# Dynamic Design Of Reserve Crew Duties For Long Haul Airline Crew

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**Abstract**

Airlines need crew to operate their flights. In case of crew unavailability, for example due to illness, the airline often uses reserve crew to still be able to operate the flight. In this paper, we apply a simulation-based optimization method to determine how much and on which days reserve crew needs to be scheduled. This method is a combination of reserve optimization and reserve evaluation. The optimization model creates sets of reserve crew that are checked by the evaluation model using simulations of disruptions of the flight schedule. On top of this, we introduce the concept of mixed reserves as a new type of reserve crew scheduling with variable duties and length. Using flight, disruption and reserves data from a major European airline, it is found that using our method leads to less reserve crews. Based on the simulation of a large set of schedule disruptions, it was observed that we would need 12% less working days allocated to schedule recovery.

## 1 Introduction

Airline crew management is an essential process within the domain of airline operations. Without crew, flights cannot be operated. To ensure that crew is available for flights, the airline creates crew schedules. One of the difficulties in crew scheduling is that these schedules have to be created well before they are operated. This leaves them vulnerable to disruptions. Some of these possible disruptions are crew illness or extreme weather at an airport causing crew delays. As crew is the second largest cost of an airline after fuel [7], it is important to plan for these disruptions in the crew scheduling process. Changes to the original crew schedules can lead to significant losses for the airline [1, 2, 11].

Two types of measures are used by the airline to account for disruptions in the schedules: proactive and reactive disruption management [9]. Proactive disruption management focuses on adapting crew schedules to limit the effects of disruptions on operations. Techniques used are scheduling reserve crews or aircraft, synchronize crew and aircraft connections, add slack time or let crew and aircraft stay together as much as possible [11, 13]. In contrast, reactive disruption management is not affecting the crew schedules when they are created, but it considers recovering the schedule after a disruption. This crew recovery problem focuses on finding solutions to restore the operations while minimizing cost for the airline. Solutions could be using scheduled reserve crew or rescheduling other activities like training so crew is made available to cover disrupted flights.

Assigning crew a reserve duty is a costly measure as this crew cannot be used for production [11]. A reserve duty is a set of consecutive days that can be used to recover a disrupted schedule or specific flight. This reserve duty can be partially or fully swapped with other activities in the schedules [14]. So from a schedule recovery point of view, the availability of reserve crew is an easy and effective solution to fix the schedule as no other actions have to be taken. However, if there are few disruptions, the reserve crew could be unused which means costly non-productive days for the airline. The opposite issue is that if there are more disruptions than reserve crew, the airline has to rely on other recovery options such as rescheduling of activities. This often way more costly from a schedule recovery perspective, so the airline cannot rely on this for all disruptions. Therefore, the problem is to find the right amount of reserve crews to schedule. Hereby taking into account that enough reserves should be available to provide easy and effective recovery solutions, but also not too many causing unused reserves and thus non-productive days.

The problem of determining the right number of reserve crews is a dynamic and complex problem. It can be determined based on the demand for reserve crews, which in turn can be derived from expected schedule disruptions. However, the amount and magnitude of disruptions are highly uncertain when schedules are created. Additionally, the complexity of the problem is due to the fact that also the start day and length of reserve duties have to be taken into account. Scheduling reserve crews on the wrong days during the week leads to both unused reserves and unavailable reserves for recovery. This is especially relevant for long-haul crew as typical flight duties are often multiple days and cannot be broken up. If a long-haul flight is disrupted on a specific day this means that a reserve crew for multiple days from that moment onward is necessary. Short-haul flight duties are also typically a few days, but they consist of many legs and these can often be broken up in parts. This means that different reserve duties could be utilized to cover parts of the original short-haul duty. Still, there should be balance between the demand for reserve crews and the available reserve crew in the schedules.

Despite the high costs for crew and the need for efficient design of crew schedules, the design of reserve crew duties if often assumed to be already solved [12, 17] and used as an input for the crew rostering problem. Sohoni et al [16] create an integrated planning and rostering approach for reserve crews that gives monthly schedules of on-duty and off-duty days as an output. The work of Paelinck [15], Bijvank [8] and Bayliss [5, 3, 4, 6] is focusing specifically on the reserve crews in context of cabin crew. However, the reserve duties in these references are defined only through duty start times with a fixed length for reserve duties. This assumption is too conservative: in practice, reserve pairings vary in length from day to day or even on the same day to give more flexibility and to adjust it to crew availability requirements.

| | MON | TUE | WED | THU | FRI | SAT | SUN |
|---|---|---|---|---|---|---|---|
| Pure | RES | RES | RES | RES | RES | RES | |
| Mixed | RES | RES | FLT | FLT | FLT | FLT | |

Figure 1: Pure reserve duty (top) and mixed reserve duty (bottom).

On top of this, in this paper we broaden the view on reserve duties by introducing a new type of reserve duties that is also used in practice: mixed reserve duties. A mixed reserve duty is defined as a number of consecutive days that can be used for a reserve duty followed by a flight duty that is disrupted when the reserve duty is used. The traditional reserve duties are redefined as pure reserve duties: a number of consecutive days that can be used for a reserve duty that are not followed by a flight duty. These two types of reserves are visualized in Figure 1. The advantage of a mixed reserve duty is that only a few reserve days have to scheduled before a flight duty, which is less costly if this reserve duty is not used. It means that less pure reserve duties are required, as the mixed reserve duty can also be used to recover disrupted flights. Additionally, using mixed reserves means that disruptions in the schedule can move forward as a disruption flight is recovered but the flight duty in the reserve duty is disrupted automatically. These reserve duties should therefore still be combined with regular pure reserve duties in a reserve pattern that can stop the disruption moving forward.

| | MON | TUE | WED | THU | FRI | SAT | SUN | MON | TUE | WED | THU | FRI | SAT | SUN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ID 1 | RES | FLT | FLT | FLT | | | | | | | | | | |
| ID 2 | | RES | FLT | FLT | FLT | | | | | | | | | |
| ID 3 | | RES | RES | RES | RES | FLT | FLT | FLT | FLT | | | | | |
| ID 4 | | | RES | RES | RES | RES | | | | | | | | |
| ID 5 | | | RES | FLT | FLT | FLT | | | | | | | | |
| ID 6 | | | | RES | RES | RES | RES | | | | | | | |
| ID 7 | | | | RES | FLT | FLT | FLT | | | | | | | |
| ID 8 | | | | | RES | RES | RES | RES | | | | | | |
| ID 9 | | | | | RES | RES | FLT | FLT | FLT | FLT | FLT | | | |
| ID 10 | | | | | | RES | RES | FLT | FLT | FLT | | | | |
| ID 11 | | | | | | RES | RES | RES | RES | | | | | |
| ID 12 | | | | | | | RES | FLT | FLT | FLT | FLT | | | |
| ID 13 | | | | | | | RES | RES | RES | RES | FLT | FLT | FLT | FLT |

Figure 2: A reserve pattern of a week with 13 reserve duties, showing the reserve days in green and flight duty days in red.

Relaxing the assumption on fixed reserve length and adding mixed reserve duties adds to the dynamic nature and complexity of the problem. The solution space is increased as many more combinations of reserve duties have to be considered. We define this combination of reserve duties as a reserve pattern, i.e. a set of reserve duties. An exemplary reserve pattern for a week can be seen in Figure 2.

The goal of this paper is to demonstrate a novel method that can be used to construct reserve patterns specifically for long-haul airline crew, while accounting for a variable reserve length and including mixed reserve duties in the patterns. These reserve patterns are designed so the gap between expected reserve demand and scheduled reserve duties is minimized. In Section 2 the method is described in detail. Subsequently, the application of the method in a case study with a major European airline is given in Section 3. Finally, the paper is concluded in section 4.

# 2 Method

In this section, we describe the methodology used to determine airline crew reserve patterns. The goal of the method is to determine the best possible reserve pattern given an expected reserve demand. The reserve demand is the need for reserve crews when flights are disrupted and the original crew is not available anymore. Airline operations is an uncertain process and therefore exact reserve demand is also uncertain. To meet this demand for reserve crews, the reserve duties are created. They can be used in a reserve pattern with varying length, varying start day of the week and can be mixed and pure duties. This means that there are hundreds of reserve duties possible in a reserve pattern. As a selection of these reserve duties are used in a reserve pattern there are millions of possibilities to consider. Therefore, we have applied simulation-based optimization to the reserve pattern design problem. It is a combination of a reserve pattern evaluation model based on simulations and a reserve pattern optimization algorithm. The evaluation model determines the quality of any reserve pattern and the reserve pattern optimization model aims to improve the quality of a reserve pattern. In the next three subsections, the modelling of reserve demand (Subsection 2.1), pattern evaluation (Subsection 2.2) and pattern optimization (Subsection 2.3) are described.

## 2.1 Reserve Demand

The main input for the reserve pattern design problem is the reserve demand. The demand is modelled as a stochastic process, depending on airline operations. It is assumed that the demand for reserve crews can be estimated based on historic flight disruptions for similar flight schedules. As flight schedules do not vary much between seasons from year to year, the disruptions that happened in similar seasons in the years before can be used as an estimation for the disruptions in the current schedules. These flight disruptions are modelled as disruption probabilities for which data from a major European airline is used. An example of these disruptions is crew illness. The reserve pattern is made for a specific flight schedule and optimized towards the expected disruption probabilities for each respective flight duty in the schedule. The flight duties or flight pairings are often very similar each week in a season, so therefore the reserve pattern is made for a weekly flight schedule. The flight schedule that is used for the case study described in Section 3 is partly visualized in Table 1. In this table, on each row a flight, departure day, disruption probability, route days and rest days of these flights are given.

Table 1: Part of the flight schedule used in the case study with on each line a flight, with id, departure day, disruption probability and flight duty length (days).

| **Flight ID** | **Departure day** | **Disruption probability** | **Flight duty length (days)** |
|---|---|---|---|
| 1 | MON | 0.048 | 7 |
| 2 | MON | 0.038 | 7 |
| 3 | MON | 0.055 | 6 |
| 4 | TUE | 0.052 | 7 |
| 5 | TUE | 0.039 | 8 |
| 6 | TUE | 0.055 | 5 |
| ... | ... | ... | ... |

## 2.2 Pattern Evaluation

The ideal reserve pattern is a pattern that matches the reserve demand perfectly. As the reserve demand is modelled as a stochastic process, two outcomes are possible. On the one hand, reserve demand can be lower than the reserve duties available. In this case, some of the reserve duties are unused by the airline. On the other hand, reserve demand can be higher than available reserve crews. The airline needs to resort to other recovery options such as swaps in the rosters to recover the schedule. The airline crew is often compensated with a premium when these swaps are necessary. This premium compensation is either a monetary compensation for the crew or additional days off to compensate for the changes in their roster. These additional recovery options are, however, limited as not all activities in the rosters can be changed. Therefore, the airline cannot rely solely on these additional options for all disruptions that occur.

Based on this, three components to determine the quality of a reserve pattern can be defined: reserve budget, premium days and service level. The reserve budget is the total amount of reserve days in the reserve pattern. If no reserves are available to cover for a disrupted flight, the model assigns a premium. The measure for premium compensation used in the model is chosen to be days as the reserve budget is also measured in days. It is assumed that it is always possible to find crew for a disrupted flight, but the amount of premium days required depends on the flight duty. Lastly, we define the service level as the amount of times premium compensation is required to recover the schedule. This service level should meet a specific requirement as set by the airline. In this paper, this threshold is set at a maximum of 3 times premium compensation in a week. This means that a service level requirement of for example 95% means that in 95% of the weeks a maximum of three times premium compensation is required. It is a measure for an airline operator to determine their preference for reserves over premium days, or in other words, a measure for the robustness of the rosters.

In sum, a reserve pattern is evaluated based on the amount of reserve budget and premium days required given the stochastic disruption process. Additionally, a service level requirement should be met to ensure a maximum of alternative recovery options required in the schedule. To determine these values, a simulation model is developed that estimates these numerically. The concept of the simulation model is a disruption recovery model that simulates the operation of an airline flight schedule, where flights are disrupted and recovered. By using repeated simulations of the flight schedule the reserve patterns can be dynamically evaluated. In other words, using the flight disruption probabilities on all flights in the schedule and the model can then determine whether these disrupted flights can be covered by reserves or premium days are required. A flowchart of the simulation model can be seen in Figure 3.

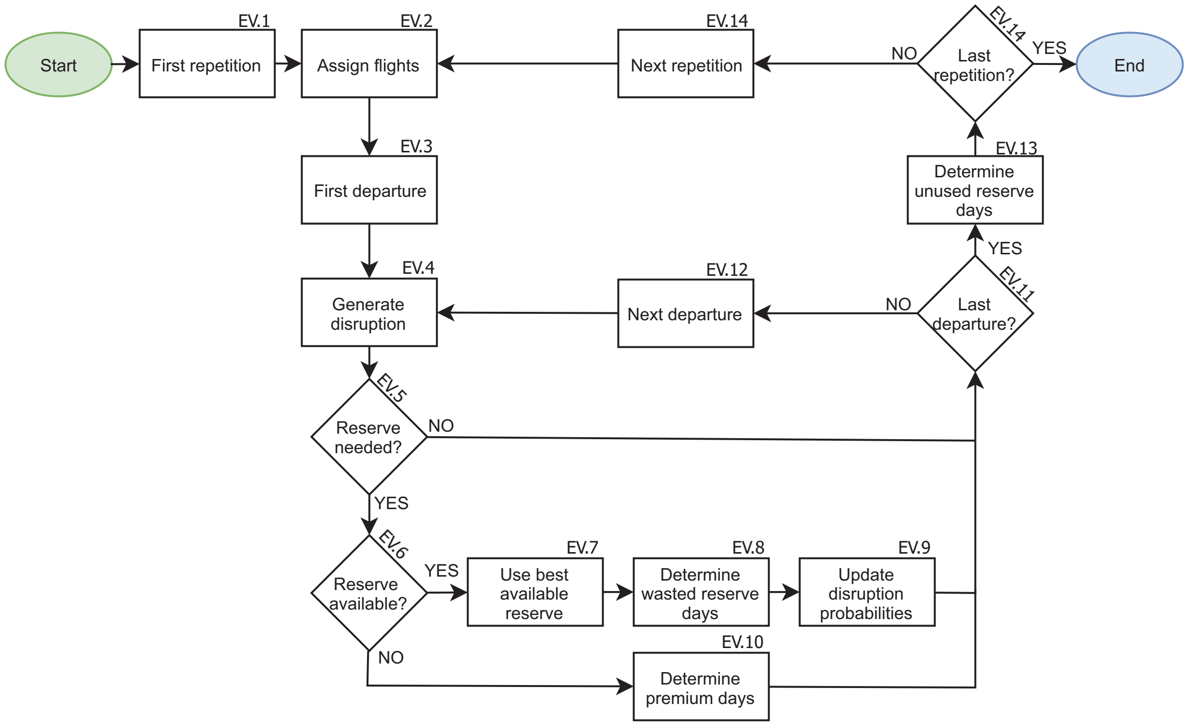


Figure 3: Flowchart of the reserve pattern evaluation model.

After starting the simulation model with the first repetition in EV.1, the next step (EV.2) is to assign the flights to mixed reserve duties. Referring back to Figure 2, flight duties are defined in mixed reserve duties. For each mixed reserve duty a flight from the flight schedule is selected that is covering the flight duty in the reserve duty. This is done randomly between each flight that fits the flight duty. Sensitivity tests have been performed and it is found that this random process does not influence the performance of the algorithm (see Subsection 3.3). After the flights are assigned to the mixed reserve duties, each departure is considered in order of crew reporting time. Starting with the first departure (EV.3), a random number generator is compared with the flight disruption probability (EV.4) and if it hits that threshold (EV.5), it is disrupted and a reserve is needed if available. If a reserve is necessary, the recovery process starts (EV.6).

If a reserve is available, the best one is picked based on the fit of the reserve duty with the disrupted flight (EV.7). Among other feasibility constraints, for example, a disrupted flight duty of 3 days can better be solved with a reserve duty of 3 days than a reserve duty of 5 days as that leads to wasted days. After selecting the reserve, the amount of wasted reserve days (EV.8) is determined. This is the amount of days of the reserve duty that are not used to cover the disrupted flight. Additionally, when a mixed reserve duty is used, the flight duty in the mixed reserve duty is disrupted automatically. The disruption probability for this flight is changed to 1.0 so that it will be the next disrupted flight (EV.9). If no reserves are available to cover the disrupted flight, the number of premium days are determined (EV.10). If this flight was is not the last flight (EV.11), the same process starts again with the next departure in the schedule (EV.12). After the last departure, the number of unused reserve days is determined (EV.13). This is the amount of reserve days from unused reserve duties. If this is the last repetition of the model (EV.14) the simulation ends, otherwise the next repetition is started.

The model simulates a weekly flight and reserve schedule, but the reserve and flight schedule extend beyond the week. For example a flight duty that starts on Saturday and ends Tuesday the next week. The model incorporates these 'week over week' effects. Reserve duties in the pattern that span towards the next week can also be used to cover flight disruptions in the new repetition, as visualized in Figure 4. This week over week effect ensures simulation continuity and best represents the actual usage of reserves. Due to this simulation continuity effect, the first 10 repetitions are used as warm-up of the simulation process and are not used for determining the quality. Additionally, the last repetition is therefore also not used.

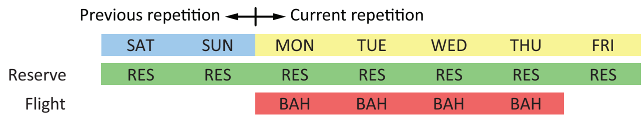


Figure 4: Flights could be covered by reserve duties from previous repetitions.

Then, the pattern evaluation model gives an output for each repetition that is used: reserve budget, premium days, wasted reserve days and unused reserve days. Based on this output, also the service level can be determined given the requirement. If a service level of 95% was required, the output is checked whether in at least 95% of the repetitions (weeks) a maximum of 3 times premium compensation is used. The different outputs from the model can then be used to compare different reserve patterns.

## 2.3 Pattern Optimization

To create a reserve pattern, a Greedy Randomised Adaptive Search Procedure (GRASP) was adopted [10]. The GRASP algorithm is a construction-based method that adds reserve duties one by one to a reserve pattern until a specified reserve budget or threshold is reached. The steps taken by the pattern optimization algorithm are depicted in Figure 5.

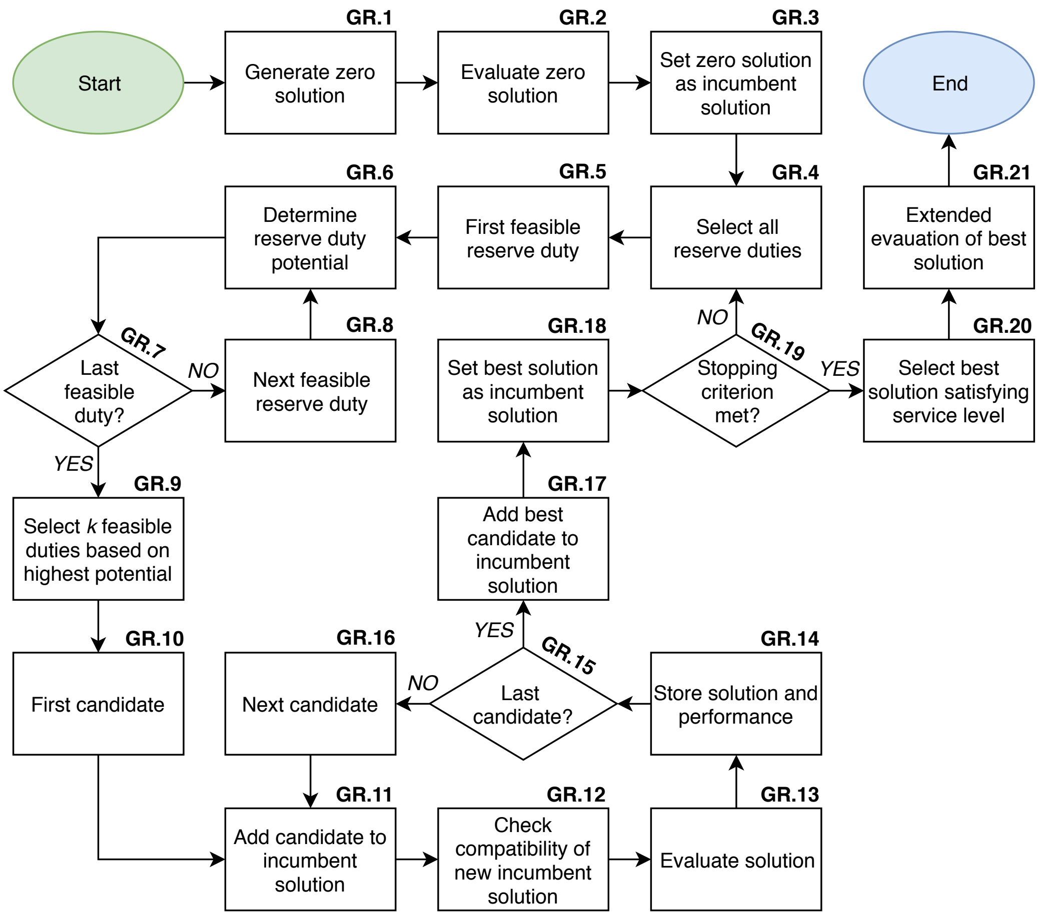


Figure 5: Flowchart of the reserve pattern optimization model using a GRASP algorithm.

The algorithm starts with a zero solution (GR.1), which is an empty reserve pattern. In other words, it is the assignment of zero reserve duties to the reserve pattern. This step is necessary for the model to determine a performance benchmark for the GRASP algorithm (GR.2). Starting from this zero solution (GR.3), all possible reserve duties are selected (GR.4). Using the first feasible reserve duty from the list (GR.5), its reserve duty potential is calculated (GR.6).

The reserve potential is a measure of the benefit to the objective that a reserve duty can have when it is added to the incumbent solution. This reserve potential is essential to determine the added value of a reserve duty. As there are hundreds of possible reserve duties to add to the reserve pattern, this measure helps to determine which duties have the highest potential to decrease disruptions. It is calculated by determining the decrease in effective disruption probability for all flights in the flight schedule by adding a given reserve duty to the reserve pattern. The effective flight disruption probability is defined as the initial disruption probability decreased by the availability of reserves in the pattern that can cover this flight.

The first step to determine the reserve pairing potential is to set the initial potential $P$ to 0.0 and the initial availability $r$ for a given reserve duty to 1.0. Then for each flight $f$ in the flight schedule, the decrease in disruption probability $\Delta p$ for this flight caused by the reserve duty is determined using Equation 1. In this equation, $p_{\text{eff},f}$ is the effective disruption probability of the flight, before the reserve pairing is added, and $r$ is the reserve availability.

$$\Delta p = p_{\text{eff},f} \cdot r \tag{1}$$

After determining the decrease in disruption probability for this flight, the reserve availability for this reserve duty is decreased using Equation 2. This is necessary as the reserve would not be available anymore if it is used for this flight, which is a probability of $p_{\text{eff},f}$.

$$r = r(1.0 - p_{\text{eff},f}) \tag{2}$$

The last step is to update the reserve pairing potential $P$ using Equation 3, where $w_{p,f}$ are the premium days that would be necessary if this flight cannot be recovered by a reserve duty.

$$P = P + w_{p,f}\Delta p \tag{3}$$

In sum, given an existing reserve pattern and for each flight in the flight schedule, the decrease in effective disruption probability is determined. This is multiplied with the amount of premium days necessary if the flight would be disrupted without reserve duty available. In the end, the sum determines which reserve duty has the highest potential to improve the reserve pattern. Therefore, the reserve potential can be regarded as a measure of the amount of premium days that can be prevented by a reserve duty. After determining the potential for the first reserve duty, a check is performed whether it is the last duty in the list (GR.7). If no, the next reserve duty in the list is evaluated (GR.8) until the potential for each duty is determined. The next step in the model is selecting $k$ feasible reserve duty candidates based on highest potential (GR.9). It is necessary to restrict the model to for example 20 duties instead of all hundreds of duties.

Each of the candidates is then added to the incumbent solution in a separate instance and evaluated by the pattern evaluation model. After selecting the first candidate (GR.10), it is added to the incumbent solution (GR.11) and the compatibility is checked (GR.12). This check means for example checking if there are still flight duties available for a mixed reserve duty. If no flight duties are available, the mixed reserve duty is not feasible anymore. The pattern evaluation model then determines the quality of the pattern with this candidate added (GR.13) and the performance is stored (GR.14). Then it is checked whether all candidates are evaluated (GR.15) and if no, the next candidate is evaluated (GR.16). If yes, the best candidate is selected and added to the incumbent solution (GR.17) and this solution is set as the new incumbent solution (GR.18).

Subsequently, the GRASP method checks whether a stopping criterion is met, such as a reserve days budget (GR.19). The model could use this stopping criterion to enforce a specific maximum of reserve days or reserve duties in the pattern if the airline chooses to. If a criterion is not met, again a set of available duties is selected (GR.4) and evaluated. If a criterion is met, the best solution is chosen out of all reserve patterns generated based on its performance (GR.20). This does not have to be the final solution, as a reserve pattern with fewer reserve duties added can have a higher performance. It can also be a solution from a previous iteration with fewer reserve duties in the reserve pattern. After selecting the best solution satisfying a predetermined service level requirement (GR.20), this best solution is evaluated again extensively using the pattern evaluation model (GR.21). This extended evaluation is performed based on many more repetitions of the evaluation model. Every time the pattern optimization is run, a slightly different reserve pattern can be obtained as there is stochastic in the problem. It is recommended to run the optimization model a few times to determine the best reserve pattern.

# 3 Case Study Results

In this section, a case study performed with a major European airline is discussed. The simulation-based optimization method is compared with the reserve pattern of the airline. For the case study, a weekly flight schedule for one division at the airline is taken. The flight schedule contains about 80 flight duties per week that vary between 5 and 12 days. Additionally, the disruption probabilities for each of the flights in the flight schedule is determined based on one year of historic data for all destinations in the schedule. From this set, the flight duties that are part of a mixed reserve duty are excluded as these are secondary disruptions. The disruption probabilities are then calculated for each flight duty in the schedule.

To determine the performance of the reserve pattern generated by the simulation-based optimization method with the airline reserve pattern on two experiments. The first experiment is an unconstrained set-up for the method, which is evaluated by the total amount of reserve days and premium days required. In other words, the objective for the method is to minimize the sum of reserve and premium days given the disruption probabilities. The second experiment constrains the reserve days in the pattern by defining that the method should ensure at least as many reserve crews in the pattern as the airline solution. This experiment demonstrates if the method is able better place the reserve crews during the week than the airline solution to minimize recovery actions and thus premium days necessary.

The performance for both the airline solution and the generated reserve patterns by the GRASP method are determined by the pattern evaluation model. The settings required in the pattern evaluation and pattern optimization model for the experiments are given below:

- Pattern evaluation model number of repetitions is equal to 25000.
- Service level requirement: GRASP requirement should equal the airline solution. In other words, after the airline solution is evaluated the service level that is obtained is used as a requirement for the GRASP method.
- Flight duties in mixed reserve duties are assigned randomly.
- Stopping criterion for GRASP: for experiment 1 it is only stopped if there is no improvement in quality of the pattern, for experiment 2 it is a minimum reserve days in the pattern equal to the airline solution.
- PC used for all experiments: Dell Latitude 7480 with Intel Core i7-8650U (8M Cache, Quad Core, 1.9GHz) and 8GB DDR4 RAM.

In addition to the settings for the case study, the metrics to compare the airline solution and GRASP method solution are described below:

- **Reserve days** (days) in the reserve pattern
- **Premium days** (days) necessary after evaluating the reserve pattern
- **Unused reserve days** (days) after evaluating the reserve pattern, to get a measure on how efficiently the reserves are placed
- **Service level** (percentage) using maximum 3 flights covered with a premium per week as a measure
- **Optimization time** (minutes) for the GRASP method

This section describes first the two experiments (subsection 3.1 and 3.2), after which some sensitivity analyses on important parameters is demonstrated in subsection 3.3.

## 3.1 Experiment 1: Unconstrained reserve days

The first experiment is focused at evaluating the GRASP method with the airline solution without constraints on reserve days. First, the airline solution is simulated and evaluated which provides a service level that is used as a service level requirement for the GRASP method. The results for the first experiment can be found in Table 2.

First of all, the service level of the airline solution is 97.14% and this requirement is met by the GRASP method that has a service level of 97.34%. It can be observed that the amount of reserve days using the GRASP method is decreasing from 45 to 38, while the average amount of premium days necessary to recover the schedule from disruptions increases from 2.31 to 3.44. The main gain can therefore be found in the amount of unused reserve days: from 21.97 to 14.92 on average. Despite the increase in premium days for the GRASP method, the service level still increases slightly. Finally, the optimization time for the GRASP method is just 8.3 minutes.

Table 2: Performance measures for experiment 1 for the airline solution and the GRASP method

| **Performance measure** | **Airline** | **GRASP** | **Difference** |
|---|---|---|---|
| *Reserve days [d]* | 45 | 38 | −7 |
| *Premium days [d]* | 2.31 | 3.44 | +1.13 |
| *Unused reserve days [d]* | 21.97 | 14.92 | −7.05 |
| *Service level [%]* | 97.14 | 97.34 | +0.20 |
| *Optimization time [m]* | | 8.3 | |

From these results, it can be concluded that the GRASP method chooses a more opportunistic approach when creating a reserve pattern compared to the airline. Fewer reserve duties are planned and it relies more on other recovery options (measured via premium days) when a disruption occurs. Still, while this can cause more risks during recovery as alternatives have to be found, the service level requirement is met and even slightly better. In the end, the results show that the airline solution needs 45+2.31 = 47.31 days for reserves and recovery and the GRASP method needs 38+3.44 = 41.44 days. An improvement of 5.87 days per weekly flight schedule, which is a decrease in days of 5.87/47.31 = 12.4%. Therefore it can be said that the solution provided by the GRASP algorithm performs better than the airline solution.

## 3.2 Experiment 2: Constrained reserve days

In this second experiment, a constraint on the reserve days is added to the model. In practice, airlines use a specific reserve budget that is used to determine how many reserve days should be in the weekly pattern. Therefore, this experiment is set-up to demonstrate how the GRASP algorithm performs compared to the airline solution with at least the same amount of reserve days as a stopping criterion. Additionally, the same service level requirement as experiment 1 is used: 97.14 %.

Table 3: Performance measures for experiment 2 for the airline solution and the GRASP method

| **Performance measure** | **Airline** | **GRASP** | **Difference** |
|---|---|---|---|
| *Reserve days [d]* | 45 | 46 | +1 |
| *Premium days [d]* | 2.31 | 1.78 | −0.53 |
| *Unused reserve days [d]* | 21.97 | 20.58 | −1.39 |
| *Service level [%]* | 97.14 | 98.47 | +1.33 |
| *Optimization time [m]* | | 8.5 | |

The results for the second experiment can be seen in Table 3. The airline solution has the same results as experiment 1 as the reserve pattern is not changed. The GRASP solution however shows different results. First of all, the reserve days constraint is met with 46 reserve days in the pattern by the GRASP algorithm. It can be concluded that the GRASP algorithm was not able to find a better reserve pattern using only 45 reserve days, but 46 days were necessary. The main result from this experiment is the amount of premium days necessary to recover the rosters, a decrease from 2.31 days to 1.78 days. The decrease as a percentage is 0.53/2.31 = 22.9%. This also results in an improvement in service level, from 97.14 % to 98.47 %. This decrease in premium days necessary per week means that recovery with alternative options is less often necessary than the airline solution. The amount of unused reserve days decreases slightly from 21.97 days to 20.58 days. Finally, the optimization time is similar to the result from experiment 1 with 8.5 minutes.

This second experiment demonstrates the capability of the GRASP algorithm to better place the reserve duties where they are necessary. Additionally, about the sum of reserve days and premium days necessary for recovery is similar for the airline solution and GRASP solution. This is caused by constraining the reserve days leading to high number of unused reserve days. Moreover, the reserve days constraint demonstrates the use in practice and compared with that the amount of premium days necessary is decreased.

## 3.3 Sensitivity Analysis

In addition to the experiments performed with the method, sensitivity analyses are performed around certain key parameters of the method. The three parameters that are analyzed are the following: flight schedule size (problem size), mixed reserve assignment policy in the evaluation model, and service level. These analyses are described below. To compare the results in the analyses, one KPI is defined as the objective. This objective is the sum of the reserve and premium days when using the reserve pattern created by the method. All of the results are compared based on this value rather than all 5 values as used in the experiments. It does not affect the conclusions drawn in these analyses.

### 3.3.1 Flight Schedule Size

The first parameter that is analyzed is the problem size or flight schedule size. As the reserve pattern that needs to be generated depends on the amount of flights in the flight schedule, the scalability of the GRASP algorithm and the simulation model can be tested with this analysis. It is tested by multiplying the amount of flights in the flight schedule up to 5 times. This multiplication of flights is performed by copying the flight schedule and adding slight variations. The results can be seen in Figure 6. The average objective function value is a linear function with the amount of flights in the schedule and the average run-time slightly increases with each multiplication, but with a multiplication factor of 5 there are already 400 flights in the schedule. With optimization problems the run-time often increases exponentially, so this analysis demonstrates that the GRASP method in combination with the evaluation model can be used effectively for large problems. It should be noted that the run time for multiplication factor 1 is lower than the experiments, which is caused by executing less repeats of the method in this analysis.

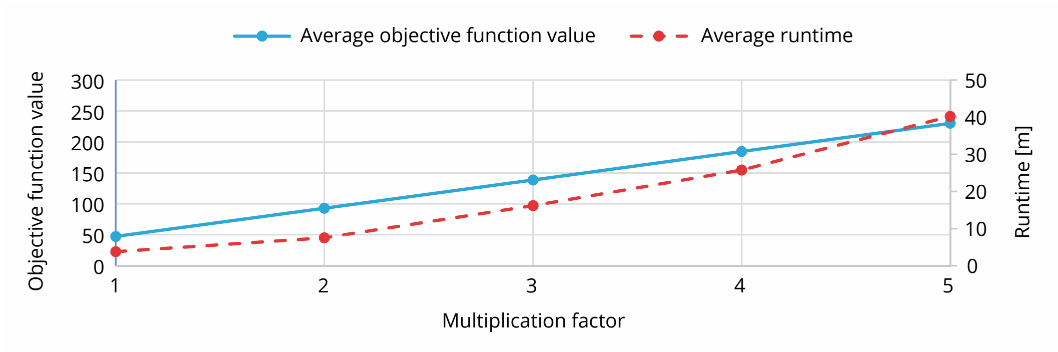


Figure 6: Objective function value comparisons between different input schedule sizes in the evaluation model.

### 3.3.2 Mixed reserve assignment policy in the evaluation model

The second parameter that is analyzed is the reserve assignment policy in the evaluation model for mixed reserve duties. As often multiple flight duties can be used in a mixed reserve duty, a selection has to be made. The flight duties that can be used can have different disruption probabilities by themselves which affects the evaluation method. This sensitivity analysis is performed to determine whether the policy for assigning flight duties to the mixed reserve duties is affecting the objective function value or run time. The standard policy used is to randomly pick a flight duty between all possible flight duties, but the alternative policy would be to pick the flight with the lowest disruption probability first. This alternative policy could be applied so that the flight duty in the mixed reserve duty has a lower disruption probability. The results of the analysis can be observed in Table 4. There are very minimal differences in average objective value and average run time between the different assignment policies. It can be concluded that both methods can be used and the equal probability is therefore chosen.

Table 4: Comparison between mixed flight assignment policies in the evaluation model.

| **Parameter value** | **Average objective value** | **Average run time** [s] |
|---|---|---|
| *Equal probability* | 47.34 | 25.1 |
| *Lowest disruption first* | 47.31 | 25.2 |

### 3.3.3 Service level

The third parameter that is analyzed is the service level. The service level is a measure of how often a number of premium days used for recovery is exceeded in a simulation. In Figure 7 the optimal objective function value (7-a) and the corresponding reserve budget (7-b) and number of premium days (7-c) are shown for a range of service level constraint values. Each line in the figures is a different amount of premium days. For example, the blue line (0) indicates the relation between objective function value and service level for a premium day threshold of zero. So the service level in that case means the amount of weeks in the simulation that more than 0 premium days were necessary for recovery. The higher this amount of premium days that can be used within a service level, the more reserve budget is necessary to recover flight disruptions. This can be seen in all figures, where the objective function value and reserve budget are higher for lower amounts of premium days in the service level requirement. Additionally, to reach a service level close to one, a large amount of reserve budget is necessary as almost no week can be flown with premium day recovery actions higher than the requirement. It demonstrates the variability of service level with respect to the objective function as defined here. It does not affect the experiments as a service level requirement is chosen based on the airline solution.

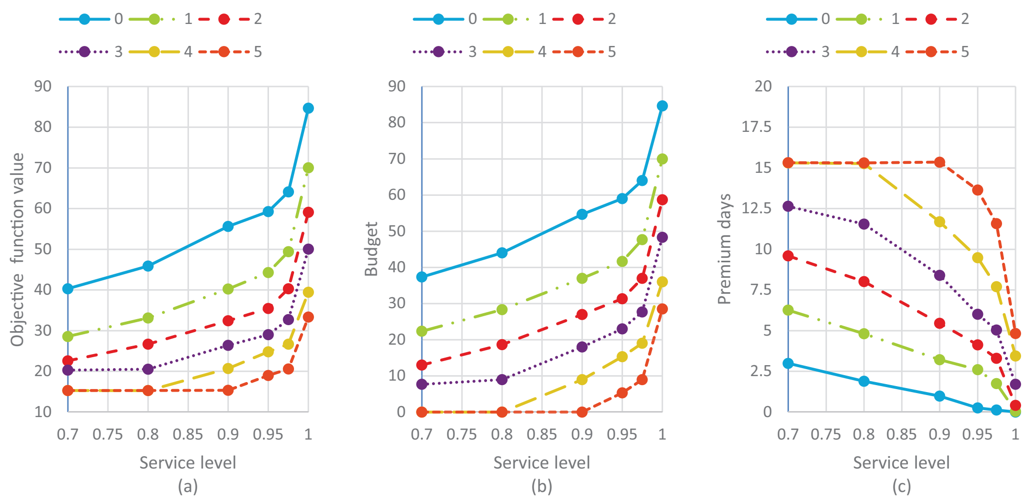


Figure 7: Objective function value comparisons between different values for the service level constraint for the GRASP method. Each line represents a number of premium days that may be flown per week.

## 4 Conclusions

Crew schedule recovery is an expensive and complex process for an airline. Disruptions are uncertain and recovering them means either proactively creating more robust schedules or reactively trying to find a solution in the rosters that could lead to premium compensation for the crew. In this paper, we demonstrated a novel method to dynamically create reserve patterns for airline crew that can be used proactively during the crew rostering process. The simulation-based optimization approach proved successful compared to the airline process in two experiments. In a first experiment, it is demonstrated that the sum of reserve days and premium days could be decreased with 12.4% per week. This is obtained by having less reserve duties in the pattern, but this also lead to more often premium compensation. In a second experiment, it is found that while keeping at least the same amount of reserve days in the pattern, the premium compensation could be decreased with 22.9%. This experiment shows that the reserve duties could be placed more efficiently in the pattern compared to the airline solution, which leads to less unused reserve duties and less premium compensation. Additionally, is is found the method can also be used for large problem sizes as the run time does not increase drastically for flight schedules up to 5 times larger than the experiments. In the context of the airline, the method can be used to automatically and dynamically create better reserve patterns based on the current expected reserve demand.

On top of the dynamic elements of the method, the model also uses two new features for reserve pattern generation: mixed reserve duties and variable length for reserve duties. This means that especially for long-haul crew scheduling reserve patterns can be generated more efficiently. The method could be extended to also take this into account additional short-haul recovery options (such as splitting flight duties). However, this will increase the run time for the reserve pattern evaluation model as more recovery options have to be evaluated. Additionally, the evaluation model now assumes flights are disrupted chronologically and only at one point in time. This approach is very fast to evaluate the schedule, but in reality flights can be disrupted in a non-chronological order which could lead to additional run time. Lastly, the option of cancelling a flight when it is disrupted is not included in the evaluation model, while this could be used in practice occasionally.

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