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Inherent delays and operational reliability of airline schedules

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Abstract

This paper explores the inherent delays of airline schedules resulting from limited buffer times and stochastic disruptions in airline operations. The reliability of airline schedules is discussed and a set of measuring indices is developed to evaluate schedule reliability. It is found that significant gaps exist between the real operating delays, the inherent delays (from simulation) and the zero-delay scenario. Delay propagation and its impact on schedule reliability are also discussed. Results show that airline schedules must consider the stochasticity in daily operations. Schedules may become robust and reliable, only if buffer times are embedded and designed properly in airline schedules.

Keywords: Schedule reliability; On-time performance; Inherent delay; Markov Chain; Simulation model

1. Background

The airline scheduling requires schedule design, fleet assignment, aircraft routing and then crew scheduling. General optimisation objectives of schedule planning may include: minimising operating costs, maximising profits and maximising the utilisation of fleet and crew. Since the optimisation process tends to generate tight aircraft routing plans, schedule buffer times are usually embedded when tackling aircraft routing problems. The function of embedded buffer times is to control small-scale delays, while maintaining the on-time performance (OTP) of flights and the operational reliability of schedules. Given the nature of stochastic disruptions (either large or small scale) from daily flight operations and other uncontrollable issues such as weather, we can observe the 'delay propagation phenomenon' in airline networks. This describes the propagation of flight delays from a delayed flight to other flights in the network through aircraft routing, passenger connections or crew connections (Abdelghany et al., 2004).

After finishing schedule planning, aircraft routing plans are generated for different fleets. It is generally believed by industry schedulers that once the routing plans are designed, there exists an 'inherent OTP status' for a schedule, which reflects the schedule planning philosophy used by an airline, e.g. the trade off between using buffer times to pad a schedule and maximising fleet utilisation. This concept is illustrated in Fig. 1 below. For ideal schedule operations, all delays are absorbed by buffer times, labelled the Perfect Case, while the real-world operating results after schedule operation is labelled the Reality Case. In-between the Perfect Case and the Reality Case on the right of Fig. 1, there exists a Dream Case reflecting the inherent OTP status of a schedule plan. Since it is not economically feasible to pad a schedule to eliminate delays, the inherent OTP status (the Dream Case) of a schedule reflects implicitly the 'OTP expectation' of an airline for the real OTP in future flight operations.

Currently, the expected OTP can only be realised roughly through the amount of buffer times used for each flight segment in a schedule, e.g. ground buffer times and/or airborne buffer times. During schedule operations, delays may impact an individual flight as well as other flights via delay propagation. This explains the general understanding in the airline industry why some flights tend to be late, if they are scheduled to

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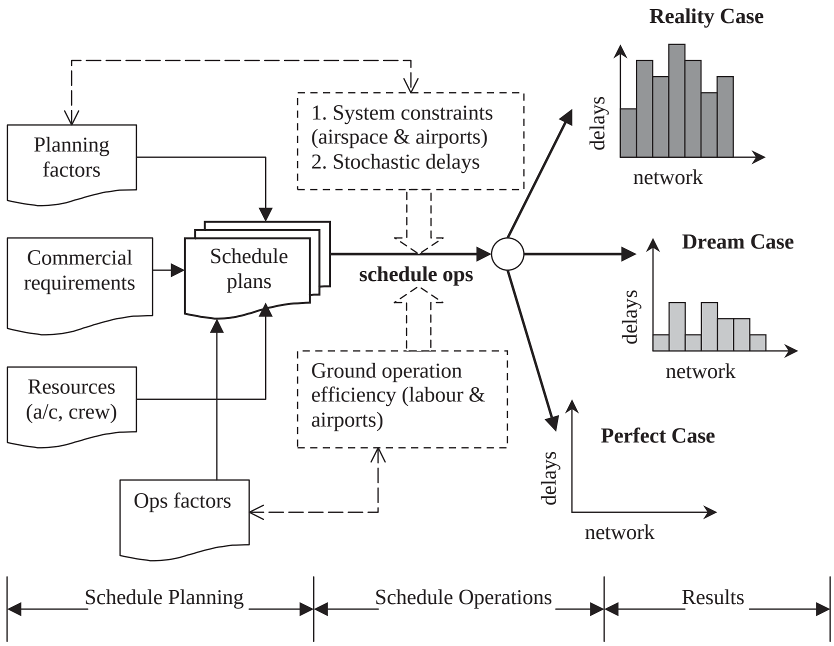

Fig. 1. Key factors influencing OTP of airline schedules.

follow certain flights in aircraft routing (Watterson and De Proost, 1999). Although experienced airline schedulers can capture this concept and adopt it in schedule planning to improve schedule reliability and robustness, it is still difficult for airlines to evaluate the expected OTP before schedule implementation. A key issue for airlines is also to evaluate the performance of real OTP after schedule implementation and more importantly: how the real OTP is performing against the expected OTP?

Therefore, it is the objective of this paper to explore the inherent OTP status of airline schedules. A simulation model is developed based on Markov Chain algorithm to describe the stochastic nature of aircraft turnaround operations and aircraft routing in a network. To evaluate the operational reliability of airline schedules, a number of reliability indices are developed and other related issues regarding airline schedule reliability are also discussed in the paper.

2. Modelling inherent delays and schedule reliability

2.1. Model considerations and approach

Running an airline schedule is a huge task. On the one hand, airlines try to maintain high schedule OTP because OTP influences the travel experience of passengers, in particular delay-sensitive travellers as well as passengers' re-purchase intention and loyalty to a specific airline (Lee and Moore, 2003). On the other hand, disrupting events occurring in airline operations divert the OTP from the operating target and cost airlines excessive delay costs. The economic impact of flight delays due to large-scale disrupting events, e.g. airport closure due to storms, is estimated to account for 40% of total annual delay costs in the National Air Space in the US, whilst the remaining 60% of costs are due to small-scale delays (Shavell, 2000). There is a significant amount of work in the literature dealing with both the schedule optimisation issue and the schedule recovery strategies, e.g. Teodorovic and Stojkovic (1995); Barnhart et al. (1998). Progress in this field has been significant and has brought forward our understanding of complex schedule recovery issues. Less attention, however, has been given to address the other key delay source, i.e. small-scale disruptions, which cost airlines no less than those due to large-scale disruptions. Hence, the scope of this paper is to focus on 'minor delays' in airline operations and the impact of delay propagation phenomenon in a network.

Delays to airline schedules may result from many different causes. Some are due to airport capacity limits, while some may be due to disrupting events, e.g. missing check-in passengers at airports. According to delay analyses carried out by Eurocontrol, around 47% of delays are due to airline-related operations at airports such as aircraft turnaround operations, while the remaining delays are due to other causes such as air traffic control, weather and airport capacity constraints (Eurocontrol, 2001). Based on this, the model we develop here is limited to modelling airline operations at airports, which mainly include aircraft turnaround operations. Since all flights are connected by aircraft routings in a network and this is the main cause of delay propagation, we also consider aircraft en-route operations between airports in a network.

During the time of irregular airline operations due to large-scale disruptions, delays propagate in airline networks via resource connections, e.g. crew transfer, passenger transfer and baggage handling. The behaviour of delay propagation during such an irregularity is quite different from the one due to minor delays. Since the punctuality data available for this research is from a non-hubbing airline in Europe, the simulation model used in the paper does not explicitly consider resource connections used by network carriers. This simplification is valid for non-hubbing schedules subject to minor delay impacts or weak-hubbing schedules, which contain more buffer times between transfers (such as British Airways's operation at London Heathrow Airport). Generalisation is needed for the model in the future, if it is to be applied to a strong-hubbing schedule.

Most disruptions in airline operations are unpredictable and stochastic in nature such as missing check-in passengers at terminals, late connecting passengers and baggage due to late inbound aircraft. These disruptions delay airline operations at airports and can only be managed by embedded schedule buffer times. To model a complex and stochastic airline schedule system, simulation models are employed. The advantage of this approach is its capability of dealing with complex systems as well as catching the stochasticity embedded in the system. Also, the simulation model allows us to observe how the whole system behaves given the interactions between fixed flight schedules and stochastic disrupting events emerging in operations.

The OTP of airline schedules is usually measured against the published schedules with 15 min delay time allowance. This measurement indicator is usually called D + 15 OTP in the industry. OTP can also be measured by the time a flight is delayed against the published flight times. In this paper, when evaluating the inherent OTP of airline schedules, we use both measures, i.e. D + 15 and delay times as OTP indicators.

2.2. Modelling aircraft routing in a network

An airline schedule comprises flights among a number of destinations operated by aircraft fleets that may contain different aircraft types. Each aircraft is assigned a number of flights during a cycle time (1 day for domestic and 1 week for international operations) so each flight in a schedule is flown exactly once by one aircraft in the fleets. Those flights assigned to the same aircraft during the cycle period form the 'route' for the aircraft to operate. The operation of a route by an aircraft is usually referred as aircraft rotation (or aircraft routing), which involves multiple departures, arrivals, en-route operations in the airspace, and turnaround operations on the ground at airports. Hence, the simulation is composed of two sub-models, called Turnaround model and En-route model. The simulation model described herein is based on an earlier model developed by Wu and Caves (2002a, 2003b, 2004a).

2.2.1. Modelling aircraft turnaround operations

There have been a few attempts to model the complex aircraft turnaround operations. Some have approached this issue by using critical path method to identify critical workflows (Braaksma and Shortreed, 1971; Hassounah and Steuart, 1993), whilst others used analytical models to describe turnaround operations (Wu and Caves, 2002b, 2003a, 2004b). To capture the stochasticity in turnaround operations, some models were developed using Monte Carlo simulation techniques and Markov Chain algorithms (Mederer and Frank, 2002). Given the unique characteristics of aircraft turnaround operations, a hybrid approach combining Markov Chain algorithm and discrete-event simulation is employed in the Turnaround model:

Markov Chain algorithm: Two major processes in aircraft turnaround operations have been identified as critical to the punctuality of turnarounds: passenger processing and cargo/baggage processing. These operations consist of a series of sequential service activities in which delays to one activity may cause down-line delays to following activities. Also, the service time of each activity is itself a stochastic variable subject to aircraft types, the number of passengers, the work efficiency and availability of ground staff. To model the stochastic while sequential interactions between activities in these two processes, a Markov Chain model is developed. Each process is modelled as a semi Markov Chain, which moves between activities from the arrival state towards the departure state with disruption states in between, if any. Two processes are modelled as parallel Markov Chains and implemented by Monte Carlo simulation.

Discrete-event simulation: Some aircraft services are independent from above mentioned turnaround processes, e.g. aircraft fuelling and engineering check. Considering the uncertainty of these individual activities, discrete-event driven simulations are used to supplement the Markov Chain model.

The Turnaround model is described by following Eqs. (1)–(4), where D_{ij}^{D} denotes the departure delay of flight (i,j) from Airport i to j; t_{ij}^{ATD} is the actual time of departure of flight (i,j), which forms a probability density function (PDF), denoted by $f_{ij}^{\mathrm{ATD}}(t)$; S_{ij}^{D} is the given scheduled departure time.

$$D_{ij}^{\mathrm{D}} = t_{ij}^{\mathrm{ATD}} - S_{ij}^{\mathrm{D}}, \tag{1}$$

where t_{ij}^{ATD} is influenced by two variables, namely the actual arrival time of a previous flight (h,i), denoted by t_{hi}^{ATA}, and a stochastic turnaround operation time, T_{ij}^{OP}. T_{ij}^{OP} is the longest time required to finish all turnaround activities including two major turnaround processes (passenger processing and cargo/baggage processing), delays from disruptions, and other aircraft service activities as described in (Eq. (2)).

$$\begin{aligned} t_{ij}^{\mathrm{ATD}} &= t_{hi}^{\mathrm{ATA}} + T_{ij}^{\mathrm{OP}} \\ &= t_{hi}^{\mathrm{ATA}} + \max\left[T_{ij}^{\mathrm{cargo}}, T_{ij}^{\mathrm{pax}}, T_{ij}^{\mathrm{events}}\right]. \end{aligned} \tag{2}$$

For instance, T_{ij}^{cargo} is the time required to finish cargo and baggage process for flight (i,j). A number of n activities need to be carried out in this process and each activity k has a stochastic operating time and an expected operating time, ε_k is given in (Eq. (3)).

$$T_{ij}^{\mathrm{cargo}} = \sum_{k=1}^{n} \varepsilon_k \text{ for activity } k \in \Omega. \tag{3}$$

Activity k is modelled as a Markov Chain state, which transits to any state at any time t with a state transient probability function, $A_k(t)$ as shown by (Eq. (4)). By the same token, the time required to finish passenger processing, i.e. T_{ij}^{pax} is also modelled as a Markov Chain.

$$\sum_{k=1}^{n} \varepsilon_k = \sum_{k=1}^{n} (E[t]) = \sum_{k=1}^{n} \left(\int_0^\infty t A_k(t)\,\mathrm{d}t \right). \tag{4}$$

Discrete events may delay aircraft departure if the finish time of an event exceeds the scheduled departure time. Discrete events are modelled as stochastic variables in (Eq. (5)), where $\varepsilon_q^{\mathrm{e}}$ is the expected disruption time of event q with occurrence probability P_q^{e}.

$$\begin{aligned} T_{ij}^{\mathrm{events}} &= \max[\varepsilon_q^{\mathrm{e}}] = \max\left[P_q^{\mathrm{e}} E[t]\right] \\ &= \max\left[P_q^{\mathrm{e}} \int_0^\infty t \Phi_q^{\mathrm{e}}(t)\,\mathrm{d}t \right]. \end{aligned} \tag{5}$$

2.2.2. Modelling aircraft en-route operations

The en-route model is described by (Eqs. (6) and (7)). D_{ij}^{A} denotes the arrival delay of flight (i,j) at destination Airport j; t_{ij}^{ATA} is the actual time of arrival of flight (i,j), that forms a PDF, denoted by $f_{ij}^{\mathrm{ATA}}(t)$; S_{ij}^{A} is the given scheduled arrival time at Airport j. The actual time of arrival of flight (i,j), t_{ij}^{ATA}, is accordingly determined by two stochastic variables: the actual time of departure of flight (i,j) at Airport i and the expected en-route flight time between Airport i and j, denoted by $\int_0^\infty tf_{ij}^{\mathrm{ER}}(t)\,\mathrm{d}t$ in (Eq. (7)).

$$D_{ij}^{\mathrm{A}} = t_{ij}^{\mathrm{ATA}} - S_{ij}^{\mathrm{A}}, \tag{6}$$

$$t_{ij}^{\mathrm{ATA}} = t_{ij}^{\mathrm{ATD}} + \int_0^\infty tf_{ij}^{\mathrm{ER}}(t)\,\mathrm{d}t. \tag{7}$$

Delays due to constrains of airport capacity and airspace congestion are modelled aggregately by the en-route operation time variable in Eq. (7), that counts from the time an aircraft is pushed back at a gate till the time an aircraft is on chock at the destination airport. Accordingly, the actual turnaround time for an aircraft is the time between on and off chock at a gate.

2.3. Evaluating schedule reliability

The operational reliability of an airline network is the outcome of the interaction between fixed schedules and stochastic flight operations. Airline schedules are designed and usually optimised to achieve the maximum profits possible. A trade-off situation exists, where an airline tries to utilise/optimise its resources (fleet and crew), while considering the flexibility/reliability of schedule operations. To allow some space to manoeuvre in irregular operations and maintain a target OPT, buffer times (slack times) are widely used to relax airline schedules.

As shown earlier in Fig. 1, it is not economically feasible to achieve the 'Perfect Case', in which delays are fully controlled by buffer times. Neither is it methodologically sound to measure the performance of operating results, i.e. the 'Reality Case' against the 'Perfect Case', because airline schedule planning is not aimed at achieving the 'Perfect Case' but has only allowed limited flexibility to cover delays from minor delays. Hence, it is proposed in this paper that the 'inherent OTP', i.e. the 'Dream Case' could be used as the performance measurement benchmark of the 'Reality Case'. The advantage of this new approach is to allow airlines measure the performance gap between the real operating results and the expected results coming after schedule planning. This measure will pinpoint those weak links in aircraft routing schedules, so as to improve the reliability and robustness of schedule planning. However, a drawback of this approach is the need to run a simulation model to generate the measurement benchmark, i.e. the 'inherent' OTP status.

The developed aircraft rotation simulation model is therefore used to generate the inherent OTP status for measuring schedule reliability. Based on this methodology, a number of reliability indices are formulated by Eqs. (8)–(10).

$$R_{ij}^{\mathrm{D}} = \frac{ED_{ij}^{\mathrm{D}}}{D_{ij}^{\mathrm{D}}}, \quad R_{ij}^{\mathrm{A}} = \frac{ED_{ij}^{\mathrm{A}}}{D_{ij}^{\mathrm{A}}}, \quad R_{ij} = \frac{(ED_{ij}^{\mathrm{D}} + ED_{ij}^{\mathrm{A}})}{(D_{ij}^{\mathrm{D}} + D_{ij}^{\mathrm{A}})}, \tag{8}$$

where in (Eq. (8)), $R_{ij}^{\mathrm{D}}/R_{ij}^{\mathrm{A}}$ denotes the departure/arrival reliability of flight (i,j), respectively; $ED_{ij}^{\mathrm{D}}/ED_{ij}^{\mathrm{A}}$ represents the expected departure/arrival delay of (i,j), while

D_{ij}^{D} and D_{ij}^{A} the actual departure and arrival delay of (i,j). Hence, R_{ij} is used to evaluate the operational reliability of flight (i,j). By the same token, the reliability of aircraft rotation k is modelled in Eq. (9), where R_k represents the reliability of rotation k. The network reliability, denoted by R_{NET} in Eq. (10) is used to evaluate the network-wide reliability of a schedule. Reliability indices developed here can be used tactically to measure the performance of individual flights such as R_{ij}, and strategically to measure the overall reliability of a network system such as R_k and R_{NET}.

$$R_k = \frac{\sum_{(i,j)\in k} (ED_{ij}^{\mathrm{D}} + ED_{ij}^{\mathrm{A}})}{\sum_{(i,j)\in k} (D_{ij}^{\mathrm{D}} + D_{ij}^{\mathrm{A}})} \ \forall (i,j) \in k \ \forall k \in K, \tag{9}$$

$$R_{\mathrm{NET}} = \frac{\sum_{(i,j)\in k}^{K} (ED_{ij}^{D} + ED_{ij}^{A})}{\sum_{(i,j)\in k}^{K} (D_{ij}^{D} + D_{ij}^{A})} \ \forall (i,j) \in k \ \forall k \in K. \tag{10}$$

3. Model application

3.1. Data sources and model inputs

Flight schedules and punctuality data from a European carrier are used to test the aircraft rotation model. Due to an information confidentiality agreement with the carrier (denoted by Airline P hereafter), flight numbers and airport names are replaced by assigned codes. Since Airline P's schedule is planned for high aircraft utilisation, a long schedule buffer time (30–50 min) is usually embedded in the turnaround time of midday flights. A single aircraft type is used by Airline P and the scheduled turnaround time varies from 20 to 40 min at different ports. The long turnaround times are mainly planned for out-station operations and those ports with lower punctuality performance in the past.

Since the aircraft rotation model is implemented by Markov Chain algorithms and discrete-event simulation (using Monte Carlo techniques), some parameters are required to configure the simulation model. Two sets of parameters are essential for the model: schedule data and statistics of real-world turnaround operations data. The schedule data required include the planned departure/arrival times of flights and the standard operation times of activities in a turnaround, i.e. the minimum turnaround time. The minimum turnaround time depends on two factors including aircraft types and real operating time at ramps. The former is limited by aircraft design, while the latter varies subject to the amount of resources allocated to a turnaround at a specific port. The difference between the scheduled turnaround time and the minimum turnaround time is the schedule buffer time, which may also reflect the 'degree of flexibility' being considered in schedule planning.

Statistics driven from past punctuality data are required to configure the simulation model. These data include: the statistics of normal and abnormal activities including the occurrence probability and basic statistics (mean and variance). With the schedule data and the statistics of disruptions, the aircraft rotation model is used to generate 'the inherent status' of airline schedules. Two sets of sample parameters are shown in Table 1 representing turnaround operations at two airports. It is found from past records that turnaround operations at Airport 14 experience more disruptions, especially in passenger processing. Each airport in the simulation model has a corresponding configuration like those in Table 1, so to model the real-world operating environment at different airports in an airline network. The schedule of Airline P is ran by the simulation model for 1000 times (representing 1000 days operation) to limit simulation noises.

3.2. Simulation results—network overview

Simulation results and real-world operating delays are used to calculate the departure/arrival reliability of each aircraft rotation plan (R_k) and the overall network departure/arrival reliability (R_{NET}). Results are shown in Figs. 2 and 3. We can find that the reliability of individual rotations varies from as low as 13% to as high as 71% for departure and from 8% to 65% for arrival. The network-wide departure reliability is 36% and the arrival reliability is 33%. Consequently, the network reliability of the whole schedule is measured 35%. To compare the real-world OTP with the inherent OTP, scenario analyses are conducted:

- *Scenario A*: the real delays of the schedule (obtained from Airline P).
- *Scenario B*: the inherent delays of the schedule (from simulation).
- *Scenario C*: longer turnaround time (10 more minutes) for early morning flights.
- *Scenario D*: longer turnaround time (10 more minutes) for mid-day flights.
- *Scenario E*: longer turnaround time at the base airport of Airline P.

When real delays of individual flights are compared with simulated delays (representing the 'inherent status') in Fig. 4, significant gaps are found between two cases. Results in Fig. 4 reveal that significant gaps exist in some aircraft routing plans such as aircraft No. 2, 3, 5 and 10. This implies that delays in real-world operations

Table 1
Example parameters used to simulate ground operations at AP14 and AP17

Parameters	Operation at Airport 14	Operation at Airport 17
Scheduled turnaround time	30 min	40 min
Expected turn time	20 min	30 min
Cargo unloading (loading)	10 min each	15 min each
Pax deplane (enplane)	10 min each	15 min each
Standard deviation for cargo and passenger processing times	3–5 min	3–5 min
Probability to have:		
normal cargo unloading	90.9%	96.9%
cargo processing delays	0.1%	0.1%
ramp handling delays	9.0%	3.0%
Probability to have:		
normal cargo loading	84.9%	91.9%
cargo processing delays	0.1%	0.1%
ramp handling delays	9.0%	3.0%
passengers and baggage delays	6.0%	5.0%
Probability to have:		
normal pax boarding	70.0%	94.6%
crew delays	11.0%	0.4%
passenger delays	9.0%	1.0%
missing passengers	10.0%	4.0%
Probability to have:		
normal departure procedures	89.8%	98.4%
flight operation delays	0.6%	0.6%
departure process delays	9.0%	0.4%
weather delays	0.6%	0.6%

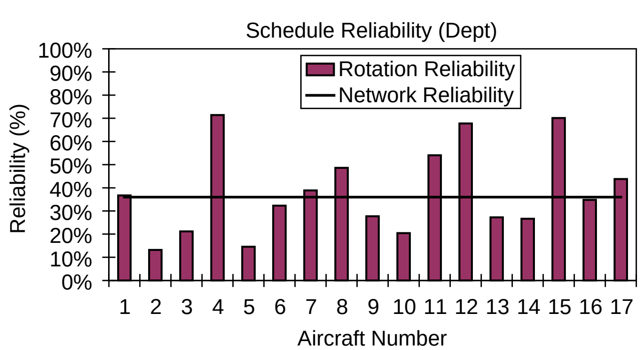

Fig. 2. Rotation reliability and network reliability (departure) of Airline P.

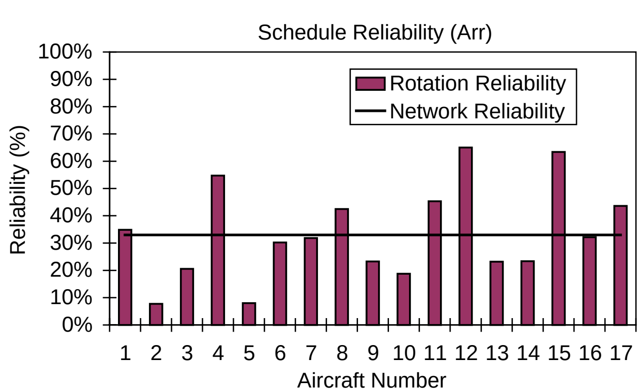

Fig. 3. Rotation reliability and network reliability (arrival) of Airline P.

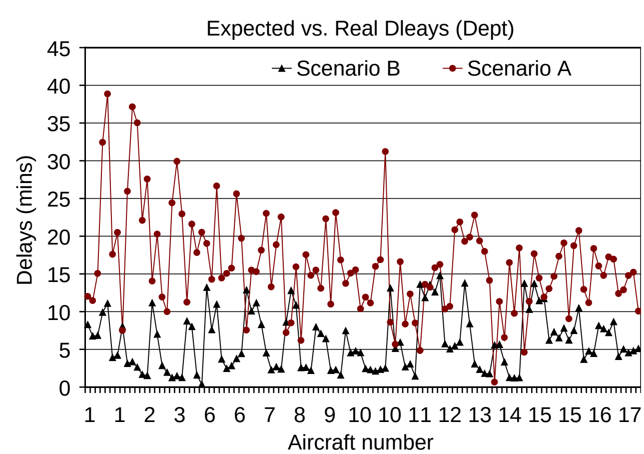

Fig. 4. Comparison between real delays (A) and the inherent delays (B).

are significantly higher than the 'inherent status' expected after schedule planning. While some rotations may exhibit low reliability, other rotations such as aircraft No. 4, 11, 12 and 15 show a relatively high operating reliability and smaller gaps in Fig. 4. To further investigate the causes for variant schedule reliability, aircraft No. 8 is chosen for a case study representing a rotation with medium operational reliability.

3.3. Simulation results—aircraft No. 8

Simulation results of aircraft No. 8 are shown in Figs. 5 and 6 (Scenario B) together with operating delays from past punctuality data (Scenario A). Results show that real operating delays of early segments, e.g. flight PP81 and PP82 are close to expectation, but later segments, e.g. PP84, PP85, and PP86 have higher delays than expected. A further investigation of the gaps between Scenario A and B shows that more airborne buffer time is allowed for later segments. The aircraft routing plan for aircraft No. 8 is given in Table 2. From Table 2, we can find that a long turnaround time (80 min) is scheduled for PP84 at AP17. The scheduled long turn time is expected to absorb accumulated delays from earlier segments (with 40-min buffer time) so as to control the potential propagation of delays in aircraft rotation.

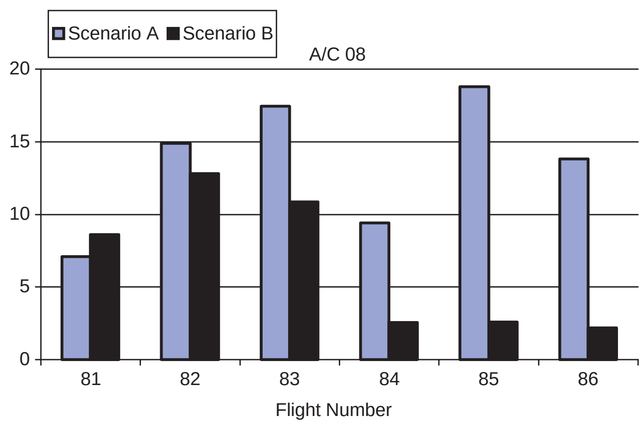

Fig. 5. Simulation results (departure delays) of the rotation schedule of A/C 08.

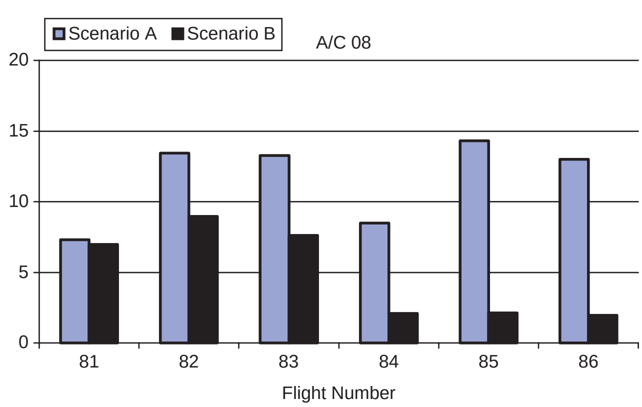

Fig. 6. Simulation results (arrival delays) of the rotation schedule of A/C 08.

It is seen in Figs. 5 and 6 that the average departure delay of PP84 is less than earlier segments in both scenarios. Delays from later flights of the rotation, however, still increase. Table 2 also shows that aircraft turn time for most flights in this rotation is just enough for standard turnaround operations. As a result, accumulated delays are not likely to be controlled by the schedule, except the mid-day long buffer times of PP84. Any further delays to Flights 85 and 86 will result in higher departure/arrival delays and possibly will propagate till the end of rotation. It is observed from these two figures that the developing trend of delays in Scenario B (Dream Case) is consistent with the one in Scenario A (Reality Case). This also validates the effectiveness of the model in capturing the stochastic characteristics of schedule operations in the real world.

OTP results from two cases are compared in Fig. 7. We can find that real operations of early segments have better OTP than expected. The overall developing trend of OTP shown in Fig. 7 is also consistent with the developing trend of delays as seen in Fig. 5.

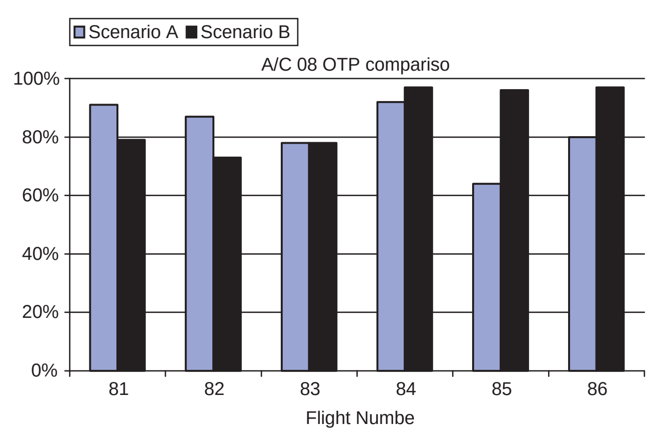

Fig. 7. Simulation results (D + 15 OTP) of A/C 08.

Table 2
Rotation schedule of A/C 8

Flight number	From	To	STD	STA	Block time	Mean block time	Block buffer time	Turn time	Std. turn time
81	AP14	AP8	5.35	6.50	75	71	4		
82	AP8	AP14	7.10	8.25	75	67	8	20	20
83	AP14	AP17	8.55	11.00	125	115	10	30	30
84	AP17	AP14	12.20	14.35	135	125	10	**80**	40
85	AP14	AP15	15.10	17.35	145	135	10	35	30
86	AP15	AP14	18.15	20.40	145	141	4	40	40

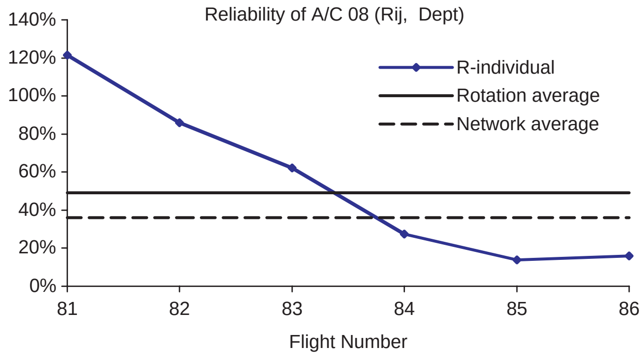

Fig. 8. Departure reliability of flights operated by A/C 08.

When the departure reliability of individual flights in the rotation is shown in Fig. 8, we can find that the first three segments have relatively high reliability. The departure reliability of the first flight is higher than 100% because the real operating delays are less than delays from the Dream Case. It implies that the ground operational efficiency of this flight is better than expected. Lower reliability values are found in last three flights resulting from wider gaps between real operating delays and expected delays as seen in Figs. 5 and 6. The departure reliability of the overall rotation is about 50%, when compared with the overall departure reliability of the network, 36%.

4. Maintaining schedule reliability

The impact of delay propagation in airline networks is well known in the industry and the impact on airline operations could be tremendous and more severe for network carriers due to the close connections between resources (crew and aircraft) and passengers. However, the real impact of delay propagation is usually hard to visualise because of the complex connections between flights and the huge number of flights to observe. Two scenarios, C and D, are conducted by using the simulation model to visualise delay propagation along aircraft routings and the impact of managing turn-around operations on schedule reliability.

4.1. Delay propagation in an airline network

To investigate the impact of delay propagation, two flights operated by Aircraft No. 12, namely PP121 in the morning representing Scenario C and PP125 in the mid-day representing Scenario D, are configured in the simulation model to take 10 min more than the standard turnaround time (20 min) to finish turnaround operations. Results of Scenario C and D are compared with Scenario A in Figs. 9 and 10, respectively. It is seen that

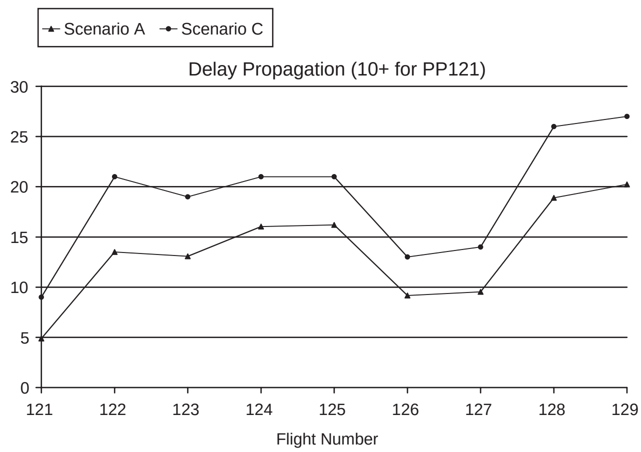

Fig. 9. Delay propagation after PP121 (Scenario A and C).

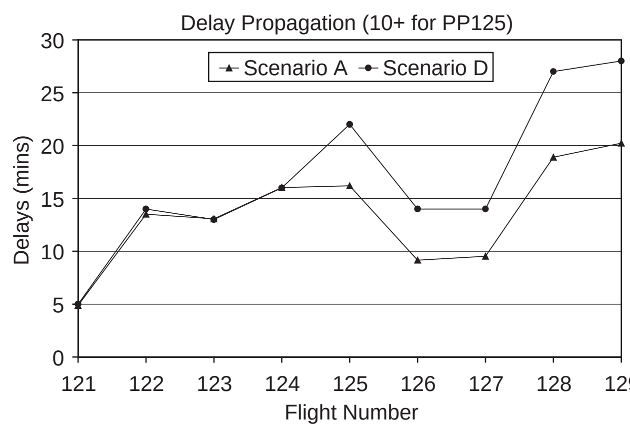

Fig. 10. Delay propagation after PP125 (Scenario A and D).

the longer service time for PP121 causes higher departure delays. As seen in Fig. 9, delays of PP121 propagate along aircraft routing and result in high departure delays for PP129, though some delays are absorbed by built-in buffer times of each flight ranging from 5 to 10 min as shown in Table 3. The reduction of delays between PP125 and PP126 is due to a long buffer time (30 min) for the turnaround of PP126, which takes effects and controls delay propagation to a lower level.

In scenario D, it is seen in Fig. 10 that departure delays start building up after PP125 and propagating along the rotation to PP129. The long buffer time of PP126 absorbs some propagated delays from PP125 and controls the delay level around 10 min for PP126. The impact of 10-min delay for PP125's turnaround reflects on the 15-min delay of a down-line flight, PP129. Since the schedule of Airline P is not a hubbing schedule and does not involve heavy passenger/baggage transfer between flights, the delay propagation effect shown by this example is limited for the impacted rotation only. For network carriers (i.e. operating a hub-and-spoke network), the delay propagation effect due to a minor

Table 3
Rotation schedule of A/C 12

Flight number	From	To	STD	STA	Block time	Mean block time	Block buffer time	Turn time	Std. turn time
121	AP7	AP14	5.40	6.55	75	69	6		
122	AP14	AP7	7.25	8.40	75	70	5	30	30
123	AP7	AP14	9.00	10.15	75	69	6	20	20
124	AP14	AP7	10.45	12.00	75	70	5	30	30
125	AP7	AP14	12.20	13.35	75	69	6	20	20
126	AP14	AP1	14.35	16.05	90	79	11	**60**	30
127	AP1	AP14	16.25	17.50	85	77	8	20	20
128	AP14	AP7	18.20	19.35	75	70	5	30	30
129	AP7	AP14	19.55	21.10	75	69	6	20	20

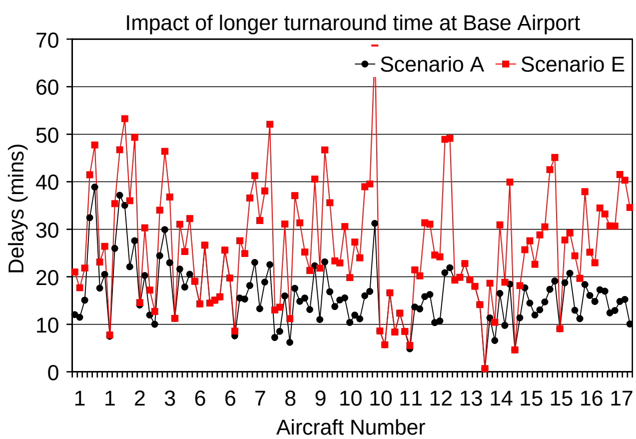

Fig. 11. Impact of low efficiency in turnaround operations at base airport of P.

10-min delay could be even more significant (Abdelghany et al., 2004; Beatty et al., 1998).

4.2. Managing turnaround operations at major hubs

To study the significance of operations control on aircraft turnaround services, results of Scenario E in Fig. 11 show the scenario in which ground services at the base airport of Airline P take longer time (10 more mins) to finish. It is seen that longer turnaround time at the base airport causes more departure delays to those flights turned around at the base, if the schedule remains unchanged. This also results in more severe delay propagation in aircraft rotations as demonstrated in Fig. 11 by aircraft 2, 7 and 10. Total departure delays in this scenario increase from 1816 mins in Scenario A to 2989 mins with a significant 65% increase. The huge impact of delays in Scenario E is a result combining ground service disruptions to 82% of total flights in 1-day operation and severe delay propagation in the network.

5. Conclusion

A new approach to evaluate the OPT of airline schedules is developed based on the results of simulated inherent delays. Simulations reveal gaps between real operating delays and inherent delays of a schedule, with delays in the morning tending to propagate along aircraft rotations and result in higher delays to later flights in the rotation, unless delays are controlled by embedded schedule buffer times. Scenario analysis shows the vulnerability of an airline schedule to external disruptions and also shows the limited reliability/flexibility being built in during schedule planning process.

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