Recovery Policies to Mitigate Airline Disruptions: Case Study of a European Airline

Lucas Montenegro[1*]; Vasco Reis[1]; Rui C. Oliveira[1]; António J. M. Castro[2]

[1]Department of Civil Engineering, Instituto Superior Tecnico, Universidade de Lisboa

[2]LIACC, Universidade do Porto

[*]Corresponding author: lucas.montenegro@tecnico.ulisboa.pt ; Tel: +351 937 978 615

Abstract

With billions travelling by air, airlines can be a considerable source of delays. This study is aimed at analysing the causes of delays, as well as the different recovery solutions for the three most important dimensions within an airline: aircraft, crew and passengers. A software previously developed for automating the recovery process of irregular operations (Disruption Management) is used to interpret analytical data from a case study of a medium-sized European national airline. A set of indicators are established to compare the different recovery solutions. The most efficient integrated recovery actions are suggested by comparing the costs that have an impact in these solutions, with the introduction of *passenger goodwill* or quality costs.

By comparing the different costs and factors that have an impact on the integrated recovery actions, this study expects to identify solutions that can minimize the costs associated with delays while maintaining customer satisfaction. The latter may be reached by introducing an indirect cost factor - *passenger goodwill* – whilst maintaining or reducing the weight of other direct costs in the utility function. The novelty of this study is the application of an integrated approach to evaluate and compare solutions for airline disruptions. Thus, the three most important dimensions are considered, also including the *passenger goodwill*, which are quality operational costs that represent the effect of punctuality on customer satisfaction. The analyses resulted in coefficients that give greater importance to the crew dimension. However, some of the results may not entirely represent the reality of an airline.

Keywords: *Airline Disruption Management, Integrated approach, passenger goodwill, MASDIMA, Excel Solver*

1. Introduction

Over 4 billion people currently travel by air throughout the globe, with IATA [1] forecasting an increase to over 7 billion passengers transported annually by 2034 - more than twice the number of passengers currently flying [2]. Air travel is considered the fastest and most reliable mode of transport available, having become increasingly cheaper and more accessible to the wider public. However, the efficiency of its operations relies on various external factors and, with more passengers and planes in the air, it is more bound to be affected by unexpected events, described as irregular operations. Amadeus points out that only 77% of all flights operated in Europe, North America and Asia arrived on time in 2012 [3]. Thus, these delays widely affect airports, passengers, aircraft and crew, representing major costs for all stakeholders involved.

Irregular operations (IROP) or airline disruptions are considered any situation that alters the original schedule, leading to flight delays and/or cancellations. The impact of such disruptions and their consequent delays is tremendous. Accordingly, a study carried out by the Air Transport Association concludes that delays cost both customers and airlines roughly U$65 billion in 2000 [4]. This figure may vary according to the scale of the airline's network, size and region where it operates, though consensus states that it may have an impact of approximately 8% on the airline's annual revenue [2]. Some authors estimate that better recovery solutions during irregular operations may help reduce costs in at least 20%, vital to both large and small airlines [5].

In order to prevent losses in profit, passenger satisfaction and the impact on operations, carriers should have a system that can pro-actively prevent disruptions, rapidly identifying the irregular event and its source, creating a suitable recovery plan. Unsolved disruptive operations can cause a cascading effect on other flights, having a great impact on the airline's network, leading to further delays and cancellations. Most air carriers try to anticipate stochastic events by creating some flexibility in their schedules, such as introducing time buffers, which can be used in recovering from unexpected events and consequent delays [6]. One example of time buffers imposed by airlines is the greater turnaround time between flights, as an increase in ground time of an aircraft between subsequent flights might cut the delay of the previous flight, avoiding delay propagation. However, several airlines are tempted to build a time schedule with very little slack in order to make greater use of all their resources, maximizing profits, thus, with little time being left in case of unexpected events.

Disruptive flights can originate from various sources, typically as a result of a local event that may spread throughout the airline's operations. Thus, managing the impact of those on an air carrier's network may come as a major challenge. Various authors have explored the different ways which such delays and cancellations can be managed and mitigated, developing different algorithms to solve the issue on the perspective of the three most common dimensions englobing air transportation, with the recovery actions taken mainly depending on the dimension (crew, passenger, aircraft, ground handling, among others) to be considered.

With this in mind, this paper is aimed at studying the causes of airline delays, as well as the different recovery solutions for the three most important dimensions within an airline: aircraft, crew and passengers. A software previously developed for automating the recovery process of irregular operations (MASDIMA [7]) is used to interpret the analytical data of a medium-sized European airline. This traditional airline operates over 3,000 weekly flights to over 80 destinations worldwide.

Using this airline as a case study, a set of flight data comprising a period of 60 days will be used to compare the recovery actions taken by the human Operations Control Centre (OCC) controllers with the recovery solutions proposed by the software. For this purpose, a set of weighting coefficients will be estimated using Excel Solver so that the solutions proposed by the automated system can be similar to the actions taken by the human operators.

Therefore, a set of metrics are established to evaluate the quality of these recovery solutions, i.e., the ones that generate most efficient integrated recovery actions. This analysis will be carried out by comparing the costs that have an impact in these solutions, as well as quantifying the utility parameter of each solution and partial-solution. By comparing the different costs and factors that have an impact on the integrated recovery actions, it is expected to identify solutions that can minimize the costs associated with delays. An additional factor will be used to analyze this impact: soft costs, i.e., the effect of punctuality on customer satisfaction.

The novelty of this study is the application of an integrated approach to evaluate and compare alternative solutions for airline disruptions, including the passenger's perspective on airline disruption. Furthermore, the software to be used comprises a multi-agent system through an automated negotiation process to reach the best solution according to the airline's interest.

This paper is divided as follows. In **Section 2** an overview of Airline Disruptions is, as well as a brief discussion of the typical costs involved in Disruption Management and the main recovery actions taken. Finally, a brief literature review is carried out on the main recovery methods developed throughout the literature to tackle airline disruptions. In **Section 3**, the Case Study is presented, with details of the Research Methods used. **Section 4** includes Results and Discussions. Finally, **Section 5** draws the final Conclusions and opportunities for Future Works.

2. Airline Disruptions: an overview

The impact on airline operations may originate from various sources, namely weather conditions, strike actions, third-party issues (problems in air traffic control, for instance), local transport networks, crew logistics, natural disasters, civil unrests, local anomalies (regional problems), mechanical and technical problems, operational issues (such as issues with ground handling and maintenance) and health (passengers being taken ill causing delays).

According to the American Aviation Authority (FAA) [8], weather accounted for over 69% of all significant delays (over 30 minutes) in the US in 2016, being the greatest cause of airline irregular operations (IROPs) worldwide and commonly unpredictable [3]. Irregular operations are defined as disrupted airline operations, with perturbations that may lead to disruptions in the network [9]. When analysing the year-round operations of a medium-sized European airline in 2009, Castro (2013) [7] concluded that ATC problems accounted for 18% of the airline delay, i.e., irregular operations, followed by 17% from handling operations (late passenger boarding, cargo loading, etc) and 16% from aircraft rotations. The same author pointed out that delays originated from meteorological problems were more significant in the winter and autumn months. This can be explained by the greater amount of weather instability during this period of the year, namely with frosty or foggy conditions in the early hours of the day, as well as strong gusty winds, restricting take-off and landing operations at airports around the globe.

When considering an adequate course of action to solve a disruptive airline operation, carriers need to coordinate the various resources involved, with aircraft, crew and passengers being the three most important resources to be considered in an airline's operation, besides other resources, such as handling, baggage, catering, etc. The process of solving these problems is defined by Kohl *et al.* (2004) [6] as *Disruption Management*: the process of monitoring and scheduling resources close to the day of operations. Even though aircraft, crew and passengers are the most important aspects to be dealt with in the case of a disruption, other resources, such as ground staff, catering and gate operations, should also be considered, though more flexibly than the others, as they are less costly. The Disruption Management problem is considered a three-stage process, consisting of monitoring, event detection and resolution of problems [10], with disruptions being dealt at both an airline and an airport level [11].

Airline Operations Control Centres (OCCs) are responsible for managing operational disruptions, overseeing daily operations, as well as co-ordinating recovery actions among the different units within an airline (crewing, ticketing, maintenance, etc.) by optimally allocating limited operational resources, while minimising extra costs due to disruptions with the desired trade-off between the goal of operational recovery and commercial interests [12]. This process starts by recognising and identifying the problem, subsequently considering the different alternative solutions. Thus, all airlines rely on their OCCs to manage their resources, proactively taking measures that can minimise the impact on operations or prevent additional costs to the company, constantly monitoring flights to minimise the impact of occasional delays. As reported by Clarke (1995) [13], airline operations are usually handled in tactical and strategic phases, with strategic operations dealing with schedule planning and resource allocation to the various areas of the operation. Furthermore, it is important to note that control centres typically manage and schedule the main resources separately, only joining them on the day of the operation. Before dealing with the disruption itself, carriers carry out an intensive planning process to define the timetable for all the resources involved in their operations.

OCCs are organised differently from airline to airline, varying in dimension and structure, depending on the airline's network and size, as well as on the geographic distribution of its operation. Nevertheless, seven roles are common to all OCCs, with the structure and shape being subject to the carrier's own tradition and culture: operation time-window, supervisor, flight dispatchers, aircraft manager, crew manager, maintenance services and passenger services [5]. Each role represents the different resources involved in the airline's daily operation, with each operational group creating solutions that will benefit the resource which they manage. Despite this independent resource management, all areas involving the operations of an airline are synchronised to ensure an efficient interaction between resources. Operations dispatchers (ODs), for instance, play an important role in the OCC, being assigned to handle disruptions by making the necessary changes to the schedule in order to minimise the adverse effects of these events [14].

According to IATA [15], regardless of their setup, OCCs must be autonomous in their operational decision, with the authority to implement operational decisions under a collaborative process, as well as among all the departments and roles involved. This level of autonomy is extremely important to ensure that the decisions taken can fulfil the needs of the various sectors within the airline.

Several authors argue that the final operational decisions rely on OCC supervisors or controllers, the only operational group within the OCC with the authority to approve or reject actions that may resolve operational irregularities [13], [16], [17]. These supervisors tend to base their decisions on personal judgements and past-experiences, the so-called rule-of-thumb, with each airline Operations Control Centre adopting a different set of solutions and rules that best cater their needs.

Airlines follow several different cost structures, with different variables and factors considered. Nonetheless, despite the differences in cost structures, several costs are involved in the operations of an airline: the operational costs. According to Camilleri (2018) [18], operational costs are the costs related to the operations of an airline when flights actually occur, spanning between direct and indirect operational costs.

Aircraft-related costs differ between aircraft-type, with factors such as aircraft size, age and efficiency being considered. These costs include fuel costs, take-off, landing and parking charges, maintenance costs, navigation fees and handling fees, etc [18]. When considering crew costs (CC), they should consider a set of labour legislations, according to the limits established for duty-hours, days off, etc., which vary between countries. Finally, passenger costs (PC) can be calculated by the sum of meal, hotel and compensation costs. Compensation costs are the costs airlines are obliged to pay to delayed passengers, with each country and/or region establishing different amounts to be paid, as for instance, EU flight compensation regulation 261/2004.

Passengers have different perspectives of what impact delays have on their journeys, which may compromise their willingness to do to future business with the airline. Amadeus [19] defines this customer perspective on delays as *soft costs.* Soft costs, quality costs or even *passenger goodwill,* represent the effect of punctuality on customer satisfaction. Estimating these costs is a complex task, as it involves several factors, varying according to the passenger's profile and purpose of travel [20]. These authors developed a system that is capable of estimating these quality costs in the recovery problem, taking into account the importance that delays have on passengers, creating an agent that considers passenger profiles. According to Amadeus [19], the customer point of view is not often considered in IROPs, though they may represent a significant part of the overall costs in such events.

A study suggested a formula to calculate these quality costs, which considers how much each passenger values a minute of delay, considering the different passenger profiles [7]. Thus, in the formulation proposed, *quality costs can be represented by the relation between the number of passenger profiles in a flight and the delay cost for each passenger with those profiles from their point of view*. Three different passenger profiles were considered: business (those travelling in business or first class), pleasure (travel in economy class) and illness (ill doctor on-board, accompanied by a doctor or nurse). Nevertheless, it is important to point out that this passenger segmentation might be revenue-driven, rather than the typical segmentation between *business passengers*, for those travelling for work/on business, and *leisure passengers,* those on holidays.

Disruptions vary in scale, requiring different courses of action. In the case of greater delays, more refined solutions may have to be created than time buffers in order to prevent delay propagation. As resources in an airline are greatly synchronised, even small delays may have a knockout effect on other flights and resources. Operators create a wide range of rapid solutions to recover the airline from its disrupted state, all of which can be feasible, though the most adequate action to be taken relies on the recovery policies taken by each airline.

According to Clausen *et al.* (2001) [21], the biggest airlines tend to solve the disruption management process in a sequential form, firstly dealing with aircraft, then crew, ground operations and finally passengers. Thus, each resource is analysed separately, with a general solution that covers all resources being later established. It is important to point out that passenger recovery englobes a wide range of services involving passengers, such as baggage handling, flight dispatching, among others. Therefore, it may be plausible to consider this dimension as a *resource*, given that it does not directly and only involve passengers, who are a source of revenue to airlines.

Bisaillon *et al.* (2011) [4] argue that this sequential treatment of recovery problems may not ensure the best recovery solutions, despite the simplifications in decision making. Furthermore, it may impose an implicit hierarchy and level of importance to the different dimensions of resources from an airline. This implicit hierarchy is to be avoided at times, as resources should be treated with equal level of importance, despite the different costs related to each resource. Thus, integrated recovery approaches are considered preferable. Figure 1 illustrates the decision mechanisms associated to this traditional sequential approach to disruption management.

Figure 1. Typical sequential approach to Disruption Management.

Source: Castro, A. J. M., 2013, p.170

The choice of a recovery plan to be considered is highly important to an airline, as disruptions represent an enormous source of financial losses. The average cost of delaying a full aircraft was estimated in a report by EUROCONTROL [22] as being of 100 euros per minute. Thus, in disruption management, one of the main objectives is to minimise costs. These costs can be broken-down as aircraft, crew and passenger costs.

A delayed aircraft can lead to great financial losses, as aircraft, especially narrow-bodies, tend to be scheduled to operate a great number of daily flights, with a single delayed flight culminating in several other disrupted flights. As narrow-body aircraft are usually deployed on short-haul flights, they tend to have a stronger impact on an airline's operations, as they are expected to perform several rotations a day. In turn, wide-bodies, which usually operate long-haul flights, have a greater margin to recover from delays between rotations.

The same happens to crew, who can easily miss their following operating flight in the case of a delay, or even be taken ill, preventing them from operating their assigned flight. As for passengers, a disrupted flight can also lead to a missed connecting flight or lost baggage, with airlines having the responsibility of rebooking them onto other flights, on a different airline at times, as well as providing minimum assistance. In addition, as previously discussed, quality costs should also be taken into account, as dissatisfied passengers are less likely to fly with the airline again.

Therefore, an integrated recovery solution should be a priority for carriers, as it can more easily respond to the three main resources involved: aircraft, crew and passengers. However, airlines tend to neglect solutions focused on passengers in disruption management, not considering opinions from customers, nor measuring the impact of delays on passenger satisfaction. Passengers tend to value transparent information regarding delays, with a passenger-tailored solution leading to greater loyalty to the airline, in line with the concept of soft costs previously introduced.

In a bolder recovery solution, some researchers highlight the increasing importance given to intermodal transportation as an alternative to disruption specially for short flights, integrating air, rail and road transportation [11]. This solution has gradually been adopted by some European airlines, as multimodality is a promising alternative to reach higher efficiency levels with lower costs. This argument can be corroborated with a study in which it was proved that it is possible to lower the impact on disrupted passengers by improving intermodal transportation [23]. In sum, a different array of solutions can be created to recover airlines and their flights from IROPs. The best alternative to be adopted will vary according to the airline's needs, considering the resource at its highest priority. This decision is usually based on rules-of-thumb, i.e., on previous knowledge and experience from the OCC operator, and on the airline's recovery policy.

Various authors have focused on developing and studying a wide range of methods for recovery from irregular airline operations, designing systems capable of recovering the various resources involved in the airline industry. Some authors stress the need of developing software agents that can carry out repetitive recovery tasks instead of the human controllers in the Operation Control Centre (OCC), reducing margin of errors and enhancing the recovery solutions [17]. When human operators deal with a large volume of data and variables simultaneously, they are bound to neglect some crucial information that would be relevant to reach the optimal solution. However, two studies claim that human controllers should mostly be involved in the main stages of disruption management, as automation provides limited decision-making support at such stages [6], [24]. Thus, human experts are capable of dealing with novelty events during disruptions as well as being responsible for the final decision. Nevertheless, Clausen *et al*. (2010) [25] argue that automated systems are able to generate more proactive solutions to mitigate and minimise delays, with operations research playing an important role in this dynamic disruption management environment. These authors also point out that most recovery models are solved similarly to the corresponding planning and scheduling problems carried out for aircraft and crew.

Three main recovery scopes are commonly identified in the literature: aircraft recovery, crew recovery and integrated recovery. The latter integrates the first two resources (aircraft and crew) with the passenger dimension, generating solutions that take into account the passenger's perspective and pondering between the best recovery alternative for each resource or all three resources combined. However, most studies have mostly focused on aircraft recovery, as aircraft is considered a limited resource and despite the legal duty requirements for crew, the crew resource can be repositioned more easily with standby and deadhead crewmembers [6]. Furthermore, there are less aircraft than crewmembers and the rules for aircraft scheduling are usually simpler. As for the crew recovery problems, most formulations are based under the theory that the flight schedule is recovered before the actual crew re-scheduling, based on a hierarchical recovery structure.

Some authors noted that a majority of the studies analysed employ Operational Research (OR) methods, relying mostly on integer programming solutions methods, with a considerable number of models applying metaheuristics to solve the recovery problems [17]. However, in one work it is argued that these OR techniques require precise mathematical models, though they may not be entirely efficient [14]. Thus, heuristic approaches can be considered more useful in these types of problems, producing near-optimal solutions in shorter periods of time.

Castro (2013) [7] developed a multi-agent system for the integrated approach of aircraft, passengers and crew, denominated MASDIMA. MASDIMA can be described as a new concept of Disruption Management, considering several restrictions to minimise delays and costs. The author used real flight data from September 2009 from a European airline to test the different behaviours taken by human operators, comparing with a Q-Negotiation approach developed and the Traditional Sequential Approach.

In order to act as a human-independent system, three different sub-organisations, representing the aircraft, crew and passenger dimensions, were created in MASDIMA. These sub-organisations of agents act as managers, in replacement of a human team, being capable of coordinating the different activities within the roles of each dimension and to cooperate with the other managers.

Every sub-problem solved by each manager generates a partial solution. The quality of each partial solution is then measure by a utility parameter. This utility is calculated for each sub-problem, from a value ranging between 0 and 1.0, with 1.0 being considered the optimal solution.

The utility function is a combination of delay and cost parameters for each dimension involved, as well as coefficients that characterise the relative importance of each dimension in the overall solution. Thus, the overall solution, i.e., the supervisor utility, considers all three dimensions simultaneously, with their respective levels of importance. This supervisor utility can be calculated according to Equation 1.

$$u_{sup} = 1 - \left\{\alpha_1 \left(\beta_1 \left(\frac{ad}{max(ad)}\right) + \beta_2 \left(\frac{ac}{max(ac)}\right)\right) + \alpha_2 \left(\beta_3 \left(\frac{cd}{max(cd)}\right) + \beta_4 \left(\frac{cc}{max(cc)}\right)\right) + \alpha_3 \left(\beta_5 \left(\frac{pd}{max(pd)}\right) + \beta_6 \left(\frac{pc}{max(pc)}\right)\right)\right\} \quad (1)$$

With $\sum_{i=1}^{3} \alpha_i$ and $\sum_{j=1}^{6} \beta_j$

Where α_1, α_2, α_3 represent the importance of each dimension – aircraft, crew and passengers, respectively – in the problem. β_j represent the importance of each attribute in the problem, with β_1, β_3 and β_3 representing the importance of the delay attribute in each sub-problem for the aircraft, crew and passenger dimensions, respectively. In turn, β_2, β_4 and β_6 expresses the importance of the cost component in each sub-problem for the aircraft, crew and passenger dimensions, respectively. Thus, it is important to highlight, that the supervisor agent represents the integrated goals of the OCC, with a global view of the problem, considering the three dimensions when choosing the best recovery action.

As for *ad, cd* and *pd,* they represent aircraft delay, crew delay and passenger delay components. In turn, *ac, cc* and *pc* represent the value of aircraft cost, crew cost and passenger cost components, respectively. Regarding the values of max(ad), max(ac), max(cd), max(cc), max(pd) and max(pc), which represent the maximum values of each attribute within the partial-solution of each dimension, they are previously defined so that the score function can generate values between [0,1].

In sum, the Multi-agent System (MAS) developed aims to reach a distributed and decentralised general approach for an integrated and dynamic disruption management, with multiple interacting intelligent agents solving disruption problems in parallel, with equal levels of importance.

3. Case Study

A medium-sized traditional European airline is used as a case study to compare the solutions proposed by MASDIMA with the recovery actions taken by human controllers in the OCC. The airline in study operates over 3,000 weekly flights to over 80 destinations worldwide, with a fleet of over 100 airplanes: more than 80 aircraft from the Airbus family (being 27 wide-body aircraft used in long-haul flights) and other 20 regional aircraft. The airline also employs over 7,000 people, being the national airline of the country where it operates.

A set of flight data, comprising a period of 60 days, will be used to compare the solutions proposed by MASDIMA with the ones adopted in reality, as well as to estimate the set of weighting coefficients from the utility function, so that the solutions proposed by MASDIMA would represent the actions taken by the human operators. In order to compare the quality of these solution and actions, a set of metrics (performance indicators) are established.

To estimate the coefficients from the supervisor utility function (Equation 1), the set of flight data will be analysed by the Method of Least Squares using Microsoft Excel Solver. With Excel Solver, it is possible to find an optimal value for a previously defined objective function. By selecting a group of adjustable cells, Solver will change the value of the changeable parameters in order to optimise the value of the objective function. Within the software, GRG (Generalised Reduced Gradient) solver is an efficient search tool to be used in non-linear optimisation problems, being characterised as a deterministic method, due to the use of non-random sampling [26]. In addition, this solver method needs a set of initial values in order to estimate the parameters.

Therefore, the data from the table including real flights (i.e., what happened in reality, as a result of the decisions either taken by the human operators in the OCC or by MASDIMA) will be used to compare the solutions proposed by MASDIMA (*solution_flights* table) and the flights identified as impacted (i.e., flights that were considered disrupted, either because of delay or any other disruptive event). In order to estimate the coefficients, the squared difference between the utility of real flights and the utility solution flights will be calculated for each event and considered as the squared error. Thus, the sum of these squared differences (to be minimised) will be used as the objective function in this study, with the coefficients from the supervisor utility function considered as adjustable parameters. For this purpose, Excel Solver will be used to minimise the sum of the squared differences (SSD), assuming non-negative parameters, as the coefficients must range between [0,1]. In addition, some constraints will be added to the analysis, to limit the value of some parameters, comparing the effect of these constraints in the results of the coefficients found. Furthermore, Central differences will be the options for derivatives used, as these generate greater accuracy in nonlinear problems, as pointed out by [27].

By using the least squares method, it is possible to find the set of parameters that best describes the experimental data by assuming a certain relation between the variables, as well as by minimising the sum of the squared errors. In the field of air transportation, the least squares technique was used to estimate the effect of delay propagation through an airline schedule [28]. More specifically, Microsoft Excel Solver was used to analyse experimental data by least square fitting in the fields of pharmacology, with one study [29] estimating the coefficients of an equation for describing simple enzyme kinetics and another for hydrologic modelling [26].

In order to compare the quality of the solutions proposed by MASDIMA and the actions taken by the human controllers in the OCC, a set of metrics or performance indicators were used. Four different scenarios will be compared: *impact flights* (flights that were originally identified as disrupted for any reason), *solution flights without goodwill* (recovery solutions proposed by MASDIMA without considering quality solutions, i.e. *passenger* goodwill), *solution flights with goodwill* (recovery solutions proposed by MASDIMA considering quality costs) and *real flights* (what happened in reality, with recovery actions either implemented by human controllers from the OCC or implemented based on the solutions proposed by MASDIMA). In most indicators, the *impact flights* table will serve as comparison basis to measure the level of recovery or improvement from the initial delays and costs predicted for each disruptive event.

Considering the different table structure of flight data provided by MASDIMA, a comparison between the *schedule_flights, impact_flights, solution_flights* and *real_flights* tables will be made. A direct comparison between *schedule_flights* and *real_flights* can provide information on the performance of the OCC with no interference from MASDIMA. In turn, a comparison between *solution_flights* and *real_flights* can determine the potential of MASDIMA when compared with the OCC. Finally, a comparison between *impact_flights* and *real_flights* can determine the potential, from either the OCC or MASDIMA, in recovering flights identified as disrupted. Thus, the scenarios considered for analysis will be as follows:

- *Scenario 1 - impact_flights s_gw vs. real_flights* (without considering quality costs, i.e. passenger goodwill);
- *Scenario 2 - impact_flights c_gw vs. real_flights* (considering quality costs);
- *Scenario 3 - solution_flights s_gw vs. real_flights*;
- *Scenario 4 - solution_flights c_gw vs. real_flights.*

The data provided by MASDIMA were provided in SQL format. For the data considered, the aircraft manager within MASDIMA can propose two possible recovery actions in *solution_flights*: KEEP (do-nothing, i.e., no recovery action to be taken to recover the disruption) or EXCHANGE (exchange the aircraft with a different one that is available). In turn, the crew manager can propose the following recovery actions: KEEP (do-nothing) or OTHER (which can represent any other recovery action). As for the passenger manager, the following actions can be proposed: KEEP (do-nothing) or REACCOMMODATE (re-accommodate to another flight). It is important to highlight that MASDIMA offers other more specific recovery actions, though the airline in study only chose to have these implemented. For the actual recovery actions (*real_flights* table), one additional recovery description was created: MISSED, in the passenger dimension, when the passengers missed their connection flight.

Subsequently, it was determined which actions were performed in reality and, more specifically, if it was an action employed by the OCC controller or an action suggested by MASDIMA. It was considered that the action employed was proposed by MASDIMA if, what happened in reality, was exactly the same as what was proposed by the software, although the OCC controller did not necessarily take the proposal from the software into consideration.

To calculate the utility scores of the supervisor, some initial values of coefficients were used. These initial values are a result of a series of experiments carried out with MASDIMA in the airline in study, considering feedback from the human OCC controllers.

For each scenario, a set of constraints were created, in order to vary the value of the coefficients to find the optimal solution. In addition, some criteria were established in order to determine which results could be considered the optimal solution, as well as to exclude other results that generated coefficients that did not represent reality, despite being mathematically feasible.

Table 1 shows the constraints employed for each scenario analysed, where *Alpha_sum* and *Beta_sum* represent the sum of the alpha and beta coefficients from the supervisor utility function (Equation 1).

Table 1: Constraints employed for each analysis scenario.

Constraint 1	Alpha_sum = 1 ; Beta_sum=1
Constraint 2	Alpha_sum =1 ; Beta_sum = 1; alpha_ac >=0.1; alpha_cw>=0.1; alpha_px>=0.1
Constraint 3	Alpha_sum =1 ; Beta_sum = 1; All alpha >=0.1; All beta >= 0.01
Constraint 4	Alpha_sum =1 ; Beta_sum = 1; alpha_ac >=0.1; alpha_cw>=0.1; alpha_px>=0.1; beta_ac_SUM >=0.1; beta_cw_SUM>=0.1;beta_px_SUM>=0.1
Constraint 5	Alpha_sum =1 ; Beta_sum = 1; beta_ac_SUM >=0.1; beta_cw_SUM>=0.1;beta_px_SUM>=0.1
Constraint 6	Alpha_sum = 1 ; Beta_sum=1

Alpha, beta = coefficients of the utility function (Equation 1).

Besides these constraints, a series of iterations were carried out for each constraint imposed, within each analysis scenario. It is important to add that some iterations were not performed for some of the constraints employed. Table 2 shows the iterations considered.

Table 2: Iterations considered for each constraint imposed and for every analysis scenario.

Original Value	Initial Values used.
Iteration 1	From the initial values, vary all coefficients.
Alpha	From the initial values, vary only Alpha coefficients, with Beta remaining fixed at the initial values.
Alpha 2	From the values generated in the Alpha iteration, vary all coefficients.
Beta	From the initial values, vary only Beta coefficients, with Alpha remaining fixed at the initial values.
1.00E-01	From the initial values, vary all coefficients with a reduced precision of 10^{-1}.
Alpha_cw_px	From the initial values, vary all coefficients, except alpha_cw and alpha_px.
Alpha_ac	From the values generated in the Alpha_cw_px iteration, vary all coefficients, with alpha_ac remaining fixed at the initial value.
Alpha_ac'	From the initial values, vary all coefficients, with alpha_ac remaining fixed at the initial value.

4. Results and Discussion

Data from 110 routes (78 short-haul and 32 long-haul routes) were considered. Of the 60 days analysed, 41.2% of the scheduled passenger flights were identified as disrupted for any reason, with over 40% representing a 15 minutes delay.

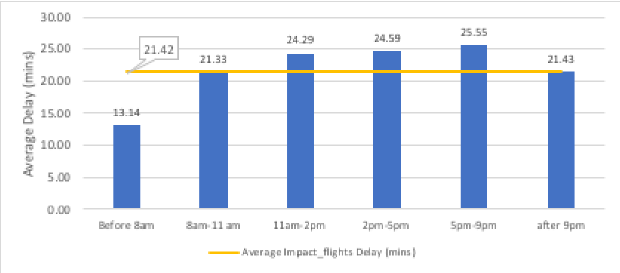

Figure 2: Average Delay of flights from impact_flights Table per Period of Day.

Figure 2 presents the average delay per period of day. By observing these results, it is noted that the greatest delays on average occurred during the afternoon and evening (2pm-5pm and 5pm-9pm), with these greater delays being airport-related (AIRP). On the other hand, the early morning period led to smallest delays, with delays of 13 mins on average. The maximum delay observed for the period in study was of approximately 25 hours (1,489 mins) on a long-haul flight due to aircraft or crew rotation problems (ROT). Furthermore, it can be noticed that, both in the approach considering quality costs (*solution_flights cgw*) and without considering quality costs (*solution_flights sgw*), MASDIMA generated recovery solutions with approximately the same delay as in the *real_flights* table, after intervention from either the OCC controller or MASDIMA. This can be further evidenced in Figure 3, which shows the Average Flight Departure Recovery Ratio for the real flights and both solutions from MASDIMA. It can be noticed that the recovery solutions which considered quality costs led to a higher recovery ratio, i.e., these recovery solutions represented greater recovery from the initial delay. In turn, the actual flights (*real_flights*) could provide lower recovery ratios, though the difference between the solutions from MASDIMA without considering quality costs was of only 0.03; thus, with very similar recovery ratios.

The fact that the actual flights, covering the recovery actions from the OCC and MASDIMA, generated slightly lower delays may be due to the fact that MASDIMA mostly considers block times, i.e., the time between departure from the gate at the departure airport and arrival at the gate at the arrival, instead of that flight times when calculating the possible solutions to the flights. This is because the airline in study not always provides the information of the actual flight plan to the software, with MASDIMA consequently using this block times, which are usually greater than the actual flight times from the flight plan.

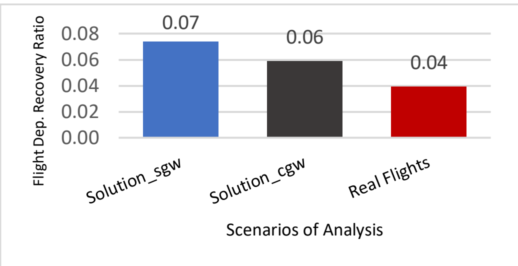

Figure 3: Average Flight Departure Recovery Ratio ($\overline{FD}_{rcv}$).

When considering the average cost recovery ratios, it could be observed that the solutions generated by MASDIMA, on average, led to better total costs, crew costs, passenger costs and quality costs recovery ratios, i.e., positive values, when compared to the figures from real flights in most of the periods of day. The difference in passenger cost recovery ratios between the solutions generated by MASDIMA in both scenarios (*c_gw* and *s_gw*) and the real flights is clearly noticeable, with MASDIMA generating recoveries of over 50%, while some real flights even generating greater passenger costs than initially detected, i.e., negative recovery ratios. However, the real flights resulted in slightly better aircraft cost recovery ratios than the solutions, as presented in Figure 5. This can be explained not only by the use of block times by MASDIMA, but also by the way it considers fuel consumption, a major cost-driver of aircraft costs. Due to the way in which this information is provided to MASDIMA by the airline, the fuel consumption calculated in the solutions is based on an average consumption per minute of block-time, not considering a real-time cost calculation with data from the flight plan, nor considering the different refuelling costs per airport. This estimation by MASDIMA also results in greater aircraft costs. On the other hand, it may be argued that OCC controllers can indeed generate better recovery solutions, based on previous experience and knowledge of the airline's culture and of which recovery actions are more appropriate in certain routes. Nonetheless, the recovery solutions from MASDIMA still lead to better total cost recovery ratios. It is worth noting that a comparison of Total Cost Recovery from the *solution_flights sgw* table was not included in Figure 4, as this table would necessarily give lower values of total costs, given that passenger goodwill costs are not included in this scenario. Thus, only a comparison between *real_flights* and *solutions_cgw* was made for this metric.

When observing the crew cost recovery ratios (Figure 6), it is evident that MASDIMA was mostly unable to generate recovery solutions that could reduce crew costs ($\overline{CC}_{rcv} = 0$), with negative recovery ratios, i.e., greater costs, seen in the real flights. This inability to generate recovery actions that can lower the costs of disrupted crew members in all scenarios considered can possibly be explained by the great complexity involving the recovery of disrupted crew members, due to labour legislations on the limits of duty hours and rest. Figure 4 and Figure 5 illustrate the total and average aircraft cost recovery ratios, respectively.

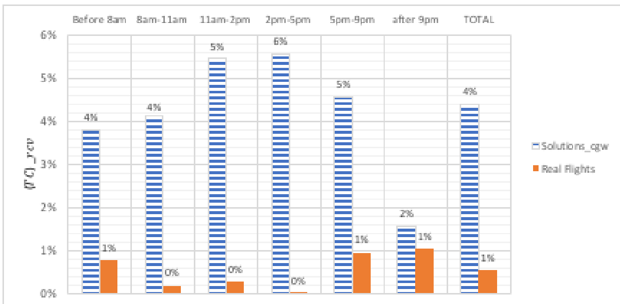

Figure 4: Average Total Cost Recovery Ratio ($\overline{TC}_{rcv}$) of solution_flights_cgw and real_flights.

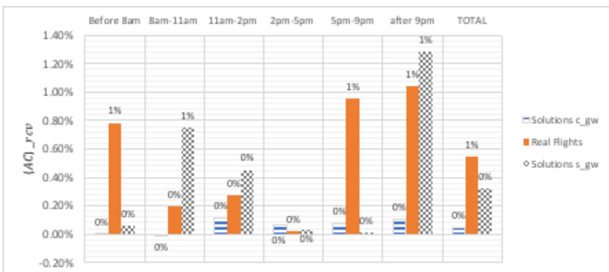

Figure 5: Average Aircraft Cost Recovery Ratio ($\overline{AC}_{rcv}$) of the three approaches.

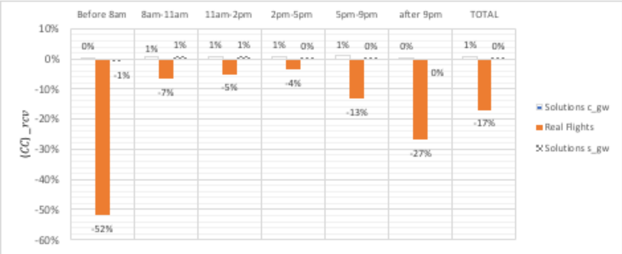

Figure 6: Average Crew Cost Recovery Ratio ($\overline{CC}_{rcv}$) of the three different approaches.

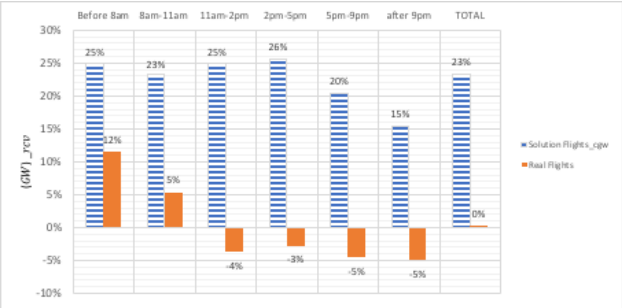

Figure 7: Average Quality Cost Recovery Ratio ($\overline{GW}_{rcv}$) of the solution_cgw and real_flights.

The effect of considering quality costs is clearly evidenced in Figure 7, with the software generating much better recovery ratios than those of real flights. This can corroborate the idea that OCC controllers and, more specifically, most airlines do not entirely consider the passenger's perception of delays in Disruption Management. Furthermore, it is observed that by introducing this factor, the software was still able to generate recovery solutions with similar crew costs than calculated in the approach without considering these quality costs. Thus, it can be argued that the introduction of the *passenger goodwill* parameter does not affect crew costs. However, a slight increase in aircraft costs is noticed in this approach, probably as some actions that might prevent passengers from missing their connections will result in an increase of flight costs.

It was concluded that the actions taken by the OCC, i.e., those different to what was proposed by MASDIMA, in at least one of the dimensions accounted for 5,190 (36%) and 4,736 (33%) of the flights in the *solution_flights sgw* and *solution_flights cgw* approaches, respectively. It is worth noting that more flights were recovered by the OCC in the scenario without considering quality costs, when compared to the scenario with quality costs, which is in line with the conclusions made from the other results.

Several iterations were carried out for each constraint imposed and for every scenario considered. From these coefficients, some iterations were considered optimal or close to optimal. However, despite some results exhibiting mathematically optimal results, with an SSD equal to zero, the weighting coefficients from these iterations would sometimes lead to unfeasible weighting coefficient solutions of the utility scores. One example is the results from Iteration 1, for Constraint 1 in Scenario 3, presented in Table 3. It can be seen that, despite generating beta coefficients that would give greater importance to aircraft delays and costs, i.e., a weighting coefficient solution that would generate greater local importance to the aircraft dimension, the *alpha_ac* calculated was zero. Thus, even though the aircraft dimension was given a greater local importance, in the overall and integrated vision of the problem, it had zero importance, with the crew dimension having the greatest value of alpha in this iteration.

Table 3: Results from Iteration 1, for Constraint 1 imposed in Scenario 3.

Name	Original Value	Iteration 1
beta_delay_ac	0.333	0.850
beta_delay_cw	0.133	0.000
beta_delay_px	0.201	0.000
beta_cost_ac	0.111	0.150
beta_cost_cw	0.111	0.000
beta_cost_px	0.111	0.000
alpha_ac	0.334	0.000
alpha_cw	0.333	0.640
alpha_px	0.333	0.360
SSD	1.67E-03	0.00E+00

Alpha, beta = coefficients of the utility function (Equation 1); SSD = sum of the squared differences.

Consequently, some results were not considered as optimal solutions, in spite of leading to complete minimum values of SSD.

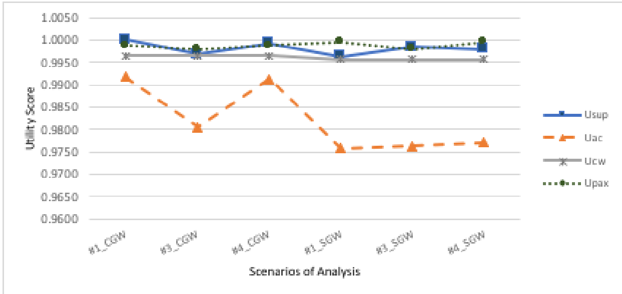

Figure 8: Average Utility Scores (real_flights) for the optimal solutions of Scenarios 1 and 2, where $\bar{U}_{sup}$, $\bar{U}_{ac}$, $\bar{U}_{cw}$ and $\bar{U}_{px}$ represent the supervisor, aircraft manager, crew manager and passenger manager utility scores, respectively.

Table 4: Results from the optimal weighting coefficient solutions from Scenarios 1 and 2.

	Constraint								
	#1_SGW	#3_SGW		#4_SGW	#1_CGW		#3_CGW	#4_CGW	
Coefficient	Beta	Iteration 1	Beta 2	Beta 2	Iteration 1	Beta 2	Beta	Beta 2	1.00E-01
beta_delay_ac	0.000	0.056	0.014	0.049	0.791	0.000	0.010	0.000	0.558
beta_delay_cw	0.075	0.010	0.129	0.025	0.000	0.000	0.010	0.000	0.000
beta_delay_px	0.000	0.018	0.010	0.000	0.000	0.000	0.010	0.000	0.000
beta_cost_ac	0.401	0.538	0.559	0.751	0.192	0.413	0.365	0.402	0.173
beta_cost_cw	0.213	0.010	0.278	0.075	0.000	0.587	0.568	0.498	0.154
beta_cost_px	0.312	0.368	0.010	0.100	0.018	0.000	0.037	0.100	0.115
alpha_ac	0.334	0.100	0.100	0.100	0.000	0.000	0.334	0.334	0.068
alpha_cw	0.333	0.800	0.100	0.439	1.000	0.000	0.333	0.333	0.710
alpha_px	0.333	0.100	0.800	0.461	0.000	1.000	0.333	0.333	0.222
SSD	8.94E-04	1.17E-04	1.23E-04	2.35E-04	0.00E+00	0.00E+00	1.21E-03	1.25E-03	9.23E-04

Table 5: Results from the optimal weighting coefficient solutions from Scenario 3.

	Constraint				
	#1_SGW	**#2_SGW**	**#4_SGW**	**#5_SGW**	**#6_SGW**
Coefficient	1.00E-01	Beta 2	Alpha 2	Beta 2	Alpha_ac'
beta_delay_ac	0.318	0.190	0.241	0.000	0.000
beta_delay_cw	0.000	0.023	0.009	0.047	0.000
beta_delay_px	0.000	0.000	0.003	0.010	0.746
beta_cost_ac	0.548	0.522	0.559	0.800	0.000
beta_cost_cw	0.038	0.263	0.091	0.053	0.000
beta_cost_px	0.096	0.002	0.097	0.090	0.254
alpha_ac	0.000	0.100	0.100	0.010	0.334
alpha_cw	0.527	0.100	0.364	0.487	0.666
alpha_px	0.473	0.800	0.536	0.503	0.000
SSD	3.74E-04	1.94E-04	0.000	1.11E-04	0.00E+00

Table 6: Results from the optimal weighting coefficient solutions from Scenario 4.

	Constraint								
	#1_CGW		**#2_CGW**		**#3_CGW**	**#4_CGW**		**#5_CGW**	**#6_CGW**
Coefficient	Alpha	Beta 2	Beta	1.00E-01	Alpha 2	Beta	Beta 2	Beta 2	Alpha_cw_px
beta_delay_ac	0.333	0.000	0.000	0.516	0.134	0.000	0.000	0.008	0.333
beta_delay_cw	0.133	0.000	0.000	0.000	0.010	0.000	0.000	0.000	0.133
beta_delay_px	0.201	0.000	0.000	0.000	0.010	0.000	0.000	0.000	0.201
beta_cost_ac	0.111	0.183	0.360	0.217	0.150	0.350	0.100	0.092	0.111
beta_cost_cw	0.111	0.817	0.589	0.156	0.010	0.550	0.800	0.800	0.111
beta_cost_px	0.111	0.000	0.051	0.111	0.685	0.100	0.100	0.100	0.111
alpha_ac	0.000	0.000	0.334	0.119	0.010	0.334	0.774	0.833	0.334
alpha_cw	1.000	0.000	0.333	0.781	0.980	0.333	0.100	0.000	0.666
alpha_px	0.000	1.000	0.333	0.100	0.010	0.333	0.126	0.167	0.000
SSD	2.84E-03	0.00E+00	1.13E-03	1.05E-03	1.77E-07	1.16E-03	3.06E-04	1.94E-04	1.63E-05

Based on the results from the iterations carried out with Excel Solver, it can be noticed that the supervisor utility score of the real flights was increased on average by 0.06% in Scenarios 2 and 4, by 0.12% in Scenario 3 and reduced by 0.03% in Scenario 1 with the new weighting coefficients calculated, from initial values of $\overline{U}_{sup}$= 0.9981 in the approaches without considering quality costs and $\overline{U}_{sup} = 0.9985$ when considering quality costs. The average utility scores of scenarios 1 and 2 are presented in Figure 8 where $\overline{U}_{sup}$, $\overline{U}_{ac}$, $\overline{U}_{cw}$ and $\overline{U}_{px}$ represent the supervisor, aircraft manager, crew manager and passenger manager utility scores, respectively. These metrics were calculated based on the solutions of the weighting coefficients presented in Tables 4-6 and, with the cells marked in grey representing the coefficients that remained fixed for in the constraint scenario.

Regarding the local utility scores, in the aircraft dimension, the initial utility score in the *real_flights* Table was of $\overline{U}_{ac\_sgw}$= 0.9946 in the scenarios with no passenger goodwill and $\overline{U}_{ac\_cgw}$= 0.991 in the scenarios considering passenger goodwill. With the new coefficients generated, the aircraft manager utility score decreased on average 1.40% and 0.12% in Scenarios 1 and 2, while remaining on average the same in Scenario 4 and decreasing by 1.10% in Scenario 3. In turn, in the crew dimension, the initial values of the real flights were of $\overline{U}_{cw\_sgw}$ = 0.9972 and $\overline{U}_{cw\_cgw}$ = 0.99 in the approaches without and with quality costs, respectively. In this dimension, the manager utility score increased in all Scenarios studies, rising by up to 0.80% on average in Scenario 1. Finally, in the passenger manager's perspective, which exhibited initial utility scores in the *real_flights* table of $\overline{U}_{px\_sgw}$ = 0.9974 and $\overline{U}_{pc\_cgw}$ = 0.9962, the coefficients produced mostly led to an upsurge of this utility score, rising by up to 0.18% in Scenarios 2 and 4, when considering passenger quality costs.

Although an improvement in the supervisor utility score may seem negligible, when considering the airline's revenue of approximately 3 billion euros in 2017, this increase in $\overline{U}_{sup}$ may result in annual savings of millions of euros. However, it cannot be concluded that these results, from recovery actions taken by the OCC controllers, would necessarily generate better recovery solutions than those suggested by MASDIMA, given the approximations aforementioned.

When considering the optimal weighting coefficient solutions, *alpha_ac* decreased on average by 35% in Scenarios 1 and 2, and by 63% in Scenarios 3 and 4. On the other hand, *alpha_cw* increased on average by 77% in Scenarios 1 and 2, and by 105% in Scenarios 3 and 4. In turn, *alpha_px* decreased on average by 42% in all Scenarios. This trend shows a clear preference to the crew dimension in the global and integrated solution, while clearly neglecting the passenger and crew dimensions. Nevertheless, these results may not entirely be in line with what is found in the literature, in which most authors argue that a greater preference is given to the aircraft dimension. Although these results may not entirely reflect the reality of the OCC, the mathematical explanation to the inclination in preference to the crew dimension, over the aircraft and passenger dimensions, can be explained by the high crew costs seen.

While most of the weighting coefficients do not represent the reality of the Operations Control Centre, some iterations could generate weighting coefficients that would corroborate the results found in the literature, in which greater preference is given to the aircraft dimension while almost neglecting the passenger dimension. This can be evidenced in Scenario 4, for constraints 4 and 5, which resulted in values of *alpha_ac* of 0.774 and 0.833, respectively, with values of *alpha_cw* and *alpha_px* between 0 and 0.167. For both constraints, greater importance was given for the local coefficients of costs (*beta_cost*), with the delay being considered locally irrelevant, leading to low or null values of *beta_delay* coefficients. This greater importance to costs rather than delays can be explained by the extremely high costs associated to aircraft, as well as by the fact that most of the disruptions analysed generated small delays. Although these solutions could more closely represent the reality of the OCC, they generated values of supervisor utility of 0.9982, with negligible variation from the initial scenarios and, thus, not improving the overall solution. This non-improvement of the overall solution is in line with the greater preference given by OCC controllers to one resource dimension, while giving less importance to the passenger and crew dimensions.

Regarding the values of *global fairness (GF)* from the optimal weighting coefficient solutions generated show that, despite improving the supervisor utility scores on average, the coefficients resulted in less fair solutions. In the scenarios without quality costs considered, the global fairness increased by 400% in Scenario 1 and by 1.4% in Scenario 3, while increasing by 152% and 43% in Scenarios 2 and 4, respectively. This growth in global fairness corroborates the conclusions made from the overall results of the alpha coefficients, in which a clear preference is given to one dimension within the airline. Finally, it is important to point out that, considering the reduced time period of flight data, some of the findings and conclusions drawn from the results of these comparisons may not represent the reality of the airline for its all-year-round flight operations.

5. Conclusions

In this paper, the problem and concept of Airline Irregular Operations (IROP) is discussed. Disruptions or IROPs can be a great cause of financial to losses to airlines, which have enormous costs associated to their operations.

When considering the extreme growth in air travel, as well as the impact that this industry has on society worldwide, carrying billions of people and cargo across the globe, this subject is of great interest.

Having carried out the experiments and comparing Having carried out the experiments in Excel Solver, comparing Scenarios with or without quality costs, it was found that the solutions led to a greater importance of the crew dimension, in terms of the global recovery solution employed by the Operations Control Centre (OCC). This finding was linked to the possible lack of synchronisation of certain information between the airline's OCC system and MASDIMA. As OCC operators have access to some information that MASDIMA's system does not have, they may be able to take options that can better minimise costs and delays, especially for the aircraft and crew dimensions. Another factor that can possibly explain this is the natural human aversion to having real-life problems solved by machines, despite these usually being more efficient than humans.

Despite finding mathematically feasible results, with certain weighting coefficients leading to total minimisation of the sum of the squared differences (SDD = 0), most results may not entirely represent the reality of the OCC, or even be feasible. According to general consensus in the industry and in the literature, OCC operators tend to give greater importance to the aircraft dimension. Nevertheless, weighting coefficients that could possibly represent the actions taken by the OCC controllers were found in two of the constraints imposed on Scenario 4, in which a greater overall importance is given to the aircraft dimension (greater values of *alpha_ac*), as well as greater local preference to the beta coefficients associated with costs. However, these weighting coefficients did not improve the overall supervisor utility, with the quality of the solution remaining the same, possibly due to the greater preference given to the aircraft dimension.

Regarding the *global fairness (GF)* of the solutions, it was found that the coefficients which resulted from the optimal solutions led to a greater unfairness or imbalance between the different dimensions. Thus, the results show a greater preference towards one dimension over the others, corroborating the findings aforementioned. Nevertheless, the solutions from MASDIMA still produced lower Total Costs than the solutions from the real flights, despite the airline not entirely implementing the system in their operations.

Considering that the analyses of Scenarios 1 and 2 can determine the potential, from either the OCC or MASDIMA, in recovering flights identified as disrupted, it can be concluded that after employing recovery actions on the disrupted flights, the total costs associated to these disruptions increased, with a slight improvement to the initial delay. Regarding the analyses of Scenarios 3 and 4, which can determine the potential of MASDIMA when compared with the OCC, it can be noticed that MASDIMA could recover approximately 10% of the total costs from the initial disruptions, also with a slight improvement to the initial delays. As it is not possible to clearly identify which of the recovery actions were in fact taken by the software and which were taken by the human controllers, it is not entirely possible to state that MASDIMA had a better performance than the OCC. However, when only considering the comparison between the solutions generated by the software and the results of the real flights, it is clear that the recovery solutions, with and without quality costs, generated only by MASDIMA were able to greatly reduce costs when compared to the recovery actions taken by either the OCC or MASDIMA in reality.

References

[1] IATA, "2036 Forecast Reveals Air Passengers Will Nearly Double to 7.8 Billion," 2017. [Online]. Available: https://www.iata.org/pressroom/pr/Pages/2017-10-24-01.aspx. [Accessed: 06-Aug-2018].

[2] Amadeus, "Shaping the future of Airline Disruption Management (IROPS)," 2016.

[3] Amadeus, "Passengers first: Re-thinking irregular operations," Amadeus IT Group SA, 2013.

[4] S. Bisaillon, J. F. Cordeau, G. Laporte, and F. Pasin, "A large neighbourhood search heuristic for the aircraft and passenger recovery problem," *4or*, vol. 9, no. 2, pp. 139–157, 2011.

[5] A. J. M. Castro, A. P. Rocha, and E. Oliveira, "Towards an Autonomous and Intelligent Airline Operations Control," pp. 1429–1434, 2012.

[6] N. Kohl, A. Larsen, and A. Ross, "Airline Disruption Management - Perspectives , Experiences," pp. 1–36, 2004.

[7] A. J. M. Castro, "A Distributed Approach to Integrated and Dynamic Disruption Management in Airline Operations Control," (PhD Thesis, Universidade do Porto), 2013.

[8] (FAA) Federal Aviation Administration, "Air Traffic By The Numbers," 2017.

[9] G. Wei, G. Yu, and M. Song, "Optimization model and algorithm for crew management during airline irregular operations," *J. Comb. Optim.*, vol. 1, no. 3, pp. 305–321, 1997.

[10] A. Mota, A. J. M. Castro, and L. P. Reis, "Recovering from Airline Operational Problems with a Multi-Agent System : a Case Study," *Prog. Artif. Intell. EPIA 2009.*, vol. Vol. 5816, 2009.

[11] F. J. J. Serrano and A. Kazda, "Airline disruption management : yesterday, today and tomorrow Airline disruption management : yesterday , today and tomorrow," *Transp. Res. Procedia*, vol. 28, pp. 3–10, 2017.

[12] C.-L. Wu, *Airline Operations and Delay Management: insights from airline economics, networks and strategic schedule planning.*, 1st ed. Surrey: Ashgate Publishing Limited, 2010.

[13] M. Clarke, "The Airline Operation Control Centre : an overview of Garuda's Operation Control (EM) at Cengkereng Jakarta, Indonesia," 1995.

[14] T. K. Liu, C. R. Jeng, and Y. H. Chang, "Disruption management of an inequality-based multi-fleet airline schedule by a multi-objective genetic algorithm," *Transp. Plan. Technol.*, vol. 31, no. 6, pp. 613–639, 2008.

[15] IATA, "Operations Control (OCC) Agenda." 2014.

[16] C. Jeng, "Real-time decision support for airline schedule disruption management," vol. 6, no. 27, pp. 8071–8079, 2012.

[17] A. J. M. Castro and E. Oliveira, "A new concept for disruption management," vol. 225, pp. 269–290, 2010.

[18] M. A. Camilleri, "Aircraft Operating Costs and Profitability," in *Travel Marketing, Tourism Economics and the Airline Product*, Cham, Switzerland: Springer Nature, 2018, pp. 191–204.

[19] Amadeus, "Airline Disruption Management," 2016.

[20] A. J. M. Castro and E. Oliveira, "Quantifying Quality Operational Costs in a Multi-Agent System for Airline Operations Recovery," vol. 4, no. July, 2009.

[21] J. Clausen, J. Larsen, A. Larsen, and J. Hansen, "Disruption Management - Operations Research between planning and execution," 2001.

[22] A. Cook and G. Tanner, "European airline delay cost reference values," 2015.

[23] Y. Zhang and M. Hansen, "Real-Time Intermodal Substitution: Strategy for Airline Recovery from Schedule Perturbation and for Mitigation of Airport Congestion," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2052, no. April, pp. 90–99, 2008.

[24] P. J. Bruce, *Understanding Decision-making Processes in Airline Operations Control*, Second Edi. Routledge, 2016.

[25] J. Clausen, A. Larsen, J. Larsen, and N. J. Rezanova, "Disruption management in the airline industry-

Concepts, models and methods," *Comput. Oper. Res.*, vol. 37, no. 5, pp. 809–821, 2010.

[26] R. Barati, "Application of Excel Solver for Parameter Estimation of the Nonlinear Muskingum Models," *KSCE J. Civ. Eng.*, vol. 17, no. 5, pp. 1139–1148, 2013.

[27] D. Fylstra, L. Lasdon, J. Watson, and A. Waren, "Design and use of the Microsoft Excel Solver," *Interfaces (Providence).*, vol. 28, no. 5, pp. 29–55, 1998.

[28] R. Beatty, R. Hsu, L. Berry, and J. Rome, "Preliminary Evaluation of Flight Delay Propagation through an Airline Schedule," in *Air Traffic Control Quarterly*, 1998, vol. 7, no. 4, pp. 259–270.

[29] G. Kemmer and S. Keller, "Nonlinear least-squares data fitting in Excel spreadsheets," *Nat. Protoc.*, vol. 5, no. 2, pp. 267–281, 2010.