Research Article

A stochastic sequence planning model for the runways with multiple exits

Kadir Dönmez*
Aircraft Maintenance Department, Faculty of Aeronautics and Astronautics, Samsun University, Samsun, Turkey
**Correspondence:* *kadir.donmez@samsun.edu.tr*

DIO: 10.51513/jitsa.1138520

Abstract: The runway exit points (REPs) of the airport are constructed considering the operational performance of different types of aircraft based on historical flight data. In sequence planning, it is assumed that aircraft will vacate the runway from an expected exit point. However, real performance can be uncertain, and the same type of aircraft may vacate the runway from different exit points rather than the expected point. In addition, the runway occupancy times (ROTs) of aircraft that vacate the runway from the same exit point may not be equal. This situation brings two types of uncertainty when making traffic plans in an airport with several REPs. The first uncertainty is the REP of the aircraft, and the second is the ROT uncertainty considering the exit points. In this study, a two-stage stochastic programming model was developed for aircraft sequencing in an airport that has multiple runway exit points. In the model, both runway exit and ROT uncertainties are considered. A runway with multiple exit points at an airport in Turkey was selected and flight track data of 154 arrival flights to this runway was examined. Various expected time of arrival and departure (ETAD) scenarios were generated based on real data and integrated into the mathematical models. The proposed model was then compared with deterministic and first come first serve (FCFS) approaches in terms of total delay. As a result of the comparison and analyses, the presented stochastic programming model provided robust solutions and delay savings compared to the other approaches.

Key words: Aircraft sequencing, runway occupancy time uncertainty, runway exit point uncertainty, stochastic programming, arrival-departure delays.

Çoklu terk ediş noktası bulunan pistler için stokastik sıralama planlama modeli

Özet: Havalimanlarında pisti terk ediş taksi yolları farklı tipteki uçakların operasyonel performansları göz önünde bulundurularak geçmiş verilere dayalı olarak tasarlanmaktadır. Sıralama planlaması yapılırken uçakların pisti beklenen bir noktadan terk edeceği varsayılmaktadır. Ancak gerçek performanslar farklılık gösterebilmektedir. Aynı tip uçaklar pisti farklı noktalardan terk edebilmektedir. Bunun yanı sıra pisti aynı noktadan terk eden uçakların pist meşguliyet süreleri de farklılaşabilmektedir. Bu durum birden fazla pisti terk ediş taksi yolu içeren havalimanlarında trafik planlaması yapılırken iki farklı belirsizlik unsurunu ortaya çıkarmaktadır. Bunlardan ilki pisti terk ediş noktası (REP) belirsizliği diğeri ise pist meşguliyet süresi (ROT) belirsizliğidir. Bu çalışmada REP ve ROT belirsizlikleri göz önüne alınarak birden fazla terk ediş noktasına sahip pisti bulunan havalimanlarında geliş-kalkış sıralaması için stokastik programlama modeli geliştirilmiştir. Türkiye'de bir havalimanına gerçekleşen 154 geliş operasyonun radar verileri incelenmiş ve matematiksel modele entegre edilmiştir. Gerçek verilere dayalı olarak üretilen çeşitli beklenen iniş ve kalkış senaryoları matematiksel modelde koşturulmuştur. Daha sonra önerilen stokastik model deterministik ve ilk gelen ilk hizmet alır (FCFS) yaklaşımları ile toplam gecikme açısından kıyaslanmıştır. Sonuç olarak önerilen modelin belirsizliklere karşı sağlam sıralamalar sunmayı başardığı ve diğer yaklaşımlarla kıyaslandığında önemli gecikme kazanımları sağladığı gözlenmiştir.

Anahtar Kelimeler: Uçak sıralama, pisti terk ediş noktası belirsizliği, pist işgal süresi belirsizliği, stokastik programlama, geliş-kalkış gecikmeleri.

---

* Corresponding author.
E-mail address: *kadir.donmez@samsun.edu.tr*
ORCID: 0000-0002-1236-0498
Received 30.06.2022; accepted 29.09.2022
Peer review under responsibility of Bandirma Onyedi Eylul University.

1. Introduction

Runway exit points (REPs) are designed based on historical data and aircraft performance calculations related to the different types of aircraft (ICAO, 2005) as well as environmental and operational variables of the related airport (Trani et al., 1990). ICAO published a manual that indicates the most suitable REP locations in airports (ICAO, 2005). In this report, four types of aircraft are identified based on their threshold crossing speeds. This speed is determined as 1.3 times the stall speed in the landing configuration at maximum certified landing mass at sea level. The aircraft are categorized in the manual as A (DC3, DHC6, DHC7, etc.), B (DC6, DC7, Fokker F27, Fokker F28, etc.), C (A300, A310, A320, A330, B727, B737, B747-SP, etc.) and D (A340, B747, B777, etc.). The accumulated rapid exit usages in distance (nm) from the threshold depending on aircraft type are given in the same manual, which are represented in Table 1.

Table 1. Accumulated rapid exit usage by distance from threshold (m) (ICAO, 2005)

	50%	**60%**	**70%**	**80%**	**90%**	**95%**	**100%**
A	1170	1320	1440	1600	1950	2200	2900
B	1370	1480	1590	1770	2070	2300	3000
C	1740	1850	1970	2150	2340	2670	3100
D	2040	2190	2290	2480	2750	2950	4000

As seen in Table 1, the probabilities of the rapid exit distance are differentiated according to the type of aircraft. In addition, there are several possibilities for the same type of aircraft. For example, an aircraft in category A can vacate the runway from a point between 1170 and 2900 m with different probabilities.

Air traffic controllers (ATCos) at an airport with multiple exit points make sequencing plans considering separation requirements and operational conditions. The ATCos consider that aircraft will vacate the runway from the expected REPs declared in the Aeronautical Information Publication (AIP) or the most probable exit points observed from real operations. However, in some cases aircraft can vacate the runway earlier or later than the expected exit point, which brings uncertainty to operation planning. Initial plans can result in higher delays when uncertain conditions are realized. For our case study, Antalya airport (LTAI) in Turkey was used. The expected runway exits of the arriving flights to the runway are declared in the AIP considering ICAO wake turbulence categories (ICAO, 2017). According to the AIP Turkey, Heavy (H), Medium (M), and Small (S) category aircraft are expected to vacate the runway from C2, D, and D, respectively. The runway layout and the rapid exit taxiways are shown in Figure 1 (AIP Turkey, 2022).

Figure 1. LTAI ground layout

The declared exit points are shared as a guide rather than an obligation. However, it is requested that pilots who are not able to vacate via the taxiways declared in the AIP must inform ATC during the final approach phase (AIP Turkey, 2022). If a pilot cannot inform the ATCos and cannot leave the runway from the expected point this may need an intervention by the ATCOs, which may require sequence changes of arrivals and departures or re-setting the separation minimums between consecutive aircraft. Even when a pilot informs the ATCos, an intervention may still be required to provide the separation minimums between consecutive aircraft in the operation, causing additional delays for the following aircraft. To avoid sequence change, which is a challenging situation for both controllers and pilots, robust sequences should be made that consider all the uncertainties in REPs.

Considering only REP uncertainty may not be enough because the runway occupancy times (ROTs) of the aircraft vacating the runway from the same exit point may not be equal. This uncertainty can also affect the aircraft sequence on the runway. In this regard, a two-stage stochastic programming model that considers both REP and ROT uncertainties was developed in this study. Various expected time of arrival and departure (ETAD) samples were solved and compared to other methods including deterministic and FCFS approaches.

1.1. Literature review

In literature, the air traffic management system is investigated including several uncertainties in the air (Tielrooij et al., 2013) and on the ground (Rappaport et al., 2009). There are several studies that the weather conditions are considered to be one of the major uncertainties in the air affecting flight times and airborne delays (Alonso et al., 2000; Cecen et al., 2020; Matthews et al., 2009). Ground uncertainties, on the other hand, are examined including pushback times (Hanbong Lee & Balakrishnan, 2012), taxi times (Atkin et al., 2008), ROTs (Martinez et al., 2018), etc. ROT uncertainty is one of the important ground uncertainties that affect runway capacity. This uncertainty directly affects the operations in the air as well as on the ground and may cause significant delays (Meijers, 2019). There are several attempts to predict the ROT of aircraft (Dai & Hansen, 2020; Jeddi et al., 2006; Meijers, 2019; Nguyen et al., 2020), however, this uncertainty includes a number of factors, such as aircraft weight, pilot performance, wind direction, and speeds, ground humidity, etc. (Shone et al., 2021). Even for professionals, it is not easy to predict the ROTs (Martinez et al., 2018). Therefore, stochastic approaches have been suggested to improve runway operations considering ROT uncertainties (Hockaday & Kanafani, 1974; Nikoleris & Hansen, 2016; Stamatopoulos et al., 2004). All these approaches indicate that the efficiency of air traffic management may increase by considering the ROT uncertainties. In this study, the ROT uncertainty of aircraft is considered in a mathematical model to validate the efforts made in previous studies. In addition, REP uncertainty is also integrated into the model to increase the model's sensitivity to uncertainties on the runway.

2. Methodology

In this study, a two-stage stochastic programming model was developed considering both REP and ROT uncertainties. Various ETAD samples with a demand of 40 aircraft in an hour were solved to find the possible delay savings of the model compared to other methods, including FCFS, and deterministic approaches. In the first stage of the problem, FCFS and deterministic sequences were obtained without considering any uncertainty in the system. In the deterministic approach, while obtaining the sequence decisions, it was assumed that the aircraft will vacate the runway from the most probable exit point based on historical data (D point with 57sec ROT in our case study). Then, in the second stage, these sequence decisions obtained from first come first serve (FCFS) and deterministic (DET) models were applied with uncertainties. As a result, the value of the expected solution for FCFS (VES(FCFS)) and deterministic (VES(DET)) were obtained. In the stochastic model, on the other hand, both REP and ROT uncertainties were considered to obtain a sequence decision and the solution of the stochastic model (STC) was obtained directly. The total delay was obtained by applying the sequence decisions of the models. A comparison of these results enables us to find the best sequence strategy under REP and ROT uncertainties. The methodology of the study is summarized in Figure 2.

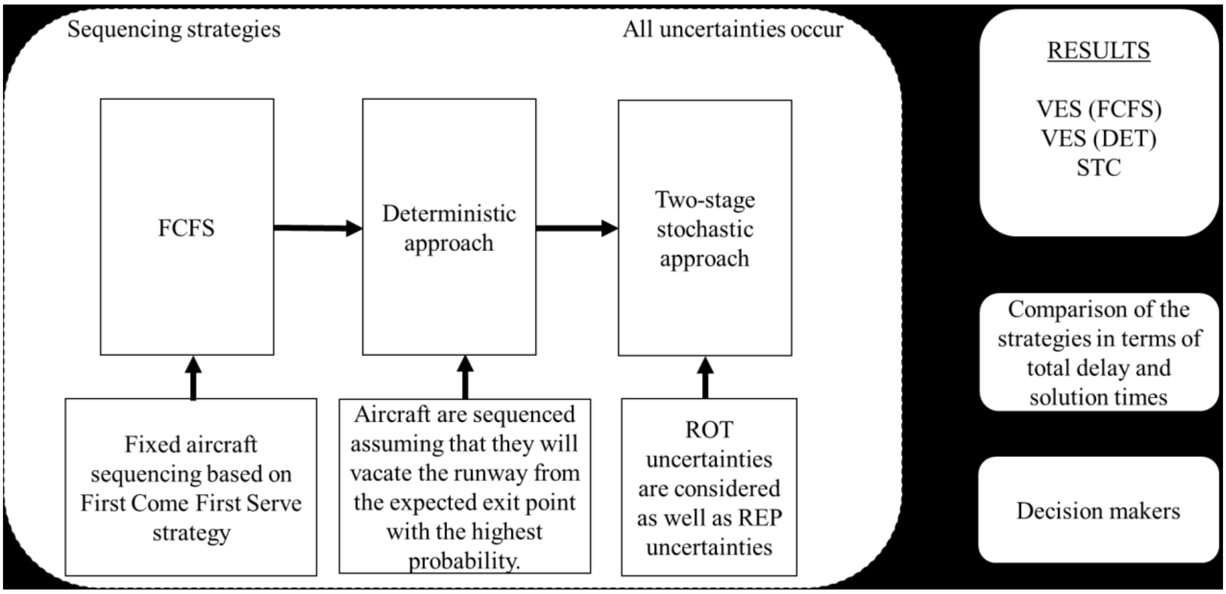

Figure 2. The methodology of the study

2.1. Data analysis

A total of 154 arrival flights' tracks were analyzed from 7 different days in April and May 2022. There were no significant differences between the observation days in terms of meteorological conditions and the wind was calm during the operations. The flight data includes flight IDs, aircraft type, wake turbulence categories, flight types (domestic or non-domestic), and flight tracks. The flight tracks include longitude-latitude, ground speeds, directions, altitudes, and time stamps. Based on the flight tracks, the REPs and ROTs of arrivals were obtained. The passing time of the runway threshold was taken to be the beginning of the runway occupancy. The passing time of the point where the aircraft completely vacate the runway was considered the end of runway occupancy. Figure 3 presents the number of aircraft including the flight type (domestic and non-domestic), accordingly, 81% of the flights to the airport were non-domestic and 19% were domestic. As seen in Figure 4, M and H category aircraft consist of 92%, and 8% of all arriving flights, respectively.

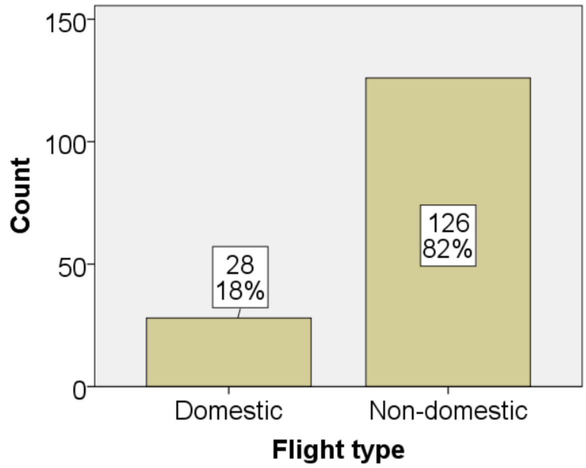

Figure 3. Number of arrival operations based on flight type

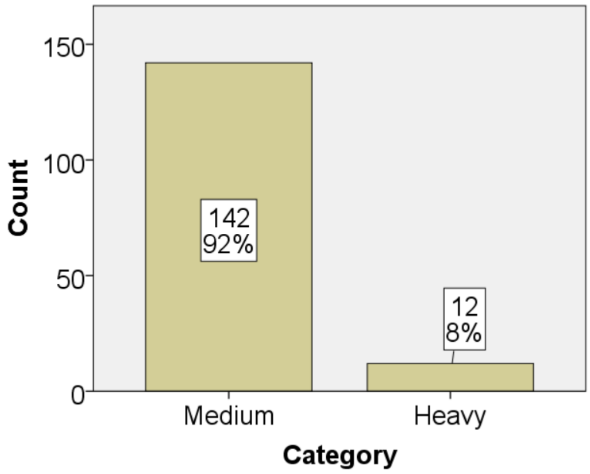

Figure 4. Number of arrival operations based on wake turbulence category

2.2. REP and ROT scenarios

As presented in Figure 5, 69%, 27%, and 4% of all flights vacated runways from D, C2, and B1, respectively. While the average ROTs for these points were 57, 79, and 130 seconds (Figure 6).

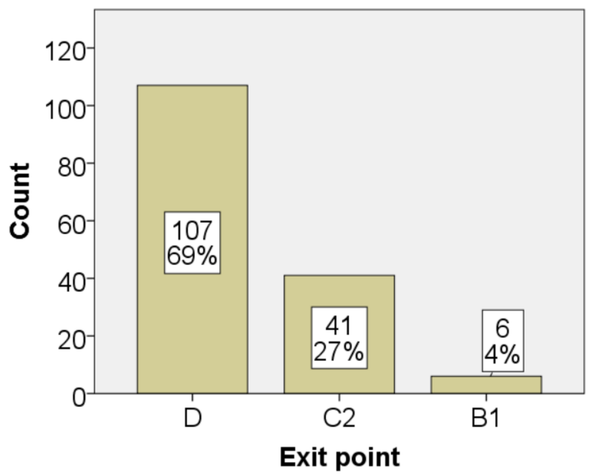

Figure 5. Frequency of the usages of the REPs

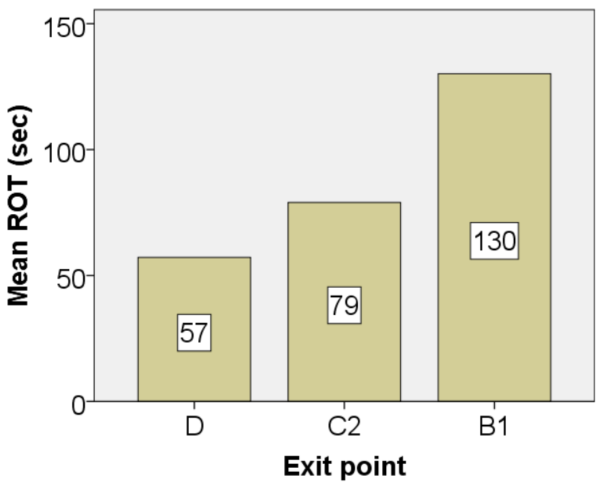

Figure 6. Mean ROTs based on REPs

Considering only the REP distributions, three scenarios can represent the uncertainties and can be integrated into the mathematical model. The scenarios are given in Table 2.

Table 2. REP scenarios and probabilities

Scenario	REP	Average ROT (sec)	Probability
Scenario 1	D	57	0.69
Scenario 2	C2	79	0.27
Scenario 3	B1	130	0.04

As mentioned above, only considering the REP uncertainties may not provide efficient sequences, because the ROT of aircraft can be different for the same REPs. ROT scenarios were determined with 15 seconds intervals to represent the ROT uncertainties. As a result, 3, 5, and 4 different ROT scenarios were considered for D, C2, and B1 exit points, respectively. Figure 7 shows the ROT intervals considering the REPs.

In our two-stage stochastic programming model, the medians of each interval were used to represent the interval. Therefore, the number of scenarios increased to 12 including for both REP and ROT probabilities, as given in Table 3.

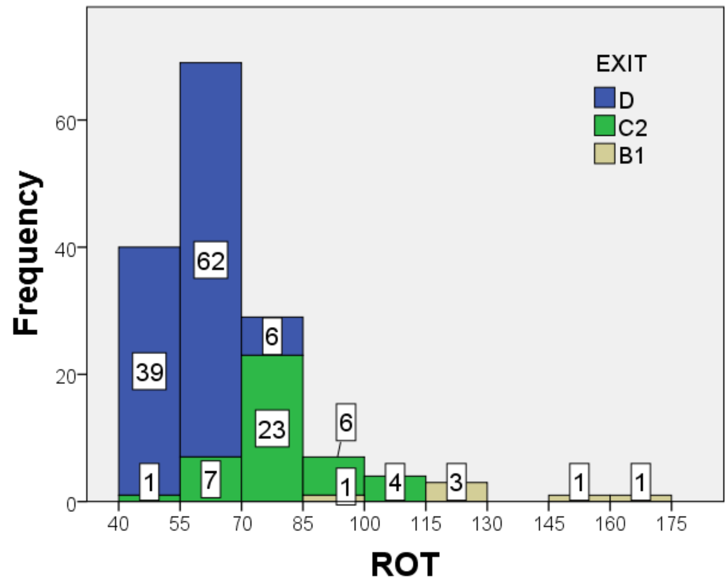

Figure 7. ROT distributions based on REPs

Table 3. The scenarios include the REP and ROT uncertainties.

Scenario	REP	Interval	Median of ROT (sec)	REP Probability	ROT Probability	Overall probability
Scenario 1	D	40-55	47.5	0.69	0.364	0.251
Scenario 2	D	56-70	63	0.69	0.579	0.400
Scenario 3	D	71-85	78	0.69	0.056	0.039
Scenario 4	C2	40-55	47.5	0.27	0.024	0.006
Scenario 5	C2	56-70	63	0.27	0.170	0.046
Scenario 6	C2	71-85	78	0.27	0.560	0.151
Scenario 7	C2	86-100	93	0.27	0.146	0.039
Scenario 8	C2	101-115	108	0.27	0.097	0.026
Scenario 9	B1	86-100	93	0.04	0.166	0.007
Scenario 10	B1	116-130	113	0.04	0.500	0.020
Scenario 11	B1	145-160	152.5	0.04	0.166	0.007
Scenario 12	B1	161-170	168	0.04	0.166	0.007

The Mann-Whitney U test was performed to find out whether there is a significant difference between the aircraft categories in terms of average ROTs. As a result, no significant difference between heavy and medium category aircraft in terms of average ROTs was found (p=0.748, U: 929.0). Mean ROTs of heavy and medium category aircraft were 65.8 and 66.3, respectively. Although different expected REPs for M and H category aircraft are declared in the AIP, the ROT distributions and performances of these aircraft types do not have statistically significant differences in our case study. The observed ROTs considering the aircraft types and categories are given in Figure 8. A total of 12 different aircraft types were observed in the operations.

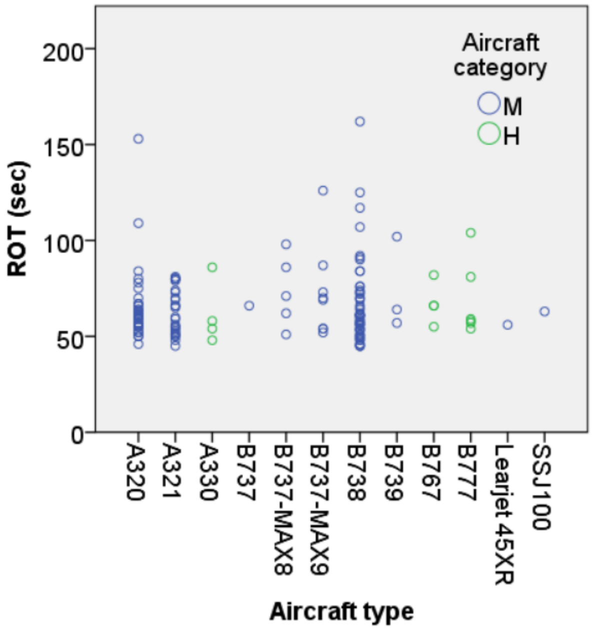

Figure 8. ROTs considering the aircraft types and categories

We also tested to see if there was a significant difference between the flight types (domestic and non-domestic) in terms of average ROTs. Again, no significant difference was found (p=0.818, U: 1715.0) between the flight types presented in Figure 9. As a result of these findings, the scenarios were not expanded to include aircraft categories and flight types.

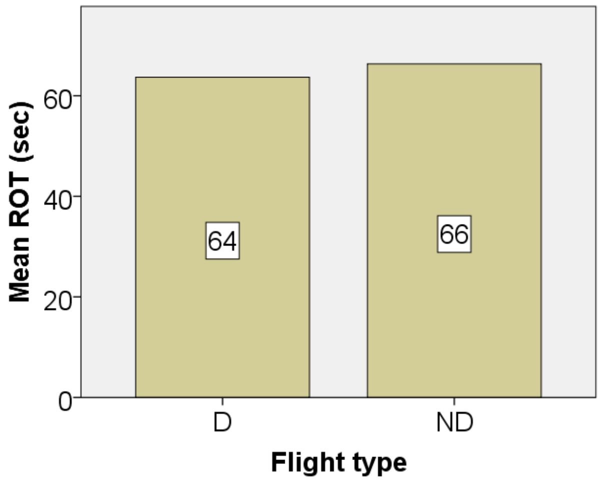

Figure 9. Mean ROTs considering the flight types

Note that the arrival-departure rate was determined as 50%-50% and the H-M rate was determined as 92%-8% based on real operations. However, the arrival rate increase scenarios were also examined to find out the arrival rate sensitivity of the model.

3. Mathematical Model

The proposed two-stage stochastic programming model includes the aircraft sequencing and scheduling problem for a single runway. This problem describes the sequencing of arrivals and departures with the objectives under several operational constraints, such as separation or flight time. The indices and the sets of the problem are as follows. i and j $\in I$ describe the set of aircraft where I $= \{1,2 \ldots .40\}$, $s \in S$ describes the set of scenarios where $\mathrm{S1} = \{1,2 \ldots .12\}$, and r $\in R$ describes the set of runways where R= {1}. There are several operational parameters to solve the problem including s_i, f_i, t_i that describe the system entry time of the ith aircraft, flight duration during the final approach path of the ith arrival aircraft, and the taxi duration of the ith departure aircraft, respectively. M, P_s, and $W_{i,\mathrm{j}}$ describe the large enough number, probabilities of the scenarios including REP and ROT uncertainties, and the separation parameter between the consecutive ith and jth aircraft, respectively. In stochastic programming, two types of decision variables are included in the problem, which are the first stage and the second stage decision variables. $a_{i,j}$, is a binary first stage variable that is 1 if the ith arrival aircraft is assigned to the touchdown point of the runway before the jth aircraft, and 0 otherwise. There are four second-stage variables in the problem: $l_{i,s}$, $d_{i,s}^{air}$, $d_{i,s}^{queue}$, and td_s describe the touchdown time of the ith aircraft, the airborne delay of the ith arriving flight, the queue delay of the ith departing aircraft, and the total delay of arrival and departure aircraft in scenario s, respectively. Based on these parameters and decision variables some operational constraints are included in the model. Equations (1) and (2) determine the arrival touchdown times and departure times for each scenario (including both REP and ROT uncertainties), respectively.

$$l_{i,s} = s_i + f_i + d_{i,s}^{air} \qquad \forall \mathrm{i} \in I,\ \forall \mathrm{s} \in S\ \ op(i) = 1 \qquad (1)$$

$$l_{i,s} = s_i + t_i + d_{i,s}^{queue} \qquad \forall \mathrm{i} \in I,\ \forall \mathrm{s} \in S\ \ op(i) = 2 \qquad (2)$$

The maximum airborne delays for arrivals and queue delays for departures are limited to 600 seconds by Equations (3) and (4), respectively.

$$d_{i,s}^{air} \leq 600 \qquad \forall \mathrm{i} \in I,\ \forall \mathrm{s} \in S\ \ op(i) = 1 \qquad (3)$$

$$d_{i,s}^{queue} \leq 600 \qquad \forall \mathrm{i} \in I,\ \forall \mathrm{s} \in S\ \ op(i) = 2 \qquad (4)$$

Arrivals are assumed to be delayed by the controller, if necessary, before arriving at the final approach fix. Equation (5) ensures that all the aircraft are assigned to the same runway.

$$\sum_{r}^{R} x_{i,\mathrm{s},r} = 1 \qquad \forall \mathrm{i} \in I, \forall \mathrm{s} \in S \qquad (5)$$

Separations must be ensured between successive aircraft. ICAO regulates the separations for landing and take-off phases depending on the wake turbulence categories of aircraft (Dönmez et al., 2021; ICAO, 2017). However, a higher separation time than the ICAO wake turbulence separations is required in our case. For this type of runway, the minimum separation requirements are determined by authorities, based on the ROTs of aircraft (Dönmez et al., 2021). In our case, 4 NM separations must be ensured between successive arrivals. This corresponds to 110 seconds considering 130 kts constant final approach speed, and a 1-minute separation must be ensured after a departure aircraft begins its departure roll (2 minutes if the leading aircraft is H and the trailing is M category). Departure aircraft can take off after an arrival vacates the runway. Table 4 shows the separation requirement of the runway in our study.

Table 4. Separations

	Trailing aircraft	**Arrival**	**Departure**
Leading	Arrival	4 NM (110 seconds)	ROT of arrival
Aircraft	Departure	1 minute	1 minute*

*2 minutes if the leading aircraft is H and the trailing is M category.

Constraints (6) and (7) ensure the safe separation between successive aircraft.

$$l_{i,s} - l_{j,s} \geq W_{i,\mathrm{j}} - M \cdot a_{i,\mathrm{j}} \qquad \forall \mathrm{i,j} \in I, \forall \mathrm{s} \in S \qquad (6)$$

$$l_{j,s} - l_{i,s} \geq W_{i,j} \ - M \cdot (1 - a_{i,j}) \qquad \forall i, j \in I, \forall s \in S \qquad (7)$$

Equation (8) calculates the total delays for each scenario. Equation (9) describes the objective function to minimize the total delay by considering all scenarios and probabilities.

$$td_s = \qquad \sum_{i}^{I} d_{i,s}^{air} + d_{i,s}^{queue} \qquad (8)$$

$$z1 = \qquad min \sum_{s}^{S} td_s \cdot P_s \qquad (9)$$

4. Results

In this section first 50%-50% arrival-departure mix traffic conditions were generated and solved for 10 different ETAD distribution samples for all models. All models were compared in terms of total arrival and departure delays. Then, the arrival rate was increased to 75% to examine the sensitivity of the model for arrival volume. In addition, arrival departure delay distributions in these samples were examined for both 50% and 75% arrival rate samples. Finally, the average solution times of the samples for all models were examined. Table 5 shows the delays (sec) for 10 different ETA samples with a 50% arrival rate.

As seen in Table 5, deterministic sequences were not feasible in 40% of the samples. This is because delay constraints in the model cannot be satisfied when the sequences are applied under REP and ROT uncertainties. In the STC model, on the other hand, all sequences have resulted in feasible solutions. Also, average delay savings of 12.34% and 0.55% were found compared to FCFS and DET models. As a result, the STC model presented robust and efficient sequences compared to the other models.

Table 5. Results of the ETA samples with a 50% arrival rate

“	Model results			Delay savings of STC model %	
	VES(FCFS)	**VEST(DET)**	**STC**	**Compared to FCFS**	**Compared to DET**
1	1681.51	1547.09	1540.32	8.40	0.44
2	1902.09	Infeasible	1838.35	3.35	Not calculable
3	2292.43	1633.51	1633.51	28.74	0.00
4	2419.58	Infeasible	2191.48	9.43	Not calculable
5	2315.38	2122.51	2113.28	8.73	0.43
6	1599.93	1341.18	1318.53	17.59	1.69
7	1410.65	Infeasible	1267.31	10.16	Not calculable
8	2382.05	1915.57	1910.18	19.81	0.28
9	2230.06	Infeasible	1847.20	17.17	Not calculable
10	1895.86	1904.00	1895.30	0.03	0.46
Average	**2027.86**	**1743.98**	**1735.19**	**12.34%**	**0.55%**

Table 6 shows the result of the samples with 75% arrival rates. As seen in Table 6, the average saving of the STC model increased to 1.73% compared to the DET model. Also, note that all solutions provided by the DET model were feasible for all samples. This is because a more homogeneous mix is obtained with a lower number of departure aircraft entering between arrivals in the traffic mix. This mix allows that feasible sequences under uncertainties could be obtained with the deterministic approach. However, the STC model still offered a more robust and efficient solution compared to both FCFS and DET models.

Table 6. Results of the ETA samples with a 75% arrival rate

Sample	Model results			Delay savings of STC model %	
	VES(FCFS)	VES(DET)	STC	Compared to FCFS	Compared to DET
1	962.01	970.71	955.24	0.70	1.59
2	1341.38	1370.34	1334.60	0.51	2.61
3	1167.55	1075.07	1057.53	9.42	1.63
4	1201.95	1117.09	1094.20	8.96	2.05
5	1405.22	1319.52	1312.74	6.58	0.51
6	1093.73	989.00	988.99	9.58	0.00
7	890.84	914.38	890.85	0.00	2.57
8	1081.15	1081.15	1051.22	2.77	2.77
9	1432.94	1182.60	1147.59	19.91	2.96
10	1275.58	1105.41	1098.68	13.87	0.61
Average	**1185.24**	**1112.53**	**1093.16**	**7.23%**	**1.73%**

The delay distributions considering arrival and departure delays are also examined. Figures 10 and 11 present the models' results in terms of average delays of the samples that were solved with a 50% and 75% arrival rate, respectively.

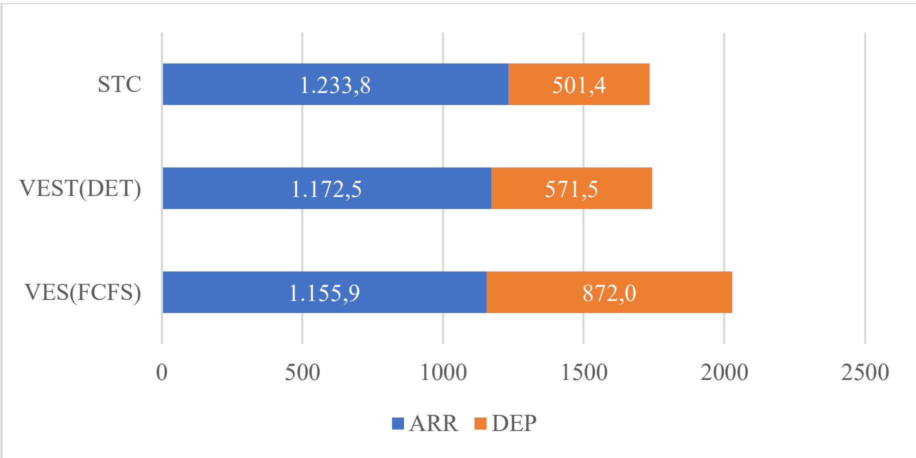

Figure 10. Arrival-departure delays (sec) in samples with a 50% arrival rate

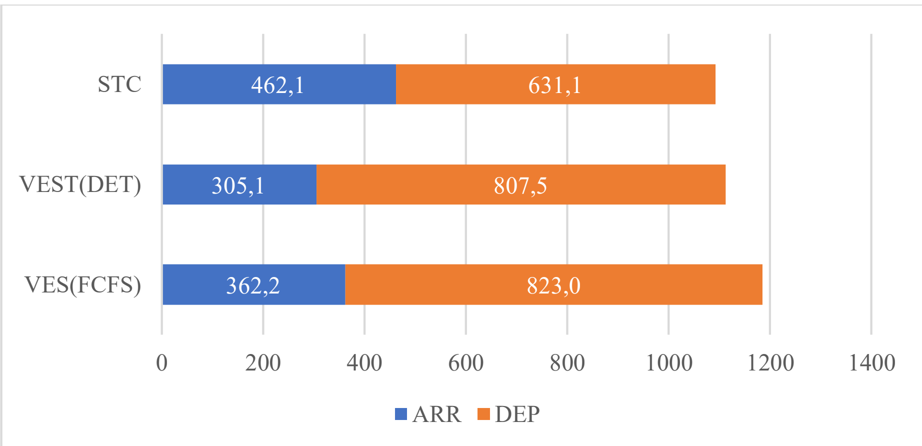

Figure 11. Arrival-departure delays (sec) in samples with a 75% arrival rate

As seen in Figures 10 and 11, although the STC model resulted in higher arrival delays, it resulted in lower departure delays and total delays for both 50% and 75% arrival rates. This is due to the objective function of the models considering the total delays while providing optimal sequences. Another efficiency metric in air traffic optimization problems is the average solution time (AST) of a sample. Lower solution times indicate a higher solution time efficiency of the models. The AST of the samples is presented in Figure 12 for all models.

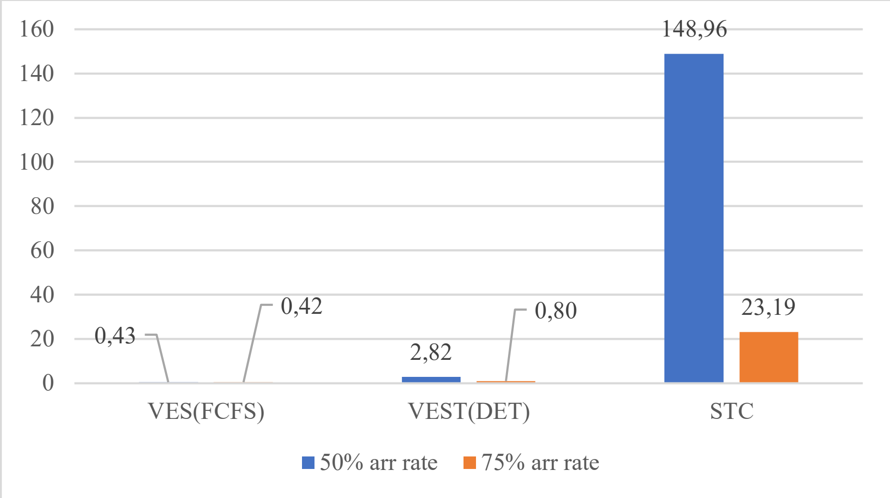

Figure 12. ASTs (sec)

As presented in Figure 12, the AST of the FCFS and DET models are significantly lower than the STC model. This is due to the STC model considering all uncertainties while providing the sequences. The DET model did not consider any uncertainty in the first stage of the problem, hence the ASTs of the samples were lower than the STC. FCFS, on the other hand, has fixed sequences, therefore the model finds solutions quickly. As seen in Figure 12, the AST of the STC model significantly decreased as the arrival rate increased.

5. Conclusion, discussion, and future work

In this study, a two-stage stochastic model was developed to find optimal arrival-departure sequences in terms of total delay for runways with multiple exits. The presented model considers both REP and ROT uncertainties. The developed model was also compared to other methods, such as FCFS and deterministic approaches. Various traffic samples with different arrival rates were solved to make clear comparisons between the models. As a result, the stochastic model was found to provide robust and efficient solutions compared to other models.

While the sequences presented by the STC model were applicable for 100% of all samples with a 50% arrival rate, the sequences presented by the DET model were not feasible in 40% of the samples for the objective of the minimization of the total delay. In addition, the delay savings of the STC model compared to the deterministic approach increased as the arrival rate increased. Note that the DET approach in this study considers the most probable runway exit of the aircraft while presenting a sequence. Therefore, the DET approach returned significantly better results than FCFS since it is based on historical data. It is noteworthy that the STC model has an advantage even over such a DET model. In the DET approach, if there were no historical data, sequences may be planned that assume aircraft will leave from the runway end or taxiway C2, which may result in more delays.

The STC model provided delay savings of up to 28.74% and 2.7% delay savings compared to FCFS and DET models, respectively. Considering arrival departure delay distributions, although sequences provided by the STC model resulted in higher arrival delays, it resulted in lower departure delays and total delays. This is due to the objective function of the models being determined considering the total delays while providing optimum sequences.

Although the AST of the STC model is higher than the other approaches, considering that the air traffic control planning horizon is approximately 2 hours, it was observed that the STC model gave solutions well within this time (between 0.1 and 2.5 minutes), for scenarios with 40 aircraft. However, considering that the aircraft sequencing scheduling problem increases exponentially with the number of aircraft, it should be noted that heuristic algorithms may be needed for scenarios involving higher aircraft numbers.

The result of this study indicates that the STC model can be easily applied to runways with multiple exit points and provides efficient and robust solutions compared to other models, within acceptable time limits. However, the model can be improved by observing and analyzing more radar track data. Observing more flights can increase the number of possible scenarios. Also, including two-way operations considering sudden wind changes in the model can increase its realism. However, all these conditions may increase solution times, and heuristics and metaheuristic approaches may be needed, which can be performed with future work.

Researchers' Contribution Rate Statement

All stages of the study were carried out by the corresponding author.

Acknowledgement

This research received no specific grant from any funding agency

Conflict of Interest Statement

There is no conflict of interest to declare.

References

AIP Turkey. (2022). Aeronoutical Information Publication; https://www.dhmi.gov.tr/Sayfalar/aipturkey.aspx

Alonso, A., Escudero, L. F., & Teresa Ortuño, M. (2000). A stochastic 0–1 program based approach for the air traffic flow management problem. *European Journal of Operational Research*, *120*(1), 47–62. https://doi.org/10.1016/S0377-2217(98)00381-6

Atkin, J. A. D., Burke, E. K., Greenwood, J. S., & Reeson, D. (2008). On-line decision support for take-off runway scheduling with uncertain taxi times at London Heathrow airport. *Journal of Scheduling*, *11*(5), 323–346. https://doi.org/10.1007/s10951-008-0065-9

Cecen, R. K., Cetek, C., & Kaya, O. (2020). Aircraft sequencing and scheduling in TMAs under wind direction uncertainties. *The Aeronautical Journal*, *April*, 1–17. https://doi.org/10.1017/aer.2020.68

Dai, L., & Hansen, M. (2020). Real-Time Prediction of Runway Occupancy Buffers. *2020 International Conference on Artificial Intelligence and Data Analytics for Air Transportation (AIDA-AT)*, 1–11. https://doi.org/10.1109/AIDA-AT48540.2020.9049165

Dönmez, K., Çetek, C., & Kaya, O. (2021). Aircraft Sequencing and Scheduling in Parallel-Point Merge Systems for Multiple Parallel Runways. *Transportation Research Record: Journal of the Transportation Research Board*, 036119812110494. https://doi.org/10.1177/03611981211049410

Hanbong Lee, & Balakrishnan, H. (2012). Fast-time simulations of Detroit Airport operations for evaluating performance in the presence of uncertainties. *2012 IEEE/AIAA 31st Digital Avionics Systems Conference (DASC)*, 4E2-1-4E2-13. https://doi.org/10.1109/DASC.2012.6382349

Hockaday, S. L. M., & Kanafani, A. K. (1974). Developments in airport capacity analysis. *Transportation Research*, *8*(3), 171–180. https://doi.org/10.1016/0041-1647(74)90004-5

ICAO. (2005). *Aerodrome Design Manual (Doc 9157) Part 2 Taxiways, Aprons and Holding Bays*.

ICAO. (2017). *Procedures for air navigations services Air traffic management (Doc. 4444)*.

Jeddi, B. G., Shortle, J. F., & Sherry, L. (2006). *Statistics of the Approach Process at Detroit Metropolitan Wayne County Airport*. *703*, 1–8.

Martinez, D., Belkoura, S., Cristobal, S., Herrema, F., & Wächter, P. (2018). A boosted tree framework for runway occupancy and exit prediction. *SESAR Innovation Days*, *December*.

Matthews, M., Wolfson, M., DeLaura, R., Evans, J., Reiche, C., Balakrishnan, H., & Michalek, D. (2009). Measuring the Uncertainty of Weather Forecasts Specific to Air Traffic Management Operations,. *Aviation, Range, and Aerospace Meteorology Special Symposium on Weather-Air Traffic Management Integration*, 1–17. http://tinyurl.com/cg5ldwc

Meijers, N. P. (2019). *Data-driven predictive analytics of runway occupancy time for improved capacity at airports*. *December*. https://dspace.mit.edu/handle/1721.1/128034%0Afiles/300/Meijers - 2019 - Data-driven predictive analytics of runway occupan.pdf%0Afiles/301/128034.html

Nguyen, A., Pham, D., Lilith, N., & Alam, S. (2020). *Model Generalization in Arrival Runway Occupancy Time Prediction by Feature Equivalences*. *Icrat*.

Nikoleris, T., & Hansen, M. (2016). Effect of Trajectory Prediction and Stochastic Runway Occupancy Times on Aircraft Delays. *Transportation Science*, *50*(1), 110–119. https://doi.org/10.1287/trsc.2015.0599

R**appaport, D., Yu, P., Griffin, K., & Daviau, C.** (2009). Quantitative Analysis of Uncertainty in Airport Surface Operations. *9th AIAA Aviation Technology, Integration, and Operations Conference (ATIO)*, *September*, 1–16. https://doi.org/10.2514/6.2009-6987

Shone, R., Glazebrook, K., & Zografos, K. G. (2021). Applications of stochastic modeling in air traffic management: Methods, challenges and opportunities for solving air traffic problems under uncertainty. *European Journal of Operational Research*, *292*(1), 1–26. https://doi.org/https://doi.org/10.1016/j.ejor.2020.10.039

Stamatopoulos, M. A., Zografos, K. G., & Odoni, A. R. (2004). A decision support system for airport strategic planning. *Transportation Research Part C: Emerging Technologies*, *12*(2), 91–117. https://doi.org/10.1016/j.trc.2002.10.001

Tielrooij, M., Borst, C., Mulder, M., & Nieuwenhuisen, D. (2013). Supporting arrival management decisions by visualising uncertainty. *SIDs 2013 - Proceedings of the SESAR Innovation Days*, *November*.

Trani AA, Hobeika AG, Sherali HD, Kim BJ, Sadam CK. (1990) Runway Exit Designs for Capacity Improvement Demonstrations.