Assessing ATM performance interdependencies through Bayesian Networks

Preliminary applications and results

Andrada Bujor, Andrea Ranieri
Advanced Logistics Group (ALG)-Indra Business Consulting
Barcelona, Spain
[aranieri],[abujor]@alg-global.com

***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 drawbacks 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 at 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 Air Navigation Service Providers (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). 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 these KPAs, a quantitative target for RP1 and RP2 measured according to a Key Performance Indicator (KPI), has been set by the Performance Scheme, 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 Scheme: Capacity and Cost-effectiveness. This is justified by the availability of complete and consistent series of historical data, which was available for these two. The model could easily be extended to incorporate the rest of KPAs as soon as a comparable set of observations would be available. The resulting model could provide to be useful both to observe and analyse the historical performance in these KPAs at a general European as well as at a local level, but also to predict future compliance with performance targets, 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 Performance Review Unit (PRU) aims to estimate a cost function for the provision of Air Navigation service, in order to assess the cost-efficiency of the service 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 Communication, Navigation, Surveillance infrastructure) and a variable part that may be affected by the volume of traffic or size of operations. This implies that 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 model's framework consists of a Cobb-Douglas cost function estimated through regression and based on observed data describing traffic volume, Air Traffic Controller (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 function's coefficients depending on the assumptions made related to the error term: Ordinary Least Squares (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 or support staff 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 labour 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 presented in this paper, 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 analysed in the past is the one between the cost of ATFM delays and the lack of capacity to AUs. 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 of a direct relationship between delay and operational costs. A delay at-gate (Calculated Take-Off Time) 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 AU could accept another longer route if reducing $[(1.1n \div 1.3n) + 10]$ 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 Area Control Centers (ACCs), to reach a given delay target. As the ratio between Capacity and Traffic increases, the Air Navigation Service (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 Air Traffic Flow Management (ATFM) Delay at overall ECAC level[1].

Besides the 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 behaviour 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 been created by the EDF[2] R&D Department. In ATM, Bayesian Networks have been applied to the effective prevention of aircraft collisions in the air [9] and on the ground [10].

1 European Civil Aviation Conference (ECAC) currently counts with 44 Member States.

2 The EDF Group is a leading energy player.

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 [16]. 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.

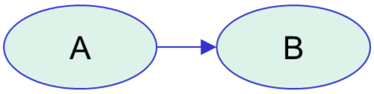

Figure 1. Graphical representation of dependency of variable B on A

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 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 value “moderate” allows for computing the new probability distribution for B: P(B=TRUE)= 0.4 and P(B=FALSE)= 0.6.

Several 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

A Bayesian Network can be constructed either manually, based on knowledge and experience acquired from previous studies and literature, or automatically from data. Most of the times a combination of the two is required to obtain a realistic model (see chapter 8 of [16] for more details about data-driven modelling). Model structure rules impose the absence of cycles and limited 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 ATM performance model presented in this paper was built applying a combination of data-driven process with manual adjustments, based on experience and knowledge. The aim for this methodology was to obtain a model reflecting reality. Therefore, the first step was to obtain the correlation matrix for all the variables involved, to assess the correlation among of pairs. Subsequently a data-driven process was applied to build the BN. The programme provides different options for the structure of the model by applying algorithms as the Bayesian Search Algorithm [16], which was used in this case. The final architecture presented in Fig.2 was determined by applying this algorithm and refining it with previous knowledge.

The variables employed were already defined by prior ATM performance studies. The selection of variables is constrained by the availably of historical data, (Table V). ACE reports and the econometric study performed by the Performance Review Unit [1] quantify ANS performance with variables as ANSP Size, Traffic Complexity, ATCO productivity and Adjusted ATCO cost. ATFM Delay reflects the quality of service of an ANSP or of ATM, for this reason it is frequently found in performance studies, such as [2], [3] or [4]. In order to homogenize variables units, the ATFM Delay and the Adjusted ATCO cost are divided by the number of flight hours. This way, these variables are in line with the ATCO productivity node (ATCO hours/Flight hours). Following the same reasoning, the Flight Hours node has been added to represent the traffic volume.

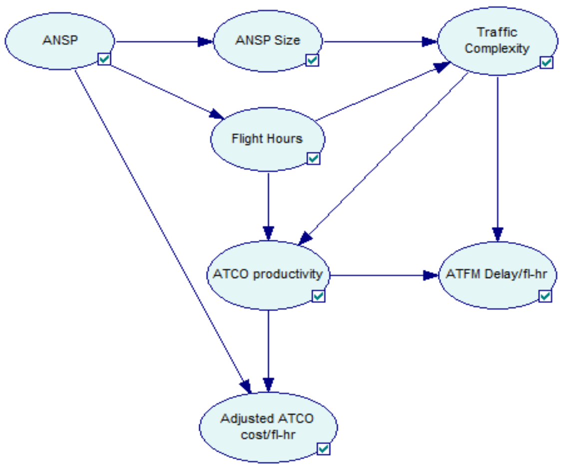

Figure 2. Performance model’s structure

Table III below provides the definition of all model’s nodes.

TABLE III. NODES DEFINITION

Node	*Definition*
ANSP	Body that manages flight traffic on behalf of a company, region or country.
ANSP Size	Area of airspace in km^2 controlled by an ANSP
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.
Flight hours	Number of annual IFR flight hours controlled
ATCO productivity	Ratio between Flight Hours and En Route ATCO hours on-duty (Number of hours the En Route ATCO have been on duty during a year)
ATFM Delay/fl-hr	Ratio between the total annual ATFM Delay due to all causes and the Flight hours (min/fl-hr).
Adjusted ATCO cost /fl-hr	Ratio between the En Route ATCO cost per hour (adjusted by applying the PPP[3]) and the Flight Hours (€/fl-hr).

The building of the model is based on data reflecting the annual performance of the ATM system during 8 years, from 2003 to 2011. The geographical scope of the model covers the ANSPs present in Table IV. Further on, Table V outlines the data extracted from the annexed data to ATM Cost Effectiveness (ACE) report and Performance Review Report (PRR) for 2003 to 2011. ATCO unit employment cost differs for each ANSP, due to the national economies and associated to the cost of living, but also by the internal management policies of the ANSP. For this reason, ACE reports examine the ATCO costs in the context of the Purchasing Power Parity (PPP).

TABLE IV. 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		

3 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.

TABLE V. DATA COLLECTED

Variable (Values per year and per ANSP)	*Data source*
ATFM Delay	PRR 2003-2011
Traffic Complexity	
Flight hours	ACE 2003 - 2011
En Route ATCO hours on-duty	
En Route ATCO cost per hour adjusted by PPP	

The main constraint of using Bayesian Networks is that they usually work with discrete variables. This means that each quantitative variable, originally defined in the continuous domain, has been discretized along three states (i.e. Low, Medium and High State), each one including the same number of samples. 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.

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.

V. ANALYSIS AND RESULTS

The first use of the model is for the behavioural analysis of past performance. This can be done by setting evidence on some nodes, i.e. setting one specific value among the possible ones and observing how this affects the other variables of interest.

Within the BN structure defined in GeNIe, each node can be considered an input or an output, depending on the aim of the analysis. Nodes are considered inputs if they have evidence set. This means that one of the three states of the node is fixed (High, Medium or High). The remaining variables of the structure, which do not have evidence set, take the role of outputs. Hence, different studies can be performed changing roles among nodes in order to identify the dependencies between them.

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 scale and 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 37% probability of having a high cost per flight hour in this case, due to economies of scale. In contrast for larger ANSPs the probability of having a large ATCO cost per flight hour in case of low traffic is equivalent to 13% to 14%. Fig.3 also indicates the presence of economies of density: smaller ANSPs have in general spare capacity, since by increasing traffic (flight hours) the probability of having a high ATCO cost per flight hour diminishes. On the other hand, for larger ANSPs these economies of densities seem to be already exploited, since by increasing traffic (flight hours), the probability of having a high ATCO cost per flight hour increases.

The presence of the economy of densities and scale in ANS is confirmed by the econometric study performed by the performance Review Unit (PRU) [1]. It states that ANSP with spare capacity (small ANSPs in our case) may accommodate additional traffic without changing the network structure (the same number of sectors). The economy of densities softens when traffic grows so much that requires new sectors to be open and in consequence more ATCOs on duty. This later behaviour can be identified in Fig.3 in the case of medium and larger ANSPs, as they seem to operate with a capacity closer to the demand than the smaller ones. Another result of PRU's study is that the size of the airspace is associated with greater costs. This is corroborated by this study through the presence of weak economic efficiency of ANSPs controlling smaller airspaces and low traffic.

ANSPs' different behaviour caused by their size can be also identified by analysing 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, for which a high number of flight hours is deterministically linked with high complexity.

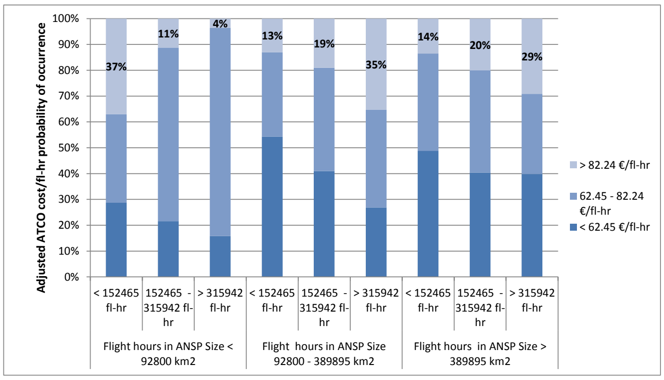

Figure 3. Adjusted ATCO cost/fl-hr probability of occurrence depending on the number of Flight hours and the ANSP size

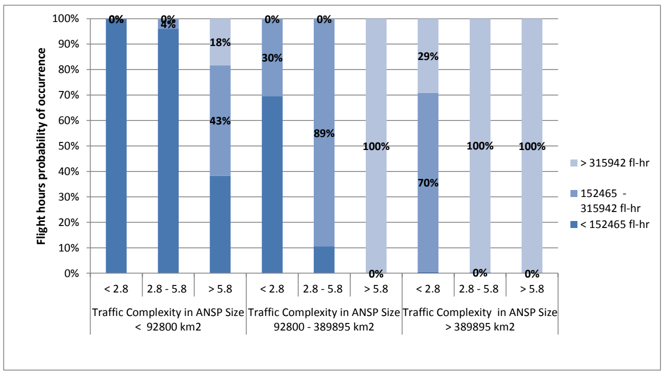

Figure 4. Flight hours probability of occurrence depending on Traffic Complexity and the ANSP size

B. *The influence of Traffic Complexity*

Another clear relationship is the one between traffic complexity and ATFM delay as showed in Fig.5: 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. The same tendency although less marked, can be observed between the ATFM delay and the number of flight hours. In fact as shown in Fig.5, moving from low to high traffic complexity environment implies an increase of 33% of the probability of observing high ATM delays (i.e. from 17% to 50%), while this increase is limited to 15% when moving from low to high flight hours (i.e. from 24 to 39%).

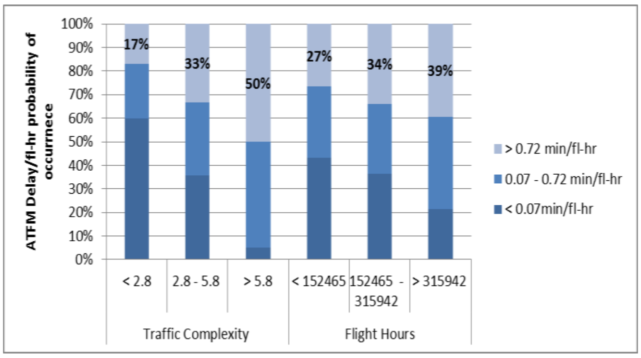

Figure 5. ATFM Delay/fl-hr probability of occurrence depending on Traffic

C. *The influence of ATCO productivity*

Working with the maximum ATCO productivity is not always favourable. 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.6 represents two scenarios which have in common high traffic and high productivity, but different complexity. Fig.7 represents the other two scenarios which have in common high traffic and low productivity, but different complexity. Fig.6 shows that maintaining a high productivity when the traffic becomes more complex implies roughly the same cost, but it causes much more delay per flight hour (+32% probability of high delay/fl-hr, i.e. from 20% to 52%). The same tendency can be observed in the lower ATCO productivity scenario (Fig.7), but the increase in the probability of having high delays when traffic complexity increases is moderate (+14%, i.e. from 10% to 24%) and is coupled with a considerable increase in probability of generating high costs (+25%, i.e. from 20% to 45%).

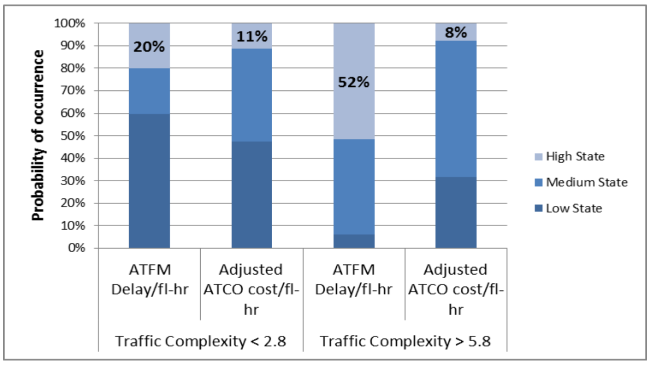

Figure 6. ATFM Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours > 315942 and ATCO productivity > 1.36 ATCO-hr/fl-hr scenario

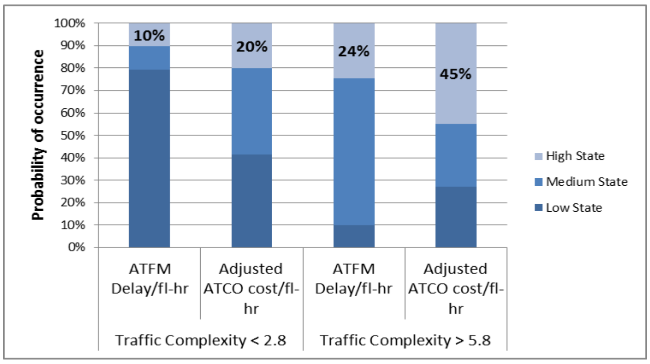

Figure 7. ATFM Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in a Flight hours > 315942 and ATCO productivity < 1 ATCO-hr/fl-hr scenario

This can give an idea of the importance of considering traffic complexity when dimensioning resources at an ANSP level, since improvements in one KPI often imply direct and indirect losses on other KPIs. The differences between different ANSPs sizes again can be observed in this case, by comparing the three figures below (Fig.8,9,10).

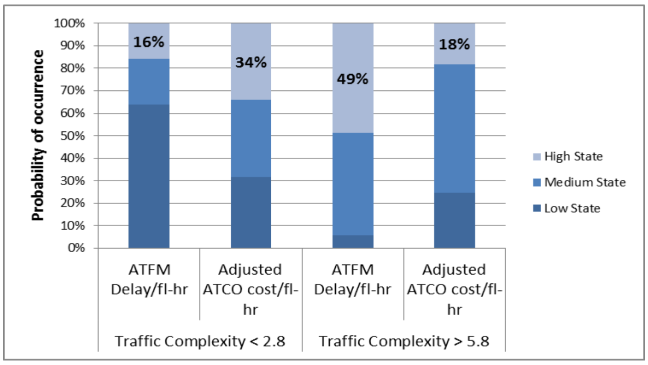

Figure 8. ATFM Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in an ANSP size < 92800 km^2

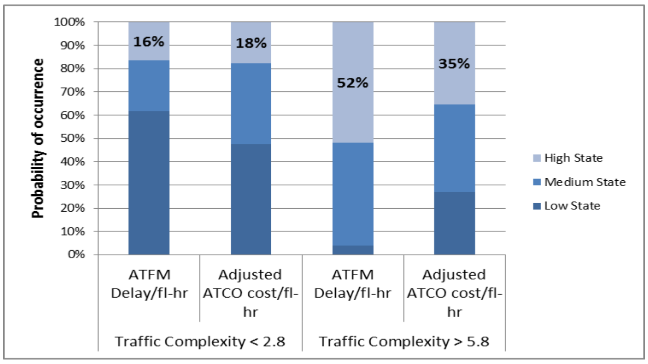

Figure 9. ATFM Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in an ANSP size between 92800 - 389895 km^2

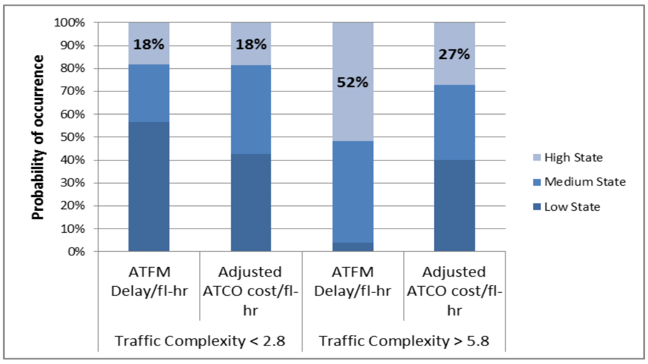

Figure 10. ATFM Delay/fl-hr and Adjusted ATCO cost/fl-hr probability of occurrence in an ANSP size > 389895 km^2

VI. PREDICTIVE USE OF THE MODEL

Another interesting application of the model is represented by its predictive nature and consists in assessing the probabilities of compliance with the performance targets as imposed by the Performance Scheme Regulation (EC Reg. 390/2013).

To fit this purpose 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 the Unit Rate value and the units of some variables change, while the already existing node Flight hours becomes Flights and the ATFM Delay/fl-hr becomes ATFM Delay/flight, as defined in Table VI. These modifications allow the model to be aligned with the KPIs for Capacity and Cost-efficiency targeted for the second reference period (RP2), as illustrated in Table VIII.

Additional data is needed in order to align this study with the Performance Scheme targets, such as the Cost efficiency KPI: "Unit Rate". Contrary to the other ANSPs, MUAC and EANS (see Table IV) are not covered by the Central Route Charges Office (CRCO) annual reports, so their corresponded Unit Rate value have been extracted from annual reports published in their official websites, [12] and [13] respectively.

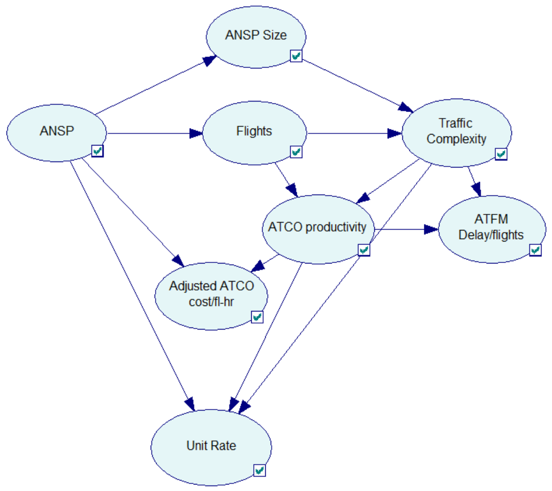

Figure 11. Performance model's structure for target-setting application

TABLE VI. NEW NODES FOR THE MODEL

Node	*Definition*
Flights	Number of annual IFR flights controlled
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[4]/100) * √(MTOW/50)
ATFM Delay/Flight	Ratio between the total annual ATFM Delay and the Flights (min/flight)

TABLE VII. ADDITIONAL DATA COLLECTED

Variable (Values per year and per ANSP)	*Data source*
Flights	ACE 2003 - 2011
Unit Rate	[15] and CRCO Reports 2008-2011

TABLE VIII. CAPACITY AND COST EFFICIENCY RP2 PROPOSED TARGETS

KPA	**KPI**	**Union wide targets for RP2 (2015-2019) [17]**				
Capacity	Average En-route ATFM delay	0,5 minutes per flight, to be reached for each calendar year.				
Cost-efficiency	DUC (Determined Unit Cost) Baseline 2014: 62.97 €/SU (in EUR_{2009})	***2015***	***2016***	***2017***	***2018***	***2019***
		56,64	54,95	52,98	51,00	49,10

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.

The ATFM Delay/flight discretization changes from 3 states to only two, where the threshold between these new states is fixed at 0.5 minutes per flight. The new variable "Unit Rate" is also discretized along two states: below 49.10 €/SU and above it. The purpose of these modifications is to align the model with the performance targets reported in Table VIII. Hence, the Cost efficiency target is accomplished if the Unit Rate is below 49.10 €/SU (target for 2019) and Capacity target is accomplished if ATFM Delay per flight is below 0.5 minutes per flight (target for 2015-2019 period).

When determining the probability of fulfilment of RP2 targets the increase of traffic foreseen for the future must be taken into account through the related node "Flights". Even if the forecast number of IFR movements varies considerably from State to State, we consider an average of 1 million flights per year per ANSP in our analysis, implying the correspondent node evidence to be set to High state (i.e. more than 655638 flights) in line with the figures provided in [18].

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; ATFM Delay/Flight) as shown in Fig. 12 below. According to the model, there is a probability of 38% to comply with both performance targets at the same time 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 behaviour. 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, hopefully allowing increasing this probability.

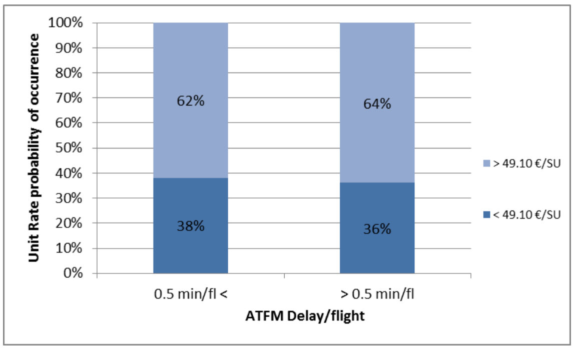

Figure 12. Unit Rate probability of occurrence depending on the ATFM Delay/flight

On the other hand targets are imposed per state and each ANSP is responsible to achieve them whilst presenting different traffic increase levels ([18]), 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. There are ten ANSPs (Aena, Belgocontrol, DCAC Cyprus, EANS, HCAA, HungaroControl, IAA, M-NAV, MUAC and ROMATSA) presenting a probability higher than 50% of complying with at the same time with both the Capacity and the Cost Efficiency targets for 2019. All the other ANSPS included in this study present lower probability. Fig. 13 below shows the probabilities of achieving both targets for all the ANSPs considered by the model.

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

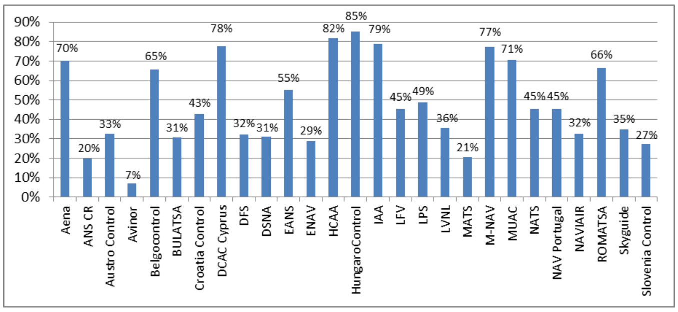

Figure 13. ANSPs probabilities of compliance with Cost Efficiency and Capacity targets for RP2

It should be noted however that in reality each ANSP, based on its individual contribution to general performance, derives its own local target values at national or FAB level, which are based on the European ones but may not coincide with them.

VII. CONCLUSIONS

The use of Bayesian Networks for the historical analysis and assessment of future performance patterns of European Air Traffic Management 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 dealing 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 Performance Review Unit. 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 shortcomings 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 suggests 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.

REFERENCES

[1] EUROCONTROL Performance Review Unit "Econometric cost-efficiency benchmarking of Air Navigation Service Providers", May 2011

[2] A. Cook, G. Tanner, and Anderson, "Evaluating the true cost to airlines of one minute of airborne or ground delay", University of Westminster for Performance Review Commission (EUROCONTROL), 2004.

[3] A. Cook, J. Andrew, "European airline delay cost reference values", University of Westminster for EUROCONTROL Performance Unit, 2011.

[4] EUROCONTROL Performance Review Commission, "Performance Review Report 2010", May 2011.

[5] L. Castelli, M. Labbé, and A. Violin. "A Network Pricing Formulation for the revenue maximization of European Air Navigation Service Providers", Transportation Research Part C: Emerging Technologies, 2013, vol. 33, p. 214-226. .

[6] R.Graham, N.Pilon, H.Koelman, P.Ravenhill, "Performance Framework and influence models in ATM", Digital Avionics Systems Conference, Orlando – Florida, October 25 to 29, 2009.

[7] M. Petkovic "Dynamic Bayesian Networks: A State of the Art", Technical Report no. TR-CTIT-01-34, 2001.

[8] P. Truccoa, E. Cagnoa, F. Ruggerib, and O. Grande, "A Bayesian belief network modeling of organizational factors in risk analysis: A case study in maritime transportation," Reliability Engineering & System Safety, 2008 vol. 93, Issue 6, pp. 845–856.

[9] M. Neil, B. Malcom, and R. Shaw, "Modelling Air Traffic Control environment using Bayesian belief networks" 21st International System Safety Conference, Canada, August 2003.

[10] S. Stroeve, H. Blom, and G. Bakker, "Systemic accident risk assessment in air traffic by Monte Carlo simulation," Safety Science, 2009, vol. 47, pp. 238–249.

[11] Genie, Developed by the Decision Systems Laboratory of the University of Pittsburgh and available at http://genie.sis.pitt.edu.

[12] Maasticht Upper Area Control, Annual Reports 2006-2011, www.eurocontrol.int/articles/maastricht-upper-area-control-centre-muac-publications.

[13] EANS Annual Report 2003-2011, www.eans.ee/company/economic-performance/annual-reports.

[14] EUROCONTROL Performance Review Commission "Performance Review Report 2012", May 2013.

[15] L. Castelli, A. Ranieri " Air Navigation Service Charges in Europe", 7th USA/EUROPE ATM R&D Seminar, Barcelona – Spain, July 2007.

[16] B. Kjaerulff, L. Madsen " Bayesian Networks and Influence Diagrams: A Guide to Contstruction and Analysis", ISBN 978-1-4614-5104-4.

[17] European Commission Implementeing Decision 2014/132/EU, setting the Union-wide performance targets for the air traffic management network and alert thresholds for the second reference period 2015-19, 11/03/2014.

[18] EUROCONTROL STATFOR "7-year IFR Flight Movements and Service Units Forecast: 2014-2020", 03/02/2014.