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Scenario-based stochastic programming for an airline-driven flight rescheduling problem under ground delay programs

Young-Bin Woo [a], Ilkyeong Moon [a,b,*]

[a] Department of Industrial Engineering, Seoul National University, Seoul, Republic of Korea
[b] Institute for Industrial Systems Innovation, Seoul National University, Seoul, Republic of Korea

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ABSTRACT

We address an airline-driven flight rescheduling problem within a single airport in which a series of ground delay programs (GDPs) are considered. The objective of the problem is to minimize an airline's total relevant cost (TRC) consisting of delay costs, misconnection costs, and cancellation costs that would result from flight rescheduling. We introduce three solution approaches—the greedy approach, the stochastic approach, and the min-max approach—that revise the daily flight scheduling whenever the schedule is affected by a GDP or further GDP changes. The greedy approach simply searches for a solution using currently updated static GDP information, and the other two approaches provide a solution by considering possible scenarios for changes of the GDP. Using real-world data in existing literature and some generated scenarios, we present extensive computational results to assess the performance of the approaches. We also report the values of information on GDP the solution approaches refer to. Deliberating various cost parameter settings an airline might consider, we discuss the value of information in implementing the proposed solution approaches.

1. Introduction

Aircraft operations are subject to many sources of uncertainty. Sources of uncertainty includes bad weather, accidents, and control over the national airspace, which might have a significant impact on carrying out flight schedules. If such uncertain events occur, an airport might temporarily shut down, or significantly curtail air traffic in order to secure the safety of aircraft operations. These operational changes make aircraft unable to take off at the initially planned times or cause flights to be cancelled. This disruption results in a low utilization rate of operational resources such as aircraft. It also results in poor service to passengers. Airlines have to reschedule their flights that are affected in the near future due to operational disruption such as severe weather events (Diao and Chen, 2018; Hu et al., 2016; Ng et al., 2017). Therefore, airlines are concerned about the impact of uncertain events on aircraft operations, and try to optimize their internal objectives with minimal changes.

When operational disruption likely to be realized in the near future due to sources of uncertainty, central authorities (e.g., the Federal Aviation Administration (FAA), Eurocontrol, the Air Traffic Control Center (ATCC), etc.) regulate the flow rate of an airport associated with the operational disruption. Subsequently, the release times of the flights, that are scheduled to enter the airport and impacted by the restrict capacity (i.e., airport acceptance rate), are adjusted. There is a common way for the central authorities to control the release times of some flights scheduled to enter an airport, called *ground delay program* (GDP). The GDP is used to delay

* Corresponding author at: Department of Industrial Engineering, Seoul National University, Seoul, Republic of Korea.
E-mail addresses: ybwoo@snu.ac.kr (Y.-B. Woo), ikmoon@snu.ac.kr (I. Moon).

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aircraft on the ground before leaving for the destination airport. Flights in a GDP could be held at their origin airport, or worse, they could be cancelled (Abdelghany et al., 2007). Generally, it is more economical for aircraft to wait on the ground than on the air. In particular, if the aircraft is still at its origin airport before take-off, waiting on the ground is a reasonable decision to reduce operating costs while satisfying the airport acceptance rate (Liu et al., 2008).

However, the flight schedule revised by GDP decision-making may not be the best schedule for an airline company. The revised schedule is rather in the interest of central authorities' operational aspect. When the initial flight schedule run out, the airline tries to exchange its slots that have not yet been executed in order to develop a plan that better meets its objectives. Generally, the criteria adhered to are related to minimizing the penalty incurred for not performing the initial schedule as planned. For instance, an airline's decision-makers might try to minimize the total relevant cost (TRC), including delay costs, misconnection costs, and cancellation costs (Bard and Mohan, 2008; Brunner, 2014; Luo and Yu, 1997), or might try to minimize the maximum delay (Ball and Lulli, 2004).

This study investigates the problem of airline-driven flight rescheduling in which a series of uncertainties can be realized. The airline's decision-making point is when the *scheduled arrival times* (or release times at origin airports) of flights are updated by a GDP. At this point, the airline's decision-makers consider three strategies. First, the *greedy* strategy is used to establish flight rescheduling in consideration of static arrival times when changes of scheduled arrival times are issued by a GDP. Second, the *stochastic* strategy is used to design flight rescheduling by considering the probability of an uncertain event and the modified scheduled arrival time for that event. Third, the *conservative* strategy is used to establish flight rescheduling, considering the opportunity cost of uncertain events that have the worst impact on airline operations. This study introduces solution approaches to provide flight rescheduling based on the above strategies, which are the greedy approach, the stochastic approach, and the min-max approach. Using real data, we show in this paper whether or not the presented approaches can provide a feasible solution within the set time limit. Also in this paper, computational experiments show the proximity of the solutions obtained by the approaches to the global optimal solution. We also discuss the significant importance of the results and offer managerial insights that might improve an airline's operation management.

The remainder of the study is organized as follows. In Section 2, we review the relevant literature on flight rescheduling under the GDP, and characterize our problem in the context of existing literature. In Section 3, we describe the airline-driven flight rescheduling problem and then present the solution approaches to solve the problem. In Section 4, computational experiments are conducted using real-world data in existing literature. The performances of the solution approaches are also investigated in this section as well. In addition, we assess and discuss the value of information that is required in order to implement the proposed solution approaches. The results and implications for airline management are summarized in Section 5.

2. Literature review

There are two bodies of literature that investigate how to control air traffic flow in occurrence of an uncertain disruption event, such as bad weather. One is on a centralized framework and is optimal for designing GDPs. Odoni (1987) first formally introduced the topic of air traffic management. An uncertain event disrupts flight operations during a specific period. For example, bad weather affects visibility. To prevent accidents during flight operations, the air traffic flow rate (i.e., the capacity of an airport) needs to be restricted. Generally, the flights related to such disruption receive modified arrival times if corresponding airplanes are still on the ground. This is because it is safer and less costly for the flights to absorb this delay on the ground rather than in the air (Yan et al., 2018). This is known as *ground holding problem* (GHP) (Richetta and Odoni, 1993). Richetta and Odoni (1994) handled a single airport GHP considering uncertainty in arrival capacity under dynamic settings. Capturing all possible occurrences of uncertainty in arrival capacity as a scenario tree with probability, the authors developed a stochastic programming formulation. Since then, several studies have developed stochastic models using a scenario tree as a way to consider changes of uncertain states. Ball et al. (1999) introduced a model for the static stochastic GHP in which probabilistic scenario information on the uncertain capacity of a single airport is available. They proved the following: that their mathematical model corresponds to a dual network flow problem, that the constraint matrix of the model is totally unimodular, and that the LP relaxation yields an integer solution. Mukherjee and Hansen (2007) considered a single airport GHP and proposed a dynamic stochastic integer programming model to minimize the total ground and airborne delay costs. The authors dealt with slot exchanges between airlines. Slot exchanges are controlled by the central authority, FAA and major airlines in the U.S., in order to improve air traffic flow management. Glover and Ball (2013) introduced a stochastic multi-objective integer program with capacity scenarios for a single airport, which was to minimize the total expected delay and the total expected inequality cost. Using real data, the authors investigated the trade-off between efficiency and equity in GDP planning. Jacquillat and Odoni (2015) investigated an integration of strategic scheduling interventions and tactical airport capacity utilization to handle airport congestion. They proposed an integrated model that combines a stochastic model of airport congestion, a dynamic programming model to control resource utilization, and an integer programming model for scheduling. The stochasticity of their model aims to capture the uncertainty related to the actual arrival and departure queuing processes. Montlaur and Delgado (2017) compared two optimization strategies—on-ground delay at origin, and airborne delay close to the destination airport—in order to minimize flight delays and passenger delays. Meanwhile, some previous works on a centralized framework designing a GDP addressed a GHP under a multi-airport setting in order to investigate the inter-relationship between different airports (Brunetta et al., 1998; Navazio and Romanin-Jacur, 1998; Vranas et al., 1994). These models assumed that the capacity of the airports is deterministic and known in advance with certainty.

The other body of relevant literature is on an airline-driven decentralized approach to air traffic flow management. Although substantial studies in air traffic flow management have investigated optimal GDP designs, they all presented the centralized model, wherein the central authorities, such as the FAA, Eurocontrol, and the ATCC, control the air traffic flow and issue GDP decisions by optimizing a certain centralized objective. However, decision-making about GDPs is not in an airline's best interest in meeting its

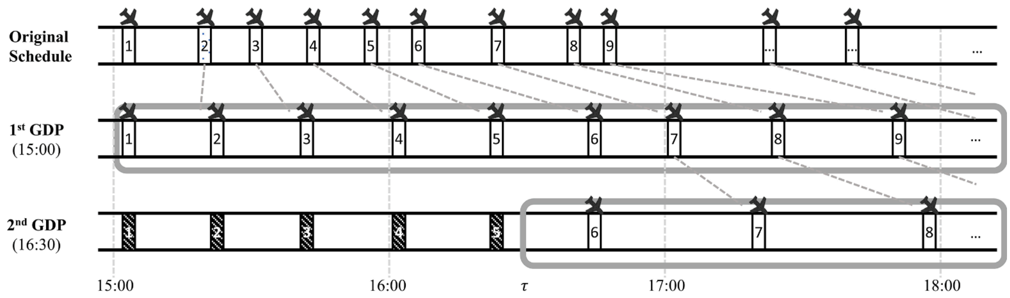


Fig. 1. An example of a series of GDPs.

internal objectives. Luo and Yu (1997) assess the benefits of an airline-driven decentralized approach for GDP decisions. They introduced a flight airline-driven flight rescheduling problem in which the scheduled arrival times of relevant flights were modified by the currently initiated GDP. They considered two objective functions that are to minimize the maximum delay among outbound flights and to minimize the number of delated flights. To solve the problem, they proposed a mixed integer programming formulation (MILP) that included valid inequalities to enhance convergence speed. Bard and Mohan (2008) considered an airline-driven flight rescheduling problem with missed connections and modelled it as a dynamic program. They proposed a branch and bound procedure to limit the state space of the dynamic program. In computational experiments with real data, it was shown that problems of practical size can be solved within minutes. As an extension to the work of Luo and Yu (1997) and Bard and Mohan (2008), Brunner (2014) developed a mixed integer programming formulation that incorporated all objectives, such as delay cost, misconnection cost, and cancellation cost. The author also introduced valid inequalities and showed that high-quality solutions could be found within seconds using the formulation with the valid inequalities. However, these works on an airline-driven decentralized approach only considered the deterministic capacity of an airport. Yan et al. (2018) developed a decentralized approach by incorporating airlines' objectives and operational characteristics into its GDP design process. They designed a novel FAA/airline-integrated simulation platform and showed that airlines' recovery potentials could turn into the cost reduction benefits in an even and equitable manner among airlines. However, they did not address the uncertain capacity of an airport.

To the best of our knowledge, there is no study dealing with the airline-driven flight rescheduling problem with probabilistic scenario information on the uncertain capacity of an airport even if a large body of study exists on both deterministic and stochastic versions of GHPs or airline-driven flight rescheduling problems. In this study, we propose a stochastic solution approach that searches for a solution using possible information on a series of changes of GDPs. The performance of the stochastic approach is evaluated by comparing the solution found without any possible information against the global optimal solution obtained with perfect information.

3. Airline-driven flight rescheduling

3.1. Problem statement

An airline manages a set of flights scheduled to arrive at an airport. Flight $i \in I$ has been assigned an arrival slot. All slot assignments of flights have been determined at the beginning of the planning period. The flight must operate according to its assigned slot. However, a central authority, such as the FAA, Eurocontrol, and the ATCC, can issue a GDP for uncertain events such as bad weather, triggering a GDP to an airport. The GDP then modifies the scheduled arrival times of some flights which will be subjected to the new restriction. The airline-driven flight rescheduling problem is regulated when a GDP is initially issued for the airline. The planning period of the problem is about half a day.

A subsequent GDP could be delivered to the airport by uncertain events. If a subsequent GDP is implemented later, the remaining scheduled arrival times relevant to the next GDP may further increase. An example of a series of GDPs is illustrated in Fig. 1. Each number represents a slot for flight. The current GDP is issued at 15:00, for example, and the scheduled arrival times after that time are modified based on the GDP. When the GDP is issued, the airline is given the authority to reschedule the flight operations for 20 min through the airport collaborative decision-making (A-CDM) system (Incheon International Airport: Airport Collaborative Decision Making Operations Manual (Korean), 2017). At this point, the airline can reassign an inbound flight, which is scheduled to arrive at the GDP airport and not yet depart at its origin airport, to one of the remaining slots based on the possible scenarios predicted by the airline. The patterned numbers in the figure describe the expired slots, and the grey box represents a time frame defined by a GDP. In this example, the airline does not change any slot assignment of the flight. Some minutes later, another uncertain event triggers a subsequent GDP. Similarly, the remaining scheduled arrival times after the second GDP point are modified based on the relevant proposal.

If an aircraft cannot operate at the initially planned arrival (or departure) time, a delay occurs for the arrival (or departure) flight. Delay time is defined as the difference between the initial arrival (or departure) time and the time when an aircraft is going to arrive at (or depart from) the airport. Some flights might be cancelled if the relevant airplane cannot reserve the airplane's turnaround time and the minimum ground time for preparing the next itinerary. Similarly, some crew members might miss the connection to their next airplane if the airline cannot reserve the crew's minimum turnaround time. Delays, cancellations, and misconnections of crew

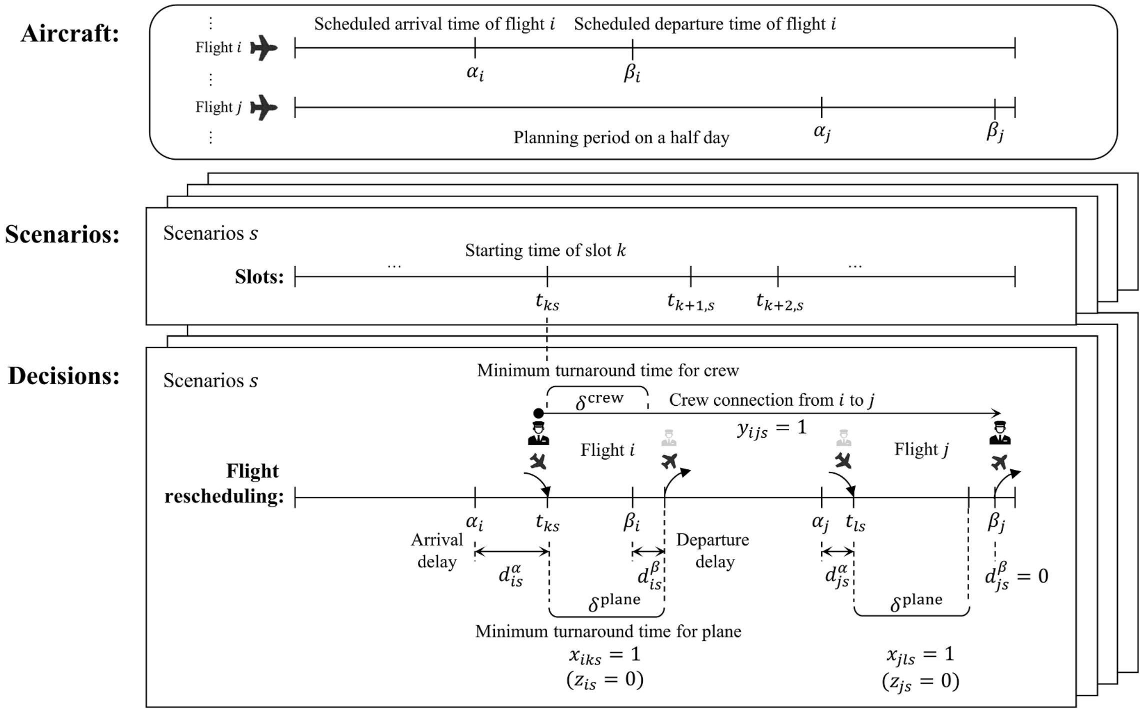


Fig. 2. Airline-driven flight rescheduling with GDP scenarios.

members will result a cost for the airline. Thus, the airline wants to reschedule flights to reduce such relevant costs (Brunner, 2014).

Fig. 2 describes airline-driven flight rescheduling with GDP scenarios. Flight rescheduling is performed by reassigning aircraft, which have not yet operated, to one of the remaining slots. It should be noted that an aircraft may be cancelled without any slot assignment. Changes to the aircraft allocation slots cause delays in related flights (i.e., arrivals and departures). At this time, both arrival and departure delays of flight i, α_i and β_i are allowed within maximum allowed arrival and departure delays, $\overline{d}_i^{\alpha}$ and $\overline{d}_i^{\beta}$, respectively, where the superscripts α and β indicate the arrival delay type and departure delay type. Both the maximum allowed arrival and departure delay are the upper limit of the delay that the airline can arbitrarily set. Meanwhile, it is known that flight attendants boarding a specific aircraft are going to transfer to the next connecting flight. There are minimum turnaround times, δ^{plane} and δ^{crew} guaranteed for the next flight transfer. If the minimum turnaround time of a crew member is not guaranteed in the event of cancellation or delay of the flight, the crew member cannot transfer to the next flight. As mentioned above, the airline adjusts its flight schedule at the time when a GDP is triggered. Considering possible scenarios for future disruptions, the airline tries to minimize the expected TRC, which consists of the delay cost, the crew's misconnection cost, and the flight cancellation cost. Delay cost is calculated by an incremental cost function of delay time. The incremental function reflects that small delay times can be allowed or neglected, but long delay times can incur a considerable penalty. It should be noted that the threshold-delay model, which is a common delay measure, is a special case of the incremental cost function. A crew's misconnection cost incurs when the crew's initial transfer plan cannot be followed due to the flight's rescheduling. Similarly, a flight cancellation cost is charged when a flight cannot be operated because of the flight's rescheduling.

3.2. Solution approach

Airlines are concerned about committing to flight rescheduling when a series of GDPs are expected to be triggered. If airlines know that GDPs will be issued, one may find the global optimal solution based on the static information by using the existing optimization model (Brunner, 2014). However, a GDP could be terminated early while an airline tries to reschedule its flight operations. Alternatively, the GDP could be extended by making changes in the airport acceptance rate and the scope of the GDP. If the airport acceptance rate increases after a certain time in the near future, scheduled arrival times after that defined time further increase. Such further changes can arise anytime before the schedule is executed. In the following subsection, some solution approaches that airlines can take are introduced.

3.2.1. Stochastic solution approach

Even though airlines do not know what GDP will be issued in the future, they estimate possible scenarios to protect against uncertainties such as weather condition. The scenarios estimated by an airline include one case where the current GDP remains unchanged, $(s = 0)$, and other cases where the flow rate of the GDP airport further decreases and scheduled arrival times change again, (s ≥ 1). Using the possible scenarios, flight rescheduling can be established by minimizing the expected objective function value. A scenario-based stochastic program that searches for a stochastic solution can be presented as follows.

The following notations are used to develop a mathematical model.

Sets

I	set of flights
K	set of available slots associated with the GDP
L	set of intervals of delay cost
S	set of scenarios ($S = \{0, 1, 2, \cdots\}$)
M	set of origin airports
I_s^{GDP}	subset of flights associated with the GDP in scenario s
$I_s^{GDP}(m)$	subset of flights originating from airport m in scenario s

Parameters

α_i	initially planned arrival time of flight i
β_i	initially planned departure time of flight i
δ^{plane}	minimum turnaround time for a plane between arrival and departure
δ^{crew}	minimum turnaround time for a crew between arrival and departure
$\overline{d}_i^{\alpha}$	maximum allowed delay time of arrival of flight i
$\overline{d}_i^{\beta}$	maximum allowed delay time of departure of flight i
r_{ij}^{crew}	1, if a crew is connecting between flights i and j; 0 otherwise
τ_s	time when a subsequent GDP will be issued in scenario s
t_{ks}	scheduled arrival time associated with slot k in scenario s
t_l	break point associated with interval l
r_l	constant of incremental delay cost function associated with interval l
c_l^{delay}	cost per unit delay time associated with interval l
c^{crew}	cost per misconnection of crew
c^{can}	cost per cancellation of flight
M	arbitrary big number

Decision variables

x_{iks}	1, if flight $i \in I_s^{GDP}$ is assigned to slot k on scenario s
y_{ijs}	1, if crews on flight i connecting to flight j cannot make their connection in scenario s; 0 otherwise
z_{is}	1, if flight i arriving at the GDP airport is cancelled in scenario s; 0 otherwise
d_{is}^{α}	arrival delay at GDP airport of flight i in scenario s
d_{is}^{β}	departure delay at GDP airport of flight i in scenario s
w_{is}^{α}	arrival delay cost of flight $i \in I_s^{GDP}$ in scenario s
w_{is}^{β}	departure delay cost of flight $i \in I_s^{GDP}$ in scenario s

Finally, a scenario-based stochastic program for solving the problem can be arranged as follows.

$$\min \mathbb{E}_{s\in S}\left\{\sum_{i\in I_s^{GDP}}\left(w_{is}^{\alpha}+w_{is}^{\beta}\right)+\sum_{i,j\in I}c^{\text{crew}}r_{ij}^{\text{crew}}y_{ijs}^{\text{crew}}+\sum_{i\in I_s^{GDP}}c^{\text{can}}z_{is}\right\} \tag{1}$$

$$\text{s.t.}\, c_l^{\text{delay}}d_{is}^{\alpha}+r_l\leq w_{is}^{\alpha}\forall s\in S, i\in I_s^{GDP}, l\in L \tag{2}$$

$$c_l^{\text{delay}}d_{is}^{\beta}+r_l\leq w_{is}^{\beta}\forall s\in S, i\in I_s^{GDP}, l\in L \tag{3}$$

$$\sum_{i\in I_s^{GDP}:\alpha_i\leq t_{ks}}x_{iks}\leq 1,\forall s\in S, k\in K_s \tag{4}$$

$$\sum_{k\in K_s:\alpha_i\leq t_{ks}}x_{iks}+z_{is}=1,\forall s\in S, i\in I_s^{GDP} \tag{5}$$

$$x_{ik0}=x_{iks},\forall s\in S\backslash\{0\}, i\in I_s^{GDP}, k\in K: t_{ks}<\tau_s \tag{6}$$

$$d_{i0}^{\alpha}\leq d_{is}^{\alpha}\forall s\in S\backslash\{0\}, i\in I_0^{GDP}\backslash I_s^{GDP} \tag{7}$$

$$d_{i0}^{\beta} \leq d_{is}^{\beta} \forall s \in S\backslash\{0\}, i \in I_0^{GDP}\backslash I_s^{GDP} \tag{8}$$

$$d_{is}^{\alpha} = \sum_{k \in K_s : \alpha_i \leq t_{ks}} (t_{ks} - \alpha_i) x_{iks}, \forall s \in S, i \in I_s^{GDP} \tag{9}$$

$$\sum_{k \in K_s} t_{ks} x_{iks} + \delta^{\text{plane}} - \beta_i \leq d_{is}^{\beta}, \forall s \in S, i \in I_s^{GDP} \tag{10}$$

$$\alpha_i + \delta^{\text{crew}} + d_{is}^{\alpha} \leq \beta_j + d_{js}^{\beta} + \overline{d}_i^{\alpha} y_{ijs}, \forall s \in S, i, j \in I : r_{ij}^{\text{crew}} = 1 \tag{11}$$

$$\alpha_i + d_{is}^{\alpha} \leq \alpha_j + d_{js}^{\alpha} + \overline{d}_j^{\alpha} z_{js} \forall s \in S, m \in M, i, j \in I_s^{GDP}(m) : \alpha_i < \alpha_j \tag{12}$$

$$z_{is} \leq y_{ijs}, \forall s \in S, i \in I_s^{GDP}, j \in I : r_{ij}^{\text{crew}} = 1 \tag{13}$$

$$z_{js} \leq y_{ijs}, \forall s \in S, i \in I, j \in I_s^{GDP} : r_{ij}^{\text{crew}} = 1 \tag{14}$$

$$x_{iks}, z_{is}, y_{ijs} \in \mathbb{B}, \forall s \in S, i, j \in I_s^{GDP}, k \in K \tag{15}$$

$$0 \leq d_{is}^{\alpha} \leq \overline{d}_i^{\alpha}, \forall s \in S, i \in I_s^{GDP} \tag{16}$$

$$0 \leq d_{is}^{\beta} \leq \overline{d}_i^{\beta}, \forall s \in S, i \in I_s^{GDP} \tag{17}$$

The objective function (1) is to minimize the expected TRC over finite set of scenarios. It should be noted that scenario $0 \in S$ represents the base scenario regulated by the current GDP (or initial GDP). If the GDP remains unchanged, then the decisions associated with scenario 0 is just realized. On the other hand, if the GDP is revised again, the decisions after the subsequent GDP issuance time are revised. The first term represents the delay costs that are incurred for both arrival and departure delays. The next term describes the misconnection cost of the crew, which is incurred when crews cannot make the connection to their next departure flight in time. The last term is the total flight cancellation cost. Constraints (2) and (3) calculate the arrival and departure delays defined by the incremental delay cost function. Constraints (4) and (5) stipulate the slot assignments of GDP flights. Constraint (4) assures that a slot should be assigned to only one flight. Constraint (5) assures that each GDP flight should be allocated to only one remaining slot or else is cancelled. The qualification $\alpha_i \leq t_{ks}$ enforces that flight i cannot arrive earlier than its initially planned arrival time, α_i. Constraints (6)–(8) state that a slot assignment of a GDP flight cannot be changed if the slot is unavailable or expire on scenarios $s > 1$. Constraint (6) represents that the slot assignment of a flight before the issuance time of a recent GPD should be maintained in the following revision on scenarios $s > 1$. Constraints (7) and (8) ensures that the arrival and departure delays of a flight on scenarios $s > 1$ cannot be less than the delays in the base scenario. Constraints (9) and (10) define arrival and departure delays. Constraint (9) determines the arrival delay for all the GDP flights based on their new slot assignments. Constraint (10) sets a lower bound on the departure delay for the flights. The lower bound is calculated as the new arrival time plus the minimum turnaround time, minus the initially planned departure time. Constraint (11) determines whether or not the crew on arriving flight i can make its transfer to its departure flight, j (i.e., $y_{ijs}^{\text{crew}} = 0$). Constraint (12) ensures that the initially planned arrival sequence of aircraft from the same airport is maintained. For instance, suppose two flights, i and j, with $\alpha_i < \alpha_j$; then, the sequence i before j must be maintained in the final assignments. The constraint is inactive when one of the flights is cancelled. Constraints (13) and (14) enforce that crew connections are not allowed if one of the related flights is cancelled. Variable definitions are given in Constraints (15)–(17).

3.2.2. *Greedy approach*

The greedy approach provides a solution using only static information currently given, without information on possible GDP scenarios. No studies exist that deal with this exact problem situation, but the situation can be extended from existing studies. The following methodology provides a solution by searching for an optimal solution when static information is obtained using the existing MILP proposed by Brunner (2014). In order to define the objective function in the same way, the delay cost function is substituted with the incremental delay cost function. The detailed formulation is provided in Appendix A. The procedure of the greedy approach is shown in the following.

Procedure of the greedy approach

01.	**Begin**
02.	Initialize all flight schedules that have not yet been executed.
03.	Solve the problem using Brunner's MILP with the incremental delay cost.
04.	**If** a feasible solution is obtained
05.	Update the optimal solution as the flight schedules.
06.	**Else**
07.	Keep the current flight schedules.
08.	**Repeat**
09.	Execute a remaining flight schedule.

(*continued on next page*)

(*continued*)

Procedure of the greedy approach
10. **If** the GDP has been updated, **then** go to Step 02.
11. **Until** there is no remaining flight schedules.
12. **End**

3.2.3. Min-max solution approach

Some airlines might be interested in minimizing the costs incurred in worst-case scenarios regarding further changes of the GDP. While this solution may not be effective for practical applications, it can be a meaningful measure for evaluating solutions obtained with other approaches. The flight rescheduling based on conservative strategy can be obtained with the following mathematical model.

$$\min\max_{s\in S}\left\{\sum_{i\in I_s^{GDP}}\left(w_{is}^{\alpha}+w_{is}^{\beta}\right)+\sum_{i,j\in I}c^{\mathrm{crew}}r_{ij}^{\mathrm{crew}}y_{ijs}^{\mathrm{crew}}+\sum_{i\in I_s^{GDP}}c^{\mathrm{can}}z_{is}\right\} \tag{18}$$

s.t. Constraints (2)-(17)

4. Computational experiments

In this section, an airline's flight rescheduling according to different scenarios is simulated based on different approaches, such as the stochastic approach, the greedy approach, and the min-max approach. An experimental setup that includes the airline's real flight schedule and scenario generation is explained in Section 4.1. Detailed results are presented in Section 4.2. Section 4.3 summarizes the significant importance of the results and provides managerial insights that will improve an airline's operation management.

4.1. Experimental setup

An airline's original flight schedule is referred to as real data in existing literature (Brunner, 2014; Luo and Yu, 1997). The data is from American Airlines' daily flight schedule at the Dallas/Fort Worth Airport. There are 71 flights in GDP and the GDP spanned three hours in duration. The planning period of the airline-driven flight rescheduling problem is half a day for one specific season. The data was considered as the base scenario on which a GDP had been issued, and there is no change of the GDP. Including the base scenario, some hypothetical scenarios on subsequent GDPs were assumed and then used to attain the solution. The hypothetical scenarios correspond to new situations in which there are changes in GDP due to weather conditions or external restrictions (Liu et al., 2008). There are some existing studies that calculate or predict GDP scenarios (Liu et al., 2017; Liu et al., 2019). However, since finalizing GDP scenarios is not the scope of our study, the possible scenarios were simply generated based on the ration-by-schedule (RBS) principle. The RBS principle goes by the rule "first scheduled, first served," so in a subsequent GDP scenario the revised arrival times are kept in the order in which they were initially scheduled. In generating a single scenario, the two factors are defined, which are the constrained flow rate and the next time point in which a subsequent GDP would be issued. For each scenario, inbound flights after the time point are defined as GDP flights, and their scheduled arrival times are modified to meet the constrained flow rate (Liu et al., 2008). The probability of the base scenario was set to θ, and that of the other scenarios was set to the even proportion of $(1-\theta)/|S|$. The data and possible scenarios are described in more detail in Appendix B.

The maximum computation time of the solution approaches was fixed to 20 min. This was because an airline can update its flight schedule only within 20 min immediately after the current GDP is activated (Incheon International Airport: Airport Collaborative Decision Making Operations Manual (Korean), 2017). If the computation time exceeded 20 min when solving the airline-driven flight rescheduling problem, the searching procedure was terminated and output the best solution(s) found so far. All computations were performed on a 3.6 GHz processor with 16 GB. The solution approaches were coded in C# using Concert Technology, which is a library of the CPLEX solver engine licensed by IBM ILOG. The version of the CPLEX solver engine used was 12.8, and the default settings of the solver engine were used to implement the solution approaches.

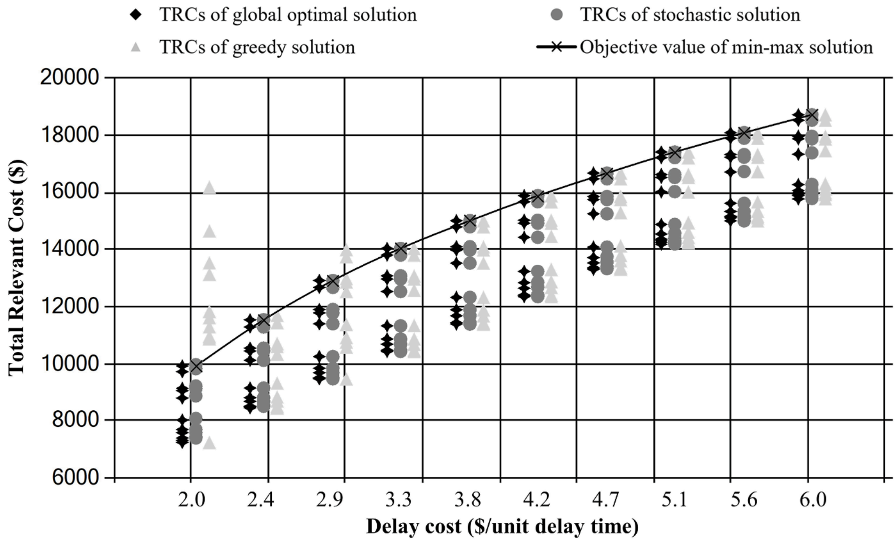
To compare the absolute performance of the proposed solution approaches, the objective value of the global optimal solution was calculated. The global optimal solution corresponded to an optimal flight schedule searched for given perfect information about the implemented GDP(s). Since an airline does not get prior information on subsequent GDP(s), there may be a loss of objective value in providing a solution without perfect information. When comparing the stochastic solution with the global optimal solution, the difference between the two objective values is known as the *expected value of perfect information* (EVPI) (Birge and Louveaux, 2011).

In implementing the stochastic solution approach, the process of constructing possible scenarios with certain probabilities was involved. However, this process can be costly for an airline, and a solution obtained using the information may not be as good as expected. Therefore, this study assessed how valuable it might be to predict possible scenarios with certain probabilities. The *value of the scenario information* (VSI) was calculated as the difference between the objective value calculated using the information (i.e., stochastic solution) and the objective value calculated not using the information (i.e., greedy solution). The EVPI and VSI are calculated in monetary unit. Both the EVPI and VSI are meaningful in reporting the value of perfect information and scenario information in the same unit as the objective function value.

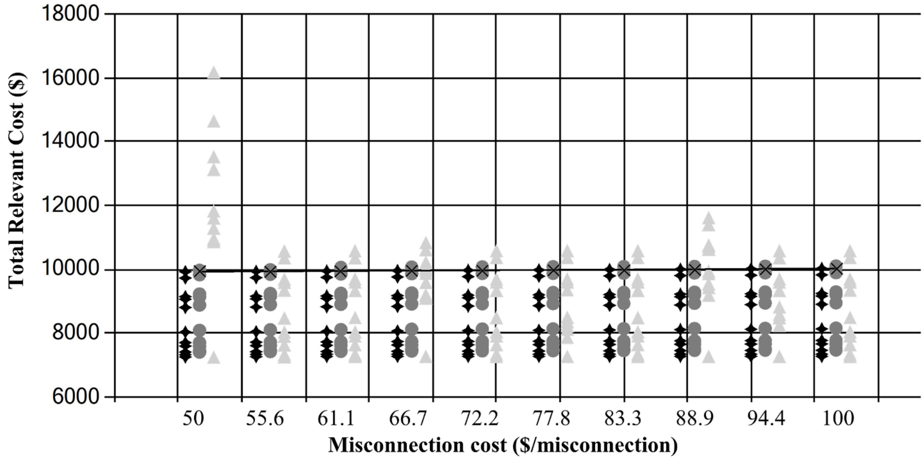
Table 1
The results of the solution approaches.

Scens.	Optimal solution			Stochastic solution				Greedy solution				Min-max solution			
	TRC ($)	# of MCXN	# of CAN	TRC ($)	Opt. gap	# of MCXN	# of CAN	TRC ($)	Opt. gap	# of MCXN	# of CAN	TRC ($)	Opt. gap	# of MCXN	# of CAN
base	7524	9	2	7676	152	10	5	7524	–	10	5	10,089	2565	8	10
1	9342	9	6	9461	119	10	5	11,265	1923	10	5	10,048	706	12	7
2	9263	9	6	9379	116	10	5	11,164	1901	10	5	10,204	941	13	7
3	8246	9	6	8331	84	10	5	11,615	3369	10	5	10,237	1990	15	7
4	9004	9	6	9115	112	10	5	11,225	2221	10	5	9966	962	18	6
5	7670	9	4	7714	44	10	5	14,980	7310	10	5	10,071	2400	16	7
6	7583	9	2	7703	120	10	5	16,517	8934	10	5	10,128	2545	10	8
7	7846	10	5	7846	–	10	5	14,368	6522	10	5	10,139	2293	13	6
8	7959	10	5	7960	1	10	5	13,460	5501	10	5	9926	1967	14	6
9	10,099	9	6	10,178	79	10	6	12,094	1995	10	6	10,099	–	9	6
10	9905	9	6	10,042	137	10	5	11,897	1992	10	5	10,156	251	10	6
ETRC	8458			8554				11,791				10,096			

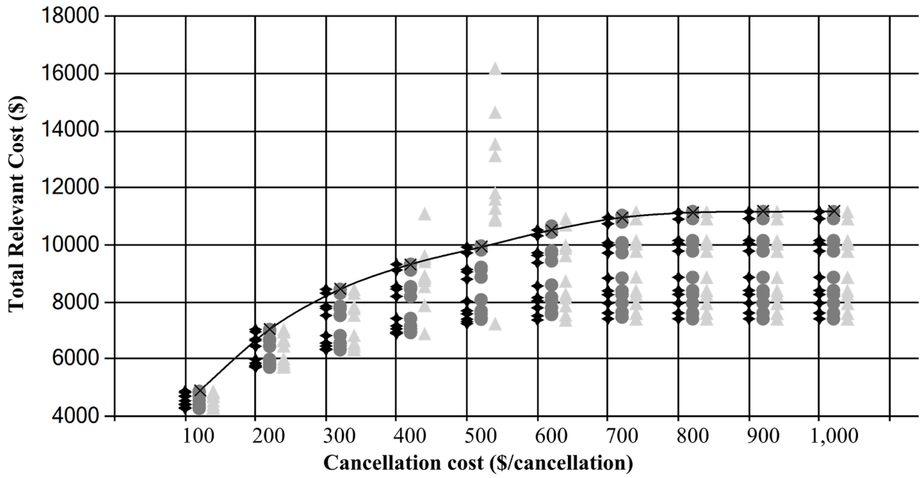
Abbreviations: MCXN, misconnections; CAN, cancellations.



(a) Scatter plot of TRC under varying a set of delay costs



(b) Scatter plot of TRC under varying misconnection cost



(c) Scatter plot of TRC under varying cancellation cost

(caption on next page)

Fig. 3. Scatter plots of TRC under varying cost parameters.

4.2. Experimental results

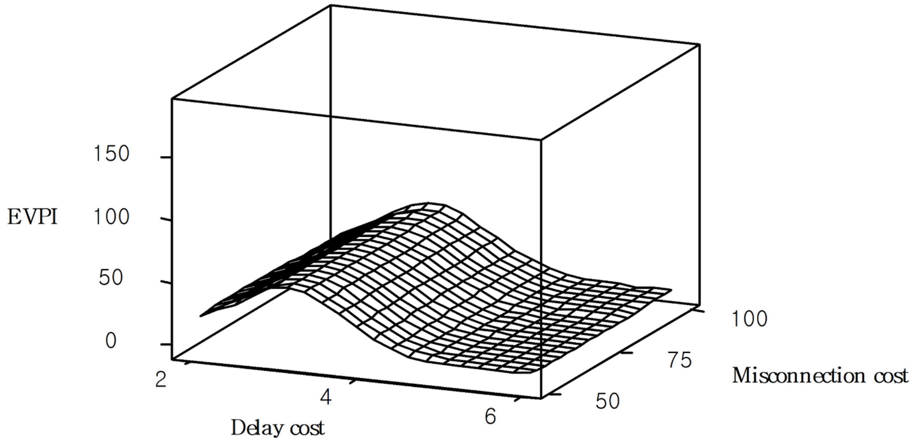
The computational results of flight rescheduling decisions obtained by the solution approaches are summarized in Table 1. All the solution approaches (i.e., stochastic, greedy, and min-max approaches) provided revised flight schedules within the maximum computation time. Each row shows the total relevant cost finally realized by the solution approaches associated with the corresponding scenario. As mentioned above, the base scenario represents a case in which the first issued GDP continues as planned, without any further uncertainty. In the base scenario, obviously, the TRC of the solution of the greedy approach calculated was the same as that of the optimal solution. Meanwhile, in the other scenarios, some TRCs calculated by the solution approach were significantly different from the TRC of the optimal solution. The stochastic solutions provided the TRCs that were relatively close to the optimal TRCs in all the scenarios. The min-max solution provided the same objective value as the largest of the optimal TRCs, which is related to scenario 9.

To investigate how changes of parameters affect flight rescheduling solutions and both the EVPI and VSI, we carried out a sensitivity analysis. In the sensitivity analysis, three types of cost parameters were controlled in the default instance setting. The first of cost parameters is a set of delay costs, c_l^{delay}, and they are changed from 2 to 6, 3 to 11, and 4 to 16, respectively for each interval. The second one is misconnection cost of crew, c^{crew}, and changed from 50 to 100. The last one is cancellation cost, c^{cancel}, and changed from 100 to 1000. Each cost parameter was modified a total of 10 times. For convenience of description, a set of delay costs hereafter is represented by the value of c_1^{delay}.

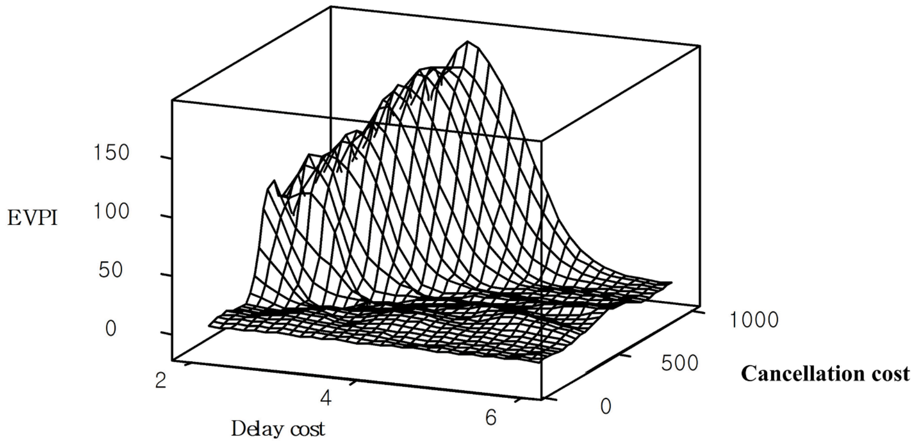
As a result, calculation experiments were performed for a total of 1000 parameter settings. Fig. 3 presents scatter plots of TRCs calculated by the solution approaches under varying cost parameters. Each chart in Fig. 3 describes the only result of changing a cost parameter in the default setting. In the figure, each point describes a TRC associated with a scenario under a certain parameter setting. Black diamond, gray circle, and light-gray triangle symbols represent TRCs calculated by the optimal, stochastic, and greedy solutions, respectively. The solid line shows the objective value obtained by the min-max solution approach. The value corresponds to the minimum TRC for the worst-case scenario. As shown in the figure, the TRCs realized by the stochastic solution approach were close to the optimal TRCs, and the TRCs were less sensitive to the parameter settings. Meanwhile, the TRCs realized by the greedy approach were relatively far from the optimal solution in some parameter settings, and even worse than the minimum TRC for the worst-case

Table 2
Expected TRC of global optimal solutions, stochastic solutions, greedy solutions, and min-max solutions.

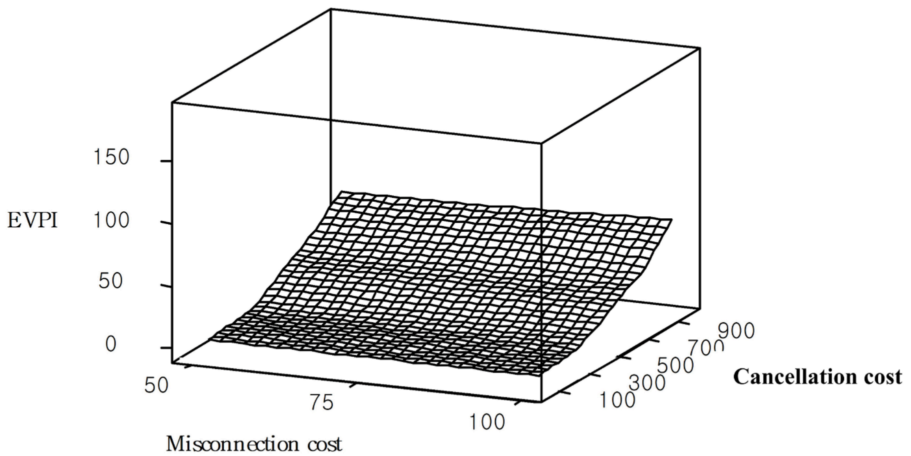
Setting		Expected TRC ($) / Relative gap to global optimum (%)							EVPI	VSI
Parameter	Value	Global solution	Stochastic Solution		Greedy Solution		Min-max solution		($)	($)
Delay cost	2.0	8458	8554	1.1	11,791	39.4	10,096	19.4	95.4	3288.1
	2.4	9496	9514	0.2	9581	0.9	11,535	21.5	17.3	67.2
	2.9	10,649	10,649	0.0	11,520	8.2	12,913	21.3	0.2	870.9
	3.3	11,703	11,703	0.0	11,708	0.0	14,037	19.9	0.1	4.9
	3.8	12,690	12,690	0.0	12,690	0.0	15,007	18.3	0.2	−0.1
	4.2	13,624	13,629	0.0	13,638	0.1	15,882	16.6	5.3	8.8
	4.7	14,502	14,514	0.1	14,524	0.2	16,675	15.0	12.1	10.0
	5.1	15,333	15,339	0.0	15,352	0.1	17,413	13.6	5.8	13.0
	5.6	16,102	16,105	0.0	16,109	0.0	18,088	12.3	3.2	3.9
	6.0	16,817	16,827	0.1	16,838	0.1	18,716	11.3	9.9	11.1
Misconnection cost	50.0	8458	8554	1.1	11,791	39.4	10,096	19.4	95.4	3288.1
	55.6	8232	8315	1.0	8563	4.0	9932	20.7	83.4	247.5
	61.1	8241	8328	1.1	8568	4.0	9943	20.7	86.8	239.8
	66.7	8249	8338	1.1	9341	13.2	9954	20.7	89.2	1002.3
	72.2	8256	8344	1.1	8570	3.8	9965	20.7	88.3	225.6
	77.8	8263	8350	1.1	8704	5.3	9976	20.7	87.3	354.3
	83.3	8269	8355	1.0	8570	3.6	9987	20.8	85.9	215.1
	88.9	8276	8361	1.0	9698	17.2	9998	20.8	84.8	1337.6
	94.4	8283	8366	1.0	8825	6.5	10,009	20.8	83.7	458.4
	100.0	8289	8372	1.0	8571	3.4	10,020	20.9	82.6	199.1
Cancellation cost	100	4500	4501	0.0	4502	0.0	4875	8.3	0.8	1.0
	200	6177	6181	0.1	6189	0.2	7039	14.0	3.6	7.8
	300	7062	7062	0.0	7064	0.0	8446	19.6	0.0	2.0
	400	7711	7720	0.1	8697	12.8	9320	20.9	9.0	976.9
	500	8458	8554	1.1	11,791	39.4	10,096	19.4	95.4	3288.1
	600	8645	8733	1.0	8813	1.9	10,521	21.7	88.5	79.4
	700	8884	8912	0.3	8938	0.6	10,959	23.4	27.8	25.9
	800	8932	8937	0.1	8937	0.1	11,134	24.7	4.3	0.1
	900	8936	8937	0.0	8937	0.0	11,164	24.9	0.4	0.1
	1000	8936	8937	0.0	8937	0.0	11,165	24.9	0.3	0.2



(a) Surface plot of EVPI under varying a set of delay costs and misconnection cost

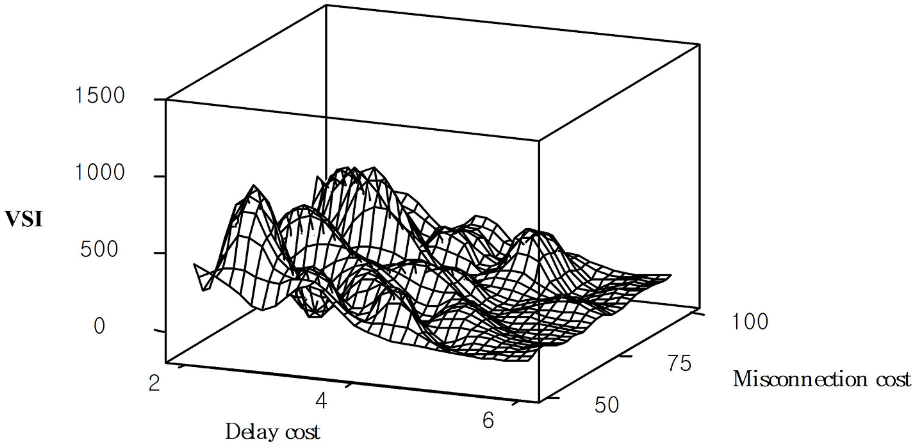


(b) Surface plot of EVPI under varying a set of delay costs and cancellation cost

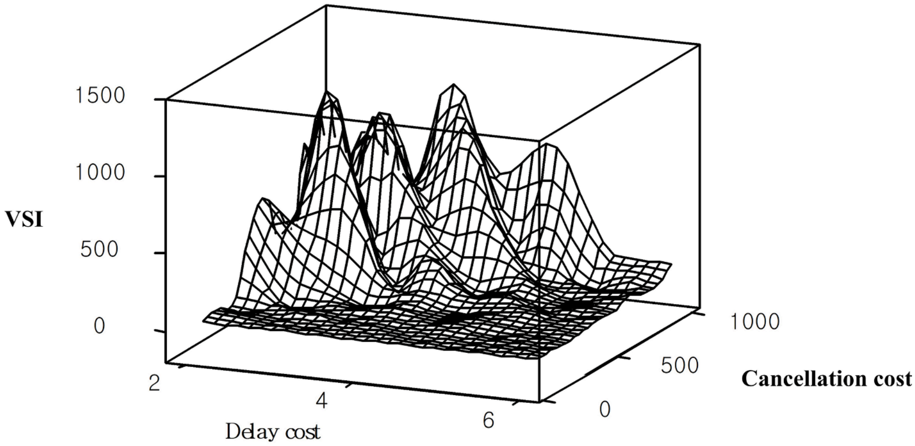


(c) Surface plot of EVPI under varying misconnection cost and cancellation cost

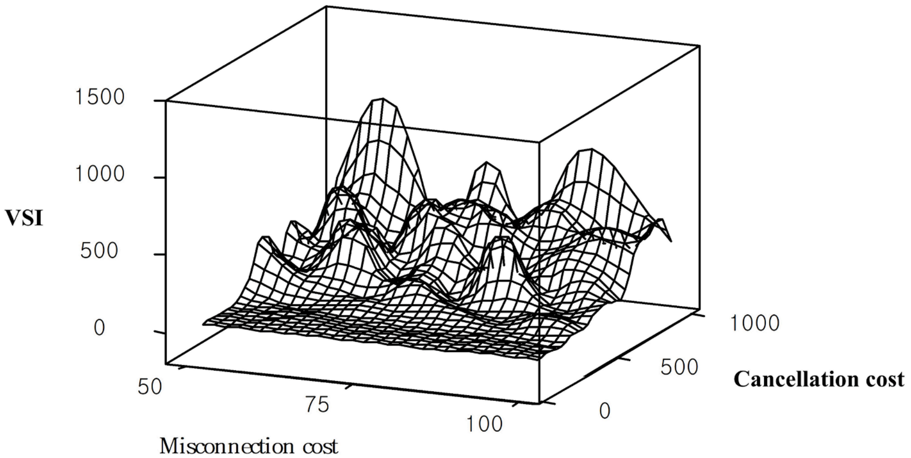
Fig. 4. EVPI under varying two types of cost parameters.



(a) Surface plot of VSI under varying a set of delay costs and misconnection cost



(b) Surface plot of VSI under varying a set of delay costs and cancellation cost



(c) Surface plot of VSI under varying misconnection cost and cancellation cost

Fig. 5. VSI under varying two types of cost parameters.

scenario. This result shows that airlines may not be unable to respond effectively to uncertainties if they establish flight reschedules without any possible scenarios. Table 2 summarizes the results of Fig. 3. The expected TRCs of the optimal solution, stochastic solution, greedy solution, and min-max solution were calculated for each parameter setting. The relative gaps between the objective values and the global optimum is also reported as percentage values. The relative gaps show how close the objective values from different approaches to those of the global optimal solution. In the default instance setting, the EVPI and VSI are calculated as $95.4 and $3288.1, respectively. This shows that the cost incurred due to the absence of complete information was very low, 1.1 percent of the optimal solution. Meanwhile, it can be seen that if the possible scenarios are unavailable, the greedy approach provided a solution that differed significantly from both the optimal and stochastic solutions.

Corresponding to the interpretation described above, the stochastic solution approach searched for a solution close to the optimal solution. The greedy approach calculated a considerably high expected TRC for some parameter settings. The EVPI recorded a relatively low value below 100. However, VSI changed considerably, depending on the parameter settings. In some cases, it was 39.4 percent different from the optimal solution.

However, there are limitations in evaluating the performance of the solution approaches with the result of a single parameter change. This is because the solution approaches provide a flight schedule considering the relative penalty cost of delay, disconnection, and cancellation. Figs. 4 and 5 show surface plots of the EVPI and VSI for two parameter changes out of 1000 parameter settings. Each plot shows the average value of the EVPIs, which were calculated on the two cost parameter settings. As shown in Fig. 4(a) and Fig. 4(c), the changes of misconnection cost do not have a significant impact on the EVPI. Meanwhile, the EVPIs fluctuated in response to changes in delay cost and cancellation cost, as shown in Fig. 4(b). When the cancellation cost was relatively higher than the delay cost, the large EVPI was recorded. This result means that the stochastic approach finds a solution close to the optimal solution in most parameter settings, but when the cancellation cost is greater than the delay cost, it is possible that the TRC calculated by the stochastic approach is indifferent to the optimal TRC. Fig. 5 shows that the VSIs fluctuate very significantly depending on the parameter setting. Similar to the result in Fig. 4(b), very small VSIs were calculated when the cancellation cost was smaller than the delay cost. The small values of VSIs mean that it is possible that the greedy approach provides a good solution close to the stochastic solution or the optimal solution. However, the main reason for this result is that a large number of flights were cancelled rather than delayed, because the cancellation penalty was cheaper than the delay penalty.

4.3. Managerial insights

Whenever a GDP is issued, airlines try to adjust their flight schedules to improve their internal objectives. Airlines should carefully formulate rescheduling plans, because a rescheduling plan established at the current time will affect the next rescheduling plan when a subsequent GDP is updated. In making flight rescheduling decisions, airlines might consider using the greedy approach, the stochastic approach, or the min-max approach. The greedy approach attains a rescheduling solution under consideration of static information on both the current GDP and the revised arrival times, whereas the other approaches search for a solution using possible scenarios for upcoming uncertain events. Airlines are allowed to adjust their flight schedules up to only 20 min after a GDP, and calculating possible scenarios in advance may be costly. Therefore, airlines deciding which approach to use must take into account not only the comparison of the solution performance of the approaches, but also the opportunity cost of attaining possible scenarios.

The experimental results showed that an airline could seek flight rescheduling solutions close to the optimal or stochastic solution in a second by using the greedy approach, although only static information on the current GDP is available, rather than information about possible scenarios. However, in implementation, the considerable optimality gaps in some scenarios showed that the greedy approach does not always provide an effective solution in terms of an airline's total penalty cost. Meanwhile, the airline can achieve more effective solutions compared to the greedy approach by using the stochastic approach. The high levels of the VSIs, which are the objective gaps between stochastic solutions and greedy solutions, explain that it is meaningful to airlines to obtain the possible scenarios in advance of using the stochastic approach. In the parameter settings where the cancellation cost is relatively small, both stochastic and greedy solutions were close to the global optimal solution. This is because it is best to cancel a lot of flights rather than to delay them. Since airlines' flight cancellations are usually subject to a host of penalties, it is therefore difficult to conclude that determining possible scenarios is negligible. In implementation, the optimal ratio of a stochastic solution was reported as 1.3 percent for the worst case of parameter settings. This means that even without perfect information (i.e., without knowing exactly which GDP scenario will be realized), airlines can search for a very close to the global optimal solution with the stochastic approach. The min-max approach found a better solution than the greedy solution in very limited cost parameter settings. Compared to the stochastic solution, the saving of TRC was very low, even in the worst-case scenario.

Given the hurdle of time sensitivity, the stochastic approach provided solutions within five minutes. Therefore, an airline is given at least 15 min of spare time to explore possible scenarios in advance. If some reasonable scenarios can be searched during this time frame and the VSI recoded for the airline's preferred parameter setting is lower than the cost of attaining possible scenarios, then implementing the stochastic approach is competitive regarding the improvement of an airline's operations management.

5. Conclusions

This study investigated the problem of airline-driven flight rescheduling in which a series of uncertain events can occur. The objective of the problem was to minimize the TRC that consists of flight delay costs, flight misconnection costs of crew members, and flight cancellation costs. Delay costs were calculated by an incremental cost function of delay times. The incremental cost function is a general version including the threshold-delay model, which is one of common delay measures. Three types of strategies, i.e., greedy, stochastic, and conservative strategies, an airline's decision-makers might consider were dealt with. Corresponding to the three strategies, the greedy approach, the stochastic approach, and the min-max approach were designed, respectively. The greedy approach, which refers to the wait-and-see approach, reschedules GDP flights using the static information currently verified whenever a GDP is activated, and the authority to change the slot allocations is granted. The stochastic approach rearranges the flight schedule using stochastic information on future disruptions. It is assumed that hypothetical possible scenarios have been prepared as stochastic information. The stochastic solution minimizes the expected TRC over the possible scenarios. The min-max approach is used to minimize the TRC for the worst-case scenario. As one of our main contributions, we developed the formulation of a scenario-based stochastic programming model, which corresponds to the stochastic solution approach.

Using real data from existing literature, we evaluated the performance of the proposed solution approaches. All the solution approaches provided feasible solutions on the airline-driven flight rescheduling problem within 20 min, which is the time limit airlines are given in which to rearrange their schedules. We conducted a sensitivity analysis on a number of cost parameter settings. To compare the absolute performance of the proposed approaches, we calculated global optimal solutions under perfect static information on GDP(s). In the computational results, the low EVPIs explained that the stochastic solution approach could find solutions close to the global optimal solutions, although no perfect information was provided. Meanwhile, the high VSIs showed that there can be a significant penalty for neglecting to attain any possible scenarios when implementing the greedy approach. Future research should consider slot swapping between airlines. As shown in other studies on flight rescheduling, slot swapping between airlines can be expected to improve internal objectives. Given the confines of limited information presented by GDPs, the impact of slot swapping on airlines' internal objectives could be analyzed in further research.

CRediT authorship contribution statement

Young-Bin Woo: Conceptualization, Methodology, Investigation, Software, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Ilkyeong Moon:** Conceptualization, Validation, Writing - review & editing, Supervision.

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Appendix A

This section presents the modified Brunner's MILP model which provides a flight rescheduling with static information of the GDP considering an incremental delay cost function. The formulation is slightly changed by adapting notations used in this paper:

$$\min \sum_{i\in I_0^{GDP}} \left(w_{i0}^{\alpha} + w_{i0}^{\beta}\right) + \sum_{i,j\in I} c^{\text{crew}} r_{ij}^{\text{crew}} y_{ij0}^{\text{crew}} + \sum_{i\in I_0^{GDP}} c^{\text{can}} z_{i0} \tag{A.1}$$

$$\text{s.t.} c_l^{\text{delay}} d_{i0}^{\alpha} + r_l \le w_{i0}^{\alpha} \forall i \in I_0^{GDP}, l \in L \tag{A.2}$$

$$c_l^{\text{delay}} d_{i0}^{\beta} + r_l \le w_{i0}^{\beta} \forall i \in I_0^{GDP}, l \in L \tag{A.3}$$

$$\sum_{i\in I_0^{GDP}:\alpha_i \le t_{k0}} x_{ik0} \le 1, \forall k \in K_0 \tag{A.4}$$

$$\sum_{k\in K_0:\alpha_i\le t_{k0}} x_{ik0} + z_{i0} = 1, \forall i \in I_0^{GDP} \tag{A.5}$$

$$d_{i0}^{\alpha} = \sum_{k\in K_0:\alpha_i\le t_{k0}} (t_{k0} - \alpha_i) x_{ik0}, \forall i \in I_0^{GDP} \tag{A.6}$$

$$\sum_{k\in K_0} t_{k0} x_{ik0} + \delta^{\text{plane}} - \beta_i \le d_{i0}^{\beta}, \forall i \in I_0^{GDP} \tag{A.7}$$

$$\alpha_i + \delta^{\text{crew}} + d_{i0}^{\alpha} \le \beta_j + d_{j0}^{\beta} + \overline{d}_i^{\alpha} y_{ij0}, \forall i,j \in I : r_{ij}^{\text{crew}} = 1 \tag{A.8}$$

$$\alpha_i + d_{i0}^{\alpha} \le \alpha_j + d_{j0}^{\alpha} + \overline{d}_j^{\alpha} z_{j0} \forall m \in M, i,j \in I_0^{GDP}(m) : \alpha_i < \alpha_j \tag{A.9}$$

$$z_{i0} \le y_{ij0}, \forall i \in I_0^{GDP}, j \in I : r_{ij}^{\text{crew}} = 1 \tag{A.10}$$

$$z_{j0} \le y_{ij0}, \forall i \in I, j \in I_0^{GDP} : r_{ij}^{\text{crew}} = 1 \tag{A.11}$$

$$x_{ik0}, z_{i0}, y_{ij0} \in \mathbb{B}, \forall i, j \in I_0^{GDP}, k \in K \tag{A.12}$$

$$0 \le d_{i0}^{\alpha} \le \overline{d}_i^{\alpha}, \forall i \in I_0^{GDP} \tag{A.13}$$

$$0 \le d_{i0}^{\beta} \le \overline{d}_i^{\beta}, \forall i \in I_0^{GDP} \tag{A.14}$$

Appendix B

This section presents a set of reasonable parameters used in Brunner (2014). The minimum turnaround times of plane and crew, δ^{plane} and δ^{crew}, were fixed with 30 min and 20 min, respectively. The maximum allowed time for delays was set to 500 min for $\overline{d}_{is}^{\alpha}$ and $\overline{d}_{is}^{\beta}$. The misconnection cost of crew members and the cancellation cost of a flight, c^{crew} and c^{cancel}, were 50 and 500, respectively. For the incremental delay cost function, each interval, in which different unit costs occurred, was fixed by 60 min. There were three intervals. The cost per unit delay time, c_l^{delay}, was set to 2, 3, and 4, and associated with each interval, respectively. Correspondingly, the constant value of the incremental delay cost function was set to 0, -60, and -180, and associated with each interval, respectively. The initial flight schedule and the schedule revised by a GDP are presented in Table B.1. The current GDP has been issued at 0. The initial flight

Table B1
Flight information at DFW Airport and the schedule delivered by the central authority.

Flights	Slot	Original schedule				Schedule rearranged by the central authority				
ID	ID	Arrival	Departure			Arrival		Departure		
		Time	Time	Origin	Crew	Time	Delay	Time	Delay	Crew
F01	S01	0	59	MCI	F72	50	50	80	21	0
F02	S02	1	46	PDX	–	51	50	81	35	
F03	S03	1	48	ATL	F03	53	52	83	35	1
F04	S04	1	53	OKC	F55	54	53	84	31	1
F05	S05	2	58	LBB	F05	55	53	85	27	1
F06	S06	9	57	MSY	F73	62	53	92	35	0
F07	S07	10	64	MFE	F08	64	54	94	30	1
F08	S08	12	64	MSP	F74	65	53	95	31	0
F09	S09	15	51	IAD	F06	68	53	98	47	1
F10	S10	18	500	ORD	F75	71	53	500	0	1
F11	S11	22	65	HRL	F11	77	55	107	42	
F12	S12	61	121	DCA	F21	104	43	134	13	
F13	S13	64	500	PHL	–	106	42	500	0	
F14	S14	65	500	CLT	–	107	42	500	0	
F15	S15	67	500	BHM	–	109	42	500	0	
F16	S16	68	500	CMH	–	110	42	500	0	
F17	S17	69	500	MCO	–	110	41	500	0	
F18	S18	82	500	STL	–	111	39	500	0	
F19	S19	85	500	OMA	–	113	38	500	0	
F20	S20	86	157	ORD	–	114	38	157	0	
F21	S21	86	153	SNA	F12	115	39	153	0	0
F22	S22	86	159	HOU	–	116	40	159	0	
F23	S23	78	500	BDL	–	117	39	500	0	
F24	S24	78	500	COS	–	118	40	500	0	
F25	S25	79	500	TPA	F57	119	40	500	0	1
F26	S26	80	154	SAN	F26	120	40	154	0	1
F27	S27	80	134	SAT	–	120	40	150	16	
F28	S28	84	500	LGA	F37	121	37	500	0	1
F29	S29	84	500	SJC	F27	122	38	500	0	1
F30	S30	84	159	HSV	F30	123	39	159	0	1
F31	S31	84	500	IAH	–	124	40	500	0	
F32	S32	89	500	IND	F76	127	38	500	0	1
F33	S33	89	500	JAN	–	128	39	500	0	
F34	S34	91	149	SEA	F34	130	39	160	11	1
F35	S35	92	174	DTW	–	131	39	174	0	
F36	S36	93	500	CLE	F56	133	40	500	0	1
F37	S37	93	138	LAX	–	134	41	164	26	
F38	S38	95	158	PBI	–	137	42	167	9	
F39	S39	98	161	SF0	F42	140	42	170	9	1
F40	S40	99	160	PIT	F77	141	42	171	11	1
F41	S41	100	500	BOS	–	146	46	500	0	

(continued on next page)

Table B1 (*continued*)

Flights	Slot	Original schedule				Schedule rearranged by the central authority				
ID	ID	Arrival	Departure			Arrival		Departure		
		Time	Time	Origin	Crew	Time	Delay	Time	Delay	Crew
F42	S42	100	151	ATL	F58	147	47	177	26	1
F43	S43	100	500	BNA	–	148	48	500	0	
F44	S44	100	500	OKC	–	149	49	500	0	
F45	S45	101	172	ONT	F53	150	49	180	8	1
F46	S46	101	163	AUS	F45	152	51	182	19	1
F47	S47	103	500	RDU	–	155	52	500	0	
F48	S48	103	500	MIA	–	156	53	500	0	
F49	S49	103	500	ORD	–	157	54	500	0	
F50	S50	103	500	DEN	–	158	55	500	0	
F51	S51	104	500	JAX	–	160	56	500	0	
F52	S52	104	156	MSY	F52	160	56	190	34	1
F53	S53	106	153	RIC	F39	161	55	191	38	0
F54	S54	108	163	JFK	–	163	55	193	30	
F55	S55	108	161	MEM	–	165	57	195	34	
F56	S56	109	154	MSP	–	169	60	199	45	
F57	S57	112	160	ORF	F78	171	59	201	41	0
F58	S58	113	167	IAD	–	172	59	202	35	
F59	S59	114	500	GSO	–	173	59	500	0	
F60	S60	114	165	MCI	F79	175	61	205	40	0
F61	S61	126	500	BWI	–	181	55	500	0	
F62	S62	128	500	PHX	–	184	56	500	0	
F63	S63	128	500	DSM	F35	185	57	500	0	0
F64	S64	137	500	ORD	–	190	53	500	0	
F65	S65	184	500	SJC	–	220	36	500	0	
F66	S66	191	500	LAX	–	221	30	500	0	
F67	S67	191	500	LAS	–	223	32	500	0	
F68	S68	197	500	ORD	–	226	29	500	0	
F69	S69	204	500	LGA	–	227	23	500	0	
F70	S70	210	500	BNA	–	228	18	500	0	
F71	S71	229	500	ORD	–	229	0	500	0	
F72	S72	0	45	DFW	–	–	–	45	–	
F73	S73	0	59	DFW	–	–	–	59	–	
F74	S74	0	49	DFW	–	–	–	49	–	
F75	S75	0	56	DFW	–	–	–	56	–	
F76	S76	0	194	DFW	–	–	–	164	–	
F77	S77	0	161	DFW	–	–	–	161	–	
F78	S78	0	162	DFW	–	–	–	162	–	
F79	S79	0	168	DFW	–	–	–	168	–	

schedule defines the arrival and departure times of flights α_i and β_i. The connections of crews between flights, r_{ij}^{crew}, are also described in the initial flight schedule. In the revised schedule, the arrival times represent the scheduled arrival times of slots, t_{k0}.

For possible scenarios, ten scenarios were randomly generated. In generating a scenario, the constrained flow rate and the next time point were obtained by $N(1.5, 0.15)$ and $U(60, 180)$. Correspondingly, all the constrained flow rates were 1.81, 1.88, 1.58, 1.64, 1.59, 1.46, 1.49, 1.46, 1.4, and 1.45, respectively; all the next time points were 103, 103, 123, 112, 151, 168, 145, 139, 76, and 103, respectively. In each scenario, the starting times of slots, $t_{k0,}$ were calculated by adding the inverse of the constrained flow rate to the initial arrival times after the time point, cumulatively. The probability of the base scenario, θ, was set to 0.2, and the probability of the other scenarios was set to 0.08. The whole metadata is available on Mendeley data repositoy (Woo and Moon, 2021).

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