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An Optimization Model for Flight Rescheduling from an Airport's Centralized Perspective for Better Management of Demand and Capacity Utilization

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Abstract: Over-capacity flight scheduling by commercial airlines due to the surging demand in recent years creates congestion and significant delays at major airports. This attitude towards maximizing throughput calls for tactical flight rescheduling to comply with airports' capacity limitations and distribute the peak hour demand over the course of a day. Such displacements of flights may cause significant problems and costs for airlines and some cancellations or missed connections for passengers. This paper presents an optimization model for flight rescheduling at a schedule-coordinated airport to minimize congestion and flight delays at peak hours. The optimization model is used to make better scheduling intervention decisions considering airport resource constraints and safety of operation. A simulation algorithm is also developed to replicate arrival and departure processes in such an airport. The simulation adheres to a first come first served (FCFS) discipline and enforces runway capacity constraints and minimum turnaround times. We compare the delays caused by an ad hoc FCFS operation with those of the optimization model. Computational results from a case study demonstrate that a reduction of 52.6% and 61% in total delay times for arrival and departure flights, respectively, can be achieved. The optimization model also facilitates the implementation of a collaborative decision-making system for better coordination of airport traffic flow management with commercial airlines.

Keywords: flight scheduling; airport congestion; flight delays; schedule optimization; simulation of arrival and departure processes; runway capacity

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1. Introduction

The management of airport demand and capacity presents complex challenges due to the existence of multiple stakeholder incentives and performance objectives in the face of a scarcity of resources [1]. The unprecedented growth in demand in the aviation industry in recent years has been associated with over-capacity flight scheduling by most commercial airlines. Direct consequences of such developments include increased congestion at airports, flight delays, and discomfort for passengers, especially when a major disruption occurs. Because of the connectivity of an airline's resources (aircraft, crews, and passengers) in a flight network, the delay of an upstream flight can propagate across multiple downstream flights [2]. Statistics show that about 22% of flights in the USA were delayed in 2023, of which 30.6% of the delays occurred due to circumstances within the airline's control: 33.7% due to the late arrival of aircraft due to delays in previous flights, and 24% were attributed to airport operations, heavy traffic volume, and air traffic control [3].

Despite the significant effort that airlines put into flight schedules, the execution of their operations often deviates from original schedules due to airport capacity limitations and unexpected disruptions such as aircraft breakdowns, crew sickness, or severe weather conditions [4]. This is why more researchers have begun to work on the tactical rescheduling of inbound and outbound flights based on available runway slots and other resources in schedule-facilitated or fully coordinated airports. A schedule-coordinated airport requires a level of coordination to manage demand because airline demands significantly exceed the capacity of the airport. Thus, planned flight times need to be adjusted to satisfy airline and passenger service level expectations [5]. However, an optimal schedule from an airport's centralized perspective may not be optimal concerning airlines' preferences, and could impose higher costs on the airlines. At the tactical level, when flight schedules need to change due to airports' limitations, commercial airlines would have to adjust their schedules based on slot limitations at schedule-coordinated airports. Any airline that operates a flight to and from a schedule-coordinated airport needs to receive access to the airport in the form of a slot. Optimization models have been proposed to support slot allocation decisions at schedule-coordinated airports. These models primarily aim to minimize the deviations in flight schedules from the airlines' requests [6].

The airline operation control center is responsible for handling resource violations that might occur during operation. When this information is analyzed to evaluate the impact of flight displacements on other downline flights, an updated schedule is proposed. This process may take several iterations before an agreement can be reached on the final schedule, which is a time-consuming process. In recent years, many airports have tried to implement a collaborative decision-making (CDM) framework to facilitate this process while enforcing safety regulations. In a CDM environment, airline flight scheduling and airport operations become more synchronized [7]. This is a complicated process and needs analytical models and tools to facilitate communication. CDM is a truly fundamental innovation, but the benefits from this concept are yet to become fully operationalized. This research is motivated by exploring the interdependencies between airline flight scheduling and airport capacity limitations to improve resource allocation. Ideally, such scheduling activities between airlines and airports can be formalized into a CDM system.

Operations research (OR) has contributed significantly to the aviation industry by improving its operations and accommodating its high growth rates [8]. Airline scheduling and airport resource allocation are natural contexts for the application of OR techniques and optimization models. In particular, these applications are well-suited to the use of large-scale, discrete optimization, and have motivated the publication of over 1000 articles over the last 50 years [9]. Despite the long-term development of this field, there are still scientific challenges associated with developing novel mathematical models and solution approaches to deal with integrated airline scheduling, considering the resource limitations and slot allocation of airports [10]. Airport slot allocation has been proposed as a short-term measure for dealing with the excessive demand at overly congested (Level 3) airports [9]. Optimal scheduling intervention is another approach to adjusting flight schedules at a busy airport to minimize system-wide delays [10]. It has been shown in a case study that by rescheduling 1% of flights by up to 15 min each, one can reduce expected network-wide delays by 20–30% [10]. Flight rescheduling at airports without scheduling limits, such as the majority of North American airports, can be used to reduce potential delays through limited interference with airline competitive scheduling. Improving airport capacity utilization is related to air traffic flow and capacity management (ATFCM), which tries to enhance the efficiency of operations by optimizing the allocation of airport resources for both arriving and departing aircrafts. Slot allocation is a key mechanism for achieving flow–capacity balance and dealing with airport congestion under airport-declared capacity constraints [11,12]. Many existing optimization models that are concerned with the effective use of runway systems have achieved increased utilization through the removal of slack times [8]. Although having less slack time may bring more economic benefits, it could lead to less robustness and increased costs in practice [8].

The existing literature on airport capacity utilization is diverse. Most papers on optimization models for existing flight schedules have primarily focused on minimizing flight displacements or expected delays. There exist models in the literature that optimize slot allocation at a single airport for a single day. Zografos and others [4] proposed an integer linear programming model and employed a linear relaxation of it to allocate time slots for a single airport. Ribeiro and others [6] developed a model based on IATA slot allocation guidelines to effectively utilize the announced capacity of airports, providing better satisfaction to air carriers when compared with actual allocation results. Pyrgiotis and Odoni [13] proposed a demand smoothing model to minimize the maximum and total displacements of flight times. An integer programming model was developed in [13] to simulate the effects of schedule limits on airlines' schedules of flights. This approach was then extended in [14] by jointly optimizing schedule coordination and operating procedures at a busy airport. Their results suggested that this approach is a flexible and advanced way of allocating scarce airport capacity without having to assume fixed or declared capacities. It also provides a better trade-off between schedule displacement and flight delays and could significantly improve airport demand management. In contrast, slot coordination in China primarily relies on the published capacity of an airport as the sole reference for setting coordination parameters [15]. An integer programming model was presented in [15] to address the efficient allocation of incremental airport time slot resources. Recently, some scholars have turned their attention to the issue of fairness in allocating slots [16], where both efficiency and fairness objectives are incorporated into the scheduling mechanism for congested airport slots. However, there is still a research gap in developing optimization models for tactical flight rescheduling such that both airports' capacity limitations and airlines' preferences are simultaneously considered. Katsigiannis and Zografos [9] have recently presented a method for joint consideration of airlines' flight flexibility and its integration with the dynamic allocation of total airport capacity.

This paper presents an optimization model for flight rescheduling at a schedule-coordinated airport to minimize congestion and flight delays. Given an existing flight schedule for an airport on a particular day that has been created during the strategic planning phase, this optimization model produces a feasible modified schedule considering the runway capacity and the minimum turnaround times without canceling any flights. The outcome of such an optimized schedule is a reduction in potential delays and better distribution of demand on the actual day of operation.

This paper considers airports' capacity parameters exogenously and does not adjust them according to the characteristics of the slot requests and the operating procedures of the airport. The contribution of this paper is in the development of an optimization model and a simulation algorithm for rescheduling flights at an over-capacity schedule-coordinated airport to minimize total delays. The optimization model is a modification of the model presented in [14] in that it explicitly enforces runway capacity constraints in a mixed-integer linear programming formulation, which was not clear and rather complicated in the original model. Other minor modifications and corrections were also made in the definition of displacement variables and constraints. The simulation algorithm has been developed specifically in this research to validate the optimization results and compare them with the potential delays resulting from ad hoc operations in practice. The logic behind the simulation algorithm is novel and different from the existing simulation methods. The application of the algorithm to a case study is shown using real data from one of the world's busiest airports, for which the optimization and simulation results are reported.

The next section describes the mathematical models, as well as the simulation algorithm, used to verify the results. A case study on Hartsfield–Jackson Atlanta International Airport operation, and the experimental data used therein, are also explained in Section 2. The optimization results are presented in Section 3 and compared with simulated and previously scheduled flight data. The discussion of the results is in Section 4 and finally, the conclusion and future research are contained in Section 4.

2. Materials and Methods

Consider an airport at which all of the incoming and outgoing flights are to be rescheduled due to over-capacity scheduling or a ground delay program due to poor weather conditions. The methods used in this research include an optimization model and a simulation algorithm to analyze the balance between demand and capacity and potential delays in the flights. The main inputs for this study are (i) estimates of the airport runway capacity and configurations under various weather conditions, and (ii) the original schedule of flights for a particular day of operation, as well as the planned connections between the arrival and departure flights. In this section, we present the optimization model first, and then briefly explain the algorithm developed in this project to simulate the arrival and departure processes for any given flight schedule. The last section describes the case study and data used for the computational experiments.

2.1. Mathematical Formulation

Table 1 defines the sets, parameters, and variables used in this paper.

Table 1. Notations.

Sets and Parameters	Description
$\mathcal{T}$	The set of periods, $t \in \{1,2,3,\ldots,\ T\}$
$\mathcal{F}^{arr}$	The set of arrival flights scheduled to land at the airport
$\mathcal{F}^{dep}$	The set of departure flights scheduled to take off from the airport
$\mathbb{C} \subset \mathcal{F}^{arr} \times \mathcal{F}^{dep}$	A subset of flight pairs $(i,j) \in \mathcal{F}^{arr} \times \mathcal{F}^{dep}$ such that flights i and j are flown by the same aircraft
S_{it}^{arr}	1; if flight $i \in \mathcal{F}^{arr}$ is originally scheduled to land no later than period t 0; otherwise
S_{jt}^{dep}	1; if flight $j \in$ $\mathcal{F}^{dep}$ is originally scheduled to take off no later than period t 0; otherwise
$T_{ij}^{min}/T_{ij}^{max}$	The minimum/maximum turnaround time between flights i and j such that $(i,j) \in \mathbb{C}$
Λ_t^{arr}	Maximum number of allowable arrival flights in period t
Λ_t^{dep}	Maximum number of allowable departure flights in period t
Decision Variables	**Description**
$u_i^+,\ u_i^-$	Positive or negative displacement of arrival flight $i \in \mathcal{F}^{arr}$
$v_j^+,\ v_j^-$	Positive or negative displacement of departure flight $j \epsilon \mathcal{F}^{dep}$
w_{it}^{arr}	A binary array representing the newly scheduled arrival of flight $i \in \mathcal{F}^{arr}$
w_{jt}^{dep}	A binary array representing newly scheduled departure of flight $j \epsilon \mathcal{F}^{dep}$
δ^+, δ^-	Maximum of all positive or negative flight displacements

It is common practice to discretize the time into 15 min periods. However, we use 5 min intervals in the optimization model to avoid unnecessarily large schedule displacements. The novelty of this formulation lies in the structure of the scheduling parameters S_{it}^{arr} and S_{it}^{dep}, as defined in [13]. The array S_{it}^{arr} (similarly S_{it}^{dep}) is of the form $(1,\ldots,1,0,\ldots,0)$ if flight i is originally scheduled to land (or take off) no earlier than period t, where the last 1 in the array corresponds to period t.

The parameters T_{ij}^{min} and T_{ij}^{max} are expressed as numbers of 5 min periods. If flights i and j are connected by an aircraft, we set the corresponding value of T_{ij}^{min} to the minimum turnaround time required to complete the ground operations for the type of aircraft and make it ready for the next flight. The decision variables w_{it}^{arr} and w_{jt}^{dep} take the same form as the input parameters S_{it}^{arr} and S_{it}^{dep}. By convention, we assume that $w_{i,\mathrm{T}+1}^{arr} = w_{i,\mathrm{T}+1}^{dep} = 1$. The displacement variables $(u_i^+,\ u_i^-)$ and (v_j^+, v_j^-) are also expressed as numbers of 5 min periods and allow for positive or negative displacement, i.e., a flight can be rescheduled for a later or earlier time of the day.

The objective function is to minimize the total displacements of arrival and departure flights on a particular day. The maximal displacement of any flight, denoted by δ, could be considered as the second objective function. However, we restrict it by assigning a fixed value to δ so that it would not interfere with the first objective, based on various initial runs of the model. The optimization model for scheduling interventions at a busy airport can be formulated as follows:

$$\text{Min z} = \sum_{i\epsilon\mathcal{F}^{arr}}(u_i^+ + u_i^-) + \sum_{j\epsilon\mathcal{F}^{dep}}(v_j^+ + v_j^-) \tag{1}$$

Subject to:

$$w_{i1}^{arr} = 1;\ \forall i\epsilon\mathcal{F}^{arr}, \tag{2}$$

$$w_{j1}^{dep} = 1; \forall j\epsilon\mathcal{F}^{dep}, \tag{3}$$

$$\sum_{t\epsilon\mathcal{T}}(w_{it}^{arr} - S_{it}^{arr}) = u_i^+ - u_i^-;\ \forall i\epsilon\mathcal{F}^{arr}, \tag{4}$$

$$\sum_{t\epsilon\mathcal{T}}(w_{jt}^{dep} - S_{jt}^{dep}) = v_j^+ - v_j^-;\ \forall j\epsilon\mathcal{F}^{dep}, \tag{5}$$

$$\sum_{t\epsilon\mathcal{T}}(w_{jt}^{dep} - w_{it}^{arr}) \geq T_{ij}^{min};\ \forall (i,j)\epsilon\mathbb{C} \tag{6}$$

$$\sum_{t\epsilon\mathcal{T}}\left(w_{jt}^{dep} - w_{it}^{arr}\right) \leq T_{ij}^{max};\ \forall (i,j)\epsilon\mathbb{C} \tag{7}$$

$$w_{it}^{arr} \geq w_{i,t+1}^{arr};\ \forall i\epsilon\mathcal{F}^{arr},\ \forall t\epsilon\mathcal{T}, \tag{8}$$

$$w_{jt}^{dep} \geq w_{j,t+1}^{dep};\ \forall j\epsilon\mathcal{F}^{dep},\ \forall t\epsilon\mathcal{T}, \tag{9}$$

$$\sum_{i\epsilon\mathcal{F}^{arr}}\left(w_{it}^{arr} - w_{i,t+1}^{arr}\right) \leq \Lambda_t^{arr};\ \forall t\epsilon\mathcal{T}, \tag{10}$$

$$\sum_{j\epsilon\mathcal{F}^{dep}}\left(w_{jt}^{dep} - w_{j,t+1}^{dep}\right) \leq \Lambda_t^{dep};\ \forall t\epsilon\mathcal{T}, \tag{11}$$

$$\begin{cases} u_i^+ \leq \delta^+;\ u_i^- \leq \delta^-;\ \forall i\epsilon\mathcal{F}^{arr}, \\ v_j^+ \leq \delta^+;\ v_j^- \leq \delta^-;\ \forall j\epsilon\mathcal{F}^{dep}, \end{cases} \tag{12}$$

$$\text{Integer } u_i^+,\ u_i^-,\ v_j^+, v_j^- \geq 0;\ \text{binary } w_{it}^{arr} \text{and } w_{jt}^{dep};\ \forall i\epsilon\mathcal{F}^{arr},\ \forall j\epsilon\mathcal{F}^{dep}, \forall t\epsilon\mathcal{T}. \tag{13}$$

This is a mixed-integer linear programming model. Constraints (2) and (3) ensure that all arriving and departing flights are scheduled. Constraints (4) and (5) define the rescheduled arrival and departure times, respectively, based on the decisions on displacements of the original flight schedules. The combination of Constraints (4) and (5) ensures that flight block times are kept unchanged. Constraints (6) and (7) enforce the minimum and maximum turnaround times. Constraints (8) and (9) ensure that w_{it}^{arr} and w_{jt}^{dep} are non-increasing for each flight, consistently with their definition. Constraints (10) and (11) ensure that the aggregate number of scheduled arrivals and departures in each period t does not exceed the runway capacity limits. Constraint (12) defines the maximum of all positive and negative displacements for all incoming and outgoing flights, and finally, Constraint (13) defines the variables' type and sign constraints.

2.2. Simulation of Arrival and Departure Processes

In this study, an algorithm has been developed to simulate arrival and departure processes using the first come first served (FCFS) discipline, while respecting runway capacity limitations in a schedule-coordinated airport. The capacity is defined as the number of arrival or departure slots that can be safely assigned to incoming or outgoing flights from the airport in each 15 min time interval during a day. The number of arrival or departure slots for each 15 min time interval depends on the minimum separation time between two consecutive landings or take-offs for safe operations. The minimum safe separation interval between successive flights is a critical safety measure that mitigates the risk of in-flight incidents by ensuring a sufficient buffer to prevent the aerodynamic effects of one aircraft from adversely affecting another. We assume a 3 min minimum safe separation time for arrivals, and 2 min for departures. After assigning a time for a flight in a certain interval, the value of the delay is calculated, which is the difference between the flight time that we can reschedule for after slot allocation and the original scheduled time. The arrival delay, caused by shifting some flights to subsequent time intervals, may propagate to those departure flights that are connected to the arrival flight by some airline resources (aircraft, crew members, and/or passenger connections). In this study, we consider flight connections only by aircraft tail numbers, since other connection data were not available. We assume fixed taxi and turnaround times, under the assumption that there are no capacity limitations for ground operations resources. The simulation of the departure process is performed similarly. However, before starting the allocation of flights to runways, we check the minimum ready time after the execution of ground operations following the aircraft's actual arrival. An arrival delay will result in a departure delay if there is not enough slack between the two connected flights. We ensure that a minimum turnaround time of 35 min is maintained between each pair of connected arrival and departure flights that are performed by a certain aircraft. After taking into account the ground operations time, the delay is calculated, which is the difference between the scheduled and actual times. The details and flowchart of the simulation algorithm can be found in [17].

2.3. Case Study and Computational Experiments

The data used in our experiments were collected from the Federal Aviation Administration (FAA) Airport Capacity Profiles 2022. Specifically, data were obtained from the FAA website for Hartsfield–Jackson Atlanta International Airport (ATL) on 24 March 2023, which happened to be the busiest day in 2023 [18]. It included all departure and arrival statistics (scheduled time, actual time, flight delay, etc.) for all the flights going to or departing from the USA airports. The connections between flight pairs were found using the tail numbers of the aircraft performing those flights. ATL is the number two weather-affected airport, largely because of system delays and thunderstorms at ATL [18]. We collected statistics for 881 arrivals and 873 departures, as well as for 739 connecting flights at ATL on that day.

According to the FAA, the capacity benchmark is defined as the maximum number of flights an airport can routinely handle in an hour, for the most commonly used runway configuration in each specified weather condition. In our research, we analyzed the capacity of the 5 parallel runways in this airport. ATL normally assigns three runways for arrivals and two for departures. We assumed that each runway was designated for either incoming or outgoing flights, but not for both at the same time. To validate the simulation code, we ran the algorithm considering the capacity of 20 arrivals and 20 departures in each 15 min interval and observed that the simulated data closely matched the actual data [17]. It should be noted that the simulation algorithm enforced runway capacity limitations for safer operation, whereas the actual data were the result of ad hoc operation based on FCFS discipline. After validating the simulation code, the algorithm was run with an operational capacity of 15–15 flights in each 15 min interval. This was equivalent to enforcing a 3 min separation time for arrivals, and 2 min for departures.

3. Results and Discussion

We implemented the optimization model in GAMS 24.0 and solved it using CPLEX 12.5.1.0 on a personal computer with a 2.5 GHz Intel Core i7 processor and 12 GB of RAM. All the reported solutions to the model are optimal and were found in less than 5 min. The simulation algorithm was implemented in Python 3.12.

Tables 2 and 3 demonstrate the computational results of this study. We report three measures of delays for the arrival flights using the actual data and the simulated and optimized schedules in Table 2. Similarly, the results for the departure flights are reported in Table 3. The actual data are the same as reported on the FAA website for ATL airport on a particular day [17]. The results under the simulated arrivals column were obtained by processing the flights in a queue on a FCFS basis while enforcing runway capacity limitations. The optimization results on flight displacements are reported under two scenarios: with and without allowing for negative displacements of the flights from their original schedules. It is noted that such displacements could be implemented in the schedule well ahead of the actual day of operation, and should not be considered as delays. In other words, if all the flights were rescheduled based on the optimization results, the same number of arrival/departure flights could be handled in a day without any delay caused by airport capacity limitations. However, in practice, we may still observe some delays even with the optimized schedule, due to overlapping some flights within some time intervals. That is why we ran the simulation algorithm on the optimized schedule as input, to test the potential delays caused by the optimal schedule.

Table 2. Comparison of actual, simulated, and optimized schedules for arrival flights.

	Actual Arrivals	Simulation of the Original Arrival Schedules	Optimized Schedule (with Positive Displacements)		Optimized Schedule (with Neg. and Pos. Displacements)		Simulation of the Optimal Arrival Schedules	
Total delay or displacement times (min.)	6279	7862	7745	−0.01%	3725	−52.6%	1564	−75%
Maximum delay or displacement of a flight (min.)	196	45	60	+33%	60	+33%	9	−80%
Number of delayed or displaced flights	285	591	338	−0.43%	296	−50%	465	−21.3%

Table 3. Comparison of actual, simulated, and optimized schedules for departure flights.

	Actual Departures	Simulation of the Original Departure Schedules	Optimized Schedule (with Positive Displacements)		Optimized Schedule (with Neg. and Pos. Displacements)		Simulation of the Optimal Departure Schedules	
Total delay or displacement times (min.)	8001	7917	6590	−16.7%	3075	−61%	1616	−80%
Maximum delay or displacement of a flight (min.)	199	31	60	+93.5%	60	+93.5%	5	−83.8%
Number of delayed or displaced flights	341	678	334	−50.7%	308	−54.5%	478	−29.4%

The results in Table 2 illustrate that simulation of the arrival process with a capacity of 15 flights in each 15 min interval led to a 25% increase comparing with the actual delay times, and more than doubled the number of delayed flights. However, the maximum delay that any arrival flight would have experienced was 45 min, which is much lower than the 196 min observed in the actual operation. This observation was expected since the lower airport capacity used in the simulation experiments exacerbated delays. It can be seen in [17] that our simulation results would closely match the actual data if we assumed the runway capacity of 20 for both the arrival and departure flights. Our simulation algorithm assumes designated runways for arrival and departure flights while enforcing a three-minute separation time for consecutive arrivals and two minutes for consecutive departures to ensure safety of operations. The lower actual delay times could also be attributed to the fact that the airport operation control may have utilized some runways for both arrival and departure flights with possibly less separation time whenever possible to achieve higher throughput.

To utilize the full capacity of airport runways during off-peak hours, we ran the optimization model in (1)–(13) allowing both positive and negative displacements of flights to happen, and the results turned out to be significantly better for both arrival and departure flights, as reported in Tables 2 and 3. For practical reasons, the maximum allowable positive (negative) displacement for a flight was restricted to 60 (15) minutes. In fact, the comparison herein is made between the optimization and simulation results using the same values for the runway capacities. The results in Table 2 show that the total displacement times in the optimized schedule with positive displacements are about the same as the simulated delay times. However, when we allow negative displacements in the optimization model, the result is 52.6% lower than the simulated delay times for the arrival processes. As mentioned before, such displacements should not be considered as delays, and can be accommodated well ahead of the actual operation day. Using the optimized schedule as input, we ran the simulation algorithm again to estimate the potential delays caused by the optimal schedule. The last column of Table 2 shows that the total displacement times decreased by 75%, and the maximum delay of a flight was reduced by 80%. This significant improvement achieved by the optimization model could be attributed to better utilization of the airport resources during the operation day.

Figure 1 demonstrates how the optimization model distributed the arrival flights over the course of a day. It also shows that the number of the arriving flights was cut off at 15 in both the simulation and optimization results.

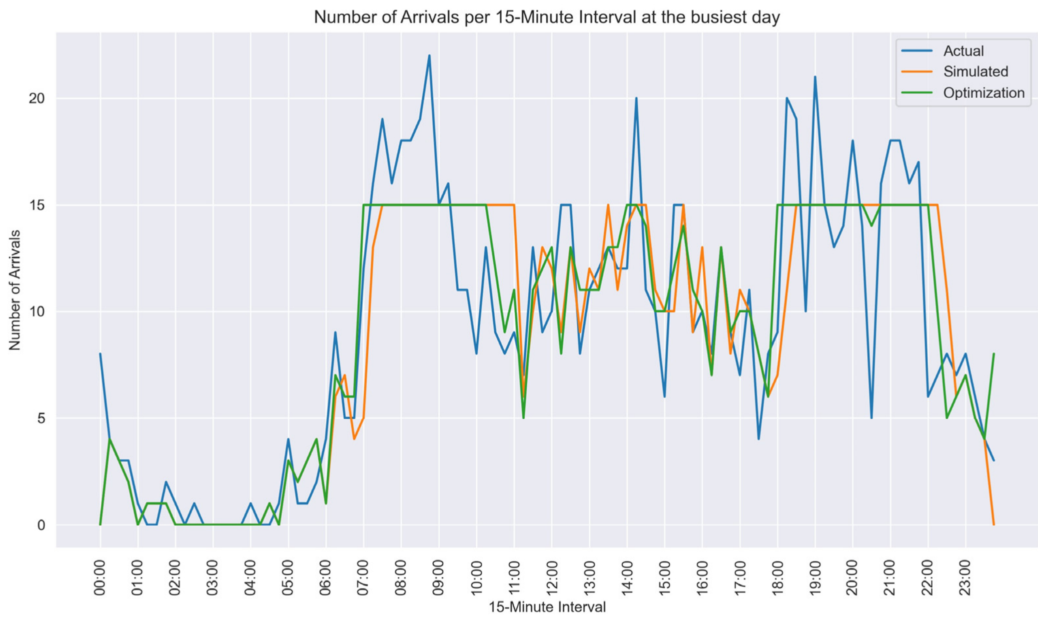

Figure 1. Number of arrival flights based on the actual, simulated, and optimized schedules.

The results in Table 3 illustrate that simulation of the departure process with a capacity of 15 flights in each 15 min interval led to a slight decrease in the actual delay times and approximately doubled the number of delayed flights. However, the maximum delay that any departure flight would have experienced was 31 min, which was much lower than the 199 min observed in the actual operation. This observation was expected since the lower runway capacity used in the simulation experiments exacerbated the total delay times and the number of delayed flights, as explained for the arrival process. To make fair evaluations, we compared the optimization results with those of the simulation, since the same values for the runway capacities were used in both models. The results in Table 3 show that the total flight displacement times in the optimized schedule (with positive displacements only) were 16.7% lower than the simulated delay times, which was much better than the simulation results for the departure process. Yet, when we allowed negative displacements in the optimization model, the result was 61% lower than the simulated delay times. Furthermore, the number of displaced flights became 308, which was lower than the 678 delayed departure flights by 54.5%. As mentioned before, such displacements should not be considered as delays. Using the optimized schedule as input, we ran the simulation algorithm again to estimate the potential delays caused by the optimal schedule. The last column of Table 3 shows that the total displacement times decreased by 80% and the maximum delay of a flight was reduced by 83.8%, as compared with those obtained by the simulation of the original departure schedules. This significant improvement achieved by the optimization model could be attributed to better utilization of the airport resources during the operation day. We observed that the optimization model could achieve significant improvements in the total delay times for both arrival and departure flights.

Figure 2 demonstrates how the optimization model distributed the departure flights over the course of a day. It also shows that the number of departing flights was cut off at 15 in both the simulation and optimization results.

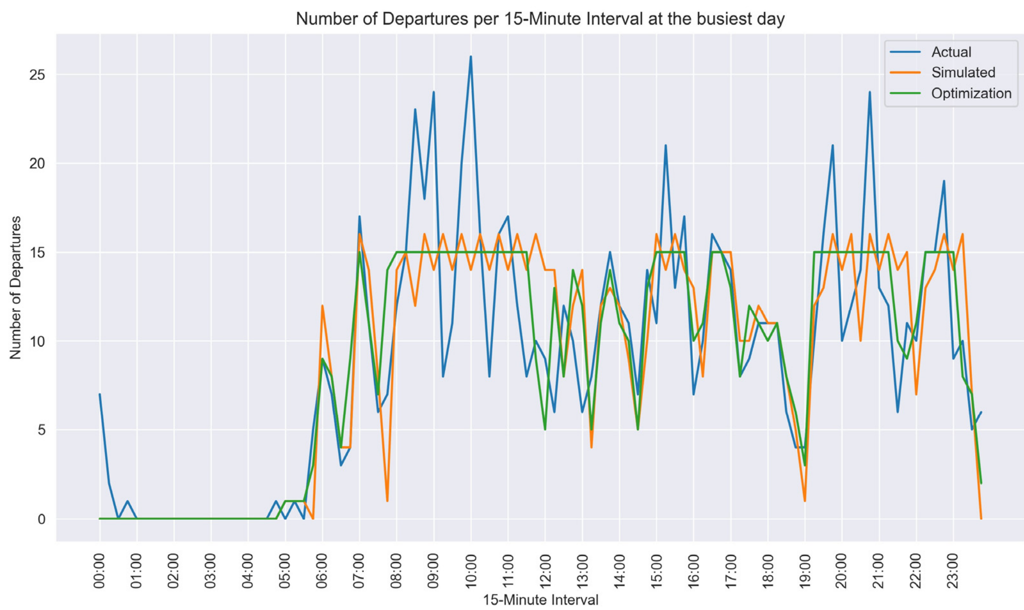

Figure 2. Number of departure flights based on the actual, simulated, and optimized schedules.

4. Conclusions

In this study, an optimization model has been developed for flight rescheduling at a schedule-coordinated airport. The model demonstrates the potential for a significant reduction in delays and congestion by moderately rescheduling the flight times. Furthermore, by distributing the peak hour demand over the course of the operation day, better utilization of airport resources and less congestion can be achieved. Mitigating flight delays at such a busy airport can significantly reduce propagated delays in the downstream flight network.

Computational results show that total displacements or potential delay times could be reduced by 52.6% and 61% for arrival and departure flights, respectively. This is achieved by allowing flights to be rescheduled to a maximum of one hour later or 15 min earlier without eliminating any flights or missing connections at ATL airport. However, we realize that scheduling interventions at a selected airport may not be easily accepted by airlines unless their challenges and interests are addressed.

Similar results in [14] showed that with a moderate level of flight rescheduling, peak arrival and departure delays at John F. Kennedy International Airport could be reduced by 20–40% and by 40–60%, respectively. Applying capacity limits at Newark Liberty International Airport as reported in [13] showed that with a similar scale of operations as in our case study, the total flight displacements were 5730 min, while the maximum shift in the scheduled arrival or departure time of any flight was set to 30 min. Therefore, it is observed that the delay savings from flight displacements at congested airports could be significant.

The simulation of optimized flight schedules at ATL suggested that this type of airport-wide cross-airline coordination could reduce the total delays and maximum delay times that any flight may experience due to airport capacity limitations by 75–80% and 80–84%, respectively. The combination of optimization and simulation developed in this paper provides the basic tools for significantly improving airport demand management and avoiding delay propagation across a flight network.

Our future research will focus on extending this optimization model to account for propagated delays in the downstream flight network. We aim to adjust flight schedules considering airport resource constraints and congestion to reduce total delay propagations. We will also calculate the total propagated delays on the subsequent connection flights after a tail number departs from the airport until it completes its rotation. This propagated delay calculation will be used as another objective function in the optimization model, leading to a multi-objective optimization model. It is expected that the results of such a new schedule intervention paradigm will be more acceptable to airlines. We believe that the new model could be a good common ground for the successful implementation of a CDM system in the near future.

Author Contributions: A.S. conceived and designed the study, developed the simulation and optimization models, analyzed the results, and wrote the paper; K.P. contributed to fund acquisitions, design of the study, project administration, and conceptualization, and supervised the work; A.K. developed the codes for data extraction and conducted the simulation experiments, and helped with writing some sections; L.A.-H. contributed to fund acquisitions and resources for the work, advised on the project work, and edited the draft. All authors have read and agreed to the published version of the manuscript.

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