AIRLINE RESCHEDULING WITH AIRCRAFT UNAVAILABILITY PERIOD

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By

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We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

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Airlines design their initial schedules under the assumption that all resources will be available on time and flights will operate as planned. However, some disruptions occur due to mechanical failures and unexpected delays of maintenance, making the aircraft unavailable for a certain period of time. These deviations from the initial plan result in high operational costs in addition to the serious inconveniences experienced by passengers. In the literature, it is a common practice to develop sequential approaches at which aircraft and passenger recovery problems are consecutively handled. In this study, we address them simultaneously and propose an integrated math-heuristic framework with an aim to maximize the profit of the airline. In the first phase, we develop a nonlinear mixed integer optimization model for aircraft recovery and utilize conic programming approach to mitigate computational difficulty. We incorporate cancellation and re-routing decisions for flights utilizing cruise time controllability which results in nonlinear fuel burn and CO_2 emission cost functions. In the second phase, we develop a passenger recovery algorithm that makes individual itinerary based recovery decisions under the seat capacity restrictions and provide realistic cancellation cost formulations. Lastly, we propose an integrated search algorithm to maintain the integration between two phases through fixing assignment variables in the first phase. We compare the performance of the proposed algorithm to the base policy where all disrupted flights are directly cancelled. We observe improvements in terms of profit and the number of overnight passengers.

Keywords: Disruption management, integrated recovery, conic quadratic mixed integer programming, cruise time controllability.

ÖZET

YERDE KALAN UÇAKLARIN YENİDEN ÇİZELGELEME PROBLEMİ İÇİN BÜTÜNLEŞİK BİR YAKLAŞIM

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Hava yolu şirketleri uçuş çizelgelerini tüm kaynakların zamanında hazır olacağı ve uçuşların planlandığı gibi gerçekleşeceği varsayımı altında hazırlar; ancak bazı uçaklar mekanik aksaklıklar ve planlanmış bakımların beklenmedik şekilde uzaması sonucunda yerde kalır. Uçağın yerde kalmasıyla mevcut çizelgede meydana gelen sapmalar yüksek operasyonel maliyetlere ve yolcu memnuniyetsizliğine yol açar. Literatürde genel olarak önce uçak, devamında ise yolcu çizelgelerini onaran ardışık yaklaşımlar geliştirilmiştir. Bu çalışmada ise uçak ve yolcu onarımını birlikte ele alan, hava yolu şirketinin kârını en çoklamayı hedefleyen bütünleşik bir yaklaşım önerilmektedir. İlk aşamada uçak onarımı için doğrusal olmayan karmaşık tamsayılı bir model geliştirilmiş ve konik programlama ile çözülmüştür. Bu modelde değişken seyir sürelerinden yararlanılarak uçuşlar için iptal ve yeniden rotalama kararları birlikte ele alınmıştır. Seyir sürelerinin kontrol edilebilir olması doğrusal olmayan yakıt tüketim ve CO_2 emisyon maliyet fonksiyonlarını beraberinde getirmiştir. İkinci aşamada ise uçakların koltuk kapasitesi kısıtı altında her yolcu güzergahını bireysel olarak değerlendirilip onarım kararı veren bir yolcu onarım algoritması çalıştırılmakta ve uçuş iptali durumunda gerçekçi bir maliyet hesabı yapılmaktadır. Son olarak, bahsedilen aşamalar arasındaki entegrasyonu sağlamak için bütünleşik bir algoritma önerilmiştir. Bu bağlantı ilk aşamadaki atama değişkenlerinin sabitlenmesiyle sağlanmıştır. Geliştirilen bütünleşik yaklaşımın verdiği çözüm ile yerde kalan uçağın tüm uçuşlarının iptal edildiği temel çözüm karşılaştırıldığında maliyet ve onarılan yolcu sayısı açısından iyileştirmeler gözlemlenmiştir.

Anahtar sözcükler: Aksaklık yönetimi, bütünleşik çizelge onarma, konik karmaşık tamsayılı programlama, kontrol edilebilir seyir zamanları.

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Chapter 1

Introduction

The aim of the Integrated Aircraft and Passenger Recovery Problem is to come up with a schedule which maximizes the profit of the airline while also mitigating the passenger inconvenience in the case of a disruption. Considering the short response time requirement as well as the problem setting with numerous parameters and decision variables, it is challenging to generate such a comprehensive recovery solution. The complexity of the problem requires the use of optimization tools in this large-scale system. In this study, in order to solve this integrated problem, a math-heuristic algorithm is developed and implemented in Java with a connection to IBM ILOG CPLEX, a commercial optimization software.

1.1 Motivation

Air transportation fosters mobility and provides a crucial level of connectivity on a global scale. As being a convenient transportation option, the number of passengers who utilize air travel maintains positive growth rates. Due to the high and increasing demand, competition between airlines has intensified in recent years. Each airline aims to capture a greater portion of the market demand and tries to use its resources in the best possible way to enhance the profitability of its operations.

Due to the competitive nature of the airline industry, tight schedules are designed and aircraft are utilized as much as possible to generate more profit. Airlines design their initial schedules under the assumption that all required resources will be available on time and flights will operate as planned. However, some irregularities might occur during actual operations and original schedules can easily be disrupted. Bratu and Barnhart [1] discussed main sources of disruption and highlighted the effect of airline resource shortages including the absence of aircraft and crew members. That is to say, mechanical failures can be observed and aircraft might need to undergo unscheduled maintenance making the aircraft unavailable for a period of time. Also, crew members may not show up due to sickness or may arrive late. Moreover, airport conditions and airspace capacity can be restrictive. All of these possible irregularities, so-called disruptions, prevent airlines from continuing their original schedules.

Among airline resources, aircraft is the scarcest one and hence even minor perturbations in aircraft schedules might result in severe disruptions. Depending on the unavailability duration, flight delays and cancellations become inevitable. A recent example is that after two fatal crashes of Boeing 737 Max aircraft in October 2018 and March 2019, aviation authorities grounded the entire fleet of that type as a safety precaution. The fleet is not permitted to fly until further notice. This capacity loss critically disrupted initially generated flight schedules of airlines. In particular, Southwest Airlines, Air Canada and American Airlines face the most disruption as they have the highest number of Boeing 737 Max in their fleets [2]. In another recent example, a major US airline has faced unscheduled maintenance disruptions arising from contract negotiations. In such scenarios, unless real-time and efficient recovery solutions are readily available, aircraft shortages may result in substantial loss of profit and decrease level of service for airlines.

In cases of disruptions, holding departure times, i.e. delaying flight legs, cancellations, swapping aircraft and crew members are the most common recovery actions. It is the responsibility of Airline Operations Control Center (AOCC) to take such actions and manage operations of aircraft, crew and passengers centrally. Interdependencies between different entity types make it even more challenging to generate a comprehensive recovery solution. The complexity of airline networks as well as the high operational costs necessitates the use of optimization tools in this large-scale system. Due to the quick response requirements and large number of variables, it is not easy to propose a single formulation for the integrated airline recovery problem. Instead, it is a common practice to adopt sequential approaches which recover aircraft, crew and passenger schedules respectively.

In the sequential schedule recovery framework, passenger recovery corresponds to the final stage. In prior stages, passenger reallocation and spill options are not considered. Without using a fully integrated approach, it is not possible to find the optimal trade-off between operating and passenger-related costs. Due to the lack of integration, passengers might experience large impacts of re-timing and cancellation decisions which are made in advance. Passengers may face long delays or miss their onward connections. On the other hand, airlines should place a special emphasis on passenger convenience in order to maintain a competitive edge in the market and to increase profit in the long run.

1.2 Contributions

In this study, we aim to develop a framework to help airlines in handling schedule perturbations caused by the unavailability of aircraft. Instead of adopting a sequential schedule recovery framework as commonly done in literature, we address aircraft and passenger recovery problems simultaneously. We work on this integrated problem within the context of aircraft unavailability period. This is the crucial contribution of our study to the disruption management literature. When an aircraft becomes unavailable, it might not be possible to operate all flights. In this regard, we consider utilizing exchange of aircraft and cruise time controllability as recovery tools along with the cancellation option. We propose a novel math-heuristic algorithm to solve the integrated airline service recovery problem.

In the first two phases, we solve aircraft and passenger recovery problems, respectively. Given the results, we fix some aircraft assignment variables in the first phase to ensure operation/cancellation of certain flights and thereby maintain the integration between two phases. This continues in an iterative manner and terminates at a predetermined time limit.

Each passenger in the system can be characterized by the itinerary that she/he follows. An itinerary might either be a single flight leg or a composition of multiple legs. Therefore, passengers who travel on the same flight do not necessarily belong to the same itinerary. There might be continuing flights for some passengers or some passengers might have already reached to the final destination. In this study, we work on integrated networks at which aircraft routings and passenger itineraries are superimposed. Due to the interdependence among entities, cancellation or re-timing decisions which are made for flight legs directly affect itineraries. As a significant contribution, we differentiate between direct and connecting passengers and make individual passenger itinerary based recovery decisions under seat capacity restrictions. In the case of a disruption, we prioritize affected passengers and first recover the ones who might bring more profit to airline. This allows us to use limited resources, in our case available seats, in a smarter way.

Due to the high level of competition in airline industry, it is significant to quantify the passenger-related disruption costs and measure the inconvenience if a flight is cancelled. In disruption management literature, cancellation cost is calculated by multiplying a penalty coefficient with the number of passengers on the flight. However, this does not correspond to the actual value. Another contribution of our study is that we calculate the actual profit value and provide actual cancellation cost formulations. In the first phase of our proposed algorithm, the mathematical model developed for aircraft recovery gives an approximate profit value. This is because the model does not take passenger itineraries and re-accommodation options into account. However in the second phase, making individual passenger itinerary based decisions allows us to update the profit in a dynamic manner. By adjusting the objective for each itinerary, we end up with actual calculations and thereby measure the cost of cancellation.

In sum, the main contributions of this study can be listed as follows:

- We consider the integrated aircraft and passenger recovery problem within the context of aircraft unavailability period.
- We devise a novel math-heuristic algorithm which makes individual passenger itinerary based recovery decisions under seat capacity limitations.
- We propose actual profit and cancellation cost formulations depending on passenger itineraries.

1.3 Overview

The remainder of this thesis is organized as follows: In the next chapter, a comprehensive literature review surrounding the disruption management is provided. Extensive information regarding cruise time controllability, tools for proactive and reactive disruption management are given.

Chapter 3 is devoted to the problem definition and the math-heuristic algorithm. At the beginning, the framework of the problem is analyzed. Flight blocks which are the building blocks of the schedules that we use for the computational experiments are described. The math-heuristic algorithm devised to solve the integrated recovery problem is introduced. The objective, possible decisions which can be given for disrupted blocks and main stages of the algorithm are briefly explained. Lastly, calculation of the fuel consumption and CO2 emission during the cruise stage are provided.

Following the problem definition, the math-heuristic algorithm is explained in detail in Chapter 3. First, mathematical model for aircraft recovery is given as Phase I. Sets, parameters, decision variables and the mathematical formulation are explicitly stated. For the second phase, steps of the passenger recovery algorithm as well as the calculation of the actual profit value are described. Then the integrated search algorithm which provides the connection between these two phases is explained in detail. Finally, a numerical example is provided to highlight the important steps of the proposed algorithm.

In the computational study chapter, Chapter 4, performance of the math-heuristic algorithm is tested. Different strategies are defined by allowing certain recovery actions in the first place. Then performance of these strategies are analyzed under four different disruption scenarios. Profit of the airline and the number of overnight passengers are determined as performance measures. Recovery solutions are evaluated based on these criteria. Finally in Chapter 5, concluding remarks and future research directions are provided.

Chapter 2

Literature Review

Airline schedule planning is a comprehensive process which involves schedule design, fleet assignment, aircraft routing and crew scheduling. Firstly a flight schedule needs to be determined regarding the forecasts for demand. Then, fleet assignment problem is solved, which aims to assign fleets or aircraft types to the flight legs so as to minimize the operating costs. Next, aircraft routing is done to produce a sequence of flights or routes to be flown by individual aircraft. Finally, crew members are assigned to each flight segment of a given time period. All the planning stages are completed in advance. Therefore, on or before the day of the operation, some irregularities might occur causing disruptions. In order to deal with them, several approaches are proposed in the literature. These approaches can be categorized into two depending on the timing of handling disruptions: (1) Preventative actions can be taken and disruptions can be addressed proactively; (2) Following a disruptive event, flight schedules, aircraft routings, crew pairings and passengers can be repaired. Kohl et al. [3] provided an overview of planning processes in the airline industry and described the general framework of disruption management. Reviews on airline disruption management can be found in Ball et al. [4] and Clausen et al. [5] as well. In this section, we provide a detailed literature review about proactive and reactive disruption management as well as cruise time controllability.

2.1 Proactive Disruption Management

During the schedule design phase, airlines generate tight schedules by maximizing the utilization of aircraft with an aim to fulfill the market demand and maintain a competitive edge. However, such schedules can easily be disturbed and become unstable due to cancellations and delays. In order to minimize the impact of propagated delays, mitigate passenger disruptions and reduce operational costs, it becomes crucial to design schedules which are less sensitive to disruptions. Hence, there is an emerging trend in the literature towards robust scheduling.

Rosenberger et al. [6] presented a robust fleet-assignment model (FAM). First, they defined the flight cycle as the sequence of flights that begins and ends at the same airport. They used the cancellation of a cycle as a way to generate slack time in the schedule. In the proposed model, they isolated hub airports. That is, they avoided generating routes which begin at a hub, ends at a different hub airport. Using hub-and-spoke network structure, they showed that FAM which have limited hub connectivity and contain many short cancellation cycles in aircraft rotations yield more robust schedules. Lonzius and Lange [7] conducted an empirical study to investigate the impact of limiting hub connectivity and using swap mechanism on air traffic delays. On the other hand, Ageeva [8] developed a robust aircraft maintenance model at which there exist overlapping routes within an aircraft rotation. Overlapping routes which contain common airports enabled swap of aircraft during operations and hence increased the flexibility for controllers.

Smith and Johnson [9] introduced the concept of station purity which corresponds to putting a limit on the number of fleet types serving a particular station. Since each fleet type consists of crew-compatible families, it is possible to swap aircraft or crew members within the same type for operational or profitability purposes. They developed a FAM at which station purity is imposed. This enabled them to generate more swap opportunities in the case of a disruption, to limit aircraft dispersion in the network and hence increased robustness of the schedule. Due to the large problem size, they proposed a solution approach based on station decomposition and solved the fleet assignment problem using a column generation algorithm.

As an alternative to swap mechanism, adding extra buffer times between flight legs can be a way to handle uncertainties in airline operations. Note that the delay of a flight might sustain in the downstream flights of the same aircraft and this might result in misconnection of passengers. Considering the unpredictable nature of irregularities, buffer times are intended to absorb the delays and reduce the likelihood of delay propagation. Wu [10] incorporated buffer times into the existing schedule and proposed a sequential optimization algorithm with an objective to enhance the operational reliability of the schedule. He considered each flight in an aircraft routing sequentially. He took historical operating delays and total available slack time into the account while adding buffer times. He run simulation models to measure the performance of new schedules.

Lan et al. [11] presented two novel approaches to minimize passenger disruptions and achieve robust schedules. In the first approach, they provided a mixed integer model which minimizes total propagated delay by allowing changes in aircraft routings. Then in the second part of their study, they considered passenger itineraries as well. They aimed to minimize the number of connecting passengers who miss their onward flights due to insufficient connection time between their flights. They allowed re-timing departure times within a small time window. For both parts, they proposed branch-and-price algorithms to solve realistic-size problems.

Dunbar et al. [12] addressed aircraft routing and crew assignment problems simultaneously. With this integrated approach, they accurately estimated the overall propagated delay by capturing the dependencies between aircraft and crew members. They introduced a new approach to minimize the total cost incurred due to propagated delay in this integrated framework. In a similar study, Liang et al. [13] worked on the robust weekly aircraft maintenance routing problem and the tail assignment problem together. Again the objective was to minimize the total expected propagated delay (EPD). They proposed a new weekly line-of-flights network model so as to handle nonlinear cost formulations of EPD. By this means, they extended the work of [12] by providing more accurate computation of EPD. They proposed two-stage column generation approach to efficiently solve this problem.

2.2 Reactive Disruption Management

Considering the uncertainty in operations, airlines design robust schedules which are less susceptible to disruptions. However, proactive approaches might not be sufficient to absorb delays and recover all of the entities which are aircraft, crew members and passengers. Therefore, within the scope of reactive disruption management, airlines take recovery actions to reduce costs resulting from disruptions and to maintain passenger convenience following the occurrence of an unforeseen event. As AOCC are expected to come up with real-time solutions, it is common to follow sequential approaches which recover each entity type in order. In recent literature, integrated methodologies are proposed so as to capture dependencies within the system.

2.2.1 Aircraft Recovery

Since aircraft is the scarcest resource, many studies have been conducted about the aircraft recovery problem. Teodorovic and Guberinic [14] first introduced the concept of aircraft unavailability and considered a disruption scenario at which one aircraft is excluded from the fleet for a period of time. They ignored maintenance constraints and assumed fleet commonality; that is, all aircraft have the same capacity and technicality. With an objective to minimize total passenger delay, they developed a model to operate all flights with one less aircraft. The model gives reassignment and re-timing decisions for flights and it is solved by branch and bound methods. As an extension to [14], Teodorovic and Stojkovic [15] again worked on disruption scenarios with aircraft shortage. First, they developed an approach to minimize total number of cancelled flights and then searched for a schedule which requires same number of cancellations but yields the minimum total passenger delay. They proposed a greedy heuristic algorithm to solve this lexicographic optimization problem.

In comparison to other airline resources such as crew members, number of aircraft is considerably smaller. Hence, the size of problem instances is appropriate for network flow formulations. Jarrah et al. [16] presented two minimum cost network flow models: one for delay and one for cancellation. In addition to departure time holding and flight cancellation options, they allowed aircraft swapping and utilization of standby aircraft as well. Besides, cost terms for re-timing or cancelling flights were determined with respect to a dis-utility function defined by the authors. Both models were solved based on the successive shortest path method and gave the set of delayed and cancelled flights respectively. The major drawback of this study is that the interaction between re-timing and cancellation options cannot be captured since the models are solved separately, not in a single decision process. Cao and Kanafani [17] extended the work [16] by incorporating ferrying and multiple aircraft swapping.

As an alternative approach, time-space networks can be used to handle the perturbations occurred due to aircraft shortage. Yan and Yang [18] utilized time-space representation assuming a single fleet type. They built pure network flow models for cancellation and ferrying of spare aircraft and solved them using the network simplex algorithm. Moreover, they developed more comprehensive approaches which allow flight delays as well. In order to add this feature, time-shifted copies of the initial flights were added to the network. They applied Lagrangian relaxation with sub-gradient method to solve these network flow models with side constraints. Yan and Tu [19] extended this work to multi fleet recovery problem.

Rosenberger et al. [20] modeled the aircraft recovery problem as a set-packing problem in which each flight leg is either cancelled or takes place in exactly one route. They attempted to find a set packing that minimizes the cost of rerouting and cancellation. Instead of evaluating all possible routes, they reduced the problem size by developing an aircraft selection heuristic which determines the subset of aircraft to reroute.

Abdelghany et al. [21] proposed a decision support tool for aiding flight controllers during irregular operations. They integrated a schedule simulation model and a resource assignment optimization model to be used within a rolling horizon scheme. The schedule simulation model detects future flight delays based on resource availability and legality rules whereas the optimization model is responsible for determining recovery actions. This tool enables control centers to generate proactive recovery plans that integrate all airline resources and avoid potential delays in advance.

2.2.2 Passenger Recovery

Passengers are directly affected from re-timing and cancellation decisions which are made for flights. Seelhorst [22] and Xiong and Hansen [23] discussed the connection between passenger-related parameters and airlines' flight cancellation decisions. Since passenger schedules highly depend on other resources (aircraft and crew members), it is not reasonable to consider them as independent entities. Therefore in the literature, passenger recovery problem is integrated with aircraft and crew recovery problems.

Lettovsky [24] is the pioneer of the integrated recovery research. Aircraft, crew and passenger recovery problems were jointly addressed for the first time. He presented a mixed integer linear programming model, aimed at maximizing profit of the airline. To efficiently solve this large-scale optimization problem, he used a decomposition scheme. That is, instead of considering all decision variables and constraints simultaneously, integrated problem was partitioned into three sub-problems corresponding to each of the resources. Sub-problems were solved at different stages and related cuts were added to master problem accordingly. Similarly, Petersen et al. [25] provided a fully integrated formulation and proposed an algorithm based on Bender's decomposition to solve it.

Bratu and Barnhart [1] developed a passenger centric approach to find the optimal trade-off between passenger disruption and airline operating costs. They discretized time, generated flight copies having different departure times and proposed a multi-commodity network flow model that determines delays and cancellations. In this model, they defined a binary decision variable which indicates whether an itinerary is disrupted or not. The aim was to minimize operating costs, like traditional models, but the disruption costs experienced by passengers were incorporated into the objective function with this variable as well. As in [1], Thengvall et al. [26] devised a network model with side constraints to resolve aircraft shortages while considering disruption costs of passengers. Different from other studies, they focused on stability aspect of rescheduling. To put it another way, they set an objective to find a schedule with minimal deviations from the original one. They solved LP relaxation of the network formulation and used rounding-heuristic when integrality is not achieved.

For passenger recovery, Zhang and Hansen [27] suggested real-time intermodal substitution strategy which corresponds to the utilization of ground transportation modes as an alternative to air transportation. They built a large-scale non-linear mathematical model to be implemented in hub-and-spoke networks. In addition to delay and cancellation options, it was allowed to substitute flights with buses in hub airports. The objective was to mitigate congestion at hub airports while minimizing cost of passenger inconvenience and transportation. They proposed an approximation algorithm which to get a solution and reduce computation time.

Jafari and Zegordi [28] incorporated passenger related decisions to the formulation provided in [21]. They presented an assignment model which recovers aircraft and disrupted passengers simultaneously using a rolling horizon framework. They set an objective to minimize the total cost which includes aircraft assignment, delay, cancellation and disrupted passenger cost terms. In addition to re-timing, cancellation and aircraft swapping recovery tools, they considered overflying, ferrying and utilization of reserve aircraft while generating a recovery plan.

For integrated aircraft and passenger recovery problem, Bisaillon et al. [29] proposed a large neighborhood search algorithm which consists of three phases: construction, repair and improvement. In the first phase, a feasible rotation for each aircraft was constructed by changing aircraft type assignment, cancelling or delaying flights to some extent. In the repair phase, disrupted passenger itineraries were re-accommodated to alternative paths by repeatedly solving shortest path problems. In the last phase, it was allowed to delay flights for a certain amount of time in an attempt to accommodate additional passengers while also preserving the feasibility. If a cost improvement was obtained, then the incumbent solution was updated. As long as the time limit was not violated, maximum allowable delay was updated and new accommodation options were investigated. Sinclair et al. [30] extended the work of [29] by introducing a number of refinements in each phase.

Jozefowiez et al. [31] also devised a three-phase algorithm for the integrated flight, aircraft and passenger rescheduling problem. In order to obtain an initial feasible solution, all disrupted flights and itineraries were removed from the original plan in the first phase. Compared to previously mentioned algorithms, feasibility was maintained in a considerably shorter amount of time. Next, passengers who were initially assigned to disrupted itineraries were reallocated to new ones so that they can reach their destination airports. As the final step, new flight legs were generated and inserted to existing aircraft rotations to re-accommodate passengers. This methodology outperformed the approach provided in [29].

Maher [32] drew an analogy between knapsack and passenger recovery problems. In this context, aircraft with a fixed seat capacity corresponds to a knapsack whereas passengers represent the items to be put into the knapsack. He presented a novel approach at which cancellation variables are modeled as knapsack variables to demonstrate the possible reallocation options for passengers in the case of a cancellation. He aimed to find the optimal redistribution of passengers from cancelled legs to alternative operating flights. He applied column-and-row generation solution approaches to reduce the computation time.

In a recent study, Zhang et al. [33] proposed a three-stage math-heuristic framework to solve joint aircraft scheduling and passenger itinerary recovery problem in sequential manner. In the first stage, new aircraft rotations were determined by using multi-commodity network flow based formulations. Then, flights were rescheduled by minimizing the cost incurred due to disrupted passenger connections. At the last stage, new itineraries were evaluated to re-accommodate disrupted passengers with the aim of minimizing delay and cancellation costs.

2.3 Cruise Time Controllability

A flight is composed of three main phases: climb, cruise and descend. Cruise corresponds to the longest phase of a flight at which most of the aircraft's fuel is burned. For schedule design, cruise times are determined under the assumption that aircraft will be operated at their maximum range cruise (MRC) speeds. Flying at MRC speed is the most economical option as it requires the least amount of fuel to travel a particular distance. On the other hand, speeding up the aircraft saves time, opens up space in the existing schedule and reduces time-related costs. In this regard, it is a crucial tool for recovery.

Cook et al. [34] introduced delay recovery opportunities which become available by speeding up flights to some extent. They focused on the trade-off between reducing fuel cost and environmental impact versus reducing delays. In order to quantify this, they defined a cost index parameter which calculates the ratio of time-related costs to fuel-related costs dynamically. Dynamic estimation of cost terms was intended to aid airlines to control cruise speeds and manage flight delay costs.

Aktürk et al. [35] put an emphasis on flight time controllability and its environmental implications while considering the trade-off between delay minimization and fuel consumption. Although higher cruise speed allows recovery in a shorter time horizon, it leads to higher fuel burn and CO_2 emission. Therefore they developed a nonlinear mixed integer recovery optimization model which takes the cruise speed as a decision variable and adopted a conic quadratic optimization approach to mitigate computational difficulty.

Duran et al. [36] proposed a robust airline scheduling model considering the uncertainty of block-times. Cruise times were accepted as controllable variables whereas non-cruise times were designated to be random variables. In an attempt to obtain robust schedules, they used both idle time insertion and aircraft speed control while satisfying minimum passenger connection service level. Uncertainty associated with the random variables was modeled with chance constraints which were expressed using second-order conic inequalities. Gurkan et al. [37] also allowed the passenger misconnection up to a certain probability. To that end, chance constraints and second-order conic reformulation were used as in [36]. In this study, they integrated robust schedule design, aircraft fleeting and routing problems while using cruise speed control. As an extension to this study, Şafak et al. [38] attacked the same integrated problem and devised a two-stage algorithm that solves aircraft-path assignment and robust schedule design sequentially.

Arıkan et al. [39] addressed the integrated aircraft and passenger recovery problem. In addition to traditional recovery actions, they added cruise time controllability into their solution space. They formulated a conic quadratic mixed integer programming model which considers aircraft and passenger related costs simultaneously. The objective was to find the optimal trade-off between cost components: delay cost for aircraft and passengers, spilled passenger cost, swap cost, and increase in fuel cost. They measured the performance of integrated aircraft–passenger recovery approach by comparing it with push-back recovery plan. Later, Arıkan et al. [40] extended the flight network representation proposed by Sherali et al. [41] and used it as an alternative to traditional time-space network scheme. They controlled arrival and departure times with continuous variables and hence eliminated the disadvantage of discretization in re-timing decisions. Moreover, they integrated recovery decisions for all entity types: aircraft, crew members and passengers. Inclusion of all entities to the same network representation provided an advantage while identifying the interdependencies between them.

2.4 Summary

Airlines design their initial schedules relying on the assumption that flights will operate as planned and all resources will be available on time. However, on or before the day of operation, some disruptions might occur due to irregularities including adverse weather conditions, mechanical failures and maintenance delays. In order to lower the operational costs and maintain the passenger convenience, disruption management becomes a crucial field in the literature. Proactive and reactive models are developed to handle disruptions.

Robust optimization which helps being prepared for the unexpected flight delays is widely studied in the literature. The objective is to generate schedules which are less sensitive to disruptions. In addition to the operational cost, total propagated delay and the number of disrupted passengers are used to measure the robustness of a schedule. It is a common approach in the literature to make decisions regarding fleet re-assignment, flight re-timing and addition of buffer times into the existing schedule.

Reactive disruption management is another stream in the literature. Instead of taking preventative actions, recovery plans are generated following a disruptive event. Earlier studies mostly address aircraft recovery problem since aircraft is the scarcest resource. For the other entities, crew members and passengers, sequential approaches are adopted. In the recent years, passenger convenience has attained more importance and it becomes crucial to capture dependencies within the system. Therefore, there is an emerging trend towards developing integrated recovery approaches.

In this study, we work on airline rescheduling within the context of aircraft unavailability period. We address integrated aircraft and passenger recovery problem and contribute to the reactive disruption management literature by proposing a novel math-heuristic algorithm.

Chapter 3

Problem Definition and the Math-heuristic Algorithm

In this section, we provide a background information about the problem setting and explain the structural concepts. In an attempt to help airlines in handling disruptions which occur due to unavailability of aircraft, we introduce our math-heuristic algorithm.

3.1 Problem Definition

In this study, we work on integrated aircraft and passenger schedule recovery problem and deal with disruption scenarios which stem from the unavailability of aircraft. We use a schedule which is constructed with respect to hub-to-spoke paradigm and utilize flight block structure. A *block* can be defined as a set of flights which involves an initial outbound flight from hub to a demand point, its return flight to hub and all flights in between. Note that the aircraft which is scheduled to operate a particular block is at hub airport at the beginning and at the end of each block. It is important in terms of keeping track of aircraft's location. In this study, we consider disrupted flights in block structure and evaluate each block as a whole. That is to say, any cancellation decision given holds for the rest of the flights within the same block.

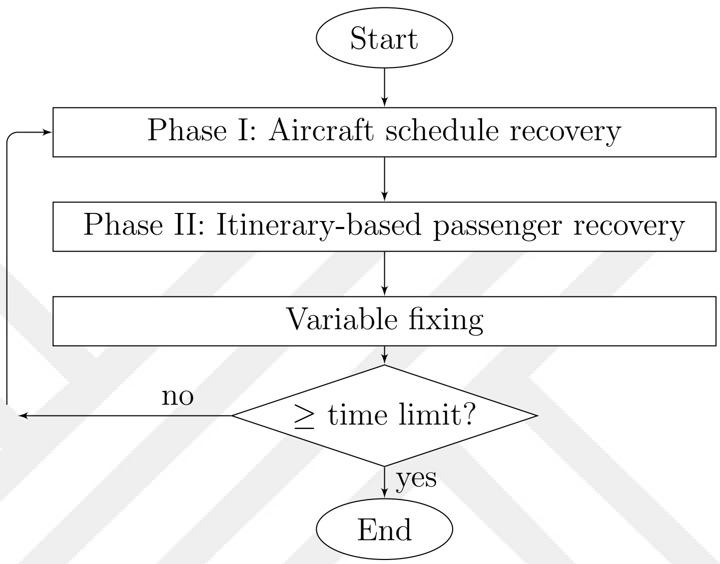

Figure 3.1: Flow chart of the Math-heuristic Algorithm

Our objective is to maximize the profit of airline while mitigating passenger dissatisfaction. To that end, we propose a math-heuristic algorithm which is depicted in Figure 3.1. In the first phase, we develop a mathematical model to solve aircraft recovery problem. We consider recovery actions (cruise time controllability and exchange of aircraft) along with cancellation. In this regard, three decisions can be given for a disrupted flight block: (1) It can be accommodated into the existing schedule by adjusting cruise times; (2) it can be flown by another aircraft after an exchange of unavailable aircraft and an operating one; or (3) it can be cancelled. As we work on integrated networks where passenger itineraries and aircraft routings are superimposed, we put a special emphasis on passengers in the second phase. We make individual passenger itinerary based recovery decisions and calculate the actual profit value. Depending on this calculation, we fix some assignment variables modeled in Phase I to control cancellation or operation of certain flights. Under a predetermined time limit, we solve this integrated problem in an iterative manner.

With the proposed approach, we aim to find the optimal trade-off between operating and passenger-related costs. Among cost components, fuel and CO_2 emission corresponds to the largest portion of the operating expenses. It is also crucial for our algorithm since we use cruise time controllability as a recovery tool. In this context, there is a trade-off between incurring additional fuel cost by shortening cruise times and opening up space for disrupted flight blocks. As in [38], in order to calculate the fuel burn, we use the cruise stage fuel flow model proposed by the Base of Aircraft Data (BADA) project of EUROCONTROL [42]. We define the fuel burn (kg) as a function of cruise time f (minutes) while also taking aircraft type t into account. It can be expressed as follows:

$$F^t(f) = \alpha^t \frac{1}{f} + \beta \frac{1}{f^2} + \gamma^t f^3 + \nu^t f^2.$$

In this formula, the non-negative aircraft-specific coefficients $\alpha, \beta, \gamma, \nu$ are computed based on the methodology provided in [38]. Fuel consumption coefficients specified for each aircraft type, mass of aircraft, air density and gravitational acceleration are determinant factors for this calculation. Besides, in [43] it is stated that CO_2 emission (kg) is directly proportional to the fuel burn. Therefore, total fuel and CO_2 emission cost can be calculated as follows:

$$c^t(f) = c_0 F^t(f),$$

where c_0 denotes the unit fuel and emission cost (\$\kg).

3.2 The Math-heuristic Algorithm

As introduced above, the math-heuristic algorithm encompasses two phases: (1) aircraft recovery and (2) itinerary-based passenger recovery. First, a nonlinear mixed integer optimization model is developed to recover aircraft schedules. In the second phase, an algorithmic solution approach is proposed to recover passengers considering their itineraries. Then, an integrated search algorithm takes the set of cancelled flights as input. In an attempt to find another cancellation set which yields a better objective value, it makes a search over the solution space by fixing variables in the first phase. The whole process is iterated until the time limit is reached. We provide the details of this math-heuristic algorithm in the following subsections.

3.2.1 Phase I: Mathematical Formulation for Aircraft Recovery

In this section, we present the mathematical formulation developed for aircraft recovery problem to be used at the first phase of our math-heuristic algorithm. We first list sets, parameters, decision variables used in model and then provide the constraints along with objective function.

Sets

E	set of existing, i.e. non-disrupted, flights
E_O	set of existing flights departing from the hub airport
E_I	set of existing flights arriving to the hub airport
D	set of disrupted flights
D_O	set of disrupted flights departing from the hub airport, i.e. set of initial flights of disrupted flight blocks
D_I	set of disrupted flights arriving to the hub airport, i.e. set of final flights of disrupted flight blocks
B	set of flight blocks of unavailable aircraft
N_b	set of flights in each disrupted flight block b, $b \in B$
C_E	set of pairs of existing consecutive flights of the same aircraft, (i, j), $i \in E, j \in E$
C_D	set of pairs of initial and final flights of disrupted flight blocks, $(f(b), l(b))$, $b \in B$
C_{N_b}	set of pairs of consecutive flights in disrupted flight block $b \in B, (i, j), i \in N_b, j \in N_b$
P_i	set of pairs of consecutive flights of the unavailable aircraft starting from flight i, $(p, q), p \in D, q \in D, i \in D_O$
F_i	set of flights which includes flight i and its successors, $i \in E \cup D$

$\mathcal{Y}_i$	set of possible flights whose aircraft can be exchanged with the aircraft of flight $i \in E_O \cup D_O$
T	set of aircraft types where $t^* \in T$ denotes the unavailable aircraft

Parameters

p_i	predecessor of flight $i \in E$
$f(b)$	first flight of block $b \in B$
$l(b)$	last flight of block $b \in B$
$t(i)$	aircraft type of flight $i \in E$
$[l_i^t, u_i^t]$	lower and upper bound for the cruise time of flight $i \in E \cup D$ with aircraft type $t \in T$
$[d_i^l, d_i^u]$	lower and upper bound for the departure of flight $i \in E \cup D$
η_i	non-cruise time of flight $i \in E \cup D$
τ_i^t	turnaround time required to prepare aircraft type $t \in T$ for the next flight after $i \in E \cup D$
κ^t	seat capacity of aircraft type $t \in T$
μ_i	number of passengers on flight $i \in E \cup D$
π_i	ticket price of flight $i \in E \cup D$
σ_i	spill cost per passenger of flight $i \in E \cup D$
ϕ_i	overnight cost per passenger of flight $i \in E \cup D$

Decision Variables

d_i	departure time of flight $i \in E \cup D$
a_i	arrival time of flight $i \in E \cup D$
f_i^t	cruise time of flight $i \in E \cup D$ with aircraft type $t \in T$

$$x_{ij} \quad \begin{cases} 1 & \text{if flight } i \in E_I \cup D_I \text{ is followed by flight } j \in E_O \cup D_O \text{ in the route of an aircraft} \\ 0 & \text{otherwise} \end{cases}$$

$$y_{ij} \quad \begin{cases} 1 & \text{if aircraft of flight } i \in E_O \cup D_O \text{ and } j \in E_O \cup D_O \text{ are exchanged} \\ 0 & \text{otherwise} \end{cases}$$

$$z_i^t \quad \begin{cases} 1 & \text{if aircraft type } t \text{ is assigned to flight } i,\ i \in E \cup D,\ t \in T \\ 0 & \text{otherwise} \end{cases}$$

Model

$$\max \sum_{t\in T\setminus t^*}\sum_{i\in E\cup D} \pi_i \min\{\mu_i,\kappa^t\} z_i^t - \sum_{t\in T\setminus t^*}\sum_{i\in E\cup D} c_i^t(f_i^t) - \sum_{i\in E\cup D} \phi_i \min\{\mu_i,\kappa^{t^*}\} z_i^{t^*}$$
$$- \sum_{i\in E_O}\sum_{j\in D_O}\sum_{k\in F_j} \sigma_k \max\{0,\mu_k-\kappa^{t(i)}\} y_{ij}$$

$$\text{s.t.} \sum_{t\in T} z_i^t = 1 \qquad i\in E\cup D \tag{3.1}$$
$$z_i^t = z_j^t \qquad i\in D_O, j\in N_b : f(b)=i \tag{3.2}$$
$$\sum_{i\in E_I} x_{in} + \sum_{i\in E_O\cup D_O} x_{mi} + \sum_{i\in E_O} y_{in} + z_n^{t^*} \geq 1 \quad (n,m)\in C_D \tag{3.3}$$
$$|z_j^t - z_i^t| \leq (1-x_{ij}) \qquad i\in E_I, j\in D_O, t\in T \tag{3.4}$$
$$|z_j^t - z_i^t| \leq (1-x_{ji}) \qquad i\in E_O, j\in D_I, t\in T \tag{3.5}$$
$$\sum_{i\in E_I} x_{ij} \leq 1 \qquad j\in D_O \tag{3.6}$$
$$\sum_{i\in E_O} x_{ji} \leq 1 \qquad j\in D_I \tag{3.7}$$
$$\sum_{j\in D_O} x_{ij} \leq 1 \qquad i\in E_I \tag{3.8}$$
$$\sum_{j\in D_I} x_{ji} \leq 1 \qquad i\in E_O \tag{3.9}$$
$$\text{If } x_{ij}=1, \text{ then } a_i + \sum_{t\in T}\tau_i^t z_i^t \leq d_j \qquad i\in E_I, j\in D_O \tag{3.10}$$
$$\text{If } x_{ji}=1, \text{ then } a_j + \sum_{t\in T}\tau_j^t z_j^t \leq d_i \qquad i\in E_O\cup D_O, j\in D_I \tag{3.11}$$
$$\sum_{i\in E_O}\sum_{j\in E_O} y_{ij} = 0 \tag{3.12}$$
$$\sum_{i\in E_O}\sum_{j\in D_O} y_{ij} \leq 1 \tag{3.13}$$
$$y_{ij} = y_{ji} \qquad i\in E_O\cup D_O, j\in \mathcal{Y}_i \tag{3.14}$$
$$|z_{p(i)}^t - z_i^t| \leq \sum_{j\in\mathcal{Y}_i} y_{ij} \qquad i\in E_O, t\in T \tag{3.15}$$
$$|x_{in} - x_{mj}| \leq \sum_{k\in\mathcal{Y}_j} y_{jk} \qquad (i,j)\in C_E, (n,m)\in C_D \tag{3.16}$$

$$\text{If } \sum_{n \in D_O} x_{in} + \sum_{k \in \mathcal{Y}_j} y_{jk} = 0, \text{ then } \quad a_i + \sum_{t \in T} \tau_i^t z_i^t \leq d_j \qquad (i,j) \in C_E \tag{3.17}$$

$$y_{ij} \leq z_k^{t^*} \qquad i \in E_O, j \in D_O, k \in F_i \tag{3.18}$$

$$y_{ij} \leq z_k^{t(p(i))} \qquad i \in E_O, j \in D_O, k \in F_j \tag{3.19}$$

$$\text{If } y_{ij} = 1, \text{ then } a_p + \tau_p^{t(p(i))} \leq d_q \qquad i \in E_O, j \in D_O, (p,q) \in P_j \cup (p(i), j) \tag{3.20}$$

$$|x_{in} - x_{mk}| \leq 1 - y_{jk} \qquad k \in \mathcal{Y}_j, (i,j) \in C_E, (n,m) \in C_D \tag{3.21}$$

$$d_i + \sum_{t \in T} f_i^t + \eta_i = a_i \qquad i \in E \cup D \tag{3.22}$$

$$\text{If } z_i^{t^*} = 0, \text{ then } d_i^l \leq d_i \leq d_i^u \qquad i \in E \cup D \tag{3.23}$$

$$l_i z_i^t \leq f_i^t \leq u_i^t z_i^t \qquad i \in E \cup D, t \in T \backslash t^* \tag{3.24}$$

$$\text{If } z_{f(b)}^t = 1, \text{ then } a_i + \tau_i^t \leq d_j \qquad (i,j) \in C_{N_b}, b \in B, t \in T \backslash t^* \tag{3.25}$$

$$x_{ij} \in \{0,1\} \qquad i \in E_I \cup D_I, j \in E_O \cup D_O \tag{3.26}$$

$$y_{ij} \in \{0,1\} \qquad i \in E_O \cup D_O, j \in E_O \cup D_O \tag{3.27}$$

$$z_i^t \in \{0,1\} \qquad i \in E \cup D, t \in T \tag{3.28}$$

For given flight schedule, unavailable aircraft and disruption period, our objective is to come up with a recovery plan which maximizes the profit of airline. Profit value can be calculated as follows: Revenue - Fuel and CO_2 Emission Cost - Overnight Passenger Cost - Spilled Passenger Cost.

For each flight, the model either makes an operation or a cancellation decision. First component of the objective is the revenue generated by ticket sales of operating flights and it is directly proportional to the number of passengers assigned to them. Note that flights which belong to the unavailable aircraft, i.e. cancelled, do not contribute to the revenue. In our setting, there are three types of operating flights: (1) flights which are accommodated into the rotation of an available aircraft thanks to the cruise time controllability, (2) flights which are initially assigned to the unavailable aircraft but recovered after an exchange of aircraft, (3) flights which are not subject to change and operate as planned. It is important to mention that in order to operate flights by shortening cruise times, additional fuel and emission cost is incurred. Likewise, due to the insufficient seat capacity, some passengers might be spilled after an exchange of aircraft. This is also penalized in the objective. The impact of such trade-offs can be measured by comparing the generated revenue with the related cost terms.

Second term corresponds to the nonlinear fuel and CO_2 emission cost which is expressed as a function of cruise time and aircraft type. It can be calculated by using the following formula:

$$c_i^t(f_i^t) = \begin{cases} c_0(\alpha_i^t \frac{1}{f_i^t} + \beta_i^t \frac{1}{(f_i^t)^2} + \gamma_i^t (f_i^t)^3 + \nu_i^t (f_i^t)^2), & \text{if } z_i^t = 1, t \neq t^* \\ 0, & \text{if } z_i^t = 0, \end{cases}$$

where $\alpha, \beta, \gamma, \nu$ are the non-negative aircraft-specific fuel consumption coefficients. This formula indicates that fuel and CO_2 emission cost is incurred only if a flight is assigned to an operating aircraft. As the cost function is defined based on the indicator assignment variable, it is discontinuous making the epigraph $E_F = \{(f,t) \in R^2 : c(f) \leq t\}$ nonconvex. In the next proposition, we describe the convex hull of E_F. We drop the indices i and t for simplification. A more detailed information regarding the convexification of the epigraph and representation by conic quadratic inequalities can be found in Akürk et al. [44] and Günlük and Linderoth [45] .

Proposition 1. *[Şafak et al. [38]] The convex hull of the set E_F can be expressed as*

$$t \geq c_0(\alpha p + \beta q + \gamma r + \nu h) \tag{3.29}$$

$$z^2 \leq pf \tag{3.30}$$

$$z^4 \leq f^2 qz \tag{3.31}$$

$$f^4 \leq z^2 rf \tag{3.32}$$

$$f^2 \leq hz \tag{3.33}$$

Inequalities (3.30-3.33) *can be represented by conic quadratic inequalities.*

Next term is a penalty for overnight passengers who have to stay overnight at their origin locations due to the cancellation of flights. Finally, the last term represents the cost of spilled passengers due to inadequate seat capacity of exchanged aircraft.

Constraint (3.1) ensures that each flight is assigned to exactly one aircraft type. Note that set of aircraft types encompasses the unavailable aircraft as well, $t^* \in T$. If flight i is assigned to the unavailable aircraft t^*, i.e. $z_i^{t^*} = 1$, then this indicates that flight i is cancelled. Constraint (3.2) maintains the block structure that any decision given holds for the rest of the flights within the same block. That is, they are assigned to same aircraft type. Constraint (3.3) guarantees that a disrupted flight block is either recovered or cancelled. It can be placed into the schedule of an operating aircraft, flown by another aircraft through exchange or cancelled. When a disrupted flight block is accommodated into the existing schedule of an operating aircraft, it comes before or after an operating flight making $x_{ij} = 1$ or $x_{ji} = 1$. In such cases, constraints (3.4)-(3.5) assign the aircraft type of that particular aircraft to initially disrupted flight block. Constraints (3.6)-(3.7) ensure that a disrupted flight follows or is followed by at most one existing flight. Similarly, constraints (3.8)-(3.9) assure that an existing flight immediately precede or is preceded by at most one disrupted flight. For the flights which are assigned to the same aircraft, we need to define order of succession among operations. Constraint (3.10) guarantees that if a disrupted outbound flight follows an inbound existing flight, then the later should depart after the arrival time of flight i plus its turnaround time. Same limitation holds if a disrupted inbound flight is followed by an existing outbound flight as in constraint (3.11).

Since we want to keep the new schedule as similar as possible to the existing one, we only let exchange of aircraft at hub airport on condition that one is operating and the other is unavailable. Constraint (3.12) indicates that exchange of two operating aircraft is not an allowable option whereas constraint (3.13) puts a limit on the number of exchanges. Symmetry of the exchange decision is maintained by constraint (3.14). Constraint (3.15) makes a connection between aircraft type assignment and exchange decisions. If there is no exchange between the aircraft of flight i and flight j, aircraft of flight i has the same fleet type assignment with its predecessor $p(i)$ as planned. This enables to preserve the initial schedule. Again, if there is no exchange before the departure of flight j and the disrupted flight block which is represented by (n, m) is operated between existing consecutive flights i and j, then constraint (3.16) guarantees that $x_{in} = x_{mj}$, keeping the sequence of existing flights as in the original schedule. Constraint (3.17) assures that if there is no disrupted flight succeeding flight i and aircraft assignment does not change after it, then the requirement for the minimum aircraft connection time needs to be satisfied for existing flight pair (i, j). On the other hand, if aircraft of flight i and unavailable aircraft are exchanged at hub airport, then constraint (3.18) assigns flight i and its successors to unavailable aircraft which means that they are all cancelled. Besides, flight j and previously disrupted flights which follow flight j are recovered. Constraint (3.19) assigns these flights to the aircraft type of $p(i)$. As the initially disrupted flight pairs are assigned to an operating aircraft, constraint (3.20) controls the precedence relations between consecutive pairs including $(p(i), j)$. Constraint (3.21) enforces that $x_{in} = x_{mk}$ for disrupted flight pair (n, m) if the aircraft of flight j and k are exchanged, i.e. $y_{jk} = 1$.

Constraint (3.22) defines the arrival time of flight i by taking both cruise time and non-cruise time into consideration. Constraints (3.23)-(3.25) are valid for the flights which are not cancelled. Constraint (3.23) applies lower and upper bounds for departure of each flight which is assigned to an operating aircraft. Constraint (3.24) makes sure that cruise time falls into a range which is determined with respect to the aircraft type and allowable compression rate due to technical limitations. Constraint (3.25) controls the precedence relationship within an operating flight block. Constraints (3.26)-(3.28) define the domain of each decision variable.

3.2.2 Phase II: Itinerary-based Passenger Recovery Algorithm

In the previous section, corresponding to Phase I of the math-heuristic algorithm, we solve aircraft recovery problem and obtain decisions for each flight. We do not make a distinction between passengers who are on the same flight and accept them equal regardless of their itineraries. In this regard, we do not differentiate between direct and connecting passengers as well. Moreover, passenger re-accommodation is not considered in Phase I, even if there exist alternative paths between certain origin and destination pairs with available seat capacity. Therefore, the objective value obtained at the end of Phase I only gives us an approximate profit of the airline. In this section, we propose the Passenger Recovery Algorithm (PRA) which makes individual itinerary based recovery decisions and calculate the actual profit accordingly. For this calculation, algorithm starts with the objective value of Phase I and make adjustments on it. In the previous phase, while calculating the revenue, passengers who are assigned to cancelled flights are not included. In PRA, if a passenger is recovered then the ticket price which he/she pays originally is added to the actual profit value. Also, this passenger may not have to stay overnight anymore, so the objective is adjusted by adding the overnight cost.

For passenger re-accommodation, as long as the seat capacity is not exceeded, we consider two options in PRA: (1) A passenger can be re-assigned to an alternative direct flight which shares the same origin and destination airports with the passenger's original itinerary, or (2) the passenger can be re-routed and reach to the destination over another hub airport. Seat capacity is a limited resource so that it should be used in the best possible way to increase profit of the airline. In the case of a disruption, any re-accommodation decision given for a particular passenger might directly affect the others. This is because, if a previously available seat is occupied, then it is no longer be a re-accommodation option for other disrupted passengers. To that end, in PRA we prioritize the passengers with respect to their contributions to the objective value. Given a cancelled flight, we first determine the set of passenger itineraries which are disrupted due to the cancellation of that flight. Then, among these itineraries, we give the highest priority to the connecting passengers whose first leg of connection is disrupted. Otherwise, they would miss their continuing flights which considerably lowers the objective value.

We evaluate passenger re-accommodation options along with itinerary information. We assume that passenger itineraries are composed of either a single flight leg or two legs. The logic followed in the algorithm can be extended for multiple legs as well. In the algorithm, Cases 1-3 are associated with the connecting passengers whose first leg is cancelled. Cases 4-7 show the steps when the second leg of a connection is disrupted. Lastly, rest of the cases are related to direct passengers.

We use the following additional notation for PRA:

obj	objective value of Phase I
$\mathcal{O}$	adjusted objective value
$\mathcal{F}$	set of operating, i.e. non-disrupted, flights
$\mathcal{C}$	set of cancelled flights
ori_c	origin airport of flight $c \in \mathcal{C}$
des_c	destination airport of flight $c \in \mathcal{C}$
$\mathcal{SE}_c$	set of operating flights between ori_c-des_c s.t. $dep_e \leq dep_c, c \in \mathcal{C}, e \in \mathcal{SE}_c$
$\mathcal{SL}_c$	set of operating flights between ori_c-des_c s.t. $dep_l \geq dep_c, c \in \mathcal{C}, l \in \mathcal{SL}_c$
$\mathcal{SH}_c$	set of pairs of operating flights (h_1, h_2) s.t. h_1 is between ori_c-H, h_2 is between H-des_c and $arr_{h_1} + \lambda_{h_1 h_2} \leq dep_{h_2}, c \in \mathcal{C}, h_1, h_2 \in \mathcal{F}, h \in \mathcal{SH}_c$
rec_c	number of recovered passengers on flight $c \in \mathcal{C}$
pen_c	penalty term for cancelling flight $c \in \mathcal{C}$
$\mathcal{D}_c$	set of disrupted itineraries due to flight $c \in \mathcal{C}$
ν_d	number of passengers on itinerary $d \in \mathcal{D}_c$
nb_d	number of disrupted passengers on itinerary $d \in \mathcal{D}_c$
d'	first flight leg of itinerary $d \in \mathcal{D}_c$
d''	second flight leg of itinerary $d \in \mathcal{D}_c$, if exists
avc_i	available capacity on flight i
λ_{ij}	minimum time required for passengers to connect from flight i to j
γ	passenger delay cost per minute
ζ	cost of flying an additional flight per passenger

Algorithm 1 Itinerary-based Passenger Recovery Algorithm (PRA)

procedure PRA
    $\mathcal{O} \leftarrow obj$
    Sort flights in $\mathcal{C}$ with respect to lost revenue in descending order
    for each $c \in \mathcal{C}$ **do**
        $rec_c \leftarrow 0, pen_c \leftarrow 0$
        Let $\Delta t_l := max\{arr_l - arr_c, 0\}, l \in \mathcal{SL}_c$.
        Let $\Delta t_h := max\{arr_{h_2} - arr_c, 0\}, h \in \mathcal{SH}_c$.
        % Connecting pass. whose 1^{st} leg of connection is disrupted:
        for each $d \in \mathcal{D}_c$ such that $c = d'$ and d'' exists **do**
            $nb_d \leftarrow \nu_d, \mathcal{L}_c \leftarrow \mathcal{SL}_c, \mathcal{H}_c \leftarrow \mathcal{SH}_c$.
            while $\mathcal{L}_c \neq \emptyset$ and $nb_d > 0$ **do**
                Let $r := argmin_{i \in \mathcal{L}_c} \Delta t_i$
                if $arr_r + \lambda_{rd''} \leq dep_{d''}$ (Case 1) **then**
                    $\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_r\}(\pi_{d'} + \phi)$ Re-accommodation
                    CapacityUpdate (nb_d, avc_r) (late)
                end if
                $\mathcal{L}_c \leftarrow \mathcal{L}_c \backslash \{r\}$.
            end while
            while $\mathcal{H}_c \neq \emptyset$ and $nb_d > 0$ **do**
                Let $r := argmin_{i \in \mathcal{H}_c} \Delta t_i$
                if $dep_{r_1} \geq dep_c$ and $arr_{r_2} + \lambda_{r_2 d''} \leq dep_{d''}$ (Case 2) **then**
                    $\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_{r_1}, avc_{r_2}\}(\pi_{d'} + \phi - \zeta)$
                    AdditionalFlightCapacityUpdate $(nb_d, avc_{r_1}, avc_{r_2})$ Re-routing
                end if
                $\mathcal{H}_c \leftarrow \mathcal{H}_c \backslash \{r\}$.
            end while
            if $nb_d > 0$ (Case 3) **then**
                $\mathcal{O} \leftarrow \mathcal{O} - nb_d \pi_{d''}$
                $pen_c \leftarrow pen_c + nb_d(\phi + \pi_{d'} + \pi_{d''})$ Overnight
                $rec_c \leftarrow rec_c + (\nu_d - nb_d)$
            end if
        end for
        % Connecting pass. whose 2^{nd} leg of connection is disrupted:
        for each $d \in \mathcal{D}_c$ such that $c = d''$ **do**
            $nb_d \leftarrow \nu_d, \mathcal{L}_c \leftarrow \mathcal{SL}_c, \mathcal{H}_c \leftarrow \mathcal{SH}_c$.
            while $\mathcal{SE}_c \neq \emptyset$ and $nb_d > 0$ **do**
                Let $e \in \mathcal{SE}_c$.
                if $arr_{d'} + \lambda_{d'e} \leq dep_e$ (Case 4) **then**
                    $\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_e\}(\pi_{d''} + \phi)$ Re-accommodation
                    CapacityUpdate (nb_d, avc_e) (early)
                end if
                $\mathcal{SE}_c \leftarrow \mathcal{SE}_c \backslash \{e\}$.
            end while

while $\mathcal{L}_c \cup \mathcal{H}_c \neq \emptyset$ and $nb_d > 0$ **do**
Update $\Delta t = \min_{i \in \mathcal{L}_c \cup \mathcal{H}_c} \Delta t_i$.
Let $r := argmin_{i \in \mathcal{L}_c \cup \mathcal{H}_c} \Delta t_i$
if $r \in \mathcal{L}_c$ (Case 5) **then**
$\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_r\}(\pi_{d''} + \phi - \gamma \Delta t)$
CapacityUpdate (nb_d, avc_r)
end if
if $r \in \mathcal{H}_c$ and $arr_{d'} + \lambda_{d' r_1} \leq dep_{r_1}$ (Case 6) **then**
$\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_{r_1}, avc_{r_2}\}(\pi_{d''} + \phi - \gamma \Delta t - \zeta)$
AdditionalFlightCapacityUpdate $(nb_d, avc_{r_1}, avc_{r_2})$
end if
$\mathcal{L}_c \cup \mathcal{H}_c \leftarrow \mathcal{L}_c \cup \mathcal{H}_c \setminus \{r\}$.
end while

Re-routing & Re-accommodation (late)

if $nb_d > 0$ (Case 7) **then**
$pen_c \leftarrow pen_c + nb_d(\phi + \pi_{d''})$
$rec_c \leftarrow rec_c + (\nu_d - nb_d)$
end if

Overnight

end for
% Direct passenger:
for each $d \in \mathcal{D}_c$ such that $d' = c$ is a single-leg itinerary **do**
$nb_d \leftarrow \nu_d, \mathcal{L}_c \leftarrow \mathcal{SL}_c, \mathcal{H}_c \leftarrow \mathcal{SH}_c$.
while $\mathcal{L}_c \cup \mathcal{H}_c \neq \emptyset$ and $nb_d > 0$ **do**
Update $\Delta t = \min_{i \in \mathcal{L}_c \cup \mathcal{H}_c} \Delta t_i$.
Let $r := argmin_{i \in \mathcal{L}_c \cup \mathcal{H}_c} \Delta t_i$
if $r \in \mathcal{L}_c$ (Case 8) **then**
$\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_r\}(\pi_{d'} + \phi - \gamma \Delta t)$
CapacityUpdate (nb_d, avc_r)
end if
if $r \in \mathcal{H}_c$ and $dep_{r_1} \geq dep_c$ (Case 9) **then**
$\mathcal{O} \leftarrow \mathcal{O} + min\{nb_d, avc_{r_1}, avc_{r_2}\}(\pi_{d'} + \phi - \gamma \Delta t - \zeta)$
AdditionalFlightCapacityUpdate $(nb_d, avc_{r_1}, avc_{r_2})$
end if
$\mathcal{L}_c \cup \mathcal{H}_c \leftarrow \mathcal{L}_c \cup \mathcal{H}_c \setminus \{r\}$.
end while

Re-routing & Re-accommodation (late)

if $nb_d > 0$ (Case 10) **then**
$pen_c \leftarrow pen_c + nb_d(\phi + \pi_{d'})$
$rec_c \leftarrow rec_c + (\nu_d - nb_d)$
end if

Overnight

end for
end for
return $rec_c, pen_c, \mathcal{O}$
end procedure

procedure CapacityUpdate (nb_d, avc_f)
  $nb_d \leftarrow nb_d - min\{nb_d, avc_f\}$
  $avc_f \leftarrow avc_f - min\{nb_d, avc_f\}$
end procedure
procedure AdditionalFlightCapacityUpdate $(nb_d, avc_{h_1}, avc_{h_2})$
  $nb_d \leftarrow nb_d - min\{nb_d, avc_{h_1}, avc_{h_2}\}$
  $avc_{h_1} \leftarrow avc_{h_1} - min\{nb_d, avc_{h_1}, avc_{h_2}\}$
  $avc_{h_2} \leftarrow avc_{h_2} - min\{nb_d, avc_{h_1}, avc_{h_2}\}$
end procedure

Let $c \in \mathcal{C}$ be a cancelled flight which supposed to depart from ori_c and arrive to des_c. Also, let nb_d denote the number of passengers on itinerary d who are disrupted due to the cancellation of flight c.

Case 1, 5 and 8: Let r be an element of the set $\mathcal{SL}_c$. To put it another way, take r as a direct flight between the same origin and destination pair as c with a later departure time. Therefore, it can be interpreted as a late alternative for the disrupted flight c. $min\{nb_d, avc_r\}$ passengers can be recovered without adding an extra flights to their paths. However, passengers on flight r arrive at the destination airport later compared to the existing schedule. In Case 1, as the minimum connection time is not violated, passengers can be recovered and they continue their path with flight d''. Since they arrive at the designated airport, $des_{d''}$ as planned, no delay cost is incurred. In Case 5 and 8, Δt corresponds to the deviation from the initial schedule regarding arrival time whereas $min\{nb_d, avc_r\}\gamma\Delta t$ stands for the inconvenience cost incurred due to passenger delay.

Case 2, 6 and 9: For the passengers who cannot be recovered by either earlier or later direct flights, an alternative path can be taken into consideration. They can reach to their destination airports over another hub airport, H. In this regard, let $r \in \mathcal{SH}_c$ where r_1 and r_2 denote the two operating flight legs between $ori_c - H$ and $H - des_c$ respectively. By adding an extra flight, $min\{nb_d, avc_{r_1}, avc_{r_2}\}$ passengers can be rerouted and they can follow $ori_c - H - des_c$ path. Taking the minimum of avc_{r_1} and avc_{r_2} provides completeness and prevents passengers to stay at hub airport H. Due to this additional flight, people need to deal with extra check-in procedures. It also increases the risk of missing the upcoming flights.

Therefore, besides the passenger delay cost, adding an extra flight is penalized as well. The term $min\{nb_d, avc_{r_1}, avc_{r_2}\}\zeta$ can be interpreted as a disincentive for adding an extra flight to an itinerary. Note that this recovery option is feasible only within connected networks. In connected networks, spoke airports are served from different hubs and hub airports are connected by regular flights. Unless there are alternative ways to reach a particular airport, rerouting cannot be possible. In Case 2, delay on the first leg of connection which might occur due to this additional flight has no impact on the passengers' arrival time to destination airport. Hence, no delay cost is incurred. However, in Cases 6 and 9, rerouted passengers are delayed by Δt minutes which is also considered in the actual profit calculation.

Case 3, 7 and 10: As a terminating condition, if the passengers of itinerary d cannot be recovered by any means, then they have to stay overnight at origin airport. For each cancelled flight, penalty term pen_c is updated in these cases. pen_c is intended to measure the loss of profit if the airline prefers to cancel flight c considering each passenger itinerary separately. Observe that in Case 3 $nb_d\pi_{d''}$ is subtracted from the objective value different from the other cases. To understand the logic behind this adjustment, let us consider a connecting passenger whose first leg of connection, flight c, is cancelled. Due to the cancellation, the passenger who supposed to be at des_c has to stay at origin airport, ori_c. Also, note that the continuing flight of the passenger departs from des_c. Although second flight leg is operated as planned, the passenger cannot take place on this flight. Therefore, revenue can not be generated from the ticket sales of the second leg for such passengers.

Case 4: Let e be an element of the set $\mathcal{SE}_c$. That is, it shares the same origin and destination airports with flight c with an earlier departure time. So, it can be evaluated as an early alternative for the second flight leg of the original itinerary. Since the passenger connectivity is still satisfied between first and second leg, $min\{nb_d, avc_e\}$ passengers can be recovered by allocating available seats. Note that those passengers can be informed in advance so that they will not be entitled to any compensation. Passengers who utilize flight e reach the destination airport earlier and hence no delay cost is incurred.

3.2.3 Integrated Search Algorithm with Variable Fixing

In the literature, it is a common practice to develop approaches that solve aircraft and passenger recovery problems sequentially. However, such methods lack the integration within the system as they are handled independently from each other. Passengers, which are considered at the last stage, are adversely affected from the re-timing and cancellation decisions which are given in advance. In this study, we work on aircraft and passenger recovery problems in first two phases and develop an algorithm which integrates two phases through variable fixing.

In order to maintain the connection between phases, we propose the Integrated Search Algorithm (ISA) which is developed based on the variable fixing idea. Flow chart of ISA is provided in Figure 3.2. The objective is to find a better solution in terms of the profit of the airline by enforcing some flights to operate or to cancel. For ISA, we first define two new sets which are denoted as $\mathcal{FO}$ and $\mathcal{FC}$ to cover fixed operating and cancelled flights. The algorithm starts with solving Phase I and II. Then, it takes the cancellation set which is obtained from PRA as input. For each cancelled flight, it checks whether it is possible to recover all disrupted passengers or not. Note that passengers who are assigned to the same flight can be recovered by different ways, so it is not necessary to make a single decision. If all recovery is possible for the cancelled flight c, $rec_c = \mu_c$, then it is added to fixed cancellation set $\mathcal{FC}$. This is because, even with one less flight all passengers can be transported to their destination airports. Hence, there is no need to operate that flight anymore.

While updating $\mathcal{FO}$, set of fixed operating flights, the following logic is used: Among all disrupted flights, the algorithm chooses the one which yields the highest penalty value to the airline, c^*. Then c^* is added to $\mathcal{FO}$, i.e. fixed to be operated. That is, for the next iteration, the algorithm will make a search over the remaining flights while determining the cancellation set, $\mathcal{C}_k$. As c^* is not a candidate for cancellation anymore, the solution space will be different. Fixing a binary assignment variable eliminates a branch in the solution space reducing the size of it. Unless the time limit is exceeded, the algorithm switches back to Phase I and the aircraft recovery model is solved with additional constraints. Note that $\mathcal{C}_k$ differs at each iteration since the corresponding assignment variables are fixed. At each iteration, algorithm checks whether the current set of cancellation gives a better objective value or not. If so, the incumbent solution is updated but otherwise it is discarded. In sum, ISA works in an iterative manner and return the best possible cancellation set as well as the profit value at the end.

Different from the notations in PRA, we add an index to $\mathcal{C}$ to represent the set of cancellation at each iteration k. The following additional notations are used for ISA:

$\mathcal{FO}$	set of fixed operating flights
$\mathcal{FC}$	set of fixed cancelled flights
$\mathcal{C}_k$	set of cancelled flights at iteration k
$\mathcal{C}^*$	cancellation set of the best possible solution
obj^*	objective value of the best possible solution
t_{total}	total solution time
$\bar{t}$	time limit

Algorithm 2 Integrated Search Algorithm (ISA)

procedure ISA
  $\mathcal{FC} \leftarrow \emptyset$, $\mathcal{FO} \leftarrow \emptyset$, $\mathcal{C}^* \leftarrow \emptyset$, $obj^* \leftarrow obj$, $t_{total} \leftarrow 0$, $k \leftarrow 0$
  while $t_{total} < \bar{t}$ **do**
    Aircraft Recovery Model $(\mathcal{FC}, \mathcal{FO})$
    Passenger Recovery Algorithm $(\mathcal{C}_k)$
    for each $c \in \mathcal{C}_k$ **do**
      if $rec_c = \mu_c$ **then**
        $\mathcal{FC} \leftarrow \mathcal{FC} \cup \{c\}$
      end if
    end for
    Let $c^* := argmax_{i \in \mathcal{C}_k} pen_i$
    $\mathcal{FO} \leftarrow \mathcal{FO} \cup \{c^*\}$
    if $\mathcal{O} > obj^*$ **then**
      $obj^* \leftarrow \mathcal{O}$
      $\mathcal{C}^* \leftarrow \mathcal{C}_k$
    end if
    Update t_{total}, $k \leftarrow k + 1$
  end while
  return $\mathcal{C}^*, obj^*$
end procedure
procedure Aircraft Recovery Model $(\mathcal{FC}, \mathcal{FO})$
  Solve the model in Phase I with the following additional constraints:
  $\sum_{t \in T \setminus \{t^*\}} z_i^t = 1 \quad i \in \mathcal{FO}$
  $z_i^{t^*} = 1 \quad i \in \mathcal{FC}$
  return $\mathcal{C}_k$
end procedure

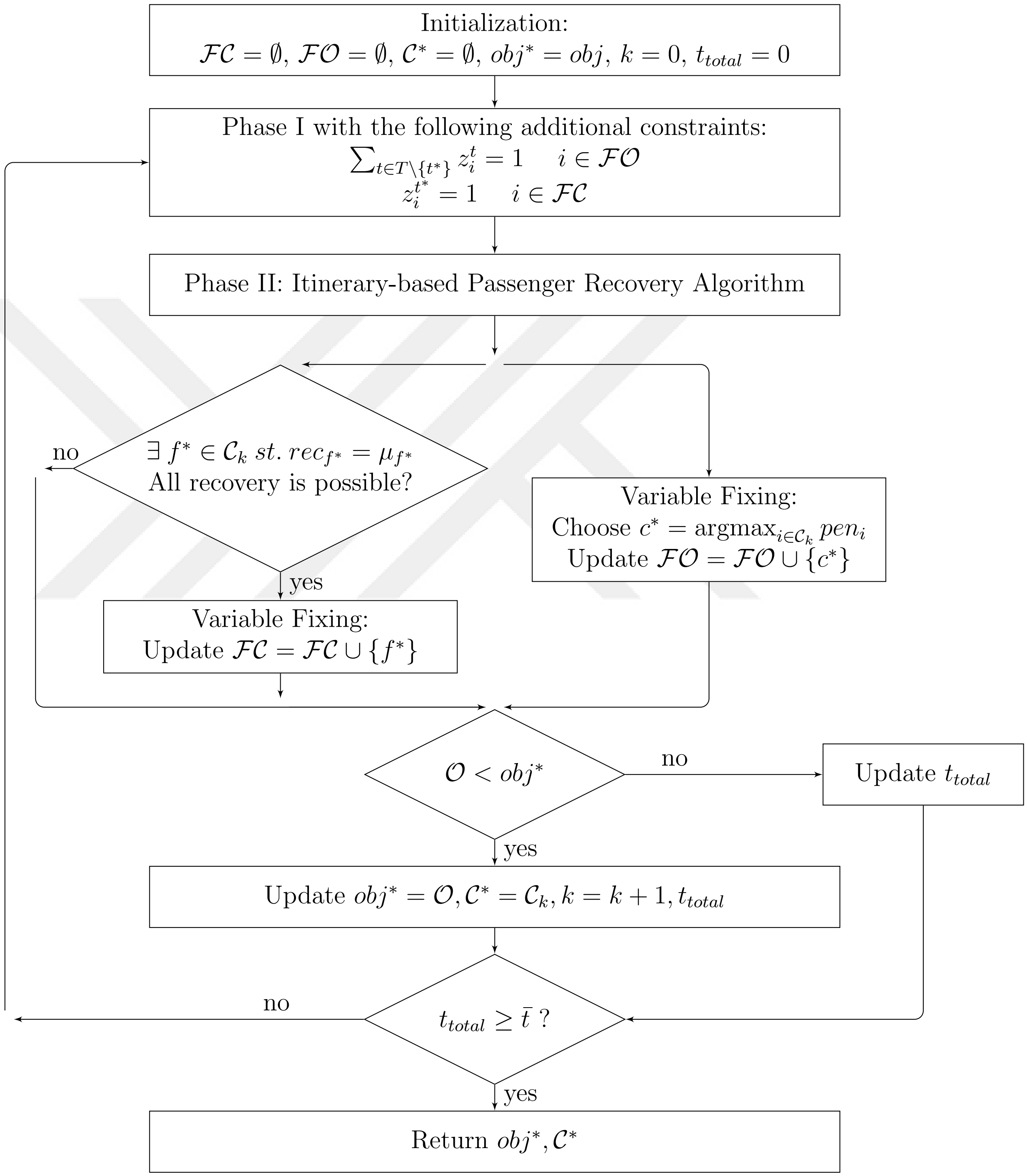

Figure 3.2: Flow chart of the Integrated Search Algorithm

3.3 Numerical Example

In this section, we give a numerical example to illustrate how recovery or cancellation decisions are made for flights of an unavailable aircraft. To solve this integrated aircraft and passenger recovery problem, we take original flight schedule, corresponding passenger itineraries, characteristics of aircraft and disruption information (unavailable aircraft, disruption period) as input. We consider a sample schedule for five aircraft, each completing its route at hub airport, ORD. Table 3.6 shows aircraft assignment, flight number, origin and destination airports, base ticket price for those origin and destination pairs, planned departure and arrival in local ORD time, planned flight time and the number of passengers of flights in the sample schedule.

Tail #	Flight #	Dep. Airport	Arr. Airport	Dep. Time	Flight Time	Arr. Time	# of Pass.	Base Price
N03442	0	DEN	ORD	07:40	02:20	10:00	110	168
	1	ORD	DEN	14:15	02:40	16:55	130	168
	2	DEN	ORD	19:30	02:45	22:15	117	168
N15425	3	ORD	ATL	08:15	02:15	10:30	119	165
	4	ATL	ORD	12:00	02:15	14:15	118	165
	5	ORD	MCO	16:30	03:00	19:30	104	150
	6	MCO	ORD	20:45	02:45	23:30	94	150
N15438	7	ORD	DEN	07:10	02:20	09:30	121	168
	8	DEN	ORD	11:30	02:30	14:00	119	168
	9	ORD	IAH	15:00	03:00	18:00	110	187
	10	IAH	ORD	20:00	03:00	23:00	99	187
N03449	11	DFW	ORD	09:50	02:40	12:30	126	187
	12	ORD	DFW	15:15	02:30	17:45	127	187
	13	DFW	IAH	18:30	01:15	19:45	97	199
	14	IAH	ORD	20:45	02:50	23:35	110	187
N27261	15	ORD	MSP	09:30	01:55	11:25	108	128
	16	MSP	ORD	12:00	01:50	13:50	143	128
	17	ORD	ROC	17:00	02:20	19:20	123	227
	18	ROC	ORD	20:30	02:30	23:00	109	227

Table 3.6: Original schedule

Figure 3.3 gives the time-space network representation of the original schedule. Horizontal and vertical axes represent time line and airports respectively. Arcs which emanate from the origin airport at planned departure time and end at the destination airport after planned block time correspond to flight arcs. Ground arcs represent the turnaround time spent on ground which is required to prepare the aircraft for the next flight. Turnaround times are calculated by multiplying base turn-time with the airport congestion coefficients. Until next departure, aircraft stay idle on ground.

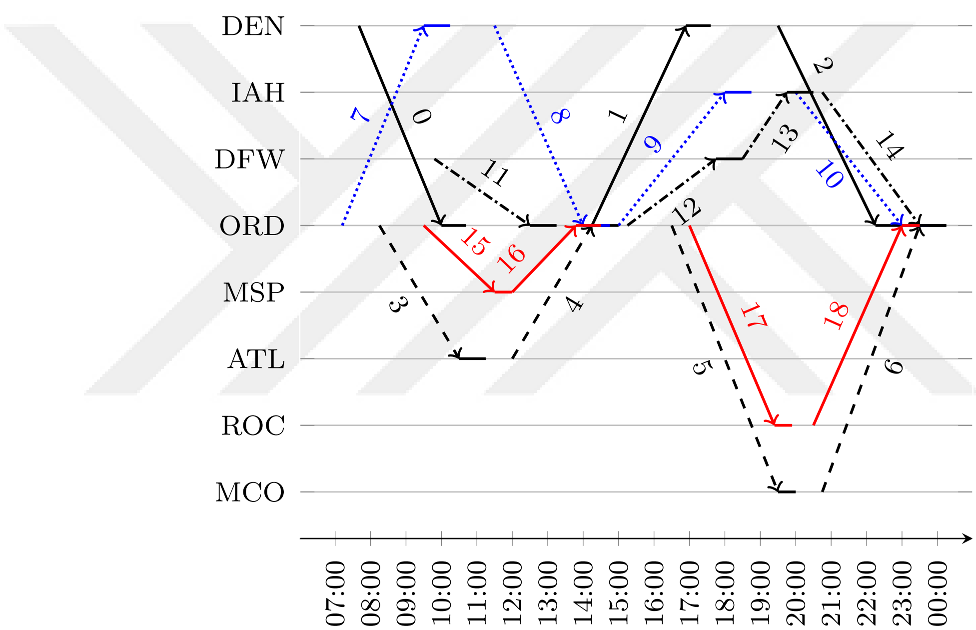

Figure 3.3: Time space network of the original schedule

We assume that passenger itineraries are composed of either a single fligt leg or two legs. Itineraries are displayed in Table 3.7. Each flight is included as a single-fight itinerary. Moreover, itineraries which require connection of passengers are expressed with sequential flight numbers. Such passengers might require to switch aircraft and hence need some time to make a connection to a continuing flight. We set all minimum connection times to 30 minutes.

In this example, we assume that aircraft N03442-N03449, N15425-N15438 and N27261 are Boeing 727-228, Boeing 737-500 and McDonnell Douglas 83 respectively, each having different seat capacities and fuel burn rates. In the original schedule, for each flight we assume that aircraft fly at Maximum Range Cruise (MRC) speed and non-cruise stages take 30 minutes. This implies that cruise

Itinerary	# of Pass.	Itinerary	# of Pass.
0	73	10	99
0-5	21	11	105
0-17	16	11-17	21
1	130	12	109
2	117	13	97
3	119	14	110
4	104	15	108
4-17	14	16	94
5	44	16-5	18
6	94	16-9	10
7	121	16-12	18
8	89	16-17	13
8-5	21	17	50
8-17	9	18	109
9	100		

Table 3.7: Planned passenger itineraries

stages last 30 minutes less than the planned block times provided in Table 3.6.

In daily operations, some aircraft might become unavailable and hence flights cannot be operated as planned. One possible reason is that an aircraft might undergo an emergency maintenance or the maintenance duration of a particular aircraft might be extended. On the given schedule, let us assume that aircraft N27261 undergoes maintenance at ORD airport and it is unavailable between 09:00-19:00. Apparently, flights 15, 16 and 17 are disrupted since the corresponding aircraft cannot depart at planned departure time. Although the departure of flight 18 does not coincide with the unavailability period, it is also disrupted. This is because the aircraft N27261 which supposed to be at ROC airport by 19:20 is still at ORD and hence it is not possible to operate ROC-ORD flight. With this unavailability information, two flight blocks (ORD-MSP-ORD and ORD-ROC-ORD) are disrupted.

One feasible solution is to cancel all of the flights which are initially assigned to the unavailable aircraft without making any further changes in the existing schedule. Characteristics of that solution approach is provided in Table 3.8. An alternative way of handling disruptions is to consider recovery options along with cancellation decision. As a recovery tool, cruise time controllability can be utilized. We allow the compression of cruise times up to 15%. Speed of aircraft can be increased to shorten flight times; thus, disrupted flights can be accommodated into the schedule of one of those operating aircraft. Another option is that unavailable aircraft can be exchanged with an operating one. That is to say, disrupted flights of unavailable aircraft are recovered and flown by the exchanged aircraft. On the other hand, flights of that particular aircraft are cancelled since they are assigned symbolically to the unavailable one. While deciding on the cancellation set, exchange alternative gives a flexibility to operate flights which generate more profit to airline. In this example, to preserve the initial schedule, we only allow exchange of aircraft at hub airport (ORD) only if one is operating and the other is unavailable.

	All Cancellation (Base Policy)	Iteration 1	Iteration 2 (Proposed)
Cancelled flights	15,16,17,18	5,6	9,10
# of recovered passengers	0	242	273
→ Phase I	0	242	242
→ Phase II	0	0	31
# of overnight passengers	483	218	198
% Imp Overnight	-	55.1	59.2
Total compression (min)	0	34	34
Total passenger delay (min)	0	0	1815
Compression cost ($)	0	471	471
Passenger delay cost ($)	0	0	1815
Overnight cost ($)	24150	11835	10834
Objective ($)	90958	141344	142181
% Imp Objective	-	64.8	66.1

Table 3.8: Comparison of results after each iteration

We set a time limit of 60 seconds and run our math-heuristic algorithm for this disruption scenario. At iteration 1, first disrupted flight block which involves flights 15 and 16 is accommodated into the schedule of the aircraft N03442 between flights 0 and 1. So as to open up sufficient time for this accommodation, speed of aircraft is adjusted. Cruise time of flight 0, 15 and 16 are compressed by 14, 10 and 10 minutes respectively, increasing the utilization of the aircraft N03442. Hence, 242 passengers are recovered at Phase I of the algorithm. Due to the insufficient capacity of aircraft N03442, 9 passengers of flight 16 are spilled and stay overnight. Note that flight 16 belongs to different itineraries and corresponding passengers are not equally important considering their contributions to airline's profit. To clarify, consider a direct passenger in itinerary 16 and a connecting passenger in itinerary 16-5. If the later one is spilled, then the passenger not only misses the first flight but also cannot take place on the next flight as it departs from ORD. Therefore, lost revenue is higher for the case when a connecting passenger is spilled instead of a direct one. In this example, among all the passengers of flight 16, 9 direct passengers are spilled. Moreover, aircraft N27261 and N15425 are exchanged at ORD airport after the later one completes flight 4. To put it another way, N15425 operates the second disrupted flight block, i.e. flights 17 and 18, whereas unavailable aircraft N27261 takes over flights 5 and 6. This means that flights 5 and 6 are cancelled. Again, due to the insufficient seat capacity of aircraft N15425, 1 passenger of flight 17 is spilled. Since there exist no alternative flights between ORD and MCO in either direction, passengers of flights 5 and 6 cannot be recovered and have to stay overnight. As the recovery is not possible, for the next iteration the algorithm enforces those flights to operate by fixing the related variables in the mathematical model with the aim of finding a better solution. In fact, under that time limit, solution of iteration 2 yields the highest profit value. We give the time-space network for the proposed schedule in Figure 3.4.

In the proposed solution, again cruise speed control mechanism is used to recover first flight block. Different from the previous iteration, aircraft N27261 and N15438 are exchanged upon the completion of flight 8. Hence, flights 9 and 10 are cancelled. 7 passengers who are initially assigned to flight 9 are rerouted and determined to follow ORD-DFW-IAH path. As they arrive to their destination airport 105 minutes late and have to fly one additional flight, cost of delay and flying an extra flight are considered in the objective value as well. Besides, 24 passengers of flight 10 are re-assigned to flight 14, a late alternative. In total, 31 passengers are recovered at Phase II. Observe that ticket prices of the cancelled flights 9 and 10 are higher compared to the cancelled flights at the previous iteration. However, when the actual profit is calculated considering

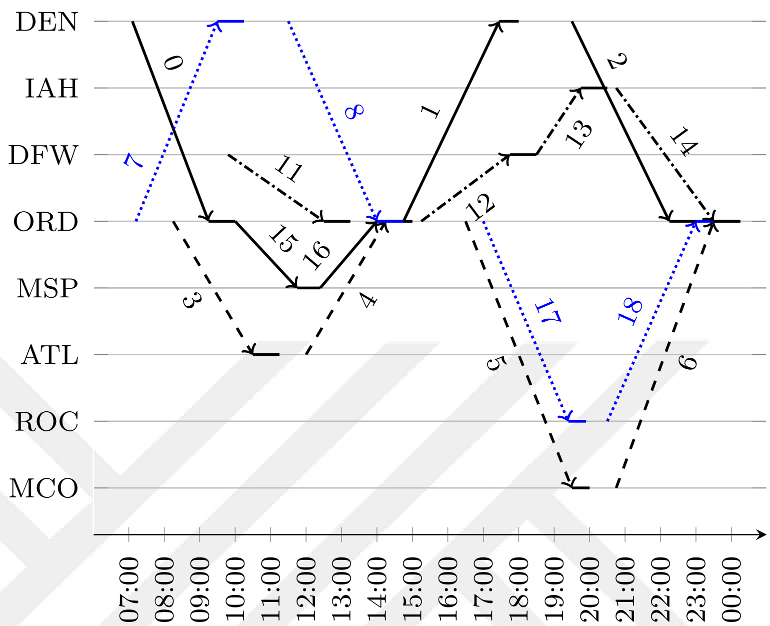

Figure 3.4: Time space network of the proposed schedule

individual passenger itinerary based recovery decisions, overall profit is increased and number of overnight passengers are decreased. If the ticket price was the only measure for the profitability of the flight, this solution could not have been achieved.

Assuming c_{fuel} =1.2 \$/kg and c_{CO_2}= 0.02 \$/kg, profit values, passenger analysis and corresponding cost components for the proposed schedule and the schedule where all disrupted flights are cancelled are provided in Table 3.8. Compared to the solution where disrupted flights are cancelled directly, number of cancelled flights is decreased from 4 to 2. However, this is not the only reason behind the increase in profit. The proposed algorithm allows to change aircraft and hence to operate more profitable flights. As well as the reduction in overnight cost, increase in revenue which is generated from the ticket sales compensate for the increase in compression and passenger recovery costs. Therefore, the resulting schedule improves the airline's profit by 66.1% and decreases the number of overnight passengers by 59.2% in comparison with the base policy where all disrupted flights are directly cancelled. If all aircraft were available, then airline would have reached its planned profit value. However, unavailability of aircraft causes loss of profit. % improvement of profit is calculated by dividing the difference between loss of profit when all disrupted flights are cancelled and when the proposed algorithm is implemented to the former one. This calculation enables us to exclude the contribution of unaffected flights of the original schedule.

3.4 Summary

In this section, we first explain the flight block structure in hub-to-spoke networks and fuel consumption calculations so as to provide a basis for our algorithm which involves two main phases. In the first phase, we propose a nonlinear mixed integer optimization model to address aircraft recovery problem. For each disrupted flight block, we allow three options: It can be accommodated into the existing schedule by shortening its cruise time, re-assigned to an operating aircraft or cancelled as a last choice. Then in the second phase, passengers are incorporated into the algorithm. Each passenger itinerary is evaluated separately considering the limited number of available seats. As long as the seat capacity is not exceeded, passengers can be re-accommodated to early/late direct flight alternatives or they can be rerouted and reach to their destinations over another hub airport. Dependencies between the entities, aircraft and passengers, necessitate the integration between these two phases. To that end, we develop an integrated search algorithm which is based on variable fixing idea. Lastly, we provide a numerical example to highlight the important steps of the proposed algorithm.

Chapter 4

Computational Results

In this section, we test the performance of math-heuristic algorithm developed for integrated aircraft and passenger recovery problem. We propose different strategies by allowing certain recovery actions. We evaluate and compare the performance of these strategies with respect to solution quality under time limit. All computational experiments are performed on 2.4 GHz Intel Core i7-4700HQ CPU with 16 GB memory. The proposed algorithm is implemented in Java with a connection to IBM ILOG CPLEX Optimization Studio 12.6.2.

In order to test the practicality of the integrated algorithm, we use a sample schedule which is generated based on the work of [35]. Flight information along with aircraft schedules is extracted from "Airline On-Time Performance" database, provided by Bureau of Transportation Statistics (BTS). Extracted data involve information regarding tail numbers, origin and destination airports, departure and arrival times. In this sample schedule, Chicago O'Hare International Airport (ORD) and Dallas/Fort Worth International Airport (DFW) serve as hub airports. It is generated in a way that all aircraft originate their first flight from these hub airports and revisit there at least once within the same day. It includes 208 flights which are operated by 53 different aircraft. This schedule can be found in Appendix A. We consider disruption scenarios at which one aircraft is unavailable at a time. We assume that mechanical failures are detected and aircraft undergo maintenance at hub airports. Therefore, aircraft have to stay at hub airport during the period of unavailability. Whenever the technical problem is solved or the maintenance is completed, aircraft become ready to operate.

We consider six aircraft types each having different features. Number of seats, mass, wing surface area, fuel consumption coefficients, maximum range cruise (MRC) speed and base turntime for each type are displayed in Table 4.1. Depending on the historical data regarding fuel prices, we assume unit cost of fuel, c_{fuel} = 1.2 \$/kg and unit cost of CO_2 emission, c_{CO_2}= 0.02 \$/kg [46]. We will also provide an analysis for different fuel cost settings in Section 4.2. We use the cruise stage fuel flow model proposed by the Base of Aircraft Data (BADA) to calculate the fuel burn as in [38]. Turnaround times are calculated by multiplying the base turntime with the congestion coefficient of the destination airport. Table 4.2 shows the airport congestion coefficients stated in [36]. The higher the congestion level is, the more time aircraft needs to spend on ground until it takes off again for a new flight.

Aircraft type	1	2	3	4	5	6
Number of seats	134	122	148	172	180	218
Mass (kg)	74000	50000	61200	62000	64000	135000
Surface (m^2)	157.9	105.4	118	122.4	122.6	283.3
$C_{D0;CR}$	0.018	0.018	0.0211	0.024	0.024	0.021
$C_{D2;CR}$	0.06	0.055	0.0468	0.0375	0.0375	0.049
Cf_1	0.53178	0.46	0.7462	0.94	0.94	0.763
Cf_2	276.72	300	638.59	50000	100000	1430
Cf_{CR}	0.954	1.079	0.9505	1.095	1.06	1.0347
MRC speed (km/h)	867.6	859.2	867.6	855.15	868.79	876.7
Base turntime (min)	32	36	26	28	30	40

Table 4.1: Aircraft parameters

We assume that passenger itineraries are composed of either a single flight leg or two legs. Direct passengers travel from an origin to destination airport whereas the connecting ones travel to the designated location by transferring from the hub airport. For passengers who make a connection to a continuing flight, we set all minimum connection times to 30 minutes. Each flight is included as a single-leg itinerary. Also, if there exist two flights one of which arrives to and the other

Airport	Location	Coef.	Airport	Location	Coef.
MIA	Miami, FL	1.96	DCA	Washington, DC	1.17
ORD	Chicago, IL	1.88	SAN	San Diego, CA	1.1
LAX	Los Angeles, CA	1.82	STL	St.Louis, MO	1.1
DEN	Denver, CO	1.82	MCI	Kansas City, MO	1.04
DFW	Dallas, TX	1.74	AUS	Austin, TX	1
LGA	New York, NY	1.69	RDU	Raleigh/Durham, NC	1
BOS	Boston, MA	1.69	MSY	New Orleans, LA	0.96
ATL	Atlanta, GA	1.64	SNA	Santa Ano, CA	0.96
PHX	Phoenix, AZ	1.56	SAT	San Antonio, TX	0.9
LAS	Las Vegas, NV	1.56	RSW	Fort Myers, FL	0.9
SFO	San Fransisco, CA	1.44	SJU	San Juan, PR	0.85
MSP	Minneapolis, MN	1.32	PBI	West Palm Beach, FL	0.81
PHL	Philadelphia, PA	1.32	TUS	Tuscan, AZ	0.77
EWR	Newark, NJ	1.25	MCO	Orlando, FL	0.72
FLL	Fort Lauderdale, FL	1.25	EGE	Eagle, CO	0.72
SLC	Salt Lake City, UT	1.17	HDN	Hayden, CO	0.64

Table 4.2: Airport congestion coefficients

departs from a common airport and the minimum passenger connection time is satisfied, then this pair is added to two-leg itineraries. However, if the origin of the first flight and the destination of the later one are the same, then such pairs are removed from two-leg itineraries to make reasonable passenger connections. Note that each aircraft has different number of seats depending on its type. First, number of passengers assigned to each flight is generated randomly considering seat capacities and 70% seat occupancy rate is ensured for each flight. Then, passengers in each flight are allocated randomly to the itineraries which involve that particular flight.

For ticket prices, origin and destination airports as well as the time of the day are two determinant factors. Base ticket prices are obtained from the report provided by US Department of Transportation [47]. Base ticket prices from the hub airports ORD and DFW can be found in Appendix B. These values show average fares between certain origin and destination pairs, regardless of the time and direction of the flight. In order to incorporate the time factor, we use the segmentation idea provided in [48]. We divide the day into three segments to differentiate between peak and unfavorable times from the perspective of passengers. Segments are displayed in Table 4.3 and they are in descending order of preference. Hence, the highest fare is incurred for first segment and so on. We calculate the ticket prices by multiplying base fare with segmentation coefficient. We set these coefficients to 1.2, 1.0 and 0.8, respectively.

Segment	Time Interval
1	06:00-08:59 and after 17:00
2	09:00-11:59 and 15:00-16:59
3	12:00-14:59

Table 4.3: Time intervals for the price segmentation

In this study, we work on networks where passenger itineraries and aircraft routings are superimposed. Therefore, it is significant to understand and model the passenger behaviour while applying the recovery strategies. In our math-heuristic algorithm, we model passenger behaviour in cases of cancellation and delay by corresponding cost parameters. If a flight is cancelled and recovery is not possible in any phases, then passengers have to stay overnight at their origin airports. Also, due to the departure delays or re-routing actions, passengers might arrive at their destination airports late compared to their planned arrivals. Both of the cost terms reflect the compensation for accommodation, meals and other essential needs. They can be interpreted as the measures of passenger inconvenience and enable penalization of loss of customer goodwill. As proposed in [49], we let the overnight cost per passenger as \$50 and delay cost per minute per passenger as \$1.09 in our experiments. In Section 4.2, we will provide an analysis for higher overnight cost settings as well. We calculate spill cost by adding overnight cost and ticket price. Lastly, cost of flying an additional flight is set to \$10, a small value, to create a disincentive when direct alternatives are available as well.

4.1 Recovery Strategies

In the case of a disruption, one feasible solution is to cancel all flights of the unavailable aircraft without taking further actions, yet it might not be the best possible approach. We consider this as the base policy and evaluate alternative approaches in comparison with this strategy. Besides cancellation, exchange of aircraft and cruise time controllability are tools that can be used for rescheduling. So as to keep the final schedule as similar as possible to the initial one, we only permit exchange of aircraft at hub airport (ORD) only if one is operating and the other is unavailable. Moreover, in the original schedule we assume that all aircraft fly at MRC speed and non-cruise operations take 30 minutes. Therefore, cruise times can be calculated by subtracting 30 minutes from the planned flight time. We allow the compression of cruise times up to 15% due to technical limitations. Possible recovery strategies which are constructed by combining these tools are listed in Table 4.4. If a tool is marked as 1, then this means that it is allowed to be used for that strategy and 0 otherwise. Characteristics of these strategies can be explained as follows:

Strategy	Exchange (0/1)	Compression (0/1)
S1 (Base Policy)	0	0
S2	1	0
S3	0	1
S4	1	1

Table 4.4: Recovery strategies

Strategy 1 (Base Policy): It gives an immediate solution without changing the rest of the schedule. Only the affected flights are removed from the operating flights set, $z_i^{t^*} = 1 \; \forall i \in D$. No re-timing decisions are made for the non-disrupted flights keeping the departure and cruise times same as the original schedule. If Airline Operations Control Center (AOCC) needs to make an urgent decision, it can be considered as a feasible approach. However, it could yield high operational costs and all passengers in cancelled flights need to stay overnight increasing passenger inconvenience. Passengers could be re-routed but AOCC might miss the opportunity of recovery by using this strategy.

Strategy 2: Among recovery tools, only the exchange of aircraft is allowed within the scope of Strategy 2. Exchange of aircraft provides a flexibility while determining the cancellation set. Flights which are initially assigned to the unavailable aircraft can be flown by another aircraft. Instead, flights of that particular operating aircraft are cancelled as they are symbolically assigned to the unavailable one. Changing the aircraft assignment might be beneficial for airline by operating more "profitable" flights or decreasing the operational costs through fuel burn reduction. During disruption periods, it might not be feasible for airlines to operate all flights due to limited resources. When cancellation is inevitable, airlines prefer to operate more profitable flights. Different from the other approaches in literature, ticket price is not the only measure for the profitability of flights in this study. To clarify, consider two flights with equal number of passengers but different ticket prices. In the case of cancellation, lost revenue is higher in direct proportion to higher price. However, one needs to check whether the disrupted passengers can be recovered or not as well. Profit generated from the recovered passengers might compensate for the difference between ticket prices. In such a case, the one with higher ticket price should be cancelled. Another possible explanation is that, the flight with lower ticket price might be the first leg of connecting passengers. Again, AOCC should avoid cancellation of it because otherwise passengers would miss their connections causing a considerable loss of profit. One drawback of the exchange is that, it might cause spill of passengers due to insufficient seat capacity. As a significant contribution of this study, we calculate the actual profit in the case of cancellation considering each passenger itinerary individually. Therefore, we are able to compare flights in terms of profitability and make cancellation decisions accordingly. The impact of utilizing exchange of aircraft can be observed from the results of Strategy 2.

Strategy 3: In tight schedules, idle times might not be sufficient to accommodate new flights into the existing schedule. At that point, aircraft cruise speed can be adjusted to open up some time by shortening predetermined flight times. In disruption scenarios, disrupted flight blocks can be interpreted as new round-trip flights to be placed into the existing schedule. In Strategy 3, we allow cruise time compression and intend to observe its effects on recovery solutions. Although it incurs additional fuel burn and CO_2 emission cost, it is the best possible option in terms of passenger recovery. Unless there exist spilled passengers due to the lack of seat capacity, it enables AOCC to recover all passengers at once without considering alternative re-routing options. Maintaining the passenger convenience could easily compensate for additional fuel, CO_2 emission and spill cost.

Strategy 4: It represents the combination of the recovery tools: exchange of aircraft and cruise time compression. Therefore, it encompasses all of the advantages listed under Strategies 2 and 3. As well as the individual benefits of both tools, using them simultaneously is also favorable for airlines. If cruise times of flights are shortened by speeding up aircraft which are planned to land to hub airports, then these aircraft become available at hub earlier than expected. This generates more exchange alternatives and hence enlarges the solution space. Having a larger solution set enhances the flexibility of AOCC.

Unless indicated otherwise, we run our algorithm for 60 seconds. We designate the profit of airline and the number of passengers who have to stay overnight as performance measures. We evaluate the solution quality with respect to these criteria. We consider the base policy as a reference point and make comparisons accordingly. The improvement percentages for overnight passengers are calculated using the following formula:

$$\text{Overnight Improvement (\%)} = 100 \times \frac{Overnight_{Base} \text{ - } Overnight_{Proposed}}{Overnight_{Base}}$$

where $Overnight_{Base}$ and $Overnight_{Proposed}$ denote the number of overnight passengers under base policy and the proposed strategy, respectively. For the improvement in terms of profit, we follow a similar logic with loss of profit values. If all aircraft were available, then airline would have reached its planned profit value, $P_{Original}$. In the case of disruption, a deviation occurs, but only a small portion of flights are subject to change. Rest of them remain as in the original schedule and hence their contribution to the objective value does not change. In order to exclude the impact of unaffected flights, we make our calculations with respect to the loss of profit values. When the base policy is applied, loss of profit can be calculated as $P_{Original}$ - P_{Base}. Likewise, $P_{Original}$ - $P_{Proposed}$ corresponds to the loss of profit value when the proposed strategy is implemented. The improvement percentages for marginal profits are calculated using the following formula:

$$\text{Profit Improvement (\%)} = 100 \times \frac{Loss_{Base}\text{ - }Loss_{Proposed}}{Loss_{Base}}$$

4.2 Scenario Analysis

In order to observe which recovery tools work well under which circumstances, we take the schedule provided in Appendix A as the original schedule and investigate four disruption cases. Characteristics of the unavailability scenarios can be found in Table 4.5. This table shows the unavailable aircraft, duration of the disruption and affected flights which are initially assigned to that unavailable aircraft. We generate 10 instances for each case by randomly generating number of passengers on each flight. For the first two cases, unavailability period is short in a sense that only one flight block is disrupted. For the other cases, aircraft is not able to serve throughout the day and two flight blocks are affected from this unavailability. In Case 1, it is apparent that flight 206 is disrupted since the aircraft cannot depart at planned departure time. Even though the departure of the next flight, 207, does not coincide with the unavailabilty period, it is also affected. This is because the aircraft cannot reach to the airport where flight 207 is supposed to depart. Therefore, it is indifferent if the unavailability period is between 16:00 and 19:00 or 16:00 and any time after 19:00. In Case 2, disruption period is still short but distinctly this flight block can fit into the existing schedule if cruise times are adjusted. Case 3 and 4 both involve the disrupted flight blocks which will be examined under first two cases. For the Case 3, we make a slight change in the original schedule as denoted with * in Table 4.5. We shift the departure of flight 201, which is assigned to aircraft N352, by one hour so as to prevent accommodation of the first disrupted flight block into the schedule of that operating aircraft. Finally, Case 4 is intended to reflect a scenario where both exchange and compression tools have significant contributions to the objective.

We conduct computational experiments for all cases under four strategies.

Unavailability Scenario	Unavailable Aircraft	Unavailability Duration	Affected Flights
Case 1	N251	16:00-19:00	206/207
Case 2	N251	09:30-14:00	204/205
Case 3	N251*	09:30-22:00	204/205/206/207
Case 4	N251	09:30-22:00	204/205/206/207

Table 4.5: Unavailability scenarios

Recall that first strategy represents the base policy. For Strategies 2 and 3, we only allow exchange of aircraft and cruise time compression, respectively. The last one is the combination of these recovery tools. For each case, Table 4.6-4.9 show characteristics of recovery plans generated by all strategies. Number of cancellations, number of recovered passengers at each phase, cost components and improvement percentages are listed. Using these strategies, we do what-if analysis to measure how changes in a set of recovery actions impact the profit of airline and passenger convenience.

	S1	S2	S3	S4
# of cancellations	2	1	2	1
# of recovered passengers	0	28	0	25
→ Phase I	0	0	0	0
→ Phase II	0	28	0	25
# of overnight passengers	253	89	253	90
% Imp. Overnight	0	64.8	0	64.4
Total compression (min)	0	0	0	5
Compression cost ($)	0	0	0	43
Passenger delay cost ($)	0	0	0	310
Overnight cost ($)	12650	8264	12650	6938
Objective ($)	4605744	4645523	4605744	4645924
% Imp. Profit	0	62.3	0	62.9

Table 4.6: Comparison of different recovery strategies for Case 1

What if either cruise time compression or exchange of aircraft is not allowed? (Strategy 1, Base Policy) Cancelling the disrupted flights provides an immediate feasible solution. Since no re-timing decisions are made, departure times remain constant for the operating flights. Therefore, passenger delay cost is zero. Additional fuel and CO_2 emission cost is not incurred as well. In all cases, S1 yields the lowest profit along with highest overnight cost. Therefore, it should be considered

	S1	S2	S3	S4
# of cancellations	2	2	0	0
# of recovered passengers	0	11	253	253
→ Phase I	0	0	253	253
→ Phase II	0	11	0	0
# of overnight passengers	253	244	0	0
% Imp. Overnight	0	3.6	100	100
Total compression (min)	0	0	21	21
Compression cost ($)	0	0	116	116
Passenger delay cost ($)	0	2703	0	0
Overnight cost ($)	12650	12215	0	0
Objective ($)	4605744	4606599	4657779	4657777
% Imp. Profit	0	1.6	98.1	98.1

Table 4.7: Comparison of different recovery strategies for Case 2

as a last resort.

What if only exchange of aircraft is allowed? (Strategy 2) While determining the set of flights to be cancelled, exchange of aircraft is a crucial tool. It has a significant effect on the number of cancellations, overnight passengers and profit. In recovery solutions of Case 1 and 3, number of cancellations are decreased by one when exchange is allowed. This is because the algorithm prefers not to operate one long haul flight instead of cancelling two short haul flights. This action leads to a considerable decrease in number of overnight passengers along with an increase in profit value. Another observation is that number of passengers who are recovered at Phase II are increased as well. The model makes cancellations in a way that the solution set creates more re-accommodation options for passengers. This also leads to a decrease in the number of overnight passengers.

What if only cruise time compression is allowed? (Strategy 3) Cruise time controllability allows us to accommodate disrupted flight blocks into the existing schedule by shortening their cruise times. In Case 2, by utilizing this function, all disrupted passengers are recovered at the same time which leads to great savings from overnight cost. As all the affected passengers are recovered at once, there is no need for re-accommodation. Compared to the results obtained from S1, number of overnight passengers are decreased by 100% whereas the profit is

	S1	S2	S3	S4
# of cancellations	4	3	4	3
# of recovered passengers	0	40	0	45
→ Phase I	0	0	0	0
→ Phase II	0	40	0	45
# of overnight passengers	503	305	503	292
% Imp. Overnight	0	39.2	0	41.7
Total compression (min)	0	0	0	3
Compression cost ($)	0	0	0	38
Passenger delay cost ($)	0	3921	0	4070
Overnight cost ($)	25155	16585	25155	16154
Objective ($)	4593239	4634544	4593239	4636933
% Imp. Profit	0	35.1	0	37.1

Table 4.8: Comparison of different recovery strategies for Case 3

improved by 98.1%. Compression cost which stands for the additional fuel and CO_2 emission is even negligible compared to the increase in profit. Same impact is observed in Case 4 when compression tool is allowed to be used. Hence, it is highly preferable in terms of passenger recovery.

What if exchange of aircraft and cruise time compression are both allowed? (Strategy 4) Increasing the speed of an aircraft directly reduces the flight block time, and thereby making the aircraft available at hub airport earlier. This creates a new exchange option for some cases. For instance, in Case 1 displayed in Table 4.6, when S3 is applied, there is no change in the solution compared to S1 and none of the cruise times are compressed. This is because it is not possible to place a disrupted block into the existing schedule by shortening flight times. Using the idle times and changing the departure times are not sufficient for such a placement. So it is not meaningful to incur additional fuel and CO_2 emission costs. Aircraft continue to operate at MRC speed. However when S4 is used, it is observed that the model makes a compression of 5 minutes. Moreover, difference between the results of S2 and S4 indicates that unavailable aircraft is exchanged with another aircraft when S4 is applied, otherwise objectives would be the same for both strategies. Therefore, we can conclude that the model prefers to shorten a flight time by increasing the speed of an aircraft to generate a new exchange option. Creating a larger solution set with compression is a strong advantage of

	S1	S2	S3	S4
# of cancellations	4	2.4	2	1
# of recovered passengers	0	41	253	278
→ Phase I	0	0	253	253
→ Phase II	0	41	0	25
# of overnight passengers	503	265	250	88
% Imp. Overnight	0	47.2	50.3	82.6
Total compression (min)	0	0	21	30
Compression cost ($)	0	0	116	209
Passenger delay cost ($)	0	8557	0	1442
Overnight cost ($)	25155	14392	12505	5420
Objective ($)	4593239	4646106	4645274	4685100
% Imp. Profit	0	45.1	44.6	78.8

Table 4.9: Comparison of different recovery strategies for Case 4

this strategy. Likewise, in Case 4 compression durations are not same for S3 and S4. The reason behind the difference is to generate a new exchange alternative as in previous example.

In Tables 4.6-4.9, total delay cost depends on the number of passengers who are recovered at Phase II. In Case 1 under S2, 28 passengers are recovered but no delay cost is incurred. This indicates that they are connecting passengers who are rerouted to early alternatives in the second leg of their connections. Before continuing their next flight, they are notified in advance and hence they can be assigned to earlier flights. For the other cases, passengers are either assigned to late alternatives or fly an extra flight and reach destination airports later than planned. We observe that delaying a passenger is less costly and hence more preferable option compared to staying overnight.

In this study, another significant contribution is that we deal with passenger itineraries individually. In terms of their contributions to the overall profit, passengers are not equally important. Ticket price of the flight which the passenger is assigned to, type of the passenger (direct or connecting) and the potential re-accommodation alternatives are determinant factors. In Case 1, although the number of overnight passengers is increased, profit is higher for S4 compared to S2. This shows that increase in profit does not necessarily imply the decrease in overnight passengers. At that point, profitability of passengers surpasses the quantity. This example highlights the importance of making individual itinerary based decisions.

When airlines face with disruption scenarios, unless real-time and efficient recovery solutions are available, unavailability of aircraft might result in loss of customer goodwill and damage their profits substantially. In Table 4.10, % improvement of profits are compared under different time limits: 45 and 60 seconds. We observe that even after 45 seconds, the results remain same except for a few strategies. Therefore, we do not feel the need to extend solution time beyond 60 seconds. Moreover, 10 replications are performed for each case and strategy to see whether random number of passengers have any effect on objective values. Minimum, maximum and average improvement percentages under different time limits are provided in Tables 4.10 and 4.11. From these tables we can conclude that the randomization does not have a significant effect on the overall performance of the algorithm.

		45 sec			60 sec		
		min	avg	max	min	avg	max
Case 1	S1	-	-	-	-	-	-
	S2	51.8	62.3	75.9	51.8	62.3	75.9
	S3	0	0	0	0	0	0
	S4	54.4	62.9	75.9	54.4	62.9	75.9
Case 2	S1	-	-	-	-	-	-
	S2	0	1.6	15.3	0	1.6	15.3
	S3	97.6	98.1	98.3	97.6	98.1	98.3
	S4	97.6	98.1	98.3	97.6	98.1	98.3
Case 3	S1	-	-	-	-	-	-
	S2	17	34.5	44.6	21.3	35.1	44.6
	S3	0	0	0	0	0	0
	S4	2.7	32.7	44.6	22.4	37.1	44.6
Case 4	S1	-	-	-	-	-	-
	S2	26	42.9	49.9	26	45.1	61.6
	S3	39.4	44.6	51.2	39.4	44.6	51.2
	S4	71.5	78.8	91.8	71.5	78.8	91.8

Table 4.10: % improvement of the profit under different time limits

Among all strategies, it is evident that Strategy 4 dominates the rest of the

		45 sec			60 sec		
		min	avg	max	min	avg	max
Case 1	S1	-	-	-	-	-	-
	S2	59.6	64.8	72.6	59.6	64.8	72.6
	S3	0	0	0	0	0	0
	S4	56.4	64.4	72.6	56.4	64.4	72.6
Case 2	S1	-	-	-	-	-	-
	S2	0	3.2	23.6	0	3.2	23.6
	S3	100	100	100	100	100	100
	S4	100	100	100	100	100	100
Case 3	S1	-	-	-	-	-	-
	S2	23.2	39.9	53.4	23.2	39.2	53.4
	S3	0	0	0	0	0	0
	S4	31.5	40.2	48.2	31.5	41.7	53.4
Case 4	S1	-	-	-	-	-	-
	S2	34	45.7	57.3	34	47.2	57.3
	S3	45.8	50.3	55.9	45.8	50.3	55.9
	S4	78	82.6	89.5	78	82.6	89.5

Table 4.11: % improvement of the number of overnight passengers under different time limits

policies. Both exchange and compression tools enable our model to achieve better results but when they are allowed simultaneously, % improvement of overnight passengers and profit are higher. Therefore, we can propose AOCC to use this strategy for the integrated aircraft and passenger recovery problem.

What If Analysis on Overnight Cost: Due to the high level of competition in airline industry, we put a special emphasis on passenger convenience. Therefore, we perform an experimental design and run our algorithm with S4 for three overnight cost settings. For low (L), medium (M) and high (H) values, we set the overnight cost per passenger to 50$, 150$ and 250$ respectively. Tables 4.12-4.14 display the results for these three settings. In order to observe how changes in overnight cost impact the number of overnight passengers, we plot a graph for each case. This is depicted in Figure 4.1.

	Case 1	Case 2	Case 3	Case 4
# of cancellations	1	0	3	1
# of recovered passengers	25	253	45	278
→ Phase I	0	253	0	253
→ Phase II	25	0	45	25
# of overnight passengers	90	0	292	88
% Imp. Overnight	64.4	100	41.7	82.6
Total compression (min)	5	21	3	30
Compression cost ($)	43	116	38	209
Passenger delay cost ($)	310	0	4070	1442
Overnight cost ($)	6938	0	16154	5420
Objective ($)	4645924	4657777	4636933	4685100
% Imp. Profit	62.9	98.1	37.1	78.8

Table 4.12: Performance of Strategy 4 for low overnight cost setting ($\phi = 50$)

	Case 1	Case 2	Case 3	Case 4
# of cancellations	1	0	3	1
# of recovered passengers	44	253	47	283
→ Phase I	0	253	0	253
→ Phase II	44	0	47	30
# of overnight passengers	82	0	287	86
% Imp. Overnight	67.6	100	42.9	82.9
Total compression (min)	0	21	0	23
Compression cost ($)	0	116	0	142
Passenger delay cost ($)	3593	0	4268	574
Overnight cost ($)	15177	0	44270	15496
Objective ($)	4632353	4657777	4610141	4677087
% Imp. Profit	64	98.1	40.1	80.4

Table 4.13: Performance of Strategy 4 for medium overnight cost setting ($\phi = 150$)

	Case 1	Case 2	Case 3	Case 4
# of cancellations	1	0	3	1
# of recovered passengers	56	253	49	283
→ Phase I	0	253	0	253
→ Phase II	56	0	49	30
# of overnight passengers	80	0	284	86
% Imp. Overnight	68.4	100	43.5	82.9
Total compression (min)	0	21	0	23
Compression cost ($)	0	116	0	142
Passenger delay cost ($)	6557	0	5500	574
Overnight cost ($)	22270	0	72394	24086
Objective ($)	4628740	4657777	4581161	4668497
% Imp. Profit	64.2	98.1	40.6	81.1

Table 4.14: Performance of Strategy 4 for high overnight cost setting ($\phi = 250$)

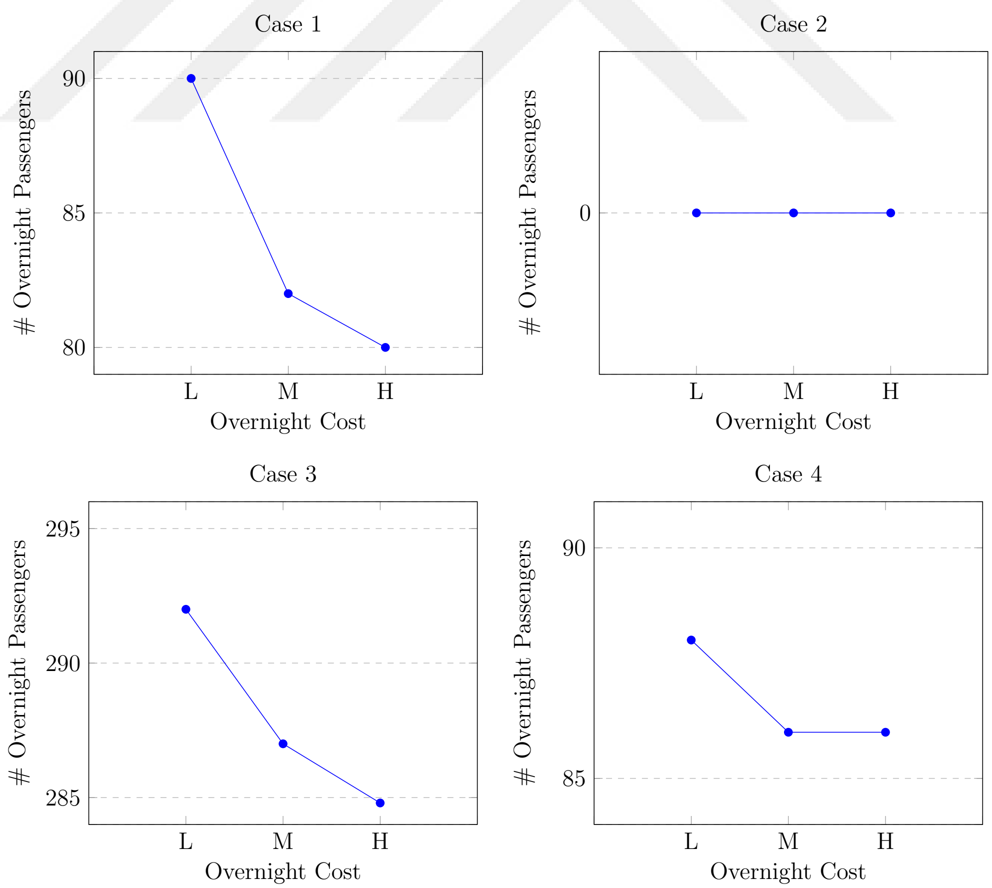

Figure 4.1: Number of overnight passengers for different overnight cost settings

In Case 1, the number of overnight passengers are 90, 82 and 80 for L, M and H levels respectively. As can be seen in Figure 4.1, number of overnight passengers are decreased when overnight cost increases, but instead passenger delay cost is increased. This indicates that passengers are more inclined to arrive their destination airports late to some extent instead of staying overnight. We also observe an increase in the number of passengers who are recovered at Phase II. In an attempt to save from overnight cost, the model prefers to cancel flights in a way that more re-accommodation options become available for disrupted passengers. These observations also hold for Case 3. In Case 4, what we observe is that passengers who need to stay overnight is decreased by 2 from L to M. However, it remains constant for the highest cost setting. This highlights the fact that further re-accommodations are not possible due to the limited number of available seats. Different from the other scenarios, overnight cost has no impact on Case 2 since all of the passengers are recovered at Phase I. For all cases, it is seen that improvement percentages in higher cost settings (M,H) are greater than or equal to the lowest one (L).

What If Analysis on Fuel Cost: Fuel cost, which is a significant portion of the total expenditure of airline operations, is highly variable. Therefore, in addition to the overnight cost per passenger, we take the fuel cost as an experimental factor to observe how changes in fuel cost affect the profit value. We set the unit cost of fuel to 0.6, 1.2 and 1.8 $/kg for low (L), medium (M) and high (H) values. For each case and factor level combination, we run our algorithm with S4 and S1. Profit values under these strategies and the difference between them are given in Table 4.15. Here, the difference can be interpreted as the value of our proposed math-heuristic algorithm. It shows how much we can improve the profit by allowing exchange of aircraft and cruise time compression instead of directly cancelling all affected flights.

As expected, an increase in overnight or fuel cost results in a lower profit value. A significant observation is that the difference between the profit values of S4 and S1 increases as the overnight cost increases in all cases, regardless of the fuel cost level. That is, the value of our algorithm is higher for higher overnight cost settings. Our algorithm creates a better impact and achieves better savings when

	Over.	L	L	L	M	M	M	H	H	H
	Fuel	L	M	H	L	M	H	L	M	H
Case 1	S4	5406978	4645924	3885546	5397998	4632353	3876646	5389254	4628740	3867942
	S1	5365861	4605744	3845627	5340561	4580444	3820327	5315261	4555144	3795027
	Diff.	41117	40180	39919	57437	51909	56319	73993	73596	72915
Case 2	S4	5421801	4657777	3893754	5421801	4657777	3893754	5421801	4657777	3893754
	S1	5365861	4605744	3845627	5340561	4580444	3820327	5315261	4555144	3795027
	Diff.	55940	52033	48127	81240	77333	73427	106540	102633	98727
Case 3	S4	5395792	4636933	3875297	5367442	4610141	3852841	5337492	4581161	3824111
	S1	5353356	4593239	3833122	5303046	4542929	3782812	5252736	4492619	3732502
	Diff.	42436	43694	42175	64396	67212	70029	84756	88542	91609
Case 4	S4	5450634	4685100	3919566	5441874	4677087	3912786	5433114	4668497	3904196
	S1	5353356	4593239	3833122	5303046	4542929	3782812	5252736	4492619	3732502
	Diff.	97278	91861	86444	138828	134158	129974	180378	175878	171694

Table 4.15: Profit values for different factor level combinations

the overnight cost is high. For instance, Figure 4.2 represents how this difference varies between three overnight cost settings for Case 4. As can be observed from this figure, the largest difference is obtained when both factors are set to their highest values. Moreover, for a fixed overnight cost level, when the fuel cost increases, difference values might slightly decrease as in Case 4. However, they are still considerable and applying S4 contributes to the profit of the airline in a substantial manner. Figure 4.3 shows the profit values for different fuel cost settings when the overnight cost is high as an example.

4.3 Summary

In this section, we conduct computational experiments to test the performance of our math-heuristic algorithm. We first explain how aircraft schedules and passenger itineraries are generated. We give the aircraft and airport specific parameters. Taking these values as input, we describe the calculation of fuel consumption and turnaround times. Then, we move on to cost parameters. We explain how origin and destination pairs as well as the time of the day affect ticket prices. We also provide the cost of flying an additional flight, staying overnight and delay cost per minute per passenger.

Afterwards, we introduce recovery strategies which can be followed in the case

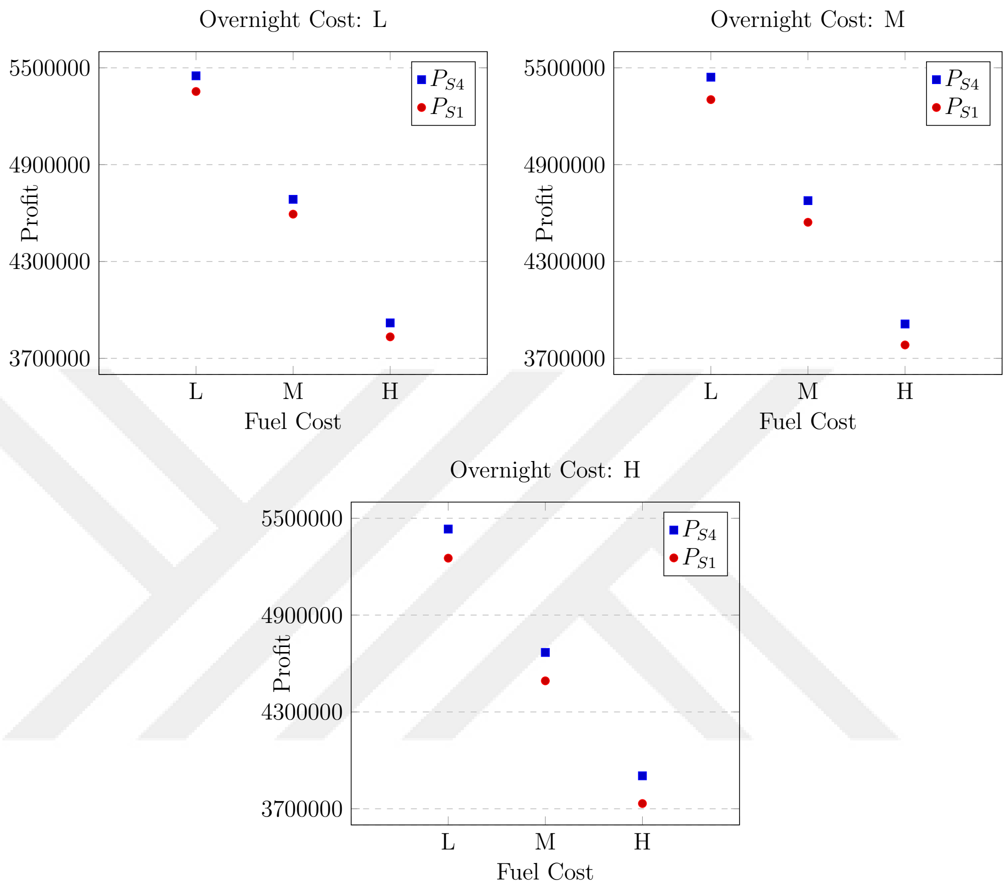

Figure 4.2: What-if analysis on fuel cost for Case 4

of a disruption. We set cancellation of all affected flights as the base policy. We only allow exchange of aircraft and cruise time compression for strategies 2 and 3. For Strategy 4, we combine both recovery tools. We specify two performance measures to evaluate the quality of recovery plans: profit of airline and the number of overnight passengers. Then we investigate four unavailability scenarios under aforementioned strategies. We present number of cancelled flights, recovered passengers at each phase, cost components and improvement percentages as results.

We conduct what-if analysis to observe how altering the set of recovery actions impact the profit of airline and passenger satisfaction. Lastly, we set up an experimental design for different overnight and fuel cost settings.

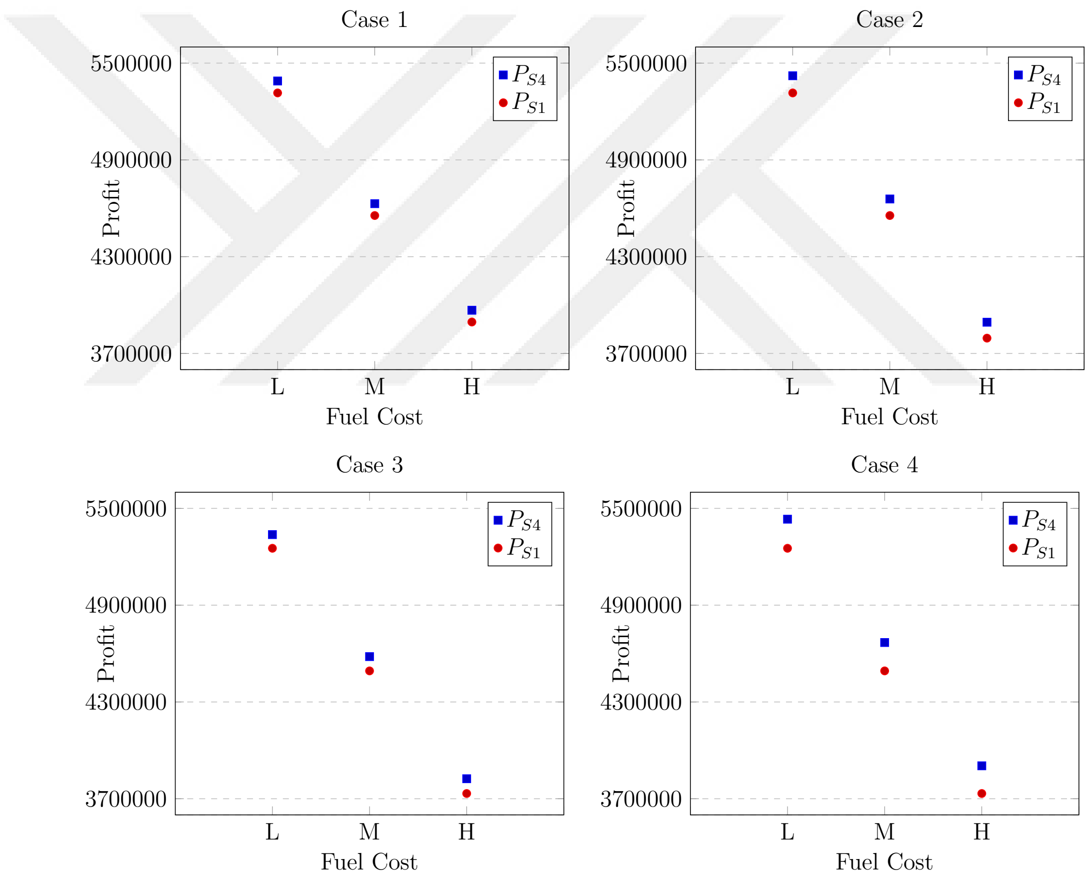

Figure 4.3: Profit values for different fuel cost settings with high overnight cost

Chapter 5

Conclusions and Future Work

A background information regarding the integrated aircraft and passenger recovery problem, contributions and the motivation behind this research are provided in Section 1. In this section, a brief summary of this thesis along with contributions to the disruption management literature and possible future research directions are discussed.

5.1 Summary and Contributions

In this study, we focus on disruption scenarios at which aircraft become unavailable due to mechanical failures or extension on maintenance durations. We intend to develop a structural framework to aid airlines in handling disruptions at operational level. To this end, we study integrated aircraft and passenger recovery problem and propose a novel math-heuristic algorithm to solve it. We aim to come up with a recovery plan which maximizes the profit of airline while also mitigating the passenger dissatisfaction.

Given the unavailable aircraft and disruption duration, our algorithm proceeds in two phases. In the first phase, we propose a mathematical formulation for aircraft recovery. We allow changes in fleet type assignment by using exchange of aircraft as a recovery tool. Moreover, we do not take cruise times as constant so that speeding up aircraft to shorten cruise times in another way to deal with disruptions. Lastly, if the recovery is not possible by any means, then cancellation option can be utilized. In the second phase, we devise an itinerary-based passenger recovery algorithm which evaluates each itinerary separately. As long as there exist available seats, passengers are either re-accommodated to alternative flights or rerouted over another hub airport. The integration between these phases is maintained by the integrated search algorithm through variable fixing.

As a significant contribution, we make recovery decisions based on passenger itineraries in the second phase. This allow us to re-accommodate passengers who are initially assigned to the same flight to different paths. Moreover, before searching recovery alternatives, we prioritize passenger itineraries with respect to their contributions to the objective value. Since each aircraft has a fixed seat capacity, any allocation decision might affect the other by reducing the available capacity. Therefore, prioritization enables us to use limited resources, in this case available seats, in a better way.

We work on networks where aircraft routings and passenger itineraries are superimposed. As being an integrated approach, our algorithm captures the dependencies between aircraft and passenger schedules. By taking these dependencies into the account, we provide the actual cancellation cost formulations. This is another crucial contribution of our research since passenger convenience is of high importance for airlines. In this regard, we manage to find the optimal trade-off between operating and passenger-related costs.

5.2 Future Work

In this thesis, we address aircraft and passenger recovery problems simultaneously. We assume that crew members are always available on time and therefore, they do not cause any infeasibility in the whole network. As an extension to this study, crew recovery problem can also be addressed in this integrated setting. Thereby, interdependencies between all entity types (aircraft,crew,passengers) can be captured.

We differentiate between direct and connecting passengers according to their itineraries. In addition to this distinction, fare class can also be a determinant factor while distinguishing the relative importance of each passenger. Economy and business class passengers can be evaluated separately in further studies. This can be a significant aspect in the sense that they contribute to the objective in different portions.

In this study, we consider flight blocks as round-trip flights which begin and end at the same airport. We assume that if the first leg is not operated, then the return flight should also be cancelled. This is because the aircraft cannot reach to corresponding departure airport of the return flight. To solve this issue, ferrying an available aircraft or utilization of reserve aircraft can also be included to the set of recovery tools for future studies. This may increase the flexibility of operations and enlarge the solution space.

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Appendix A

Original Schedule with 208 Flights

Tail No	Flight No	Departure	Arrival	Departure Time	Flight Time	Arrival Time
N00	0	ORD	LGA	06:15	02:14	08:29
N00	1	LGA	ORD	09:25	02:50	12:15
N00	2	ORD	DFW	13:35	02:15	15:50
N00	3	DFW	ORD	17:00	02:30	19:30
N11	4	ORD	LGA	06:50	02:15	09:05
N11	5	LGA	ORD	10:00	02:50	12:50
N11	6	ORD	LGA	13:55	02:20	16:15
N11	7	LGA	ORD	17:15	02:50	20:05
N22	8	ORD	DFW	06:45	02:15	09:00
N22	9	DFW	ORD	10:10	02:20	12:30
N22	10	ORD	AUS	13:25	02:50	16:15
N22	11	AUS	ORD	17:00	02:45	19:45
N22	12	ORD	LGA	20:40	02:05	22:45
N33	13	ORD	SAN	07:45	04:30	12:15
N33	14	SAN	ORD	13:00	04:30	17:30
N33	15	ORD	ATL	18:15	02:10	20:25
N33	16	ATL	ORD	21:20	02:05	23:25
N44	17	ORD	SFO	07:40	04:55	12:35
N44	18	SFO	ORD	13:30	04:25	17:55
N44	19	ORD	TUS	19:15	03:55	23:10
N55	20	ORD	PHX	07:10	04:00	11:10
N55	21	PHX	ORD	11:55	03:30	15:25
N55	22	ORD	LGA	16:25	02:25	18:50
N55	23	LGA	ORD	20:00	02:35	22:35
N06	24	ORD	STL	06:20	01:10	07:30
N06	25	STL	ORD	08:35	01:15	09:50
N06	26	ORD	SAT	10:45	03:00	13:45
N06	27	SAT	ORD	15:00	03:00	18:00
N06	28	ORD	PHL	18:45	02:05	20:50
N17	29	ORD	BOS	06:35	02:10	08:45
N17	30	BOS	ORD	09:35	03:05	12:40
N17	31	ORD	SNA	13:30	04:15	17:45
N17	32	SNA	ORD	19:10	03:50	23:00
N28	33	ORD	SFO	09:45	04:55	14:40
N28	34	SFO	ORD	15:45	04:25	20:10
N28	35	ORD	MSP	21:20	01:30	22:50
N39	36	ORD	DCA	06:45	01:40	08:25
N39	37	DCA	ORD	09:15	02:10	11:25
N39	38	ORD	LAS	13:25	04:05	17:30
N39	39	LAS	ORD	18:20	03:40	22:00
N410	40	ORD	SNA	08:25	04:40	13:05
N410	41	SNA	ORD	14:00	04:00	18:00
N410	42	ORD	MIA	19:25	03:00	22:25
N511	43	ORD	RSW	06:45	02:45	09:30
N511	44	RSW	ORD	10:20	03:05	13:25
N511	45	ORD	EWR	14:55	02:45	17:40
N511	46	EWR	ORD	18:45	02:45	21:30
N012	47	ORD	FLL	07:25	02:55	10:20
N012	48	FLL	ORD	11:10	03:15	14:25
N012	49	ORD	DEN	15:35	02:45	18:20
N012	50	DEN	ORD	19:35	02:40	22:15
N113	51	ORD	MCI	06:25	01:30	07:55
N113	52	MCI	ORD	08:40	01:30	10:10
N113	53	ORD	DFW	12:00	02:15	14:15
N113	54	DFW	ORD	15:00	02:20	17:20
N113	55	ORD	DEN	18:50	02:45	21:35
N214	56	ORD	MSP	06:40	01:30	08:10
N214	57	MSP	ORD	09:00	01:25	10:25
N214	58	ORD	SAN	11:35	04:20	15:55
N214	59	SAN	ORD	16:45	03:55	20:40
N214	60	ORD	BOS	21:50	02:05	23:55
N315	61	ORD	EWR	06:35	02:05	08:40
N315	62	EWR	ORD	09:30	02:40	12:10
N315	63	ORD	DCA	13:10	01:45	14:55
N315	64	DCA	ORD	15:45	02:15	18:00
N315	65	ORD	LAS	19:00	04:10	23:10
N416	66	ORD	LAX	08:50	04:35	13:25
N416	67	LAX	ORD	14:30	04:15	18:45
N416	68	ORD	BOS	19:45	02:15	22:00
N517	69	ORD	LAS	08:30	04:05	12:35
N517	70	LAS	ORD	13:25	03:35	17:00
N517	71	ORD	DCA	18:00	01:45	19:45
N018	72	ORD	MIA	07:35	03:10	10:45
N018	73	MIA	ORD	11:55	03:20	15:15
N018	74	ORD	MIA	16:20	03:05	19:25
N018	75	MIA	ORD	20:20	03:00	23:20
N119	76	ORD	ATL	06:30	02:00	08:30
N119	77	ATL	ORD	09:15	02:15	11:30
N119	78	ORD	MCO	12:25	02:40	15:05
N119	79	MCO	ORD	15:50	03:05	18:55
N220	80	ORD	MSY	08:50	02:25	11:15
N220	81	MSY	ORD	12:00	02:30	14:30
N220	82	ORD	PHL	15:35	02:05	17:40
N220	83	PHL	ORD	18:30	02:35	21:05
N321	84	ORD	PBI	09:20	02:55	12:15
N321	85	PBI	ORD	13:00	03:20	16:20
N321	86	ORD	STL	17:15	01:10	18:25
N321	87	STL	ORD	19:10	01:20	20:30
N422	88	ORD	DFW	07:45	02:30	10:15
N422	89	DFW	ORD	11:35	02:20	13:55
N422	90	ORD	STL	14:50	01:05	15:55
N422	91	STL	ORD	17:00	01:20	18:20
N422	92	ORD	SLC	19:15	03:40	22:55
N523	93	ORD	RDU	06:50	01:50	08:40

Table A.1: Original schedule with 208 flights

Tail No	Flight No	Departure	Arrival	Departure Time	Flight Time	Arrival Time
N523	94	RDU	ORD	09:25	02:15	11:40
N523	95	ORD	PHX	12:35	03:55	16:30
N523	96	PHX	ORD	17:15	03:25	20:40
N024	97	ORD	EWR	08:00	02:20	10:20
N024	98	EWR	ORD	11:25	02:40	14:05
N024	99	ORD	MCO	15:00	02:40	17:40
N024	100	MCO	ORD	18:25	02:55	21:20
N125	101	ORD	DFW	09:05	02:15	11:20
N125	102	DFW	ORD	12:35	02:20	14:55
N125	103	ORD	STL	15:50	01:10	17:00
N125	104	STL	ORD	18:00	01:20	19:20
N125	105	ORD	PBI	20:15	03:00	23:15
N126	106	ORD	EGE	08:10	02:55	11:05
N126	107	EGE	ORD	12:25	02:45	15:10
N126	108	ORD	SNA	18:40	04:30	23:10
N327	109	ORD	LAX	07:00	04:30	11:30
N327	110	LAX	ORD	12:40	04:05	16:45
N327	111	ORD	RDU	17:45	01:55	19:40
N428	112	ORD	SJU	08:30	04:50	13:20
N428	113	SJU	ORD	14:25	05:35	20:00
N428	114	ORD	MCI	21:10	01:25	22:35
N529	115	ORD	HDN	09:50	02:50	12:40
N529	116	HDN	ORD	13:40	02:50	16:30
N529	117	ORD	DFW	17:15	02:20	19:35
N529	118	DFW	ORD	20:20	02:10	22:30
N030	119	DFW	ATL	09:00	02:15	11:15
N030	120	ATL	DFW	12:30	02:10	14:40
N030	121	DFW	AUS	16:30	01:00	17:30
N030	122	AUS	DFW	18:30	01:00	19:30
N131	123	DFW	IAH	08:40	01:20	10:00
N131	124	IAH	DFW	11:00	01:15	12:15
N131	125	DFW	AUS	15:00	01:00	16:00
N131	126	AUS	DFW	17:05	01:00	18:05
N131	127	DFW	ORD	18:35	02:15	20:50
N232	128	DCA	DFW	08:05	02:55	11:00
N232	129	DFW	SAN	12:00	03:00	15:00
N232	130	SAN	DFW	16:30	03:00	19:30
N333	131	DFW	SAN	10:00	03:00	13:00
N333	132	SAN	DFW	14:05	03:00	17:05
N333	133	DFW	ORD	17:45	02:15	20:00
N333	134	ORD	DFW	20:45	02:20	23:05
N434	135	IAH	DFW	08:00	01:15	09:15
N434	136	DFW	SFO	10:45	03:45	14:30
N434	137	SFO	DFW	16:00	03:45	19:45
N535	138	DFW	SFO	09:00	03:45	12:45
N535	139	SFO	DFW	13:45	03:45	17:30
N535	140	DFW	TUS	20:30	02:30	23:00
N036	141	DFW	PHX	08:45	02:30	11:15
N036	142	PHX	DFW	12:00	02:30	14:30
N036	143	DFW	ORD	15:15	02:15	17:30
N036	144	ORD	DEN	18:30	02:45	21:15
N137	145	BOS	DFW	08:15	03:30	11:45
N137	146	DFW	SAT	13:50	01:00	14:50
N137	147	SAT	DFW	15:30	01:00	16:30
N137	148	DFW	ORD	17:15	02:15	19:30
N137	149	ORD	RDU	20:20	02:40	23:00
N238	150	DFW	MSY	12:00	01:15	13:15

Tail No	Flight No	Departure	Arrival	Departure Time	Flight Time	Arrival Time
N238	151	MSY	DFW	14:00	01:15	15:15
N238	152	DFW	SNA	16:30	03:15	19:45
N238	153	SNA	DFW	20:45	03:05	23:50
N339	154	DFW	MSY	09:45	01:15	11:00
N339	155	MSY	DFW	12:05	01:15	13:20
N339	156	DFW	SNA	16:30	03:15	19:45
N339	157	SNA	DFW	20:45	03:05	23:50
N440	158	ORD	DFW	10:00	02:15	12:15
N440	159	DFW	SFO	13:00	03:45	16:45
N440	160	SFO	DFW	18:00	03:45	21:45
N541	161	DFW	RSW	09:35	02:25	12:00
N541	162	RSW	DFW	13:00	02:30	15:30
N541	163	DFW	LAS	16:30	02:50	19:20
N541	164	LAS	DFW	20:00	03:00	23:00
N042	165	MCI	ORD	08:50	01:30	10:20
N042	166	ORD	DFW	11:45	02:15	14:00
N042	167	DFW	SAN	14:45	03:00	17:45
N042	168	SAN	DFW	19:00	03:00	22:00
N143	169	SAT	DFW	08:50	01:05	09:55
N143	170	DFW	LAX	10:45	03:30	14:15
N143	171	LAX	DFW	16:00	03:30	19:30
N143	172	DFW	MIA	20:20	02:40	23:00
N244	173	LGA	DFW	07:15	03:30	10:45
N244	174	DFW	SAN	12:00	03:30	15:30
N244	175	SAN	DFW	16:30	03:30	20:00
N244	176	DFW	STL	21:00	01:40	22:40
N345	177	AUS	DFW	07:00	01:05	08:05
N345	178	DFW	MIA	10:45	02:30	13:15
N345	179	MIA	DFW	14:30	02:30	17:00
N345	180	DFW	LGA	19:00	03:20	22:20
N446	181	SAT	DFW	09:05	01:10	10:15
N446	182	DFW	LAS	12:00	03:00	15:00
N446	183	LAS	DFW	16:30	03:00	19:30
N446	184	DFW	LGA	20:30	03:10	23:40
N547	185	ORD	DCA	07:30	02:00	09:30
N547	186	DCA	ORD	10:30	02:10	12:40
N547	187	ORD	EWR	13:50	02:25	16:15
N547	188	EWR	ORD	17:45	02:30	20:15
N048	189	ORD	DEN	07:00	02:45	09:45
N048	190	DEN	ORD	11:00	02:50	13:50
N048	191	ORD	BOS	15:00	02:20	17:20
N048	192	BOS	ORD	19:00	02:15	21:15
N149	193	ORD	MSP	08:00	01:40	09:40
N149	194	MSP	ORD	10:50	01:45	12:35
N149	195	ORD	SLC	13:30	03:40	17:10
N149	196	SLC	ORD	18:45	03:30	22:15
N250	197	ORD	FLL	08:15	03:00	11:15
N250	198	FLL	ORD	12:30	03:05	15:35
N250	199	ORD	ATL	16:45	02:10	18:55
N250	200	ATL	ORD	20:00	02:20	22:20
N352	201	ATL	ORD	07:30	02:20	09:50
N352	202	ORD	BOS	13:45	03:00	16:45
N352	203	BOS	ORD	19:30	02:50	22:20
N251	204	ORD	MSP	09:30	01:45	11:15
N251	205	MSP	ORD	12:25	01:40	14:05
N251	206	ORD	ROC	16:00	02:30	18:30
N251	207	ROC	ORD	19:30	02:20	21:50

Table A.1: (continued)

Appendix B

Base Ticket Prices

Airport	Base Price ($)	Airport	Base Price ($)
ATL	203	MSP	200
AUS	221	MSY	182
BOS	168	PBI	263
DCA	233	PHL	257
DEN	228	PHX	204
DFW	206	RDU	205
EGE	200	RSW	173
EWR	267	SAN	215
FLL	164	SAT	237
HDN	200	SFO	261
LAS	238	SJU	270
LAX	244	SLC	246
LGA	176	SNA	276
MCI	191	STL	228
MCO	167	TUS	285
MIA	180		

Table B.1: Base ticket prices from ORD airport

Airport	Base Price ($)	Airport	Base Price ($)
ATL	175	MSY	156
AUS	160	ORD	206
BOS	222	PBI	200
DCA	282	PHL	257
DEN	176	PHX	220
EGE	176	RDU	255
EWR	298	RSW	282
FLL	186	SAN	195
HDN	176	SAT	199
LAS	176	SFO	215
LAX	191	SJU	290
LGA	222	SLC	211
MCI	175	SNA	291
MCO	182	STL	222
MIA	233	TUS	295
MSP	176		

Table B.2: Base ticket prices from DFW airport

Vita

Yücel Naz Yetimoğlu was born on July 10, 1995 in Ankara, Turkey. She graduated from TED Ankara College Foundation High School in 2013. She attended Bilkent University with scholarship and graduated from the Industrial Engineering Program of Faculty of Engineering in 2017 as class salutatorian. She continued her education by pursuing a master degree in the same department. Since then, she has been working with M. Selim Aktürk on her graduate study. She had been on the grant 2210 awarded by The Scientific and Technological Research Council of Turkey (TUBITAK) during her M.S. study.