intuit

Interactive Toolset for Understanding
Trade-offs in ATM Performance

# Understanding Trade-offs in ATM Performance

## State-of-the-art and Future Challenges

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# Contents

# Executive summary

The ongoing ATM modernisation programmes, including SESAR, build on ICAO Global ATM Operational Concept, one of whose cornerstones is performance orientation. A performance-based approach is defined by ICAO as one based on: (i) strong focus on desired/required results; (ii) informed decision making, driven by the desired/required results; and (iii) reliance on facts and data for decision making. A performance framework is intended to translate stakeholders' expectations into a shared set of values and priorities and be the basis for impact assessment, trade-off analysis and decision making.

ATM performance results from the complex interaction of interdependent policies and regulations, stakeholders, technologies and market conditions. Trade-offs arise not only between KPAs, but also between stakeholders, as well as between short-term and long-term objectives. While a lot of effort has traditionally been devoted to the development of microscopic performance models, there is a lack of useful macro approaches able to translate local improvements or specific regulations into their impact on high-level, system-wide KPIs.

**The goal of INTUIT is to explore the potential of visual analytics, machine learning and systems modelling techniques to improve our understanding of the trade-offs between ATM KPAs, identify cause-effect relationships between indicators at different scales, and develop new decision support tools for ATM performance monitoring and management**. The specific objectives of the project are:

- to conduct a systematic characterisation of the ATM performance datasets available at different spatial and temporal scales and evaluate their potential to inform the development of new indicators and modelling approaches;
- to propose new metrics and indicators providing new angles of analysis of ATM performance;
- to develop a set of visual analytics and machine learning algorithms for the extraction of relevant and understandable patterns from ATM performance data;
- to investigate new data-driven modelling techniques and evaluate their potential to provide new insights about cause-effect relationships between performance drivers and performance indicators;
- to integrate the newly developed analytical and visualisation functionalities into an interactive dashboard supporting multidimensional performance assessment and decision making for both monitoring and management purposes.

# 1. The problem of ATM performance management

## 1.1 Performance management

Performance is a recurrent theme in management and it is of interest to both academic scholars and business managers. Typically, the process of **performance management** includes three main activities (Vom Brocke and Rosemann, 2010): (i) selection of goals, (ii) integration of relevant information to measure the achievement of the organisation's goals, and (iii) interventions made by managers in light of this information with a view to improving future performance in relation with those goals.

In the last decades, many different tools to manage business performance have arisen. Planning and budgeting is probably the approach most widely used. It consists in setting a set of goals linked with a budget for a determined period of time and creating a process by which the plans and budgets are regularly revised to ensure that the most important opportunities or activities are funded. The Balance Scorecard is another popular management tool designed to articulate the strategic objectives of a business and align them with performance measures and action plans. It proposes the definition of a set of interrelated strategic objectives in different areas (e.g., financial, sales, organisation, human resources, etc.), the identification of a set of drivers on a cause-effect manner, and the monitoring of the strategic objectives by appropriate measurements. **Key Performance Indicators (KPIs)** are the navigation instruments that organisations use to reduce the complex nature of organisational performance to a small number of key indicators which make performance more understandable, indicating whether the organisation is on track or must veer off to the prosperous path. In practice, the word KPI is overused and often describes any metric in business, rather than the vital few which are clearly linked to the business strategy and provide answers to business performance questions. In addition to these performance management tools, many organisations are increasingly implementing **performance dashboards** designed to effectively communicate performance information by using visual elements.

## 1.2 Performance management in ATM: policy context

Performance orientation is one of the key pillars of the Single European Sky: by setting down EU-wide and local targets, as well as performance monitoring and corrective actions, the SES Performance Scheme aims to drive performance improvements in European aviation. The key provisions of the SES Performance Scheme are contained in Article 11 of the Framework Regulation which can be found in Regulation 549/2004 (European Union, 2004), as well as in Regulation 691/2010 (European Union, 2010) and Regulation 390/2013 (European Union, 2013) laying down the performance scheme for air navigation services and network functions. These activities are focused initially on the fields of safety, capacity, environmental and cost efficiency, as they are expected to be the most critical areas to be improved in the following years.

The Performance Scheme is organised around fixed Reference Periods (RPs) before which performance targets are set both at EU-wide level and National/FAB level: RP1: from 2012 to 2014, and RP2: from 2015 to 2019. The targets set down are legally binding for EU Member States and designed to encourage air navigation service providers (ANSPs) to be more efficient and responsive to traffic demand, while ensuring adequate safety levels. As many stakeholders are impacted by these activities, setting down targets at the different levels is a complex process. Figure 1 summarises the process for RP1. The complexity of the process is evidenced by the fact that it took one year to agree on the different Performance Plans.

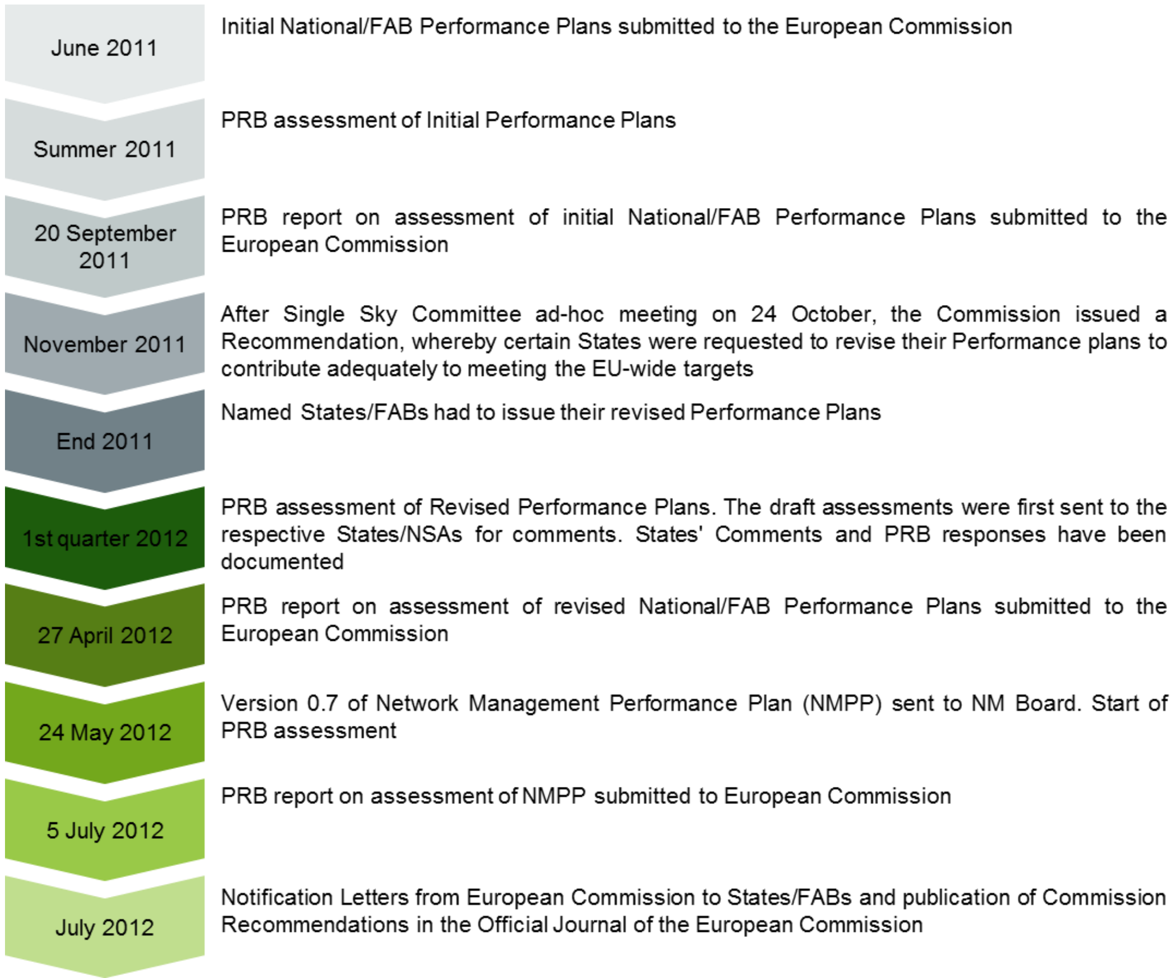


**Figure 1. Performance Plans approval process for RP1**

The following table summarises the level of targeting and monitoring for each of the 4 KPAs currently targeted by the SES. In the next periods, more indicators are expected to be included in the list, which will increase the complexity of the target setting process. Setting down targets for different performance indicators must be done carefully, as many of them have interdependencies. Setting a high target for one indicator may limit the maximum achievable target for other indicators, and actions designed to improve one particular indicator may produce unintended negative consequences in another. Most indicators are related to more than one indicator and these dependencies are usually tied to the spatial and temporal scope one is targeting, which makes the evaluation of interdependencies a challenging task.

| KPA | ANS Performance Indicator | RP1 | RP2 |
|---|---|---|---|
| **Safety** | Effectiveness of safety management (EoSM) | Monitoring | EU target[1] / FAB target[1] / National Monitoring[2] |
| | Application of severity classification scheme (RAT methodology) | Monitoring | EU target[1] / FAB target[1] / National Monitoring[2] |
| | Application of Just Culture (JC) | Monitoring | FAB targets / National Monitoring[2] |
| | Separation infringements | Monitoring | FAB monitoring / National Monitoring |
| | Runway incursions | Monitoring | FAB monitoring / National Monitoring |
| | ATM-specific occurrences at ATS unit | Monitoring | FAB monitoring / National Monitoring |
| | Airspace infringements | | FAB monitoring / National Monitoring |
| | Level of occurrences reporting | | FAB monitoring / National Monitoring |
| | Application of automatic data recording for separation minima infringement monitoring | | FAB monitoring / National Monitoring |
| | Application of automatic data recording for runway incursion monitoring | | FAB monitoring / National Monitoring |
| **Environment** | Horizontal flight efficiency of last filed flight plan (KEP) | EU target | EU target[3] |
| | Horizontal flight efficiency of actual trajectory (KEA) | | EU target / FAB target |
| | Effectiveness of booking procedures for FUA | Monitoring | EU monitoring / National Monitoring |
| | Rate of planning of CDRs | Monitoring | EU monitoring / National Monitoring |
| | Effective use of CDRs | | EU monitoring / National Monitoring |
| | Additional time in taxi-out phases (related to outbound traffic) [4] | | National Monitoring / Airport monitoring |
| | Additional time in terminal airspace (related to inbound traffic) [4] | | National Monitoring / Airport monitoring |
| **Capacity** | En-route ATFM delay | EU target / Nat-FAB targets | EU target / FAB target / Local Monitoring |
| | Arrival ATFM delay | Monitoring | EU monitoring / National targets / Airport Monitoring |
| | ATFM slot adherence | | National Monitoring / Airport monitoring |
| | ATC pre-departure delay | | National Monitoring / Airport monitoring |
| | Additional time in taxi-out phase | Monitoring | |
| | Additional time in arrival sequencing and metering area (ASMA) | Monitoring | |
| **Cost-efficiency** | Determined Unit Cost (DUC) for en-route-ANS (called Determine Unit Rate in RP1) | EU target / Nat-FAB targets | EU target / En-route charging zone targets |
| | Determined Unit Cost (DUC) for terminal ANS | | EU target[5] / Terminal charging zone targets |
| | Terminal costs | Monitoring | |
| | Terminal unit rate | Monitoring | |
| | Costs of Eurocontrol | | EU monitoring |

[1] Separate targets for NSA and ANSP; [2] Indication of the contribution at national level; [3] NM accountable; [4] Moved from Capacity KPA in RP1 to Environmental KPA in RP2; [5] This indicator applies from 2017 onwards, subject to the decision referred to in Article 10 (3) of the Performance regulation.

## 1.3 Performance dashboards and multi-criteria decision support tools

A **performance dashboard** provides a single-page, at-a-glance overview of performance areas so as to provide managers with the necessary insights to make better-informed decisions. Taking advantage of recent mathematical and computing advances, performance dashboards are incorporating new tools and techniques for better achieving their objectives.

The integration of **visual analytics** in performance dashboards has allowed the evolution from simple charts to actionable visual information that synthesises information and derives insights from massive, dynamic, ambiguous and often conflicting data; detects the expected and discovers the unexpected; provides timely, defensible, and understandable assessments; and communicates assessment effectively for action.

The use of **multi-criteria decision support tools** may bring several advantages to performance management: (i) they are useful to understand the decision making framework and to discover the core of decision problems; (ii) they help stakeholders reveal their preferences regarding the objectives and the alternatives to achieve them in an explicit way; and (iii) they make it possible to assess the consensus rate among different stakeholders on a specific issue.

# 2. Interdependencies and trade-offs between KPAs: ATM performance modelling

Performance measurement is a field in which several authors have recognised that much more has to be done in order to better identify the cause-and-effect relationships between performance drivers and indicators (Bititci and Turner, 2000; Flapper, Fortuin and Stoop, 1996; Neely, 2000). Some approaches have opted for simplification, by considering only linear and one-way cause and effect chains (Kaplan and Norton, 2001), while other approaches take into account that the casual relationships are mostly a fuzzy mess of interactions and interdependencies (Xirogiannis et al., 2008). The rationale in the second approach is that a large number of multidimensional factors can affect performance and the integration of those multidimensional effects into a single unit can only be done through subjective, individual or group judgement: the authors argue that techniques suited to fuzzy paradigms should be considered, as it is impossible to have an objective measurement for each different performance dimension. Chytas et al. (2011), for example, propose a methodology using fuzzy cognitive maps to generate a dynamic network of interconnected KPIs, simulating each KPI with imprecise relationships and quantifying the impact of each KPI on other KPIs to adjust performance targets.

Regarding ATM performance, in 2012, the review of the SES Performance Scheme included as a key theme the need for a balanced approach taking into account the local context and its evolution, as well as the interdependencies and trade-offs between KPAs. The PRB considered that RP2 performance plans should provide a full description and evaluation of interdependencies, including the interaction with safety, and that plans should also describe how these interdependencies are to be monitored (EUROCONTROL, 2012). At the level of the SJU, there have been initiatives aimed at defining an ATM performance framework which identifies the interdependencies between indicators. Two techniques have been mainly used: Bayesian networks and influence diagrams.

**Bayesian networks**. An ATM performance model based on Bayesian networks was developed at ACC level by the ATM Performance Model project contracted by the SJU to a consortium formed by ALG, ENAC and EADS. Due to the lack of consistent and coherent data at aggregated European level and the specific performance characteristics and behaviour of each ANSP, the model could not be built at the most general ECAC level. Interdependencies between capacity, environmental flight efficiency and cost-efficiency were taken into account for the development of the model; safety was left out due to the lack of adequate data. Different databases from EUROCONTROL were used, mainly the NEST tool for obtaining ACC detailed data related to airspace capacity and design, and flights information. Several relationships between indicators, such as the tight relationship between airspace capacity and cost efficiency, were revealed by the model. Nevertheless, the conclusions identified the need to dig dipper into the issue by adding data related to safety, further analysing the discretisation used and increasing the temporal scope to more than 2 summer AIRAC cycles. The study also acknowledged the need of including the missing European ACCs and building dedicated models for each considered airspace in order to enhance accuracy when not modelling the whole Europe. The use of Bayesian Networks to approach the development of an ATM performance model has been discussed by Ranieri (2014). Among the advantages mentioned is the possibility of building knowledge from historical data and the extrapolation of influence diagrams, which provides an intuitive representation of the cause-effect relationships between variables. The drawbacks include the need to transform original variables to maintain computational complexity to a manageable level.

**Influence diagrams** (a generalisation of Bayesian networks). The SESAR WPC2 – Task 002 (Davies, 2009) developed a methodology to identify performance needs in the areas of quality of service and cost effectiveness. The proposed methodology consists of four steps: (i) identify the scope of the assessment by defining the characteristics of the operational environment; (ii) understand current performance, by using influence diagrams to model best-in-class and assess what is contributing to/restricting current performance; (iii) undertake stakeholder discussion (enabled by the conceptual understanding of the influence factors for each KPA as presented in the influence diagrams) to capture stakeholder-specific performance needs; and (iv) balance these needs by informed discussion to define performance needs (in consultation with stakeholders) at specific points in the network. Steps ii-iv imply the use of influence diagrams to capture the key drivers of each KPI. This study, however, left out the consideration of interactions between KPAs.

## Challenges and opportunities

The criticism about the static nature of performance measurement systems, as well as the relationships and trade-offs between different measures, justify the need for further research in the field of performance modelling. The main challenges include data inconsistency, data complexity reduction and relationships between KPIs at inter and intra KPA level. Visual analytics techniques can help explore the data to inform data dimensionality reduction and assess the effect of the adopted level of discretisation. A combination of fuzzy logic and machine learning techniques could be used to deal with sets of continuous values. Different classification techniques can be explored to deal with missing data. Complex relationships between indicators could be studied by using visual analytics and data analysis techniques inherited from complex systems science, such as functional networks and community detection. In the next section we describe in more detail different techniques that could be explored.

# 3. Techniques for ATM performance analysis, modelling and management

## 3.1 Visual analytics: exploration of space-time patterns

Visualisation is mainly used as the most effective way to discover unexpected patterns and relationships among big and often heterogeneous datasets (Yau, 2011) as well as to present, evaluate, explore, simulate and play with several facets of the real world (Fuchs et al., 2011; Bimber and Raskar, 2005; Cawood and Fiala, 2007). Both the commercial and academic sides have in the last years been actively involved in the process of setting up grounding theories to successfully deal with the challenge of extracting knowledge and visually representing data facets. Many solutions are currently at the disposal of researchers and companies to face the challenges raised by the data deluge in a variety of domains — see, e.g., Zhang et al. (2012) and Harger and Crossno (2012) for comprehensive reviews of both commercial and open-source tools. In the field of performance monitoring, visual analytics techniques can inform three main areas: discovery of relevant relationships between variables; trade-off evaluation; and uncertainty assessment.

**Relationship discovery**. Finding meaningful relationships between a set of KPIs can be a valuable source of decision making information. For instance, it can allow the reduction of the number of KPIs to be monitored; it can help detect cause-effect connections; it can allow analysts to monitor the integrity of a system; and it can help figure out how a system could evolve according to the temporal dimension. Statistical techniques such as correlation, regression analysis and (multivariate) analysis of variance ((M)ANOVA) have been found to be particularly useful to reveal these relations (Hair, 1995). From a visual point of view, several approaches could be suitable to highlight a particular facet of KPI relationships. Line charts have been traditionally used to represent evolutions over time and the perceptual efforts to correctly interpret comparisons among temporal trends is relatively low. Parallel coordinates project a multi-dimensional space onto a 2D plane where each variable is represented as a metric (vertical/horizontal) bar, allowing the representation of variable trends across multiple scenarios as well as time. Scatter plots help identify the kind of relationship (e.g., linear, quadratic, random) between two different KPIs by placing points onto a Cartesian plane. Scatter plot matrices have been proposed to put into a grid layout the scatter plots resulting from analysing each pair of attributes, thus enhancing the perceptual exploration of variable trends. Heat maps can be used to represent how strong two variables are related to each other; in this case variables are arranged to form a squared matrix of cells, and a suitable colour scale is used to colour each of them to encode the variable relationship measure (e.g., p-value, co-variance). Recently, a treemap-based method has been patented to display data representing KPIs of a service business with a hierarchical structure (Fenstermaker and Day, 2011). The same visual metaphor could hold in the context of ATM performance: in this case, KPAs and KPIs could be, for instance, the main structures of the hierarchy.

**Trade-off evaluation**. A severe issue in policy assessment concerns the need to take into account different policy options and evaluate their benefits according to requirements that disagree or collide with each other. In this case, a proper visual analytics tool has to provide means to evaluate the benefits and drawbacks of the options under analysis. Therefore it is important to rely on visualisation techniques able to handle the inherent multidimensionality these data are carrying on, by considering both their abstract (Kehrer and Hauser, 2013) and spatio-temporal dimensions (Andrienko et al., 2006). One common way to provide a comprehensive look to scenario analysis consists in the adoption of multiple, coordinated techniques (Roberts, 2007), such as parallel coordinates (Inselberg et al., 1991; Andrienko et al., 2001), histograms and their variant time histograms (Kosara et al., 2004), scatterplot matrices (Monmonier, 1989; Elmqvist et al., 2008) and glyphs. The last ones have recently received the attention of the visualisation community for facilitating the encoding of two or more data attributes in a compact form, resulting in a clever use of the screen space (Ward, 2008; Borgo et al., 2013). Despite their compelling layouts and design schemes, glyphs may suffer from perceptual issues that may affect how users gain understanding of the domain (Fuchs et al., 2013; Fuchs et al., 2014). Another major drawback is their placement, especially when considering glyphs overlapping either among themselves or with some other visual elements (Ward, 2002).

**Uncertainty representation**. Strictly related to the concept of evaluating several options in a typical decision making process is the idea of uncertainty. Properly dealing with uncertainty is fundamental for decision makers because data uncertainty heavily affects the process of forecasting and therefore the assessment of policy options. The rising interest about this topic in the recent past (Johnson and Sanderson, 2003) has led to a number of proposals and practical solutions to communicate it visually. The comprehensive review about uncertainty in data visualisation by Brodlie et al. (2012) certifies the global advances made in this area. The authors discuss two complementary features: i) visualisation of uncertainty, i.e., how to depict uncertainty of data, and ii) uncertainty of visualisation, dealing with how much inaccuracy occurs when processing data through the pipeline. Despite the advances in visualisation science, visualising uncertainty is still an unresolved problem under different points of views. From the simplistic, but still widely used box-plot representation proposed by Tukey (1977) to represent the sense of variations within a distribution of numerical data through quartiles, to representations able to maximise the quantity of information displayed meaningfully and minimise at the same time the ratios of (unwanted) misunderstanding and misconceptions, there is still a long way to go. Possible solutions could encompass a clever combination of visualisations of competing / contradictory / conflicting features, integrated views, comparative navigation, and suitable colour scales. Correa at al. (2009) describe a framework to introduce uncertainty in the visual analytics process through statistic methods such as uncertainty modelling, propagation and aggregation, and show how usual data transformations — regression, k-means clustering or PCA analysis — could take advantage of it. Xie and colleagues (Xie et al., 2006) present two different approaches to insert data uncertainty in visualisations expressed in terms of data quality measures.

## Challenges and opportunities

Even if in some cases the existing tools can reach the highest peaks of quality and propose clever data representations, they normally rely on general-purpose approaches which hardly fit to solve specific problems into complex domains. A successful approach providing end-users with a bunch of tools to answer their own problem-oriented questions should take into account the specificities of the data, domain and tasks involved. A lot of software tools support the analysis of KPIs by providing dashboards indicating the status of each KPI. However, these tools are currently limited to a mere visualisation of the KPI values (Hesse et al., 2013), without any kind of analytical functionalities supporting the exploration of the interrelationships between KPIs, which still depends a lot on the experience of human experts. Visual analytics represent an opportunity to extract information on the dependencies between KPIs in order to enable causal analysis and decision support. The adoption of visualisation and visual analysis methodologies would bring several benefits, such as facilitating the interpretation of data and the understanding of complex relationships; evaluating the impact of (a set of) policies in a more effective way; facilitating the communication between stakeholders and policy makers in a simple and more direct style, avoiding technical and bureaucratic expressions; and detecting possible problems before they arise.

## 3.2 Data science and systems modelling techniques

The two main categories in data science are knowledge discovery and predictive modelling. Knowledge discovery focuses on finding interpretable patterns describing the data. It has been defined as the nontrivial extraction of implicit, previously unknown, interesting and potentially useful information from data. Prediction involves using some variables to predict unknown or future values of other variables of interest. Predictive models used in data science typically include a machine learning algorithm that learns certain properties from a training dataset in order to make those predictions. Predictive modeling techniques include regression and pattern classification. Regression models are based on the analysis of relationships between variables and trends in order to make predictions about continuous variables. In contrast to regression models, the task of pattern classification is to assign discrete class labels to particular observations as outcomes of a prediction. These methods have been widely used in real life situations. Some examples are: diagnosis of diseases given a set of symptoms (Benett and Hauser 2013), earthquake magnitude prediction (Alarifi et al., 2012; Reyes, 2013), early warning systems in hospitals (Jarvis et al., 2013), power fault detection and prediction (Wong et al., 1997), process control in chemistry (Fan et at., 2010), metallurgic (Klinger et al., 2010; Narayanan, 2010) and logistic (Sayed et al., 2010) industries, and policy making and trade-off evaluation (Chen, 2012). Several methods typically used in data science for knowledge discovery and prediction are discussed below.

**Clustering**: clustering aims to identify a finite set of categories or clusters to describe data. Deviation detection focuses on discovering data items which belong to no category or cluster. There is a vast amount of clustering algorithms, of which the most commonly used are: i) **hierarchical clustering**, which builds a cluster hierarchy or, in other words, a tree of clusters, also known as a dendrogram. Every cluster node contains child clusters; sibling clusters partition the points covered by their common parent. Such an approach allows exploring data on different levels of granularity; ii) **partitioning relocation clustering**, which divide data into several subsets. Because checking all possible subset systems is computationally infeasible, certain greedy heuristics are used in the form of iterative optimisation. Specifically, this means different relocation schemes that iteratively reassign points between the k clusters. Algorithms include k-medoids and k-means methods; and iii) **density-based partitioning clustering**, where clusters are dense areas of points in the data space that are separated by areas of low density. A cluster is regarded as a connected dense area of data points which include density-based connectivity and density functions.

**Classification**. In classification methods, a learning function maps data items into one of several predefined classes. A set of training items is given, which are already classified and form a basis for the learning function. Some of the most commonly used classification techniques are: (i) **decision trees**, which use a tree-like predictive model to map observations about an item on several levels in the tree until reaching the final conclusion regarding the outcome of the desired function. These models consider only symbolic (discrete) values both for attributes, as well as for the resulting class. The tree may be translated into an equivalent set of mutually exclusive rules, each one corresponding to a unique path from the top node to a terminal node. Decision trees have been used for early warnings and disease diagnosis, among other applications; (ii) **fuzzy classification rules**. They are an extension of the decision tree induction technique predicting a numerical output by combining fuzzy representation and approximate reasoning for dealing with noise and uncertainty. These systems have been used, e.g., for bankruptcy prediction (Yang and Gan, 2008) and handwritten character recognition (Frosisni et al., 1998). The main difference with the standard decision trees is that the output of a tested attribute may not fully correspond to one branch, but it may have a membership degree attached to it; (iii) **Bayesian networks**. They aim at identifying cause-effect relationships. It is a probabilistic graphical modelling technique that represents a set of random variables and their conditional dependencies via a directed acyclic graph. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases (Borgelt and Kruse, 2002). They have been used to find relationships between KPIs in ATM systems (Ranieri, 2014); (iv) **influence diagrams**, which are a generalisation of Bayesian networks where not only probabilistic inference problems but also decision making problems are modelled and solved. They have also been used in ATM systems (Davies, 2009); (v) **artificial neural networks (ANNs)**, perhaps the most popular prediction technique for nonlinear systems. It consists of simple interacting processing units that are arranged in arbitrary layers with variable patterns of interconnectedness. Knowledge is represented as connection strengths (or weights) between connected units. Each processing unit spreads its activation to the connected units after combining and processing its input, using some linear or nonlinear activation function. Learning occurs when general recursive rules are applied to adapt these weights to produce desired output responses. They are commonly used for demand prediction; and (vi) **rule-based expert systems**, which employ inferred knowledge to solve problems that usually require human expertise. An expert system either supports or automates decision making in a specific area where experts perform better than non-experts. The knowledge of the system is represented by sets of logic rules which apply with a certain probability. The general workflow for the definition of these systems implies the definition of initial sets of rules representing real human knowledge and a training phase which infers new rules or refines the existing ones by using logical conclusion or implication from real data.

Examples of machine learning techniques used for **policy and trade-off evaluation** are: (i) **game-theoretic rough set**. The rough sets can be used to induce three-way classification decisions. The positive, negative and boundary regions can be interpreted as regions of acceptance, rejection and deferment decisions, respectively. A main result of probabilistic rough sets is the interpretation of three-way decisions using a pair of probabilistic thresholds. The game-theoretic rough set model determines and interprets the required thresholds by utilising a game-theoretic environment for analysing strategic situations between cooperative or conflicting decision making criteria. Different types of competition or cooperation can be formulated depending on objectives of users; (ii) **Markov decision processes (MDP)**. MDPs provide a mathematical framework for modelling decision making in situations where outcomes are partly random and partly under the control of a decision maker. They are useful for studying a wide range of optimisation problems solved via dynamic programming and reinforcement learning. Some examples are: policy iteration, dynamic decision networks and Q-learning.

Beyond machine learning we can find **simulation models**. A simulation model may be considered as a set of rules that define how the system being modelled will change in the future, given its present state. In general, for complex problems where time dynamics is important, simulation modeling is a better answer. The major approaches in simulation modeling of socio-technical systems can be broadly divided in three main groups: system dynamics (SD), discrete event simulation (DES) and agent-based modelling (ABM) (Borshchev and Filippov, 2004). The use of ABM to model ATM performance has been explored in previous SESAR projects like ACCESS (Herranz et al., 2015). In INTUIT we will in principle explore more parsimonious modelling approaches, such as system dynamics. System dynamics is the study of information-feedback characteristics to show how organisational structure, amplification (in policies), and time delays (in decisions and actions) interact to influence the success of the system (Forrester, 1958, 1961). The system behaviour is defined as a number of interacting feedback loops, balancing or reinforcing. Real world processes are represented in terms of stocks (e.g., material, knowledge, people, money, etc.), flows between these stocks, and information that determines these flows.

### Challenges and opportunities

Although completely different in nature, the problems approached with the aforementioned tools share many characteristics with ATM performance. The experience learnt from other fields can therefore be adapted to ATM performance assessment. Techniques of fuzzy classification can be explored to extend the work done by Ranieri (2014) and find further relationships between the 4 KPAs. Algorithms used to deal with missing data in classification trees can be explored to work with missing or incomplete data in ATM systems. Classification techniques used for hospital early warning systems can be adapted for the ATM to detect the advent of eventualities. System dynamic techniques or other policy trade-off evaluation models can be explored to assess the potential impacts of measures applied to improve some KPA on the overall performance of the ATM system.

## 3.3 Decision support tools for performance management

**Multi-objective optimisation**. Multi-objective optimisation is applied in problems where optimal decisions need to be taken in the presence of trade-offs between two or more conflicting objectives in such a manner that more than one objective function must be optimised simultaneously. In a multi-objective optimisation problem, typically there is not a single solution that simultaneously optimises each objective. Instead, there is a set of optimal solutions that are equally acceptable from a mathematical point of view: the Pareto optimal (or Pareto efficient) solutions. Different approaches are possible when setting and solving multi-objective optimisation problems: the goal may be to find a representative set of Pareto optimal solutions, quantify the trade-offs in satisfying the different objectives, find a single solution that satisfies the subjective preferences of a human decision maker, or a combination of these. Selecting one of the Pareto optimal solutions calls for information that is not contained in the objective functions. This is why, compared to single objective optimisation, a new element is added: a decision making process. Multi-objective optimisation has been extensively used, e.g., for supply chain network optimisation and natural resources management (Reddy and Kumar, 2009; Woodward et al., 2014).

**Multi-criteria analysis**. Multi-criteria analysis is a family of methods commonly implemented by decision support systems (DSS) to structure a decision problem in terms of possible alternative courses of action on the basis of multiple factors, and to identify the best performing solution (Massam, 1988). Multi-criteria analysis methods can effectively support the structuring, assessment and decision making processes on complex policy issues, with the main advantage of integrating a diversity of criteria in a multidimensional way. The procedures and results obtained from multi-criteria analysis can be improved with the interaction of stakeholders, and in this regard multi-criteria analysis methods are particularly suitable to be used in combination with participatory methods. There are different multi-criteria analysis methods for ranking alternatives, which can be classified according to the decision rule used (compensatory, partial-compensatory or non-compensatory) and the type of data they can handle (quantitative, qualitative or mixed). Multi-attribute utility and value theories encompass the methods based on compensatory rules, such as the Analytic Hierarchy Process (AHP) and the Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH). AHP was developed by Saaty (1977, 1980, 1988, 1996) and is one of the best known and most widely used multi-criteria analysis methods. It allows users to assess the relative weight of multiple criteria or multiple options against given criteria in an intuitive manner through pairwise comparisons. Saaty established a consistent way of converting such pairwise comparisons into a set of numbers representing the relative priority of each of the criteria, in such a manner that AHP is the only known multi-criteria analysis method that can measure the consistency in the decision maker’s judgments. Although AHP is a decision making methodology in itself, its ability to elicit accurate ratio scale measurements and combine them across multiple criteria has led to AHP applications in conjunction with many other decision support tools and methodologies. AHP has been used in combination with linear programming, integer programming, goal programming, data envelope analysis, balanced scorecards, genetic algorithms, and neural networks (Millet and Wedley, 2003). MACBETH (Bana e Costa and Vansnick, 1994) is another method based on compensatory rules, being the calculation of scores achieved by employing linear programming instead of an eigenvalue method. Outranking Methods (OMs) were first developed in France in the late sixties following the difficulties experienced with the value function approach in dealing with practical problems. Outranking methods are characterised by the limited degree to which a disadvantage on a particular viewpoint may be compensated by advantages on other viewpoints (Pirlot, 1997). The degree of dominance of one option over another is indicated by outranking. Methods such as ELECTRE (Roy, 1968) or PROMETHEE (Brans, 1982; Brans and Vincke, 1985; Brans and Mareschal, 1994) are often classified as non-compensatory procedures. This means that in comparing two alternatives, small differences in favour of one of them may be compensated by small differences in favour of the other one, but large differences may not be compensated even by large differences in the opposite direction (Vincke, 1992). A combination of multi-criteria analysis methods with fuzzy logic has been applied to the measurement and evaluation of a performance framework by Dojutrek et al. (2014).

**Visual analytics for sensitivity analysis**. Achieving a comprehensive knowledge to properly evaluate policy alternatives, especially in the presence of multiple and conflicting requirements and parameters, is one of the biggest challenges of the decision making field. Visual analytics, as the science to ease analytical reasoning through visual interfaces (Thomas and Cook, 2005), has been shown to be very effective to support tasks such as decision making and planning in several research and practical fields (Andrienko et al., 2003; Andrienko et al., 2005; Booshehrian et al., 2012; Buchmüller et al., 2015; Hurter et al., 2009; Sadransky et al., 2013; Zhang et al., 2014). The idea of a dashboard has recently gained the attention of the visualisation community. It is conceived as an interactive environment in which the user can steer his/her analytical process by visually interpreting the story that different graphics are portraying. However, "Dashboards are not an exercise in visual design either. [...] Dashboards are a curated way to present data for a certain purpose. They are not unspecified, multi-purpose analytical exploration tools. In other words: dashboards will answer a specific, already formulated question. And they will answer in the best possible way, if they are designed as such" (Curier, 2015). In that sense, a non-exhaustive list of successful examples of dashboards could be the following: Vismon (Booshehrian et al., 2012), which provides a multi-level view of models' underlying uncertainty and includes contour plots to encode policy sensitivity and trade-off analysis tools; TaxiVis (Ferreira et al., 2013), a visualisation system to support visual exploration and queries of big origin-destination and spatio-temporal data concerning taxi trips in New York City; and SWIM (Lundblad et al., 2009), which analyses both weather forecast data and ships voyage information through interactive maps linked to time graphs and parallel coordinates plot. Advanced techniques involve the visualisation of the Pareto-optimal solution(s) coming from multi-objective optimisation functions — see e.g. Level Diagrams by Blasco et al. (2008) and Self-Organizing Maps for Multi-Objective Pareto Frontiers (SOMMOS) by Chen et al. (2013). The idea behind these methods is to find a suitable characterisation of the Pareto frontier in order to display it on a two-dimensional representation. This means looking for a visual arrangement able to describe high-dimensional data as a set of 2D projected or composed spaces. Interactivity and additional information will help the user to explore solutions and their inherent benefits and trade-offs. The idea of dimension projections is also present in the work by Gleicher (2013), but in this case the (linear) projection functions (defined as explainers) are built upon user-specified annotations, so that the resulting derived dimensions represent user's concepts rather than statistical properties. In order to properly organise the data, as well as show their connection to different properties of interest, particular attention has been spent in considering trade-offs in correctness, simplicity, and diversity.

## Challenges and opportunities

The problem of improving ATM performance along the different KPAs is a clear example of finding a solution to a problem with multiple and conflicting objectives. However, to the best of our knowledge, none of the before mentioned techniques have been applied to look at ATM performance at an integrated level. Although some of them have been used to study flight trajectories and their impact on air traffic and health (Gariel et al., 2011, Buchmüller et al., 2015), there are not studies at a comprehensive KPA general level. Visual analytics, multi-criteria analysis and multi-objective optimisation could be integrated into decision support systems to select the optimal set of measures for ATM performance improvement.

# 4. The INTUIT project

ATM performance results from the complex interaction of interdependent policies and regulations, stakeholders, technologies and market conditions. Trade-offs arise not only between KPAs, but also between stakeholders, as well as between short-term and long-term objectives. To effectively steer the performance of ATM operations, metrics and indicators shall therefore be capable of capturing the full range of economic, social and environmental impacts of the ATM system, both on the different stakeholders and society at large, at different temporal and geographical scales. Performance modelling techniques shall be able to grasp the interdependencies between different KPAs and KPIs and allow the assessment of the possible future impacts of a range of policies and trends.

The need for improved indicators and modelling methodologies meeting these conditions has been acknowledged by the ATM stakeholders and the research community (EUROCONTROL, 2012). While a lot of effort has traditionally been devoted to the development of microscopic performance models, there is a lack of useful macro approaches able to translate local improvements or specific regulations into their impact on high-level, system-wide KPIs. On the other hand, the increasing availability of data at different scales, together with recent advances in the fields of data analysis and visualisation, open new opportunities to develop new ATM performance metrics and modelling techniques.

**INTUIT (www.intuit-sesar.eu) is a research project within SESAR Exploratory Research which aims to explore the potential of visual analytics, machine learning and systems modelling techniques to improve our understanding of the trade-offs between ATM KPAs, identify cause-effect relationships between indicators at different scales, and develop new decision support tools for ATM performance monitoring and management**.

## 4.1 Project objectives

INTUIT pursues the following objectives:

1. to conduct a systematic characterisation of the ATM performance datasets available at different spatial and temporal scales and evaluate their potential to inform the development of new indicators and modelling approaches;
2. to propose new metrics and indicators providing new angles of analysis of ATM performance;
3. to develop a set of visual analytics and machine learning methodologies and algorithms for the extraction of relevant and understandable patterns from ATM performance data;
4. to investigate new data-driven modelling techniques and evaluate their potential to provide new insights about cause-effect relationships between performance drivers and performance indicators;
5. to integrate the newly developed analytical and visualisation functionalities into an interactive dashboard supporting multi-dimensional performance assessment and decision making for both monitoring and management purposes.

## 4.2 Approach

The proposed research strategy comprises three main stages:

1. Multiscale characterisation of ATM performance data.
2. Data analysis and performance modelling.
3. Development of performance monitoring and management toolset.

### Multiscale characterisation of ATM performance data

#### ATM performance data collection

Under the provisions of its contract with the European Commission, the Performance Review Body (PRB) has developed an online performance monitoring dashboard which aims at supporting National Supervisory Authorities (NSAs) in their monitoring activities. This e-Dashboard presents information related to the performance scheme at different levels: EU-wide, Performance Plan (either national or FAB) and Airports. All Key Performance Indicators (KPIs) and Performance Indicators (PIs) regulated by the SES Performance Scheme are covered, together with metadata detailing the calculation of each indicator. In addition, KPIs are presented against adopted targets. The dashboard provides a download function and will therefore be one of the primary data sources for INTUIT.

Other datasets useful for the execution of the project include: (i) delay analysis data from the Central Office for Delay Analysis (CODA); (ii) network operations monitoring and reporting (public reports and ATFCM Statistics); (iii) data about network events disrupting the airspace network from the Network Operations Portal (NOP); (iv) air traffic demand from the Demand Data Repository (DDR); (v) data on capacity, labour and cost per air traffic control centre, as provided in the yearly ATM cost-effectiveness reports; (vi) performance reports and plans elaborated by EU Member States and approved by the PRB; (vii) statistics and forecasts on expected levels of air traffic in Europe produced by EUROCONTROL's Statistics and Forecast Service (STATFOR); and (viii) additional data collected by the Performance Review Unit (PRU).

#### Multi-scale data characterisation and quality assessment

The ATM system comprises different spatial and temporal scales at which different phenomena occur. The appropriate scale of observation depends on the question one is interested in, but, at the same time, there exist coupling mechanisms between phenomena taking place at different scales. The variability in delay indicators observable in a timescale of days, for example, may trigger changes in demand only observable in a timescale of months. Another example is cost efficiency over different periods of time: sacrificing efficiency in the short run may be justified, for example, to reduce the cost of managing uncertainty in the long run (Ranieri et al., 2013). Different combinations of KPIs may lead to scenarios that are the same — or apparently the same — at a certain scale, but completely different at others. Capturing the relevant features at each scale with the right level of detail, as well as the dynamic interaction and the propagation of uncertainty across scales, is an essential condition for developing useful performance macro models.

During this stage, we will identify the spatial and temporal scales relevant to ATM performance management and will perform a first qualitative assessment of the cross-scale coupling mechanisms. The collected datasets will then be assessed on quantity, validity, integrity, quality, and spatial and temporal resolution, in order to identify the information that can be extracted from each dataset (or each combination of datasets) at the different scales, as well as the associated limitations. Finally, we will review the indicators currently in use — clearly distinguishing the 'performance indicators' (PIs) used for the purpose of performance monitoring, benchmarking and reviewing, and the 'key performance indicators' used for the purpose of target setting — as well as other indicators proposed in the literature. We will adopt a long-term view, without limiting ourselves to the KPAs addressed in RP1 and RP2, but looking also at other KPAs that can be useful to inform the performance approach for RP3 onwards.

This analysis will allow us to: (i) map the available datasets to the existing indicators at the different scales; (ii) propose new metrics and indicators to characterise relevant phenomena (e.g., network resilience) that may not be considered or fully captured by the indicators currently in use or available in the literature; and (iii) depict the interrelationships and trade-offs that are not fully understood.

**Qualitative analysis of performance drivers and trade-offs**

Identifying performance drivers and trade-offs represents one of the main challenges of ATM performance analysis. Demand volatility and seasonal traffic variability are factors that affect negatively the capacity vs. cost-effectiveness performance trade-off (Grebensek & Magister, 2012). Network propagation effects are also important: if one ANSP/ACC suffers from an exceptional event (e.g., a strike or an equipment failure), a significant traffic volume will be diverted to adjacent regions, with demand volatility effectively spilling over to them.

To identify interdependencies between indicators and underlying performance drivers, we will rely on: (i) desk research, including an extensive review of research papers and policy studies; (ii) consultation with ATM stakeholders and industry practitioners, including a dedicated working session with stakeholders; and (iii) case studies for particular air traffic control centres (particularly the ACCs with the highest amount of delays).

The outcome of this qualitative analysis will be the final set of research questions to be tackled in the data analysis and modelling stage. Examples of trade-offs worth exploring are cost-efficiency with capacity, safety and quality of service; capacity with access (e.g., equipage issues), safety, quality of service and the environment; and trade-offs between the latter two.

## Data analysis and performance modelling

We will identify the data analysis and modelling approaches that appear more promising to address the research questions identified in the previous stage, and will evaluate their pros and cons in the light of the type of data available at the scales involved in each research question. The proposed approach will rely on a synergistic combination of visual analytics, machine learning and systems modelling: a visual analysis of raw data will suggest the exploration of specific patterns and trends; these patterns will then be studied through machine learning and statistical analysis techniques to inspire new modelling approaches and suggest specific hypothesis; finally, the patterns generated by the models will be analysed and compared to those extracted from real-world data, here again making use of different data analysis and visualisation techniques, in order to evaluate and validate the proposed performance models.

### Exploratory data analysis

Visual analytics will be used to explore the data for data dimensionality reduction, assessment of the uncertainty associated to the data granularity, evaluation of the effect of the adopted level of discretisation, assessment of volatility, pattern discovery, and event and outlier detection. Interactive visualisations exploiting and reinforcing the strengths of human perception will be coupled with analytical capabilities such as clustering, filtering, automatic event detection, etc.

### Machine learning and statistical analysis

We will study regression and pattern classification models commonly used in other fields, such as weather forecasting and disease diagnosis, and will adapt them to the problem of ATM performance analysis. We will explore different machine learning and statistical analysis techniques, as well as techniques for the analysis of spatio-temporal dynamics recently developed in the context of network theory (e.g., functional networks), in order to identify patterns at different spatial and temporal scales and unveil correlations and possible cause-effect relationships between KPIs at intra and inter KPA level. Individual measurements of KPIs and potential cause-effect relationships will be used to develop training algorithms to: i) recognise regular patterns, ii) identify critical indicator values in given areas, and iii) alert of possible critical outcomes. As an example, DDR data on air traffic demand, CODA data on ATFM delays, and data on capacity, labour and cost per ACC provided in the yearly ATM cost-effectiveness reports will be analysed to examine the cost-efficiency vs capacity trade-off:

- regression analysis will be used to study, for instance, the existence of a structural break in the dataset at the time of the introduction of a new regulation period (such as RP1);
- clustering analysis will be used to identify air traffic control centres (ACCs) according to their similarities along certain parameters and evaluate whether certain relationships occur differently at ACCs with different features;
- factor analysis will be used as a complementary technique, contributing to the understanding of key differences between the various clusters identified;
- association-rule learning will be explored to investigate relationships between demand, ATC capacity and delays at the level of an ACC;
- classification algorithms will be used to evaluate the performance of different types of ACCs, in accordance with the clusters and rules previously identified.

### Explanatory simulation models

Although a model can possess some level of each, explanatory power and predictive accuracy are different qualities: while explanatory modelling is primarily aimed at understanding a certain phenomenon, predictive modelling aims to makes inferences or predictions of unknown values of certain variables from known values of other variables (Shmueli, 2010). Machine learning techniques can help build models with high predictive power, but they don't necessarily have any explanatory power. While such kind of models can be very useful for short-term predictions and for the detection of early warning signs of performance problems, they may or may not capture cause-effect relationships, and must therefore be used with caution when the goal is to understand and anticipate the effects of new policies or regulations. For this reason, we will explore other modelling approaches with a stronger behavioural component, in an attempt to reproduce the evolution of performance indicators over time. The correlations and the spatio-temporal patterns found by means of machine learning and statistical analysis will be useful both to suggest modelling assumptions and to calibrate and validate the proposed models. The challenge here will be developing useful macro models capturing in an aggregated, stylised manner the dynamic behaviour of the ATM system and the interrelationships between the different scales, while keeping the model computationally tractable. For this purpose, techniques such as system dynamics will be explored.

## Performance monitoring and management tools

Based on the results of the previous stages, INTUIT will formulate the technology concept for new performance monitoring and management tools and will develop a first prototype at a laboratory scale. The prototype will integrate the functionalities described below.

### Performance monitoring tool

The performance monitoring tool will consist of a set of ad hoc visual analytics tools showing the status of the selected indicators and their evolution in time, and allowing the user to obtain deeper insights into the variables and the relationships between them. The tool will also integrate an early warning system (EWS) able to detect states of the indicator space potentially leading to performance problems.

### Performance management decision support tool

In order to support the decision making process linked to the definition of performance targets and performance management policies, INTUIT will develop a decision support tool consisting of two interrelated modules: the performance optimisation engine and the interactive dashboard.

- The optimisation engine will provide different sets of KPI values equally acceptable to satisfy the policy objectives of the performance framework (Pareto optimal or Pareto efficient solutions). The optimisation engine will find different feasible solutions of the performance models previously developed, each solution representing a trade-off between KPIs.
- The interactive dashboard will facilitate the decision making process. It will consist of: (i) a multi-criteria analysis tool, which will support the choice of one solution by facilitating the analysis of the different trade-offs provided by the various Pareto-efficient options. Different multi-criteria decision methods will be explored, aiming to find the decision rule more suitable to ATM performance management (compensatory, partial-compensatory or non-compensatory) and the type of data available (quantitative, qualitative or mixed); and (ii) a visual analytics toolset enabling stakeholders' interaction with the multi-criteria analysis tool, allowing them to define and evaluate different policy alternatives and perform sensitivity analysis.

 

## 4.3 Target outcomes and expected impact

INTUIT will develop an ATM performance monitoring and management toolset that will integrate innovative performance modelling techniques with multi-criteria and visual analytics tools in order to allow a comprehensive assessment of KPAs trade-offs and KPIs interrelationships.

The project will deliver three main outcomes:

1. a set of novel data-driven performance macro models providing an enhanced understanding of the interrelationships between KPIs;
2. a performance monitoring tool, including an early warning system based on predictive algorithms and a visualisation tool with analytic functionalities; and
3. a performance management decision support tool, consisting of a multi-objective optimisation engine that will provide a set of optimal combinations of KPI values, and an interactive dashboard which will make use of multi-criteria decision support tools and visual analytics to allow the user to perform what-if and sensitivity analyses.

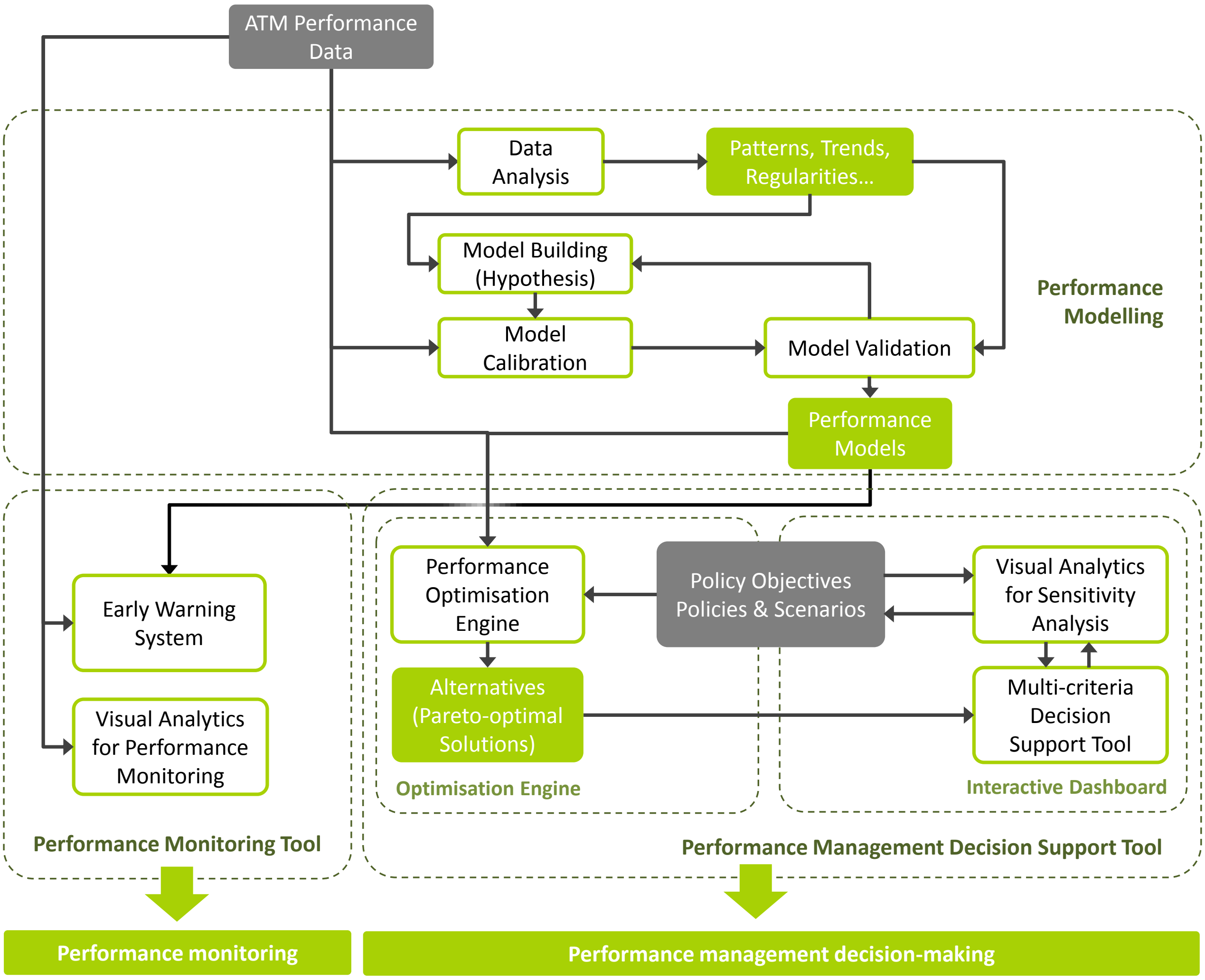


**Figure 2. INTUIT overall concept**

## Relevance to the European ATM sector

**Improvement of the performance approach in the medium term (RP3)**. Despite the exploratory nature of the research activities developed by INTUIT, we believe that the results will be called to continue evolving the tools until higher TRLs. If the R&I cycle reaches a state where the tools are proven in an operational environment, it would definitely contribute to the performance management in RP3. Additionally, the metrics and indicators derived from INTUIT will be a valuable output for the performance approach in RP3 ready for use from the very end of the project.

**Insights into the performance mechanisms underpinning ATM, airports and user community interaction**. The toolset proposed in INTUIT will provide enhanced understanding of KPI relationships and underlying drivers and trade-offs in KPAs. These insights will allow the design of better informed performance policies and objectives at European and local/sub-regional level.

**Improved collaborative contributions to the European ATM Performance Programme**. The multi-criteria analysis — reinforced with visual analytics tools — implemented in the performance management tool will stimulate discussion and facilitate a common understanding of the challenges of ATM performance in a systematic and transparent manner, facilitating broader and more effective stakeholder participation.

**Performance Review Body**. The software toolset created in the project will give the PRB a direct path to set effective mechanisms in order to encourage ANSPs to improve performance and lead to a better tuning of local regulatory targets. The insights into the interdependencies between KPIs will provide the PRB with a deeper understanding of the high-level impact of local improvements or specific regulations.

**Competitiveness of the European aviation sector**. The improvement of the cost-efficiency and the increase of quality of the ATM system will ultimate benefit all the stakeholders of the aviation sector. Additionally, the knowledge and tools delivered by INTUIT will not deal exclusively with ATM performance but may also have an application for performance assessment in other contexts, such as business or strategic performance for airlines or airports.

**Environmental and social impacts**. The knowledge and tools developed by INTUIT will provide scientific evidence in support of policy options for more cost-effective and efficient ATM management. This may result in important savings for society at large, which are particularly relevant in times of economic shortages. Particularly, an enhanced understanding of the drivers underlying cost-efficiency will allow the improvement of this KPA, enabling a more efficient and less expensive ATM system, and therefore bringing benefits for the European citizens. Similarly, the understanding of the factors influencing on flight efficiency might help reduce the environmental footprint of aviation.

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