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A multi-objective optimization with a delay-aware component for airport stand allocation

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ABSTRACT

Airport management is regularly challenged by the task of assigning flights to existing parking positions in the most efficient way while complying with existing policies, restrictions and capacity limitations. However, such process is frequently disrupted by various events, affecting punctuality of airline operations. This paper describes an innovative approach for obtaining an efficient stand assignment considering the stochastic nature of airport environment. Furthermore, the presented methodology combines benefits of Bayesian modelling and meta-heuristics for generating solutions that are more robust to airport flight schedule perturbations. In addition, this paper illustrates that the application of the presented methodology combined with simulation provides a valuable tool for assessing the robustness of the developed stand assignment to flight delays.

1. Introduction

Modern air transportation industry is encountered with a complex challenge. Air travel demand is rapidly growing every year and is estimated to double over the next two decades. The International Air Transport Association (IATA) reports that the amount of air travellers is expected to reach 8.2 billion travellers by 2037 (IATA, 2018). On the other side, air transport stakeholders are constantly pressured with changing standards and improvements in safety, passenger service and sustainability levels, as well as increasing need for modernisation of facilities.

Emerging technologies and overall demand to smoothen air passenger experience throughout the entire journey creates large investment pressure on airport stakeholders in the short time horizon. However, yet existing capacity constraints have to be also taken into consideration for the future investment areas (Symonds, 2018). If capacity development does not match the speed of traffic growth, congestion and economic problems will appear. Those problems would be a direct consequence of airlines not having access to necessary infrastructure for satisfying the increasing demand for air freight and passenger travel.

Everyday airport operations involve many aircraft and airport resources. Serving arriving aircraft and its passengers, preparing aircraft for departure and embarking its passengers require specific number of resources and corresponding equipment. At many airports these operations are performed by separate ground-handling dedicated companies, so the airport only must provide enough space for required time for making ground-handling possible. Nevertheless, while the number of aircraft passing through an airport grows from season to season, available space at an airport remains the same in most of the situations, thus, increasing the importance of facilities management by airport stakeholders. They must create an assignment schedule for the upcoming operational period, matching the existing parking positions with the requirements of airlines and passengers. However, in reality this assignment plan is often disrupted by deviations from scheduled times of arrival/departure of some flights, making the existing assignment schedule difficult to achieve and creating additional workload on decision-makers to re-make assignment schedule in time-constrained conditions.

In circumstances of limited capacity and high occupancy of terminal facilities, every deviation on arrival or departure time makes necessary to hold aircraft, affected by such deviations, waiting for availability of an appropriate parking position to be served at. This problem can sometimes be avoided by increasing buffer times between consecutive assignments to the same parking facility, however this reduces airport capacity. If the punctuality is disrupted, in the framework of a congested airport and limited airport apron space, it becomes vital to find tools that help to ease the burden of unpunctual arrivals and departures on the rest

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of daily operations and mitigate the negative impact of operational stochasticity on the terminal capacity planning and scheduling to ensure its robustness.

The existing challenge of congested airports for mitigating the negative effect of arrival and departure delays on stand assignment schedule became a motivation to look for a leveraging methodology in the field of operational research. So, this paper presents a novel methodology for coping with the impact of unpunctual flights on the stand allocation schedule, which allows to benefit from historical data, optimization techniques and simulation for optimising the use of an airport stand capacity, considering the objectives of airport stakeholders and historical flight delays.

As mentioned, this paper focuses on the stand allocation problem (SAP); which refers to the problem of assigning flights to existing parking positions (stands) in such a way that all operational and technical constraints are satisfied. This problem is also called gate allocation problem (GAP). This term differs from SAP only in the definition of main subject: It considers only the gates used by passengers to go from the terminal building into the aircraft during the boarding procedure. In its nature, both SAP and GAP are approached by the same methodologies and are similar to a job-scheduling problem (Taillard, 1993), studied for decades. The complexity of the assignment is directly related to the number of flights to be assigned, which in airport routines can be to over 500 flights and more per day, depending on the size of an airport, which makes SAP/GAP an NP-hard problem due to real-life quantity of constraints and decision variables, such as aircraft size, airline business model, airport policy in stand assignment among others. As the number of flights for large airports can surmount thousand movements per day, the task of allocation becomes very complicated to be solved manually in an efficient way. Thus, for making stand allocation according to all required conditions and avoiding errors, SAP/GAP are often approached to be solved by the means of various algorithms, described in the next section. The article continues in the following way. Section 2 performs the literature review, in Section 3 presents the methodology and a case study is presented in Section 4. Section 5 exemplifies the application of the methodology in the case study and Section 6 concludes the paper and discusses the future work.

2. Literature review

According to the methodology used, the solving approaches can be divided into three categories: exact algorithms, heuristic algorithms and combined algorithms. While the first ones are aimed to find the best solution from a mathematical standpoint, the rest are designed to determine a qualitative near-optimal solution in a reasonable computational time (J Guépet et al., 2015). Due to the complex nature of the problem, exact solutions (e.g. a branch-and-bound algorithm) have difficulty in providing mathematically-optimal solutions within reasonable computational times for large-scale stand assignment problems. Therefore, recent studies mainly focus on developing heuristic algorithms, which do not guarantee the optimal solution but may provide near-optimal solutions in reasonable computational times. However, if the solution is not found by heuristic algorithm, it is not possible to determine whenever it is due to absence of any solution or due to inability of an algorithm to perform an abundant solution search (Pearl, 1986). Nevertheless, for real-life operational challenges finding the absolute optimum is not a vital requirement in everyday operations, as nearly optimal but quickly obtained solution would serve perfectly, especially when different costs of allocation have to be taken into account and the decision has to be made in short time.

Various optimization perspectives have been targeted as well as individually and as a group of objectives. Babić et al. (1984) were ones of the first to approach SAP/GAP using linear programming with objective to minimize walking distances for the passengers, assuming no flight delays are to happen. Later, Mangoubi and Mathaisel (1985) formulated a single objective function for passenger walking distances, considering randomness of walking distances while Yan and Tang (2007) included technical constraints for specific aircraft type and effects produced by flight delays on the stand allocation schedule into penalty-based heuristic planning framework. Solving SAP/GAP by decomposition into smaller time windows or flight sequences was successfully performed by Drexl and Nikulin (2008), Jaehn (2010), Şeker and Noyan (2012), Guépet et al. (2015), Marinelli et al. (2015), Yu et al. (2016), however, these authors did not consider flight delays.

When flight delays are considered, then SAP/GAP becomes more complex since it has to deal with their stochastic nature. For solving this type of problem, the insertion of buffer time between consecutive flights assigned to the same stand has been proved as a most effective solution for improving the schedule punctuality (Hassounah and Steuart, 1993). According to Yan and Chang (1998), Yan and Huo (2001), S. Yan, Shieh, and Chen (2002) these buffer times can be used to absorb not very significant stochastic flight delays (less than 30 min), that is why they proposed a simulation framework to analyse effects of flight delays on gate assignments and evaluate buffer times and gate assignment rules. Furthermore, extreme delays impacting on the gate assignment has been evaluated by Kontoyiannakis et al. (2009).

Despite of many years of research on SAP/GAP, the focus of solving algorithms has not changed much. The full amount of real-life problem constraints is not always considered, particularly, the stochastics of flight arrivals is often neglected, however, it should be considered since it carries a lot of uncertainty to be managed by airport stakeholders. Therefore, in contrast to the researches mentioned above and to fill the gap considering such an important factor as flight delay, this work presents an innovative approach where the probabilities of having certain delay levels are estimated for each flight and this information used for creating a qualitative stand assignment schedule. By approaching to the issue in this way, the stand assignment problem is formulated as close to the operational reality as possible in order to increase the applicability of the solutions generated by the developed algorithm.

3. Methodology

To overcome challenges induced by stochasticity of airport environment while considering the expectations of different actors involved in airport activities, this paper presents a methodology for stand assignment that deals both with operational uncertainties and multi-objective optimization goals. The methodological approach consists of different algorithms and processes that interact in such a way that it is possible to generate robust solutions that consider the historical delays, current capacity and required capacity. The implementation is done using two modules. Module I estimates probabilities of flight delays and their severity based on the historical data of operational periods and formulates the corresponding statistical models. Module II allocates flights to the stands using an evolutionary approach, considering the desired technical and operational restrictions for a target flight schedule and by calculating the stand occupancy time for each flight based on the delay models from Module I.

3.1. Architecture

The design of the presented approach can be described as follows: Module I is a look-ahead component which analyses the nature of historical delays and, using Bayesian inference techniques, calculates possible future delays; and Module II – generates an optimised stand assignment, considering various objective functions and management perspectives.

Main data flows between the modules and the principal functionality is presented in Fig. 1. The process starts with the analysis of data imported from an airport performance database, which can include among others the information about scheduled and actual flight arrival times, actual and scheduled block occupancy times, as well as the weather

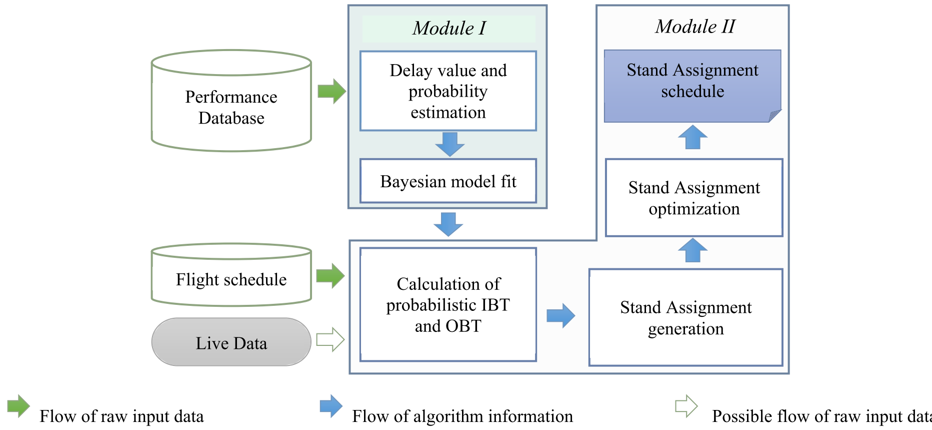

Fig. 1. Algorithm architecture and main data flows.

conditions at the time of operations and local air traffic regulations. In the scope of this paper only information about actual and scheduled time of arrival was available and therefore has been used for the initial implementations. Nevertheless, the analysis performed in Module I can also include (when available) information about airport operational environment such as weather conditions, runway configuration, flight delays in the airport of origin, which would significantly benefit Module I outcome.

Airport performance data is imported into Module I in a table format, where it is analysed and the probabilities of flight schedule deviations depending on several factors are estimated using inference based on Bayes' rule, which defines the probability of future event based on prior data of circumstances that might be related to this event. From these interdependencies and probabilities the corresponding Bayesian distributional regression models are built. These models together with the corresponding parameters (regression coefficients) are then transferred to Module II.

In Module II, the flight schedule is recalculated considering the standard information from the air traffic control tower log and the new information from Module I, estimating the possible arrival time deviation with the regression models. With this information, the estimated block occupancy times are calculated and used in the allocation algorithm (optimization phase). In the scope of this paper these estimated times are called *probabilistic in-block time* (further referred to as PIBT) and *probabilistic off-block time* (further referred to as POBT), together – *probabilistic block occupancy time* (further referred to as PBOT). As the next step, a re-calculated flight schedule, where scheduled time of arrival is replaced with PIBT and scheduled time of departure - with POBT, is processed by a metaheuristic search algorithm, which looks for a better stand assignment for the flights considering the probabilistic delays, while optimising the user-specified objective function. In this paper the objective function is a combination of four objectives, as it is described in section 3.1.2. The different elements of the presented two-module algorithmic approach are described in the following sections.

3.1.1. Module I: Bayesian models

As acquiring hidden knowledge from raw airport performance data may require long provisional analysis and fitting the corresponding models, the presented approach proposes a balanced solution to get necessary insights on the latent performance characteristics in a quite short period of time. The presented solution is based on the application of Bayes' rule in multilevel modelling, which already proved its value for research in various scientific applications (Brown and Prescott, 2014; Demidenko, 2013; Gelman and Hill, 2007; Pinheiro and Bates, 2000).

3.1.1.1. Multilevel models. The greatest benefit of multilevel models is that they allow the modelling from different perspectives of measurement at the same time, considering their complex dependencies. The heart of any multilevel model (further referred to as MLM) is the prediction of the response variable y at the data point i through the linear combination η of predicting factors, transformed by the inverse link function f adopting a certain distribution D for y: $y_i D(f(\eta_i), \theta)$.

The parameter θ describes additional distribution-specific parameters that typically do not vary across data, such as the standard deviation σ in normal models or the shape α in Gamma or negative binomial models. The linear predicting factor can generally be written as: $\eta = X\beta + Zu$. In this equation, β and u are the regression coefficients at population-level and group-level respectively and X, Z are the corresponding design matrices. The response y as well as X and Z form up the data, whereas β, u, and θ are the model parameters estimated with various sampling algorithms (Bürkner, 2017). In such a way by estimating level-corresponding coefficients it is possible to obtain a multilevel distributional regression model for the target response variable – *flight delay on arrival.*

3.1.1.2. Modelling on Bayes' rule. To estimate the regression coefficients for different performance parameters based only on historical data and use them for the inference of future data values it is necessary to estimate the joint probability distribution for both the target variable and the set of its predictors. This estimation could be done using Bayes' rule. Thus, following the Bayes' rule, the likelihood of observation A, occurring given the occurrence of observation B, can be written through the following equation: $P(A|B) = P(B|A)P(A)/P(B)$, where $P(B|A)$ denotes the likelihood of B occurring when A occurs, $P(A)$ and $P(B)$ – are the probabilities of observing both observations independently of each other (Stuart and Ord, 2010).

One of the main advantages of Bayesian modelling is that the data for the probability estimation can be used as it becomes available, so the models can be easily updated even after each operational day, if such desired. Also, thanks to the Bayesian method, the likelihood estimations are independent from "outliers" or extreme data values influences, which makes it a perfect approach for this study for consideration of hidden latent correlations between different performance variables.

In the presented case study, the estimation of delay probabilities is done on the arrival punctuality data for one week with the use of open statistical tool R, particularly with R package *brms* (Bürkner, 2017). This package performs efficient Bayesian model estimation for mixed data types and allows exporting the fitted distributional regression model parameters in any required form. It allows also to estimate an effect of each of the model parameters to the mean and variance of the response variable distribution (Bürkner, 2017). As an output of fitting the MLM with *brms* a fitted distributional regression model for the target variable – flight delay is received, where the effect of each of the chosen predictors has its own fitted linear regression function. When having such

MLM, it is possible to generate future (probable) delay values with various levels of probability, according to the chosen predictor variables, and use them for calculation of PBOT used in the schedule generated by Module II. By introducing this innovative approach it is expected to reduce the problems caused by delays thus making a more robust schedule; which is evaluated later in the paper with the case study.

3.1.2. Module II: evolutionary optimization

This module takes care of generating stand assignment, considering the input constraints, and then optimising it to ensure better value of quantitative expressions of airport stakeholders' objectives (multi-objective function). In order to make it practical for the potential stakeholders, an algorithm that considers the diverse variables that are important for the actors affected by the allocation in the airport: required level of service for passengers and airlines, cost and environmental impact, was developed. To ensure the evolvement of the optimization algorithm for the chosen airport data, it was decided to consider the following objective function, where the different objectives are described:

$$F = w_1 \times R_{apron} + w_2 \times R_{taxi} + w_3 \times R_{hold} + w_4 \times R_{service} \tag{1}$$

1 Airport management perspective: to serve more passengers through the contact stands and minimize the use of remote parking positions

$$R_{apron} = (Nflightsassigned|apron) \,/\, (TotalNflights) \tag{2}$$

Where:

- *Nflightsassigned|apron* – is the number of flights assigned to remote parking positions, that are connected to the terminal building only via bus service;
- *TotalNflights* – is the total number of flights in the schedule to allocate.

2. Airline and environmental perspective: to minimize the taxi distance to the stand

$$R_{taxi} = (AverageScheduledTaxi) \,/\, (MaxAirportTaxi) \tag{3}$$

Where:

- *AverageScheduledTaxi* – is the average taxi distance in the allocated schedule;
- *MaxAirportTaxi* – is the maximum possible taxi distance at the airport for considered runway configuration.

3. Air Traffic Control perspective: to minimize number of aircraft waiting for stand availability

$$R_{hold} = (Nflights|waiting) \,/\, (TotalNflights) \tag{4}$$

Where:

- *Nflights|waiting* – is the number of flights that must wait for the stand availability;
- *TotalNflights* - is the total number of flights in the schedule to allocate.

4 Passenger comfort perspective: to provide enough waiting space in the departure lounge

$$R_{service} = (MaxAreaPerPassenger - \ ActualAreaPerPassenger) \,/\, (MaxAreaPerPassenger) \tag{5}$$

Where:

- *MaxAreaPerPassenger*– maximum possible number of m2 per passenger, calculated for the flight with smallest number of passengers in the schedule assigned to the stand with the largest waiting lounge of the airport;
- *ActualAreaPerPassenger* – actual number of m2 per passenger, available at the assigned gate for the assigned flight

5 w_n– indicates priority weights for the corresponding perspectives, for practical implementations, the weights should be decided by negotiations of the different stakeholders of the airport. In this paper all the weights are equal to 1 in order to obtain a stand assignment equally balanced for all considered perspectives. Prioritizing one or more perspectives over the others may result in certain cost for under prioritized perspectives, so it can be used for estimation of various airport strategies and answer the questions such as how much will it cost in taxi distance to prioritise passenger comfort?

As presented, there are conflicting objectives due to the nature of the actors involved. For instance, airlines objectives would aim to minimize taxi distance preferring parking positions located as close as possible to the runway exits. This may cause a conflict with the uniform stand assignment policy of the airport operator. On the other hand, airport operators would prefer to use contact stand as often as possible to provide the best service for the airlines and spread the allocation so that there is even use of infrastructure. In addition, airlines would like to have sufficient space in the waiting lounges of the gates to provide the best level of service for passengers; again, this objective might conflict the environmental one as some gates with bigger lounge areas might not necessarily be located closest to the runway exit.

The particular restrictions to be considered in the stand assignment schedule can vary slightly depending on the particularities of each airport. The following are the restrictions implemented in the presented algorithm:

1 Spatial
   - Domestic and international flights must be assigned to the specific gates. Normally these are internal specifications of the airport e.g. international flights are assigned to gates that have access to the designated border control areas.
   - Enough space for passengers waiting to board must be provided. These values depend on the layout of each airport; for every gate there will be a specific area dedicated to the passengers waiting for boarding. This issue was approached by considering that each gate has a specific area and the number of passengers to board depends on the type of aircraft and its load factor. For instance, an A380 (450 passengers) is not preferred to be allocated to the stand next to a Boeing-777 (305 passengers) at the same time. Formula (5) was used for evaluating this condition.

2 Temporal
   - Flight delays must be considered in the assignment schedule (according to conditional delay probability distributions from Module I). In this paper, only arrival delays are considered due to unavailability of ground handling performance data and correspondence of arriving aircraft to departing aircraft.

3 Operational
   - Parking position must correspond to the size of an aircraft (large aircraft require extra space due to larger wing span). This is implemented through identification of allowed stands for each flight on the stage of processing the input data in Module II.
   - Aircraft with large number of passengers should be served at contact stands. This restriction is implemented to ensure smoother transfer experience to the passengers and it is ensured through the objective function – Formula (5).

- The use of contact stands is prioritized. This is implemented via the objective function component Formula (2).
- In case when there are no parking positions available at the moment of arrival, aircraft should wait on the apron until a position becomes available. This is implemented in the algorithm by assigning the flight to a "dummy" stand and incrementally delaying its PBOT until a suitable stand becomes available.

3.2. Evolutionary algorithm

For the optimization of stand assignment schedule with PIBT and POBT, a genetic algorithm (Goldberg, 1989) was developed. Although many solution search algorithms (among others Particle Swarm Optimization (Kennedy and Eberhart, 1995), Harmony Search Algorithm (Zong Woo Geem et al., 2001), Simulated Annealing (Kirkpatrick et al., 1983)) could be applied for the presented stand assignment problem, a genetic algorithm (GA) has been chosen for various reasons. One of the most important reasons is its ability to escape the local optima by increasing the diversity of solutions, which in the case of a multi-objective optimization is preferably to have this feature. Some local search algorithms as Tabu search and simulated annealing (S. Chick, P. J. Sánchez, D. Ferrin, and D. J. Morrice, 2003) are very good, but as time passes by it becomes more difficult to them to escape the local optima. In addition, the authors have already worked with GA previously with good results. Nevertheless, it is considered to try another optimization algorithms to compare their performance in the future work.

There are many examples of successful implementations of genetic algorithms in air transport optimization problems. Some relevant research can be found at Ghazouani et al. (2015), Mujica Mota (2015), Abdelghany et al. (2017) among others. They differ around implementation, formulation of a problem and in computational techniques used. In this paper the stand assignment schedule is represented as a NxM dimensional array, where N refers to the number of flights to be assigned to the stands and M is the number of various characteristics to be considered in the assignment. Thus, each array cell (flight) has an array of characteristics which are considered by the constraints in section 3.1.2. Fig. 2 illustrates one chromosome with the correspondent information that can be used by the algorithm. An array implementation allows to add extra characteristics if necessary.

A complete genotype which represents a potential solution is illustrated in Fig. 3.

The different operations and selection of the different chromosomes of the algorithm are presented in Pseudocode 1.

The general flow of the algorithm starts with importing target flight schedule, terminal building characteristics, weights for objective functions components and MLM data from Module I. These data are used to create an initial stand assignment solution (referred to as "Adam chromosome" in Pseudocode 1), which serves as a base to create a set of solutions by making random changes of assigned stands into different ones. After that, the quality of the generated solutions (chromosomes) is evaluated by the objective function for each of the chromosomes and the one with the smallest value is saved and marked as best chromosome. Next, the set of chromosomes is subjected to random crossover (where several chromosomes exchange their assigned stands with each other), thus creating a set of new chromosomes with different stand assignment. This procedure is followed by randomly changing some of the chromosomes by the function called *Mutation*. The chance of mutation is generated randomly for each of the chromosomes. After that, the entire set is evaluated again by computing the objective function for changed and new chromosomes and the best chromosome marking is updated if needed. This is followed by evaluating if the algorithm has reached the stopping criteria defined by user, and if so, the algorithm stops and exports the best solution into the data file.

```
GET Stop_Criteria
IMPORT
   FlightSchedule,
   Constraints,
   ModuleI.output
CREATE
    Adam chromosome, A
  GENERATE
    Set(chromosomes), S = RandomChange(A)
WHILE CurrentSituation <> Stop_Criteria
  REPEAT
    FOR  X = 1 TO count (S) DO
        Calculate objective function F(x)
        IF value F(x)> Best_Val THEN
           Best_val = value F(x)
           Best_Chrom = X
        IF CurrentSituation = Stop_Criteria
           THEN BREAK
        DO Crossover(Xi, Xj)
           IF MutationChance = TRUE
           Mutation (X)
EXPORT Best_Chrom
```

The number of algorithm iterations, total running time or certain objective function value can be established as the stopping conditions for the algorithm of Module II, according to user needs. Therefore, the solution quality improvement is only restricted by user preferences.

In the following section the implementation of the two-module approach in a real-case study is presented.

4. Case study: Mexico city international airport

Mexico City International Airport (IATA code: MEX) is the main airport in Mexico and one of the busiest airports in the world with its traffic increasing by 10% on average annually since 2012 (Moody's Investors Service, 2018). Such constant growth rapidly led to congestion and nowadays MEX is serving almost 50% more passengers than it was designed to. As a consequence, the local economy is already suffering from lack of aviation connectivity and due to that it is expected to lose up to $20 billion in future GDP by 2035 if airport capacity is not increased (International Airport Review, 2018).

According to Airport Council International (2018) Mexico City International Airport is on the 20th place in the ranking of world airports with biggest number of aircraft movements with approximately 450 thousands landings and take-offs annually. However around 20% of MEX departures in 2018 have suffered from substantial delay (more than

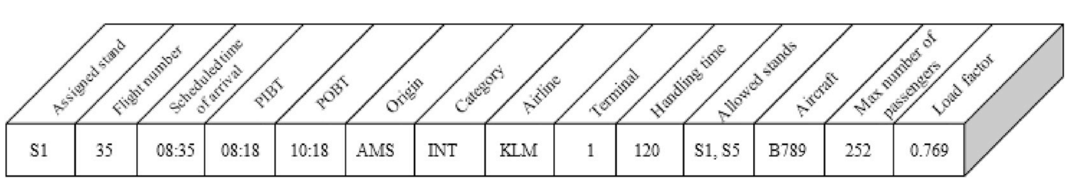

Fig. 2. Chromosome's content.

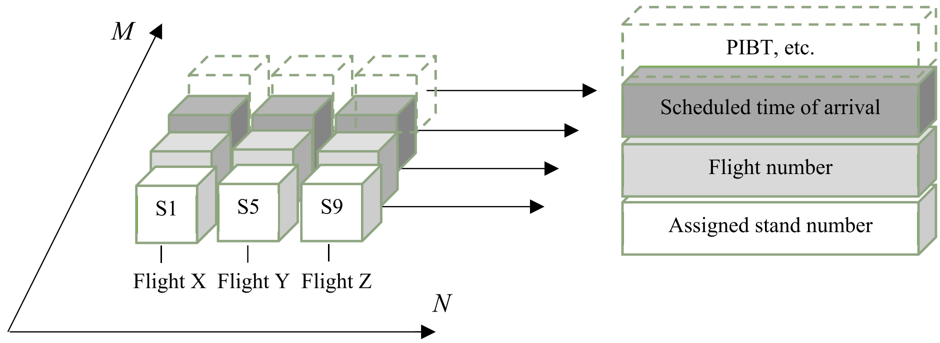

Fig. 3. Stand assignment schedule coded for genetic algorithm in Module II.

15 min from scheduled time of departure), which resulted in an average delay of approximately 50 min per flight (see Fig. 4). Since 2013 MEX operates at its maximum capacity (SCT, 2013), so the actual number of flights affected by such high delay is even bigger.

Furthermore, delayed or early arrivals complicate the situation further, creating additional burden on the existing terminal capacity. Such perturbations and dense flight schedule make MEX an attractive case to test the functionality of the proposed algorithm.

Mexico City International Airport has 2 terminals, both used for international as well as domestic flights, and there are 26 airlines operating at it. These terminals are separated by two parallel runways, not operating simultaneously due to not enough separation between each other. Some other relevant information on MEX can be found in Table 1. Since 2017 MEX has been declared with a capacity of 61 operations per hour with maximum of 40 landings (SCT, 2017).

Available at AICM (2018) an official on-time performance report has been considered for this case study. The analysed report consists of one-week operations from 28.05.2018 to 03.06.2018, both arrivals and departures, with actual time of arrival/departure and scheduled time of arrivals/departure, which allowed us to extract information about arrival delay. Nevertheless, there was no open access information about individual departure delays per each aircraft, therefore in the scope of this research only on the arrival delays are considered (i.e. difference between actual time of arrival and scheduled time of arrival), however, the algorithmic framework presented can be used as well with departure delays if the appropriate information is available.

Deviation from scheduled time of arrival (STA) per day and hour of analysed schedule for one week can be seen in Fig. 5. Positive values denote late arrival of a flight, and negative values denote early arrival. Further in this paper both types of deviation from scheduled time of arrival both positive and negative are referred to as delays. In the graph only the delays within 2 h interval are presented. However, the presence of quite a high number of early arrivals as well as severe delays (more than 30 min) can be clearly noticed. Out of 3917 flights arrived during the studied week 2091 flight arrived more than 15 min (red dashed line on the graph) later or earlier than scheduled, which constituted more than 53.4% of all studied passenger flights. Early arrivals (earlier than 15 min) constituted approx. 36.6% of week arrivals. Regarding the statistics of arrival delay per days of week, it is important to notice that only on Thursday 50% of the flights stayed in the limits of 15 min deviation from arrival schedule. Moreover, approx. 7.3% of the studied flights trespassed the limits of 60 min deviation from the arrival schedule, which for the airport operating beyond its maximum capacity is an extremely severe complication.

Table 1
Mexico City International Airport characteristics (AICM, 2019; IAS, 2019).

	Terminal 1	Terminal 2
Surface area	54,8 ha	24,2 ha
Contact aircraft parking positions	33	23
Remote aircraft parking positions	11	17
Airlines	20	6
Passenger throughput in 2017	2, 26 billion passengers	1, 75 billion passengers

Regarding hourly performance, as demonstrated on the lower part of Fig. 5, it is important to notice that there is a lot of variability in most of the hours of the day, which means that operational day is constantly under the pressure of disruptions. And for some hours, like from 4am to 9pm for instance, the deviation from scheduled time of arrival exceeds 60-min threshold.

When examining statistics for the 52 airlines, on the selected week schedule, it is important to notice (Fig. 6) that the top 10 airlines (which correspond to the ones with the biggest number of flights) have a rather stable performance. Only few of the top airlines exceeded average delay value of 15 min.

However, the overall punctuality is very poor. A comparison of Fig. 6 with Fig. 7 shows that 7 out of Top 10 airlines with the biggest number of flights in the studied schedule also appear in the rank of the ones with

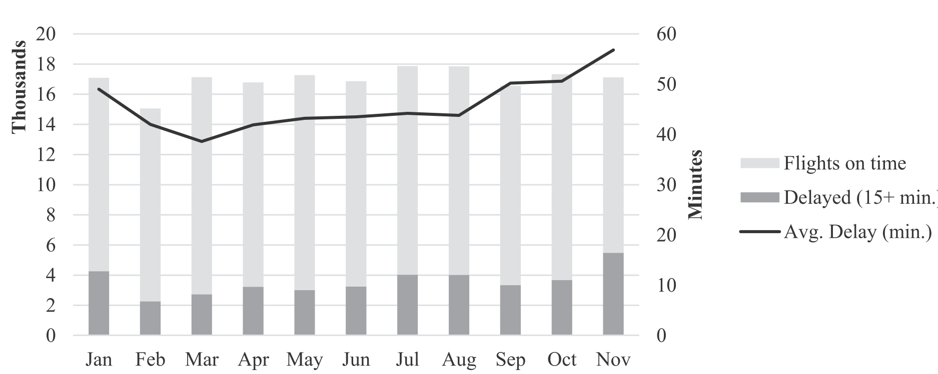

Fig. 4. MEX Departure performance statistics for 2018 (Flightstats, 2018).

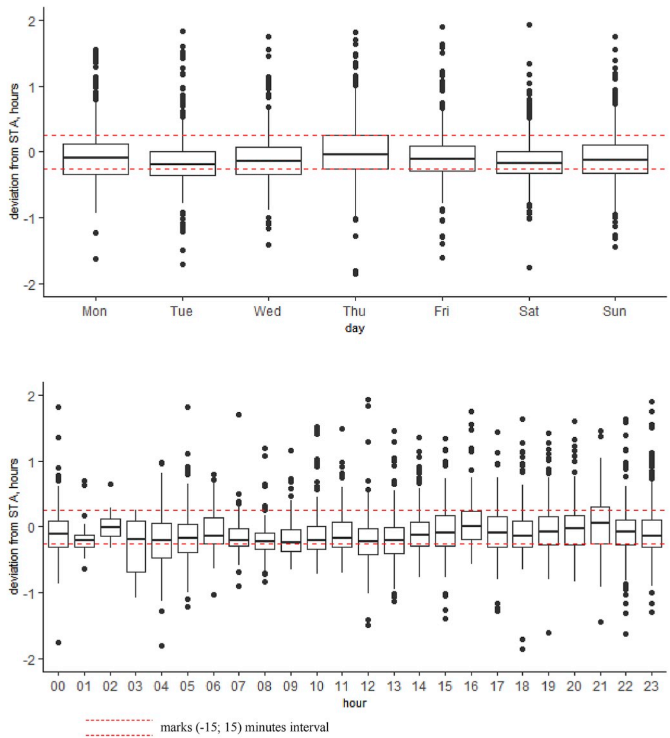

Fig. 5. Deviation from scheduled time of arrival (STA): statistics per day and hour.

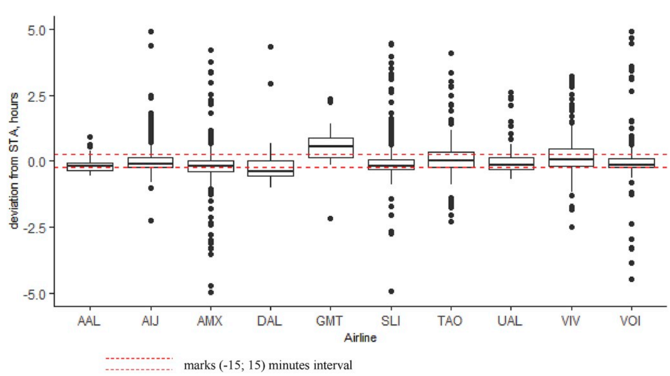

Fig. 6. Top 10 airlines with the biggest number of flights and deviation from scheduled time of arrival (STA).

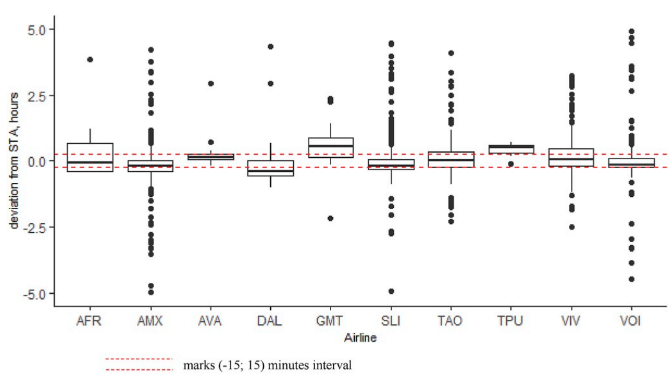

Fig. 7. Top 10 airlines with the biggest mean deviation from scheduled time of arrival (STA).

worst punctuality. Flights of AMX, SLI and VIV quite often exceed the value of 120 min deviation from their scheduled time of arrival, as it can be seen in Fig. 7. The largest average delay, which constitutes in a deviation of more than 1 h, occurred in the arrival of less than 3% flights out of a total flight schedule.

5. Two-module approach: the case of MEX

The delay model for this case study has been built on the correlation of delay level with the time of the day of arrival and the airline. After processing MEX one-week operational data in Module I considering two available variables - hour of arrival and airline name - as predictors of arrival delays, the corresponding MLM has been obtained and a sample of the resulting parameters are presented in Table 2. The complete table can be found in Appendix A. These parameters are linear regression coefficients for predictor variables *Airline and Hour* and allow to generate arrival delay value based on the corresponding airline name and hour of scheduled arrival. Detailed explanation of the layout, presented in Table 2, can be found at Bürkner (2017).

After generating delay values through the obtained MLM and randomly sampling from the obtained data, the resulting distribution with parameters from Table 3 was compared to the observed arrival delay. This comparison is presented in Fig. 8 (*yrep* represents simulated data, *y* – original historical data) and as it can be noticed from this figure, the distribution shape for simulated flight delays quite closely matches the distribution shape of historical flight delays which suggests that delay has a strong dependency on hour of the day and airline type.

Following the algorithmic implementation, the obtained MLM from Module I, along with a target 1-day flight schedule, is imported into Module II, where the 1-day flight schedule has been assigned to the available parking positions, as described in Section 3.

In order to evaluate the potential of the algorithm, the handling operations were assumed for domestic flights to have a block occupancy time of 60 min and international flights of 120 min. This has been considered by Module II and after running it with available input and constraints, the obtained results are illustrated in Table 3. This flight schedule has been generated considering the expected delays forecasted by Module I.

The obtained stand assignment has no instances of overlapping assignment of different flights to the same stand, which assume no need of direct ATC involvement in regular operational conditions (no rare weather phenomena, no unique air traffic regulations in the area).

Regarding the optimization part of Module II, the values for the

Table 2
Sample of Module I output.

Population-Level Effects:	Estimate	Est.Error	Q2.5	Q97.5
Intercept	−10,24	2,02	−14,15	−6,32
AirlineAFR	10,21	7,27	−2,63	27,35
AirlineAIJ	7,60	1,07	5,52	9,68
AirlineAMX	5,32	1,10	3,16	7,46
AirlineDAL	1,42	1,69	−1,93	4,69
AirlineGMT	16,60	2,66	11,51	21,89
AirlineSKU	210,35	223,77	−69,48	457,40
AirlineSLI	4,78	1,05	2,73	6,83
AirlineTAO	7,11	1,34	4,53	9,73
AirlineVIV	8,91	1,31	6,39	11,47
AirlineVOI	9,67	1,18	7,38	11,99
hour03	−5,74	4,11	−13,98	2,26
hour05	8,10	2,02	4,19	12,02
hour06	6,69	1,88	2,98	10,35
hour16	9,07	1,92	5,36	12,72
hour21	10,13	1,93	6,26	13,83
hour23	0,21	2,03	−3,84	4,19

Family: student.
Formula: Delay ~ Airline + Hour.
Samples: 3 chains, each with iterations = 3500; warmup = 1750; thin = 1; total post-warmup samples = 5250.

Table 3
Part of Module II output.

Origin	Flight	Category	Airline	Scheduled Arrival Time	Terminal	Stand	Handling Time	Equip	Aircraft Type
VSA	3249	INTERNATIONAL	VIVA AEROBUS	28-05-18 0:00	T-1	G39_A	120	EA32	Large
TGZ	3259	DOMESTIC	VIVA AEROBUS	28-05-18 0:00	T-1	G15	60	EA32	Large
MTY	185	DOMESTIC	VOLARIS	28-05-18 0:10	T-1	G12	60	EA32	Large
HMO	763	DOMESTIC	VOLARIS	28-05-18 0:10	T-1	G13	60	EA21	Large

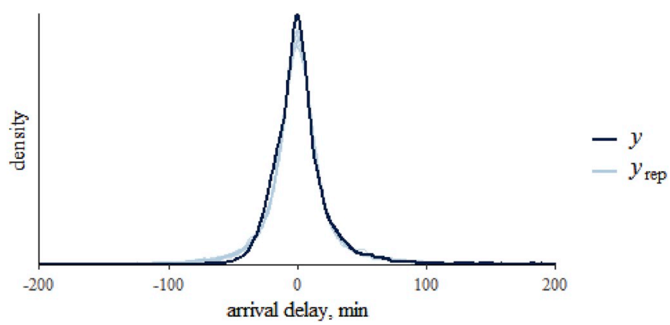

Fig. 8. Historical arrival delay distribution vs simulated MLM arrival delay distribution.

multi-objective function components can be found in Table 4:

As it can be seen in Table 4, after 30 min, the optimization algorithm of Module II gives quite a significant improvement for all the objectives considered. Additionally, it is important to mention that reduction in both total taxi distances and number of flights assigned to the remote parking positions, can lead to significant fuel consumption economy, which in its turn leads to economic and environmental savings for the airlines. And also, to improvement in passenger service, as less passenger time is spent on waiting to reach the terminal building and proceed further to passengers' destination.

6. Validation of the two-module approach

For further evaluating the quality of the presented two-module stand assignment approach, a validated simulation model of Mexico City International Airport has been used. More information about the model and its functionality can be found at Mujica Mota and Flores (2019). This simulation model considers the design and characteristics of MEX layout and runway dimensions, as well as corresponding taxi ways. This model can be considered as a digital twin of MEX and is suitable for initially testing such novel operational approaches.

With the simulation model of Mexico City, it has been tested how the integration of Bayesian modelling into the stand assignment impacts the number of aircraft that have to wait for their assigned stand to become available in the presence of stochastic arrival delays. The following three scenarios were chosen for comparison. These scenarios have one common characteristic - no intended buffer times between consecutive flights assigned to the same stand were included into the assignment schedule. Such feature allows to fully observe the impact of flight arrival deviation on the airport performance, while often in reality some arrival deviations are absorbed by the buffers.

Table 4
Optimization results of Module II.

Metric	1st generated solution	Solution generated after 30 min of running evolutional optimization	% improvement compared to 1st generated solution
Number of flights assigned to remote parking positions	259,0	217,0	16,2%
Total taxi distance for assigned schedule, km	900,9	848,6	5,8%
Number of flights assigned to wait for availability of suitable stand	7	0	100,0%
Average area per passenger at the boarding gate, m^2	2,3	3,0	28,8%

- *Base Case.* It assumes an ideal performance situation: everything goes according to the flight schedule and all flights arrive and depart punctually. Stand assignment is generated and optimised with the use of Module II only (actual block occupancy times correspond to the scheduled block occupancy times).
- *Case 1.* Flights arrive considering its stochasticity generated from a delay distribution model, learnt in Module I. Thus, it is possible to have a positive or negative delay (early arrival). Stand assignment is generated and optimised with the use of Module II only.
- *Case 2.* Flights arrive with stochastic deviation, generated from delay distribution model, learnt in Module I. Stand assignment is generated with the use of both Module I and Module II (PBOT is used).

To get representative data from the experiments runs for the chosen three scenarios, 30 replications of the scenarios have been executed with duration of 30 h. This provides enough time to execute an entire flight schedule of one operational day of 564 arrivals with possible arrival time deviations. For all three scenarios the number of aircraft that must wait for the stand availability have been tracked, as well as the waiting time for such availability.

Fig. 9 displays the statistics of stand availability waiting time for the performed experiments runs. As it can be seen, the Base case does not present any variability since all the operations are on time. Once the variability of the real system is introduced (Case 1), it results in significant waiting time with a mean value of 88.4 min per aircraft. Regarding Case 2, when arrival deviations are considered in the stand assignment

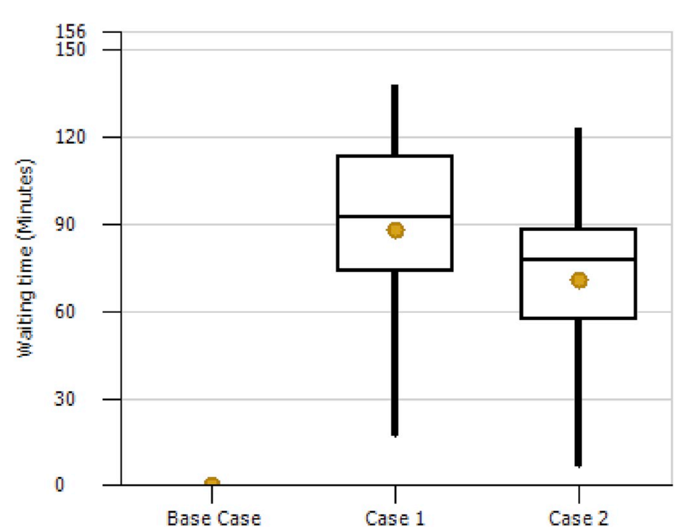

Fig. 9. Simulation experiments statistics for waiting time.

and the two-module approach is used to produce an optimised and delay-aware stand assignment, the average waiting time is decreased by 15.5% compared with Case 1 with mean of 71.2 min per aircraft. Furthermore, as it can be noted from Fig. 9, in Case 2, 75% of waited aircraft had a waiting time of less than 88 min, while in Case 1 more than 50% of waited aircraft had to wait longer than that. This comparison demonstrates improvement in the waiting situation for more than half of the total number of waiting aircraft compared to the stand assignment of Case 1.

Regarding the number of aircraft that had to wait for a stand (Fig. 10), it can be noticed that the average value of Case 2 is 39% less than of Case 1, and what is more important from managerial point of view is the variability; as it can be seen from Fig. 10, the dispersion of number of aircraft is considerably reduced, since it changed from up to 15 to 10. This means that in the real system it will be less likely that some AC would not have a stand. And if translated to the number of arrivals per day, Case 2 illustrates that in average only 4 aircraft out of 564 flights were forced to wait for a stand in average, while for Case 1 the value corresponds to 7 making a reduction of 43%. These numbers extrapolated to a yearly operations mean a lot of time, fuel, and money spent by the airlines, airport and passengers.

The results from the approach suggests that by considering some characteristics of the flights and environment it is possible to decrease in half the number of potential stand occupancy conflicts (for the example presented). As it was illustrated with the case study, the algorithmic framework has the potential to produce better schedules considering the historical delay, different perspectives and the technical restrictions present in the system. As mentioned before the presented approach is an innovative combination of Bayesian inference, optimization and simulation that has not been previously presented.

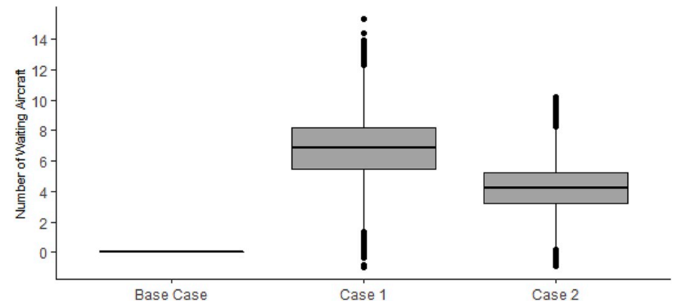

Fig. 10. Simulation experiments statistics for number of aircraft waiting for stands.

7. Conclusions and further research

This paper presents an innovative delay-aware approach that combines Bayesian methods and multi-objective heuristic optimization with variability for aiming at solving one of the most complex airport capacity management problems – stand allocation in airports. The implementation is done via a two-module approach in which each module performs key functionality that will provide value for the final solution. It generates robust solutions; in the first iteration of Module I, it provides airport stakeholders with a problem-aware stand assignment. Then, new probabilistic values of stand occupancy times are considered by an optimization algorithm of Module II. In order to validate the effects of the presented approach application on airport performance, simulation was also introduced into study to include the variability of the real system.

The combination of all the elements makes a very robust approach that can be implemented for any type of airport just by specifying the particular restrictions. Together with simulation, the methodology facilitates delay risk management and delay impact assessment on the slot adherence. In the case presented, the methodology showed a clear decrease of the number of aircraft waiting for the stand availability by 40% and decrease of total taxi distance by nearly 6%.

The implementation of the presented approach in the stand allocation planning process is an innovative one that for the first time together with simulation can help easing the burden of arrival and departure time deviations on the airport capacity, optimise airport capacity allocation from various management perspectives and can help to release capacity resources that are usually blocked by extensive buffer times between allocated flights.

Furthermore, the presented stand assignment methodology is formulated in such a way that any additional constraints can be added to the optimised assignment in Module II, which provides with the flexibility to tackle various assignment strategies and goals. In addition, Module I can be also enriched with departure punctuality historical data of a real airport or weather conditions ensuring a more holistic view during the delay model estimation. On the other hand, if the corresponding requirements are included in Module II, the stand allocation problem could also be tackled taking into account the slot adherence instead of comparison of scheduled and actual arrival and departure times.

As future work, other variables would be considered in Module I for providing more accuracy on the expected delay, and the use of information obtained from the Simulation model will be incorporated in the optimization loop in order to provide even more robust solutions as the authors have already applied in other ATM problems with good results.

Acknowledgements

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Appendix A

Output of Module I.

Population-Level Effects:	Estimate	Est.Error	Q2.5	Q97.5
Intercept	−10,24	2,02	−14,15	−6,32
AirlineABX	12,92	6,86	−0,38	26,21
AirlineACA	2,40	2,51	−2,78	7,10
AirlineAFR	10,21	7,27	−2,63	27,35
AirlineAIJ	7,60	1,07	5,52	9,68
AirlineAJT	−1,91	11,23	−25,46	18,22
AirlineAMX	5,32	1,10	3,16	7,46

(*continued on next page*)

(*continued*)

Population-Level Effects:	Estimate	Est.Error	Q2.5	Q97.5
AirlineANA	2,31	5,00	−7,08	12,45
AirlineARE	118,79	66,99	35,23	217,63
AirlineASA	1,02	2,88	−4,52	6,78
AirlineAVA	14,71	2,47	9,83	19,62
AirlineAZA	1,17	5,29	−9,41	11,58
AirlineBAW	0,85	4,31	−7,89	9,00
AirlineCHH	−3,57	9,39	−19,80	14,89
AirlineCKS	80,03	79,31	−45,68	269,10
AirlineCLU	36,43	53,99	−39,37	119,48
AirlineCLX	8,12	5,93	−2,71	20,43
AirlineCMP	−0,70	1,76	−4,18	2,69
AirlineCPA	9,14	13,15	−5,69	44,40
AirlineCSN	9,23	9,03	−7,15	29,95
AirlineDAL	1,42	1,69	−1,93	4,69
AirlineDLH	2,51	4,06	−5,23	10,37
AirlineESF	23,35	3,39	16,60	29,95
AirlineGEC	−7,74	8,99	−26,17	8,46
AirlineGMT	16,60	2,66	11,51	21,89
AirlineGTI	190,34	17,29	159,57	221,68
AirlineIBE	2,88	2,99	−2,99	8,58
AirlineICL	46,61	12,75	22,16	71,47
AirlineJBU	−8,53	2,17	−12,77	−4,30
AirlineJOS	10,05	4,63	1,18	19,35
AirlineKLM	10,23	4,39	1,02	18,53
AirlineLAN	23,80	4,55	14,10	32,35
AirlineLPE	1,79	4,08	−6,48	9,57
AirlineMAA	58,98	31,69	5,18	112,37
AirlineQCL	7,92	10,40	−11,98	29,05
AirlineQTR	9,24	7,54	−5,23	24,95
AirlineRPB	−0,11	4,94	−9,51	9,99
AirlineSKU	210,35	223,77	−69,48	457,40
AirlineSLI	4,78	1,05	2,73	6,83
AirlineSWA	2,88	1,86	−0,78	6,56
AirlineTAI	−0,70	3,00	−6,50	5,41
AirlineTAM	12,66	4,51	3,46	21,46
AirlineTAO	7,11	1,34	4,53	9,73
AirlineTNO	8,32	2,99	2,68	14,37
AirlineTPU	9,33	4,87	0,50	20,09
AirlineUAE	−1,27	7,42	−14,49	14,96
AirlineUAL	3,48	1,42	0,71	6,34
AirlineUPS	−1,87	4,64	−10,80	7,48
AirlineVIV	8,91	1,31	6,39	11,47
AirlineVOC	20,09	4,20	11,75	28,27
AirlineVOI	9,67	1,18	7,38	11,99
AirlineWJA	6,27	2,59	1,26	11,28
hour00	0,27	2,43	−4,29	4,71
hour01	0,23	2,30	−4,33	4,68
hour02	0,72	4,00	−7,53	8,18
hour03	−5,74	4,11	−13,98	2,26
hour04	−5,39	2,48	−10,30	−0,62
hour05	8,10	2,02	4,19	12,02
hour06	6,69	1,88	2,98	10,35
hour07	2,87	1,95	−0,99	6,64
hour08	0,11	1,89	−3,69	3,77
hour09	1,68	1,90	−2,09	5,42
hour10	4,12	1,90	0,37	7,82
hour11	1,92	1,92	−1,86	5,69
hour12	1,27	1,92	−2,49	5,06
hour13	2,04	1,91	−1,81	5,71
hour14	2,41	1,95	−1,46	6,18
hour15	4,95	1,90	1,10	8,58
hour16	9,07	1,92	5,36	12,72
hour17	8,61	1,93	4,76	12,25
hour18	5,46	1,96	1,60	9,31
hour19	5,33	1,94	1,41	9,11
hour20	6,42	1,94	2,61	10,15
hour21	10,13	1,93	6,26	13,83
hour22	0,23	2,06	−3,74	4,21
hour23	0,21	2,03	−3,84	4,19

Family: student.
Formula: Delay ~ Airline + Hour.
Samples: 3 chains, each with iterations = 3500; warmup = 1750; thin = 1; total post-warmup samples = 5250.

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