Optimising security screening resources during airport access mode disruptions

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***Abstract*—Airport access mode disruptions have a significant impact on passenger arrival times and thus on congestion level at security screening systems. During such events, information sharing between ground and air transportation stakeholders could be a key lever to optimize airport operations at a tactical level. In this work, an online reallocation of airport security teams across the different security screening checkpoints is considered. Three integer linear programming formulations of the problem are proposed to increase the level of service of an airport when a disruption occurs. A study case based on one day of operations at Paris-Charles de Gaulle airport is considered. Results show that reallocating airport security staff when outbound passengers are delayed could significantly improve airport security system performances. The different allocations obtained lead to a drop in the maximum waiting time up to 72%. In addition, the average waiting time and the number of stranded passengers at the airport are reduced.**

***Keywords*—Airport Operations, Security Screening System, Disruption Management, Integer Linear Programming**

I. Introduction

The European Commission shines a light on what the aviation should look like in the future, in its Flight Path 2050 [1]. In this vision, passenger-oriented metrics receive growing attention to assess the performance of the Air Transportation System (ATS). For instance, one goal is that "90% of travellers within Europe are able to complete their journey, door to door, within 4 hours". For that purpose, several European projects have been launched since 2020 such as MODUS [2], X-TEAM D2D [3], TRANSIT [4] or IHMOTEP [5] to improve the integration of the ATS with Ground Transportation Systems (GTS).

However, to date, no strong coordination mechanisms between GTS and ATS have been implemented. Especially, when a disruptive event occurs on one airport access mode, such as a subway shutdown, the overall airport performances are impacted. Such disruption is likely to induce unexpected peaks of congestion at the airport. These peaks can drastically reduce the Level of Service (LOS) of airport security screening system, as observed for instance at Amsterdam-Schipol during the unexpected fast recovery from COVID19 in Summer 2022 [6]. Large queuing times at security screening system lead to severe delays for passengers and threaten the 4-hour door-to-door goal. In this situation, optimizing the allocation of security staff teams across the different security checkpoints at a tactical level is crucial to improve airport operations efficiency.

This work underlines potential benefits that could be obtained thanks to information sharing between GTS and ATS. We assume that during airport disruptive events, the Airport Operation Center (AOC) receives regular updates on expected passenger arrival times. This information can be communicated either by ground transportation stakeholders or directly by passengers affected by the disruption. Based on these new forecasts, the number of passengers expected at each security checkpoint can be updated for the next hours. Consequently, the AOC is able to optimize the allocation of security staff across the airport security screening system. More precisely, we propose an online reallocation of teams across airport's security checkpoints. Considering a given number of teams that are available per hour, the goal is to find the optimal allocation among the set of security checkpoints to improve the LOS of airport security screening system. This can be achieved by minimizing either the maximal passenger waiting time, the average waiting time or even the total number of passengers stranded at the airport. Subsequently, the problem addressed in this paper will be referred as Online Security Screening Resources Allocation Problem (OSSRAP).

This paper is organized as follows: previous related works are introduced in Section II. A detailed description of the OSSRAP is proposed in Section III. To solve this problem, three Integer Linear Programming (ILP) formulations are proposed in Section IV depending on the objective function targeted. The resolution approach retained and a greedy algorithm are described in Section V. The study case, based on one day of operations at Paris-Charles De Gaulle airport (CDG), and the results obtained are presented in Section VI and VII respectively.

II. State of the art

Queuing lines are often observed in airport operations, either on the airside (like aircraft waiting at runway threshold) or in terminals (such as passengers waiting at check-in counters, at border controls, or even at security screening checkpoint). De Neufville et al. [7] highlight that queuing theory can be powerful to improve the handling of airport operations. This approach, using several assumptions on the demand, provides analytical results that can be applied to design optimal control strategies. Queuing theory is part of stochastic modeling and considers variability in the demand rate and/or in the service rate [8]. This variability can induce the formation of waiting lines even if the service rate (i.e. the number of passengers that can be served during a certain duration) is higher than the demand rate (i.e. the number of passengers entering in the queuing system during a certain duration). Indeed, if a large group of passengers enters in the system at the same time, a waiting line will be formed. Thus, queuing theory is especially useful to design control policies at a strategic level when the demand rate can be highly variable. On the airside, Pujet et al. [9] implement a virtual queue to control departure process and avoid aircraft waiting at runway threshold. Jacquillat and Odoni [10] combine a control strategy of the arrival and departure service rates with a stochastic and dynamic queuing model to estimate airport delays depending on a flight schedule or airport capacities. On the terminal side, Zhang [11] designs a staffing policy at border-crossing stations by adjusting the number of servers depending on an expected queue length of the system. However, such criteria does not always prevent passengers from high delays.

One main drawback of using queuing theory to design optimal control strategies relies on assumptions made on the demand distribution. For instance, when the demand distribution is not following a Poisson distribution (as it is the case for passenger arrivals at the airport), analytical results are much more challenging to get, especially for large-scale problems.

To tackle this issue, simulation models with discrete events are often used to design control policies for real queuing systems. Kierzkowski and Kisiel [12] develop a simulation model to control security system operations at Wroclaw Airport. They highlight potential cost benefits by authorizing queuing formation in the scheduling phase while keeping acceptable LOS. They use the maximum queue length as a criterion to be minimized. The control strategy is dynamic and defines the number of lines that should be opened or closed depending on queue length observed during the simulation. Mota et al. [13] make a distinction between passengers, depending on characteristics that influence their speed in the security screening process (such as business, family or passengers with reduced mobility). They show that this distinction helps in improving security line policies by adapting the system to these different categories. They highlight that the capacity could be increased up to 20% by designing a proper category in combination with new technology on a study case around Mexico's airport. Mota et al. [14] use simulation to study the impact of 'smart passengers' on departing passenger flow in airports. This new category of passengers, live sharing information with airport stakeholders, can reduce their time spent in airport queuing systems by using new specific processes or facilities. Perez et al. [15] use a simulation approach to study the dynamic allocation of security screening resources at Phoenix Sky Harbor International Airport. They minimize either the passenger queuing time or queue length under staff resource constraint per 15-min interval. The allocation is optimized through feedback received from the simulation model.

The main weakness of control strategies based on simulation is that they generally require a high number of iterations to find an efficient control policy. This often leads to high computational time especially when the instance of the problem is large. Moreover, such strategies are not guaranteed to be optimal. In this work, we propose to model and solve the OSSRAP with help of linear programming. Indeed, this exact method is frequently used to tackle resource allocation problem [16]. We use the advantage of information sharing and regular updates on passenger's location to get accurate forecasts on demand level at each security checkpoint and thus work in a deterministic context. Consequently, our approach do not consider stochastic delays and only focus on minimizing overload delay. Next section presents a detailed description of the OSSRAP.

III. Problem Description

First, a general description based on discussions with CDG operators is provided. Then, the queuing model and the evaluation of passenger waiting times that will be used in the mathematical modeling are introduced. Finally, the assumption on data availability, reflecting the 'online' characteristic of this problem, and the design of a suitable time window to solve the OSSRAP are presented.

A. *Description of the OSSRAP*

Several security checkpoints compose CDG airport security screening system. For simplicity, we assume that each security checkpoint and each departure flight are coupled with one boarding room. Thus, all local passengers of one flight will go through the same security checkpoint. Each checkpoint consists of a set of lines and a common queuing system. For simplicity, fast lines for business passengers are not considered in this work. The number of opened lines for each security checkpoint can change during the day depending on the evolution of the expected number of passengers. Each line can be operated by one security team comprising five or six agents. A prediction of passenger arrival times is generated at the strategic level by CDG operators to estimate, for each security checkpoint, the number of operating lines required per hour. For the OSSRAP, we retain a resource pooling assumption. This means that for each hour, a total number of lines can be opened over the whole airport. Thus, the only decisions rely on dispatching the different teams across the set of security checkpoints during the day. **The goal is to find an allocation of the number of lines to open, for each security checkpoint, for each hour, under resource pooling constraint to improve the LOS**. Several criteria can be targeted to optimize the allocation such as minimizing the maximum passenger waiting time, the average waiting time or even the number of stranded passengers (i.e. local passengers that will miss their flights). The first one favors the fairness between passengers contrary to the second one that could lead to large waiting times for several passengers. As an order of magnitude, CDG operators qualify as unacceptable an allocation leading to waiting time

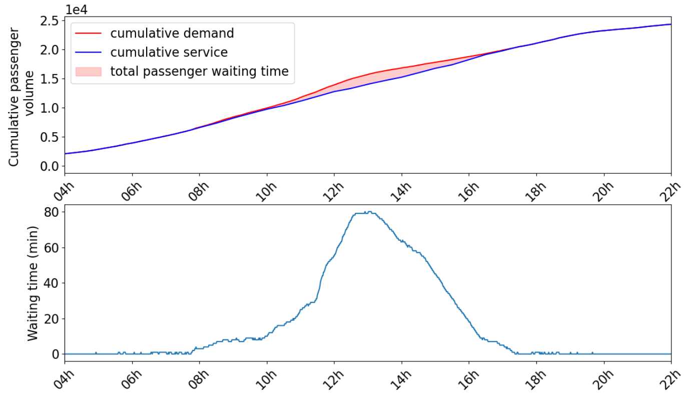


Figure 1. Example of one cumulative diagram (top figure) and its associated waiting time evolution (bottom figure). The top figure displays the evolution of the cumulative service (blue curve) and demand (red curve). The red area corresponds to the total passenger waiting time.

higher than 30 minutes. Moreover, 90% of passengers should wait less than ten minutes. Three mathematical models with three different objective functions will be presented in Section IV.

B. *Queuing system modeling*

The First-In First-Out (FIFO) hypothesis is retained to model each security checkpoint queuing system. Each opened line is assumed to provide a constant service rate per hour. CDG operators estimate that an operated line accommodates 120 passengers per hour on average. In order to evaluate the passenger waiting time in a deterministic context, cumulative services (i.e. the total number of passengers served since the beginning of operations) and cumulative demands (i.e. the total number of passengers entered in the queuing system since the beginning of operations) can be used as shown in Figure 1. The waiting time of a passenger entering in the queuing system at time t is the time that the cumulative service overtakes the cumulative demand at t. For instance, when the thousandth passenger of the day enters in the queuing system (i.e. the cumulative demand equals to 1000), he will have to wait until the service served a thousand of passengers (i.e. until the cumulative service reaches 1000).

C. *Data online feature handling*

We make the assumption that forecasts of passenger arrival times at security screening checkpoints are updated during airport access disruption thank to communication links between stakeholders. We assume that passengers arrival times are updated every hour. However, these forecasts are reliable only for a short time span due to the uncertainty related to disruptive situations. Thus, taking operational decisions for the evening during the morning in a disruptive context seems irrelevant. Teams reallocation across the different security checkpoints will then be solved for a specific time window after the first update of passenger arrival times following the beginning of the disruption. Then, it could be solved again on a new time window once a new update on passenger arrival times is received. To handle the online characteristic of passenger arrival time data, we propose to solve the problem on a 2-hour length time window. From the operational point of view, a succession of problems will be solved for a 2-hour time window and solved every hour from the beginning of the disruption until the end of the day. The methodology retained is summarized below:

Algorithm 1 SlidingTimeWindowManagement($t_{\mathrm{MIN}}, t_{\mathrm{MAX}}$)

$t_{\mathrm{start}} = t_{\mathrm{MIN}}$
$t_{\mathrm{end}} = t_{\mathrm{MIN}} + \Delta_{\mathrm{window}}$
repeat
  Solve OSSRAP between t_{start} and t_{end};
  Compute queue length on each security checkpoint at $t_{\mathrm{start}} + \delta_{\mathrm{sliding}}$ (input for the next time window problem);
  $t_{\mathrm{start}} = t_{\mathrm{start}} + \delta_{\mathrm{sliding}}$;
  $t_{\mathrm{end}} = t_{\mathrm{end}} + \delta_{\mathrm{sliding}}$;
until $t_{\mathrm{start}} \leq t_{\mathrm{MAX}} - \delta_{\mathrm{sliding}}$;

where t_{MIN} represents the beginning of the disruption, t_{MAX} the end of the day, Δ_{window} the time window duration (equals to two hours) and $\delta_{\mathrm{sliding}}$ the sliding time of the window (equals to one hour). It should be noted that decisions taken between t_{start} and t_{end} also have an impact on waiting time of passengers that are already queuing at t_{start}. Thus, the evaluation of waiting time needs also to be computed for passengers arrived before t_{start} and not served yet.

Next section presents the mathematical modeling retained for the OSSRAP on one time window.

IV. Mathematical modeling

Three Integer Linear Programming (ILP) formulations of the OSSRAP are defined below. Each of them differs from the other ones through the objective function considered. The first one (ILP0) aims at minimizing the maximum passenger waiting time while the second (ILP1) and the third one (ILP2) minimize the average passenger waiting time and the number of stranded passengers respectively. Each model is proposed for a 2-hour time window during the day of operations. In order to help the reader in the understanding of the mathematical modeling, the different time steps that are introduced are displayed in Figure 2.

A. *ILP0 : security screening reallocation to minimize the maximum passenger waiting time*

Data:

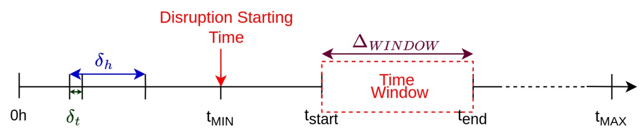


Figure 2. Illustration of the different time steps considered in the mathematical model.

- $\mathcal{S}$: set of security checkpoints;
- t_{MIN}: starting time of the disruption;
- t_{start}: starting time of the time window considered to optimize staff allocation;
- $\forall s \in \mathcal{S},\ t^s_{\text{start}}$: starting time used for security checkpoint s to compute passenger waiting time (potentially before t_{start} if a queue is already formed);
- δt: time step used for passenger arrival (=10 minutes);
- $\mathcal{T} = \{t_{\text{start}}, t_{\text{start}} + \delta t, ..., t_{\text{end}}\}$ set of discrete time considered during the time window;
- $\forall s \in \mathcal{S},\ \mathcal{T}^s = \{t^s_{\text{start}}, t^s_{\text{start}} + \delta t, ..., t_{\text{end}}\}$ set of discrete times considered during the time window associated to the security checkpoint s;
- δh: time step used to decide line opening across the different security checkpoints (=60 minutes);
- $\mathcal{H} = \{t_{\text{start}}, t_{\text{start}} + \delta_h, ..., t_{\text{end}}\}$ set of time intervals where decisions on line opening need to be taken (if a 2-hour time window and $\delta_h = 60$ minutes are considered, then $\mathcal{H}$ contains two intervals);
- $\forall t \in \mathcal{T},\ h_t$: time interval of $\mathcal{H}$ that contains the discrete time t;
- $\forall h \in \mathcal{H},\ L_h$: number of lines that can be opened during interval time h across the security screening system;
- θ: throughput per opened line (=120 passengers/hour);
- $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T}^s,\ d_{s,t}$: number of passengers arrived at security checkpoint s at t;
- $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T}^s,\ D^{\text{c}}_{s,t}$: cumulative number of passengers arrived at security checkpoint s between 0h and t;
- $\forall s \in \mathcal{S}, \forall t \in \mathcal{T}^s\ t < t_{\text{start}},\ Y_{s,t}$: cumulative number of passengers served at s between 0h and t (used to compute passenger waiting time before t_{start}).

Decision Variables:

First, main decision variables linked to the line opening are presented. Then, auxiliary variables used to compute cumulative services and waiting times are introduced.

Main Variables:

- $\forall s \in \mathcal{S},\ \forall h \in \mathcal{H},\ l_{s,h}$: number of lines opened during interval time h on s.

Auxiliary Variables:

- $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T},\ y_{s,t}$: cumulative service on s between 0h and t;
- $\forall s \in \mathcal{S},\ \forall (t \leq t') \in \mathcal{T}^{s^2},\ u^s_{t,t'}$= 1 if $D^{\text{c}}_{s,t} \leq y_{s,t'}$ (i.e. if the cumulative service at t' is higher than the cumulative demand at t), 0 otherwise;
- $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T}^s,\ w_{s,t}$: waiting time experienced by passengers arrived at t on s;
- W: maximum passenger waiting time.

Constraints:

- Maximum number of available teams for each hour: $\forall h \in \mathcal{H},\ \sum\limits_{s \in \mathcal{S}} l_{s,h} \leq L_h$;
- Definition constraint for cumulative service: $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T},\ y_{s,t} \leq y_{s,t-\delta t} + \theta \times l_{s,h_t}$;
- Cumulative service lower than cumulative demand: $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T},\ y_{s,t} \leq D^{\text{c}}_{s,t}$;
- Growth characteristic of cumulative service: $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T} \backslash \{t_{\text{start}}\},\ y_{s,t} \geq y_{s,t-\delta t}$;
- Growth characteristic of variables u^s_t: $\forall s \in \mathcal{S},\ \forall (t \leq t' \leq t'') \in \mathcal{T}^{s^3}\ u^s_{t,t'} \leq u^s_{t,t''}$;
- Upper bound constraints on variables u^s_t for $t < t_{\text{start}}$: $\forall s \in \mathcal{S},\ \forall (t \leq t') \in \mathcal{T}^{s^2}/t' < t_{\text{start}},\ u^s_{t,t'} \leq 1 - \frac{1}{M}(D^{\text{c}}_{s,t} - Y_{s,t'})$ with $M = D^{\text{c}}_{s,t} + 1$;
- Upper bound constraints on variables u^s_t for $t \geq t_{\text{start}}$: $\forall s \in \mathcal{S},\ \forall (t \leq t') \in \mathcal{T}^2,\ u^s_{t,t'} \leq 1 - \frac{1}{M}(D^{\text{c}}_{s,t} - y_{s,t'})$ with $M = D^{\text{c}}_{s,t} + 1$;
- Definition constraint for waiting times: $\forall s \in \mathcal{S},\ \forall \in \mathcal{T}^s, w_{s,t} = \delta t \times \sum\limits_{t' \geq t} (1 - u^s_{t,t'})$;
- Definition constraint for maximum waiting times: $\forall s \in \mathcal{S},\ \forall t \in \mathcal{T}^s,\ W \geq w_{s,t}$.

Objective function:

Minimization of the maximum waiting time:

$$min \quad W$$

B. ILP1: security screening system reallocation to minimize the average waiting time under maximum waiting time constraint

Data and decision variables remain similar than ILP0.

Constraints:

All the constraints of the ILP0 are retained and a constraint on the maximum waiting time is added:

$W \leq W_{\text{MAX}}$.

CDG operators qualify an allocation as 'unacceptable' in terms of LOS when a passenger is queuing more than 30 minutes. Thus, W_{MAX} is set to 30 minutes in the following.

Objective function: Minimization of the average waiting time:

$$min\ \frac{1}{\alpha} \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} D_{s,t} \times w_{s,t}$$

with $\alpha = max(1, \sum\limits_{s \in \mathcal{S}} \sum\limits_{t \in \mathcal{T}} D_{s,t})$

C. ILP2 : security screening reallocation to minimize the number of stranded passengers under maximum waiting time constraint

For this model, all the data, decision variables and constraints of ILP0 are retained but other ones are also introduced below to evaluate the number of stranded passengers.

Data

- $\mathcal{F}$: set of flights;
- $\forall f \in \mathcal{F},\ s_f$: security checkpoint associated to the boarding room of flight f;
- $\forall f \in \mathcal{F}, \mathcal{T}_f$: subset of $\mathcal{T}$ covering each $t \in \mathcal{T}^s_f$ when at least one passenger of f arrives at the security checkpoint;
- ΔT : transfer time from one security checkpoint to the associated boarding area;
- $\forall f \in \mathcal{F},\ t^c_f$: boarding closure time of flight f.

Auxiliary Variables:
$\forall f \in \mathcal{F},\ \forall t \in \mathcal{T}_f,\ z_{f,t} = 1$ if passengers of flight f arrived at security checkpoint at t miss their flights, 0 otherwise.

Constraints:

- Lower bound constraints on variables $z_{f,t}$:
  $\forall f \in \mathcal{F},\ \forall t \in \mathcal{T}_f,\ z_{f,t} \geq \frac{1}{t_{\text{MAX}}}(t + w_{s_f,t} + \Delta T - t_f^c)$,
  where t_{MAX} represent the ending time of the day;
- Maximum waiting time:
  $W \leq W_{\text{MAX}}$.

Objective function: Minimization of the total number of stranded passengers:

$$min \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}_f} z_{ft}$$

V. Resolution Approaches

Two resolution approaches are considered. A direct resolution of the three ILP models described in Section IV is proposed using the commercial solver Gurobi. Then, a greedy heuristic method that is assumed to imitate what airport operators could decide during crisis management is implemented.

The main steps of this heuristic are presented below:
For each hour:

1) For each security checkpoint, count the number of expected passengers plus the ones already in the queuing system;
2) Compute the share of passengers per security checkpoint;
3) Assign to each security checkpoint a decimal number of lines proportional to the demand;
4) For each security checkpoint, trunk the required number of lines;
5) If the total number of lines assigned for one hour across the security system is lower than the total number of available lines then:
   -Order security checkpoints from the highest to the lowest decimal part of the decimal number of lines (obtained in step 2). Then, open one line for each security checkpoint until reaching the exact number of available lines.

The exact resolution approach on the three ILP models and the heuristic resolution are tested on a study case considering different disruptive scenarios presented in Section VI.

VI. Study case

A study case around CDG has been designed to evaluate the different strategies of staff allocation across the different security checkpoints. First, general characteristics related to the historical day of operations retained and the data set related to passenger arrival times are presented. The methodology to estimate the initial allocation of security teams is then introduced. Finally, the modeling of access mode disruption on passenger arrival times is explained.

A. General characteristics

Two data sets supported the work reported in this paper. The first one gather flight schedule information on 21st June 2019 at CDG airport. General characteristics regarding CDG airport and this specific day are presented in Table I.

Moreover, another data set supported this work with information on passenger time stamps at the exit of security screening queuing lines during the same day of operations at CDG. This data is used as a proxy to estimate security system congestion in nominal situation. For more information on this data set, the reader can refer to [17].

We arbitrarily deviate this distribution ten minutes earlier to estimate passenger arrival times at the security system entrance (i.e. before queuing line). The passenger arrival time at the gate is computed by adding to its arrival time in the queuing system, its waiting time (computed once the team allocation is done) and an arbitrary buffer time of ten minutes to model the access time to the gate. If this final time is higher than the closure boarding time (set ten minutes earlier than the off block time reported in the flight schedule data set) then the passenger will be stranded.

Finally, a 2015 passenger survey at CDG conducted by the French Civil Aviation Authority has been used to assign passengers to ground access modes. According to this survey, the share of passengers arriving at CDG from train, road and subway are equal to 11%, 63% and 26% respectively.

B. Estimation of the number of available teams

The number of lines opened during the day of operations considered at CDG was not available. This number can be estimated by considering the predicted number of passengers per hour at each security checkpoint. Each opened line provides a service rate assumed equal to 120 passengers per hour. The number of lines is computed by opening the minimum number of lines providing a service rate higher than the number of passengers of the considered hour. Moreover, at least one line is opened on each security checkpoint for each hour. This principle is illustrated for one security checkpoint in Figure 3.

In the considered problem, the total number of lines that can be opened across the airport for each hour is computed by summing the number of lines required for each checkpoint according to the actual number of passengers observed on the historical day of operations. As an order of magnitude, this methodology leads to 34 available lines per hour on average.

C. Disruption Modeling

Simulation tools can be used to model the impact of a disruption on passenger arrival distribution. For instance Leng et al. in [18] and [19] use MATSim, an agent-based simulation tool [20], to evaluate the impact of a disruption

TABLE I. General characteristics study case considered.

Date	21/06/2019
Number of passengers	45818
Number of security checkpoints	12
Number of departure flights	567

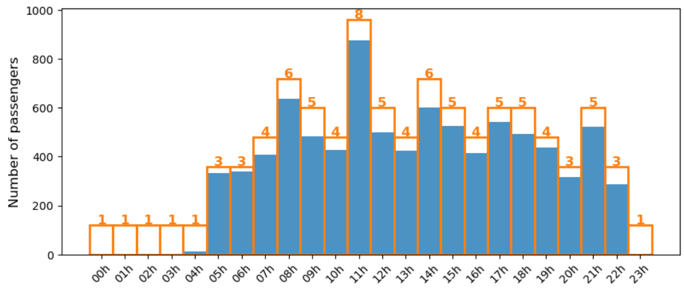


Figure 3. Illustration of the estimation of the number of lines required for one security checkpoint. The number of passengers per hour is displayed in blue. The service rate per hour is displayed in orange. The number of opened lines providing the required service rate is written above the orange bars.

on passenger travel times. In our case, since we had access to actual passenger timestamps at security checkpoints, we do not simulate passenger arrival flow. However, this data set does not provide information on passenger delay status (i.e. if one passenger experienced a delay due to ground transportation disruption). Thus, we simulate passenger delays during disruption the following way:

1) Randomly assign each passenger with a ground access mode depending on modal shares provided by the DGAC survey;
2) Select a ground access mode that will 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 security screening system. For instance, if a mode shutdowns at 10am, passengers who were supposed to arrive through this mode at the security system at 10am+Δ_A will be delayed. This parameter is arbitrarily fixed to 60 minutes;
5) Fix a maximum passenger delay D_MAX that will be 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 $T_S + \Delta_\mathrm{A}$ and $T_E + \Delta_\mathrm{A}$, delay them by a linear penalty, equals to D_MAX at $T_S+\Delta_\mathrm{A}$ and decreasing down to 0 at $T_E+\Delta_\mathrm{A}$. The decrease in the delay duration simulates the increasing knowledge of passengers facing the disruption during the day. Indeed, we assume that the probability that one passenger learns about the disruption is steadily increasing over time. Thus, they will improve their routing decisions to access the airport, leading to a reduction in their delays.

Three different disruptive scenarios with several level of severity are presented in Table II. S1 represents a disruption during the morning until the afternoon impacting passengers by a delay up to 30 minutes. S2 models a situation impacting fewer passengers than S1 (since the number of passengers using subway is three times lower than passengers using road to access the airport) but delaying them up to 45 minutes. The disruption duration is equal to the one in S1 but happen later during the day. Finally, scenario S3 is characterized by the shortest disruption (only 3-hour duration) but with the highest delay, up to 60 minutes for passengers relying on the subway to access the airport. In the following, S0 will refer to the nominal scenario.

TABLE II. DIFFERENT DISRUPTIVE SCENARIOS CONSIDERED.

Scenario Name	Mode disrupted	Starting time	Ending time	Initial delay
S1	ROAD	11AM	5PM	30min
S2	SUBWAY	3PM	9PM	45min
S3	SUBWAY	9AM	12PM	60min

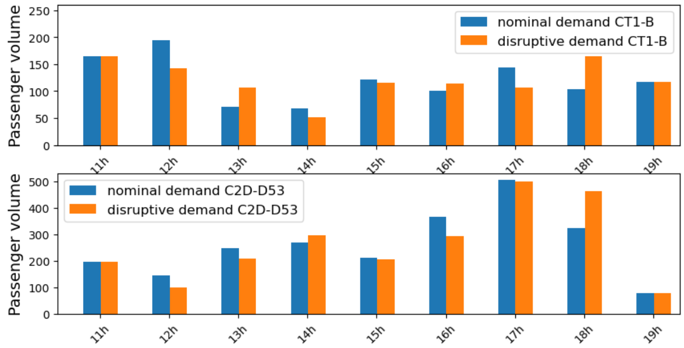


Figure 4. Illustration of the passenger arrival distribution on two security checkpoints in nominal situation (blue) and during S1 disruption (orange).

The impact of the disruption modeled through S1 on the passenger arrival time distribution on two security checkpoints is illustrated in Figure 4. The disruption does not have the same effect on each security checkpoints. For instance, at 1pm, an increase and a decrease in the number of passengers are observed on security checkpoints CT1-B and C2D-D53 respectively. In this case, a line should be open on the first security checkpoint while a line should be closed on the other one. Next section presents the computational results thanks to the different resolution approaches on this study case.

VII. Results

This section compares the different allocations obtained through the resolution approaches introduced in Section V and the relevance of reallocating lines during a disruption.

Table III summarizes the performances of the different resolution approaches and their respective allocations in the nominal scenario and the three disruptive scenarios. The performance of each allocation on each criteria considered are reported in this table. Best performances on each criteria obtained among the different resolution approaches for each scenario are highlighted in green. Worst performances than the ones obtained with the initial allocation are displayed in red.

First, one can see that the different disruptive scenarios do not have the same impact on the quality of the initial allocation. For instance, S2 is the one with the highest maximum waiting time, going from 30 to 110 minutes. Since this scenario impacts passengers that were supposed to arrive at the airport during the end of the afternoon, a higher number of passengers arriving in the evening is observed. However, the number of available lines during the evening is lower due to the small number of passengers predicted at the pre-tactical level. Thus, the system is operating over its nominal capacity, leading to large delays. S3 is the one with the highest average waiting time, potentially due to the highest congestion peak. For this scenario, the slope of the delay (presented through the disruption modeling in Section VI) is steeper than the ones of scenarios S1 and S2 (delay up to 60 minutes for only three hours of disruption). This leads to an important peak of arrivals that could explain a delay higher than the other scenarios. The initial allocation on the nominal scenario performs well with a maximal waiting time of 30 minutes and an average waiting time lower than 8 minutes. The heuristic algorithm provides an allocation with a maximal waiting time equals to 50 minutes but reduces by 0.3 minutes the average waiting time and saves 19 stranded passengers. Allocations through the resolution of the different ILP can already improve the initial allocation in the nominal scenario. The ILP0 allocation reduces by 33% the maximum waiting time, the one with ILP1 reduced by 20% the average waiting time and the one with ILP2 by 58% the number of stranded passengers. However, minimizing one criterion can induce significant increases in other criteria. In the nominal scenario, favoring the reduction in the number of stranded passengers can be done to the detriment of other passengers with an increase of 25% in the average waiting time. This leads to an average waiting time higher than the one obtained with the initial allocation.

Regarding the disruptive scenarios, the heuristic algorithm provides a better allocation than the initial one by improving all criteria. Solutions provided by the different ILPs resolution obtain better performances on almost each criteria than the heuristic allocation. An exception can be observed with S3 with ILP0 and ILP2 solutions generating an average waiting time almost one minute higher than the heuristic allocation.

Computation times of heuristic and exact methods remain lower than 0.25s and 1.5s respectively. The heuristic resolution is slightly faster than exact resolutions. Since the agent reallocation is considered only once every hour, all approaches are suitable from an operational point of view.

TABLE III. RESULTS OBTAINED THROUGH THE RESOLUTION APPROACHES ON THE DIFFERENT SCENARIOS. $\mathbf{W}$, $\overline{w}$, $\mathbf{p}$ AND $\overline{t}$ REFERS TO THE MAXIMAL WAITING TIME, AVERAGE WAITING TIME, NUMBER OF STRANDED PASSENGERS AND AVERAGE COMPUTATIONAL TIME RESPECTIVELY.

Scenario		Initial	Heuristic	ILP0	ILP1	ILP2
S0	$\mathbf{W}$	30min	50min	20min	30min	30min
	$\overline{w}$	7.83min	7.54min	7.29min	5.75min	9.74min
	$\mathbf{p}$	115	96	99	75	48
	$\overline{t}$	0s	0.221s	0.374s	1.469s	0.626s
S1	$\mathbf{W}$	60min	50min	20min	30min	30min
	$\overline{w}$	8.60min	7.93min	7.60min	6.40min	8.00min
	$\mathbf{p}$	434	341	335	278	221
	$\overline{t}$	0s	0.116s	0.313s	1.097s	0.622s
S2	$\mathbf{W}$	110min	50min	30min	30min	30min
	$\overline{w}$	8.29min	7.95min	7.53min	6.84min	8.08min
	$\mathbf{p}$	646	326	275	253	233
	$\overline{t}$	0s	0.119s	0.285s	0.497s	0.556s
S3	$\mathbf{W}$	60min	50min	30min	30min	30min
	$\overline{w}$	10.07min	9.14min	10.08min	7.50min	10.08min
	$\mathbf{p}$	603	527	538	493	454
	$\overline{t}$	0s	0.123s	0.376s	1.347s	0.642s

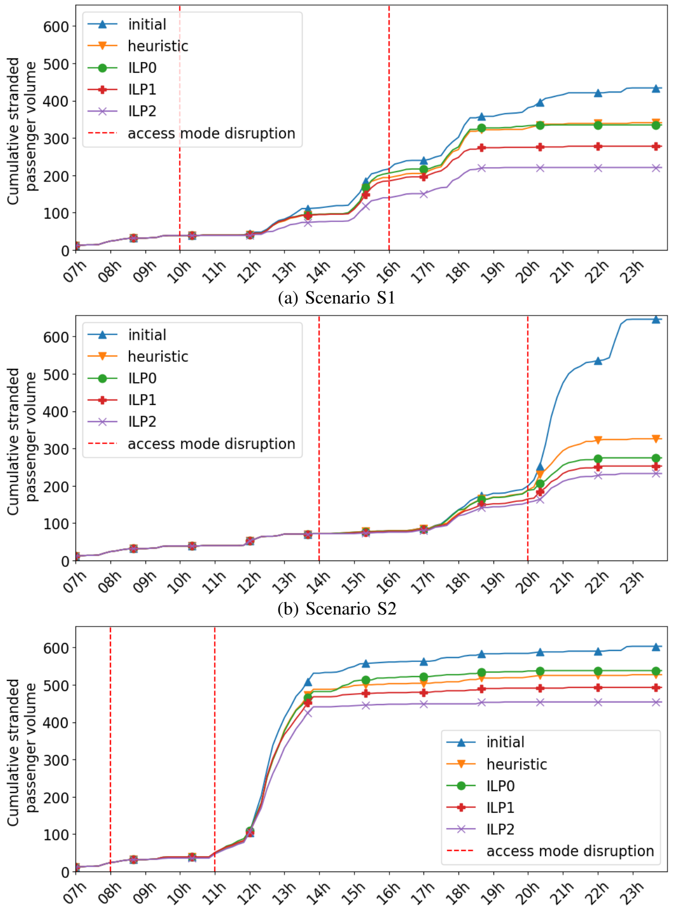
Regarding the three exact resolution approaches, ILP1 and ILP2 allocations reduce both the average waiting time and the number of stranded passengers compared to the ILP0 one. In S1, the ILP0 allocation generates a maximum waiting time lower than ILP1 and ILP2. However, in S2 and S3, the three allocations provide the same value for the maximum waiting time (equals to 30 minutes). One reason might be that the maximum waiting time is computed on a 10-minute step and thus decreasing this criterion is more challenging than decreasing the two other ones. Moreover, the 30-minute maximum waiting time imposed in ILP1 and ILP2 models help their respective allocations to perform well on this criterion.

Finally, ILP1 and ILP2 resolution provide solutions that are more or less efficient depending on the criterion selected. Thus, based on the preferences of airport operators, one solution can be better than the other one and vice versa.

Figure 5 displays the cumulative number of stranded passengers across the airport for each scenario and each allocation. According to this figure, a disruption can threaten passenger journey especially several hours after the beginning of the disruption. This is due to propagation effects of queuing lines (like traffic jam that remains even after the end of the handling of a car accident). The reallocation of agents helps in limiting the impact of the disruption on passengers arriving after the disruption, especially in S1 and S2. Indeed, a steady increase in the number of stranded passengers in S1 is observed until the end of the day with the initial allocation. On S2, the number of stranded passengers soars with the initial allocation just after the end of the disruption. Since fewer passengers were expected during the evening, the initial numbers of opened lines on several checkpoints are not sufficient to absorb the peak of arrivals due to the disruption. A further analysis on this scenario shows that, initially, passengers on the two busiest security checkpoints wait 110min and 80min respectively between 8pm and 9pm. These large waiting times led to a high increase in the number of stranded passengers; highlighting that the initial allocation is not robust to unexpected peaks of congestion.

This can be due to lack of staff at the end of the day as explained before. New allocations succeed in stopping this increase after the disruption. In S3, a high peak of stranded passengers is also observed after the disruption but not mitigated by the new allocations. Since this scenario simulate passengers suffering from a delay up to 60 minutes, several passengers are likely to miss their flight even if their queuing times is low. However, similarly to S1, reallocating agents helps in reducing number of stranded passengers having their flight way after the end of the disruption.

Other indicators are also relevant to evaluate the LOS of each allocation such as the average queue length and the share of passengers waiting less than ten minutes. Figure 6 displays the performance of both indicators for each allocation



(a) Scenario S1

(b) Scenario S2

(c) Scenario S3

Figure 5. Cumulative number of stranded passengers depending on the five allocations tested across the airport. The top, middle and bottom figures are associated to scenarios S1, S2 and S3 respectively. Each allocation has been represented with the same color across the three scenarios.

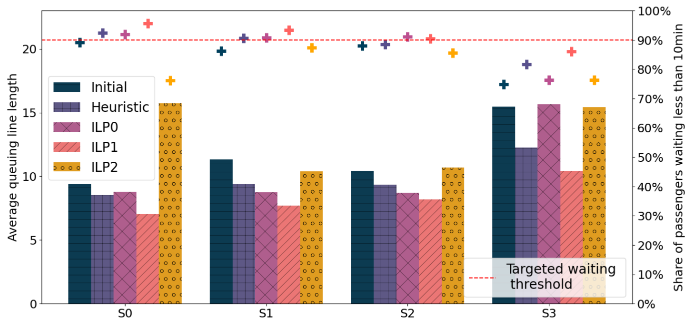


Figure 6. Bar plot of the average number of passengers in queuing systems for each couple (scenario, allocation) (left axis). A cross is displayed for each couple to show the passenger share waiting less than ten minutes (right axis).

on each scenario. As a reminder, CDG operators target 90% of passengers waiting less than ten minutes in security systems.

The average number of passengers in each queuing system seems correlated with the share of passengers waiting more than ten minutes. Thus, in general, the longer the average waiting line length is, the longer passengers will wait. However on scenario S2, the ILP1 allocation provides a lower average queue length than ILP0 but a higher share of passengers waiting more than ten minutes. The same assessment can be made for the correlation between the average queue length and the average queuing time. Again, it is not always the case since ILP0 allocation offers a lower waiting time on S0 than the heuristic allocation but a longer queuing line length. Finally, a lower average queue length is not synonym of a lower maximum waiting time, as observed for the nominal allocation on S2 and S3. Thus, this indicator is not always suitable to measure the airport LOS regarding passenger on-time performances especially on a fairness aspect.

Regarding the share of passengers waiting less than ten minutes, the initial allocation is really close to the 90% target on the nominal scenario but slightly lower for the disruptive scenarios. The ILP0 and ILP1 allocations reach the target for the scenario S0, S1 and S2. All the allocations fail in reaching this target on S3 but ILP1 allocation is the closest one with a 11% increase compared to the initial allocation.

VIII. Conclusion and Future Works

The Level of Service of airport security screening process can be drastically reduced during airport access mode disruptions. Waiting times higher than one hour have been observed for each disruptive scenario considered before security teams reallocation. Thus, waiting time can be a non negligible component of the passenger door-to-door travel time. It is essential to consider it and try to reduce it in order to reach the 4-hour door-to-door goal targeted for 2050. In this work, we highlight that efficient communication links between ground and air transportation stakeholders would be a key lever to reduce airport processing time during such disruptions. Indeed, information sharing about passenger locations would help to update load curves prediction at security checkpoints and improve the handling of airport security teams.

We propose several ILP approaches to optimize the handling of security screening resources at a tactical level. Three ILP models have been designed based on different criteria to optimize (minimizing the maximal waiting time, the average waiting time and the number of stranded passengers). The new allocations obtained for the different disruptive scenarios are generated in less than 2s through the resolution of the different ILP models with a commercial solver. For two out of three scenarios, the reallocations even succeed in recovering the initial performances obtained in the nominal scenario. Airport operators could prefer one allocation among the three proposed ones (ILP0, ILP1, ILP2) depending on the criteria identified as the most critical one. A new ILP formulation balancing between the different KPIs could also be easily designed (for instance by imposing minimum performance levels on others criteria, such as in ILP1 and ILP2 models regarding the maximum waiting time criteria).

Future research directions should be investigated. The reallocation models could be tested on other disruptive scenarios and compared in terms of robustness to the severity of disruptions. Other queuing systems could be modeled than the FIFO, such as by adding a priority queue for passengers delayed due to the disruption. The impact of a reduction or an increase in the total number of available teams on the computational time resolution and on the solution quality provided by each resolution approach could be analysed. Also, the model could be improved by considering not only overload delays but also stochastic ones. Indeed, even if the reallocation problem is considered at a tactical level, uncertainties remain in reality, especially since the time step considered is small (5min). Finally, an integration of the OSSRAP with the flight rescheduling problem presented in [21] could be designed to improve operations that are intrinsically connected.

Acknowledgment

The authors would like to thank Paris-Charles De Gaulle airport for providing the data and for their willingness to share their knowledge and expertise. This project has received funding from the SESAR Joint Undertaking under grant agreement No 893209 under European Union's Horizon 2020 research and innovation program.

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