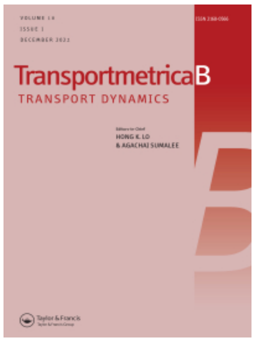

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Flight rescheduling of an airline under the ground delay program considering delay propagation in multiple airports

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ABSTRACT

The purpose of this study is to reschedule flights for an airline's profit to correspond to the airport's changed capacity. In the event of a ground delay program (GDP), the number of flights the airport can accommodate is reduced. We formulated a mixed-integer linear programming (MILP) model to reschedule flights. The MILP models were divided into two versions to handle the uncertainty of the future. In scenarios in which the GDP is changed again, an optimal model obtains solutions for each scenario. The stochastic model solution obtains a minimizing expectation cost of all scenarios. All flights are connected to both the origin and destination airports, and one aircraft may be used for more than one flight. Therefore, we considered delay propagation not only within the same airport but from other airports by extending the setup to include several airports at once. Because the objective of this study is to minimize the operation cost of airline, we also considered costs associated with airline resources such as aircrafts and crews. Related experiments were conducted including comparison between two suggested versions.

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Mixed-integer linear programming; stochastic programming; rescheduling; ground delay program; air traffic control

1. Introduction

Air transportation is increasingly an important part of the overall transportation. However, due to the characteristics of the aviation industry, it is necessary to plan flights carefully and control the flow of air traffic, compared to other means of transportation. Each airport has its own capacity, especially the airport acceptance rate (AAR), which is a capacity that can accommodate incoming aircraft considering runways, gates, and baggage lines. This rate is determined by the air route traffic control centre, which calculates the time interval between aircraft arriving and entering the airport, which is called the timeslot when the aircraft can enter. Airlines or other aircraft operators buy timeslots they want in advance, according to the International Air Transport Association (IATA) conference and the South Korea Airport Schedule Office (KASO). Flights can be organized at the corresponding time of timeslots, as shown in Figure 1. Vertical bars represent the timeslot.

Nonetheless, the AAR may decrease when weather conditions deteriorate or when there is a need to clear the airway as neighbouring countries conduct military training. The ground delay program (GDP) is one of the important ways to control air traffic in this case. When the AAR decreases because of some reason, reducing the number of incoming aircrafts per hour changes the time of slots

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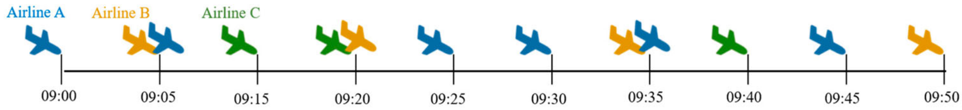

Figure 1. Flights of each airline planned in timeslots.

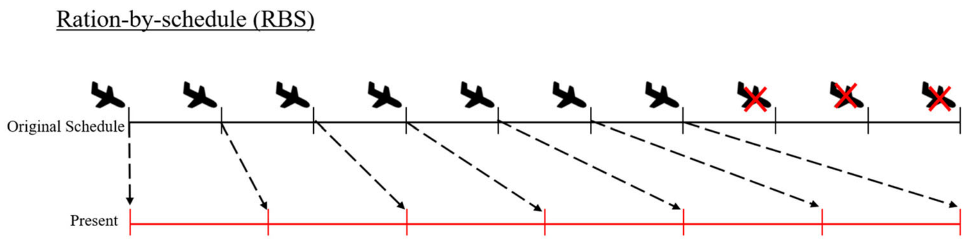

Figure 2. Rescheduling using the RBS method.

accordingly, and adjusting already departed flights to the changed timeslot causes waiting in the air. This has many disadvantages, such as fuel consumption, airway congestion, and safety problems. Therefore, having flights wait at the origin airport on the ground before departing is desirable, which is called the GDP. When the GDP is issued, flights which were planned to arrive at the GDP airport must be readjusted. The standard method used is the 'first-scheduled, first-served rule' which receives slots in the order originally planned. This is called 'Ration-By-Schedule (RBS)'. Figure 2 shows RBS algorithm. In Section 4.4, experiments were conducted to compare this method with the proposed models. The RBS method will be described in more detail in that section.

What should be considered in the readjustment is the connection of the resources required for flights. If an aircraft is used again after the arrival, the departure time will be planned at appropriate intervals, regarding taxi-in/taxi-out times, aircraft maintenance and cabin cleaning from the arrival time of the aircraft. The time for these essentials is called the minimum turnaround time of the aircraft. This must be observed even if the departure is delayed, because it is necessary for the operation of the aircraft. Crews also have minimum turnaround time if crews are connected to another flight. Contrary to the minimum turnaround time of aircraft, it may be more cost-effective for crews not to transfer rather than for flights to delay in order to ensure the crew's boarding. In this study, there is one more concept of time interval that is different from the minimum turnaround time. Let's say that the airline has set a time for safer operations, which is called buffer time. This, specifically, is the time for risk-averse operations, because there are many kinds of planned activities, such as passenger boarding time and assigned gate availability time. If this time is not guaranteed, an urgent operation condition will need to be addressed, such as ensuring additional staff or changing the order of the assigned gate.

As centralized framework, the GDP decision maker can control schedule for the overall efficiency of the airport, addressing such issues as minimizing total delay time or promising equity. Various rules and heuristics to help make decisions have been studied in this centralized framework. Even so, Yan, Vaze, and Barnhart (2018) summarized the advantages that can be acquired when considering the operational aspects of the airline, not the central authority. From the perspective of an airline, minimizing total delay time of an airport is not the most important objective. Rather than that, the more important objective when rescheduling is to minimize operating costs while considering resources that airlines have. When the GDP is implemented, airlines are given a short time to readjust their flights. An and Gang (2006) introduced several methods, such as compression and timeslot substitution, in which airlines cooperate with one another in collaborative decision making (CDM) system. However, it would be relatively inexpensive and easy to reschedule within an airline's own flights before working with other airlines. Airlines should consider various factors and costs, such as an aircraft being used on multiple flights or crews having to transfer to another flight. It is challenging to decide which flight to delay or cancel and how much to delay them. Such costs examined in this study include not only the cost of flight delays and cancellations but also the cost of failure to transfer of crews and the cost of violating buffer time between connected flights.

In addition, as the number of low-cost airlines increased, short-distance flights have been increased. Accordingly, one aircraft is often used for more than two flights within a day. Most existing studies solved the problem within a single airport. This leads to infeasibility in reality, because delay from other airports or other flights could be ignored. Therefore, research is needed to consider several airports at once, not one airport. Even though some single airport rescheduling models consider delay propagation, they consider only how the delay of arrival at the target airport could extend to departures in the same airport. In this study, a mathematical model is suggested to reschedule flights from multiple airports when the GDP is issued. The benefit of solving a problem in such a multi-airport setup is that it can consider the delay propagation many times. Not only the delay in the same airport but the delay from other airports should be examined.

When a schedule has to be changed according to the initial GDP issuance, it might be worth considering the possibility that the GDP is not a permanent method. It is important to consider the possibility that the AAR will change again at some point in the future. For example, factors that caused GDP can disappear, and the AAR may be restored to its original rate. Else, it may get worse with the AAR decreased again. Otherwise, nothing will change from the first GDP. Flights should be readjusted to meet the GDP, but it is not known what will happen again later. Therefore, to prepare for this, the model is verified by creating scenarios that may occur with base scenario, in which the GDP has been executed once. Figure 3 shows various scenarios. Rescheduling according to information available only in the present without preparation for possible changes, is costly. Therefore, a scenario-based method is used to minimize the expected cost by creating scenarios with the currently updated information about the GDP.

The remainder of this study is organized as follows: In Section 2, we review studies related to the GDP and recovery from disruptions in airports. Then, we describe problems in detail, along with mathematical formulations of our model, in Section 3. Section 4 details the computations of experiments showing the validation of suggested models in various aspects. Results and analyses of experiments are suggested in the same section. Last, conclusions are presented in Section 5.

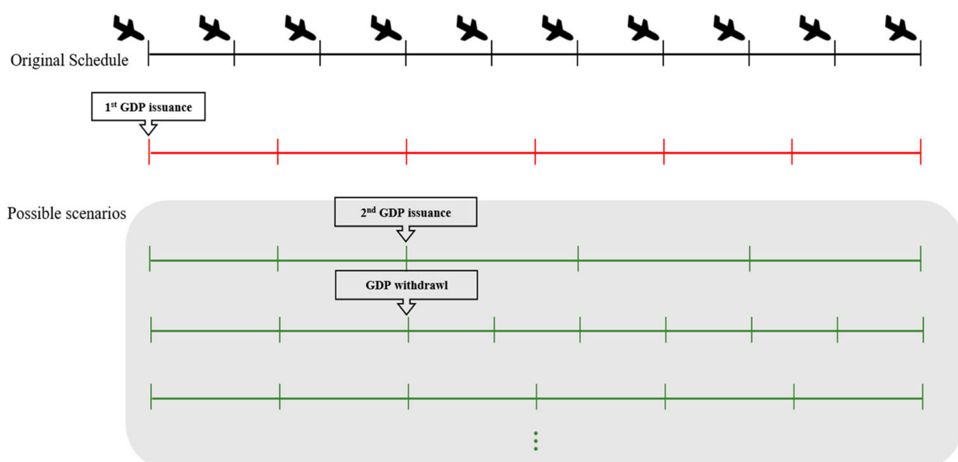

Figure 3. Example of possible scenarios at the point when the GDP first occurred.

2. Literature review

A static and deterministic Ground Holding Program (GHP) problem in a single airport was introduced first by Odoni (1987). Filar, Manyem, and White (2001) summarized papers on the recovery of airlines and airports from disruption. They categorized objectives of tactical air traffic management into three types – fuel consumption, late arrival and departure, and noise nuisance – and stated the GHP is one of important workarounds. Terrab (1990) and Richetta (1991) also suggested a deterministic single airport GHP in formulations of capacitated network formulation and minimum cost assignment formulation. Luo and Yu (1997) studied scheduling disruption by the GDP in a single airport. They presented an algorithm to minimize the total delay time solved within the polynomial time, but within a specific case. Jarrah et al. (1993) dealt with the shortage of flights or aircraft, permitting swapping aircraft among flights. Also, Cox and Kochenderfer (2015) reviewed six optimization models of a single airport's GHP and compared strengths and weaknesses of each model. Subsequently, they proposed a model to optimize a plan of GHP using Markov decision process (Cox and Kochenderfer 2016). Lee, Marla, and Jacquillat (2020) proposed a reactive and proactive joint management model optimizing aircraft recovery. They addressed the concept of minimizing the loss from past disruptions and the occurrence of future disruptions together.

With uncertainty in the AAR, stochastic versions of the GHP were followed. Various studies have been conducted to ensure robustness in scheduling problems. Ball et al. (1999) solved a stochastic GHP problem. They did not reschedule flights but determined the number of timeslots from the control centre's point of view. Terrab and Odoni (1993) experimented with the GHP in a deterministic case and a stochastic case. Then, they suggested insights comparing the suggested model with dynamic programming and a heuristic. Ng et al. (2017) tried to handle uncertainty using the min–max regret approach. Liu, Hansen, and Mukherjee (2008) involved scenarios with possible capacities of airport. To reschedule more realistically, Liu, Hansen, and Mukherjee (2008) used a scenario tree method that dynamically solves the problem by updating the probability of scenarios as realizing information. The dynamic stochastic version in a single airport was introduced by Richetta and Odoni (1994). Mukherjee and Hansen (2007) improved a dynamic stochastic integer programming setup. They allowed revisions to flights that had been assigned a ground delay. As computation time is too long, heuristics were also introduced. Navazio and Romanin-Jacur (1998) suggested a heuristic based on the limited resource critical path method, which obtained suboptimal result. Navazio and Romanin-Jacur (1998) also considered multi-connections which means there are several preceding flights of passengers who have to take a subsequent flight. Several heuristics applied the priority rule using the marginal cost in scheduling (Andreatta and Brunetta 1998; Navazio and Romanin-Jacur 1998; Terrab and Odoni 1993). The Federal Aviation Administration (FAA) exempted long-haul flights which evoked an equity problem. Ball, Hoffman, and Mukherjee (2010) suggested an algorithm called 'Ration-By-Distance (RBD)' which is structured as RBS with a priority rule.

Also, there are studies that reflect complexity between airports. Vranas, Bertsimas, and Odoni (1994a) and Bertsimas and Patterson (1998) proposed integer programming models to assign ground-holding delays optimally in a network of airports. They included transmission of delays between successive flights with coupling constraints. Vranas, Bertsimas, and Odoni (1994b) then extended the multiple airports problem to dynamic version. They used discrete time horizon where decisions were made about how many unit periods to wait. Brunetta, Guastalla, and Navazio (1998) presented a static and deterministic MILP model in a multi-airport setup, but only included single connections, not multiple connections. Jia et al. (2022) constructed the delay propagation network. They used nonlinear Granger causality, which was good for identifying interrelationships. By overcoming the curse of dimensionality, the cause of delay in the complex airport network was well identified. Wu et al. (2018) introduced and analysed delay propagation that sequential flights can have. However, as with other studies, only propagation at the same airport was described. Vlachou, Sharma, and Wieland (2019) handled a double delay problem for short-haul flights. This study is not about delay propagation but simultaneous delay. Delay in short-haul flights can come from the GDP and the Call For Release (CFR) together. With the advancement of machine learning techniques, numerous studies have emerged aiming to predict delays in airports (Gui et al. 2019, Mejri et al. 2023). Wang, Tien, and Chou (2022) developed the time delay stability (TDS) algorithm, using historical data to predict the occurrence of delay propagation between airports. They also constructed a weighted directed graph, a network model suitable for easily implementing the proposed algorithm. Their model addressed the heterogeneous inputs from multiple airports and utilized self-supervised learning and transformers to predict delays.

The objectives of the study dealing with the GDP vary a lot. Most studies focused on a centralized framework as Ball et al. (1999; 2010). Hu, Luo, and Bai (2022) applied queueing theory to address passenger congestion problem of airport. They used bi-level programming to solve the behaviour choice of passengers. Yan, Vaze, and Barnhart (2018) assessed the benefits of decentralized framework that reflects airline-driven objectives. Yan and Young (1996) solved a problem with an objective function to maximize the profit of an airline, taking into account delay and cancellation simultaneously, but not crew members or passengers. Bard and Mohan (2008) solved a timeslot reallocation problem with dynamic programming from the airlines' point of view. Radman and Eshghi (2023) solved the crew pairing problem of airline industry using decomposition technique. Brunner (2014) proposed a mathematical model to minimize airline driven costs including passenger and crew connections. Woo and Moon (2021) presented a model to help airlines reschedule when the GDP was issued. They used stochastic programming for uncertain situations from a present perspective, and its value was evaluated. De La Vega et al. (2022) addressed the rescheduling of flights transportation to maritime units. They presented a mathematical model through a case study to minimize the overall delay of the pending flights with different priorities. However, this study focused on flights closer to helicopters rather than on commercial flights at the airport, and did not incorporate capacity characteristics of the airport.

Kafle and Zou (2016) investigated a role of a buffer time in delay propagation. Slack time, explained in Navazio and Romanin-Jacur (1998) and Wong and Tsai (2012), is a delay absorption tool. This is slightly different from the concept of buffer time in our study. In our study, buffer time is used as recovery tool as well. However, buffer time here is different from the essential time required for transferring. It is introduced to provide insight to operations. To the best of our knowledge, there has been no study yet undertaken to reschedule in more than one airport simultaneously when the GDP is issued, considering not only the delay propagation of one airport but also the propagation from other airports. Furthermore, we considered airline's limited assets with purpose of minimizing cost of an airline. For robustness, not only the optimal version but also the stochastic programming method is adopted.

3. Mathematical model

3.1. Model description

We assume that departure capacity for outbound flights is infinite, while arrival capacity, the airline acceptance rate (AAR), for inbound flights is finite. If the departure capacity is limited enough for flights to wait, an airborne delay occurs. However, it is assumed that the department capacity is infinite because the time for take-off is shorter than for landing (Vranas, Bertsimas, and Odoni 1994a). Therefore, a specific timeslot is not required for departures. Moreover, one aircraft can be used for up to two flights for short-distance flights such as domestic flights. For instance, an aircraft often makes a round trip between Gimpo and Jeju in one day. When the GDP is issued, timeslots also will be changed, in keeping with the changed AAR of the airport. Airlines have time to readjust their flights relatively autonomously among the timeslots assigned to themselves.

In an airport set, some airports may be unaffected by the GDP, and several airports may be under the influence of the GDP. If there are multiple airports with the GDP implemented at once, there are eight situations to consider per airport. Let there be airport $m1, m2, m3 \in M$ which is an airport set under GDP and $v1, v2 \notin M$. For inbound *flight i* in airport $m1$, there are four cases, as follows: (1) aircraft departing at $v1$ arrives and finishes its flight on that day; (2) aircraft departing at $m2$ arrives and finishes its flight on that day; (3) aircraft departing at $v1$ arrives and leaves for

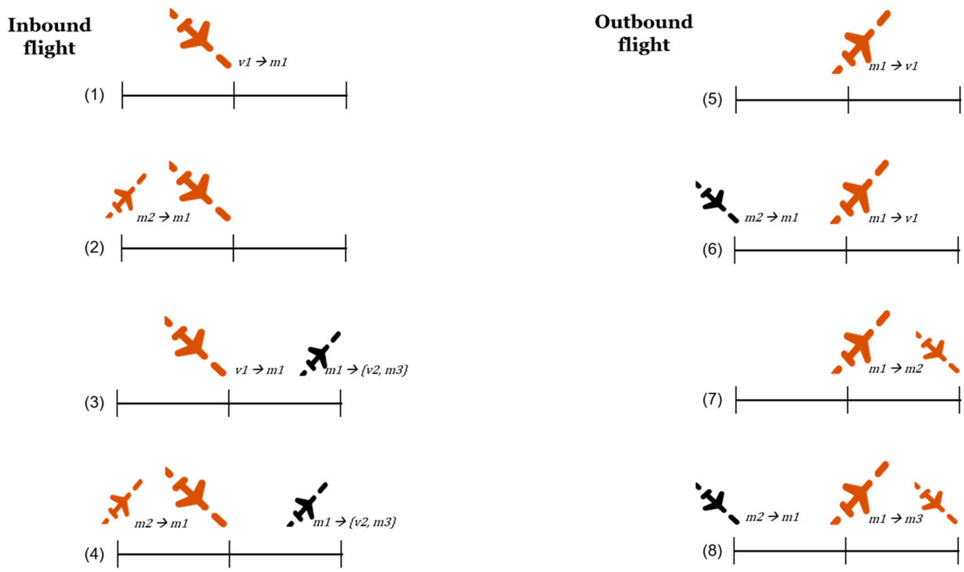

Figure 4. Eight cases for the multiple airports problem.

another airport on that day. Another airport could be a $m3$ which is under the GDP or a $v2$ which is not affected by the GDP; (4) aircraft departing at $m2$ arrives and leaves for another airport which could be under GDP or not. on that day. For outbound *flight j* in airport $m1$, there are four cases, as follows: (5) aircraft leaves for $v1$; (6) aircraft arriving from $m2$ leaves for $v1$; (7) aircraft leaves for $m2$; (8) aircraft arriving from $m2$ leaves for $m3$. Each case is depicted in Figure 4. When flights are represented in the same colour in Figure 4, they are recognized as one flight with the same flight code in reality. On the other hand, the flight, which is represented in black in Figure 4, is a different flight but the same aircraft used. Yet, we did not have to include case (5), because we assume departure capacity in the airport is infinite. Previous papers related to the GDP with delay propagation usually deal with cases (1) and (3).

When the GDP has been issued at the scheduled arrival airport of flights, it is assumed that there will usually be no disruption at the departure airport. Thus, there is no delay except ground delay by assigning a new timeslot for responding to the GDP. However, if multiple airports are rescheduled at the same time, departure airports as well as the arrival airports of flights can be considered. For example, in case (8), timeslots will be assigned for inbound *flight i* at airport $m3$ which is under the GDP. However, after arriving late of the preceding *flight i* because of the GDP in airport $m1$, it departs as *flight j* as late as the propagated delay time. Airport $m3$ has to allocate timeslot for *flight j* to reflect this delay in departure. This is illustrated in Figure 5.

If the actual arrival time is later than the pre-allocated timeslot, such as timeslot A, the existing plan is infeasible. Thus, it is necessary to readjust or cancel the flight at the time when the departure delay occurs. On the other hand, the flight could be assigned as conservatively as possible to timeslot B because the exact delay information has yet to be discovered. If the actual arrival time of the flight is much faster than the conservative pre-allocated timeslot B, airborne delay inevitably occurs. Either way, resulting costs are high for an airline. In the multiple airports model, timeslots are assigned in consideration of cases in which departing aircrafts already absorb delay and leave late.

Aircraft connections are classified in two categories. If the preceding *flight i* arrives and is connected to depart as succeeding *flight j* from the same airport, it is expressed as L1(*i,j*). If *flight j* departs and arrives as *flight n* at another airport in the airport set, it is expressed as L2(*j,n*). In other words, L1 is used for two different flights i and j at the same airport. L2 is used for one flight (using the same aircraft) of which both departure and arrival airports are in the airport set. In this case, because it is one

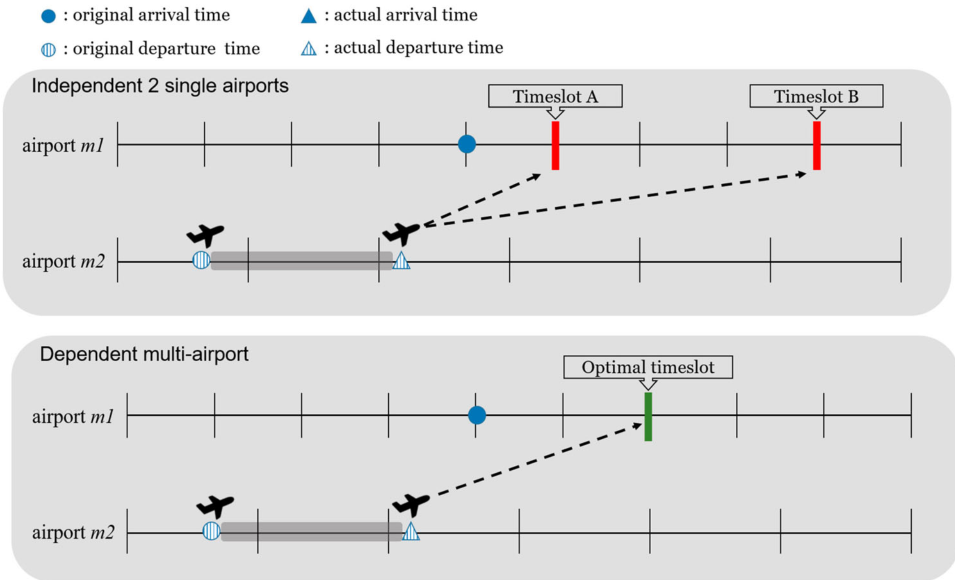

Figure 5. Timeslot assignment difference at arrival airport between single airport model and multiple airports model.

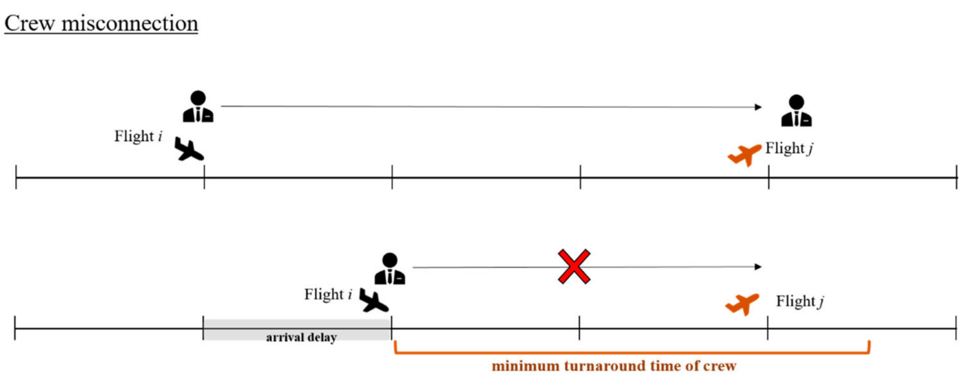

Figure 6. Example of crew misconnection with minimum turnaround time of crew.

journey, they have the same flight name, but different indexes were used here for the convenience of experiments. L2 was used to express the network of airports belonging to the airport set. If a crew is connected to depart for succeeding *flight j* from the same airport after getting off the preceding *flight i*, express it as $R(i,j)$. For L1, if *flight i* is cancelled *j* is also cancelled. In the case of L2(j,n), if one of the two is cancelled, the other is cancelled as well. Whether *flight i or j* is cancelled in $R(i,j)$, a crew fails to transfer. Each flight has a maximum allowed delay time. The violation of the buffer time, another time for safety, means that they failed to ensure specific time within the planned time interval. As a result, there will be an additional cost for urgent operations caused by original plan breakdowns, even if such plan breakdowns are not immediately propagated to departure delays of successive flights. Figures 6 and 7 describe the situation related to the minimum crew turnaround, aircraft turnaround time, and buffer time.

Assuming that the GDP has been issued, all inbound flights have to be assigned timeslots or cancelled. How much to delay is determined by which timeslot the flight will be assigned. As we mentioned in introduction, the model is verified by creating scenarios that may occur with base scenario,

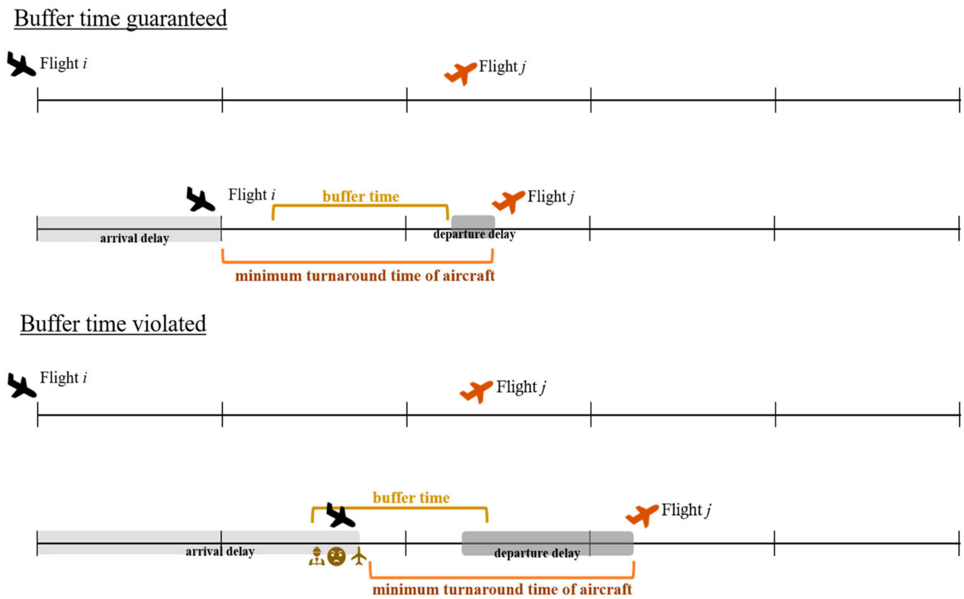

Figure 7. Examples of buffer time with minimum turnaround time of aircraft.

in which the GDP has been executed only once to reschedule flights with uncertainty. We assumed that the probability of each scenario occurring is uniform. That is, 1/(the number of scenarios). There are two ways to use scenarios. First, one may obtain the optimal value for each scenario in advance, proceed according to the base scenario, and when the scenario is actually realized, change the schedule again according to the solution obtained before. Second, one may obtain the value that optimizes the expected value of all scenarios. No matter what scenario is realized, it may be not the optimal for that scenario, but it can proceed without further changes.

3.2. Multiple airports scenario-based optimal rescheduling problem

The mathematical model is formulated as mixed-integer linear programming. Here are the notations used in model. First, we showed optimal version. We named this Multiple Airports Scenario-based Optimal Rescheduling (MSOR) Problem.

Sets

S	set of scenarios
M	set of airports
I	set of flights
I^a	set of inbound flights (I^a_m: subset of I^a whose arrival airport is m)
I^d	set of outbound fligts (I^{bo}_m: subset of I^a whose departure airport is m)
$k \in K_m$	set of timeslots of airport $m \in M$

Parameters

arr_i	scheduled arrival time of flight i
dep_j	scheduled departure time of flight$j$
$\delta^{aircraft}$	minimum turnaround time of aircraft to connecting flight
δ^{crew}	minimum turnaround time of crew to connecting flight
Δ	buffer time for preventing urgent situation of aircraft
fly_{ij}	flying time of flight between origin and destination

R_{ij}	1, if a crew is connecting between flight i and j; otherwise 0
$L1_{ij}$	1, if the same aircraft of arriving flight i is used for the departing flight j; otherwise 0
$L2_{jn}$	1, if the same aircraft of departing flight j arrives on a flight n at another airport; otherwise 0
t^k_{ms}	time of timeslot k when flights can arrive at airport m in scenario s
τ_{ms}	time when a subsequent GDP will be issued at airport m in scenario s
$\overline{d^a_i}$	maximum allowed arrival delay of flight i
$\overline{d^d_j}$	maximum allowed arrival delay
c^{delay}	flight delay cost
c^{cancel}	flight cancellation cost
c^{crew}	crew misconnection cost
c^{urgent}	urgent operation cost

Decision Variables

d^a_{is}	arrival delay time of flight i in scenario s
d^d_{js}	departure delay time of flight j in scenario s
x^k_{is}	1, if flight i is assigned to timeslot k in scenario s;otherwise 0
y_{ijs}	1, if crews of flight i connecting to flight j fail to transfer in scenario s;otherwise 0
u_{ijs}	1, if a buffer time between flight i and j is not guaranteed due to delay; otherwise 0
z^a_{is}	1, if inbound flight i is cancelled in scenario s
z^d_{js}	1, if outbound flight j is cancelled in scenario s
w^a_{is}	auxiliary continuous variable for arrival delay
w^d_{js}	auxiliary continuous variable for departure delay

The mathematical formulation of MSOR problem is as follows.

$$
\begin{aligned}
&min.\ E_{s\in S}[\Sigma_{m\in M}\{c^{delay}(\Sigma_{i\in I^a_m}(d^a_{is}-w^a_{is})+\Sigma_{j\in I^d_m}(d^d_{js}-w^d_{js}))+\Sigma_{i\in I^a_m,j\in I^d_m}(c^{crew}R_{ij}y_{ijs}+c^{urgent}L1_{ij}u_{ijs})\\
&\quad +c^{cancel}(\Sigma_{i\in I^a_m}z^a_{is}+\Sigma_{j\in I^d_m}z^d_{js})\}] \qquad (1)
\end{aligned}
$$

s.t.

$$x^k_{is}=0 \qquad \forall m\in M, s\in S, k\in K_m : t^k_{ms}\le arr_i \qquad (2)$$

$$\sum_{i\in I^a_m} x^k_{is}\le 1 \qquad \forall m\in M, s\in S, k\in K_m \qquad (3)$$

$$\left(\sum_{k\in K_m} x^k_{is}\right)+z^a_{is}=1 \qquad \forall m\in M, s\in S, i\in I^a_m \qquad (4)$$

$$d^a_{is}=\sum_{k\in K_m:arr_i\le t^k_{ms}}(t^k_{ms}-arr_i)x^k_{is} \qquad \forall m\in M, s\in S, i\in I^a_m \qquad (5)$$

$$d^d_{js}\ge arr_i+d^a_{is}+\delta^{plane}-dep_j \qquad \forall m\in M, s\in S, i\in I^a_m, j\in I^d_m : L1_{ij}=1 \qquad (6)$$

$$d^a_{ns}\ge dep_j+d^d_{js}+fly_{ij}-arr_n \qquad \forall m\in M, s\in S, n\in I^a\backslash I^a_m, j\in I^d_m : L2_{jn}=1 \qquad (7)$$

$$-\overline{d^a_i}u_{ijs}\le\{(dep_j-arr_i)-d^a_{is}\}-\Delta\le\overline{d^a_i}(1-u_{ijs}) \qquad \forall m\in M, s\in S, i\in I^a_m, j\in I^d_m : L1_{ij}=1 \qquad (8)$$

$$arr_i+d^a_{is}+\delta^{crew}\le dep_j+d^d_{js}+\overline{d^a_i}y_{ijs} \qquad \forall m\in M, s\in S, i\in I^a_m, j\in I^d_m :\ R_{ij}=1 \qquad (9)$$

$$w^a_{is}\le\overline{d^a_i}z^a_{is} \qquad \forall m\in M, s\in S, i\in I^a_m \qquad (10)$$

$$w_{is}^a \le d_{is}^a \qquad \forall m \in M, s \in S, i \in I_m^a \tag{11}$$

$$w_{js}^d \le \overline{d_j^d} z_{js}^d \qquad \forall m \in M, s \in S, j \in I_m^d \tag{12}$$

$$w_{js}^d \le d_{js}^d \qquad \forall m \in M, s \in S, j \in I_m^d \tag{13}$$

$$z_{is}^a \le y_{ijs}, z_{js}^d \le y_{ijs} \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : R_{ij} = 1 \tag{14}$$

$$z_{is}^a \le z_{js}^d \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : L1_{ij} = 1 \tag{15}$$

$$z_{js}^d = z_{ns}^a \qquad \forall m \in M, s \in S, j \in I_m^d, n \in I^a \backslash I_m^a : L2_{jn} = 1 \tag{16}$$

$$0 \le d_{is}^a \le \overline{d_i^a}, 0 \le d_{js}^d \le \overline{d_j^d} \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d \tag{17}$$

$$x_{is}^k, y_{ijs}, u_{ijs}, z_{is}^a, z_{js}^d \in \{0,1\} \qquad \forall m \in M, s \in S, i, j \in I \tag{18}$$

The objective function (1) is to minimize total relevant cost (TRC) of an airline. It uses the expectation of cost of all scenarios. However, as we use uniform distribution in occurrence of each scenario, to minimize expectation cost means to minimize cost of each scenario. It includes the total delay cost, the crew misconnection cost, the urgent operation cost and cancellation cost. As c^{delay} is cost per minute, total delay cost is proportional to the delay time. Other costs, on the other hand, are incurred at once, depending on the decision. In constraints (2), flights cannot be allocated to a timeslot at a time earlier than the original planned time. Constraints (3) allow up to one flight to be assigned to one timeslot. Constraints (4) state all inbound flights should be assigned to one timeslot or cancelled. Constraints (5) define arrival delay time as being a difference between the allocated timeslot and the original planned time. Constraints (6) ensure that subsequent *flight j* is delayed in departure so that it departs later than actual arrival time of the preceding *flight i* plus minimum turnaround time required for the same aircraft. In constraints (7), if the origin of inbound *flight n* is also in GDP airport set, *flight n* can be delayed so that it arrives later than an actual departure time plus flying time of the flight. Constraints (8) indicate the cost occurs because of the malfunction of the planned operation if the buffer time is not guaranteed due to the delay of the preceding flight. Constraints (9) imply that in case the gap between the actual arrival time and the actual departure time is less than the minimum turnaround time of the crew, the crew could fail to transfer. Constraints (10)–(13) make the delay time be zero when a flight is cancelled. Constraints (14) state crews fail to transfer even if only one of the crew's planned *flight i or j* is cancelled. Constraints (15) force a follow-up *flight j* which uses the same aircraft to be cancelled if a preceding *flight i* is cancelled. Constraints (16) require that as long as flights are connected as parameter L2, they are the same flight not only the same aircraft, so the cancellation must be the same. Constraints (17) restrict maximum allowed delay of each flight.

3.3. Multiple airports scenario-based stochastic rescheduling problem

We present stochastic version called Multiple Airports Scenario-based Stochastic Rescheduling (MSSR) problem. The stochastic version is designed to provide robust timeslot allocation that can be applied to all the created scenarios, in order to prepare for the uncertainty that the GDP will change again later. The strength of the MSSR over the MSOR is that if the GDP state changes once more, airlines can have no opportunity to change the plan again. The MSSR allows airlines to minimize losses in your initial plan in preparation for such a situation. The decision variables of the MSOR $x_{is}^k, z_{is}^a, z_{js}^d$ are changed to x_i^k, z_i^a, z_j^d which do not depend on the scenario. Everything else is the same as in the MSOR.

$$\begin{aligned} min.\ E_{s \in S}[\Sigma_{m \in M}\{c^{delay}(\Sigma_{i \in I_m^a}(d_{is}^a - w_{is}^a) + \Sigma_{j \in I_m^d}(d_{js}^d - w_{js}^d)) + \Sigma_{i \in I_m^a, j \in I_m^d}(c^{crew} R_{ij} y_{ijs} + c^{urgent} L1_{ij} u_{ijs}) \\ + c^{cancel}(\Sigma_{i \in I_m^a} z_i^a + \Sigma_{j \in I_m^d} z_j^d)\}] \end{aligned} \tag{19}$$

s.t.

$$x_i^k = 0 \qquad \forall m \in M, s \in S, k \in K_m : t_{ms}^k \leq arr_i \tag{20}$$

$$\sum_{i \in I_m^a} x_i^k \leq 1 \qquad \forall m \in M, s \in S, k \in K_m \tag{21}$$

$$\left(\sum_{k \in K_m} x_i^k \right) + z_i^a = 1 \qquad \forall m \in M, s \in S, i \in I_m^a \tag{22}$$

$$d_{is}^a = \sum_{k \in K_m : arr_i \leq t_{ms}^k} (t_{ms}^k - arr_i) x_i^k \qquad \forall m \in M, s \in S, i \in I_m^a \tag{23}$$

$$d_{js}^d \geq arr_i + d_{is}^a + \delta^{plane} - dep_j \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : L1_{ij} = 1 \tag{24}$$

$$d_{ns}^a \geq dep_j + d_{js}^d + fly_{ij} - arr_n \qquad \forall m \in M, s \in S, n \in I^a \backslash I_m^a, j \in I_m^d : L2_{jn} = 1 \tag{25}$$

$$-\overline{d_i^a} u_{ijs} \leq \{(dep_j - arr_i) - d_{is}^a\} - \Delta \leq \overline{d_i^a}(1 - u_{ijs}) \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : L1_{ij} = 1 \tag{26}$$

$$arr_i + d_{is}^a + \delta^{crew} \leq dep_j + d_{js}^d + \overline{d_i^a} y_{ijs} \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : R_{ij} = 1 \tag{27}$$

$$w_{is}^a \leq \overline{d_i^a} z_i^a \qquad \forall m \in M, s \in S, i \in I_m^a \tag{28}$$

$$w_{is}^a \leq d_{is}^a \qquad \forall m \in M, s \in S, i \in I_m^a \tag{29}$$

$$w_{js}^d \leq \overline{d_j^d} z_j^d \qquad \forall m \in M, s \in S, j \in I_m^d \tag{30}$$

$$w_{js}^d \leq d_{js}^d \qquad \forall m \in M, s \in S, j \in I_m^d \tag{31}$$

$$z_i^a \leq y_{ijs}, z_j^d \leq y_{ijs} \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : R_{ij} = 1 \tag{32}$$

$$z_i^a \leq z_j^d \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d : L1_{ij} = 1 \tag{33}$$

$$z_j^d = z_n^a \qquad \forall m \in M, s \in S, j \in I_m^d, n \in I^a \backslash I_m^a : L2_{jn} = 1 \tag{34}$$

$$0 \leq d_{is}^a \leq \overline{d_i^a}, 0 \leq d_{js}^d \leq \overline{d_j^d} \qquad \forall m \in M, s \in S, i \in I_m^a, j \in I_m^d \tag{35}$$

$$x_i^k, y_{ijs}, u_{ijs}, z_i^a, z_j^d \in \{0, 1\} \qquad \forall m \in M, s \in S, i, j \in I \tag{36}$$

4. Computational experiments

4.1. Settings

To prove this study, various experiments were conducted. The results of the experiment and its analysis are also discussed in this section. Experiments were performed with real world data from four airports in South Korea – Gimpo(GMP), Gimhae/Busan(PUS), Jeju(CJU) and Incheon(ICN) – which have had the highest traffic volume recently. Narita airport(NRT) in Japan also was considered. The data were from Korea Airportal (https://www.airportal.go.kr). The basic set of experiments uses three domestic airport data (GMP, PUS, and CJU). International airports (ICN and NRT) were used to more clearly confirm the continuous propagation of delays, which was not considered in the single airport model. The experiment with ICN and NRT is covered in Experiment 1. We explained this data in detail in Section 4.2. There are 234 flights in a day in the basic setup. Based on arrival data of each airport and departure data of each airport, we set the situation in which the GDP has been issued at the start point of the day. Since curfew time exists directly or indirectly at domestic airports, the schedule horizon is set from 7:00 (0 min.) to 23:00 (960 min.). The timeslot gets invalidated if the time of timeslot exceeds 23:00 due to decreased AAR. With the situation mentioned as base scenario, we create scenarios with two factors (Woo and Moon 2021) – GDP reissuance time and changed AAR – in a situation where the GDP occurs

Table 1. Parameters.

$\delta^{aircraft}$	δ^{crew}	Δ	c^{delay}	c^{cancel}	c^{crew}	c^{urgent}
40 min.	30 min.	30 min.	\$6/min.	\$350	\$50	\$50

first and rescheduling is required. Scenarios include the case in which traffic conditions get worse (and therefore AAR decreases more), the case in which traffic conditions get better (and AAR recovers to their original capacity), and the case in which no change occurs. We had four experiments. First, we compared the single airport model considering delay propagation once (arrival delay to departure delay) with our study. The single airport MILP was proposed by Woo and Moon (2021). Second, we checked solutions of the MSOR and the MSSR to see how much the stochastic version can replace the optimal version. Next, the MSOR was then contrasted with RBS method.

Last, we analysed sensitivity of costs. The decision to delay or cancel is bound to be sensitive to each cost. We checked solutions of various delay cost and cancellation cost. Also, experiments were conducted on how to set the standard of buffer time. The larger the buffer time that should be guaranteed, the smaller the urgent cost that occurs when it is violated, and vice versa.

The parameters used are illustrated in Table 1 below. They are referred to the values of previous studies (Brunner 2014; Woo and Moon 2021). All computations were carried out with CPLEX solver version 20.8 licensed by IBM ILOG. We used default setting in CPLEX solver and problems were coded in Python language.

4.2. Experiment 1

The scenario-based rescheduling of an airline in a single airport model was formulated by Woo and Moon (2021). They considered one delay propagation and assumed only one airport under the GDP. The multiple airports model in this experiment means only the MSOR. For comparison, the single airport model was slightly modified, including the urgent operation cost, and termed Single airport Scenario-based Optimal Rescheduling (SSOR). The details were presented in Appendix A. The experiment used 32 scenarios with basic data set: base scenario and scenario that AAR reverting back to original. Other scenarios include severe disruptions of airports where AAR changes to 0.9, 0.75, 0.6, 0.45, 0.3, and 0.15% of original rate at 840 min; where AAR changes to 0.9, 0.75, 0.6, 0.45, 0.3, and 0.15% of original rate at 600 min; and where AAR changes to the above rate at 480, 360, and 120 min respectively. The timeslots for each scenario are attached to Appendix B. The SSOR was performed for each of the three airports independently. Therefore, to compare with the MSOR, three values of the SSOR were added. The SSOR does not include delays caused by other airports, so the total delay time and cost are lower than they are with the MSOR. However, infeasibility was confirmed when solution of a single airport was substituted into MSOR. We checked solutions of two models to see the reason why the infeasibility occurred. One of the actual assignments of experiment that caused the infeasibility is shown in Figure 8. Here is the L1-L2 connection where the flight name KE1280 arriving at airport GMP departs again as KE1291 and arrives at airport CJU. Both airports need to reschedule flights because the timeslot has been changed. In that case, the MSOR assigned KE1291 in airport CJU to the timeslot, considering the delayed departure time and flying time. On the other hand, the flight could not arrive until the timeslot that the SSOR had assigned flight KE1291. Among the cases expressed in Figure 4, the SSOR often assigned an infeasible timeslot for the case (8). With this point, we charged a penalty fee if a sum of actual departure time that was modified due to delay propagation from predecessor and flying time exceeded the time of allocated timeslot at the destination when both departure and arrival airports were in an airport set. We set this penalty fee \$500 arbitrarily. Results are expressed in Table 2. Table 2 shows that then TRC of the SSOR with penalty fee got bigger than the TRC of MSOR in most of the scenarios. However, in severely delayed scenarios, the cost of MSOR was still higher. We could state that if the origin airport decided to cancel without a timeslot allocation, the destination airport reflected this decision immediately both in the SSOR and the MSOR. However, in fact, in the SSOR

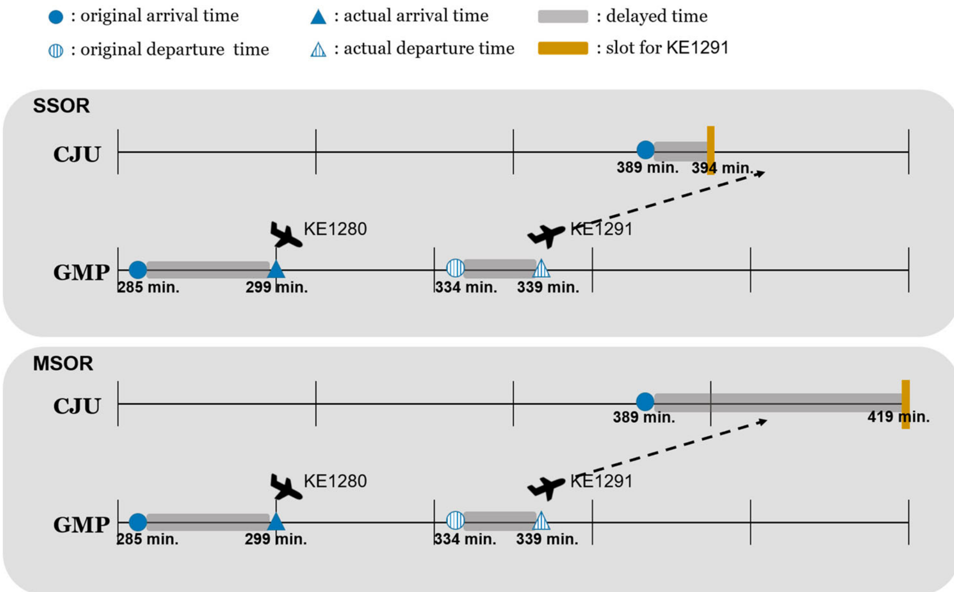

Figure 8. Example of different timeslot assignments between SSOR and MSOR in CJU and GMP.

model, each airport does not know each other's information, so it is not possible to plan by reflecting this cancellation immediately. Therefore, there will be additional penalties in this respect.

To ensure a more comprehensive assessment of this insight, the same experiment was conducted using data from international airports – ICN and NRT. There are 456 flights in total. The difference from the previous data is that domestic airports have fixed operating hours and curfew times, so an effect of the GDP cannot exceed a day. Therefore, the delay propagation of up to two flight segments was identified within a day. In the case of international airports, the rescheduling time window due to the GDP could be expanded to two days because of 24-hour operation, and three segments could be created. Parameters $\delta^{aircraft}$, δ^{crew}, and Δ have increased to 60, 50, and 45 min, respectively. As the total time horizon is from 00:00 to 24:00 of following day, new 26 scenarios were created for 2880 min of time window. Furthermore, to demonstrate that the difference in improperly allocated time is not negligible, a penalty fee system has been implemented, where a fee of $5 USD per minute is imposed to the difference between the minimum time for feasibility and the improperly allocated time, instead of a one-time occurrence. The results are presented in Table 3. We could confirm the similar tendency with Table 2.

4.3. Experiment 2

The solutions of MSOR and MSSR were compared. In comparison, as the MSOR obtained total relevant cost of each scenario, we calculated the expected value with each value. On the contrary, because the objective function is defined as the expected value of all scenarios in MSSR, we calculated the cost for each scenario with a solution. First, we experimented by increasing the number of scenarios to check the difference between MSOR and MSSR. Because the cost itself depends on generated scenarios, gaps of TRC and computation times are calculated between the two models. As Table 4 displays, TRC always had a smaller value in the MSOR than the MSSR. This is natural, because MSOR is a solution of optimization for each scenario. The gaps of TRC and computation times do not increase or decrease monotonically because the AAR of scenarios does not consistently decrease or increase gradually. In computation times, the MSSR was mostly smaller, but there were cases where it was not.

Table 2. TRC($) of MSOR, SSOR, TRC+penalty fee($) of SSOR and its gap with MSOR in GMP, PUS and CJU.

Scenario	MSOR($)	SSOR($)	SSOR+penalty($)	Gap of TRC(∗100%)
s0(base)	470,375	470,375	481,775	2.42%
s1	479,372	479,372	491,772	2.59%
s2	482,371	482,371	494,771	2.57%
s3	494,368	494,368	506,768	2.51%
s4	514,362	514,362	526,762	2.41%
s5	554,350	554,350	565,150	1.95%
s6	703,611	703,611	715,411	1.68%
s7	512,954	512,954	524,354	2.22%
s8	528,585	528,585	539,985	2.16%
s9	591,111	591,111	601,911	1.83%
s10	695,320	695,320	706,120	1.55%
s11	896,953	896,953	904,753	0.87%
s12	1,418,088	1,418,088	1,427,688	0.68%
s13	529,669	529,669	541,069	2.15%
s14	551,015	551,015	561,815	1.96%
s15	636,401	636,401	647,201	1.70%
s16	778,710	778,710	789,510	1.39%
s17	1,056,541	1,056,541	1,063,141	0.62%
s18	1,751,428	1,751,428	1,759,228	0.45%
s19	545,247	545,247	556,647	2.09%
s20	571,786	571,786	583,186	1.99%
s21	677,941	677,941	688,741	1.59%
s22	854,868	854,868	865,668	1.26%
s23	1,201,934	1,201,934	1,208,534	0.55%
s24	2,165,531	2,121,593	2,129,393	−1.67%
s25	578,458	578,458	589,858	1.97%
s26	616,192	616,192	626,992	1.75%
s27	767,181	767,181	777,981	1.41%
s28	1,018,745	1,018,745	1,029,545	1.06%
s29	1,525,012	1,525,012	1,528,612	0.24%
s30	2,744,890	2,700,952	2,710,552	−1.25%
s31	223,464	223,464	239,664	7.25%

4.4. Experiment 3

Next, the performance of proposed models was verified by comparing them with RBS. The RBS method maintains the same sequence as previously planned, so if the overall number of timeslots decreases, the planned flights at the end should be cancelled. It is known that the RBS is the optimal method minimizing total arrival delay time for all flights, regardless of airlines in an airport (Ball, Hoffman, and Mukherjee 2010).

Scenarios used in the experiment is the same as in Experiment 1. Table 5 shows TRC, the number of cancelled flights, the number of buffer time violations which evoked urgent operation, and the number of crew misconnections for each scenario in the MSOR and the RBS. The TRC expectation for all scenarios was calculated as well. The TRC expectation over all scenarios is smaller in the MSOR. In the case of scenarios where the timeslot is not much delayed, the cost difference between MSOR and RBS did not occur, because the optimization assigned timeslots in the same way as the RBS did. However, the cost difference got larger in scenarios with severe delay because the MSOR tried to ensure the situation of connected flights and minimize urgent operations. The RBS did not cancel unless the timeslot was invalidated, but the MSOR arbitrarily cancelled if the cost of delay could be greater than the cost of cancellation. Therefore, the TRC of the presented model was lower than the TRC of the RBS, which was aim of experiment.

4.5. Experiment 4

The decision to delay or cancel flight is cost sensitive. We compared the costs when choosing to assign timeslot (pure delay cost, urgent operation cost, and crew misconnection cost) and the costs

Table 3. TRC($) of MSOR, SSOR, TRC+penalty fee($) of SSOR and its gap with MSOR in ICN and NRT.

Scenario	MSOR($)	SSOR($)	SSOR+penalty($)	Gap of TRC(∗100%)
s0(base)	1,877,198	1,762,148	2,136,012	12.12%
s1	1,965,881	1,850,831	2,224,689	11.63%
s2	2,076,735	1,961,685	2,335,535	11.08%
s3	2,219,261	2,104,211	2,478,077	10.44%
s4	2,682,661	2,567,611	2,941,455	8.80%
s5	3,089,314	2,974,264	3,348,114	7.73%
s6	1,973,246	1,858,196	2,232,051	11.59%
s7	2,093,305	1,978,255	2,352,101	11.00%
s8	2,247,667	2,132,617	2,506,450	10.32%
s9	2,748,941	2,633,891	3,007,715	8.60%
s10	3,188,733	3,073,683	3,447,505	7.50%
s11	1,978,355	1,863,305	2,237,157	11.57%
s12	2,104,802	1,989,752	2,363,589	10.95%
s13	2,267,375	2,152,325	2,526,169	10.24%
s14	2,798,585	2,683,535	3,057,342	8.46%
s15	3,265,160	3,150,110	3,523,914	7.34%
s16	1,985,844	1,870,794	2,244,642	11.53%
s17	2,121,651	2,006,601	2,380,430	10.87%
s18	2,296,260	2,181,210	2,555,039	10.13%
s19	2,865,981	2,750,931	3,124,706	8.28%
s20	3,366,255	3,251,205	3,624,985	7.14%
s21	1,990,126	1,875,076	2,248,924	11.51%
s22	2,131,285	2,016,235	2,390,065	10.83%
s23	2,312,776	2,197,726	2,571,531	10.06%
s24	2,904,520	2,789,470	3,163,245	8.18%
s25	3,424,063	3,309,013	3,682,768	7.02%
s26	1,378,612	1,263,562	1,637,510	15.81%

Table 4. TRC($) and computation times(sec.) by the number of scenarios for MSOR and MSSR.

Number of scenarios	Opt. TRC($)	Sto. TRC($)	Gap of TRC(∗100%)	Opt. times(sec.)	Sto. Times(sec.)	Gap of times(∗100%)
3	375,308	376,074	0.204	55.5	55.97	0.847
6	401,922	402,361	0.109	151.3	111.52	−26.292
11	445,325	446,117	0.178	211.75	217.72	2.819
18	496,628	497,633	0.202	357.46	347.6	−2.758
22	441,989	442,654	0.150	425.15	408.98	−3.803
27	495,551	496,655	0.223	543.07	518.69	−4.489
32	457,173	457,904	0.160	600.67	598.46	−0.368
38	510,249	511,274	0.201	742.35	736.67	−0.765
44	496,864	497,835	0.195	835.65	869.5	4.051
51	511,137	512,183	0.205	1019.05	1004.894125	−1.389
58	497,770	498,693	0.186	1091.91	1094.16	0.206
65	515,236	516,324	0.211	1265.27	1251.76	−1.068

when choosing to cancel (cancellation cost, crew misconnection cost) to check how the solution differs. For scenario 30, where the GDP occurs once more and the AAR decreases the most, the total delay time of the MSOR and the number of cancelled flights with various c^{delay} and c^{cancel} are shown in Figures 9 and 10. Cancellation does not occur when c^{delay} is 3, but when c^{delay} becomes 5, delay cost increases rapidly, so cancellation of flights starts to occur, and instead the total delay time decreases.

To examine the cancellation of flights in detail, the solutions of the MSOR and the MSSR when scenario 30 occurred in '$c^{delay} = 7$' are shown in Figure 11. The first three columns of Figure 11 refer to the flight name and succeeding flight name of L1 connection and crew connection, if they exist. Next, TS means the timeslot number assigned for the flight and DT means delay time in minutes for each model. 1, 2, 3, 4 means when c^{cancel} is 120, 160, 200, and 400 in order. The solution of MSSR should be used in all scenarios, so it was very defensive about cancelling flights. This is because in the current

Table 5. TRC($), the number of cancelled flights, buffer time violations, and crew misconnections for each scenario.

Scenario	Opt. TRC	RBS TRC	Gap of TRC(∗100%)	Opt. cancel	RBS cancel	Opt. urgent	RBS urgent	Opt. crew	RBS crew
s0(base)	449,249	449,249	0.000%	0	0	1	1	0	0
s1	453,248	453,248	0.000%	0	0	1	1	0	0
s2	461,246	461,246	0.000%	0	0	1	1	0	0
s3	473,242	473,242	0.000%	0	0	1	1	0	0
s4	493,237	493,237	0.000%	0	0	1	1	0	0
s5	533,225	533,225	0.000%	0	0	1	1	0	0
s6	682,485	682,485	0.000%	2	2	1	1	0	0
s7	468,710	468,710	0.000%	0	0	1	1	0	0
s8	507,632	508,351	0.142%	0	0	1	2	0	0
s9	566,015	567,778	0.312%	0	0	1	2	0	0
s10	663,319	666,824	0.528%	0	0	1	2	0	0
s11	864,704	868,214	0.406%	0	0	3	3	0	0
s12	1,379,819	1,447,220	4.885%	5	2	3	6	1	1
s13	475,988	475,988	0.000%	0	0	1	1	0	0
s14	529,465	530,183	0.136%	0	0	1	2	0	0
s15	609,680	611,443	0.289%	0	0	1	2	0	0
s16	743,373	746,877	0.471%	0	0	1	2	0	0
s17	1,017,533	1,021,043	0.345%	0	0	3	3	0	0
s18	1,706,139	1,831,949	7.374%	7	2	4	8	2	1
s19	482,911	482,911	0.000%	0	0	1	1	0	0
s20	550,235	550,954	0.131%	0	0	1	2	0	0
s21	651,221	652,984	0.271%	0	0	1	2	0	0
s22	819,531	823,035	0.428%	0	0	1	2	0	0
s23	1,162,925	1,166,435	0.302%	0	0	3	3	0	0
s24	2,059,235	2,185,045	6.110%	7	2	4	8	2	1
s25	496,614	496,614	0.000%	0	0	1	1	0	0
s26	591,343	592,062	0.122%	0	0	1	2	0	0
s27	736,108	737,871	0.240%	0	0	2	3	0	0
s28	977,315	980,819	0.359%	0	0	2	3	0	0
s29	1,466,504	1,470,014	0.239%	0	0	4	4	0	0
s30	2,681,995	2,976,875	10.995%	13	2	6	17	2	3
s31	212,063	212,063	0.000%	0	0	0	0	0	0
Expected TRC	811447.13	829259.19	2.195%						

scenario, the cancellation cost may be cheaper due to the large delay time, but in other scenarios, it may be unnecessarily cancelled. Therefore, regardless of how much c^{cancel} is, timeslots are allocated in the order originally planned, and delays appear continuously for more than 35 min. On the other hand, in the MSOR, when c^{cancel} is the lowest, flights that would have had a delay time more than 30 min were cancelled if there is no L1 or crew-connected flight. Especially, it tends to cancel flights that do not have connecting flights themselves but that instead following flight has connections. As c^{cancel} increased, flights that had cancelled in low cost were reassigned to timeslots so that the delay time among flights was distributed evenly without being biased.

This time, we experimented on how to set the standard of buffer time. The fact that the buffer time is large means that safety takes priority. Thus, even if the buffer time is violated, the additional operation may not be huge. Accordingly, c^{urgent} is relatively small. On the contrary, if the buffer time is small, the c^{urgent} to be spent when the buffer time is not guaranteed will increase. Thus, we created pairs of (buffer time, c^{urgent}) that have inverse relationships. Also, to check if the costs affect the corresponding buffer time, computations were performed with a total of 16 pairs: (0,80), (0,160), (20,70), (20,140) (25,60), (25,120), (30,50), (30,100), (35,40), (35,80). (35,35), (35,70), (40,20), (40,40), (40,25), (40,55). Including Base scenario, in scenario 8, where the GDP changes to 80% of the AAR after 600 min from the start point, scenario 16 (80% of AAR after 360 min), scenario 24 (45% of AAR after 120 min) and scenario 26 where AAR is restored to original as the GDP is withdrawn, the number of buffer time violations occurring is shown in Figure 12. The TRC of each scenario is expressed in Figure 13.

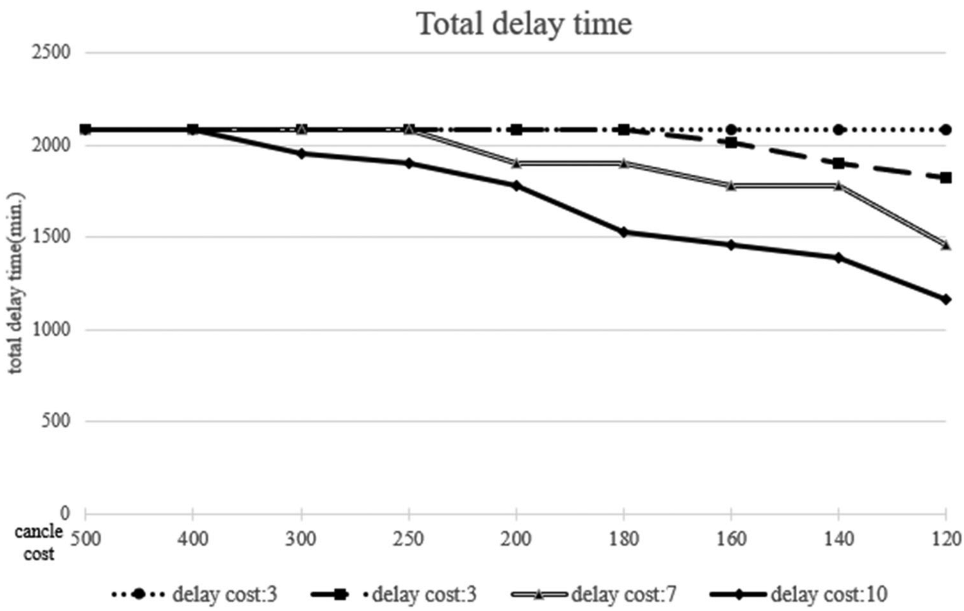

Figure 9. Total delay time(min.) by delay cost per cancel cost.

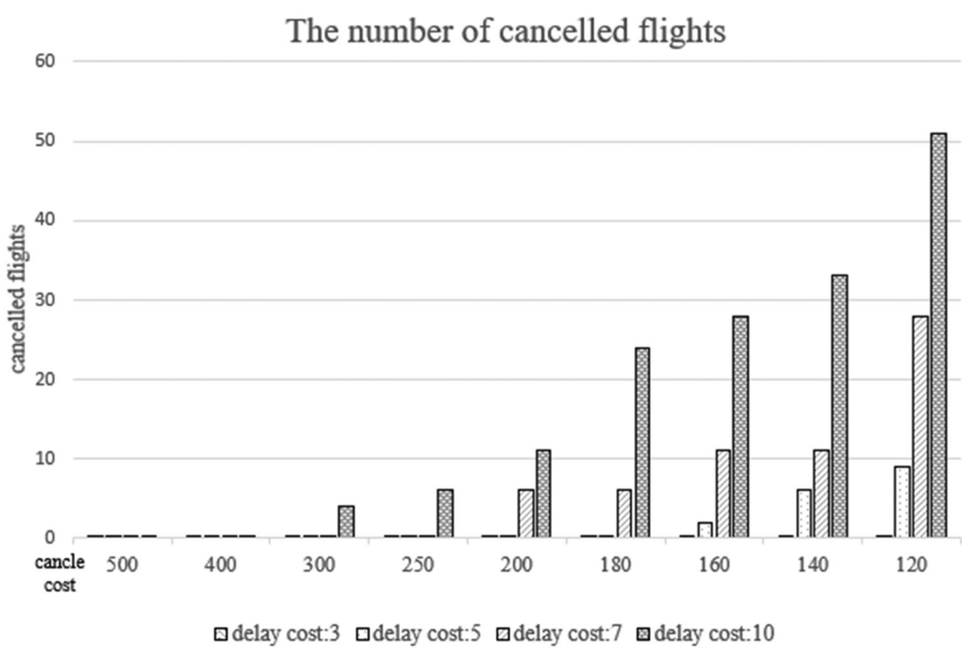

Figure 10. The number of cancelled flights by delay cost per cancel cost.

The more the AAR decreased, the higher the number of buffer time violations and the higher the TRC. However, given that the number of violations remained constant even if c^{urgent} increased at the same buffer time, it could be explained that the decision is made by reflecting other connections more closely rather than by making a decision to change timeslots in order to keep the buffer time.

Flight	L1 connection	Crew connection	MSOR TS	MSSR TS	MSOR DT	MSSR DT	MSOR TS2	MSSR TS2	MSOR DT2	MSSR DT2	MSOR TS3	MSSR TS3	MSOR DT3	MSSR DT3	MSOR TS4	MSSR TS4	MSOR DT4	MSSR DT4
KE1106			x	9	0	14.88	x	9	0	14.83	9	9	14.88	14.88	9	9	14.88	14.88
KE1220			11	10	19.33	14.88	11	10	19.38	14.83	11	10	19.88	14.88	11	10	19.88	14.88
KE1224	KE1235		10	11	9.88	14.88	10	11	9.88	14.83	10	11	9.88	14.88	10	11	9.88	14.88
KE1226			12	12	14.33	14.88	12	12	14.38	14.83	12	12	14.88	14.88	12	12	14.88	14.88
KE1228			13	13	14.33	14.88	13	13	14.38	14.83	13	13	14.88	14.88	13	13	14.88	14.88
KE1108	KE1115	KE1115	14	14	14.33	14.88	14	14	14.38	14.83	14	14	14.88	14.88	14	14	14.88	14.88
KE1230			15	15	14.33	14.88	15	15	14.38	14.83	15	15	14.88	14.88	16	15	24.88	14.88
...			...				...				...				...			
KE1101			49	49	11.24	11.24	49	49	11.24	11.24	49	49	11.24	11.24	49	49	11.24	11.24
KE1103	KE1106	KE1106	x	50	0	37.47	x	50	0	37.47	50	50	37.47	37.47	50	50	37.47	37.47
KE1002			50	51	2.47	37.47	50	51	2.47	37.47	x	51	0	37.47	51	51	37.47	37.47
KE1105			51	52	17.47	37.47	51	52	17.47	37.47	51	52	17.47	37.47	52	52	37.47	37.47
KE1107			x	53	0	37.47	53	53	37.47	37.47	53	53	37.47	37.47	53	53	37.47	37.47
KE1012	KE1015	KE1015	54	54	37.47	37.47	54	54	37.47	37.47	54	54	37.47	37.47	54	54	37.47	37.47
KE1014			x	55	0	37.47	x	55	0	37.47	x	55	0	37.47	55	55	37.47	37.47
KE1111		KE1116	55	56	12.47	37.47	55	56	12.47	37.47	55	56	12.47	37.47	56	56	37.47	37.47
KE1115			x	57	0	37.47	57	57	37.47	37.47	57	57	37.47	37.47	57	57	37.47	37.47
KE1020	KE1120	KE1120	58	58	37.47	37.47	58	58	37.47	37.47	58	58	37.47	37.47	58	58	37.47	37.47
KE1119			x	59	0	37.47	59	59	37.47	37.47	59	59	37.47	37.47	59	59	37.47	37.47
KE1121			x	60	0	37.47	x	60	0	37.47	60	60	37.47	37.47	60	60	37.47	37.47
KE1026			60	61	27.47	37.47	60	61	27.47	37.47	61	61	37.47	37.47	61	61	37.47	37.47
KE1028			x	62	0	37.47	62	62	37.47	37.47	62	62	37.47	37.47	62	62	37.47	37.47
KE1032	KE1031	KE1031	63	63	37.47	37.47	63	63	37.47	37.47	63	63	37.47	37.47	63	63	37.47	37.47
KE1125			x	64	0	37.47	64	64	37.47	37.47	64	64	37.47	37.47	64	64	37.47	37.47
KE1036			x	65	0	37.47	65	65	37.47	37.47	65	65	37.47	37.47	65	65	37.47	37.47
KE1201	KE1208	KE1208	66	66	4.39	4.39	66	66	4.39	4.39	66	66	4.39	4.39	66	66	4.39	4.39
KE1001	KE1002	KE1002	67	67	4.39	4.39	67	67	4.39	4.39	67	67	4.39	4.39	67	67	4.39	4.39
...			...				...				...				...			
KE1255			107	105	29.63	14.63	107	105	29.63	14.63	107	105	29.63	14.63	107	105	29.63	14.63
KE1297			105	106	4.63	14.63	105	106	4.63	14.63	105	106	4.63	14.63	105	106	4.63	14.63
KE1907			106	107	9.63	14.63	106	107	9.63	14.63	106	107	9.63	14.63	106	107	9.63	14.63
KE1957			x	108	0	14.63	x	108	0	14.63	109	108	24.63	14.63	109	108	24.63	14.63
KE1259	KE1272	KE1272	108	109	4.63	14.63	108	109	4.63	14.63	108	109	4.63	14.63	108	109	4.63	14.63
KE1263			110	110	14.63	14.63	110	110	14.63	14.63	110	110	14.63	14.63	110	110	14.63	14.63

Figure 11. Solutions and delay time(min.) of MSOR and MSSR for cancel cost = 120$, 160$, 200$, 400$ when delay cost = 7$.

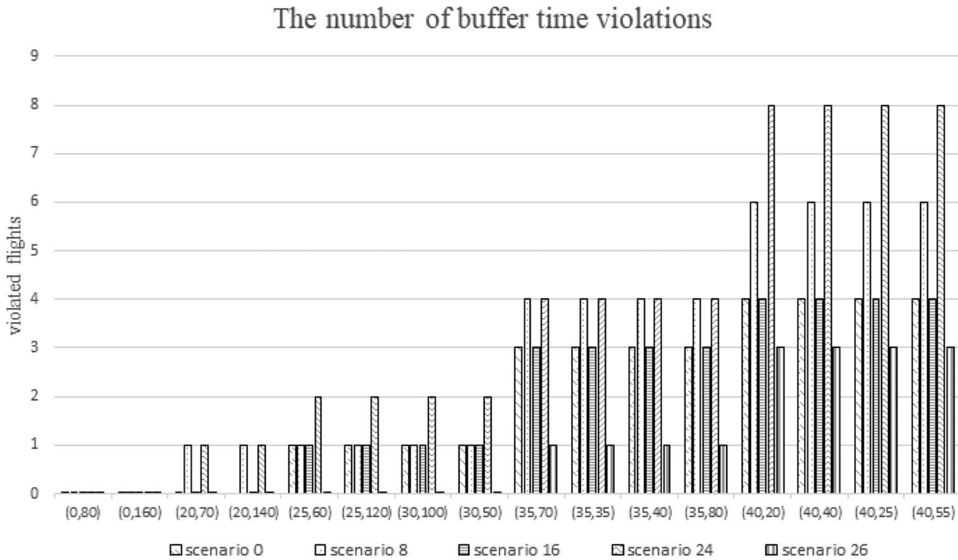

Figure 12. The number of buffer time violations by scenario per(buffer time, urgent cost).

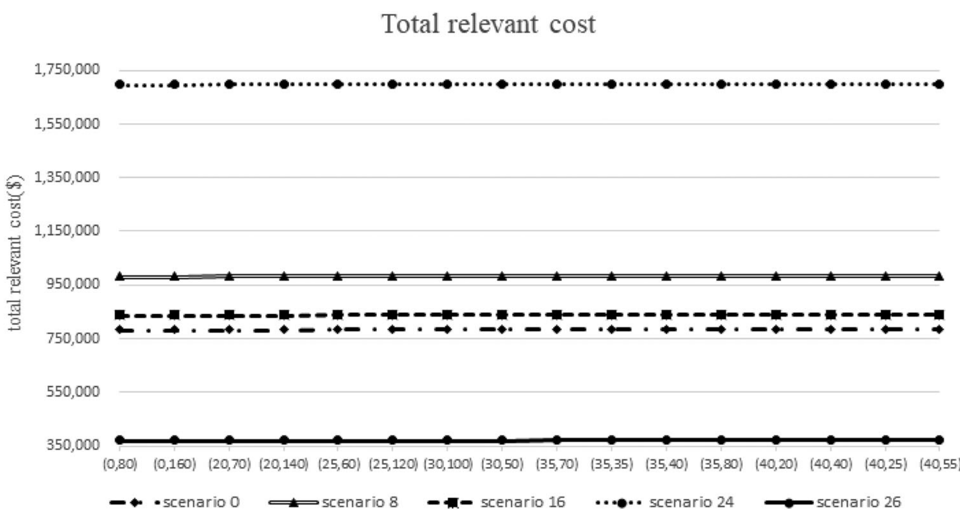

Figure 13. TRC($) by scenario per (buffer time, urgent cost).

4.6. Managerial insights

We have presented MILP models on how airlines can minimize losses, complying with the decreased AAR. The AAR decreased when the GDP, one of the airport disruption control methods, has already been implemented by central authority. Through experiment 1, we showed that the MSOR can reduce infeasibility which the SSOR have as the new assigned timeslot does not match the timeslot of the other airport which the subsequent flights are connected to. It is expected that this effect will increase as more airports are included in the airport set including international flights. Moreover, the model was compared with the RBS method. The RBS is a simple but powerful method for minimizing total delay time. For that reason, the RBS is good to use if someone is trying to increase the efficiency of the entire airport. In spite of that, because it is a rescheduling problem to help airlines operate, we set the airline driven objective function. The MSOR outperformed the RBS in terms of the cost and made the decision in consideration of the connection of flights. Also, we tried to show how the concept of buffer time can be used. In the cost analysis, as mentioned in Section 4.5, the buffer time and urgent cost seem to disaffect decision making. The result may be different if the cost of violation is very high, but the buffer time itself was not an essential time but rather a means to give stability to the operation. Thereby, we did not proceed further with different costs because it was not the intention of the concept of buffer time. A mathematical formulation using stochastic programming for robustness was also suggested. Considering that computation times of the MSOR is not that long, it may be sufficient to have scenario-based optimal MILP model. Given the specificity of aviation, the scenarios that can actually occur will not be endless. Therefore, it would be better to use the MSOR, because we can get all the solutions in advance within a reasonable computing time and change the plan with solutions of those scenario when the situation keeps varying. However, even if airlines have a dynamic model, they may have only one chance to reschedule, because it is difficult to change decisions again as airports are shared by not only one airline but many airlines. We showed through computational experiments that he cost gap between the MSOR and the MSSR does not exceed 1%. Therefore, using the MSSR is an enough alternative.

5. Conclusions

Through various experiments, we proved the advantages of expanding to multiple airports, setting an airline-driven objective function. Also, the usefulness of the stochastic version and the optimal version was calculated. There are three expected effects in this study. The first is as follows. These days, the aviation industry has more short-distance and round-trip operations due to imporved accessibility of aviation. Thus, one aircraft could be used on more than two flights in a unit schedule time in many airlines. Although there have been studies showing that delays in arriving flights will propagate as delays in departing flights, no studies have considered that when the flight which departed late because of delay propagated from predecessor flight arrives at its destination again, timeslot in arrival airport should be reassigned either. If each decision is made independently without knowing the delay of other airports, there may be situations in which inappropriate timeslots are assigned and therefore flights can be inevitably delayed in the air, or rescheduled because of infeasibility. The multiple airports model allowed timeslots to be allocated while guaranteeing feasibility. As the GDP continues to exert a persistent impact, the rescheduling time and airport set are expected to increase, resulting in the propagation of delays is unlikely to be limited to one or two occurrences. To investigate this problem, we showed these models could be utilized by doubling the time window, which yielded consistent results. Secondly, we further considered the realistic costs associated with the resources used by airlines for rescheduling. The transfer of aircraft and crews was addressed, and other operational losses that may occur in the event of delays were reflected in the concept of buffer time and urgent operation. Finally, in a situation in which the GDP occurs, possible scenarios are created, and decisions for each scenario can be derived within a reasonable time. Given that it took about 20 min for more than 60 scenarios to be calculated, we expect airlines to be able to use the model in the operational stage. What is more, the stochastic version will be available in situations where it will be practically difficult to change the timeslot order again later in the situation where it is not yet known which scenario will be realized.

Some studies focused on how much and when the GDP should be issued to reduce AAR, but they are excluded because they are not within the scope of this study, and it is assumed that the probability of scenario occurrence follows uniform distribution. The probability may change depending on the information that is realized over time, so decisions could be made more dynamically. For international flights, which are long-haul flights, and for international airports which that do not have a curfew time, we could simply change the scheduling unit to a longer unit rather than a day. The number of connections and delay propagation can be expanded more than three times with these models. Related experiments, including international airports, will be needed.

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