Impact of Weather Conditions on Airport Arrival Delay and Throughput

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Abstract. Weather events have a significant impact on airport arrival performance and may cause delays in operations and/or constraints in airport capacity. In Europe, almost half of all regulated airport traffic delay is due to adverse weather conditions. Moreover, the closer airports operate to their maximum capacity, the more severe is the impact of a capacity loss due to external events such as weather. Various weather uncertainties occurring during airport operations can significantly delay some arrival processes and cause network-wide effects on the overall Air Traffic Management (ATM) system. Quantifying the impact of weather is, therefore, a key feature to improve the decision-making process that enhances airport performance. It would allow airport operators to identify the relevant weather information needed, and help them decide on the appropriate actions to mitigate the consequences of adverse weather events. We present a methodology to evaluate the impact of adverse weather events on airport arrival performance (delay and throughput) and to define operational thresholds for significant weather conditions. Our results are computed from a dataset of over 750,000 flights on a major European hub and from local weather data during the period 2015-2018. We combine delay and capacity metrics at different airport operational stages for the arrival process (final approach, taxi-in and in-block). We introduce a new approach for modelling causal relationships between airport arrival performance indicators and meteorological events, which can be used to quantify the impact of weather in airport arrival conditions, predict the evolution of airport operational scenarios and support airport decision-making processes.

Keywords: airport performance; weather impact; uncertainty management; METAR data; Bayesian Networks; operational thresholds.

1. Introduction and problem statement

Airport arrival performance is a key element of air traffic network efficiency, as it is one of the main drivers for congestion (capacity limitation) and potentially lengthy flight delays, which spread over the network and make it vulnerable [1–5]. Airport arrival demand management involves a trade-off between mitigating congestion and maximizing capacity utilization [6,7]. This balance is also affected by the impact of air traffic delays: a significant portion of delay generation occurs at airports, where aircraft connectivity acts as a key driver for delay propagation [4,8–10].

The airport arrival system is defined by the processes, stakeholders, infrastructures and external conditions involved in the arrival of an aircraft at an airport [11,12]. Uncertainty with respect to the circumstances of the approach (e.g. aircraft performance, air traffic procedures, weather conditions) introduce a certain degree of randomness in airport arrivals and makes traffic supply a stochastic-like queue sequencing and merging problem. To ensure continuous traffic demand at airports and maximize infrastructure usage, a minimum level of queuing is required. However, additional time in holding is detrimental to operational efficiency, fuel consumption and environmental sustainability [13–15].
Therefore, there is a trade-off between approach efficiency and runway throughput (capacity). Arrival operations also depend on the times when flights are scheduled and, as such, constitute a time-varying system [1,16,17]. The combined stochastic and time-varying nature of the arrival system creates a set of “dynamics” that affect the way airlines, ANSPs and airports manage their operations [4,18,19].

Bad weather can distort transport planning and operations. Particularly, in air traffic management, poor meteorological conditions are the cause of an estimated 20% of all traffic delays in Europe [20]. Weather related delays are reported as the second most common cause of en-route air traffic flow management (ATFM) delays [20]. Apart from the associated economic costs for all involved stakeholders [21], delays have a substantial impact on the schedule adherence of airports and airlines, passenger experience, customer satisfaction and system reliability [16,22,23].

Regarding airport operations, bad weather can result in operational disruptions like Low Visibility Procedures (LVP), capacity reductions holding patterns for arrival aircraft, deviations and de-icing procedures [11,16].

From an air transportation system view, a flight could be seen as a sequence of phases. Typical standard deviations for airborne flights are 30 s at 20 min before arrival [24], but could increase to 15 min when the aircraft is still on the ground [25]. As Schultz and Reitmann demonstrated [26,27], the average time variability (measured as standard deviation) is higher during the flight phase (5.3 min) than in the taxi-out (3.8 min) and taxi-in (2.0 min) phase, but it is significantly lower than the variability of both departure (16.6 min) and arrival (18.6 min) timestamps [28]. The arrival flight phase presents a wider time-variability and therefore is subject to greater uncertainties.

Quantifying the impact of weather is, therefore, a key feature to improve the decision-making process that enhances airport performance, particularly when referring to arrival processes [29]. It would allow airport operators to identify the relevant weather information needed and help them decide on the appropriate actions to mitigate the consequences of adverse weather events.

We present a methodology to evaluate the impact of adverse weather events on airport arrival performance (delay and throughput) and to define operational thresholds for significant weather conditions.

2. Background

Operational efficiency is one of the main topics addressed by current research in the field of airport operations [12,30]. Predicting the generation and propagation of delay in the network is paramount when assessing the impact of congestion [31–34]. This is particularly critical when estimating the resilience of the ATM system, including airports as the nodes that connects the network, and the effect of different measures to achieve the expected performance [35]. Improved capacity utilisation and demand management fall within the realm of Air Traffic Flow and Capacity Management (ATFCM) [7].

Weather conditions change the flow patterns of the traffic registered at airports. Quantifying these pattern deviations is necessary when optimising arrival operations at airports under uncertainty [29]. Thus, delay generation and capacity reduction due to weather impacts are relevant to capture the complexity of the system dynamics [35].

The performance of an airport is mainly related to the number of aircraft movements handled (airport capacity–throughput) [11]. The term capacity generally refers to the ability of the airport to accommodate a traffic volume (e.g., movements) in a given time period (e.g., on hourly, daily, or yearly basis) [36]. If the air traffic demand approaches or exceeds the given airport capacity, the congestion of provided infrastructure increases which results in delays and cancellations. This demand–capacity imbalance is a key cause of unpunctual operations and affects different components of the whole airport system on both airside (e.g., runways, taxiways, aprons) and landside (e.g., passenger handling) [16,37].

Results of a data analysis from Madrid airport (our case study scenario) show that, during winter, more than 45% of the variability in daily punctuality is related to local weather impacts [20].

Regarding the spatial boundaries for the problem, in this study we will consider the Arrival Sequencing and Metering Area (ASMA) for performance reviews. The ASMA is described as a virtual cylinder (volume) of a given radius around an aerodrome and taken as a reference for measuring the efficiency in handling the arrival flow [28,38]. It is aligned with the “extended arrival” operational concepts like
E-TMA (Extended Terminal Manoeuvring Area) and E-AMAN (Extended Arrival Manager) [39]. Therefore, the spatial boundary of this study is not only the airport but also its surrounding airspace, in order to take potential holding patterns into consideration. We combine delay and capacity metrics at different airport operational stages for the arrival process (final approach, taxi-in and in-block). This allows us to study the airspace / airport (airside) integrated operations [30]. In time, we restrict actions to a tactical phase (day of operations) in order to consider the primary and initial inefficiencies of the system. We make use of the Milestones Approach, which is one of the conceptual core elements for the Airport Collaborative Decision Making (A-CDM) implementation [40]. It describes the progress of a flight from the initial planning to the take off by defining Milestones to enable close monitoring of significant events. Flight delays are defined as the difference between the scheduled and actual time (timestamps). Schedule delay is a term in transport modelling which refers to a difference between a desired time of arrival or departure and the actual time. Current weather conditions (Table 1) are usually recorded at each airport in the form of METARs (Meteorological Aviation Routine Weather Report), which our proposed models use for post-operational analysis and TAFs (Terminal Area/Aerodrome Forecast), which are useful for predictive analysis.

Table 1. Meteorological information considered in the study.

| Parameter                  | Measurement                                      |
|----------------------------|--------------------------------------------------|
| Wind direction & intensity | Azimuth [degrees] / Speed [kn]                   |
| Visibility                 | Horizontal visibility [m]                        |
| Significant weather phenomena | Rain, snow, dust, fog, etc.                     |
| Cloudiness                 | Cloud quantity, altitude [feet], type            |
| Temperature & dew point    | Air temperature [°C]                             |
| Pressure                   | Barometric pressure adjusted to sea level (QNH) [hPa] |
| Runway Visual Range (RVR)  | Distance over which a pilot of an aircraft on the centreline of the runway can see the runway surface markings delineating the runway or identifying its centreline [m] |
| Runway state               | Dry, deposit (wet, puddles, snow, ice), friction coefficient |

3. Objectives

Main objectives of the study arise from the needs observed in the literature review of the topic. The gaps we aim to fill are:

- Provide a methodology to evaluate the impact of adverse weather events on airport arrival performance (delay and throughput) and to define operational thresholds for significant weather conditions.
- Relate weather data from meteorological reports (METAR) and airport arrival performance data with scheduled and actual movements as well as arrival delays. Understand the relationships between weather phenomena and their impacts on arrival delay and throughput.
- Find the values of the explanatory variables (weather events) that leads to certain operational thresholds in the target variables (arrival delay and throughput).
- Quantification of the airport performance with regards to an aggregated weather-performance metric.

4. Data management and methodology

4.1. Data
The data preparation phase covers all activities required to set up the final dataset from the initial raw aircraft operational data (airlines, infrastructure usage, capacity, operational timestamps, delays and resource allocation) and weather data. We combine a dataset of over 750,000 flights on a major European hub (Adolfo Suárez Madrid-Barajas airport) and local weather data during the period 2015-2018. We integrate delay and capacity metrics at different airport operational stages for the arrival process (final approach, taxi-in and in-block). Data describes: (a) various meteorological conditions at landing; (b) the expected and actual times of different events, whose eventual discrepancy would result into
operational delays; and (c) some related count variables that illustrate airport performance, e.g. the experimented congestion or the accomplished throughput at different airspace locations. Variables (a) will be taken as explicative whereas (b) and (c) will be considered as dependent variables. Our goal is to find relationships between explicative and dependent variables, which will help us explain how changes in the former would induce alterations in the latter.

4.2. Methodology

We use a Bayesian Network (BN) approach to relate weather data from meteorological reports (METAR) and airport arrival performance data with scheduled and actual movements as well as arrival delays. This allows us to understand the relationships between weather phenomena and their impacts on arrival delay and throughput. Bayesian Networks (BNs) are a type of probabilistic graphical model that uses Bayesian inference for probability computations [41]. BNs aim to model conditional dependence, and therefore causation, by representing conditional dependence by edges in a directed graph. Through these relationships, one can efficiently conduct inference on the random variables in the graph through the use of factors. A BN is a directed acyclic graph (DAG), in which each node denotes a random variable, and each arc denotes a direct dependence between variables (nodes that are not connected symbolize variables that are conditionally independent of each other) [42–44]. Each node is associated with a probability function that takes, as input, a particular set of values for the node's parent variables, and gives (as output) the probability (or probability distribution, if applicable) of the variable represented by the node [43].

The dataset comprises 102 variables, after the data preparation phase we finally came up with a suitable minimal subset of 13 variables. We selected 7 explicative variables (Table 2), which account for the relevant meteorological information. We have, in turn, considered 6 dependent variables (Table 3), which describe key performance (delay and throughput) indicators.

| Variable | Description |
|----------|-------------|
| X2, wind intensity (wi) | A numeric variable, measured in whole knots. |
| X3, wind direction (wd) | A numeric variable, measured in tens of degrees. |
| X4, temperature (temp) | A numeric variable, measured in whole Celsius degrees. |
| X5, dew point (dp) | numeric variable, measured in whole Celsius degrees. |
| X6, QNH | This stands for the atmospheric pressure at sea-level, i.e., at zero altitude. It is a numeric variable, measured in whole hPa. |
| X7, visibility (vis) | A numeric variable, measured in m, and highly discretized, with unevenly spaced threshold values, ranging from 50; 100; 150; 200... up to 7,000; 8,000; 9,000; 9,999 and 1,0000+. |
| X2, wind intensity (wi) | A numeric variable, measured in whole knots. |
| X3, wind direction (wd) | A numeric variable, measured in tens of degrees. |

| Variable | Description |
|----------|-------------|
| Y1, Additional Arrival Sequencing and Metering Area (ASMA) at 60NM | A continuous variable measured in seconds. The additional ASMA time is a proxy for the average arrival runway queuing time on the inbound traffic flow, during congestion periods at airports. |
| Y2, congestion index at 60NM | A discrete count variable, taking integer values, computed as the number of other aircraft ahead in the arrival queue, i.e. the number of aircraft that landed between the time the flight under consideration crossed the ASMA border and its own landing. |
| Y3, arrival throughput at 60NM | A discrete count variable, taking integer values, calculated as the total number of landings at the airport, observed in the hour preceding the actual landing time (ALDT). |
| Y4, in-block delay. | A continuous variable measured in seconds. It represents the difference between the Scheduled In-Block Time (SIBT) and the Actual In-Block Time (AIBT). |
| Y5, additional taxi-in. | A continuous variable measured in seconds. It represents the difference between the scheduled and the actual taxi time. |
| Y6, off-block delay. | A continuous variable measured in seconds. It represents the difference between the Scheduled Off-Block Time (SOBT) and the Actual On-Block Time (AIBT). It allows us to consider the “knock-on effect”: the transmission of delays from arrivals to departures. |

Due to the characteristics of the problem attributes (heterogeneous nature -continuous or discrete / categorical- and different conditional distributions) we use a Hybrid Bayesian Network (HBN), which
allows to accommodate any type of variable as well as any kind of distribution for the network nodes [43]. Learning the structure of an HBN is an iterative process which, in the light of the available evidence and experts’ opinion, builds, tests and reformulates a sequence of tentative networks (different algorithms can be useful, e.g. Tabu search, Max-Min Hill Climbing,…) [45]. Several metrics have been devised to assess the goodness-of-fit of the tentative networks, e.g. the Schwarz’s Bayesian Information Criterion (BIC), which assigns higher scores to networks that fit the data better [41]. As an illustrative example we present the learning algorithm and network structure for the variable Y1 (Figure 1).

5. Results

The BN model allows us to identify and assess the dependencies between the relevant variables in our study, as well as to model their conditional probability distributions (CDF). To obtain the conditional probabilities at the different nodes (elicit the distributions) we followed the natural order induced by the dependence structure of the BN. We relied on Markov chain Monte Carlo (MCMC) simulations to estimate the model parameters: 3 chains, 100,000 iterations, 10% burn-in batch, and 5% thinning rate. Suitable initial values for the different chains were generated from relatively vague normal priors centred on the estimates provided by the Levenberg-Marquardt (LM) algorithm. This method minimizes the sum of the differences between the empirical cumulative relative frequencies calculated for some predefined intervals of the incumbent variable and the mixture CDF evaluated at the upper limit of the corresponding interval. For example, this procedure allows us to model temperature (X4) in terms of cloud quantity (X1) and wind direction (X3); i.e. X4 | X1, X3.

Inference over a BN can come in two forms: (a) direct & (b) backward.

(a) The first is simply evaluating the joint probability of a particular assignment of values for each variable (or a subset) in the network. For this, we already have a factorized form of the joint distribution, so we simply evaluate that product using the provided conditional probabilities.

(b) The second to find the probability of some assignment of a subset of the variables (x) given assignments of other variables (our evidence, e). For this, we must marginalize the joint probability distribution over the variables that do not appear in x or e, which we will denote as y. The proposed model also provides us with the values of the explanatory variables (weather events) that leads to certain operational thresholds in the target variables (arrival delay and throughput).

As an example, a probability > 70% of having Additional ASMA 60 NM values > 15 min (delay in the arrival process) is achieved with: X1, cloud quantity (cq) = BKN or OVC; X2, wind intensity (wi) > 12 kt; X3, wind direction (wd) = 180° - 360° (east); X4, temperature (temp) > 25°C; X5, dew point (dp) < 10°C; X6, QNH < 1,020 hPa and X7, visibility (vis) < 2,500 m.

Finally, we perform a quantification of the airport performance with regards to an aggregated weather-performance metric. Specific weather phenomena are categorized through a synthetic index, which aims to quantify weather conditions at a given airport, based on aviation routine meteorological reports. This allow us to manage uncertainty at airport arrival operations by relating index levels with airport performance results. The indicator is developed with different parameters and thresholds depending on the actual nominal conditions of the airport and validated according to those conditions. The indicator itself is a specific value composed by different inputs coming from each of the categories of the METAR
report: 1) wind speed, 2) shear wind conditions, 3) visibility, 4) meteorological phenomena and 5) cloudiness. Each of these categories has different weights and the final value of the indicator will be the sum of each individual category value. Thresholds are provided by the BN, which allows us to quantify the impact of each category on the output variables (clustering according to the effect of each variable). Main findings of the proposed models are:

- Threshold in the Airport meteorological indicator (value = 12) allows to differentiate between “good” and “bad weather”.
- Significant correlation ($R^2 > 0.7$) between “bad weather” conditions and proportion of both rate of cancellations (reduction of expected throughput) and delayed flights.
- There is a strong correlation between the proposed index and a quantified arrival delay measure (using a linear regression). If the daily weather score increases by 1, the average arrival delay (by means of median) increases by 3.39 min. The linear correlation results in $R^2 = 87\%$.
- Departure delay results confirm the ability of airport ground operations to absorb arrival delays (lower median and variation values for departure delays).
- Wind conditions (intensity and speed) present the highest impact on airport arrival performance.
- Apart from wind, the greatest impact comes from low visibility or thunderstorm conditions.
- Additional ASMA 60 NM transit time is higher in the periods of temperature above 25˚C.
- Cloud height is strongly dependent on phenomena type and intensity.
- Predominant visibility shows high dependence to atmospheric pressure and temperature.

6. Conclusions and future work

Weather has a big impact on airport arrival throughput (capacity) and on traffic delays. Meteorological conditions cannot be changed, but accurate forecasts help to be prepared and to minimize weather impact. Therefore, quantification of weather impact is a prerequisite to identify optimal mitigation measures. We propose a new approach for modelling causal relationships between airport arrival performance indicators and meteorological events. Our approach complements the traditional weather categorization tools, e.g. EUROCONTROL’s ATMAP (Air traffic management airport performance) algorithm [47], because it follows an effect-to-cause relation and provides the relationships between variables.

The functionalities of the proposed models provide us with information on relationships between variables, inference (direct & backward), operational thresholds and a weather index to classify the operational status regarding meteorological conditions. The models may be used as a post-operational tool but also for a predictive analysis. Our approach can be applied to quantify the impact of weather in airport arrival conditions (capacity and delay), predict the evolution of airport operational scenarios and support airport decision-making processes, perform a sensitivity analysis to dynamically quantify weather influences as conditions change, and generate a weather-related decision support for future airport operations. Moreover, probability distributions provided in this study could allow airports and airlines operators to forecast the average delay expected at the infrastructure as a function of the foreseen weather, in order to apply mitigation strategies.

Future work seeks to:

- Improve the accuracy of the model (more complete testing data and methodological enhancements).
- Compare the results when the methodology is applied to other airports (generalisation of the case study).
- Develop a feedback control loop and analyse potential response strategies / measures (how specific actions impact the airport arrival system state).
- Extend airport characterisation to areas other than capacity and delay (e.g. safety and financial performance).
- Research and include impact on other flight phases, particularly departure (knock-on effect).
- Identify which part of the registered arrival delay is primary and which part is due to the propagation of reactionary delay as this will help stakeholders to optimise operations.
• Implement a network view: variables aggregated at a higher level creating the possibility of estimating the amount of delay experienced at airports (systems or air transport network) as a function of weather conditions.

References
[1] Janić M 1997 The flow management problem in air traffic control: a model of assigning priorities for landings at a congested airport Transp. Plan. Technol. 20 131–62
[2] AhmadBeygi S, Cohn A, Guan Y and Belobaba P 2008 Analysis of the potential for delay propagation in passenger airline networks J. Air Transp. Manag. 14 221–36
[3] Wu C L 2005 Inherent delays and operational reliability of airline schedules J. Air Transp. Manag. 11 273–82
[4] Cook A, Tanner G, Cristobal S and Zanin M 2015 Delay propagation: new metrics, new insights Proceedings of the 11th USA/Europe Air Traffic Management Research and Development Seminar (Lisbon, Portugal)
[5] Beatty R, Hsu R, Berry L and Rome J 1999 Preliminary Evaluation of Flight Delay Propagation through an Airline Schedule Air Track Control Quarterly vol 7 pp 259–70
[6] Jacquillat A and Odoni A R 2015 An Integrated Scheduling and Operations Approach to Airport Congestion Mitigation Oper. Res. 63 1390–410
[7] Jacquillat A and Odoni A R 2017 A roadmap toward airport demand and capacity management Transp. Res. Part A Policy Pract.
[8] Campanelli B, Fleurquin P, Arranz A, Etxebarria I, Ciruelos C, Eguiituz V M and Ramasco J J 2016 Comparing the modeling of delay propagation in the US and European air traffic networks J. Air Transp. Manag. 56 12–8
[9] Rebollo J J and Balakrishnan H 2014 Characterization and prediction of air traffic delays Transp. Res. Part C Emerg. Technol. 44 231–41
[10] Gopalakrishnan K, Balakrishnan H and Jordan R 2016 Deconstructing Delay Dynamics: An Air Traffic Delay Example Proceedings of the 7th International Conference on Research in Air Transportation (ICRAT)
[11] Ashford N J, Stanton H P M, Moore C A, Coutu P and Beasley J R 2013 Airport Operations (New York: McGraw-Hill)
[12] Zografos K G, Salouras Y and Madas M A 2012 Dealing with the efficient allocation of scarce resources at congested airports Transp. Res. Part C Emerg. Technol. 21 244–56
[13] Schmitt D and Gollnick V 2016 Air Transport System (Vienna: Springer-Verlag Wien)
[14] Cook A 2007 European Air Traffic Management: principles, practice and research ed A Cook (Aldershot: Ashgate)
[15] Daley B 2010 Air Transport and the Environment ( Routledge)
[16] Wu C L 2012 Airline operations and delay management: Insights from airline economics, networks and strategic schedule planning
[17] Filar J A, Manyem P and White K 2001 How Airlines and Airports Recover from Schedule Perturbations: A Survey Ann. Oper. Res. 108 315–33
[18] Ciruelos C, Arranz A, Etxebarria I and Peces S 2015 Modelling Delay Propagation Trees for Scheduled Flights Proc. 11th USA/Europe Air Traffic Manag. Res. Dev. Semin.
[19] Pyrgiotis N, Malone K M and Odoni A 2013 Modelling delay propagation within an airport network Transp. Res. Part C Emerg. Technol. 27 60–75
[20] EUROCONTROL 2020 CODA (Central Office for Delay Analysis) Digest: All-Causes Delay and Cancellations to Air Transport in Europe - 2019 (Brussels: European Organisation for the Safety of Air Navigation)
[21] Cook A and Tanner G 2014 European airline delay cost reference (Brussels: University of Westminster commissioned by EUROCONTROL Performance Review Unit)
[22] Wu C L and Caves R E 2000 Aircraft operational costs and turnaround efficiency at airports J. Air Transp. Manag. 6 201–8
[23] Bazargan M 2010 Airline Operations and Scheduling (Aldershot: Ashgate)
[24] Bronsvoort J, McDonald G, Porteous R and Gutt E 2009 Study of aircraft derived temporal prediction accuracy using FANS Proceedings of the 13th ATRS World Conference (Abu Dhabi, UAE)

[25] Mueller E and Chatterji G 2002 Analysis of Aircraft Arrival and Departure Delay Characteristics Proceedings of the AIAA Aviation Technology, Integration, and Operations Conference (Los Angeles, CA, USA)

[26] Reitmann S, Alam S and Schultz M 2019 Advanced Quantification of Weather Impact on Air Traffic Management 13th USA/Europe Air Traffic Management Research and Development Seminar 2019

[27] Schultz M, Lorenz S, Schmitz R and Delgado L 2018 Weather Impact on Airport Performance Aerospace 5

[28] Performance Review Commission 2017 Performance Review Report—An Assessment of Air Traffic Management in Europe during the Calendar Year 2017 (Brussels: European Organisation for the Safety of Air Navigation (EUROCONTROL))

[29] Steinheimer M, Kern C and Kerschbaum M 2019 Quantification of weather impact on arrival management 13th USA/Europe Air Traffic Management Research and Development Seminar 2019

[30] Rodríguez-Sanz Á, Comendador F G, Valdés R A and Pérez-Castán J A 2018 Characterization and prediction of the airport operational saturation J. Air Transp. Manag. 69 147–72

[31] Rodríguez-Sanz Á, Comendador F G, Valdés R A, Pérez-Castán J, Montes R B and Serrano S C 2019 Assessment of airport arrival congestion and delay: Prediction and reliability Transp. Res. Part C Emerg. Technol. 98 255–83

[32] Wu C L and Caves R E 2004 Modelling and optimization of aircraft turnaround time at an airport Transp. Plan. Technol. 27 47–66

[33] Lin L C and Hong C H 2006 Operational performance evaluation of international major airports: An application of data envelopment analysis J. Air Transp. Manag. 12 342–51

[34] Rodríguez-Sanz Á, Álvarez D Á, Comendador F G, Valdés R A, Pérez-Castán J and Godoy M N 2018 Air Traffic Management based on 4D Trajectories: A Reliability Analysis using Multi-State Systems Theory Transp. Res. Procedia

[35] Rodríguez-Sanz Á, Fernández B R, Comendador F G, Valdés R A, Cordero García J M and Bagamanova M 2018 Operational Reliability of the Airport System: Monitoring and Forecasting Transp. Res. Procedia 33 363–70

[36] Horonjeff R M, McKelvey F X, Sproule W J and Young S 2010 Planning and Design of Airports (New York: McGraw-Hill)

[37] Wells A T and Young S B 2014 Airport Planning & Management

[38] EUROCONTROL 2015 Additional ASMA Time Performance Indicator document. Performance Review Unit

[39] SESAR Joint Undertaking 2017 SESAR 2020 Concept Of Operations

[40] EUROCONTROL, ACI and IATA 2012 Airport CDM Implementation: The Manual (Brussels: European Organisation for the Safety of Air Navigation)

[41] Neapolitan R E 2003 Learning Bayesian Networks (New Jersey: Prentice Hall)

[42] Pearl J 2000 Causality New York Cambridge

[43] Kjærulff U B and Madsen A L 2013 Bayesian Networks and Influence Diagrams - A guide to construction and analysis (New York: Springer)

[44] Nielsen T D and Jensen F V 2007 Bayesian Network and Decision Graph

[45] Koski T and Noble J M 2009 Bayesian Networks: An Introduction (Chichester, West Sussex: Wiley & Sons)

[46] Krauthausen P and Hanebeck U D 2010 Parameter learning for hybrid bayesian networks with gaussian mixture and dirac mixture conditional densities Proceedings of the 2010 American Control Conference, ACC 2010

[47] EUROCONTROL 2011 ATMAP: Algorithm to Describe Weather Conditions at European Airports (Brussels: European Organisation for the Safety of Air Navigation)