Assessing ATM performance interdependencies through Bayesian Networks

Preliminary applications and results

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Abstract— **The Performance model proposed by this study represents an innovative approach to deal with performance assessment in Air Traffic Management (ATM). It is based on Bayesian Networks methodology, which presents several advantages but also some drawback as highlighted along the paper. We illustrate the main steps required for building the model and present a number of interesting results obtained. The contribution of the paper is twofold: it presents a new methodological approach to deal with a problem which is of strategic importance for Air Navigation Service Providers (ANSPs) and a the same time it provides insights on the interdependencies between factors influencing performance. Both results are considered particularly important nowadays, due to the SES Performance Scheme and the transition stage between the first and second reference periods.**

Keywords-Key Performance Area; Interdependencies; Performance Target; Bayesian Network; Air Traffic Management;

I. INTRODUCTION

The Air Traffic Management (ATM) industry has long known that optimizing performance involves a delicate balance between different areas of performance. Within the current European context the need for determining and assessing such complex trade-offs becomes imperative for the European Commission and the ANSPs. On one side in fact ANSPs are required to adopt a wide array of operational and technical solutions validated by SESAR, while on the other side the Performance Scheme (EC Reg. 390/2013) is regulating the performance achievements along a first reference period (RP1 2012-2014) and a second reference period (RP2 2015-2020), imposing on the other one. For this purpose it identifies a number of performance indicators along four Key Performance Areas (KPAs): Capacity, Environmental Flight Efficiency, Cost efficiency and Safety. For each of the three former KPAs one quantitative target measured according to a Key Performance Indicator (KPI) has been set by the Regulation, with which the ANSPs are expected to comply.

The main objective of this study is to apply the methodology of Probabilistic Bayesian Networks to the building of a European ATM performance model. The aim is to identify and assess the magnitude of interdependencies between performance indicators, based on a probabilistic approach which takes into account the great variability in ANSPs performance due to both endogenous and exogenous factors as well as the uncertainty implied by future changes in the operational context. The current version of the model focuses on just two out of the four KPAs included in the Performance Regulation: Capacity and Cost-effectiveness. This is justified by the availability of complete and consistent series of historical data, which was available for these two. It could easily be extended to incorporate the rest of KPAs as soon as comparable set of observation would be available. The resulting model could provide to be useful both to observe and analyze the historical performance in these KPAs at a general European and local levels, as well as to predict future compliance with performance targets differences among taking into account all the relevant influencing factors and incorporating additional knowledge about the system as it becomes available.

II. STATE OF THE ART

In the context of this study, the word interdependency is used to define the cause-effect relationships that exist between different KPAs.

Several studies in the past have been trying to understand and quantify interdependencies, mainly between selected pairs of KPAs (measured through specific KPIs).

In [1] the PRU aims to estimate a cost function for the provision of ANS/CNS service, in order to assess the cost-efficiency of ANS/CNS differentiating between the contribution of endogenous factors (under the direct control of ANSP) and the effect of exogenous factors (outside their control). The study splits the ANSP cost structure into a fix part (capital-related for ATM systems and CNS infrastructure) and a variable part that may be affected by the volume of traffic or size of operations. Therefore, both economies of scale and economies of density are likely to exist. The former refer to the fact that larger ANSPs can benefit from scale effect, due to the important share of fixed costs into their cost base, which do not increase proportionally with traffic, thus giving lower unit costs than for smaller ANSPs (all else equal). The latter refer to the fact that an ANSP with plenty of spare capacity may accommodate additional traffic without any significant impact on costs (i.e. the additional traffic volumes are absorbed using the same resources).

The Cobb-Douglas cost function is estimated through regression, based on observed data describing traffic volume, ATCO and support staff employment costs, exogenous factors describing the ANSP operating environment plus an error term. Four estimation models are used for determining the coefficients depending on the assumptions made related to the error term: OLS, Pitt and Lee Random Effects, True Random Effects and Random coefficients model.

OLS and Random coefficients model provide larger inefficiency estimates than expected so they are not analyzed or interpreted. The Pitt and Lee model main results indicate that a 10% increase in volume of traffic leads to 5.7% increase in costs; a 10% increase in ATCO wages translates in approximately 3% increase in costs; the greater the concentration of airport traffic is, the lower the unit costs are; the size of the airspace controlled and the traffic variability are associated with greater costs, which suggests economy of scale. The difference between ANSPs performance may be influenced by traffic variability. Estimating the technical efficiency related to these results, the conclusion is that costs are 60% higher than the efficient benchmark.

Similar to the Pitt and Lee model results, the True Random Effect model suggests presence of economy of scale, based on the relationship between costs and controlled space. Additional results indicate that 3% increase in costs due to 10% increase in one of the two labor costs (ATCOs or support staff). The level of inefficiency applying this model is estimated around 13%.

As the two models give different levels of inefficiencies, it is assumed that the real value of inefficiency is probably among 13 and 60%. The ANSP inefficiency does not represent the main focus of the performance model, but the intermediate results presented by the PRU report can be compared to the results of this study, as they are based on relationships and tendencies between variables.

Castelli et al. ([5]) study the dependencies of ANSP's revenue as a function of the Unit Rate which is charged to Airspace Users. A higher cost for the ANSP generally requires higher revenues, but the price elasticity of the Airspace Users (AUs) must be taken into account in this framework, since AUs could modify some of their routes and decide flying through different (i.e. cheaper) charging zones. This implies a theoretical cap on the maximum value of Unit Rate fixed by the ANSP, which is determined through a Bilevel Programming model. On one side the ANSP wants to maximize its revenue (1st optimization), but on the other one the AU wants to minimize the en-route charges (2nd optimization).

Another performance interdependency which has been extensively analyzed in the past is the one between the cost of ATFM delays and the a lack of capacity to airspace users. The main stream of work has been carried on by the University of Westminster in collaboration with the Performance Review Unit and the main results were published first in 2004 [2] and successively updated in 2011 [3]. The most relevant conclusion of these studies consists in a direct relationship between delay and operational costs. A delay at-gate (CTOT) can be traded-off by the AU with the option of re-routing. However it is interesting to note that the study also proposes the formalization of a link between cost and flight efficiency, since depending on the delay amount (i.e. greater than 15 minutes), the AO could accept another longer route if reducing [(1.1n ÷ 1.3n) + 10] minutes the total delay.

Based on the cost of delay values published by the University of Westminster, EUROCONTROL exposes in [4] a methodology to compute the optimum Capacity/Delay trade-off and to support ANSP in the allocation of capacity requirements among Air Control Centers (ACCs), to reach a given delay target. As the ratio between Capacity and Traffic increases, the ANS costs also increase whilst the delay costs are reduced. The balance between the ANS provision costs, the delay costs and the ratio between capacity and traffic can be reached at an Optimum Operating Point, which represents the best trade-off between the cost of providing capacity and the cost of delay. If each ACC would operate at its optimum point, it would correspond to the optimum level of ATFM Delay at overall ECAC level. Once more the Capacity's link to the Delay and Costs is demonstrated.

Besides regression analysis as applied in [1], other tools and techniques have been applied in ATM to model and assess performance relationships. An integrated set of influence Diagrams have been constructed within the Episode 3 (EP3) project to show the influences between the SESAR steps and the focus areas of Capacity, Efficiency, Predictability, Environment, Flexibility, Safety and Cost Effectiveness [6]. Influence diagrams constitute a tool to represent and model the cause/effect relationships existing among several factors contributing to the modification of each individual KPA. However, the combined effect of causal factor to several KPAs is not considered by the study.

Bayesian networks represent a special class of influence diagrams, in which the type of nodes that can be used is restricted to uncertainties. They have been successfully applied in many fields including health, industry, defense, banking, marketing and information technology, due to their combined set of capabilities for both diagnostics and forecasts [7]. In fact on one hand they allow predictive reasoning, but on the other one also simulation of the behavior of a system or analysis of data related to the system using combined reasoning, therefore constituting a powerful decision making tool.

Bayesian Networks are especially appropriate to deal with the management of risks like in the case of collisions between ships as presented in [8]. A method called GLORIA dedicated to the evaluation and the ranking of risks using Bayesian networks has for example been created by EDF. In ATM Bayesian Networks have been applied to the effective prevention of aircraft collisions in the air [9] and on the ground [10].

III. BAYESIAN NETWORKS

Bayesian Networks (BNs) are defined as a directed acyclic graph in which each node represents a discrete variable, an arc represents a direct causal influence between the linked variables and the strength of this influence can be quantified using conditional probabilities [1]. The main conditional probabilities concept concerns the independence: if $P(A|B)=P(A)$, means that the two random variables A and B are independent, whereas if P(A|B,C)=P(A|C), means that A and B are conditionally independent given C. The probability encodes the conditional probabilities of a node to acquire a specific value over a set of possible ones, depending on the values acquired by its parents. Given evidence on one of the parents (i.e. setting evidence in the network), the probabilities of observing a certain value for the other nodes will change.

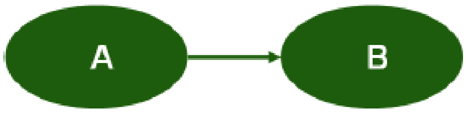

Figure 1. Graphical representation of dependency of variable B on A

For example, if A and B are two random variables with respectively the values (High, Medium, Low) and (True, False), we have to define the probability distribution of the variable A and the probability distribution of B conditionally to A.

TABLE I. EXAMPLE OF TABULAR REPRESENTATION OF PROBABILITY DISTRIBUTION OF RANDOM VARIABLE A

A	*P(A)*
High	0.7
Moderate	0.2
Low	0.1

TABLE II. EXAMPLE OF TABULAR REPRESENTATION OF PROBABILITY DISTRIBUTION OF B CONDITIONAL TO A

B|A	*High*	*Moderate*	*Low*
TRUE	0.8	0.4	0.1
FALSE	0.2	0.6	0.9

The first use of a BN is therefore to compute the probability distribution of each variable. For the variable B in the previous example will have that P(B=TRUE)=0.8*0.7+0.4*0.2+0.1*0.1=0.65 and P(B=FALSE) = 0.2*0.7+0.6*0.2+0.9*0.1=0.35

Another interesting feature of BNs is that they allow performing Bayesian inference, i.e. computing the impact of observing values of a subset of the model variables on the probability distribution over the remaining variables. For example, observing that the variable A in our example assumes vale "moderate" allows for computing the new probability distribution for B: P(B=TRUE)= 0.4 and P(B=FALSE)= 0.6.

Several tools software tools exist to create and use BNs. For the purpose of this study GeNIe [11] has been used, an open source software which includes a complete set of tools for dealing with BNs through a user friendly interface.

IV. MODEL BUILDING AND DESCRIPTION

The building of the model is based on data reflecting the annual performance of the ATM system during 8 years, from 2003 to 2011. Table III outlines the data extracted from the annexed data to ACE and PRR reports for 2003 to 2011. Additional data is needed in order to align this study with the Performance Scheme targets, such as the Cost efficiency KPI: "Unit Rate". MUAC and EANS are not included in the Central Route Charges Office (CRCO) annual reports, so its corresponded Unit Rate has been extracted by annual reports published in their official websites, [12] and [13] respectively.

ATCO unit employment cost differs in each ANSP, caused by the national economies and associated to the cost of living, but also by the internal policy of the ANSP. For this reason, ACE reports examine the ATCO costs in the context of the Purchasing Power Parity (PPP)[1].

Based on the available data, additional variables have been calculated (Table IV), in order to have a wider range of selection as well as to identify the most relevant relationships. The geographical scope of the model covers the ANSPs present in TableV.

TABLE III. DATA COLLECTED

Data source	*Variable (per ANSP)*	*Definition*
PRR 2003-2011	ATFM Delay	Amount of total annual ATFM Delay in minutes due to all causes
	Traffic Complexity	According to the definition in [14], the product of: - Traffic density – total duration of all interactions (in min) per flight-hour controlled in a given volume of airspace - Structural index – sum of: - Horizontal interactions indicator: ratio of the duration of horizontal interactions and total duration of all interactions - Vertical interactions indicator - ratio of the duration of vertical interactions and total duration of all interactions - Speed interactions indicator - ratio of the duration of speed interactions and total duration of all interactions
ACE 2003 - 2011	Number of flights	Number of annual IFR flights controlled
	Flight hours	Number of annual IFR flight hours controlled
	ATCOs	Number of En Route ATCOs on duty during a year
	En Route ATCO hours on-duty	Number of hours the En Route ATCO have been on duty during a year
	En Route ATCO cost per hour	Cost of employment of one En Route ATCO per IFR flight hour controlled
	En Route ATCO cost per hour adjusted by PPP	Cost of employment of one En Route ATCO per IFR flight hour, adjusted by applying the Purchasing Power Parity (PPP)
	ANSP Size	Area of airspace in km2controlled by an ANSP
[15] and CRCO Reports 2008-2011	Unit Rate	The unit rate is defined as the ratio between air navigation service costs and service unit. The service unit is calculated as: SU = (distance[2]/100) * √(MTOW/50)

TABLE IV. ADDITIONAL CALCULATED VARIABLES

1 Purchasing Power Parity (PPP) compares the price, in national currency, of a defined basket of goods and services, between different countries. PPP index is the ratio of the PPP exchange rate (exchange rates at which the price of the basket is the same in the two countries) to the market exchange rate.

2 Great circle distance between the entry and exit point of the charging area.

Variable	Definition
Delay/Flight	Ratio between the total annual ATFM Delay and the Flights (min/flight)
Delay/fl-hr	Ratio between the total annual ATFM Delay and the Flight hours (min/fl-hr)
ATCO productivity	Ratio between Flight Hours and En Route ATCO hours on-duty
ATCO cost/fl-hr	Ratio between the En Route ATCO cost per hour and the Flight Hours (€/fl-hr)
Adjusted ATCO cost /fl-hr	Ratio between the En Route ATCO cost per hour (adjusted by PPP) and the Flight Hours (€/fl-hr)

TABLE V. GEOGRAPHICAL SCOPE OF DATA COLLECTED

ANSP	Country	ANSP	Country
Aena	Spain	IAA	Ireland
ANS CR	Czech Republic	LFV	Sweden
Austro Control	Austria	LPS	Slovak Republic
Avinor (Continental)	Norway	LVNL	Netherlands
Belgocontrol	Belgium	MATS	Malta
BULATSA	Bulgaria	M-NAV	Macedonia
Croatia Control	Croatia	MUAC	"Maastricht"
DCAC Cyprus	Cyprus	NATS (Continental)	United Kingdom
DFS	Germany	NAV Portugal (Continental)	Portugal
DSNA	France	NAVIAIR	Denmark
EANS	Estonia	ROMATSA	Romania
ENAV	Italy	Skyguide	Switzerland
HCAA	Greece	Slovenia Control	Slovenia
HungaroControl	Hungary		

A BN can be constructed manually, based on knowledge and experience acquired from previous studies and literature, automatically from data or a combination of the two (see chapter 8 of [1] for more details about data-driven modelling). Model structure rules impose the absence of cycles and to limit the number of parents for a variable in order to keep a global understandable view of the system and to be able to fill in the conditional probabilities. The best method to obtain a model reflecting reality consists of the combination of manual, data-driven process, experience and knowledge. Therefore the first step is to obtain the correlation matrix for all the variables involved, to assess the correlation among of pair. Subsequently a data-driven process can be applied to build the BN. The structure is determined by applying a specific algorithm, such as Bayesian Search Algorithm [1].

The main constraint of using Bayesian Networks is that they usually work with discrete variables. This means that each variable has been divided in three states with the same number of samples: Low, Medium and High State. The distribution of the new discrete variables is taken as uniform by default. The boundaries between the three clusters correspond to the value of 1/3 percentile value and the 2/3 one. From this point on the analysis will make reference to three different states Low, Medium and High.

All the data previously collected is then assigned to each correspondent node of the model, so that the software is able to estimate the conditional probabilities at each node.

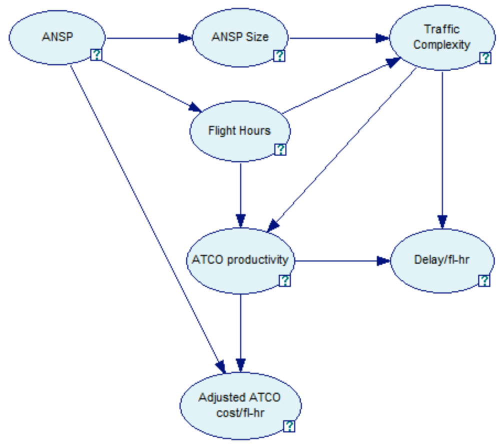

Figure 2. Performance model's structure

V. ANALYSIS AND RESULTS

The first use of the model is for the behavioral analysis of past performance. This can be done by setting evidence on some nodes according to its different possible variables and observing how this affects the other variables of interest.

A. The influence of ANSP's size

The first result obtained from the analysis of the model's output is the presence of economies of density as shown in Fig.3 below. ANSPs controlling smaller airspaces and low traffic tend to be in general less economically efficient. In fact there is a 34% probability of having a high cost per flight hour in this case, due to economies of densities. This property seems to weaken for larger ANSPs, for which, the probability of having a large ATCO cost per flight hour increases as the traffic increases.

ANSPs' different behavior caused by their size can be also identified by analyzing the relationship between traffic complexity and the number of flight hours. Fig. 4 shows that an increase in complexity is not always related to a higher number of flight hours, mainly for smaller ANSPs. The number of flight hours determines the traffic density factor of the traffic complexity, so if this remains stable and the traffic complexity value increases, it means that the structural complexity causes the variation. Therefore, the structural complexity is more important for smaller ANSPs, than for grater ones.

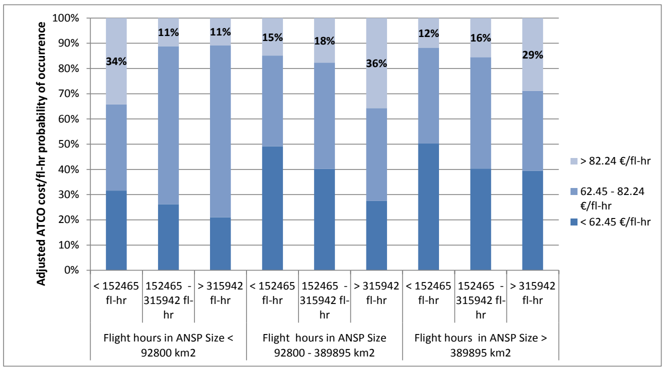

Figure 3. Adjusted ATCO cost/fl-hr probability of occurrence depending on the number of Flight hours and the ANSP size

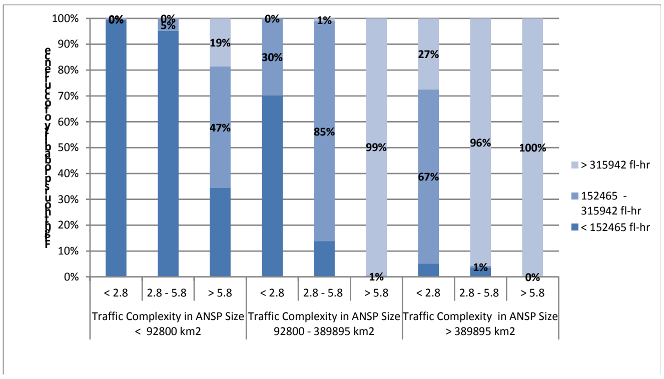

Figure 4. Flight hours probability of occurrence depending on Traffic Complexity and the ANSP size

B. *The influence of Traffic Complexity*

Another clear relationship is the one between traffic complexity and delay as showed in Fig. 5 below: the higher the complexity, the higher the probability of generating high delay per flight hour. For ANSPs with high complexity factor there is just a minimal (5%) probability of having low delays per flight hours. This can be explained by the fact that in general higher complexity implies higher ATCO workload and as consequence lower airspace capacity and higher ATFM delays, all the rest being equal. A more complex environment is also linked to higher ATCO productivity, since the amount of traffic is directly proportional to both indicators. However this relationship is less marked, probably due to the other factors influencing complexity than just the number of flight hours.

However, if we compare two scenarios, one presenting low levels of highly complex traffic (Fig. 6), and the other characterized by high levels of not very complex traffic (Fig. 7), we observe that the probability of having high ATCO productivity is doubled (28 → 56%) in the high traffic scenario with respect to the other one. This means that the number of flight hours has more influence on ATCO productivity than the traffic complexity. On the other hand, the probability of high delay per flight hour is higher in a more complex environment, even if the number of flight hours is low. The ATCO cost per flight hour presents an opposite behavior to the ATCO productivity determined by the number of flight hours. If the productivity increases, the cost decreases as more flights are controlled with the same controllers.

It is interesting to see what happens in case the number of flight hours is high and at the same time very complex (Fig. 8). The productivity seems to be affected being less probable a High State (> 1.36 fl-hr/ATCO-hr) compared to the probability of the same state in Fig. 7. An important impact of the Traffic Complexity is on the delay per flight hours, this later being considerably increased (approx. 30%) with respect to the scenario less complex.

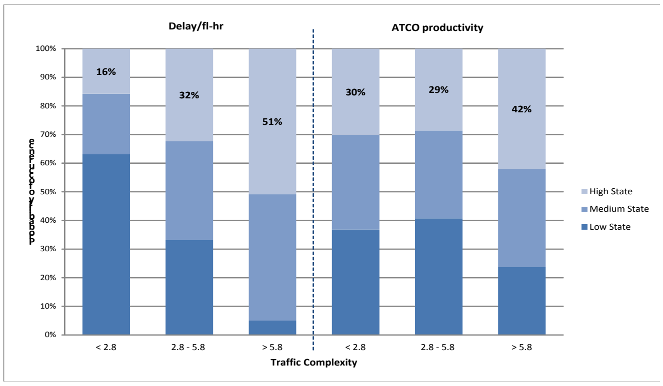

Figure 5. Delay/fl-hr and ATCO productivity probability of occurrence depending on Traffic Complexity

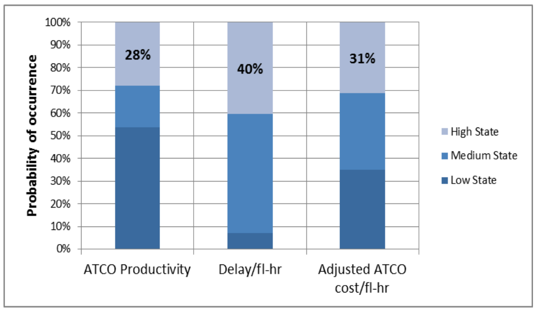

Figure 6. ATCO productivity, Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours < 152465 and Traffic complexity > 5.8 scenario

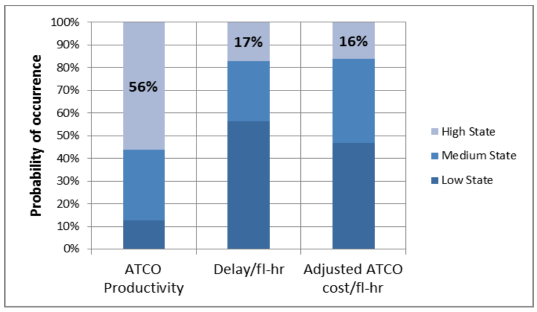

Figure 7. ATCO productivity, Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours > 315942 and Traffic complexity < 2.8 scenario

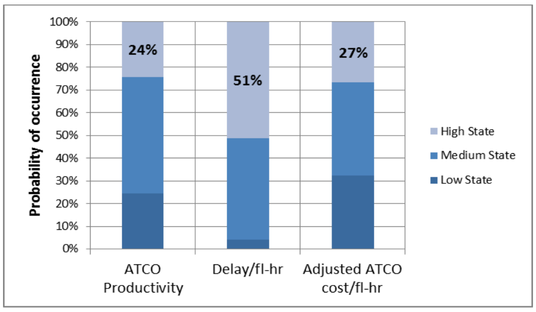

Figure 8. ATCO productivity, Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours > 315942 and Traffic complexity > 5.8 scenario

C. *Influence of ATCO productivity*

Working with the maximum ATCO productivity is not always favorable. The advantages in costs generated by a high productivity may cause disadvantages in other aspect, such as delays. In order to demonstrate this statement, four scenarios have been compared. Fig. 10 represents two scenarios which have in common high traffic and high productivity, but different complexity. Fig.11 represents the other two scenarios which have in common high traffic, low productivity, but different complexity. Fig. 9 shows that maintaining a high productivity when the traffic becomes more complex has the same cost, but it causes much more delay per flight hours (probability for high delay/fl-hr increases from 16% to 58%). The same tendency can be observed in a lower ATCO productivity scenario (Fig. 10), but the increase in the probability of having high delays when traffic complexity increase is moderate (+14%).

This can give an idea of the importance of considering traffic complexity when dimensioning resources at an ANSP level, since inprovements in one KPI often imply direct and indirct losses on another KPIs.

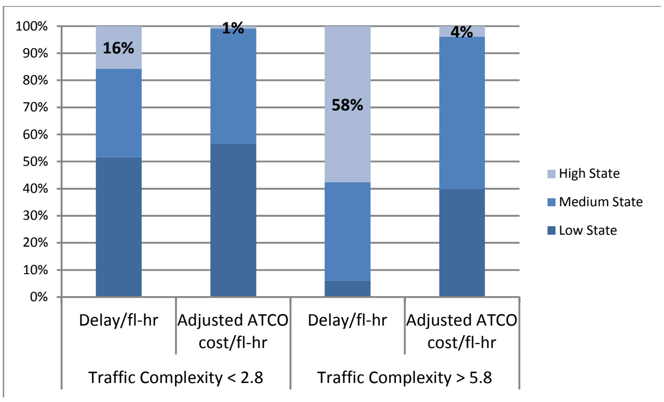

Figure 9. Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours > 315942 and ATCO productivity > 1.36 ATCO-hr/fl-hr scenario

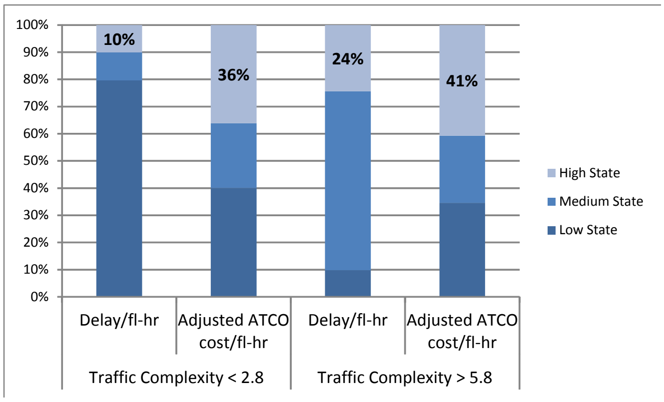

Figure 10. Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours > 315942 and ATCO productivity < 1 ATCO-hr/fl-hr scenario

VI. PREDICTIVE USE OF THE MODEL

Another interesting application of the model is introduced due its predictive nature and consists in assessing the probabilities of compliance with the performance targets as calculated by the PRB for the Performance Regulation.

To fulfill this objective the model presented in Fig.2 requires a number of modifications to align the variables (nodes) to the KPIs implied by the Regulation: an additional node is added to the model to introduce Unit Rate value and the units of some variables change, while the already existing node Flight hours becomes Flights and the Delay/fl-hr becomes Delay/flight. These modifications allow the model to be aligned with the KPIs for Capacity and Cost-efficiency targeted for RP2, as illustrated in Table VI.

The dependency between Capacity and Cost efficiency has been extensively studied in literature as outlined in Section II. Therefore, the exercise presented here will determine the probability of accomplishment of both Capacity and Cost efficiency targets.

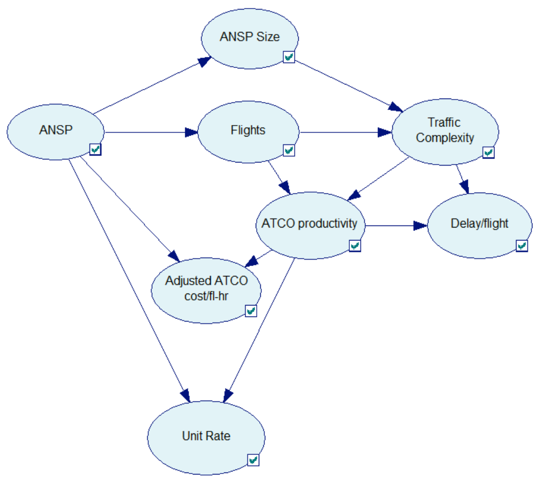

Figure 11. Performance model's structure for target-setting application

TABLE VI. CAPACITY AND COST EFFICIENCY RP2 PROPOSED TARGETS

KPA	**KPI**		**PRB final proposal for Union wide targets for RP2**				
Capacity	Average En-route ATFM delay		0.5 minutes per flight in 2014-2019.				
Cost-efficiency	DUC Determined Unit Cost Baseline 2014: 62.97 €/SU		***2015***	***2016***	***2017***	***2018***	***2019***
		€2012 prices	59.70	27.22	54.53	51.84	49.30
		€2009 prices	54.21	51.95	49.51	47.07	44.76

The boundaries between the Delay/flight discretized states are 0.05 and 0.5 min/flight and the boundaries of the Unit Rate states are 44.30 and 64.97 €/SU. As shown in Table VI, the Capacity target will be fulfilled as long as the Delay/flight does not overcome 0.5 min/flight. The Unit Rate target for 2015 is 59.70 €/SU, which is included in the Medium state (44.30 – 64.97). For the purpose of this section, it is assumed that the Unit Rate target is not accomplished if the Unit Rate is higher than 64.97 €/SU.

After few years of economic downturn, the traffic in Europe is expected to increase in the next years, having a direct impact on the ATM performance. Therefore, the increase of traffic should be taken into account when determining the probability of fulfilment of RP2 targets. Even if the real traffic levels will vary a lot between states, we consider an average of 1 million flights (High state > 655638 flights) per ANSP in our analysis, in line with the figures provided by EUROCONTROL in [17].

Once evidence on traffic level has been set in the model, results can be read in output in terms of probabilities of falling in the different cases of the pairs of variables (Unit Rate; Delay/Flight) as shown in Fig. 12 below. According to the model probabilities to comply with both performance targets at the same time varies between 60% and 67% at a general European level.

It is worth noticing however that the results obtained are based on a model built with historical data, therefore reflecting the historical system behavior. It is expected that the introduction of technological and operational innovations stemming from SESAR as well as the new regulatory approach fostered by the EC will drive a change in the way ANSPs manage their resources, allowing increasing these probabilities.

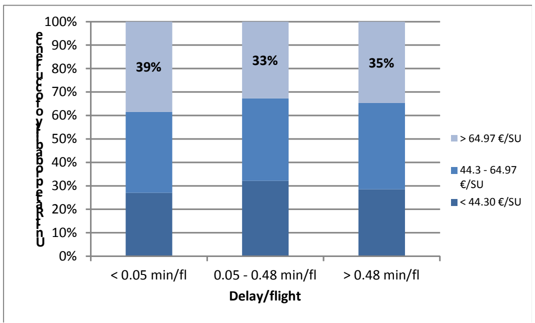

Figure 12. , Unit Rate probability of occurrence depending on the Delay/flight

On the other hand targets are imposed per state and each ANSP is responsible to achieve them whilst presenting different traffic increase levels (0), so the analysis should be differentiated per state. The presence of ANSP node in the structure offers the possibility of selecting the desired ANSP for analysis and the traffic node allows the selection of the appropriate state of traffic for 2019. Differences between ANSPs probabilities of accomplishing the target are identified by obtaining a similar graph to Fig. 12 for each ANSP. ANS CR, Avinor, BULATSA, Croatia Control, DFS, ENAV, NATS, Skyguide and Slovenia Control present a probability higher than 30% of overpassing the general European Unit Rate target of 64.97 €/SU but at the same time accomplishing the Capacity target (< 0.5 min/flight), while all the other ANSPs included in this study present lower probability. Fig. 13 below shows the case for the German ANSP DFS.

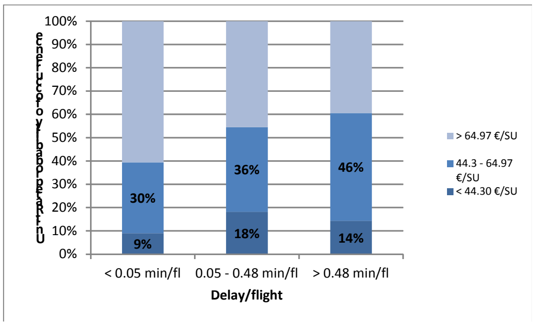

Figure 13. DFS Unit Rate probability of occurrence depending on Delay/flight

VII. CONCLUSIONS

The use of Bayesian Networks for the historical analysis and assessment of future performance patterns of European ATM presents several advantages. It allows building knowledge from historical data on performance behavior and to extrapolate an influence diagram, which combined with domain knowledge, provides an intuitive representation of the cause-effect relationships among involved variables. Such variables are treated as stochastic variables, thus allowing to deal with the stochastic nature of the underlying system in a natural and direct way. The model not only reflects the behavior of the ATM system, but also quantifies the influence of different indicators.

The models presented in this paper represent a first tentative of applying this technique to ATM, including just two KPAs for which historical data are publicly available and a number of influence factors. Far from being mature and complete, the developed models permit to get an idea of the possible applications and to obtain some preliminary results, based on the published historical performance data available from the EUROCONTROL PRU. The models could be easily modified and expanded when new historical data series would become available.

The use of the models is twofold: on one side they allow getting insights on the complex relationships among factors affecting performance, thus providing a valuable tool to support decision making when configuring resources for an ANSP. On the other hand they allow to predict future behaviors, by appropriately setting the value of key variables at forecasted levels and to observe the response of the other ones. Any node may be an input or an output, so the models can be used for target-setting as well as for assessment and they are easy to complete, refine and enhance.

On the other hand one of the main shortcoming of Bayesian Networks is that they only deal with discrete values, therefore requiring a transformation of the original variables to maintain the computational complexity at a manageable level. Moreover the use of one unique model at European level seems to achieve only generic results. The specificity of each ANSP conditions suggest that national models would be much more accurate in the results. However the presence of the ANSP node in the models' structures makes it possible to easily switch from one ANSP to another simply by setting the appropriate evidence value.

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