# Design Of Robust Operation Schedules For A Freighter Airline

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**Abstract**

Nowadays, given the optimization in use of the belly area as cargo space, the necessity of dedicated cargo planes is shrinking. That reality, together with the fact that the operational margin of that business is low, make the reduction of costs a key initiative among airliners. Air cargo carriers are very susceptible to uncertainty in the demand of transport mainly due to the following factors: small number of clients consolidate a big percentage of requests, pricing scheme and the lack of penalties regarding no-show. Recently, there has been a focus on introducing robustness into airline planning stages to minimize the effect of these disruptions in overall costs. A two-stage robust optimization model, based heavily on a multi-commodity flow problem, is proposed to aid the routing of both aircrafts and packages. Aircraft and request routing would correspond to first stage variables, while the amount of demand that is not met would correspond to the second stage ones. Due to the large scale of the problem, a Benders decomposition was implemented in order to make the instances more tractable. Our model was tested using real-life data in a small illustrative example, considering three possible scenarios. Our experiments show the applicability of our methodology, which differs from the results obtained from a deterministic model.

**Keywords:** Air Cargo Schedule Design; Two-Stage Stochastic Programming; Benders Decomposition; Robust Optimization.

# 1 Introduction

Air transport is the fastest and most reliable mode of transport. These reasons explain why air transport is the preferred mode to move perishable, highly programmed obsolescence, highly expensive goods and high capital costs. This is consistent with the fact that although the volume transported by air only reaches 1% of the aggregated tonnage moved, when looking at the aggregated value transported, air-cargo accounts for 35% of the grand total (Boeing, 2015).

Cargo can be transported in two ways: using cargo only aircrafts (CAO), or in passenger airplanes using the luggage area that was left after all the baggages were allotted (this is known as "belly" of the plane). Because passenger flights must be flown either way, with or without cargo, and that the variable cost of transporting an additional unit of cargo is almost negligible compared to the total cost of operating a flight, the profit from belly cargo goes directly into the carriers bottom line. This reason explain why airlines with large networks and wide body passenger aircraft prefer to move their cargo using their passenger network instead of using dedicated CAO. This is reflected in the fact that although freight ton-kilometers (FTK) of the industry increased by 7.5% between 2011 and 2015, freighter profits dropped by almost 12%. Moreover, load factors for CAO airplanes dropped to a historic low average of 44% in the year 2015. (IATA, 2015). Still, despite the fact that the yields and the need for CAO aircrafts is declining on a yearly basis (IATA, 2016), they play a crucial role within the industry. First, they provide a fixed capacity, as opposed to belly space that depends on how much space is left after passengers luggage. Second, there are many types of packages that are required to be transported in CAO aircrafts. As an example of these kinds of requests we can mention: very large items, items that require the large doors of CAO planes, live animals, dangerous chemicals or even human remains.

The air transportation market is characterized, among others, by the following characteristics: very low operating margins, high dependability upon jet fuel price, high level of competition and demand uncertainty. Although these characteristics are common for both cargo and passenger market, there are some key differences that completely set those cases apart. For example, while in the passenger market it is very unlikely that a person or company buys sufficient tickets to hoard a considerable part of the available seats, for the cargo case these situation is actually very common. Other core difference is the unbalance in leg demand. For passengers, roundtrip tickets are the norm, which makes schedule planning easier, while cargo demand is directional, e.g. southbound demand (cargo that is transported from the north hemisphere to the south) is notoriously different in terms of volume and transported goods than the northbound one. Finally, the pricing scheme for cargo usually does not involve a no-show penalty (Wada, Delgado, & Pagnoncelli, 2016). The lack of that specific penalty considerably increases demand uncertainty, making the planning stages even more complicated.

As mentioned before, route planning process is an extremely challenging task for CAO operations that it must be done well in advance. Crews and aircrafts must be assigned to each flight with sufficient time to build a feasible schedule with its corresponding allocation. However, given the possible demand disruptions produced by last minute *no-show* or the appearance of new requests, planners are in need to make last minute changes to the original schedule in order to fulfill the most possible number of requests with the least impact on operating costs. In order to meet certain level of service, changes are required in aircraft routing, cargo routing or even adding/canceling flights. These reactive changes in schedule are often done by hand, relying on the year-long experience of planners, but this method does not guarantee the optimality of the final planning obtained. Considering that the industry is characterized by low operating margins, introducing a solution aid method for this particular process could prove extremely beneficial.

In accordance with the former line of thought, the general objective of this paper is to develop a formulation for the generation of robust schedule in the event of demand disruption. We call this problem the air robust operations schedule design problem (ROSDP). Among the specific objectives are the following: 1) Elaborate a formulation based on stochastic mathematical programming that allows to generate robust schedule regarding changes in cargo demand, 2) solve the problem with the aid of advanced optimization techniques of integer programming that would allow the resolution of large-scale problems, 3) evaluate the performance of the proposed solution through experiments and 4) compare those results with the ones obtained from a model that does not consider stochastic demand.

The rest of the paper is organized as follows. In section 2, we present a brief literature review regarding the problem. In Section 3, we provide a formal description of the robust MIP model used, in which we introduce robustness using a two-stage stochastic programming approach. Section 4 contains numerical experiments that are based on real data, as well as a discussion on the results obtained. Finally, in Section 5, we conclude the paper and present some possible future lines of research.

# 2 Literature Review

Introducing robustness into airline schedule planning is a challenge that for the passenger case has already been addressed by various authors in the past. In this section, we discuss the existing literature on airline schedule design and we will present some alternatives for introducing solution robustness on the passengers side. However, for the air cargo market no such efforts have been made. Also, given that the proposed model involves dealing with stochastic demand, we will present a summary on two-stage stochastic programming with some implementations of this methods on other industries. Finally, in order to better explain the optimization techniques used in the resolution of the problem, a brief literature review on the Benders Decomposition method is introduced.

## 2.1 Airline Schedule Planning and Robustness

The literature regarding the planning process for airline cargo carriers is scarce in comparison to that for the case of passengers, and it does not contemplate the application of robust optimization methods to obtain more stable solutions. Yan, Chen, and Chen (2006) introduced an integrated model that solves simultaneously the airport selection, aircraft routing, and departure time setting for each flight. The solution included a MIP problem that maximized profits subject to operational constraints. Yan and Chen (2008) further extended the previous formulation to achieve coordination between the schedules of various air cargo airlines.

Derigs, Friederichs, and Schafer (2009) formulated two integrated models that combine the three planning steps: flight selection, aircraft rotation planning, and cargo routing. The aim of the proposed schedule optimization was to maximize the network-wide profit by determining the best combination from a list of mandatory and optional flights, assigning the selected flights to aircrafts and identifying optimal cargo flows. Derigs and Friederichs (2013) further addressed the problem by considering different types of aircraft. They used a solution method that included advanced optimization techniques and heuristics in order to make large scale problems more tractable. Branch and Price, column generation and the A* algorithm were used. Feng, Li, and Shen (2015) presented a review paper for the literature regarding air cargo operations, comparing theoretical studies with practical problems faced by different carriers across the whole market.

The need of introducing robustness into the planning process is not new and for the passenger case (in the air transport industry as well as in others like, for example, railroad) there have been some attempts to achieve it. Lan, Clarke, and Barnhart (2006) studied the problem that, because each airplane usually flies a sequence of flight legs, delay of one flight leg might propagate along the aircraft route to downstream flight legs and cause further delays and disruptions. Thus, they proposed a new approach to reduce delay propagation by intelligently routing aircraft. They formulated the problem as a mixed-integer programming problem with stochastically generated inputs. Gao, Johnson, and Smith (2009) addressed these same challenges by developing a new approach that integrates crew connections within the fleet assignment model and imposes station purity by limiting the number of fleet types and crew bases allowed to serve each airport. This approach aims to maximize the responsiveness and versatility of the original planning.

Liebchen and Lübbecke (2009) applied robustness into railroad planning. They presented a new concept for optimization under uncertainty: recoverable robustness. A solution is said to be recovery robust if it can be recovered by limited means in all likely scenarios. Specializing that general concept to linear programming, they showed that recoverable robustness combines the flexibility of stochastic programming with the tractability and performances guarantee of the classical robust approach. Froyland, Maher, and Wu (2013) propose a recoverable robustness technique as an alternative to robust optimization for airline carriers to reduce the effect of disruptions and the cost of recovery. They obtained a formulation using a flight string formulation that minimizes recovery costs and deviation from the original schedule. However, the time span they considered for the schedule obtained is only one day.

To the best of our knowledge, there is no literature that introduces robustness into the design of air cargo scheduling. This problem possesses the following characteristics that set it apart from the existing ones.

(i) The nature of the disruptions (external triggers that oblige modifications to be made in the original planning) is completely different from the passengers case. In the case of passengers, delays are mainly due to meteorological factors, aircraft failures and logistic problems at airports. However, for cargo disruptions are mainly due to changes in demand. Schedule design is usually made using deterministic demand values and the aim of this project is to be able to work with multiple stochastic demand scenarios.

(ii) Being able to leave demand unserved by incurring into extra cost.

(iii) The model proposed considers both time delivery windows and cargo holding costs.

## 2.2 Two-stage Stochastic Programming

In the literature we find some methods for introducing stochasticity into linear programming applications. The method we chose to achieve this task was the two-stage stochastic programming method. The classical two-stage stochastic linear program with fixed recourse was originated by Dantzig (1955) and Beale (1955) and the main idea behind it is to solve a problem with the following two kinds of variables (Birge & Louveaux, 2011):

(i) First stage variables. Variables that are computed before uncertainty is disclosed

(ii) Second stage variables. The ones that are decided after the uncertainty is revealed.

In the second stage, a number of different events may realize which are normally described using scenario. In their book, Birge and Louveaux (2011) discuss some of the most simple applications of this problem, being the news vendor problem and the farmers problem two of the most known and typical. However, in the literature we find very successful applications of this method in other industries. Xie, Huang, Li, Li, and Li (2013) developed an inexact two-stage water resources management model for multi-regional water resources planning in the Nansihu lake Basin, China. Chen, Li, Huang, Chen, and Li (2010) formulated a two-stage inexact-stochastic programming (TISP) method for planning carbon dioxide (CO2) emission trading under uncertainty. Another example is Dillon, Oliveira, and Abbasi (2017), where they propose a two-stage stochastic programming model for defining optimal periodic review policies for red blood cells inventory management. The objetive focus on minimising operational costs, as well as blood shortage and wastage due to outdating, taking into account perishability and demand uncertainty. Finally Froyland et al. (2013) used a stochastic approach to solve their RRTAP.

Dealing with Two-Stage Stochastic Programming applications is not always an easy task because of the gain in problems size this method requires. Every extra scenario considered e.g. demand unceratinty in our case, implies necessarily a set of new variables to be included into the problem, slowing down dramatically the computers solution time. In addition, the base structure of the model is already a MIP model which is, by construction very hard to solve. These are the reasons why we decided to use Benders Decomposition (Benders, 1962). The main idea behind Benders Decomposition is tackling problems with complicating variables, which, when temporarily fixed, yield a problem significantly easier to handle. In fact, successful applications are found in many divers fields, including planning and scheduling, health care, transportation and telecommunications, energy and resource management, and chemical process design (Rahmaniani, Crainic, Gendreau, & Rei, 2016).

# 3 Model

The problem is formulated as a variation of a Multi-Commodity Flow Problem considering uncertainty in cargo demand. This scheduling problem aims to minimize the operational costs considering a set of demand scenarios that vary in the requests weight. As the routing of both aircraft and requests must be unique for all possible scenarios, the model allows the scheduling to leave portions of the requests unserved, incurring in a linear penalty directly in the objective function. Below, we provide a formal definition and formulation of the robust routing problem.

## 3.1 Definitions and Notation

An airline operates with a fleet of $k \in \mathcal{K}$ aircraft with capacity $\kappa_k$, serving a set of airports $l \in \mathcal{L}$ and across a set of $s \in \mathcal{S}$ possible scenarios. Every scenario has an associated probability $p_s$, where $\sum_{s \in \mathcal{S}} p^s = 1$. The planning horizon for the recovery problem is divided into a set of relatively short periods of time $t \in \mathcal{T}$. There is a set of requests $r \in \mathcal{R}$ to be fulfilled, each of which is defined by its weight $w^{rs}$ (which may differ in each scenario $s$), the origin and destination airports, $l_r^+$ and $l_r^-$, respectively, and the time window during which it becomes available at the origin and is required to be at is destination, $t_r^+$ and $t_r^-$, respectively. The time that it takes to fly from airport $i$ to $j$, which is assumed to be fixed and independent of the aircraft, is denoted as $d_{ij}$.

To formulate the existing problem, we construct a time–space network where every node consists of an airport paired with a period, i.e., $\mathcal{N} := \{i = (l_i, t_i) : l_i \in \mathcal{L} \wedge t_i \in \mathcal{T}\}$. Over this set of nodes, we defined three different sets of arcs. The first set $\mathcal{A}^F$ contains flight arcs, and is defined as every pair of nodes that connect an airport to a different one in the future, i.e., $\mathcal{A}^F := \{(i,j) : l_i \neq l_j \wedge t_i < t_j\}$. These arcs can be used for routing both aircraft and cargo. The second set $\mathcal{A}^G$ contains ground arcs, which denote when an aircraft (or request) remains in an airport until the next period of time. This set is defined as $\mathcal{A}^G := \{(i,j) : l_i = l_j \wedge t_i + 1 = t_j\}$. The third set of arcs $\mathcal{A}^N$ corresponds to the no-service arcs, which are arcs connecting the pickup and delivery nodes of a request. If we define $i_r^+$ and $i_r^-$ as these nodes (e.g., $i_r^+ := (l_i^+, t_i^+)$), this set can be defined as $\mathcal{A}^N := \{(i,j) : \exists r \in \mathcal{R} : i = i_r^+ \wedge j = i_r^-\}$. Thus, the set of arcs of the problem is $\mathcal{A} := \mathcal{A}^F \cup \mathcal{A}^G \cup \mathcal{A}^N$.

The aircrafts start and finish nodes are fixed to ensure a continuity between previous and future schedules, starting at node $i_k^+$ and finishing at node $i_k^-$. Each aircraft is allowed to fly in specific zones. Binary parameter $\alpha_{ij}^k$ indicates whether aircraft $k$ can fly from node $i$ to node $j$, and considers the validity of the flight leg in terms of permits and travel times. Note that parameter $\alpha_{ij}^k$ can be used to reduce the size of set $\mathcal{A}^F$ to make the solution of the problem more efficient.

The objective of the problem is to find a solution that minimises both operating costs and penalty costs across all plausible scenarios, obtaining a relatively stable (robust) solution. Parameter $F_{ij}^k$ denotes the fixed cost incurred by aircraft $k$ traversing arc $(i,j)$, while parameter $V_{ij}$ represents the cost incurred by a unit of weight of a request traversing arc $(i,j)$. Finally, parameter $H$ denotes the cost incurred by a unit of weight of a request that is not served within the established delivery time windows.

## 3.2 Mathematical Formulation

To formulate the ROSDP as an MIP problem, let us define binary variables $X := \{x_{ij}^k\}$ to denote whether aircraft $k \in \mathcal{K}$ uses arc $(i,j) \in \mathcal{A}$ as part of its schedule. In an analogous way, binary variables $Q := \{q_{ij}^r\}$ will denote whether a request $r \in \mathcal{R}$ traverses a particular arc. In addition to those set of variables, let us define $Z := \{z_{ij}^{rs}\}$ as the portion of request $r$ that actually traverses arc $(i,j) \in \mathcal{A}$ in scenario $s$ and $M := \{m^{rs}\}$ as the portion of request $r$ that is not fulfilled in scenario $s$.

In the formulation of the model, we define sets $\delta^+(i)$ and $\delta^-(i)$ as all the arcs belonging to $\mathcal{A}$ that emanate from (or are incident to) node $i$. In other words, $\delta^+(i) := \{(i,j) : (i,j) \in \mathcal{N}\}$, and $\delta^-(i) := \{(j,i) : (j,i) \in \mathcal{N}\}$.

The MIP formulation for the ROSDP is then defined as minimizing the total objective function $Z$, and is defined as

$$Z = \sum_{k \in \mathcal{K}} \sum_{(i,j) \in \mathcal{A}} F_{ij}^k x_{ij}^k + \sum_{s \in \mathcal{S}} p^s \left( \sum_{r \in \mathcal{R}} \sum_{(i,j) \in \mathcal{A}} V_{ij} w^{rs} z_{ij}^{rs} + \sum_{r \in \mathcal{R}} m^{rs} w^{rs} H \right), \quad (1)$$

subject to:

$$\sum_{r \in \mathcal{R}} w^{rs} z_{ij}^{rs} \leq \sum_{k \in \mathcal{K}} \kappa_k x_{ij}^k, \quad (i,j) \in \mathcal{A}^F, s \in \mathcal{S} \quad (2)$$

$$\sum_{(i,j) \in \delta^+(i)} x_{ij}^k - \sum_{(j,i) \in \delta^-(i)} x_{ji}^k = \begin{cases} 1, & i = i_k^+ \\ -1, & i = i_k^- \\ 0, & \text{i.o.c.} \end{cases}, \quad i \in \mathcal{N}, k \in \mathcal{K} \quad (3)$$

$$\sum_{(i,j) \in \delta^+(i)} q_{ij}^r - \sum_{(j,i) \in \delta^-(i)} q_{ji}^r = \begin{cases} 1, & i = i_r^+ \\ -1, & i = i_r^- \\ 0, & \text{i.o.c.} \end{cases}, \quad i \in \mathcal{N}, r \in \mathcal{R} \quad (4)$$

$$q_{ij}^r - m^{rs} \leq z_{ij}^{rs}, \quad (i,j) \in \mathcal{A}, r \in \mathcal{R}, s \in \mathcal{S} \quad (5)$$

$$x_{ij}^k \leq \alpha_{ij}^k, \quad (i,j) \in \mathcal{A}^F, k \in \mathcal{K} \quad (6)$$

$$x_{ij}^k \in \{0,1\}, \quad (i,j) \in \mathcal{A}, k \in \mathcal{K} \quad (7)$$

$$q_{ij}^r \in \{0,1\}, \quad (i,j) \in \mathcal{A}, r \in \mathcal{R}. \quad (8)$$

$$z_{ij}^{rs} \in [0,1], \quad (i,j) \in \mathcal{A}, k \in \mathcal{K}, s \in \mathcal{S} \quad (9)$$

$$m^{rs} \in [0,1], \quad r \in \mathcal{R}, s \in \mathcal{S} \quad (10)$$

The objective function (1) corresponds to the total operational costs, and consists of the sum of fixed and the expected variable costs across all scenarios, plus the penalty function that is computed as the expected value of costs for unmet demand. Constraints (2) ensure that requests can traverse a flight arc only if there is enough aircraft capacity assigned in that arc per scenario. Constraints (3) and (4) impose conservation of flow for aircraft and requests, respectively.

Constraint (5) forces both auxiliary variables $Z := \{z_{ij}^{rs}\}$ and $M := \{m^{rs}\}$ to adopt the correct value in the model. Constraint (6) indicates whether or not an aircraft can fly a certain flight leg. Constraints (7) and (8) impose the binary nature of the variables on the model. Constraint (9) ensures that the portion of the requests transported follow a logical behaviour. Finally, constraint (10) imposes limits on the maximum amount of the requests that can be left unserved. Note that this constraint can be trivially adapted to measure the level of service.

# 4 Numerical Experiments

## 4.1 Data Description

To construct our experiment, we constructed a fictional experiment heavily based on real data provided by our partner airline. The data contains the following:

1. Tariffs for each OD pair in US$/kg. These are the same regardless of the nature of the cargo. For confidentiality reasons we cannot mention these values.

2. Block hour (Time from the moment the aircraft door closes at departure of a revenue flight until the moment the aircraft door opens at the arrival gate following its landing) cost for each type of aircraft.

3. Network information: Airport location, travel distance, aircraft speed, etc.

4. Forecasted demand.

5. Historical demand fluctuation: Variations were studied and an approximate order of magnitude was obtained for them.

The capacity of each aircraft was obtained from their manufacturers website (Boeing). These are shown in Table 1.

Table 1: Cost and capacity parameters for aircraft.

| | |
|---|---|
| B767 Capacity | 70,000 kg |
| B777 Capacity | 100,000 kg |

Using forecasted demand, we constructed requests as a consolidation of the cargo between each OD pair. For this preliminary numerical example, we considered five airports, eight requests and a planning horizon of $D = 1$ days.

## 4.2 Scenario Construction

To test our model, we consider three scenarios equally likely which considered different levels of demand disruption: Optimistic (O), Normal (N), and Pessimistic (P). Each scenario had the following characteristics as shown in Table 2.

Table 2: Demand Characteristics

| **Requests** | **Start** | **Finish** | **N** | **P** | **O** | **Weighted Average** |
|---|---|---|---|---|---|---|
| r1 | 1 | 4 | 55000 | 44000 | 66000 | **55000** |
| r2 | 3 | 2 | 90000 | 72000 | 108000 | **90000** |
| r3 | 2 | 1 | 95000 | 76000 | 114000 | **95000** |
| r4 | 5 | 4 | 48000 | 38400 | 57600 | **48000** |
| r5 | 4 | 5 | 60000 | 48000 | 72000 | **60000** |
| r6 | 5 | 3 | 68000 | 54400 | 81600 | **68000** |
| r7 | 1 | 4 | 45000 | 36000 | 54000 | **45000** |
| r8 | 4 | 1 | 62000 | 49600 | 74400 | **62000** |

For the purposes of the model, the block hours used by each aircraft between every pair of airports is fixed, and therefore the fixed cost of flying an aircraft is deterministic. Costs associated with the handling and storage of cargo within the airports are assume to be zero, but given the structure of the model, these could easily be given a value so that the final result would be as reliable as possible.

To compare and understand the impact of the ROSDP model when demand disruptions occur, we use as a benchmark the schedule obtained from its deterministic counterpart. We computed the weighted average of the requests size from the scenarios and used that data as input. We ran both models and then compared the schedules obtained. The results of this experiment is presented in the next section.

## 4.3 Computational Results

To solve the instances described above, we used a computer equipped with an Intel Core i7 2.7 GHz processor and 16 GB of RAM. The model was coded on Python v.2.7.9 and solved with Gurobi v.6.5.0.

### 4.3.1 General Results

Given that the objective of the model is to provide a stable solution across all scenarios, the result obtained will not always be more economical than the planning obtained for the deterministic case. Then, it is of more relevance to study the structure of the planning obtained, to verify if the proposed objectives were fulfilled as expected. The corresponding analysis is shown in the next section.

#### Freighter Route Structure

For each freighter, Figures 1 and 2 compare the routes obtained with the deterministic routing and the routes obtained with the proposed stochastic model after optimization. The X axis represents the time period and the Y axis represents the current location (airport) of the aircraft.

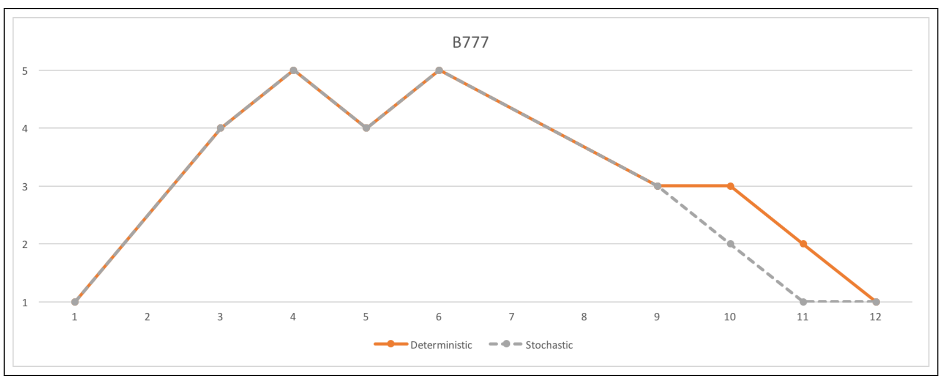


Figure 1: Schedule obtained for B777.

For the two freighters, the routing of each freighter shows significant differences between the original one and the new routing generated by the ROSDP model. For freighter B777-1, the stochastic model shows a similar routing compared with the original one until the nineth period. After that, the corresponding flight legs are anticipated. On the other hand, for the B767-1 freighter, the

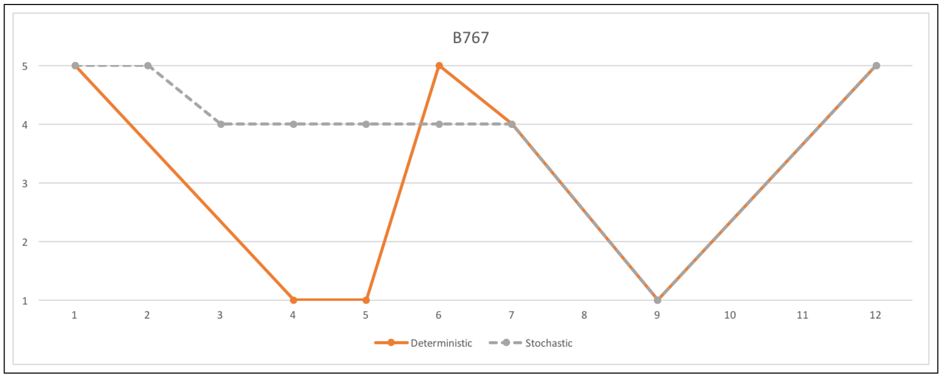


Figure 2: Schedule obtained for B767.

results are quite different. Until the seventh period the aircraft is largely unused and it is not until well advanced the planning time that the routing is resumed.

If we remember the values from Table 2, the schedules obtained for both cases make perfect sense. As it is more convenient to fly the smaller aircraft (B767), in the deterministic case the B767-1 is given a greater use since this is convenient from an economic point of view. However, since there are several orders in which the fluctuation of its size cause them to exceed the maximum capacity of said airplane. This issue occurs in the optimistic scenario for requests 5, 6 and 8. Thus, because the proposed model is capable of predicting this type of situation, in the robust solution the conflicting packages are routed through the aircraft of greater capacity. Then, although a higher cost is incurred by making more use of the most expensive asset, the expected value of the solution is lower because of minor penalties for unsatisfied demand.

Finally, it is concluded that the presented model effectively meets the objectives proposed and that it provides consistent results. However, further testing is required to verify the performance and scalability of the model on larger instances. Since it is intended to use the model in the planning stage, a horizon of one week is what is expected to be solved.

# 5 Conclusions

In this paper, we introduced the ROSDP for demand disruptions. This problem addresses the cargo airlines need for a planning method that is able to cope with demand fluctuation in order to rely less on last minute schedule recovery. These disruptions are very costly and require many resources to overcome them.

We evaluated the ROSDP model in a small illustrative example, under different scenarios of demand disruption. These experiments were compared against its deterministic counterpart. The results show that the ROSDP model is capable of delivering consistent results and that it meets the objectives set at the beginning of the research. Thus, from this perspective, the application of the ROSDP model could significantly benefit air cargo operations.

Potential areas for future research include the realization of more tests to quantify the benefits of the new model in instances of a size similar to reality. It would be desirable to have it tested for a one week timespan. In addition, in order to better support the decision-making processes of airlines, it is necessary to keep improving both the run times and the scalability of the solution algorithm. This is believed to require the use of heuristics that are specially designed large scale MIP problems. We believe that the implementation of Benders algorithm could help achieve this goal.

## Acknowledgements

We acknowledge the support of the Chilean Fund for Scientific and Technological Development (FONDECYT) through Project 11140436.

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