MODELLING DEPENDENCE OF ARRIVAL SEQUENCING AND METERING AREA TRANSIT TIME ON AIRPORT METEOROLOGICAL CONDITIONS

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ABSTRACT

Airports are considered complex system in which the coexistence of different actors competing and collaborating for the same resources under operational time uncertainties can cause a poor performance on the overall ATM (Air Traffic Management) system. In order to facilitate the process of decision making to mitigate the propagation of perturbations through the different airport processes a causal model relying on machine learning, using data mining algorithms has been implemented to predict feasible states. This paper introduces a new approach for modelling causal relationships, which can be used for further analysing of feasible scenarios by means of simulation techniques. The state space analysis of reachable airport states is a relevant approach to validate the causal model using a huge amount of historical data for predictive purposes.

Keywords: airport management, Coloured Petri nets, Bayesian networks, decision support tool.

1. INTRODUCTION

The airport is a complex transportation hub serving aircraft, passengers, cargo, and surface vehicles (Office of Technology Assessment 1984). It has three major components: airside, landside and the terminal building, which performs connection between them. Airside is an airport area, where aircraft operate: take off and land, move between the different runways and the terminal. Landside consists of roadways and parking facilities. Terminal complex mainly consists of buildings, serving passengers and air cargo. All these areas are strongly interconnected to each other through different procedures and operations, often fully or partially operated and controlled with the use of IT systems. These operational activities of airports with modernized IT systems are generating an immense amount of data, which can be used for better understanding of hidden dynamics both at the airside and at the landside. However, raw data is quite difficult to be analysed at a glance due to its large volume: for instance, Madrid-Barajas airport airside operations data for one hour of operation with maximum 46 aircraft landed and departed, would make a table of at least 25 different columns with aircraft identification information and data stamps of its movements (landing, taxi in, engine start, taxi out, take off, etc.) and services it went through. The data table of such size can be quite demanding to analyse manually. Therefore for the analysis commodity, these data can be expressed in the form of so called Key Performance Indicators. These Key Performance Indicators (KPIs) are quantitative expressions of effectiveness in achieving performance objectives (European Organisation for the Safety of Air Navigation 2014). As various areas of airport due to their nature can have various KPIs, they are usually merged into Key Performance Areas (KPAs), representing different areas of management interest. An instance of airport KPAs and KPIs is presented in Table 1. The list of KPAs and KPIs can be enlarged according to what targets management team desires to monitor and analyse.

Table 1: Example of KPAs and KPIs (Tabernier 2015)

KPAs	KPIs
Environment / Fuel Efficiency	Average fuel burn per flight.
Airspace Capacity	En-Route and Terminal Manoeuvring Area throughput (average movement per hour).
Airport Capacity	Runway throughput (average movement per hour).
Predictability	Variance of difference in actual & Flight Plan
Punctuality	% Departures < +/- 3 mins vs. schedule due to ATM causes.

Unfortunately, due to tight interdependencies between apparently isolated airport sub processes, airport performance is very sensible to any change in the programmed activities which increase drastically the complexity of airport performance analysis (European Organisation for the Safety of Air Navigation 2017a).

The understanding of the sources of occurred operational issues remains one of the main directions of air transport management scope. Note for instance that European Organisation for the Safety of Air Navigation (EUROCONTROL) aggregates the performance data obtained from European airports and in the form of publicly open documents reveals main European air transport performance problems.

According to one of such reports 2016 was a year with increased volume of flights delay, and furthermore the contribution of reactionary delay has increased up to 45% of total delay minutes (Walker 2017). A reactionary delay is a delay caused by late arrival of aircraft or crew from previous flights (European Organisation for the Safety of Air Navigation 2005). In such manner any delay occurred in the departure airport could lead to severe delays in the following successive flights and their airports of destination. Nevertheless this kind of delay is not the only reason of on-time performance decrease in 2016, as it could be seen on Figure 1.

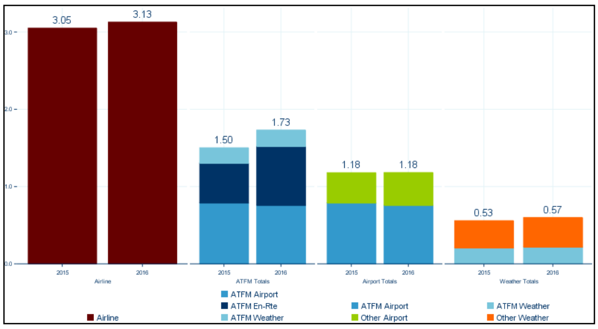

Figure 1: Primary Delay Causes in Europe 2015 vs. 2016, Minutes per Flight (Walker 2016)

Flight delays occurred due to weather conditions also constitute a considerable part of the common delay reasons structure. The fact that weather changes could not be controlled but could be predicted, motivates to obtain the way to efficiently prepare the airport system to any possible impact of weather conditions in order to reduce any negative consequence on its operational activities.

In this paper it is described an approach to model the possible dependence of one of the main airport performance indicators - Arrival Sequencing and Metering Area (further referred to as ASMA) transit time on the weather conditions of arrival airport. Section 2 describes mathematical tools that could be used for the modelling. Section 3 explains the use of Coloured Petri Nets formalism for modelling and simulation of ASMA transit time changes. Section 4 discusses some generated results, directions for further research and some concluding marks are given in Section 5.

1.1. Forecasting in Air Traffic Management

Various organisations perform forecasts for enplanements, airport operations, tracon operations and others. For instance, Federal Aviation Administration (USA) makes its forecast based on demand for aviation services. Econometric and time series modelling are typically used for this purpose. Beside of high potential powerfulness, econometric modelling includes many complex factors and parameters from internal and external infrastructure, which make its application quite difficult and skills demanding. On the other hand, time series modelling seems simpler as it consists of extrapolating knowledge from historical data into the future state. Nevertheless, such extrapolating requires solid statistical analysis and accurate historical data (Federal Aviation Administration 2016).

European Organisation for the Safety of Air Navigation (EUROCONTROL) provides customised analysis and modelling for any airport stakeholders with a use of calculations of performance indicators and different statistical metrics (European Organisation for the Safety of Air Navigation 2017b). International Civil Aviation Organization (ICAO) supports airports planning with medium and long-term forecasts of air traffic for global, regional and route-group levels (International Civil Aviation Organization 2017). These organisations provide open to public global and regional forecasts, however when it comes to the level of particular airport, these organisations could provide only an assistance in analysis and modelling, acting as an external consultant.

1.2. Causal Analysis

Many researchers offer different approaches for understanding and forecasting perturbations of various airport activities. For instance, Quadratic Response Surface (QRS) linear regression models and ensemble Bagging Decision Tree regression (BDT) models have been used to assess weather impact on maximum number of movements per time interval in few USA airports (Wang 2012). Queueing and integer programming models have been used to model the taxi-in process (Idris, Anagnostakis, Delcaire, Hansman, Clarke, Feron and Odoni 1999; Andersson, Carr, Feron and Hall 2000; Roling and Visser 2007). According to the conclusions of these works, the methods used have appeared to be quite helpful, but still not giving perfect approach for airport stakeholders. So the search needs to be continued.

Current modernisation initiatives Single European Sky ATM Research Programme (SESAR) in Europe and NextGen in USA impulse implementation of new operational concepts and technologies, aiming to transform current aviation network into highly efficient, robust and cost optimised system. In order to reach such efficiency it is necessary to understand and fully control any performance area of airport system. For measuring level of success in these tasks airport management can use performance indicators, which permit to compare actual and planned functionality of airport.

It is important to remember, that airports are not operating in isolated conditions, instead, airport operational disruptions could generate severe reactionary delays through the full aviation network. Thus, it is important the research on new efficient tools for the causal analysis of operational deviations and its prediction, considering the operational conditions that affects each particular airport for the design of mitigation mechanism in the own airport but also at network level.

2. DATA RELATIONSHIP DISCOVERY

We have been provided with Key Performance Indicators data for year 2015, used by analysists of CRIDA (Reference Center for Research, Development and Innovation in Air Traffic Management) and the data from the METAR report, consisting of recorded meteorological conditions on the territory of Madrid-Barajas airport. Some of them are listed in Table 2.

Table 2: KPAs and KPIs

KPA	KPI
TMA	Percentage of flights with holding
	Separations - en NM
	Additional time in ASMA
AIRPORT	Real turnaround time compared to planned
	Additional taxi-out time
	Time between consecutive operations on a runway
	Regulated departures adjustment to CTOT
Capacity	Difference between capacity and demand
	Available capacity
Predictability	Punctual arrivals
	Punctual departures
	Arrivals’ standard deviation
	Departures’ standard deviation
Meteorology	Wind direction Variable wind direction
	Wind intensity Gusts of wind
	CAVOK
	Predominant visibility Minimal visibility
	Temperature Dew Point Atmospheric pressure
	Phenomenon Cloudiness

For various KPIs’ data has been provided in a different form. Some values have been measured for one hour interval, others for 20 minutes interval. Meteorological data consisted of observations for every 30 minutes. Furthermore, we have been commented by CRIDA analysts on the particular interest of discovering hidden causes of perturbations of time in ASMA of radius of 60 nautical miles (NM), expressed as additional ASMA transit time (current performance reports are performed for ASMA with radius of 40 NM).

It has been noted (Klein, Kavoussi and Lee 2009; European Organisation for the Safety of Air Navigation 2015) that weather impact on airport performance is quite significant, but yet not studied well enough. Therefore it has been chosen to study weather impact on one of the KPIs of Madrid-Barajas airport. For the scope of this paper study of weather conditions impact on airport functionality, the following available data has been considered of the first study interest:

- Additional ASMA transit time – a difference between actual time spent by aircraft in ASMA area with radius of 60 NM and average time, statistically measured for particular type of aircraft (for the modelling purpose shortly referred to as ASMA).
- Number of flights with holding patterns – number of flights, which have to take a special route around aerodrome in order to wait for an appropriate moment for landing. (H)
- Wind direction (Wind) and wind intensity (WI).
- Predominant visibility on the aerodrome territory (Vis).
- Dew point (DP).
- Atmospheric pressure (Pres).
- Weather phenomenon type – if fog or any other similar phenomenon occur (Fen).
- Cloudiness (Cloud).

Among the different analytical tools (Marsland 2015; Song 2007) to discover relationship structure between observed variables, the construction of Bayesian networks seems to provide a promising approach to better understanding of complex systems, such as airport, thanks to its capability to cope with high-dimensional problems of different data types (Marsland 2015; Song 2007; Xu, Laskey, Chen, Williams and Sherry 2007) and many powerful computer programs, that made any related computations easy and rather fast.

2.1. Bayesian Networks

Bayesian networks are commonly used for representation of a knowledge about an uncertain area (Song 2007). A Bayesian network is a graphical representation of relationships between different variables, where given variables are represented as nodes and their probabilistic dependencies of each other are represented as directed arcs connecting the nodes. In such manner the absence of direct arc between some two nodes means that these two nodes are conditionally independent of each other (Marsland 2015). When a node has an outgoing arc, it is called *parent*, the nodes with incoming arcs are called *children*. The joint probability distribution P_X of the chosen variables X is represented as a product of conditional probability distributions of each variable X_i (Nagarajan, Scutari, and Lèbre 2013):

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$$P_X(X) = \prod_{i=1}^{p} P_{X_i}\left(X_i \middle| \Pi_{X_i}\right) \qquad (1)$$

Through the conditional probability distribution, calculated for every variable of the studied data, it is also possible to conclude about posterior or future data values. This conclusion is expressed as likelihood function and could serve as the base for prediction model (Gelman, Carlin, Stern, Dunson, Vehtari and Rubin 2014).

The task of discovering a Bayesian network fitting the data consists of two phases: structure and parameter learning. Various algorithms have been developed for the first phase execution. However among all of them only two algorithms have been chosen for the purposes of this paper – Silander - Myllymäki (SM) (Silander and Myllymäki 2006) and Max-Min Hill-Climbing (MMHC) (Tsamardinos, Brown, and Aliferis 2006) algorithms. These algorithms combine constraint-based and score-based algorithms strong sides and are claimed to be highly effective in various situations (Nagarajan, Scutari, and Lèbre 2013). However the approaches, used by these algorithms, are quite different.

2.1.1. Silander – Myllymäki Algorithm

This algorithm was developed for discovering the globally optimal Bayesian network without any structural constraints (Silander and Myllymäki 2006). In order to find the optimal network structure for the specific data, the algorithm has to perform several steps:

1. Find the best parents for all $n2^{n-1}$ pairs of variables, taking the calculated scores for $n2^{n-1}$ as a choice criteria (the higher the score values, the better is the fitness of a candidate variable as a parent).
2. Find the best children node, which cannot be a parent to any other variable.
3. Based on the results of Step 2, find the best arrangement of the variables.
4. Find a best network, taking into account the results of Step 1 and 3 (Silander and Myllymäki 2006).

Despite of quite high quality of the possible SM algorithm results, it has some computational complications. Thus according to the experiments performed by the authors of SM algorithm, the memory requirement for discovering a network of 32 variables is about 16 GB, although distribution of the computation process among few computers could help to overcome this restriction (Silander and Myllymäki 2006). Still, as finding a globally optimal network is NP-hard (Chickering, Meek, and Heckerman 2004), the computational time for SM algorithm is rather long and could easily take 50 hours for a dataset of 30 variables (Silander and Myllymäki 2006). Therefore in order to speed up the discovering of Bayesian network, the use of faster performing algorithm has to be considered as well. One of the most popular algorithms (Nagarajan, Scutari, and Lèbre 2013) with this characteristic is Max-Min Hill Climbing (MMHC) algorithm.

2.1.2. Max-Min Hill-Climbing Algorithm

This algorithm combines principles from local learning and both constraint-based and search-and-score techniques. First, it reconstructs the skeleton of a Bayesian network, and then orients the arcs by performing a Bayesian-scoring greedy hill-climbing search (Tsamardinos, Brown, and Aliferis 2006).

This algorithm has many similarities with the Sparse Candidate (SC) algorithm, which was one of the first successfully performing approaches, applied to large datasets with several hundred variables (Friedman, Linial, and Nachman 2000). Both SC and MMHC perform stepwise reduction of a candidate parents set for each variable and then search for a network that maximise a chosen scoring function. However they do have one important difference. The SC algorithm performs the reduction and network search steps iteratively until there is no improvement in the scoring function value, MMHC performs the candidate parent estimation only once (Nagarajan, Scutari, and Lèbre 2013), therefore fastening the computational process by several times without significant loss in correctness (Tsamardinos, Brown, and Aliferis 2006).

2.1.3. Data Preparation and Learning the Network Structure

As the dataset, provided for analysis, consisted of data for different time intervals, first it has been necessary to transfer all KPIs to the same time interval for facilitation of analysis. It was considered to perform the analysis of data for the time interval of the size of one hour (most common interval of observation that have been seen in the KPIs´ dataset). All chosen for analysis KPIs´ with smaller time interval of observations have been aggregated till the level of one hour.

Additionally, it has been noticed, that provided KPIs values do not all have the same character of values. Some KPIs are observed as *continuous* variables, others – as *discrete*:

- Continuous variable - variable, that can take on any real value within certain interval (Joshi 1989); for instance, additional ASMA time is expressed in minutes.
- Discrete variable - can take on only certain values (Joshi 1989); for instance wind intensity.

Presence of such mixed data can potentially cause a problem in the step of defining a probabilistic model, fitting the data (Nagarajan, Scutari, and Lèbre 2013). Therefore it has been decided to perform a common used solution to avoid the mentioned problem – perform *discretization* or *binning* of the data. Discretization means assigning some particular integer value to the certain intervals of continuous data. There are different ways to define the intervals for data discretization: using expert knowledge on data, using heuristics, performing discretization and structure learning iteratively, etc. (Nagarajan, Scutari, and Lèbre 2013). Taking into account common practice of KPIs´ analysis by CRIDA experts, it has been decided to discretise continuous data as shown in Table 3.

Table 3: Intervals of Discretization

Category	Additional ASMA time, % of unimpeded ASMA time	Visibility, m	Wind direction, °	Actual temperature minus Dew point temperature	Cloudiness	Phenomenon, type	Pressure, QNH
1	(∞;-15)	<50	(22,5; 67,5]	0	FEW	BR	<1013
2	[-15; -10)	[50; 400)	(67,5; 112,5]	-	SCT	DZ	1013
3	[-10; -5)	[400; 8000)	(112,5; 157;5]	-	BKN	FG	>1013
4	[-5; 5)	≥8000	(157,5; 202,5]	-	OVC	RA	-
5	[5; 10)	-	(202,5; 247;5]	-	-	SN	-
6	[10; 30)	-	(247,5; 336,5]	-	-	-	-
7	≥30	-	(337,5; 22,5]	-	-	-	-
0	0	-	VRB	<>0	0	0	-

In Table 3 the following abbreviation have been used:

- VRB – variable wind direction.
- FEW – few clouds.
- SCT – scattered.
- BKN – broken clouds.
- OVC – overcast.
- BR – mist.
- DZ – drizzle.
- FG – fog.
- RA – rain.
- SN – snow.

After data preparation both SM and MMHC algorithms have been executed subsequently in the framework of R software.
As soon as both algorithms have performed their Bayesian network learning for the chosen airport performance data, the best network can be chosen based on the best value of the network scoring functions. Both algorithms have a possibility to evaluate the learnt network with three popular statistical scoring functions: BDeu (Bayesian-Dirichlet equivalent uniform), AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). These scoring functions are common tools for selection between different statistical models and represent goodness of fit of a model to observed data (Brockwell and Davis 1991).

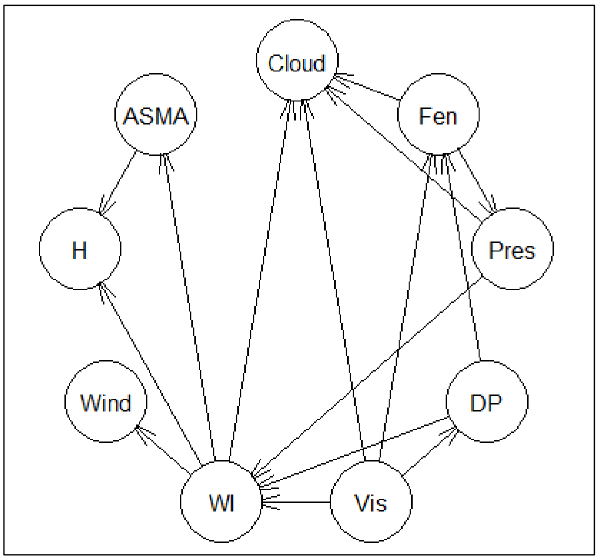

Figure 2: Bayesian network obtained with MMHC and SM Algorithms

In the case of chosen for this paper variables, both SM and MMHC algorithms have come to the same network structure, shown on Figure 2, therefore it was decided not to compare their score functions. Every arc of obtained network had probability of being true of not less than 95% and as MMHC algorithm has come to its results in a shorter computational time (less than one minute for Intel (R) i5-4300M CPU 2.60 GHz, 8 GB RAM), it has been considered to use its results for the further study.

2.2. Bayesian Inference
The knowledge obtained from Bayesian Networks about the data structure and its parameters is used for reasoning on further possible parameters of the chosen airport performance indicators. There are two main approaches for updating the posterior probabilities of data distribution: exact and approximate inference.
Variable elimination and Junction Tree are the two best-known approaches for exact inference task. First approach uses the network structure directly, taking into account the local distributions of the data variables. On contrary, the second algorithm transforms the network by clustering its nodes into a tree. However the feasibility of exact approach is restricted to small networks. Approximate inference algorithms create samples from the local distributions by the use of Monte Carlo simulations and then evaluate them. The sampling can be performed in different ways, implemented in several approximate algorithms (Nagarajan, Scutari, and Lèbre 2013).
The parameters learnt in this step take the form of regression coefficients, belonging to regression functions, describing the conditional dependence between studied variables. For this research it is considered to use the logic sampling approximate inference algorithm, already included in functionality of

one of the R software packages for Bayesian Networks. The inferenced parameters of a network have been used for mathematical expression of relationships between observed variables in arc expressions of CPN model in order to perform simulation run and state space analysis.

3. MODELLING WITH CPN FORMALISM

A Coloured Petri Net (CPN) is a formalism, aimed to design, visualise and explore the behaviour of various systems. In order to model the system with CPN formalism it is necessary to define a set of parameters as (Jensen and Kristensen 2009):

- Set of colours – to represent the model entities (key performance indicators).
- Set of places nodes – to represent combinations of the model entities.
- Set of transition nodes – to represent systems' activities (weather changes, arriving aircraft, etc.).
- Set of Arcs – to relate transition and places nodes.
- Guard functions, which are associated to the transition nodes in order to insure their enabling only in case of satisfaction of conditions, described in the corresponding guard function.

For the net elements inscriptions CPN ML, a functional programming language, is included to the modelling framework. It provides the way to make different declarations and perform modelling of data manipulation (Piera and Musič 2010). This language is used in construction of arc functions and in declarations of intervals of possible values for model parameters.
For modelling the chosen KPIs of Madrid-Barajas airport, the colours, representing weather indicators, average additional ASMA time, and number of flights with holding pattern have been chosen. Furthermore it has been considered to introduce the colour, representing system time counter, for having a tool to track system dynamics in time without increasing model complexity.
Design of the developed CPN model is shown on Figure 3.

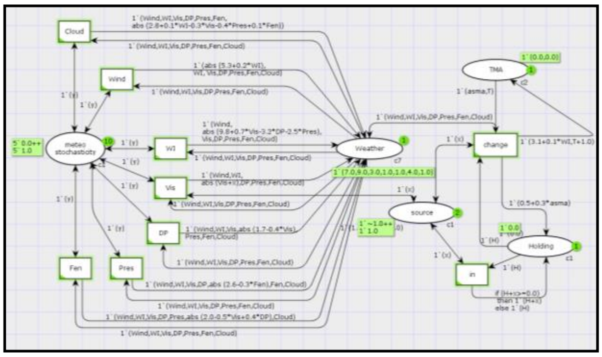

Figure 3: Weather Indicators CPN Model Design

The studied KPIs are distributed among three places as follows:

- Place Holding – number of flights with holding pattern (H).
- Place TMA – additional ASMA time and time counter.
- Place Weather – Wind, WI, Vis, DP, Pres, Fen and Cloud.

Furthermore two supporting places, ensuring the element of stochasticity, have been also added to the model. They are:

- Place Meteo stochasticity – provides tokens for stochastic weather changes.
- Place Source – provides tokens for stochastic changes in number of arriving flights with holding pattern.

In order to formulate the observed ASMA system behaviour in CPN Tools, it is required to define functions for the expressions of arc, connecting elements of the model. The arc functions have the following aspect, based on the maximum likelihood estimation parameters, obtained on the step of Bayesian inference:

$$C_i = \beta + k * C_j \qquad (2)$$

Where
C_i = represents CPN colour i, a studied metric.
β = represents intercept value.
k = represents regression coefficient.
C_j = represent CPN colour j, on which CPN colour i is conditionally dependent. When there are more metrics, on which colour i is conditionally dependent, they are included with the corresponding regression coefficients.
After introducing all necessary system parameters, series of simulation runs can be executed in order to verify and validate the model.

4. SIMULATION AND RESULTS

Default tool of CPN Tools v. 4.0.1, which can be used for model verification, is the state space analysis. This analysis consists of generating all states and state changes of a model, that can be reached from the initial state (Jensen and Kristensen 2009). CPN Tools v. 4.0.1 allows to graphically represent all possible system states through *reachability tree* (RT) – a directed graph, where root node represents initial marking of the system, and the successive nodes represent the new states, that can be reached from the initial state, if the corresponding transitions have been fired (Jensen and Kristensen 2009). Few series of state space construction (reachability tree generation) have been performed with a use of CPN Tools v. 4.0.1 software in order to explore how parameters of the system – colours, change their values. The initial markings of the model, used for state space analysis are shown in Table 4. These values have been chosen from the available historical data for the same time period as for Bayesian inference, in order to compare the system dynamics, observed in the historical data and the changes, discovered through RT construction.

Table 4: Simulation Scenarios Initial Markings

Model parameters	Scenario 1	Scenario 2	Scenario 3
	Parameter value		
ASMA time	0	3	0
Flights with holding	0	2	0
Wind direction	7	0	7
Wind intensity	0	2	9
Visibility	4	2	3
Dew point	0	1	1
Pressure	3	1	1
Phenomenon	0	4	4
Cloudiness	0	2	1

In the RT generated for all three chosen scenarios, in every tree a branch with the same weather indicators changes has been found. This has allowed to compare how ASMA transit time has developed in these RT branches and in the historical data. Figure 4, 5 and 6 represent this comparison for each of three simulation scenarios respectively for the time period of 24 hours.

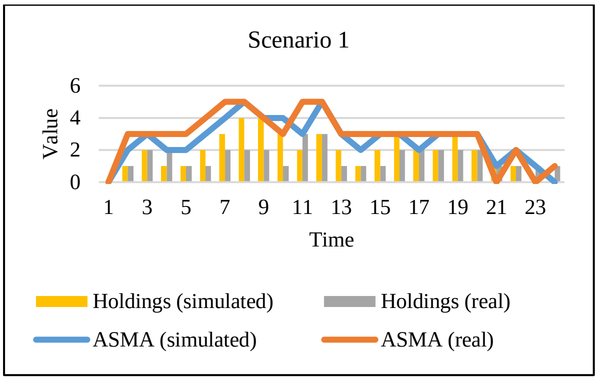

Figure 4: CPN Simulated ASMA Transit Time, Real ASMA Transit Time, CPN Simulated Holdings and Real Holdings Comparison for Scenario 1

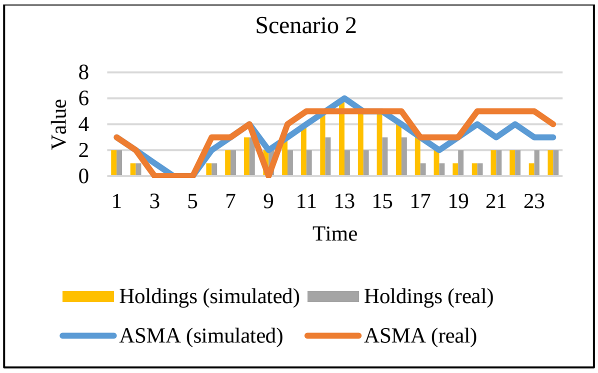

Figure 5: CPN Simulated ASMA Transit Time, Real ASMA Transit Time, CPN Simulated Holdings and Real Holdings Comparison for Scenario 2

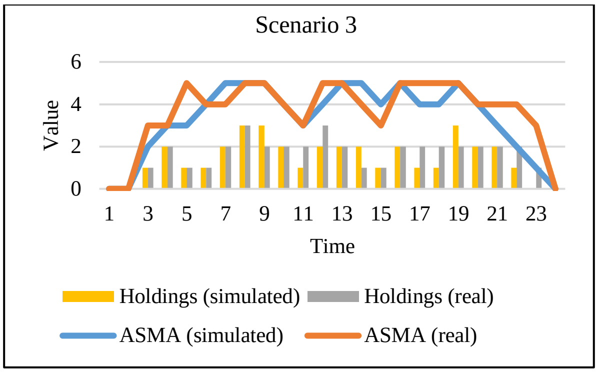

Figure 6: CPN Simulated ASMA Transit Time, Real ASMA Transit Time, CPN Simulated Holdings and Real Holdings Comparison for Scenario 3

All three simulation scenarios have demonstrated that additional ASMA time increases with the delay with the increase of number of flights with holding pattern, and also increases with the development of serious weather conditions (for instance, increasing wind intensity). This is illustrated on Figure 7. Although this correlation becomes not significant in the hours of low number of arriving aircraft (night time). The same behaviour was noted in Scenario 2 and 3 as well.

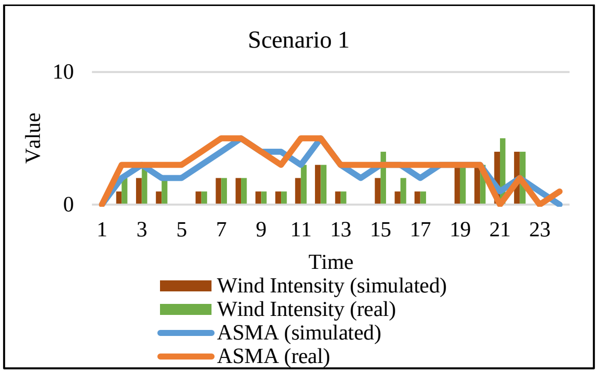

Figure 7: CPN Simulated ASMA Time and Real ASMA Time Comparison to CPN Simulated Wind Intensity and Real Wind Intensity for Scenario 1

Potentially, a set of variables, representing events, preceding the entering of the aircraft into the ASMA, can be added into the model in order to take into account influence of en-route regulations on number of flights with holding pattern.

Furthermore, it has been noticed that both number of flights with holdings and values of additional ASMA time do not increase infinitely. This phenomenon is considered to be probably related to the aerodrome capacity limit: an aerodrome can accept only finite number of aircraft per time interval (due to limited throughput of its runways). Nevertheless it is considered to perform more experiments in the future to better explore this phenomenon.

The explored through RT system dynamics raises the question of adding more metrics to the model, potentially representing en-route events for different flights and also other KPIs, not listed in Table 2, but available in the databases of Madrid-Barajas airport. After adding the new metrics to the model, Bayesian inference and new series of simulation with CPN framework should be performed with various realistic initial markings.

5. CONCLUSIONS AND FURTHER RESEARCH

This paper describes an approach to explore relationships between ASMA transit time deviations, number of flights with holding pattern and weather indicators with the use of Bayesian Network. Mathematical expressions of the discovered relationship have been used in order to build a model, capable to show possible states of the system for different scenarios of ASMA transit time changes. These scenarios are considered to be used by airport decision makers in order to design other scenarios and be prepared for any deviation that could occur in the terminal maneuvering area and its surroundings in the future and be able to explore the possible causes of any deviations of ASMA transit times occurred in the past.

It is considered also that the model could be extended and more airport performance metrics could be added to it in order to perform more wide and complex analysis, considering bigger area of airport operational activities. The noise, representing stochasticity of weather conditions for aircraft on en-route phase, preceding arrival to the studied airport, could be also added and its influence could be observed during the further research. However the computational restrictions of the used software have to be taken into account, as if the model becomes more complex, it would take more time and computational resources in order to explore all possible state spaces and perform the analysis.

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