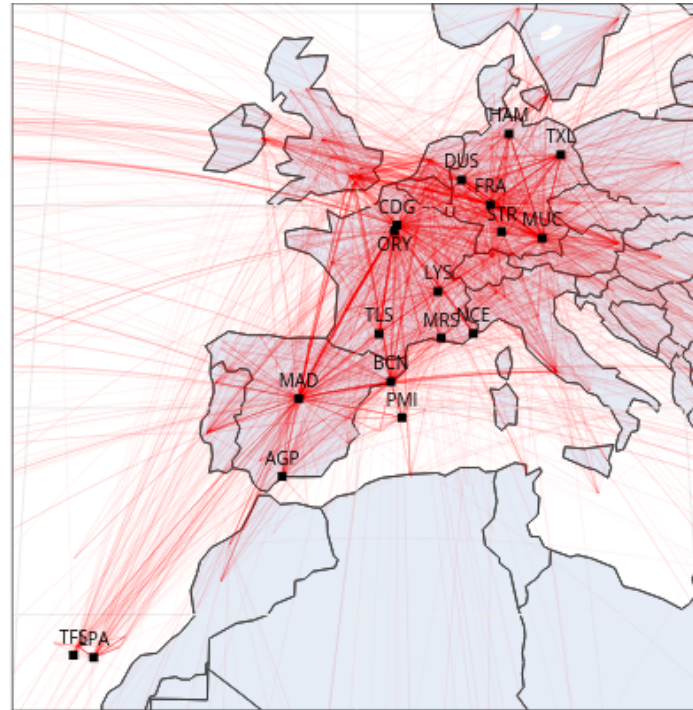


Figure 7.1: Illustration of flights operated on December 4, 2019, over the Western European air network (source: [Buire et al. \(2023\)](#)).

and intermodal (train-air) passenger connections at a hub airport, using a Constraint Programming approach ([Rossi et al., 2006](#)). Based on airport modal share and flight passenger volume, the method generates passenger volume that transfers between two scheduled legs. We limit the study by considering only passengers with at most two legs in their total journey. The number of connecting passengers simulated with the proposed methodology is presented in [Table 7.2](#). As observed in this table, the number of connecting passengers simulated with this method varies between 8168 (train-air connections at Madrid airport) and 30638 (air-air connections at CDG airport).

7.5.3 Passenger reallocation procedure

Similarly to the rebooking procedure proposed by [Ball et al. \(2010\)](#), we propose the following passenger reallocation procedure.

In the mathematical model, we assume that passengers will be accommodated on the next flight to the same destination if they miss their scheduled flights. However, each aircraft has a finite capacity, defined by the number of seats it can offer. To overcome this limitation, we present a post-processing method that effectively reallocates stranded passengers to alternative flights, considering each aircraft's capacity. Since we do not know the actual number of seats available, we assume an 80% load factor for each

Table 7.2: Number of connecting passengers per airport. A distinction is made between train-air connections and air-air connections.

Airport	Connection type	Number of connecting passengers
CDG	air-air	30638
	train-air	18022
FRA	air-air	41599
	train-air	12101
MAD	air-air	22277
	train-air	8168

aircraft. For example, if an original flight carried 50 passengers, we assume $50 \times \frac{100}{80} - 50 \approx 12$ available seats. We extend this reallocation approach to direct trains as an alternative method, again assuming an 80% load factor for each train.

The reallocation process follows a systematic sequence. We consider the chronological list of passengers who have missed their flights and a corresponding set of feasible direct alternatives for each individual. These alternatives are ranked according to the delay they cause at the passenger’s final destination. For each passenger, we offer the best available re-routing option (in terms of delay). In the case where the best alternative flight/train is full, we select the second best option, and so on. When no re-accommodation option is available, the passenger is stranded and subject to a 24-hour delay. Note that the reallocation procedure is operated after the rescheduling, i.e. flight and train delays are considered to select the best reallocation options for passengers who miss their flights.

7.6 Results

Computations are performed using an AMD Ryzen 5 4500U CPU and 16 GB RAM laptop. The resolution of the optimisation problem formulation is made with the MIP solver Gurobi, version 9.1.2 ([Gurobi Optimization, LLC, 2023](#)). The computation time is 23 seconds.

7.6.1 Passengers gain

[Figure 7.2](#) displays the distribution of buffer times for passengers transferring from a train to a flight at CDG airport. The transfer buffer time equals the difference between the actual passenger transfer time and the minimum required connection time. We only display buffer times of passengers who would have missed their flight based on the original schedule but can still make it on time if the flight is delayed. We do not

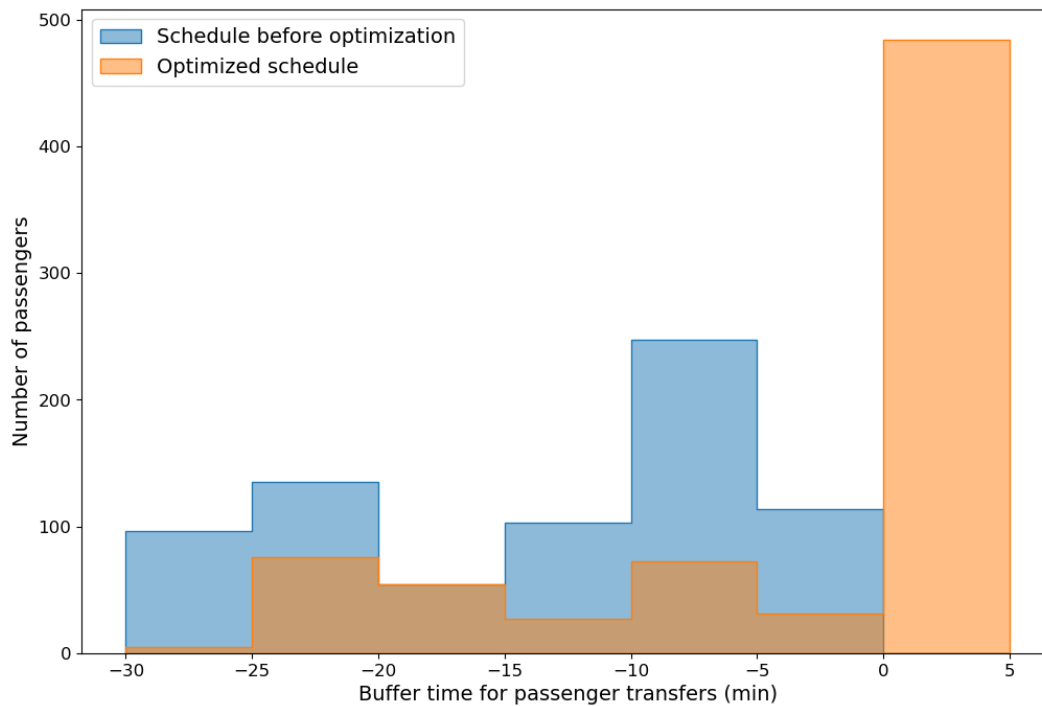


Figure 7.2: Distribution of passenger transfer buffer times before and after rescheduling. Buffer times are calculated by subtracting the minimum connecting time from the actual passenger transfer time. A negative buffer time indicates that passengers do not have enough time to transfer, caused by a delay on their first leg. This graph only shows passengers who could recover their initial flights thanks to the rescheduling (i.e. missing their flights by 30 minutes or less before rescheduling).

show passengers who arrive before the initial departure time or who arrive more than 30 minutes after the initial departure time. The figure shows a significant increase in passenger connections with a 0-minute buffer time after rescheduling. A 0-minute buffer time corresponds to a transfer time equal to the minimum connection time required for passengers to catch their flight. Consequently, the delay management strategy allows 484 of the 1221 passengers who initially missed their flights to arrive on time for boarding. The rescheduling does not induce buffer time strictly larger than 0 minutes for these passengers as this would delay the *on-time passengers* and, therefore, increase the total passenger delay.

Figure 7.3 depicts the total delay experienced by passengers before and after optimisation. The main difference between the initial and the optimised schedule lies in the number of stranded passengers. Indeed, 614 passengers have no reallocation option before optimisation and should wait until the next day to reach their final destination. After optimisation, the number of stranded passengers is reduced by 71% and the total

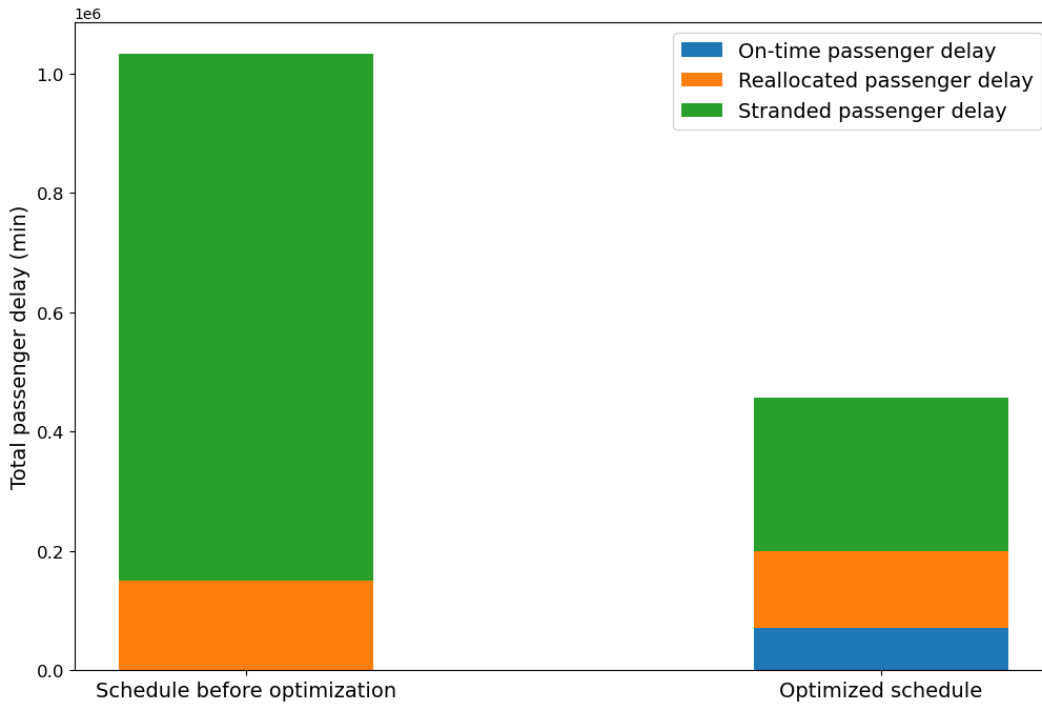


Figure 7.3: Total passenger delays before and after rescheduling, stacked by passenger types (*on-time passengers*, *reallocated passengers* and *stranded passengers*).

passenger delay by 41%. Indeed, the algorithm prioritises these passengers if the flight can wait since the cost of a missed connection is large. However, the maximum flight delay authorised to wait for passengers is 30 minutes (or 10 minutes for priority flights that need to respect their departure slots). Hence, some passengers might not have their connections if the required time to make the connection is above that limit. Therefore, several passengers remain stranded even after the rescheduling. Finally, the total delay experienced by direct passengers departing from CDG is 12810 minutes, resulting in an average passenger delay of 0.3 minutes. As a result, the rescheduling has a minimal impact on *on-time passengers*.

7.6.2 Operator cost

Regarding operator costs, Figure 7.4 displays the total vehicle (train or aircraft) delay per hour. Orange plain bars represent the total train delay, including the delay due to the strike and the one assigned during the rescheduling due to train station constraints. One can observe that most of the delayed trains are in the morning. The hatched bar corresponds to flights not departing from CDG and trains not arriving at CDG, *i.e.* the propagated delay on the network. After rescheduling, seven trains are delayed, including four at stations other than CDG. 35 flights are also delayed, out of which

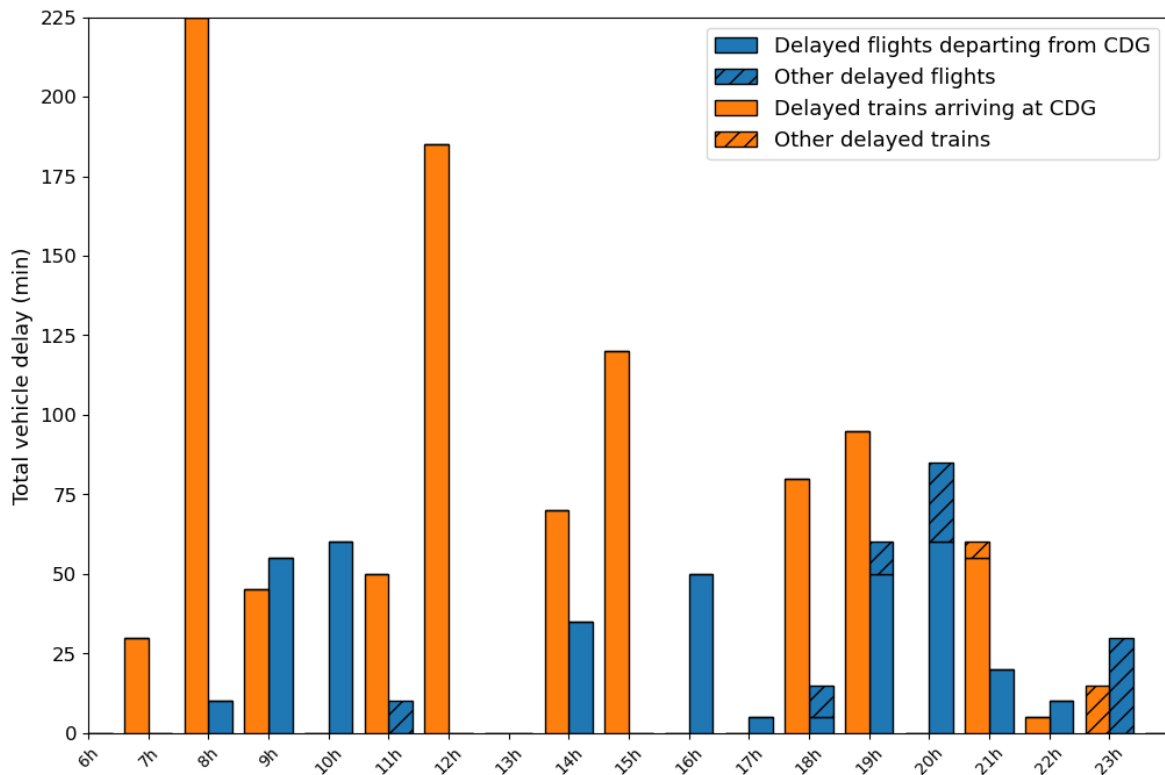


Figure 7.4: Distribution of total vehicle delays per hour. Flight and train delays are displayed in blue and orange, respectively. The hatched bars represent propagated delays.

eight are from CDG. Significant flight delays are observed during the morning rush hour (9 am and 10 am) and evening (7 pm and 8 pm). The morning hours see a surge in missed passenger connections due to significant train delays in the previous hour. The second peak of flight delays is either due to propagated delays from previous flights (displayed by hatch bars) or fewer flight reallocation options. Indeed, passengers who miss their connections at the end of the day are more likely to be stranded without reallocation options until the next day. Hence, rescheduling gives higher priority in waiting for them.

On average, due to the rescheduling, all flights across Europe experience a delay of 0.04 minutes, while the departing flights at CDG experience a delay of 0.84 minutes. The proposed rescheduling plan delays 5% of the departing flights at Paris-CDG airport by 13 minutes on average. To put this into perspective, Table 7.3 shows the characteristics of the actual delays experienced by flights during the historical operating day in question. As per the table, departing flights at CDG were operated with an average delay of 11 minutes. Therefore, our proposed rescheduling approach seems reasonable

Table 7.3: Actual flight delay on December 4th 2023 (in minutes) (source: Eurocontrol).

	CDG	All
Average actual flight delay	11.0	6.1
Maximum actual flight delay	120	1310

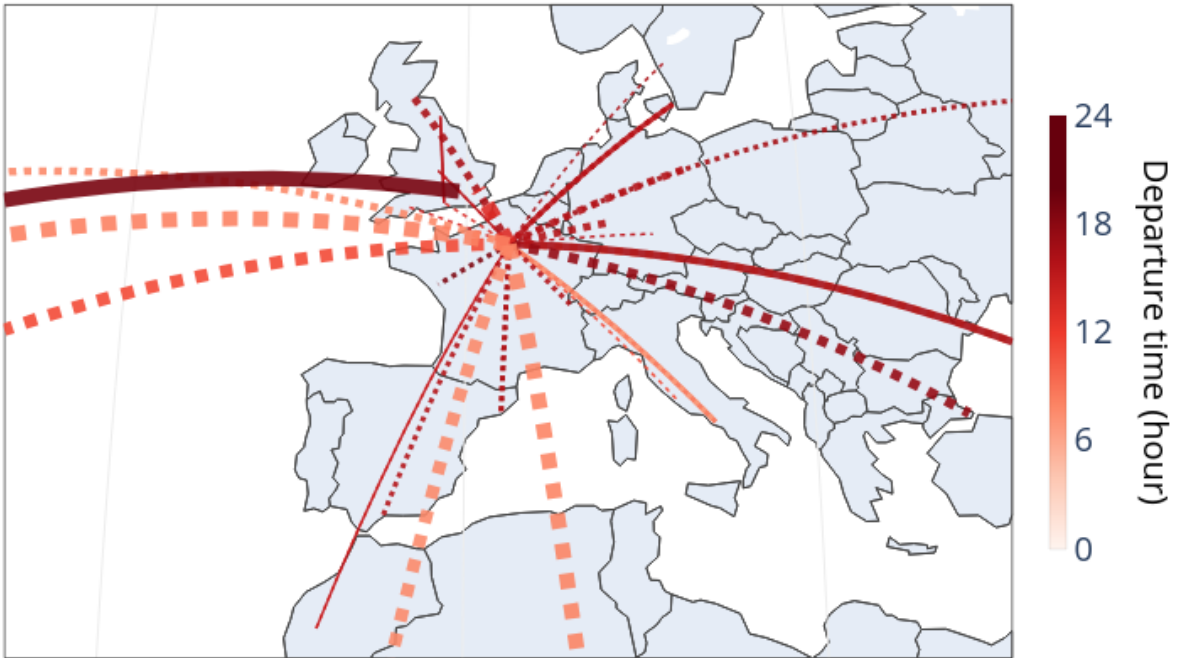


Figure 7.5: Visualisation of post-rescheduling flight delays. The linewidth and the colour-coding system indicate the delay magnitude and the departure time of the day, respectively. Dotted lines correspond to flights departing from CDG airport, plain lines to other flights.

compared to the actual delays the airport has to deal with during a typical operating day.

Figure 7.5 shows a map of delayed flights and the magnitude of these delays. The colour and the width correspond to the departure time and the delay assigned to the flight, respectively. More specifically, a darker colour indicates that the flight's departure time is later in the day, and the greater the width, the greater the delay. It can be seen that long-haul flights are generally those with the highest assigned delay. The colour of these flights also indicates that they are scheduled in the morning. In fact, these long-haul flights tend to have a daily frequency compared to short-haul flights. The re-routing time for passengers who miss their connections is, therefore, 24 hours.

On the other hand, delays on short-haul flights are generally assigned in the evening, when passengers have no more opportunities for re-routing. It can also be observed that a few flights are delayed due to network propagation. These delays occur because the turnaround time initially planned by the airlines between a delayed flight at CDG and the following flight is small. It can be observed that the rescheduling delays an evening flight by 30 minutes departing from the US due to minimum turnaround time constraints and the assumption of constant in-vehicle time. However, in practice, the previous flight operated by the aircraft could have been speeding up to recover from its departing delay, reducing the impact of the proposed delay management strategy. Such action is especially true for long-distance flights and could be included in further work.

Finally, as mentioned above, exogenous ATFM delays were not considered in this study. However, the proposed rescheduling strategy could deal with these delays by rescheduling flights to wait for connecting passengers and reduce station congestion. Taking these exogenous delays into account would have an impact on the rescheduling solution, as ATFM delays of departing flights could already reduce the number of passengers missing their rail/air connections.

7.7 Conclusion

In recent years, there has been a growing need for collaboration between air and ground transportation stakeholders in Europe to provide passengers with reliable journeys. To achieve this goal, Europe has invested in various multimodal research projects. One such project is air-rail integration, which can improve passenger experience and provide airlines and airports with accurate information about passenger connections. This collaboration could create a win-win situation for all stakeholders involved by increasing passenger demand while limiting extra expenses for the service providers.

In this context, we have presented a delay management strategy tailored to a large integrated air-rail network. We have simulated a disruption occurring on the French railway network, leading to passengers missing their connections at CDG airport. Our mitigation strategy has proved to be effective, reducing passenger delays by 71%, while only delaying 5% of departure flights at CDG airport.

Our delay management strategy considers the entire network and creates new flight and train schedules that satisfy operational constraints. Such constraints include station capacities and minimum aircraft turnaround times at other airports throughout the day. This rescheduling approach limits delay spread by identifying flights that may propagate delays.

This research contributes to improving the passenger experience when travelling across a multimodal long-distance network. We have extended the flight rescheduling recovery strategy presented in [Chapter 4](#) to the network level and the railway transportation system through collaboration with Clara Buire ([Buire et al., 2022](#)). This

extension highlights the effectiveness of tactical coordination between flights and trains to handle disruptions at one airport. By limiting the delay assignable to flights to 30 minutes, propagated delay would remain marginal, with limited impact on other airport operations.

Further research is necessary to implement the proposed delay management strategy, including operator rescheduling cost and passenger preferences. This extension could ultimately lead to better acceptance among transportation stakeholders and an improved passenger travel experience. Analysing a potential airside disruption would provide valuable insights into how the rescheduling differs based on constraint differences on the air and railway sides. Another interesting extension would be to consider dynamic cost indexing, which allows aircraft and trains to speed up to recover from delays. Finally, the rescheduling process should consider ATFM constraints such as en-route capacity and airside delays.

Part III conclusion

This third part has proposed an extension of the recovery strategies proposed in [Part II](#), presenting their impact on the airport environment. By looking at the whole picture, we have assessed the benefits of each strategy, while capturing the side effects on other airport operations and the air transportation network.

In [Chapter 6](#), we have proposed a simulation-optimisation framework to test and validate a tactical security team reallocation strategy at Mexico City Airport. By accurately representing passenger journeys and terminal configurations, we are able to extract new information and shift passenger arrival distribution to the security screening system. Our findings show that segregating passenger flow by opening a fast-track lane for delayed passengers can be an efficient solution. We also have presented a methodology for dynamically reallocating security teams during the day. Our work could form the basis of a Decision Support System for airport operators.

In [Chapter 7](#), we have studied the consequences of tactical rescheduling of flights on the European network. We have proposed a new optimisation problem to coordinate flights and trains at the tactical level in case of delays. We have introduced the notion of *total passenger delay* and a delay management strategy to decide whether to delay a flight or a train. We have tested our strategy on a disruptive scenario in the Western European air-rail network, which includes 496 airports and 72 railway stations. The disruption under consideration occurs on the French rail network, resulting in delayed passenger arrivals at CDG airport. Our results show that delaying flights up to 30 minutes significantly reduces passenger waiting time at their final destination with slight side effects. This highlights how tactical rescheduling of flights at an airport could benefit delayed passengers without disrupting the overall transportation network.

Conclusion and perspectives

The European Commission has set a promising challenge for 2050 to improve door-to-door mobility and offer fast and reliable travel to passengers ([European Commission, 2011](#)). In parallel, with the increasing awareness of climate change, passengers are shifting away from domestic flights and private cars to more eco-friendly modes of transportation, like rail or public transport, to access hub airports. This change in transportation dynamics requires new strategies for managing operations to ensure seamless travel for passengers. A new paradigm where air and ground transportation stakeholders collaborate and share information can help achieve this. Under this new paradigm, we have investigated new recovery strategies that airport operators can implement to manage disruptions occurring on passengers' journeys toward the airport.

Firstly, we have shown that the Exponentially Modified Gaussian (EMG) distribution is suitable for modelling airport passenger arrival times. This probability distribution can be used to reconstruct passengers' arrival profiles at different security checkpoints based on a flight schedule. We have proposed a reproducible framework for modelling passenger flows at Paris-Charles de Gaulle (CDG) airport to evaluate the benefits of new operator strategies for passengers.

Secondly, we have proposed recovery strategies based on security team reallocation and flight rescheduling in the context of airport access mode disruptions. These strategies aim to reduce passenger waiting times at the security screening system and to reduce the number of passengers missing their flights by delaying departing flights. We have proposed optimisation models and methods to solve these problems. Simulated Annealing has provided promising results for the reallocation of security teams, while Integer Linear Programming has been efficient in solving the flight rescheduling problem. Using a sliding time window approach, we have tested both recovery strategies over different access mode disruption scenarios on a day of operations at CDG. On the one hand, these tests have highlighted that reallocating security teams could significantly reduce both the maximum and average passenger waiting times. Moreover, opening a fast-track lane for late passengers at the right moment could significantly reduce the number of passengers missing their flights. On the other hand, the rescheduling approach succeeds in reducing around 50% the total number of stranded passengers with an average aircraft delay remaining lower than 0.6min and 7.4min for arrivals and

departures, respectively.

Thirdly, we have proposed an additional layer to validate and extend our models. We have combined security team reallocation with an airport Discrete Event Simulation framework to test the team reallocation strategy at Mexico City airport. Tests have confirmed the relevance of opening a fast-track lane for late passengers affected by an airport access mode disruption. Our simulation-optimisation framework could form the basis for a Decision Support System (DSS) tool for practical implementation in airport operation centres. Additionally, we have extended the flight rescheduling strategy at the Western European network level to capture delay propagation. Considering a French railway disruption scenario, we have shown that rescheduling flights could enable a 70% reduction in the number of stranded passengers, with a limited propagated delay over the air-rail transportation network.

Several research tracks can be considered for the future. Indeed, despite promising results, the recovery strategies and their associated optimisation models rely on strong assumptions, necessitating further refinement for practical implementation.

The modelling of the security team reallocation problem can be improved by considering security team assignment and transfer times between lanes rather than just the number of open security lanes. Solving this improved model will provide a strategy that airport operators can directly implement. As technology continues to advance, security screening systems are expected to become even more efficient and automated, which will require updates to our reallocation models to account for new system performances. However, resource reallocation strategies will continue to be relevant as workers operate these systems. Furthermore, it would be valuable to consider workforce concerns when modelling the problem to increase solution acceptance and implementation.

The modelling of the flight rescheduling problem can be enhanced by incorporating exogenous Air Traffic Flow Management (ATFM) delays. This additional information would help capture the impact of other airside operation effects, enabling a more comprehensive view of airport operations. It is also essential to consider runway sequencing, waiting time at the runway threshold or gate allocation to evaluate the performance of the rescheduling.

The integration of security team reallocation and flight rescheduling into a single optimisation problem would also be relevant since both recovery strategies are interdependent and affect the number of passengers missing their flights.

Finally, sharing sensitive information in transportation can be challenging, especially regarding delays. Stakeholders need a robust framework to facilitate their collaboration. Initiatives like the Airport Operation Centre (APOC), which involves different stakeholders, and projects like SYN AIR ([SESAR Joint Undertaking, 2023b](#)), aiming to create a platform for collaboration between transportation service providers while considering legal aspects, offer promising perspectives for realising the proposed solutions

for recovery. Our work is part of various European incentives that aim to improve air and ground transportation integration. As we move forward, collaboration encouraged by projects like MultiModX ([SESAR Joint Undertaking, 2023a](#)) is becoming crucial. Such a project provides a testing and refining platform for new transportation management strategies and offers a practical way to test the recovery strategies proposed in this thesis. By combining the different research incentives toward integrating air and ground transportation systems, a win-win situation could be obtained for transportation stakeholders and passengers, where sharing information results in enhanced efficiency, reduced delays, and improved passenger travel experience.

Publications

This work has led to several publications and dissemination into conferences and journals. They are listed below:

Publications accepted and presented in peer-reviewed conferences

Buire, C., Scozzaro, G., Marzuoli, A., Feron, E., and Delahaye, D. (2021, December). A year into the pandemic: a passenger perspective on its impact at paris-charles de gaulle airport. In 2021 IEEE International Conference on Big Data (BigData2021) (pp. 2925-2935). IEEE.

Scozzaro, G., Ji, M., Delahaye, D., Feron, E., and Mancel, C. (2022, June). Flight rescheduling to improve passenger journey during airport access mode disruptions. In International Conference on Research in Air Transportation (ICRAT 2022).

Scozzaro, G., Mancel, C., Delahaye, D., and Feron, E. (2022, December). Optimising security screening resources during airport access mode disruptions. In SESAR Innovation Days (SID 2023).

Scozzaro, G., Mota, M. M., Delahaye, D., and Mancel, C. (2023, July). Simulation-Optimisation-based decision support system for managing airport security resources. In EUROSIM 2023.

Scozzaro, G., Buire, C., Delahaye, D., and Marzuoli, A. (2023, November). Optimizing air-rail travel connections: A data-driven delay management strategy for seamless passenger journeys. In SESAR Innovation Days (SID 2023).

Publication accepted in international journals

Scozzaro, G., Mancel, C., Delahaye, D., and Feron, E. (2023). An ILP approach for tactical flight rescheduling during airport access mode disruptions. International Trans-

actions in Operational Research.

Presentations in congress

Scozzaro, G., Feron, E., and Mancel, C. (2022, February). Optimisation des opérations aéroportuaires afin d'améliorer le transport intermodal de passagers. In 23ème congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision.

Scozzaro, G., Mancel, C., Feron, E., and Delahaye, D (2023, February). Optimisation en ligne d'opérations aéroportuaires dans un contexte intermodal: application à Paris-Charles de Gaulle. In 24ème congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision.

Fundings

This study has been supported by SESAR 3 Joint Undertaking within the project 'Travel Information Management for Seamless Intermodal Transport' (TRANSIT) under grant agreement No 893209 and, within the project 'Implemented Synergies, Data Sharing Contracts And Goals Between Transport Modes And Air Transportation' (SIGN-AIR) under grant agreement No 101114845.

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