Flight Rescheduling to Improve Passenger Journey during Airport Access Mode Disruptions

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***Abstract*—Disruptions on airport access mode impact the passenger journey. This paper shows that the impact can be mitigated with a modest tactical rescheduling of flights. Operational constraints related to connecting flights, minimum turn-around time, runway throughput limitations, terminal and taxi network capacities are considered. In order to solve this optimization problem, we implement a simulated annealing coupled with a simulation-based evaluation and a sliding time window. We propose a data-driven approach to simulate the passenger arrival process at the airport. The coordination mechanism has been evaluated on several scenarios with different levels of disruption. New flight schedules and runway assignments obtained after optimization succeed in reducing up to 70% the number of stranded passengers at the airport by only assigning on average a 6-minute delay to the flight set.**

***Keywords*—Disruption management, Flight schedule optimization, Passenger-oriented metric, Intermodality**

I. Introduction

The European Commission presents the ACARE report [1] in which the Air Transportation system is depicted by 2050. One of the main goals is to ensure that "90% of travellers complete their journey, door-to-door within four hours". The door-to-door perspective is beyond the scope of the air transportation system and includes all the airport access transport modes. Thus, improving the coordination between the ground side and the air side is required to offer a reliable and seamless door-to-door journey to passengers. Especially, when a disruption occurs on one transport mode such as a subway shutdown or a car accident near the airport, a collaboration between Ground Transportation Stakeholders (GTS) and Air Transportation Stakeholders (ATS) would help to improve passengers door-to-door journey.

The TRANSIT project [2], which is part of the SESAR program in Europe, has been launched in 2020 to develop a set of coordination mechanisms based on information sharing between air and ground transportation systems. As part of this project, we highlight potential benefits for passengers considering communication between GTS and ATS under non-nominal situation events. Indeed, thanks to the progress in 4G and 5G, the exchange of information and its availability in no time is possible today. During a disruption on an airport access mode, we assume that GTS provide the Airport Operation Center (AOC) with information on passenger's status. The AOC are entitled to retain specific aircraft at the gate to help delayed passengers to catch their flights. However, holding several aircraft at the gate is likely to induce airport congestion. Thus, arriving flights need also to be regulated. Considering air-connecting passengers would help to distinguish aircraft that must be on time from the ones able to be deviated from the initial schedule. Figure 1 illustrates the different steps of this coordination mechanism.

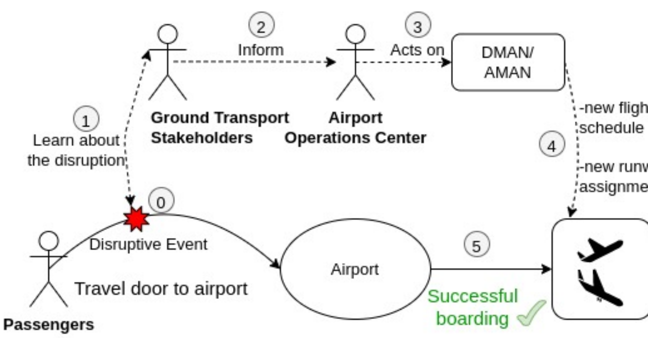

Fig. 1. Illustration of the different steps of the proposed coordination mechanism. Departure Manager (DMAN) and Arrival Manager (AMAN) are tools which help in sequencing departing and arriving flights respectively.

In order to implement this mechanism, we introduce the Passenger-oriented Flight Re-Scheduling Problem (PFRSP). This problem consists in providing a new flight schedule and a new runway assignment at a tactical level to minimize the impact of airport access mode disruption on passengers. Airport resources constraints and operational requirements are also considered.

This paper is organized as follows: Section II provides a literature review on previous works related to this subject. The framework to simulate passenger traffic is presented in Section III. A mathematical modeling of the PFRSP is proposed in Section IV. The optimization algorithm used to solve this problem and its implementation are described in Section V. Results are discussed in Section VI.

II. Litterature Review

Pujet [3] introduced the concept of virtual queuing process for departing aircraft at an airport. This concept leads to the emergence of new tools operated by ATS. For instance, DMAN is a tactical tool used by ATC controllers to manage departing flight operations while satisfying surface movement and runway usage constraints. AMAN is the equivalent tool to handle arriving flights. Bohme et al. [4] tried to integrate both tools to improve the efficiency of departure and arrival handling. Kjenstad et al. [5] implemented a sequential approach to solve arrival, surface and departure management problems. Khadilkar and Balakrishnan [6] proposed an integrated control of terminal and airside operations through dynamic programming to reduce aircraft fuel consumption and mitigate airport congestion. Ma et al. [7] proposed an integrated optimization of arrival, departure and surface operations at Paris-Charles de Gaulle airport (CDG). However, these works do not consider passengers and traffic situation on the ground side in the optimization of arriving and departing flight schedules.

Regarding collaboration between stakeholders, the Airport Collaborative Decision Making (A-CDM) [8] has been implemented in major hub airports. Through information sharing between ATS, airport operations have been significantly improved in terms of punctuality, predictability, quality of service or even regarding resources allocation. However, the flight is only a component of the passenger door-to-door journey. Consequently, the Multimodal, Efficient Transportation in Airports and Collaborative Decision Making (META-CDM) concept has been developed by Laplace et al. [9]. It highlights the possible benefits of extending the CDM concept to the ground side. Dray et al. [10] showed that multimodal recovery solutions would enable a significant improvement in passenger re-accommodation. Marzuoli et al. [11] studied the potential benefits of CDM between GTS and ATS during the Asiana Crash event. They showed that allocating a shuttle for disrupted passengers would have significantly decreased the passenger average delay at their final destination.

Several air-ground collaborations have been implemented so far. Grimme [12] compared the different intermodal services in Germany. Rail&Fly is a service allowing passengers to book a single ticket for train and flight legs. However, passengers are not re-accommodated in case of missed connection. AiRail is another example of collaboration at Frankfurt airport that allows passengers to check-in their luggage directly at train stations. Train-flight connections through this collaboration are like connecting flights. To date, no global coordination at the airport level has been implemented when a disruption occurs on an airport's access mode. To address this issue, we propose a coordination mechanism between GTS and ATS at a tactical level through the resolution of the PFRSP.

III. Modeling the passenger arrival process

In this section, the methodology used to model and simulate the passenger arriving process is illustrated. First, the modeling of passenger arrival times at the gate in nominal condition is introduced. Then, methodologies to allocate passengers to the different airport access modes and to simulate air-connecting passengers are introduced. Finally, the modeling of ground transportation disruptions is presented.

A. Inferring passenger arrival time at the gate

The passenger arrival process at the airport for this study has been calibrated thanks to a data set provided by CDG. This data set is used to infer how long passengers exit the security screening system before their flight. The passenger arrival process is modeled thanks to an Exponentially Modified Gaussian (EMG) distribution fitted to the data by the maximum likelihood method. Further details on the choice of this probability distribution to model passenger arrival process can be found in [13]. This distribution will be used to simulate passenger arrival times in nominal condition (i.e. without an airport access mode disruption).

Depending on the ground transportation mode used to access the airport, the passenger arrival time distribution at the gate can differ. For instance, passengers arriving from cars can be modeled as a continuous flow. The passenger arrival flow from subway can also be approximated by a continuous flow regarding its high frequency (one every six minutes at CDG airport) and since airport processing time can differ between passengers. Thus, the EMG distribution can be used to model passenger arrival from road and subway. However, this distribution is not suitable to model passenger arriving from train due to its low frequency. Thus, a normal distribution

TABLE I. MODAL SHARES OF GROUND TRANSPORT MODES USED TO ACCESS CDG AIRPORT IN 2015

Access mode	Train	Road	Public Transport
Modal share	11%	63%	26%

with a small standard deviation is used to model passenger arrivals from this transportation mode. The greater the standard deviation, the greater the dissimilarity in arriving times.

B. Ground access modal share

This work takes advantage of a 2015 passenger survey at CDG conducted by the Direction Générale de l'Aviation Civile (DGAC). Modal shares of transport mode used to access the airport are provided by this survey and are summarized in Table I. Continuous uniform distributions centered on these shares are used to assign one airport access mode to each passenger.

C. Modeling air-connecting passengers

Air-connecting passengers need to be considered during the design of the new flight schedule. However, information on connecting-flights are generally airlines' properties and were not accessible for this study. Thus, we develop a methodology to simulate air-connecting passengers. Consider a departure flight f. Flights arriving between 45 to 240 minutes before the departure time of f are qualified as potential connecting flights. Connecting passengers (which is around 37% according to the 2015 survey) are dispatched among these potential connecting flights. Also, a minimum transit walking time has been arbitrarily set between each pair of terminals.

D. Modeling ground transportation disruption

A first method to model the impact of a ground disruption on passengers is to shift their arrival time by a certain duration. This duration can be arbitrarily chosen depending on the level of the disruption. For instance, if a disruption on the subway occurs, passengers who had initially planned to take this mode would be delayed by a certain amount of time. Actually, access mode modal share are likely to change when a disruption occurs on one mode. Indeed, passengers who had planned to use the subway and that have been aware of a disruption may change their plan and take a taxi to reach the airport. However, such changes would also induce a delay for passengers due to the additional transfer time. Thus, we assume that all passengers who had planned to take the disrupted access mode would be delayed. Depending on which mode undergoes a disruption, the shape of the passenger arrival time distribution may also be impacted. For example, if the subway is stopped for a certain duration, this mode is likely to be crowded when it resumes due to an accumulation of passengers during the breakdown. It translates into a reduction in the standard deviation of passenger arrival time distribution for this mode. This parameter is arbitrarily divided by two during a subway disruption. If the disruption occurs on the road or the train access mode, the shape of the distribution is assumed to be similar than the nominal one, only shifted by a certain duration. This modeling is quite simple since all passengers will not react to the disruption in the same manner. However, the coordination mechanism would also work with a better modeling of the mode disruption impact on passengers.

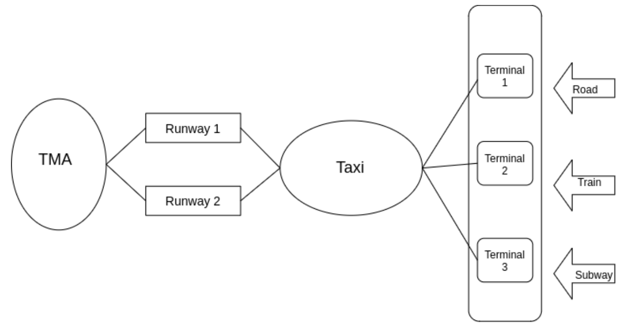

Fig. 2. Macroscopic airport modeling considered for this study

IV. OPTIMIZATION PROBLEM MODELING

In this section, we propose an optimization model for the PFRSP. Figure 2 provides a macroscopic view of the airport considered for this study. Passengers can reach the airport from several ground access modes such as subway, road, or even by train. The airport is composed of several terminals. Each terminal has a maximum airside capacity that is the number of its operating gates. The taxi network connects the terminals to the runways and has also a limited capacity representing the maximal number of aircraft that can be operated simultaneously on the taxi network. Finally, a set of runways enables flights to enter in/exit the Terminal Manoeuvering Area (TMA) and each runway has a maximum throughput.

For the sake of simplicity, in the model described below, the term 'flight' is also used for aircraft to lighten the mathematical modeling. The considered time scope is the one of an operational day and is discretized. The terminal is seen as a resource with a specified capacity without considering individual gates. The flight time duration between one entry/exit point in the TMA and one runway is computed by considering a constant deceleration/acceleration and a standard route within the TMA. For each couple (runway, terminal), the taxi-in and taxi-out

duration are assumed constant since no consideration is made on the associated terminal gate.
Data, decision variables, constraints and objective function of the mathematical model are introduced below.

A. Data

The following sets and parameters are considered as given data:

- $\mathcal{F} = \mathcal{D} \cup \mathcal{AD} \cup \mathcal{A}$: set of flights, where $\mathcal{D}, \mathcal{AD}, \mathcal{A}$ refer to a set of departing flights, arriving-departing flights and arriving flights respectively. The departing flights are associated to aircraft that are initially located at the airport while the arriving ones are associated to aircraft that will stay at the airport at the end of the day;
- $\mathcal{K}$: set of terminals;
- $\mathcal{R}$: set of runways;
- $\mathcal{T} = \{t_1, ..., t_{|\mathcal{T}|}\}$: set of time steps on the considered period. In the following, the period between two steps is constant;
- $\mathcal{CF} \subset (\mathcal{AD} \cup \mathcal{A}) \times (\mathcal{D} \cup \mathcal{AD})$: list of flight pairs having at least one connecting passenger;
- $\forall f \in \mathcal{AD} \cup \mathcal{A},\ T_f^0$: Requested Time of Arrival (RTA) at TMA entrance;
- $\forall f \in \mathcal{AD} \cup \mathcal{A},\ V_f^{\min}$ and $V_f^{\max}$: minimum and maximum speed at TMA entrance;
- $\forall f \in \mathcal{D} \cup \mathcal{AD},\ P_f^0$: requested off-block time;
- $\forall f \in \mathcal{AD},\ \alpha_f$: minimum turnaround time of f;
- $\forall (f_1, f_2) \in \mathcal{CF},\ n_{f_1 f_2}$: number of connecting passengers from arriving flight f_1 to departing flight f_2;
- $\forall (f_1, f_2) \in \mathcal{CF},\ \delta w_{f_1 f_2}$: transit walking time from terminal assigned to f_1 to terminal assigned to f_2;
- $\forall r \in \mathcal{R},\ \Phi_r^{\max}$: maximum throughput per 10-steps interval of runway r;
- O_{TN}: maximum capacity of the taxi network;
- $\forall k \in \mathcal{K},\ O_{\mathrm{k}}$: maximum capacity of terminal k;
- $\Delta T_{\min}^{\mathrm{RTA}}$ and $\Delta T_{\max}^{\mathrm{RTA}}$: maximum negative and positive delay that can be applied at TMA entrance to an arriving flight;
- $\Delta T_{\max}^{\mathrm{p}}$: maximum push-back delay that can be applied to a departing flight;

B. Decision variables

In order to model a solution of the PFRSP, we introduce up to five decisions variables associated to each flight
For each $f \in \mathcal{D} \cup \mathcal{AD}$, we define:

- $t_f \in [T_f^0 - \Delta T_{\min}^{\mathrm{RTA}}, T_f^0 + \Delta T_{\max}^{\mathrm{RTA}}]$: entering time in the TMA .
- $v_f \in [V_f^{\min}, V_f^{\max}]$: the entering speed in the TMA.
- r_f^l: landing runway associated to f.

For each $f \in \mathcal{AD} \cup \mathcal{A}$, we define:

- $P_f \in [P_f^0, P_f^0 + \Delta T_{\max}^p]$: actual off-block time. Note that this interval is asymmetric since the departure flight time is seldom earlier than the expected one.
- r_f^d: the departure runway associated to f.

Several auxiliary variables are also introduced:

- $\forall k \in \mathcal{K},\ \forall t \in \mathcal{T},\ N_t^k$: number of flights occupying terminal k at time t.
- $\forall t \in \mathcal{T},\ N_t^{\mathrm{TN}}$: number of flights occupying the taxi network at time t.
- $\forall r \in \mathcal{R},\ \forall t \in \mathcal{T},\ N_t^r$: number of flight movements on runway r between t and t+10min.
- $\forall f \in \mathcal{AD} \cup \mathcal{A},\ \forall r \in \mathcal{R}, x_{rf}^l = 1$ if f is assigned to landing runway r, 0 otherwise.
- $\forall f \in \mathcal{D} \cup \mathcal{AD},\ \forall r \in \mathcal{R}, x_{rf}^d = 1$ if f is assigned to departure runway r, 0 otherwise.
- $\forall f \in \mathcal{AD} \cup \mathcal{A},\ t_f^{\mathrm{in}}$: in-block time of f.
- $\forall f \in \mathcal{D} \cup \mathcal{AD},\ N_{\mathrm{ground}}^f$: Number of stranded passengers of departing flight f.

These auxiliary variables are function of the main decision variables and will be computed through a simulation-based evaluation as explained in Section V.

C. Constraints

Constraints related to the problem are listed below:

- *Terminal capacity constraint:*
$$\forall k \in \mathcal{K},\ \forall t \in \mathcal{T},\ N_t^k \leq O_k \tag{1}$$
- *Taxi network capacity constraint:*
$$\forall t \in \mathcal{T},\ N_t^{\mathrm{TN}} \leq O_{\mathrm{TN}} \tag{2}$$
- *Runway throughput constraint:*
$$\forall r \in \mathcal{R},\ \forall t \in \mathcal{T},\ N_t^r \leq \Phi_r^{\max} \tag{3}$$
- *Landing runway assignment:*
$$\forall f \in \mathcal{AD} \cup \mathcal{A},\ \sum_{r \in R} x_{rf}^l = 1 \tag{4}$$
- *Departure runway assignment:*
$$\forall f \in \mathcal{D} \cup \mathcal{AD},\ \sum_{r \in R} x_{rf}^d = 1 \tag{5}$$
- *Air-connecting passenger constraint:*
$$\forall (f_1, f_2) \in \mathcal{CF},\ \delta w_{f_1 f_2} \geq P_{f_1} - t_{f_2}^{\mathrm{in}} \tag{6}$$
- *Turnaround time constraint:*
$$\forall f \in \mathcal{AD},\ \delta P_f - t_f^{\mathrm{in}} \geq \alpha_f \tag{7}$$

D. Objective function

We consider two criteria to build the objective function:

- *the number of stranded outbound passengers*:

$$G = \sum_{f \in \mathcal{D} \cup \mathcal{AD}} N^f_{\text{ground}} \quad (8)$$

- *the total deviation compared to the initial schedule*

$$D = \sum_{f \in \mathcal{AD} \cup \mathcal{A}} |T^0_f - T^{\text{RTA}}_f| + \sum_{f \in \mathcal{D} \cup \mathcal{AD}} P_f - P^0_f \quad (9)$$

The overall objective function is the following one:

$$min\ \lambda \times G + (1 - \lambda) \times D, \quad (10)$$

with $\lambda \in [0, 1]$.

Next section introduces the resolution approach proposed to solve the PFRSP.

V. Resolution approach

This problem can be demonstrated as NP-Hard and provides a large search space for solutions. Moreover, the proposed coordination mechanism is expected to provide a new schedule at a tactical level. Thus, exact methods seem not fitted to this problem since they generally fail to solve difficult problems with large search space in a short time. Thus, the use of metaheuristics seems relevant to solve such problems. Since the evaluation of resource constraints is made through simulation, a single-population method like the Simulated Annealing (SA) is well designed for this problem. Conversely, with population-based methods such as Genetic Algorithm or Particle Swarm Optimization, the simulation environment would need to be duplicated for each individual of the population. This is likely to induce massive memory space allocation requirements and consequently increase the computational time. Moreover, SA is a metaheuristic that has already been proved to work well on NP-difficult problems close to the FPRSP ([7], [14], [15]). The resolution approach based on SA coupled with a simulation-based evaluation is introduced below. For a complete description of the SA, the reader can refers to [16].

A. SA coupled with a simulation-based evaluation approach

The SA is a single-solution metaheuristic based on an analogy with an annealing in metallurgy. At each iteration of the SA algorithm, the current solution is locally modified and evaluated. The new solution can be accepted depending on an acceptance probability function. The process is initialized with a high acceptance rate to favor the exploration of the state space by enabling the degradation of the criteria. As the solution research goes further, the algorithm becomes more selective until accepting only better solutions. These features are tuned with the help of the so-called hyper parameters.

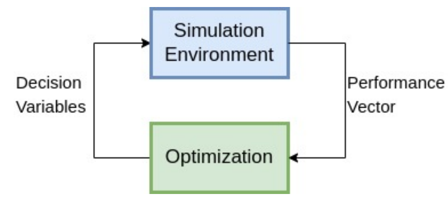

Fig. 3. Illustration of the simulation loop principle. The decision variables are evaluated thanks to the simulation environment. A performance vector is obtained after simulation to guide the optimization process in modifying decisions with poor performances. The process is repeated until a stopping criterion is reached.

SA can be coupled with a simulation process to evaluate the objective function. An illustration of this principle is proposed in Figure 3. Only one decision variable is modified to generate a neighbor of the current solution. The selection of this decision is based on the performance vector obtained after simulation. The poorer the performance of one decision, the more likely this decision will be changed. Each decision variable has a performance. For instance, if connecting passengers between f_1 and f_2 miss their connection, the variable decision related to the arriving time of f_1 and the decision related to the off-block time of f_2 will have their performance deteriorated.

Since the evaluation of the overload, throughput and air-connection constraint satisfaction are made through the simulation, the neighbor generation process does not guarantee the feasibility of the neighborhood solution. Thus, these constraints are relaxed and a penalty term is added to the objective function in case of constraint violation.

Passenger arrival times are pre-processed to compute, for each departing flight, its number of stranded passengers depending on its off-block time. A tabulation is done by computing all potential push-back delays for each flight to reduce the computation time of the simulation-based evaluation.

B. Sliding time window approach

A two-hour sliding time window, as presented in [17], is implemented to tackle the PFRSP. Each flight is associated to a status (Completed, On-going, Active, Planned). The problem is run and solved for flights operating during a two-hour time window. Then the window is shifted by 30 minutes and the status of each flight is updated. The new on-going flights will become constraints for the new active ones. This time-window has two advantages. Firstly, it reduces the computation time. Secondly, it makes sense regarding the operational context of the proposed coordination mechanism. Indeed, the passenger arrival time estimation is only accurate a few hours before the flight. Estimating during the morning the arrival time of passengers having a flight during the evening seems not relevant since the traffic information on the ground is not yet available and any disruption has not occurred yet. Assuming that most passengers plan to arrive at the airport between one and three hours before their flight, solving the problem on a two-hour time window makes sense.

Next section presents the results obtained thanks to this resolution approach on a case study at CDG.

VI. Results

A. Study case

To evaluate the proposed coordination mechanism, the simulation is run for a full day of operations with a two-hour sliding time window. A single run is done for the entire operation day. However, in practice, such mechanism would need to be run by the AOC at each passenger's status update. Suppose that every 30 minutes GTS shared this information with the AOC. The latter would forecast passenger arrival times at the gate. Then, decisions on departing and arriving flights operating between one hour and three hours after each passenger's status update are optimized. Regarding SA hyper-parameters, the number of transitions per temperature step is fixed to 10 and the temperature decay parameter to 0.99.

A nominal day at CDG is considered with 1232 operated flights. For each aircraft, the RTA, the TMA entry point, the initial runway, the landing time, the in-block time, the turn around time, the off-block time and the departure time are known. The airport is composed of three terminals and four parallel runways (two for landings (26L, 27R) and two for take-offs (26R,27L)). However, this framework could be easily applied with runways used in mixed-mode operations.

The following assumptions are made:

- the maximum number of aircraft during the day on each terminal and on the taxi network according to the initial planning are used as a proxy to set their respective maximum capacity,
- the delay that can be applied at TMA entrance is bounded between -5 and +15 min,
- the speed change allowed for arriving flights is fixed between -10% and 10%,
- the maximum push-back delay is set to +15min,
- a coefficient of 100 is applied for the violation of constraints that have been relaxed and added as a penalty term to the objective function,
- the value of the objective function parameter λ is set to 0.9. It means that one stranded outbound passenger has the same impact on the objective function than nine minutes of delay assigned across the flight set.

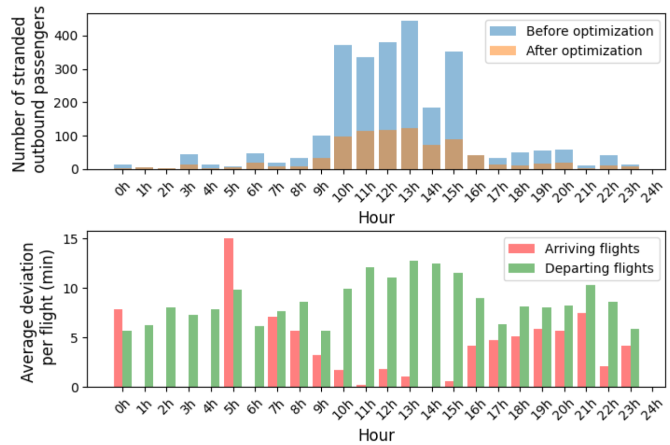

Fig. 4. Comparison of results obtained before and after optimization. The top figure displays the evolution in the number of stranded outbound passengers during the day. The blue and orange histograms refer to the volume of passengers with the initial and the optimized schedules respectively. The bottom figure shows the evolution of the average deviation from the initial schedule for departing (in green) and arriving (in red) flights.

These values have been arbitrarily fixed and can be tuned depending on airport's characteristics or on user preferences depending on what objective should be prioritized. A disruption on the subway has been modelled by delaying the passenger arrival time distribution from this mode by 45 minutes and dividing its standard deviation by 2 for flights departing between 10AM and 4PM.

The algorithm has been tested on a 2.3GHz AMD RYZEN 5 CPU. The execution time for the entire day of the algorithm is 360s. Thus, the average duration of the algorithm on a two-hour time window is lower than 8s (48 times windows run for a full day of operations). The optimized solution is compared with the initial planning in Figure 4. The evolution in the number of stranded outbound passengers and the total deviation from the initial schedule are displayed.

More than 60% of passengers who were initially stranded succeed in catching their flight with the new schedule. One can notice that several passengers are stranded even outside the disruption hours. This is due to the passenger arrival process modeling that simulates few late arrivals even during nominal condition. Consequently, the optimization method also assigns delay to departing flights occurring before and after the disruption. The average deviation applied to departing flights is equal to nine minutes. It is three times higher than the average deviation applied to arriving flights. This observation is consistent since arrival delays are only assigned to mitigate airport congestion and runway throughput limitations. During the disruption, the average delay applied to departing flights tends to be higher, ranging from 11 to 13 minutes.

Constraints on runways throughput, terminal capacities, taxi network capacity and air-connecting flights are respected.

B. Parameter sensitivity analysis

Depending on the value of the objective function parameter λ, the optimized planning can whether favor the reduction in the number of missed ground-air connections or the compliance with the initial schedule. Several runs of the algorithm were performed with different values of λ and results are displayed in Figure 5.

As one can observe in Figure 5, the more λ increases, the lower is the total number of outbound passengers and the higher is the average deviation per flight. Both the average deviation and the number of outbound passengers slightly decreased from $\lambda = 0.2$ to $\lambda = 0.3$. However, the solution associated with $\lambda = 0.3$ is not admissible since eight air-connecting passengers miss their next flight. This problem could be fixed by increasing the penalty coefficent for constraint violation. A good compromise for λ seems to be a value into the interval $[0.6, 0.9]$. Even if the value of λ is high, the average delay is always lower than ten minutes (even though this one is bounded to 15 minutes). Indeed, deviations applied to arriving flights remain on average low since they are only assigned to mitigate airport congestion or excessive runway throughput.

C. Different scenarios

Other disruptions have been tested in order to measure the efficiency of the coordination mechanism depending on the disruption intensity. Table II presents the different scenarios considered and results obtained for each of them are displayed in Figure 6. The λ parameter has been set to 0.9.

TABLE II. DESCRIPTION OF DIFFERENT DISRUPTIVE SCENARIOS

Scenario	**Mode disrupted**	**Average delay**	**Starting time**	**Ending time**
s0	subway	45min	10 AM	4 PM
s1	subway	20min	10 AM	4 PM
s2	subway	60 min	8 AM	11 AM
s3	road	45 min	10 AM	4 PM
s4	road	60 min	10 AM	1 PM
s5	train	90 min	6 AM	9 AM
s6	all modes	120 min	6 AM	11 AM
s7	no disruption			

In scenario 1, a drop of 70% in the volume of stranded outbound passengers with the optimized schedule can be observed. The coordination mechanism has a poorer performance on scenario 5 and 6 with a reduction of 30% and 10% in the number of stranded outbound passengers respectively. According to Table II, the scenario 1 corresponds to the lowest intensity disruption (20 minutes of delay per passenger) and scenario 5 and 6 to the highest ones (90 and 120 minutes of delay per passenger respectively). Indeed, since the maximum push-back delay is set to 15 minutes, the performance of the mechanism is limited for massive disruption. Thus, the higher the average delay per passenger, the lower the relative reduction in the number of passenger stranded. Also, scenario 5 is the only one that corresponds to a train disruption. Since train passenger arrivals are modelled with a normal distribution with a small standard deviation, a 90-minute delay is likely to

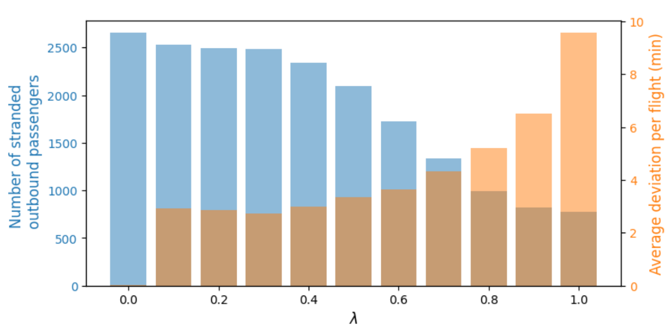

Fig. 5. Solution obtained depending on the objective function parameter λ. $\lambda = 1$ is equivalent to the problem of only minimizing the number of stranded outbound passengers while $\lambda = 0$ to the one that only minimizes the total deviation from the initial schedule.

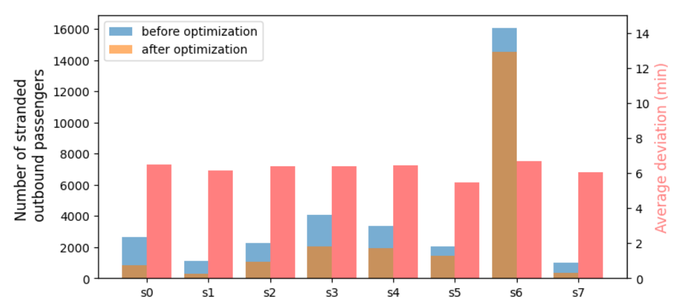

Fig. 6. Comparison of results obtained with and without coordination mechanism tested on different scenarios. The bar plot on the left displays the number of stranded outbound passengers before (blue) and after (orange) optimization on each scenario. The bar plot on the right (pink) represents the average deviation from the initial schedule after optimization.

threathen all the train-flight connections. A 15-minute delay applied to departing flights may not be sufficient to help passengers in catching their flight. In fact, the reduction in the number of stranded outbound passengers on scenario 5 is due to ground-air connections saved during non-disrupted hours. Indeed, in scenario 7 (representing a day without disruption), the algorithm succeeds in making 700 passengers on time for boarding. This volume is similar to the one saved in scenario 5. Finally, the average deviation applied to each flight after optimization remains roughly constant across the different scenarios and always under seven minutes.

VII. Conclusion

We developed a coordination mechanism between ground and air transportation systems to handle an airport access mode disruption. Through an information sharing between GTS and the AOC, several aircraft can be targeted and retained at the gate to wait for delayed passengers impacted by the disruption. We used a data-driven approach to model the passenger arrival process at CDG and proposed a mathematical modeling of the problem. This optimization model aims at taking decisions on departing and arriving aircraft to minimize the number of stranded passengers at the airport while mitigating the total deviation from the initial schedule. Operational constraints related to terminal congestion, taxi network congestion, runway throughput limitations, turn-around time and connecting flights have been considered. We implemented a simulated annealing coupled with a simulation-based evaluation and a sliding-time window to solve the optimization problem. Results show a reduction of 50% in the number of stranded outbound passengers on half of the scenarios by only assigning a six-minute delay on average per flight. Thus, a collaboration between the ground and air transportation systems could significantly improve passenger journey without compromising benefits of stakeholders.

Nevertheless, future research directions could be explored. For instance, we intend to compare the current resolution approach with an optimal baseline algorithm in terms of solution quality and computational time. The model could be refined by integrating the gate allocation problem and/or by integrating the airport security process to the PFRSP. We also intend to apply and test the proposed method on other airports and compare its performance depending on airports' features (passenger access modes, airport capacities) and on disruptive scenarios.

Aknowledgments

We thank CDG for the data provided to calibrate the model and their feedbacks. We also thank the DGAC for providing us the passenger survey. This project has received funding from the SESAR Joint Undertaking under grant agreement No 893209 under European Union's Horizon 2020 research and innovation programme. This work was also supported by the Fundamental Research Funds of CAUC No 3122019179.

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