Interfaces

Flight-Scheduling Optimization and Automation for AnadoluJet

Başak Kepir, Çağıl Koçyiğit, Işıl Koyuncu, Melis Beren Özer, Bahar Yetis Kara, Melih Akif Gürbüz

Please scroll down for article—it is on subsequent pages

INFORMS is the largest professional society in the world for professionals in the fields of operations research, management
science, and analytics.
For more information on INFORMS, its publications, membership, or meetings visit http://www.informs.org

Flight-Scheduling Optimization and Automation for AnadoluJet

Başak Kepir
KPMG Management Consultancy, Istanbul, Turkey, bkepir@gmail.com

Çağıl Koçyiğit
Risk Analytics and Optimization Chair, École Polytechnique Fédérale De Lausanne, 1015 Lausanne, Switzerland,
cagil.kocyigit@epfl.ch

Işıl Koyuncu
Department of Information Systems, Statistics, and Management Science, The University of Alabama, Tuscaloosa, Alabama 35487,
ikoyuncu@crimson.ua.edu

Melis Beren Özer, Bahar Yetis Kara
Industrial Engineering, Bilkent University, 6800 Ankara, Turkey
{melisberen@gmail.com, bkara@bilkent.edu.tr}

Melih Akif Gürbüz
AnadoluJet, Ankara, Turkey, mgurbuz@thy.com

AnadoluJet, a leading Turkish domestic airline carrier provides high-service, low-price flights to 28 locations within Turkey. Each winter and summer, AnadoluJet typically generates a new flight schedule. The company's primary scheduling concerns are aircraft fleet utilization and the waiting times of transfer passengers. Balancing the trade-off between these two criteria in a flight schedule is crucial for AnadoluJet's profitability. In this paper, we present the results of our study of AnadoluJet's flight-scheduling process. We provide a mathematical model that addresses this problem and then extend our studies and implement a heuristic algorithm for the development of a decision support system for the company. The objectives of the models we generated are to maximize fleet utilization, minimize waiting times for the majority of transfer passengers, and generate flight schedules subject to various constraints. The schedules that result from our models are superior to those that AnadoluJet's generated using its previous manual process. AnadoluJet currently uses our decision support system in its flight-scheduling process.

Keywords: low-cost carriers; flight scheduling; mathematical modelling.
History: This paper was refereed. Published online in *Articles in Advance* June 16, 2016.

A nadoluJet, a subsidiary of Turkish Airlines, provides high-service, low-price domestic flights within Turkey. The company has 18 aircraft in its aircraft fleet and services 28 locations. As one of Turkey's leading low-cost carriers, it carried 5.3 million passengers in 2012 (AnadoluJet 2013).

AnadoluJet has a hub-and-spoke network, which includes one or more nodes as hub(s) and segments that connect all other nodes (spokes) to at least one hub. In its current network structure, it designates Ankara's Esenboga Airport as the main hub primarily because of geopolitical factors. For strategic reasons, the company may also schedule flights through Istanbul. Therefore, Istanbul's Sabiha Gökçen Airport is considered a secondary hub (Haksöz 2013). Figure 1 shows AnadoluJet's flight network across Turkey.

AnadoluJet's network planning department generates flight schedules twice each year, winter and summer. In generating these schedules, the company's key concerns are to maximize fleet utilization and decrease the waiting time of transfer passengers. Fleet utilization is defined as the number of total hours all aircraft spend in the air. A transfer passenger is one who travels from one city to another with a connecting flight over a hub; for example, a transfer passenger who travels from Izmir to Erzincan might
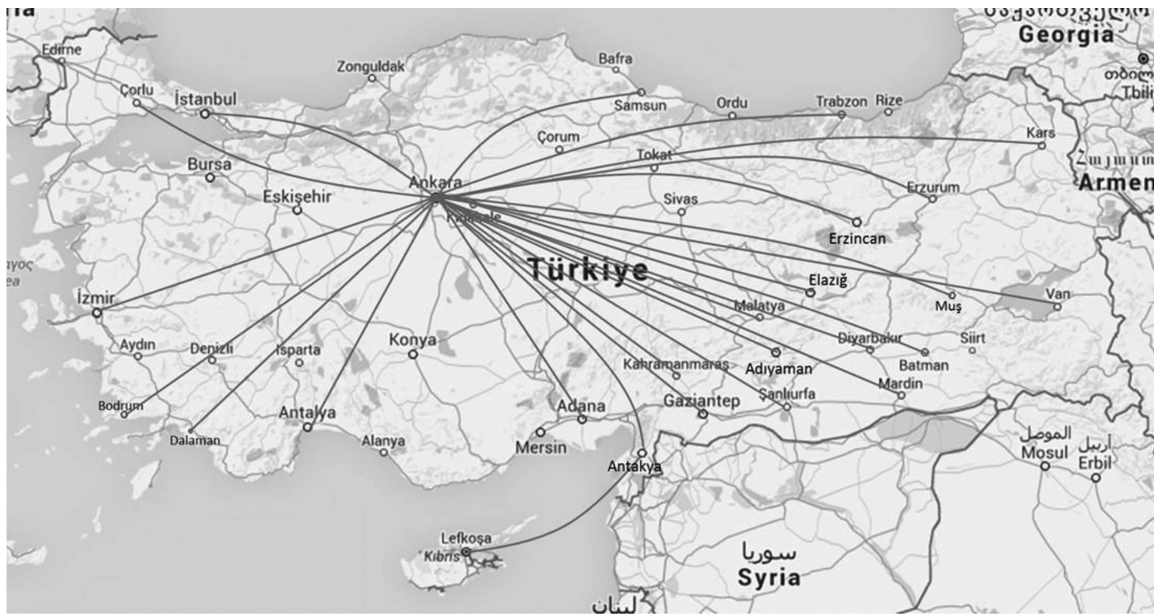
Figure 1: AnadoluJet serves 28 airports using a hub-and-spoke network; Ankara is its main hub.

change flights in Ankara. According to AnadoluJet, approximately 25 percent of its passengers state that transfer service and waiting times in Ankara must be improved. Balancing the trade-off between fleet utilization and transfer performance (i.e., minimizing waiting times for passengers connecting at a hub) and optimizing both make the network planning and scheduling problem complex.

The schedules generated are critical because they determine the timing and sources of operations, such as aircraft fleet and crew, that directly affect the company's profitability; however, manually producing flight schedules, while taking additional constraints into account, is time consuming and unlikely to generate an optimal schedule. Hence, at AnadoluJet's request, our team undertook and completed a project to provide the company with a decision support system that generates its seasonal (i.e., winter and summer) flight schedules. We developed a mathematical model and solved it using Xpress Solver. We also developed a heuristic algorithm based on the mathematical model, coded it using the Java programming language, and developed a program we called OpScheduler to give AnadoluJet a scheduling tool with multiple interfaces.

We organized the remainder of the paper as follows. In the *AnadoluJet's Flight-Scheduling Process* section, we include a brief review of relevant literature, explain the company's network structure, define the problem in detail, and discuss the constraints associated with company requests and operational limitations. In the *Methodology* section, we introduce our optimal-solution method and the heuristic algorithm we used to rapidly provide good solutions that do not require additional software. *Optimization Model* explains the objective and working principle of the mathematical model; *Decision Support System* details the objective and working principles of the heuristic algorithm and OpScheduler and discusses additional modules we added to the program. In *Results*, we use data provided by AnadoluJet to present the numerical and statistical results of the study we conducted and explain both the mathematical model and OpScheduler. *Concluding Remarks* summarizes the results of the project and discusses the benefits anticipated in terms of market share and profit. Finally, in the appendices, we discuss details of the mathematical and the heuristic models and include examples of the output from both models and of the OpScheduler interface.

AnadoluJet's Flight-Scheduling Process

Literature Review

Following the enactment of the airline deregulation act in 1978, which removed government restrictions on fares, routes, and market entry, airline network design and scheduling became a major focus in the transportation industry. Magnanti and Wong (1984) provide a detailed analysis of the network design problem, including a broad definition and detailed examination of network design and scheduling problems, variations in formulations, and possible applications to most transportation planning problems. Zhang et al. (2013) address recent studies in various areas of transportation, including network design and scheduling optimization in land transportation. In our study, we focus on airline applications.

The flight-scheduling planning process has been studied extensively in the literature. Barnhart and Cohn (2004) provide a detailed literature review on this process. Schedule generation is a major facet of the scheduling problem because it significantly impacts all airline operations and the associated revenues. The flight-schedule design literature focuses principally on costs and profitability. Soumis et al. (1980), Dobson and Lederer (1993), Marsten et al. (1996), and Erdmann et al. (2001) describe efforts to improve airline profitability by optimizing airline schedules. Most studies in the literature consider a single objective, such as minimizing total cost or maximizing total revenue. Although providing a high level of service to all locations is important, most models in the literature do not explicitly address customer satisfaction. To understand quality-of-service issues from the perspective of the passengers, Lan et al. (2006) conducted an airline scheduling study; their objective was to minimize the number of passengers affected by delays and disruptions.

Although the existing methods for addressing scheduling problems are worthwhile, they are not suitable for solving AnadoluJet's problem because of the distinct characteristics of the company's flight schedules. Considering our multiple objectives, that is, increasing fleet utilization and transfer-passenger satisfaction by decreasing the transfer times between connecting flights, adapting our problem to the traditional network design and scheduling problem formulations was difficult. Therefore, we developed a new method to solve this problem.

AnadoluJet's Flight-Scheduling Process: Characteristics

AnadoluJet's direct network has 28 flight points that it serves with a fleet of 18 aircraft. The company requested that we focus our project on the network that uses the Ankara hub, which includes 24 flight points. Because of the hub-and-spoke structure of the model, the Ankara hub must be either an origin or destination for each flight segment.

Airline schedule planning consists of four stages—schedule generation, fleet assignment, aircraft maintenance, and crew assignment; however, in this study, we restrict our attention to the schedule generation process. Because all AnadoluJet aircraft are identical, fleet assignment is not a concern in our problem. Furthermore, aircraft maintenance routing and crew assignment are beyond the scope of our project because a department other than network planning makes these decisions using the schedule as input.

The company utilizes a four-waves-per-day scheduling structure to manage the city pairs that must connect to each other. It defines a wave as a set of synchronized there-and-back flights (i.e., origin to destination and destination back to the origin) between the hub and selected destination points. The flying time of each flight in the same wave is restricted to predetermined time intervals to synchronize aircraft flying out of and back into the hub and to thus manage passenger transfers in a timely manner. Four waves per day means passengers are transported to the hub and from there to spokes four times a day, thus providing connecting passengers with up to three time options to arrive at their final destinations. Figure 2 shows this structure; each light colored bar corresponds to a there-and-back flight, and the first and last flights of each day are considered as half waves.

Although this approach facilitates the planning of passenger transfers, it results in low fleet utilization compared to the standard usage levels of Europe's leading low-cost carriers, such as EasyJet. AnadoluJet's average daily plane usage is 8.91 hours; in contrast, EasyJet's is 11 hours (EasyJet 2013). Low utilization levels occur principally because the wave structure
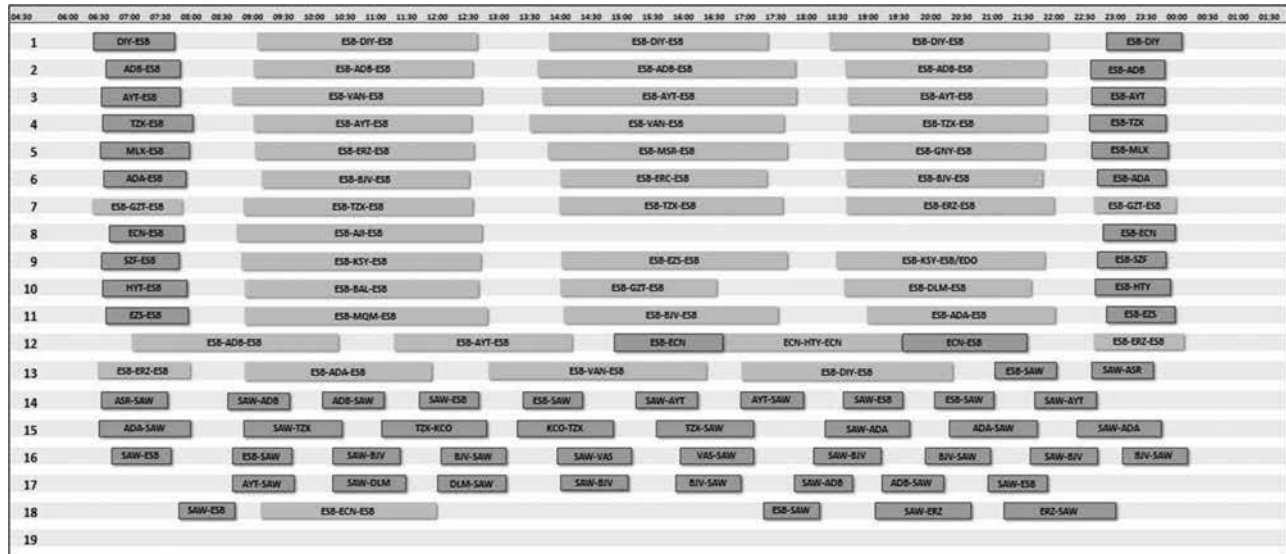
Figure 2: AnadoluJet's summer 2012 flight schedule shows both one-way flights (dark rectangles) and round-trip flights between hub and destination points (light rectangles) for all its 18 aircraft.

forces flights to wait for each other even if no significant level of transfer demand exists between corresponding destinations. Therefore, relaxing the wave structure can improve fleet utilization levels by the eliminating unnecessary waiting time between waves.

As a result of operational limitations, the problem has the following additional constraints.

• In some cities, an aircraft must stay overnight and return to the hub early the next morning to satisfy high demand for early flights from those cities. We refer to these cities as overnight-stay cities. The number of flights to a city in a given day or week and the city's status as an overnight-stay node are determined based on demand.

• A minimum ground time of 35 minutes is required between an aircraft's landing and takeoff times, and a maximum of four aircraft can take off from an airport within 5 minutes.

• AnadoluJet prefers that flights start as early as 6:00 AM and finish as late as 1:00 AM. Thus, all daily flights should be completed within 19 hours.

• Some airports do not operate for the full 19 hours because of limitations specific to their locations. The first morning flights to those cities must be scheduled so that they arrive later than the airport's opening time, and these airports cannot be overnight-stay

nodes; therefore, planes to these cities must take off so that they will arrive and then leave again before the airport's closing time.

The solution to our problem requires that we generate flight schedules that do not violate the above constraints. Moreover, maximizing aircraft utilization minimizes the number of aircraft used, thus decreasing AnadoluJet's fixed costs. Hence, our objective function implicitly affects the company's revenue and profit. This choice of objectives is based on AnadoluJet's operational needs. After a brief consultation with company decision makers (e.g., senior managers), we realized that the key performance measures can be summarized as the objectives of increasing fleet utilization and decreasing transfer-passenger wait times. An optimization model run by an automated system that addresses this problem would (1) provide planners with an optimal solution and (2) reduce the time that employees must spend on scheduling.

AnadoluJet's Flight-Scheduling Process: Challenges
As we previously state, the models discussed in the literature are not suitable for AnadoluJet's requirements; therefore, we developed a new model. We had two challenges in determining an appropriate methodology.

• Challenge 1: The methodology should fit the complexity of AnadoluJet's flight-scheduling problem. The complexity arises from addressing the two competing objectives that we describe above. A higher number of aircraft means that more resources are available to serve transfer passengers, thus improving the quality of transfer services; however, it also increases the total idle time of the aircraft fleet.

• Challenge 2: The methodology should be implemented in a decision support system that facilitates its use. This system must consider all characteristics of AnadoluJet's problem, and our algorithm must consider all constraints and preferences, thus increasing both customer satisfaction and fleet utilization.

Therefore, we designed our models to be general so that any large local carrier can apply them.

Methodology

In this section, we provide our framework for solving the problem, the technical details of our models, and the proposed decision support system.

To generate AnadoluJet's flight schedule for a given day based on the specific number of flights for each city, we developed a mathematical model. To provide the company with a tool, but without requiring additional software (i.e., a solver), we also generated a decision support system based on the principles of the mathematical model. Figure 3 shows the inputs and outputs of both models.

The models divide a day into five-minute periods; excluding the period between 1:00 AM and 6:00 AM (no flight takes off during this period), the time horizon consists of 223 periods.

Optimization Model

One objective of the mathematical model is to minimize the number of idle planes in all periods to maximize the average fleet utilization. To improve transfer-passenger satisfaction, transfer times are restricted by constraint sets. Other constraint sets originate mainly from regulations, customer demand, and the model's structure. Appendix A shows the mathematical model, which considers the following as constraints.

• One leg of each flight must be at the Ankara hub.

• An aircraft should stay overnight in particular spokes, which the decision maker determines; we refer to these as overnight-stay cities.

• Flights must take off or land during an airport's hours of operation.

• A maximum of four planes can take off from the same airport within five minutes.

• The number of planes used cannot exceed the fleet's capacity.

• For specific city pairs, which we define in our solution as city pairs with a minimum of 11 transfer passengers per day, flight connection times must be reasonable: 35–60 minutes in our model.

• A predetermined time interval (25 minutes in our model) between two consecutive flights to the same city is necessary to equitably distribute flights across a day.

For AnadoluJet's current 19-hour operating period, the mathematical model was able to schedule 100 flights over a network of 24 cities with a fleet of only 11 aircraft, and Xpress solver generated the results within a reasonable time; we provide details in the *Results* section.
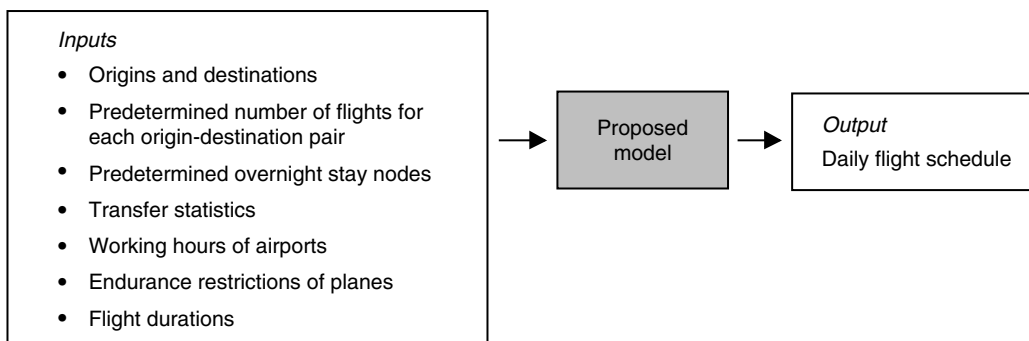

Inputs
• Origins and destinations
• Predetermined number of flights for each origin-destination pair
• Predetermined overnight stay nodes
• Transfer statistics
• Working hours of airports
• Endurance restrictions of planes
• Flight durations

Proposed model

Output
Daily flight schedule

Figure 3: Using the inputs listed in the box on the left side, our models generate daily flight schedules as output.

Decision Support System

At AnadoluJet's request, we developed a decision support system, which we called OpScheduler, to generate flight schedules and reduce the wait times between transfer flights, as necessary. The network planning department uses OpScheduler at least twice each year to assist in the flight-scheduling process. In addition to generating the schedules, OpScheduler provides a basis for what-if analysis to enable a decision maker to see the effects that any change in a flight schedule has on overall performance (i.e., on fleet utilization levels and transfer-passenger wait times).

As we stated earlier, we could not use algorithms from the literature to evaluate the trade-off between increased fleet utilization levels and decreased wait times for transfer passengers. The heuristic algorithm we developed to solve AnadoluJet's specific flight-scheduling problem is based on the same objective and principles of the mathematical model. It seeks to minimize the number of planes used and the waiting times of transfer passengers while providing a maximum number of transfer destinations in a minimum amount of time. To ensure that AnadoluJet will be able to use the models without any additional tools, we coded the heuristic algorithm in the Java programming language and developed OpScheduler, which can run on any computer on which the network planning department installs it. The program takes as input the company data, which are in Microsoft Excel spreadsheets, for its daily point-to-point transfer passengers, flight durations, and airport operation hours and generates schedules as output.

We designed the algorithm to have two phases: a scheduling phase and an improvements phase. In the scheduling phase, the algorithm creates a weekly flight schedule by assigning all required flights. In the improvements phase, it searches through the schedule generated in the scheduling phase to find possible reductions in waiting times by moving assigned flights forward or backward.

Scheduling Phase

During the scheduling process, the algorithm first assigns planes to cities with a daily flight demand of at least four flights. It next assigns fixed overnight-stay cities, which the decision maker has predetermined, to planes. It then assigns the remaining cities to planes based on daily transfer-passenger data, starting with the city with the highest number of passenger transfers. After it assigns each plane's first flights, it addresses city pairs that have the most bookings and assigns the remaining flights. At this point, the algorithm's objective is to transfer passengers who arrived at the hub in the previous period to the destinations they have booked most frequently.

Improvement Phase

After the algorithm has assigned all flights, it clusters transfer-passenger waiting times into four groups to reduce the waiting-time minimization process. Groups are classified as 35–45 minutes, 45–60 minutes, 60–90 minutes, and more than 90 minutes. The algorithm uses the following formula as a performance measure:

$$(\textit{Number of transfer passengers})$$
$$\times (\textit{Time spent waiting for transfer})$$
$$\times (\textit{Wait coefficient assigned for waiting time}).$$

In this way, possible time adjustments between transfer flights can be made by using the performance measures and the schedule can be finalized. Appendix B shows the detailed steps of the algorithm.

Performance Statistics

OpScheduler also calculates performance statistics for each weekly schedule to enable a user-decision maker to conduct what-if analyses. By this analysis, we enable that user to take a schedule as input and calculate its transfer performance in terms of waiting times. Calculating the minimum waiting times between each origin-destination pair enables a user to see the effects of any changes in transfer performance by comparing schedules or by modifying an existing schedule.

Results

In implementing the models, we considered AnadoluJet's Saturday schedule for summer 2012 and its data on the number of transfer passengers. Using this approach enabled us to compare the results of the previous scheduling structure and our proposed models. First, we solved the mathematical model using the inputs listed in Figure 3 and the Xpress optimization tool. Next, we used OpScheduler to generate a
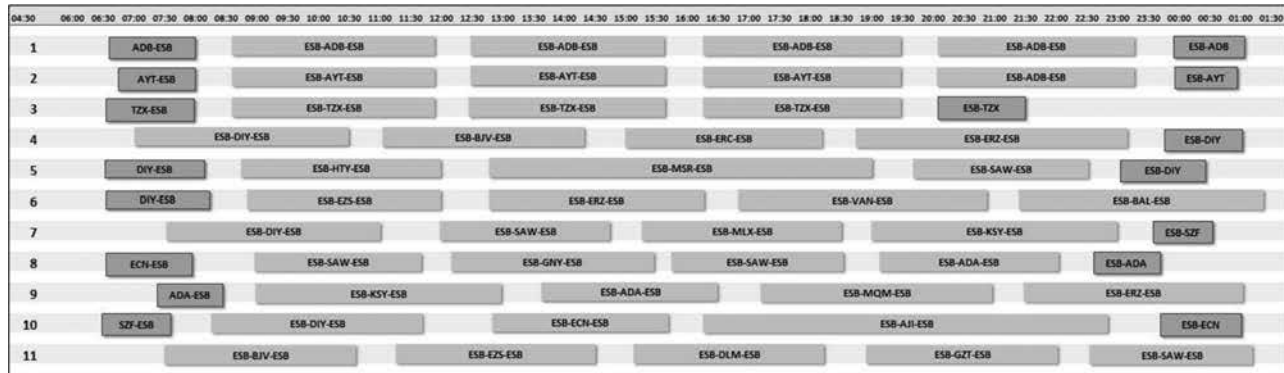
Figure 4: A Gantt chart of the flight schedule generated by the mathematical model shows one-way flights (dark rectangles) and round-trip flights (light rectangles) of 11 aircraft.

schedule. Figures 4 and 5 show the outputs of the mathematical model and the heuristic model, respectively. Each schedule that the mathematical model or OpScheduler generates can be used for each day of the week, including weekends.

We made our computations on a computer with a 2.60 GHz CPU, 32-bit operating system, and 400 GB RAM. We could not, however, generate a solution for the original mathematical model we had developed. Therefore, we performed several trials to obtain our results. For each trial, we entered the number of aircraft and solved a feasibility problem. The number of planes used (Table 1) displays the minimum feasible number of aircraft at the end of the trials. Using this method, we reduced the run time to

seconds. OpScheduler was also able to provide a solution within seconds. Therefore, we determined that the solution times are negligible for both the mathematical model and the heuristic model. OpScheduler runs the heuristic algorithm; in this paper, we consider the terms OpScheduler and heuristic model to be interchangeable.

Our results show that the summer 2012 schedule's 8.91 hours average daily plane usage increased by 31.6 percent to 11.7 hours when we used the mathematical model; it increased by 20.4 percent to 10.7 hours when we used the heuristic model. We compared the utilizations obtained with the EasyJet and Ryanair benchmarks (11 and 10.9 hours, respectively), which are important indicators of our project's
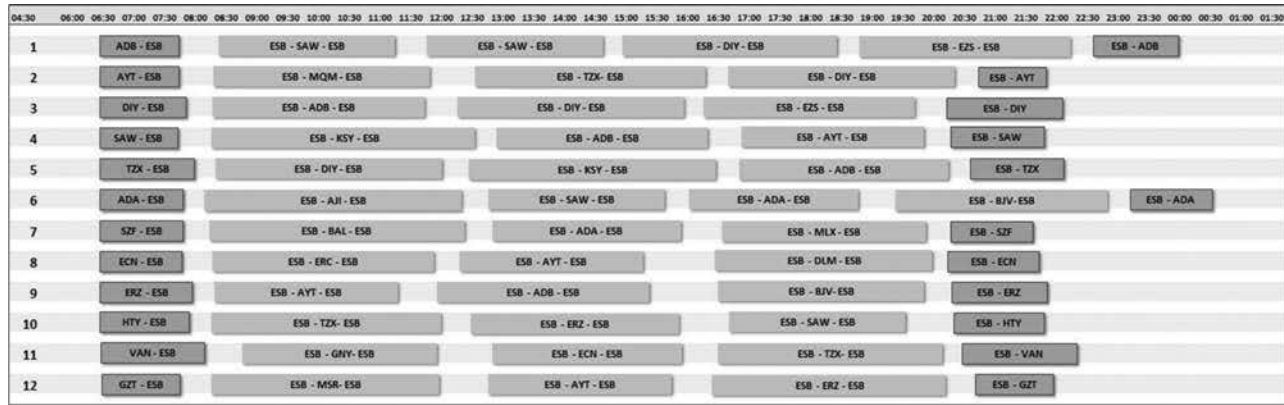

Figure 5: A Gantt chart of the flight schedule generated by the heuristic model shows one-way flights (dark rectangles) and round-trip flights (light rectangles) of 12 aircraft.

	Mathematical model	OpScheduler	Current system
No. of planes used	11	12	14
Average plane usage (hours/day)	11.7	10.7	8.91
No. of city pairs offering transfer within			
35–45 minutes	62	84	47
46–60 minutes	59	63	51
61–90 minutes	17	27	64

Table 1: The schedules generated by both the mathematical and heuristic models improve fleet utilization and transfer performance when compared to AnadoluJet's current schedule.

success because cost minimization is a primary objective of these companies (EasyJet 2013, Ryanair 2013). Table 1 shows related data.

Table 1 compares the mathematical model, Op-Scheduler, and AnadoluJet's current system. In evaluating these systems, our model's objective is to both increase transfer passenger satisfaction and optimize the aircraft fleet utilization. The intervals start with 35 minutes because of a minimum ground-time constraint for each plane. When we evaluated the models in terms of transfer performance only, based on the company's 2012 transfer-passenger data, the mathematical model offered 90 minutes of transfer time for 607 customers daily (62 percent of total transfer passengers) and the heuristic model offered 677 customers daily (69 percent of total transfer passengers).

As is evident from Table 1, the results from both the mathematical model and OpScheduler are superior to those of the current model for the 35-to-60-minute period. The origin-destination pairs that can provide transfers within one hour increased by 50.2 percent when solved with the heuristic model and by 23.4 percent when solved with the mathematical model. The current structure of the mathematical model forces city pairs with more than 39 transfer passengers to provide transfers within one hour. Therefore, for the mathematical model, we can improve the numbers in Table 1 by adding appropriate constraints. These numbers were determined based on AnadoluJet's 2012 transfer-passenger data.

Although improving fleet utilization and decreasing transfer-passenger wait times are different objectives, our goal is to maximize fleet utilization while

constraining the transfer times to specific values. Changing the proposed model so that transfer times are optimized, while obeying specific limitations for fleet utilization, becomes easy if we constrain the number of aircraft. In addition, OpScheduler can be used to improve waiting times by changing the number of aircraft. Finally, the flight schedules created by both the mathematical model and the heuristic model are realistic because they use the flight data specified by the company prior to scheduling and can be directly put into practice if desired.

Concluding Remarks

When we compared the results of the mathematical model and OpScheduler to AnadoluJet's summer 2012 flight schedule, we observed that the current wave model needed to change considerably for the company to meet its goals of fleet optimization and decreased transfer-passenger waiting times. The mathematical model decreases waiting times by removing the wave structure; as a result, airplane utilization levels increase substantially. Conversely, OpScheduler places more importance on improving transfer performance than on increasing the fleet utilization; accordingly, it adopts a hybrid model by partially preserving the wave structure. This approach provides a significant improvement in transfer performance.

The four-wave model had several limitations; for example, before taking off, airplanes were often required to wait for other airplanes to land, even in cases with no significant level of transfer demand between corresponding destinations. The result was long waiting times between flights. These restrictions kept it from providing the best solution to the scheduling problem; because our models present better solutions, they can be considered effective decision support systems for AnadoluJet.

Relaxing the wave structure and eliminating unnecessary waiting between waves also improved fleet utilization. The solutions of both models suggest using fewer planes for the same demand and therefore increasing plane utilization. By decreasing the number of aircraft used in the schedule, AnadoluJet expects a fixed-cost reduction of $4,800,000 per airplane per year. The remaining aircraft could be used

to increase the company's service network by adding new destinations.

Our system enables planners to generate optimal solutions and substantially reduces the time that employees must spend on scheduling. The time that AnadoluJet requires to construct its flight schedule using our models is substantially less than the time it required when it used the manual approach. OpScheduler saves time and effort for network planners. They can now find a solution in seconds, evaluate that solution's quality, and try other scenarios. For example, if AnadoluJet is considering adding a flight location, network planners can use OpScheduler to quickly generate a new schedule and immediately observe the impact of adding the flight location. Similarly, when transfer-passenger data change, OpScheduler can rapidly provide a report about the impact of these changes on network performance. As we discuss in the *Decision Support System* section, a user can now enter an existing flight plan or create a new plan based on the criteria that we discuss in this paper.

Thus, we can summarize the benefits of OpScheduler as follows: (1) the time required to generate a schedule decreases substantially; (2) the flexibility to add a new flight point or remove an existing point increases; (3) it enables a user to rapidly compare multiple scenarios; and (4) it enables a user to quantify the transfer performance of a given schedule.

When AnadoluJet implemented OpScheduler in May 2013, the company's network planning department estimated that AnadoluJet's market share would increase by three percent as a result of decreasing the passenger-transfer times between city pairs.

One potential future research project that we are considering is adding functionality to address demand fluctuations.

Acknowledgments

Appendix A. Mathematical Model

Mixed-Integer Programming Model

$$\text{minimize} \sum_{t \in T} \sum_{i \in I} Y_{it} \tag{A1}$$

subject to

$$X_{ijt} \leq 0 \quad \forall i, j \in I \setminus \{1\} \; \forall t \in T \tag{A2}$$

$$X_{ijt} \leq 0 \quad \forall i, j \in I \; \forall t \in D \tag{A3}$$

$$Y_{jn} = 1 \quad \forall j \in O \tag{A4}$$

$$tX_{ijt} + f_{ij} \leq n - w \quad \forall i, j \in I \; \forall t \in T \tag{A5}$$

$$\sum_{j \in I} X_{1jt} \leq mf \quad \forall t \in T \tag{A6}$$

$$\sum_{j \in I} \sum_{i \in I} X_{ij1} + \sum_{i \in I} Y_{i1} \leq p \tag{A7}$$

$$\sum_{i \in I} X_{jit} + Y_{jt} = \sum_{i \in I} X_{i,j,t-f_{ij}-w} + Y_{j,t-1} \quad \forall j \in I \; \forall t \in F \tag{A8}$$

$$\sum_{t \in T} X_{i1t} = d_i \quad \forall i \in I \tag{A9}$$

$$\sum_{t \in T} X_{1it} = d_i \quad \forall i \in I \tag{A10}$$

$$\sum_{j \in I} \sum_{t \in T} X_{1jt} = \sum_{i \in I} d_i \tag{A11}$$

$$\sum_{j \in I} \sum_{t \in T} X_{j1t} = \sum_{i \in I} d_i \tag{A12}$$

$$tX_{1it} - zX_{1iz} \geq l - M(1 - X_{1it}) \quad \forall i \in I \; \forall t, z \in T \tag{A13}$$

$$X_{i1t} \leq 0 \quad \forall i \in E \setminus \{1\} \; \forall t \in T_i \tag{A14}$$

$$X_{1it} \leq 0 \quad \forall i \in E \; \forall t \in H_i \tag{A15}$$

$$d_i = \sum_{t \in T} (tX_{1it}) + M\left(1 - \sum_{t \in T} X_{1it}\right) \quad \forall i, j \in I \tag{A16}$$

$$a_i = \sum_{t \in T} [(t - f_{i1})X_{1it}] \quad \forall i, j \in I \tag{A17}$$

$$d_j - a_j \leq hu_k + M(1 - u_k) \quad \forall i, j \in I \; \forall k \in K \tag{A18}$$

$$d_j - a_j \geq -M(1 - u_k) \quad \forall i, j \in I \; \forall k \in K \tag{A19}$$

$$\sum_{k \in K} u_k \geq s_{ij} \quad \forall i, j \in I \tag{A20}$$

$$Y_{it} \geq 0 \quad \forall i \in I \; \forall t \in T \tag{A21}$$

$$a_i \geq 0 \quad \forall i \in I \tag{A22}$$

$$d_i \geq 0 \quad \forall i \in I \tag{A23}$$

Objective (A1) is defined to be a minimization of the number of idle planes in each period. Constraint (A2) obliges one leg of each flight to be the hub. Constraint (A3) equalizes the balancing flights in virtual periods to zero. Constraint (A4) forces the flights to stay overnight in the given spokes. Constraint (A5) satisfies the operational hours. Constraint (A6) ensures that at most *mf* number of planes can

take off from the hub within a period. Constraint (A7) prevents the number of planes used from exceeding the fleet capacity. Constraint (A8) provides flow balance between incoming flights, departing flights, and waiting planes. Constraints (A9)–(A12) ensure flight demand satisfaction. Constraint (A13) ensures that there is at least one period between two consecutive flights to the same city. Constraints (A14) and (A15) ensure that flights are arranged according to early-closing and late-opening airports. Constraints (A16) and (A17) enable a user to define flight arrival and departure times as two different decision variables (M is a sufficiently large number). Constraints (A18)–(A20) provide that there are at most h periods of transfer time between flight pairs entered by the user. Constraints (A21)–(A23) are the domain constraints.

Index Sets

$T = \{-d, \ldots, n\}$: set of periods in a day.
$D = \{-d, \ldots, 0\}$: set of dummy periods in a day.
$I = \{1, \ldots, m\}$: 1 is a hub and $2, \ldots, m$ represent nodes.
$F = \{2, \ldots, m\}$: set of periods to be used in the flow balance.
K: set of transfer options.
O: set of overnight-stay nodes.
E: set of nodes with airports that have restricted operational hours.
T_i: set of periods after last allowed departure time from node i, $\forall i \in E$.
H_i: set of periods after last allowed departure time from the hub to node i, $\forall i \in E$.

Decision Variables

X_{ijt} 0–1 integer variable.
     If there is a flight from node i to node j at time t, $X_{ijt} = 1$; otherwise, $X_{ijt} = 0$ ($\forall i, j \in I \; \forall t \in T$).
u_k 0–1 integer variable.
     If required transfer time is satisfied at option k, $u_k = 1$; otherwise, $u_k = 0$ ($\forall k \in K$).
Y_{it} Integer variable. Number of idle aircraft at node i in period t ($\forall i \in I \; \forall t \in T$).
a_i Integer variable. Arrival period to node i ($\forall i \in I$).
d_i Integer variable. Departure period from node i ($\forall i \in I$).

Parameters

n: number of periods in a day.
d: number of dummy time periods in a day.
m: number of nodes.
p: number of aircraft in the fleet.
w: minimum ground time between arrival and departure of an aircraft.
d_i: daily number of flights to and from node i ($\forall i \in I$).
f_{ij}: duration of flight from node i to node j ($\forall i, j \in I$).
s_{ij}: If a transfer from i to j is required, $s_{ij} = 1$; otherwise, $s_{ij} = 0$ ($\forall i, j \in I$).

mf: maximum number of departures from hub within a period.
l: minimum number of periods between two consecutive flights to the same city.
h: restricted transfer time.

Appendix B. Heuristic Algorithm

Initialization Phase

Step 1: User determines destination points, daily flight demands to these points, and overnight-stay cities.

Step 2: User enters the transfer-passenger data and closing times for the airports. (Transfer-passenger data include number of connecting passengers daily for each city pair.)

Step 3: Assign weights to airports with respect to the opening and closing times such that the earliest closing time is assigned the highest weight (e.g., 00:30 → 1, 21:00 → 2, 16:30 → 3).

Step 4: Calculate flight durations as periods of five minutes (e.g., 55 minutes = 11 periods).

Step 5: Calculate total flight duration for each city.

Step 6: Calculate minimum number of planes necessary for the given flights and to create the outline of the schedule.

First Phase: Frequent Flights and Overnights

Step 1: Choose cities with four or more daily flights.

Step 2: Assign four flights of such cities consecutively to the first available planes.

Step 3: Update the daily flight list.

Step 4: Choose cities that have overnight flights.

Step 5: Assign flights of such cities to each plane successively.

Second Phase: Schedule

Step 1: List cities in decreasing order in terms of the number of passengers needing transfers from cities placed in the schedule to the other cities.

Step 2: Choose cities in order from the list.

Step 3: Assign flights of such cities to the first empty planes successively.

Step 4: Update the daily flight list.

Step 5: Multiply assigned airport weights by the number of transfer passengers who arrive in Ankara on the early flights and list the destination points according to the multiplicative results.

Step 6: To set the reference point, take each plane's last landing time in Ankara and set the latest time as the reference point.

Step 7: Choose the cities in order from the new list.

Step 8: Assign flights for the selected cities to planes starting from the reference point.

Step 9: Update the daily flight list.

Step 10: Determine the early-closing airports according to the updated flight list.

Step 11: Are all flights placed in the relevant periods?

If YES: Make another list for unassigned flights with an airport closing time limit.

If NO: Go back to Step 5.

Improvements Phase

Step 1: Assign weights to the transfer-passengers' waiting times (35–45 min. → 1, 45 min.–1 hr. → 2, 1 hr.–1.5 hr. → 3, 1.5 hr. and above → 4).

Step 2: According to the transfer performance, the period with the lowest multiplicative result will be the starting period of the desired destination point.

Step 3: Are all flights placed in the relevant periods?

If YES: End the program.

If NO: Go back to Step 1.

References

AnadoluJet (2013) AnadoluJet. Accessed March 20, 2016, http://www.turkishairlines.com/documents/Thy/kurumsal/faaliyet-raporu/2012/en/other-services.html.

Barnhart C, Cohn A (2004) Airline schedule planning: Accomplishments and opportunities. *Manufacturing Service Oper. Management* 6(1):3–22.

Dobson G, Lederer PJ (1993) Airline scheduling and routing in a hub-and-spoke system. *Transportation Sci.* 27(3):281–297.

EasyJet (2013) EasyJet annual report and accounts. Accessed December 10, 2012, http://corporate.easyjet.com/~/media/Files/E/Easyjet-Plc-V2/pdf/investors/result-center-investor/annual-report-2012.pdf.

Erdmann A, Nolte A, Noltemeier A, Schrader R (2001) Modeling and solving an airline schedule generation problem. *Ann. Oper. Res.* 107(1):117–142.

Haksöz C (2013) AnadoluJet: Maestro over the clouds. *Risk Intelligent Supply Chains: How Leading Turkish Companies Thrive in the Age of Fragility* (CRC Press, Boca Raton, FL), 187–206.

Lan S, Clarke J-P, Barnhart C (2006) Planning for robust airline operations: Optimizing aircraft routings and flight departure times to minimize passenger disruptions. *Transportation Sci.* 40(1):15–28.

Magnanti TL, Wong RT (1984) Network design and transportation planning: Models and algorithms. *Transportation Sci.* 18(1):1–55.

Marsten RE, Subramanian R, Gibbons L (1996) Junior analyst extraordinaire (JANE). *Proc. 36th AGIFORS, Atlanta, GA*, 247–259.

Ryanair (2013) Final annual report Ryanair Dublin. Accessed December 12, 2012, https://www.ryanair.com/doc/investor/2013/final_annual_report_2013_130731.pdf.

Soumis F, Ferland JA, Rousseau JM (1980) A model for large-scale aircraft routing and scheduling problems. *Transportation Res. Part B: Methodol.* 14(1–2):191–201.

Zhang J, Tang O, Zhao J, Huo J, Xia Y (2013) CPEL redesigns its land express network. *Interfaces* 43(3):221–231.

Verification Letter

Başak Kepir received a BSc degree in industrial engineering at Bilkent University. She worked on IT implementations of supply chain management in FMCG sector in a leading food company in Turkey. Since November 2015, she has been working in KPMG Turkey—Management Consulting.

Çağıl Koçyiğit received a BSc and an MSc in industrial engineering at Bilkent University. In 2015, she joined the Risk Analytics and Optimization chair at EPFL. Her research interests are mechanism design and game theory applications in operations management.

Işıl Koyuncu received her BSc degree in industrial engineering at Bilkent University. After receiving an MSc degree in industrial engineering from Koç University in 2015, she joined PhD program in operations management at University of Alabama. Her research interests are lean and green operations, vehicle routing for alternative-fuel vehicles, scheduling, and optimization.

Melis Beren Özer received a BSc degree in industrial engineering at Bilkent University. In 2013, she joined Industrial Engineering Graduate Program at Bilkent University. Her research interests are supply chain management, sustainable operations, and risk sensitive optimization.

Bahar Yetis Kara is an associate professor in the Department of Industrial Engineering at Bilkent University. Dr. Kara holds an MS and PhD degree from Bilkent University, and she worked as a postdoctoral researcher at McGill University in Canada. Dr. Kara was awarded with TUBA-GEBIP (National Young Researchers Career Development Grant) in 2008, and TUBITAK TWAS Incentive Award in 2010. Dr. Kara served as an associate member of the Turkish Academy of Sciences between 2012 and 2015. Her current research interests include distribution logistics, humanitarian logistics, hub location and hub network design, and hazardous material logistics.

Melih Akif Gürbüz received a BSc degree in industrial engineering and MA degree in economics at Bilkent University. His research interests are time series analyses and game theory applications in airline business. He has been working in AnadoluJet, an LCC brand of Turkish Airlines, since 2009, as a scheduling and network planning manager.