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MODELING THE IMPACT OF INCREASING AUTOMATION LEVELS ON THE SAFETY AND RESILIENCE OF AIR TRAFFIC CONTROL SYSTEMS

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УНИВЕРЗИТЕТ У БЕОГРАДУ

САОБРАЋАЈНИ ФАКУЛТЕТ

Доротеја Д. Тимотић Петковић

МОДЕЛОВАЊЕ УТИЦАЈА ПОВЕЋАЊА НИВОА АУТОМАТИЗАЦИЈЕ НА БЕЗБЕДНОСТ И РЕЗИЛИЈЕНТОСТ СИСТЕМА КОНТРОЛЕ ЛЕТЕЊА

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Keep moving forward…

ИЗЈАВА ЗАХВАЛНОСТИ

Желим да изразим искрену захвалност свим садашњим и бившим професорима са Катедре за аеродроме и безбедност ваздушне пловидбе. Хвала вам на прилици да учим од вас, на подршци током студентских дана и на знању, посвећености и ентузијазму којим годинама инспиришете генерације студената. Управо захваљујући вама развила сам љубав према ваздушном саобраћају и пронашла свој професионални и научни пут.

Искрено се захваљујем свима са којима сам делила канцеларију 215, која је током година постала много више од радног простора. Посебно хвала Николи и Емиру на подршци, пријатељству и сваком разговору који ми је значио од студентских дана па до данас. Хвала и Нађи, која је својим доласком унела ведрину у свакодневни рад и чија ми је подршка била драгоцена у завршној фази писања ове дисертације.

Посебну захвалност дугујем свом ментору, проф. др Феђи Нетјасову, на поверењу, стрпљењу, подршци и мотивацији током читавог периода докторских студија. Хвала Вам на сваком разговору, сваком савету и несебичном дељењу знања. Ваше менторство, посвећеност и искрена жеља да нас научите, подстакнете и усмерите били су ми од непроцењивог значаја током овог пута.

Велико хвала дугујем својим родитељима, сестри, баки и деки на љубави, разумевању и неизмерној подршци током свих ових година. Хвала вам што сте увек веровали у мене, бодрили ме и били мој ослонац у сваком тренутку.

На крају, највећу захвалност дугујем свом супругу Милошу и нашим дечацима, Игњату и Југу. Милоше, хвала ти што си свих ових година био уз мене, што си веровао у мене и онда када ја нисам, што си ме охрабривао, слушао, разумео и био моја највећа подршка у сваком изазову. Хвала ти за све што смо заједно створили, постигли и изградили, како у професионалном, тако и у личном животу. Игњат и Југ били су моја највећа мотивација и најјачи ветар у леђа да ову дисертацију приведем крају. Ваши осмеси, загрљаји и љубав давали су смисао сваком напору и снагу у сваком умору. Без вас тројице ово не би било могуће.

Идемо даље...

MODELING THE IMPACT OF INCREASING AUTOMATION LEVELS ON THE SAFETY AND RESILIENCE OF AIR TRAFFIC CONTROL SYSTEMS

Abstract: To improve the efficiency of the air traffic control (ATC) system and reduce the workload of air traffic controllers (ATCOs), increasing levels of automation are gradually being introduced into ATC operations. This research aims to proactively assess the impact of automation on the safety and resilience of the future ATC system by comparing two operational scenarios: one, representing the current, non-automated system and other representing the future highly automated system.

The impact on safety and resilience is model with two complementary methods. A qualitative analysis was first conducted using the Functional Resonance Analysis Method (FRAM) in order to identify the variability of functions within both scenarios. The obtained results were subsequently quantified using a Bayesian Belief Network (BBN), enabling a probabilistic assessment of the relationships between system functions and the impact of their variability on the overall performance of the system.

In addition, sensitivity analysis was performed, including *Tornado* analysis and the identification of the most influential factors, as well as *forward* and *backward* analyses, to examine how variability propagates throughout the system and affects the realization of the final system outcome.

Such an integrated approach provides a broader understanding of the key factors and activities within the ATC system following the introduction of automation. This is particularly important for future highly automated systems, where empirical data are not yet available, as it enables the identification of critical activities and factors on which proactive measures can be taken in order to preserve and enhance system safety and resilience.

Keywords: Air Traffic Control, Resilience, Safety, Automation, Functional Resonance Analysis Method, Bayesian Belief Network

Scientific field: Transport and Traffic Engineering

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МОДЕЛОВАЊЕ УТИЦАЈА ПОВЕЋАЊА НИВОА АУТОМАТИЗАЦИЈЕ НА БЕЗБЕДНОСТ И РЕЗИЛИЈЕНТОСТ СИСТЕМА КОНТРОЛЕ ЛЕТЕЊА

Резиме: У циљу повећања ефикасности система контроле летења и смањења оптерећења контролора летења, у оперативне процесе контроле летења постепено се уводе све виши нивои аутоматизације. Ово истраживање има за циљ да проактивно процени утицај аутоматизације на безбедност и резилијентност будућег система контроле летења кроз поређење два сценарија: једног који представља постојећи, неаутоматизовани систем и другог који описује будући, високо аутоматизовани систем.

Утицај на безбедност и резилијентност је моделиран применом две комплементарне методе. Квалитативна анализа је најпре спроведена применом Метода за анализу функционалне резонанције (FRAM), са циљем идентификације варијабилности функција у оба посматрана сценарија. Добијени резултати су затим квантификовани применом Бајесове мреже (BBN), што је омогућило процену вероватноће односа између функција система и утицаја њихове варијабилности на укупне перформансе система.

Поред тога, спроведена је и анализа осетљивости која је обухватила *Торнадо* анализу и идентификацију најутицајнијих фактора, као и *forward* и *backward* анализу, како би се испитао начин на који се варијабилност шири кроз систем и утиче на реализацију коначног исхода система.

Овако интегрисан приступ омогућава свеобухватније сагледавање кључних фактора и активности унутар система контроле летења након увођења аутоматизације. Ово је посебно значајно у контексту будућих високо аутоматизованих система, за које емпиријски подаци још увек нису доступни, јер омогућава идентификацију критичних активности и фактора на које је могуће проактивно деловати у циљу очувања и унапређења безбедности и резилијентности система.

Кључне речи: Контрола летења, Резилијентост, Безбедност, Метод за анализу функционалне резонанције (FRAM), Бајесова мрежа (BBN)

Научна област: Саобраћајно инжењерство

Ужа научна област: Аеродроми и безбедност ваздушне пловидбе

УДК број:

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List of acronyms:

BBN	Bayesian Belief Network
FRAM	Functional Resonance Analysis
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATM	Air Traffic Management
IFR	Instrument Flight Rules
ICAO	International Civil Aviation Organization
SES	Single European Sky
TBO	Trajectory Based Operations
CONOPS	SESAR Concept of Operations
PBO	Performance Based Operations
EUROCONTROL	European Organisation for the Safety of the Air Navigation
ANSP	Air Navigation Service Providers
FIRs	Flight Information Regions
NSA	National Supervisory Authority
ACC	Are Control Centre
ATS	Air Traffic Service
OLDI	On-line Data Interchange
AIRAC	Aeronautical Information Regulation and Control
EASA	European Union Aviation Safety Agency
RAG	Resilience Analysis Grid
DAG	Direct Acyclic Graph
SESAR	Single European Sky Air Traffic Management Research
STAMP	System-Theoretic Accident Model and Processes
CPDCs	Common Performance Conditions
MSAW	Minimum Safety Altitude Warning
CREAM	Cognitive Reliability and Error Analysis Method
SOPs	Standard Operating Procedures
RNP	Required Navigation Performance
FDPS	Flight Data Processing System
LTM	Local Traffic Management
CDM	Collaborative Decision Making
Met	Meteorological

1. INTRODUCTION

1.1. GENERAL INTRODUCTION

In recent years, air traffic volume has steadily increased, driven by passengers' growing ability and willingness to choose this mode of transportation for their journeys. As a result, the Air Traffic Management (ATM) system has come under significant pressure due to the continuous rise in global air traffic demand. Airlines' increasing requests for new flights are gradually outpacing the system's existing capacity. At the same time, economic considerations, the need to maintain and enhance operational safety, environmental objectives, efforts to reduce delays, and many other related demands remain central concerns for all stakeholders within the ATM system. Conversely, unforeseen events—such as the COVID-19 pandemic or volcanic ash disruptions can dramatically reduce or even halt air traffic within the system.

Regardless of the complexity of the situations the ATM system may face, ensuring the safety and efficiency of air traffic operations is of the highest importance. At the same time, it is essential to preserve economic stability at the local, national, and global levels, and to support the continuous advancement of the ATM system in terms of safety, financial performance, and environmental protection.

The challenges associated with the continuous growth and increasing diversity of air traffic have been recognized since the 1980s, emphasizing the need for a safer, more efficient, and environmentally sustainable ATM system capable of effectively utilizing emerging technologies (APATCHE Consortia, 2018). Over the following decades, air traffic demand generally exhibited a steady upward trend. As shown in Figure 1, this trend was temporarily disrupted by the global economic crisis in 2008, followed by a period of stagnation lasting until 2013. Subsequently, traffic volumes resumed their growth, reaching more than 11 million flights in 2019, representing an average increase of 0.8% in instrument flight rules (IFR) operations compared to 2018 (EUROCONTROL, 2020).

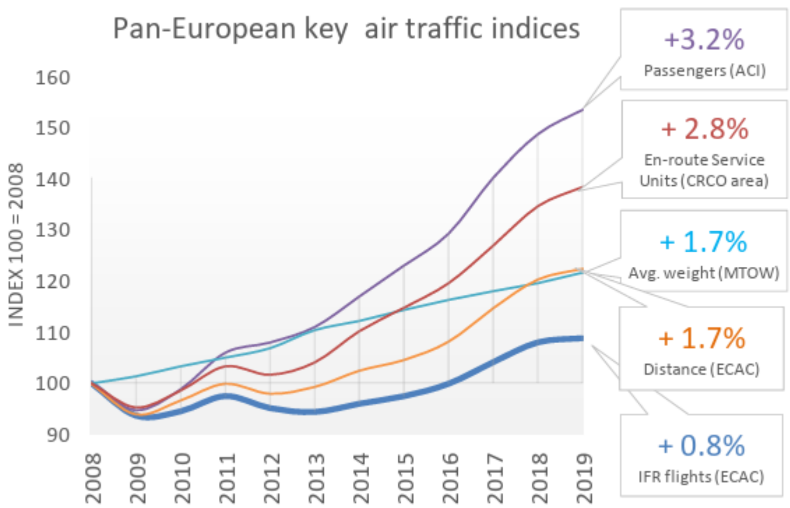


Figure 1. European air traffic indices (2008-2019)
Source: Performance Review Unit, 2020 (EUROCONTROL, 2020)

According to European Organisation for the Safety of the Air Navigation (EUROCONTROL) latest predictions on European Flight Movements (Figure 2), after traffic growth in 2019, air traffic is experiencing a sharp decline in 2020, when the number of IFR flights decreases to around 5 million, primarily due to the effects of the COVID-19 pandemic. In the following period (2021–2024), a gradual but continuous recovery of traffic is observed, approaching the pre-pandemic level by the middle of the decade. Projections after 2025 indicate that, in the base scenario, the level of traffic returns to the values of 2019 around 2025–2026, while in the medium and high scenarios it is expected to increase further, with approximately 12.4 million and 13.7 million IFR flights by 2031, respectively (EUROCONTROL, 2025). These trends indicate that air traffic is not only recovering, but entering a phase of long-term growth, which has significant implications for the capacity, safety, and resilience of future ATM systems.

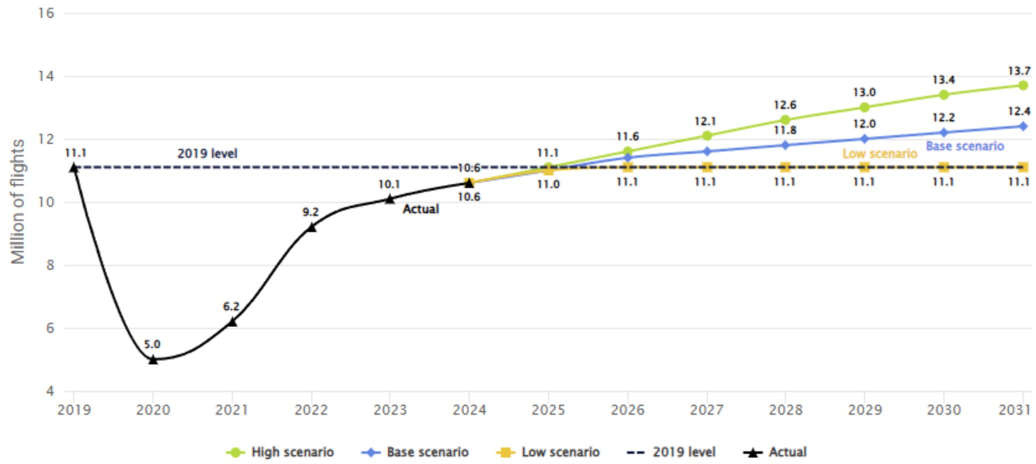


Figure 2. *Actual and future IFR movements compared to 2019*
Source: EURCONTROL 7 year Forecast 2025-2031, Autumn 2025.

Traffic growth has been accompanied by significant flight delays: in the late 1990s, the average delay per flight was 5.5 minutes (1998-1999) across the network, which then improved in the following years, reaching an average delay of 0.86 minutes per flight in 2004. However, the increase in network capacity has not kept pace with the growth in traffic demand, and en route delays are still increasing, with a trend of reaching 8.5 minutes, on average, per flight by 2035 (SESAR Joint Undertaken, 2019; SESAR Joint Undertaken, 2020). At the same time, airspace will become increasingly complex to manage due to the existence of new air vehicles such as zero-emission aircraft, drones, military, and high-altitude aircraft. Also, the aircraft vehicle management is affected by and has an impact on climate change, which encourages the aviation industry to step up efforts to improve the environmental sustainability of aviation, aiming to achieve carbon neutrality by 2050. In addition, geopolitical crises, security threats, and natural events have great pressure on aviation (SESAR Joint Undertaken, 2025).

In response to the challenges posed by increasing traffic volumes and delays, and through the joint efforts of all stakeholders in the air transport system, the International Civil Aviation Organization (ICAO) initiated the publication of two documents in 2003: the “Manual on System Requirements for Air Traffic Management” (ICAO Doc. 9882, 2008) and the “Manual on Global Aviation System

Performance" (ICAO Doc. 9883, 2009) with the aim of establishing the future global air transport system on the principles defined by them. Similarly, in 2005, ICAO launched the "Global Operational Concept for Air Traffic Management" (ICAO Doc. 9854), known as the "ICAO Concept". In this document, the future air transport system is viewed as an effective Performance Management System that enables all stakeholders to progress and increase reliability in various areas such as safety, capacity, economy, environment, etc (APACHE Consortia, 2018).

Earlier, in 1999, the European Commission developed the Single European Sky (SES) initiative with the main objective of defining a legislative framework for European aviation to address air traffic safety and airspace capacity issues. The SES was adopted in 2004. The second regulatory package, SES II, defines objectives in key areas such as safety, capacity and cost-effectiveness of air traffic, as well as environmental protection. The programme was developed in accordance with the ICAO concept and refers to the achievement of set performance targets, as well as defining a framework for their monitoring at local and national level (European Commission, 2010); (APACHE Consortia, 2018a). SES II was adopted in 2010. Building on the aforementioned initiatives, the current performance assessment of the air transport system within Europe is based on the so-called "Performance Scheme", which aims to sustainably improve performance within the air transport system by increasing the overall efficiency of air traffic service providers in all key performance areas (European Commission, 2010) (APATCHE Consortia, 2018).

As a technological support for the SES initiative, a research project called "The Single European Sky ATM Research (SESAR) project" was launched in 2004 with the main role in defining, developing, and implementing everything needed to improve the performance of the air traffic system, as well as in building a European "intelligent" air transport system. The SESAR project coordinates and connects all research and development activities (Research & Development) of the European Union regarding the air traffic system with the joint work of numerous experts on the development of a new generation of air traffic systems. Also, as a public-private partnership, a body called "SESAR Joint Undertaking (SESAR JU)" was established in 2007, responsible for the modernisation of the European air traffic system by coordinating and collecting all relevant research and innovation within the European Union (SESAR Joint Undertaken - web page).

The main objective of the SESAR project is to modernise the European air traffic system through the definition, development, and deployment of new or improved technologies and procedures, known as SESAR Solutions. SESAR Solutions are defined in a document called "The European ATM Master Plan", which is a basic document describing what is needed to achieve a high-performance air traffic system by 2035 in Europe and beyond. It also provides the main operational and technological changes necessary for the future improvement of the air traffic system (SESAR Joint Undertaken, 2020) (SESAR Joint Undertaken, 2025).

In line with the ATM Master Plan, the SESAR Concept of Operations (CONOPS) explains the evolution of the European air traffic system by introducing new initiatives: Trajectory Based Operations (TBO) and Performance Based Operations (PBO) (SESAR Joint Undertaken, 2020). Through these initiatives, the air traffic system would be optimised, while the airspace allocation would allow its users to access the required airspace with minimal restrictions (EUROCONTROL, 2019). The main idea is to ensure the digital transformation of the core infrastructure system by significantly increasing the automation and connectivity of all system elements in order to develop a more modular and agile ATM system. For these changes to be successful, changes in the way technologies are developed and deployed, as well as in the way services are provided, are also needed (SESAR Joint Undertaken, 2020). At the same time, the role of the human and its continued importance within the operational concept is recognised in the future system with the need to balance efficiency created by introduction of the automation with the existing human capabilities (EUROCONTROL, 2019). In connection with the above, the “A proposal for the future architecture of the European airspace” defines a new airspace architecture to ensure the efficient management of future traffic growth and diversity. This would establish a fully scalable airspace that would also be able to cope with all upcoming situations (SESAR Joint Undertaken, 2019); (SESAR Joint Undertaken, 2020).

1.2. THE CURRENT AIR TRAFFIC SYSTEM

The current structure of the air traffic system (Figure 3) is the result of the operational and technological evolution of ATM systems throughout history. In current architecture, flight operations are usually restricted by non-operational airspace boundaries, leading to suboptimal flight trajectories (SESAR Joint Undertaken, 2019). The control of airspace by air navigation service providers (ANSPs) is largely based on national boundaries. Each state's airspace is organized as one or more segments (Flight Information Regions - FIRs) assigned to a specific Area Control Center (ACC) (SESAR Joint Undertaken, 2019). Area control centers can be represented as nodes, while traffic flows represent the branches that connect them. In some nodes, capacity is close to reaching its maximum, which further affects the behavior of the network through the potential spread of capacity shortage problems to neighboring nodes within it. In area control centers, the airspace is subdivided into several sectors, each overseen by air traffic controllers (ATCOs) responsible for ensuring the safe and efficient flow of traffic. ATCOs are typically trained and licensed for a limited number of sectors within a given Air Traffic Control (ATC) unit and perform a central role in the majority of operational tasks. Once a controller is certified for a specific sector, maintaining that endorsement requires completing a minimum number of operational hours (e.g., 30 hours within six months) within a defined period. This requirement, established by the competent National Supervisory Authority (NSA), varies depending on the sector’s level of complexity. If the required number of hours is not met, due to reasons such as sick leave, maternity leave, or assignment to non-operational duties, the controller must undergo additional training before resuming duties in that sector. Although holding endorsements for a larger number of sectors enhances staffing flexibility, it simultaneously increases the challenge of maintaining their validity. Consequently, there is a practical upper limit to the number of sectors per controller. In large European ATC centers, airspace is therefore often organized into sector groups, with each controller authorized for only one group. While this approach supports competence management, it constrains the flexibility of allocating controllers according to operational demand, both across European ACCs and within large centers themselves.

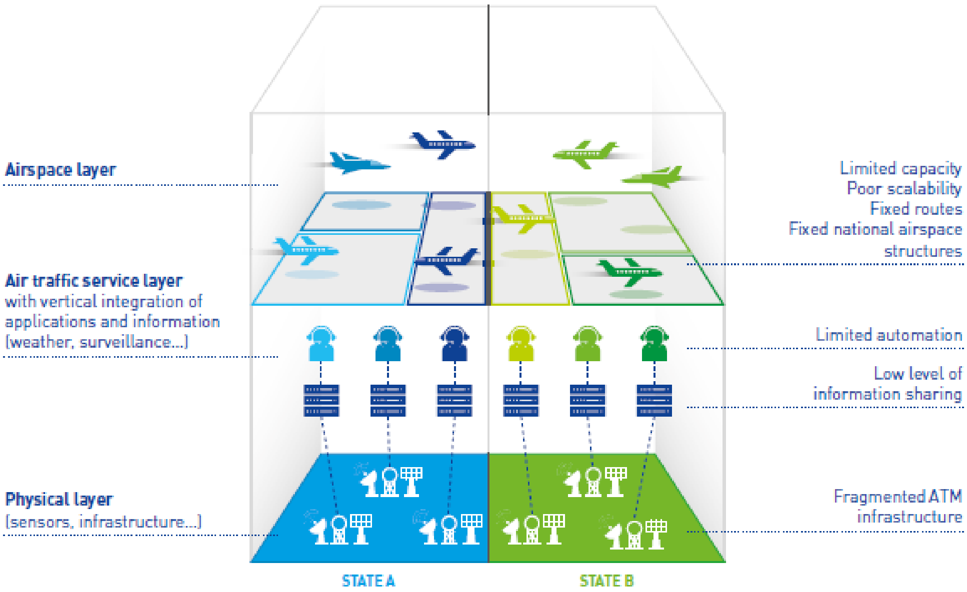


Figure 3. *The current airspace architecture*
Source: SESAR Joint Undertaking, 2019.

Also, there are limitations in routing flexibility and controller assignment without fragmenting the Air Traffic Service (ATS) infrastructure, resulting in reduced scalability and limited capacity to provide services when needed. These structural constraints are further compounded by uncertainties in flight trajectory prediction. Many factors affecting the trajectory are unknown before take-off, while dynamic changes during flight, such as inter-ACC procedures, altitude restrictions, conflict resolutions, military airspace reservations, and adverse weather, further modify flight profiles. Limited data exchange prevents downstream ACCs from having accurate information on aircraft route, altitude, and arrival time. This leads to sub-optimal flight profiles and less efficient conflict resolution. To preserve safety, capacity buffers are introduced to compensate for uncertainty, but they reduce the sector's realistically available capacity. The higher the trajectory predictability, the closer the published capacity can be to the maximum acceptable load (SESAR Joint Undertaking, 2019).

In the existing system, the possibilities for reducing the lack of information exchange are limited, because interoperability and data exchange between ACC units are based on simple standards that do not include all factors that affect the flight trajectory. Aeronautical information, meteorological data and flight data are configured only for the system responsible for a certain geographic area, while specific technologies and non-harmonized procedures further complicate their exchange with other operators. Most ANSP systems are monolithic, with proprietary interfaces that are difficult to interface with other manufacturers' systems, except through limited standardized connections (eg. On-line Data Intercfange (OLDI)) (SESAR Joint Undertaking, 2019; SESAR Joint Undertaking, 2025). The existing semi-static Aeronautical Information Regulation and Control - AIRAC cycle of regulation and management of aeronautical information does not allow dynamic changes of the system configuration. Although the coordination of the available civil-military airspace at the network level is possible, greater use of the flexibility provided by this space is needed in order to reduce airspace losses for civilian operations.

Current limitations of interoperability and data exchange further reduce the predictability, and thus the efficiency of ATM network functioning (SESAR Joint Undertaking, 2019).

Although the level of automation of the system varies across ATC areas, automation support for ATCOs can generally be assessed as low. Most of the ATCOs' tasks, especially traffic surveillance, conflict detection, and decision making, are done in the controller's mind by building up a mental picture of flight intent. In addition, a robust connection for digital data exchange is lacking, which also indicates the need for better automation tools. Some automation support is available to a controller for assessing the detailed intentions of a flight and for assessing the impact of an ATC instruction before issuing it to the pilot; an ATC instruction has to resolve a conflict but shall not create other conflicts while doing so (SESAR Joint Undertaking, 2019). All of this implies that significant human effort is still required for managing air traffic. However, a higher level of automation can increase the productivity of ATCOs, reduce their workload, and enable greater capacity in the airspace sector.

1.3. THE FUTURE AIR TRAFFIC SYSTEM

The emerging system architecture (Figure 4) conceptualizes ATM as a unified, shared, and virtualized environment, enabling the provision and use of services across different service providers (SESAR Joint Undertaking, 2019). This approach facilitates the seamless exchange of operational data, including flight information, meteorological data, and aeronautical information, thereby allowing ATC centers to provide mutual support when required by traffic complexity or unexpected disruptions, effectively functioning as a distributed back-up system.

Such transformation enhances the resilience and scalability of the ATM system by improving its capacity to dynamically adjust to fluctuations in airspace demand. Moreover, the introduction of advanced automation supports a gradual transition from predominantly voice-based communication toward data-driven communication and improved interoperability between ground systems, contributing to greater efficiency, predictability, and system robustness. At the same time, the concept of capacity on demand becomes feasible, allowing the dynamic delegation of air traffic service provision to alternative control centers with available operational capacity. Such cross-center task allocation enhances overall system flexibility and contributes to more balanced workload distribution, thereby improving both operational efficiency and controller productivity (SESAR Joint Undertaking, 2019).

Increased automation is widely recognized as a key enabler for enhancing the performance and capacity of the existing ATM system. In combination with data link technologies, which are essential for managing time- and safety-critical situations, automation reduces the need for manual intervention by ATCOs while supporting the safe handling of a greater number of aircraft simultaneously.

As the level of automation within the ATM system increases, the distribution of tasks between human operators and technical systems is fundamentally reshaped. Controllers will be relieved of a portion of routine manual activities, enabling them to focus more on complex, strategic, and non-routine situations (ATM Master Plan, 2020 edition).

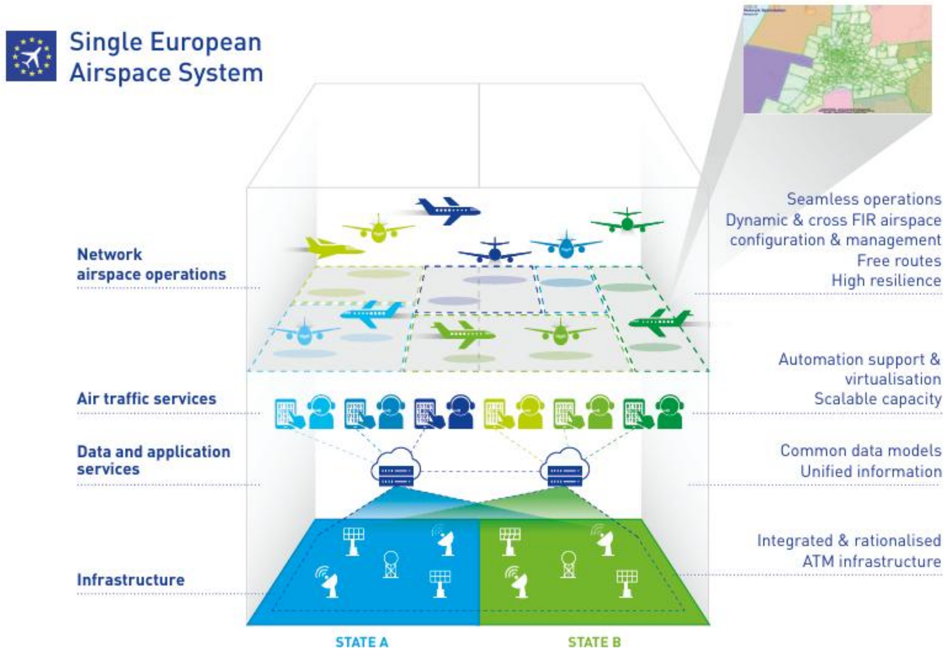


Figure 4. *The future airspace architecture*
Source: SESAR Joint Undertaking, 2019.

The progressive increase in automation within the ATM system necessitates the development of effective human–machine teaming, enabling optimal use of large volumes of data for trajectory optimization and overall system performance (ATM Master Plan, 2025 Edition). This collaboration will gradually transform the roles, responsibilities, and required competencies of human operators, including ATCOs, safety electronics personnel, and flight crews, while also giving rise to entirely new operational roles. In routine and well-defined situations, high levels of automation can be achieved without advanced artificial intelligence; however, the automation of more complex and dynamic tasks is expected to rely increasingly on Artificial Intelligence (AI)-based capabilities (ATM Master Plan, 2025 Edition). Figure 5 presents the applicable AI level of the European Union Aviation Safety Agency (EASA) for each level of automation where the level of automation is actually achieved using AI.

One of the central determinants of effective human–automation interaction is the level of trust that operators place in automated systems. In operational environments, the extent to which automation is accepted and utilized depends strongly on the operator's personal trust in the system (Parasuraman and Riley, 1997; Ferraro et al., 2018). For example, an ATCO may choose to disregard or underutilize automation if system information is incomplete or if frequent false or inaccurate alarms undermine confidence in its reliability. At the same time, trust in automation is essential in daily operations, given that ATC represents a complex, safety-critical, human-in-the-loop, and dynamic socio-technical system. Properly calibrated trust can contribute not only to operational safety but also to system resilience, particularly in unforeseen or non-nominal situations (Timotic and Netjasov, 2022).

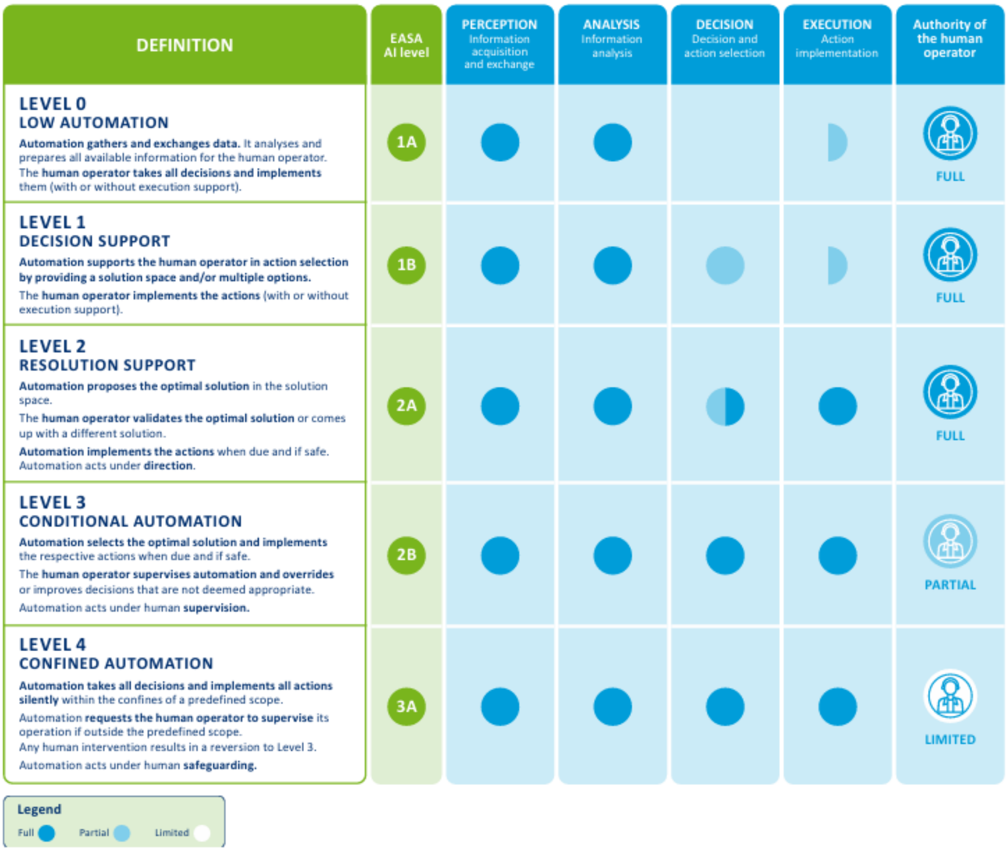


Figure 5. *Levels of automation taxonomy and correspondence to EASA AI levels.*
Source: ATM Master plan, 2025 Edition.

Another key aspect in the future ATC system would be human-automation teamwork. According to Timotic et al. (2020), trust in automation should be analyzed through the interrelationship of three key elements: the ATCO, the automated system, and the tasks to be performed. Controllers carry out cognitively demanding tasks that require sustained attention and a stable functional state, while automation serves as a supportive partner in accomplishing these tasks. In this sense, ATCos and automation are expected to function as a team. Effective teamwork requires the development of mutual and well-calibrated trust, where both human and automated agents contribute to task execution. The benefits of this teamwork include improved productivity, adaptability, and the capacity to generate more comprehensive and innovative solutions (Svensson, 2020). Moreover, coordinated human–automation cooperation can reduce the likelihood of errors that might arise if either the human operator or the automated system were to act independently.

When new technologies are introduced, the level of ATCO trust in these tools becomes especially critical. Changes in system design may alter controllers' expectations, create uncertainty regarding role distribution and responsibility, and influence their perception of control over the traffic situation (Bonini, 2001). Furthermore, openness to innovation and the ability to adapt to new processes and rules affect the development of trust in emerging technologies (Timotic et al, 2020). The capacity to learn, integrate large volumes of information, and operate effectively in a task- and procedure-driven environment is therefore closely linked to ATCo trust in new technological solutions (Bonini, 2005).

1.4. MOTIVATION OF THE DISSERTATION

As previously emphasized, the current European air traffic system and network will be unable to accommodate the projected growth in traffic volume, operational diversity, and emerging challenges without substantial technological and organizational transformation. Strategic development documents, such as the ATM Master Plan (2025 edition) (SESAR Joint Undertaken, 2025), underline the necessity of a comprehensive digital transformation of the core infrastructure, characterized by increased levels of automation and enhanced interconnectivity among system elements.

The integration of advanced automated tools, machine learning techniques, and AI into the ATC environment is expected to improve task execution and support the management of complex and dynamic operational situations. These innovations are envisioned as key enablers for enhancing overall ATM system performance, while simultaneously increasing airspace capacity and supporting ATCOs in managing growing operational demands.

Within this context, safety remains a fundamental system requirement, while resilience emerges as an important feature that must be systematically examined throughout each phase of system development and modernization. The transition toward higher levels of automation inevitably alters the role and position of the ATCO within the human–machine system. Certain tasks traditionally performed by controllers are expected to be delegated to automated tools and supporting algorithms, thereby reshaping human responsibilities toward supervision, coordination, and adaptive intervention.

The primary motivation for selecting this research topic lies in the profound impact that the introduction of automation has on the role and position of the human operator within the human–machine system. As automation assumes an increasing share of operational functions, the nature of human involvement shifts, from direct control toward supervision, intervention, and recovery. This transformation necessitates careful consideration of the balance between the efficiency gained through automation and the unique capabilities of human operators, particularly in non-nominal or degraded operational modes where adaptive recovery becomes critical.

In such conditions, the most common failures and potential degradations of automation tools must be clearly identified and thoroughly understood by human operators, in accordance with their roles and responsibilities. A proactive safety and resilience analysis conducted before and after the implementation of automation can help prevent unintended consequences, such as reduced situational awareness or overreliance on automated support. In this context, trust becomes a central element of the human–automation relationship. Accordingly, an additional motivation for this research arises from the need to establish an appropriate level of trust in newly introduced automated systems. For ATCOs, trust in system functionality is crucial for achieving an effective and balanced interaction between humans and automation. An environment in which trust in automation is properly calibrated, avoiding both blind reliance and excessive skepticism, is essential for ensuring that automation is applied safely, appropriately, and effectively.

The subject of this research is the analysis of safety and resilience in the ATM system under conditions of structural change, with particular emphasis on the introduction of advanced automation. Such transformation entails not only the deployment of new technological tools but also the adoption of new operational principles, procedures, and competencies, all of which may introduce novel challenges for human operators. The central idea of this research is to proactively examine a future ATM system for which empirical operational data are not yet available, and to assess safety and resilience both before and after the introduction of automation. This proactive perspective enables the identification of potential vulnerabilities, shifts in system roles, and emerging performance variability at an early stage, thereby supporting informed decision-making during system design and implementation. Such an approach is particularly important in complex socio-technical systems like ATM, where relying solely on reactive analyses based on past incidents or accidents may be insufficient for anticipating the consequences of transformative technological change.

Taking into account the previous, it is essential to establish an appropriate and balanced model of interaction between human operators and automation. Identifying such a model represents a prerequisite for ensuring the safe, reliable, and resilient functioning of the future ATM system in an increasingly automated operational environment. Thus, the research investigates how the introduction of automation affects the safety and resilience of the ATM system, with a particular focus on changes in the role and responsibility of ATCOs within an increasingly automated human–machine environment. The research aims to develop a model that enables the assessment and comparison of system resilience before and after the implementation of automation. Special attention is given to the analysis of human roles and the allocation of tasks between humans and automated tools. In addition, the study explores the role of human trust in automation, and its impact on overall system performance. The underlying hypotheses assume that higher levels of automation will transform controller responsibilities, positively influence system safety and resilience, and that human trust in automation plays a significant role in shaping these outcomes.

1.5. THESIS STRUCTURE

The thesis is structured into seven chapters. The first chapter provides an introduction in which the purpose of the research and the main motivation for conducting this study are presented. This chapter also introduces the current ATC system and discusses the expected development of future ATC systems, supported by statistical data illustrating air traffic trends in recent years.

Following the introductory chapter, Chapter 2 presents the theoretical background of the research. In this chapter, the concepts of Safety-I and Safety-II are explained, along with the notion of system resilience. Furthermore, a review of relevant scientific literature is provided, with particular emphasis on previous applications of the FRAM and BBN methods in the analysis of resilience within the aviation domain.

Chapter 3 describes the research methodology, including the conceptual research framework and the selection of appropriate analytical methods used to conduct the study. The qualitative modelling phase, based on the application of the FRAM method, is presented in Chapter 4, together with the analysis of performance variability within the system functions.

Chapter 5 focuses on the application of the BBN method for the development of quantitative models. Subsequently, Chapter 6 presents the sensitivity analysis of the results obtained in the previous chapter. The sensitivity analysis consists of three complementary approaches: Tornado analysis, backward analysis, and forward analysis. Finally, Chapter 7 presents the main conclusions of the dissertation and outlines potential directions for future research.

2. SYSTEM RESILIENCE

2.1. FROM SAFETY I TO SAFETY II

In the traditional approach, safety is often defined as the absence of accidents and incidents, that is, as a state in which the level of risk is reduced to an acceptable level. This way of understanding safety is known as the Safety-I approach (Hollnagel et al, 2015). Within this approach, safety is seen as a state in which as few things as possible go wrong.

According to Hollnagel et al (2015) the Safety-I approach is based on the assumption that unwanted events occur due to identifiable failures or irregularities in certain components of the system, such as technology, procedures, human factors or organizational aspects of the system. In this context, people are often seen as a potential source of risk, given that human behavior is the most variable element of the system. Also, it can be said that the aim of the accident research within Safety I approach is to identify the causes and factors contributed to the occurrence of different events, while risk assessment is mainly about the determination of probability of their occurrence (Hollnagel, 2014). In this context, safety management is reactive in nature (see the Figure 6) and based on taking the measures after an unwanted event occurs or when a certain risk is assessed as unacceptable, most often through removing the cause of the problem, improving protective barriers or a combination of these two approaches (Hollnagel, 2018).

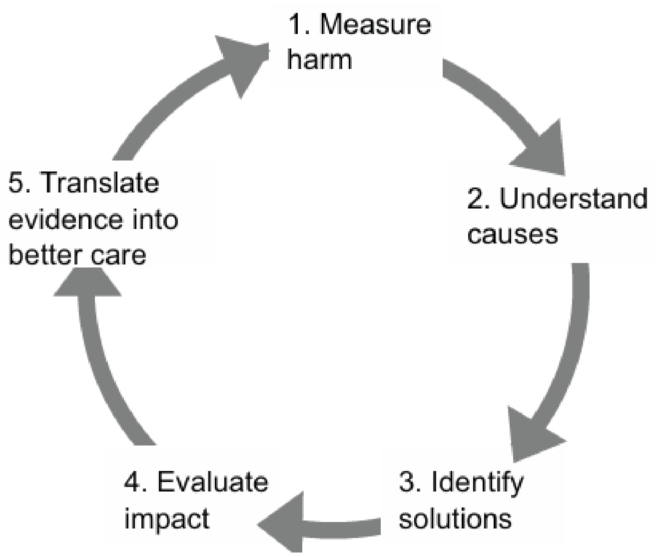


Figure 6. *Reactive safety management cycle (WHO)*
Source: Hollnagel, 2018.

In the traditional safety approach, it is assumed that systems can be broken down into clearly defined components that can be fully understood, as well as that the procedures that regulate their work are complete, comprehensive and accurate. The focus is on operator behavior, which should correspond to pre-defined expectations based on training. It is considered that the system designers have foreseen all potential emergency situations and provided appropriate mechanisms for system response (Di Gravio and Patriarca 2016 in EUROCONTROL 2009; Mirkovic et al, 2024).

Safety management needs to move from an error-preventing approach to an approach that involves ensuring that as many activities as possible in the system are successfully implemented. This perspective is called Safety-II and refers to the system's ability to function successfully in changing conditions. Within this approach, it is assumed that the variability of daily work enables the necessary adjustments to different situations and precisely contributes to the successful functioning of the system. Actually, in a system with complex interaction between functional elements, the optimized work-as-imagined is not possible to obtain in all working situations (Hollnagel, 2017). People are seen as an important resource that ensures the flexibility and resilience of the system. The focus of analysis shifts to understanding how the system normally operates successfully, with the attention on actual work (work-as-done) and very rarerly of failed outcomes such as accidents and incidents (Finkel, 2011; Hollnagel et al, 2015; Mirkovic et al, 2024).

Safety-II looks at safety through the system's ability to adapt and function successfully in different operating conditions (Mirkovic et al, 2024). Resilience Engineering includes the principles of the Safety-II approach, but has a broader framework because, in addition to safety, it also considers trade-offs between safety and other organizational goals (Woltjer et al. 2015). Safety-II and Resilience Engineering are based on the analysis of what works well in a system, including the ways in which people adapt and perform tasks in expected and unexpected situations (Hollnagel 2014). It starts from the assumption that complex systems cannot be fully understood, because their descriptions are complex, and changes in their functioning are frequent and uneven. Therefore, Safety-II and Resilience Engineering focus on continuous monitoring of system performance in order to respond in a timely manner when performance variability starts to get out of control (Di Gravio and Patriarca 2016).

Unlike the traditional approach to safety, the concept of Safety II and Resilience Engineering looks at the system proactively through learning process. It means that the accidents and incidents can still happen despite everything being done to prevent this from happening and when they actually happen, there is a need to find some ways to mitigate their negative effects and their recurrence. Thus, Safety I and Safety II approaches should be combined because Safety is one of the main goal of the system performance while striving to meet other goals. Also, Resilience Engineering strives to harmonize requirements for system safety and efficiency rather than seeing them mutually exclusive (Ranasinghe et al. 2020 cited Azadeh et al. 2014). In Figure 7 it can be seen different sources of success and failure representing the fact that the system functioning is not considered binary as function or malfunction, but it is rather related to everyday work and performance variability which represent the real source of success as well as failure (Patriarca, 2017).

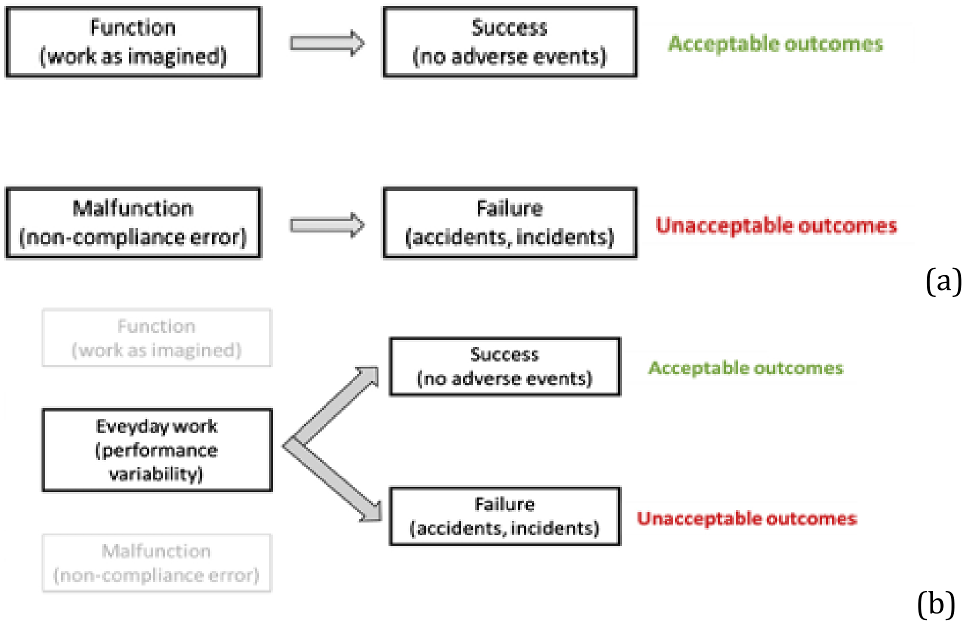


***Figure 7**. Different sources of success and failures: a) Safety I and b) Safety II*

Source: Patriarca, 2017.

2.2. UNDERSTANDING THE RESILIENCE OF AIR TRAFFIC CONTROL SYSTEM

Resilience represents an essential characteristic of the ATC system due to the large number of interconnected elements that constitute it, including human operators, technological components, and organizational structures that jointly support safe and efficient ATC under various operational conditions and environments (Stroeve et al, 2009). ATC can be defined as an ultra-safe system in which incidents and accidents are very rare events. While analyzing adverse events, important for preventing similar occurrences in the future, studying everyday system operations, including cases where activities are performed successfully, significantly broadens the learning base and contributes to enhancing safety. The interest in analyzing resilience in socio-technical systems emerged from a shift in the understanding of system safety, particularly through the development of the Safety-II perspective. Unlike the traditional Safety-I approach, which focuses primarily on accidents and incidents, Safety-II emphasizes everyday system functioning and the outcomes that arise from normal operations (Hollnagel, 2025).

In the context of ATC, resilience can be described as "the system's intrinsic ability to adapt operations before, during, or after changes and disruptions, so that it can maintain functioning operations under expected and unexpected conditions" (EUROCONTROL, 2009; Hollnagel, 2011). One of the major challenges in resilience analysis within the ATC domain lies in capturing system variability and identifying factors that may influence system performance either positively or negatively (Mirkovic et al, 2022). Performance variability reflects adaptive adjustments of human activities and often includes deviations from prescribed procedures that were not foreseen during system design. Although such adaptations are often necessary for successful day-to-day operations, they may contribute to undesirable outcomes when combined with other influencing factors (Yasue et al, 2025).

Resilience is frequently associated with the system's capacity to return to a stable state following disturbance within a certain time frame. From this perspective, resilience can be interpreted more as a property related to the actions performed by the system, rather than simply the characteristics it possesses (Patriarca et al, 2017; Patriarca et al, 2018a; Patriarca et al, 2018b). Furthermore, resilience does not only refer to recovery from disruptions, but also includes the ability of the system to evolve and improve. It encompasses adaptation to disturbances and the restoration of normal or even enhanced system performance through learning processes that may lead to structural or organizational changes, such as reorganization or rebuilding (Steen and Ferreira, 2020).

System resilience in ATC largely depends on the ability of the system to adapt to operational variability and to respond effectively to both expected and unexpected situations. As it can be seen in Figure 8, according to Timotic and Netjasov (2022) when changes are introduced into the system, such as increasing levels of automation, the level of trust that ATCOs develop toward automation becomes an important factor affecting system resilience. Trust influences how ATCOs rely on automated tools, how they monitor system performance, and how effectively they intervene when unexpected situations occur. When an appropriate level of trust is established, cooperation between ATCOs and automation can support timely responses, improve situational awareness, and enable the system to maintain stable operations despite disturbances.

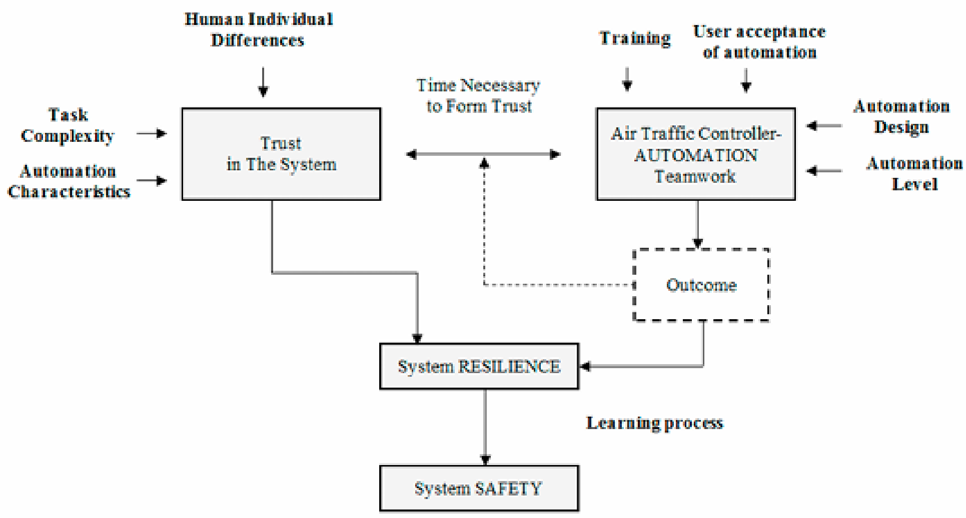


Figure 8. *Conceptual presentation of trust process and its influence on system resilience and safety*
Source: Timotic and Netjasov, 2022.

To date, many researchers have analyzed and defined system resilience; some of them have also proposed indicators for assessing resilience they highlighting the most, both for the ATM system and for the infrastructure system in general. The most prominent resilience indicators, both for the ATM system and for the infrastructure system in general, are: robustness, response time, recovery time, level of recovery, performance loss, redundancy and adaptability (Muller 2012). In addition to these, the literature also highlights indicators such as demand, delays, congestion, traffic complexity, ATCOs' workload and many others (Baspinar et al., 2021, Mirkovic et al, 2024). Also, based on the research of Yi et al (2022), the indicators that have been used to assess resilience are service quality level defined by Patriarca et al (2016), recovery rate and maximum eigenvalue by Baspinar (2021) and, resilience impact factor by Marshall et al (2018). What can be concluded from these works is that resilience indicators have in most cases been derived on the basis of some operational analyses of events that have already occurred or are just of a general nature. Still, there is a need to define certain resilience indicators that will be directly linked to the ATC system and as such be clear for use by all stakeholders.

When selecting models and methods for resilience analysis, numerous studies have focused on approaches that examine resilience at the global or organizational level, incorporating both human and technical system components and addressing performance aspects beyond purely safety-oriented considerations (Errico et al, 2016). For example, Ljungberg and Lundh (2013) applied a question-based tool known as the Resilience Analysis Grid (RAG) to evaluate system resilience and safety through the four core resilience capabilities proposed by Hollnagel (2011): the capability to anticipate potential threats and opportunities, the capability to monitor system conditions that may become critical, the capability to respond to both expected and unexpected disturbances, and the capability to learn from experience, including both successful and unsuccessful outcomes.

A comprehensive literature review conducted in (Yi et al, 2022) indicates that most studies addressing resilience assessment in the ATM system rely on experimental testing and simulation approaches. Other commonly used approaches include resilience principles and methods, complex-network theory, optimization models, and machine learning techniques. Stroeve et al. (2015) , for instance, carried out a qualitative resilience analysis considering a broad range of disturbances and work-as-done strategies at the operational level of a complex socio-technical system, examining the roles of ATCOs and airline pilots in managing various operational disruptions.

Among the available methods for resilience analysis, two approaches stand out as particularly prominent: the System Theoretic Model and Accident Process (STAMP) (Levenson, 2004) and the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2012). A qualitative framework for identifying and improving control structures in the presence of different hazards within a system is provided by STAMP, while the focus of FRAM methodology is on analyzing operational activities represented as functions, their interactions, and the variability of functional performance, typically illustrated through diagrammatic representations (Stroeve et al, 2013).

Since the FRAM method represents the main analytical approach used in this research, it is important to consider how this method has been applied in previous studies. Therefore, the following subsection presents a review of the relevant scientific literature addressing the application of the FRAM method in the analysis of resilience and safety in aviation systems.

2.3. APPLICATION OF THE FUNCTIONAL RESONANCE ANALYSIS METHOD IN RESILIENCE ANALYSIS

The FRAM method is widely applied for qualitative analysis of complex socio-technical systems in the context of accident investigation and risk analysis. A comprehensive review conducted by Patriarca et al. (2020) shows that FRAM has been most extensively applied in aviation, followed by healthcare, industrial operations, maritime transport, and railway systems. Similarly, Tian and Caponecchia (2020) indicate that within the aviation domain FRAM has been used to examine numerous aspects of the industry, including ATC operations, cockpit activities, ground handling, maintenance processes, as well as the analysis of historical safety incidents and accidents.

One of the earliest applications of FRAM in aviation involved the analysis of an aircraft accident that occurred in Colombia in 1995 with the aim to identify potential failures in operational procedures caused by variability in cockpit conditions (Sawaragi et al, 2006). Woltjer and Hollnagel (2007) also used FRAM to analyze an accident in which an aircraft fell into the Pacific Ocean to demonstrate how functional resonance emerged as a consequence of variability in functions performed by different system elements. However, the investigation revealed the involvement of multiple human, technical, and organizational factors. In both studies, eleven Common Performance Conditions (CPCs) were used to assess potential variability (Hollnagel, 2004).

De Carvalho (2011) used FRAM to investigate a mid-air collision with the objective of identifying key resilience-related factors within the ATM system. The results indicated that interdependencies among ATC functions contributed to the emergence of functional resonance and unexpected outcomes that cannot be fully explained by traditional analytical methods. In another study, Amorim and Pereira (2015) applied FRAM in an exploratory investigation of workplace accidents involving improvisation, analyzing three accident reports related to aircraft maintenance. In that study, performance variability was evaluated using the parameters of time and precision. It should be noted that the majority of these studies rely on qualitative analyses based on reports of events that have already occurred.

Beyond accident analysis, FRAM has also been applied in several studies addressing risk assessment. Woltjer and Hollnagel (2008), for example, used FRAM to examine the effects and implications of automation on the work of ATCOs and pilots. Through different FRAM instantiations, the authors illustrated how issues related to ATM operations, automation, human factors, and risk assessment could be explored using this method. Their analysis relied on qualitative assessment using CPCs and variability phenotypes to evaluate potential variability.

Macchi et al. (2009) also performed a risk analysis by applying FRAM to assess the safety of the Minimum Safety Altitude Warning (MSAW) system using principles of resilience engineering. Their approach focused on evaluating variability in functional performance and identifying unexpected combinations of events as a basis for risk identification. In this study, variability was assessed through the parameters of time and precision, while the analysis remained qualitative.

In the study by Ragosta et al. (2015), FRAM was applied within a multi-model framework aimed at analyzing and redesigning partially automated interactive systems in complex socio-technical environments such as ATC systems. In this context, FRAM was used to represent organizational functions and illustrate nonlinear relationships between human, technical, and organizational elements of the system, enabling the identification of potential sources of variability and their propagation throughout the system. As in previous studies, the analysis remained qualitative, and time and precision were used as indicators of variability.

FRAM has also been employed to examine potential changes in the interaction between human operators and technological systems following the introduction of new automation functionalities in ATC. Such analyses were conducted as part of the AUTOPACE project (Ferreira and Canas, 2019), where FRAM was applied based on previously defined operational concepts and considering two different levels of automation under three distinct non-nominal operational scenarios that were investigated within the project.

Several researchers have attempted to extend FRAM by introducing quantitative or semi-quantitative elements into the method. One of the earliest approaches involved the development of a variability score that combines the effects of CPCs with coupling amplification and damping coefficients. This approach was used in the safety assessment of the MSAW system conducted by the German Air Navigation Service Provider, Deutsche Flugsicherung (Macchi, 2010).

Hirose et al. (2016) adapted the Cognitive Reliability and Error Analysis Method (CREAM) to enable a systematic and quantitative application of FRAM in the analysis of an air crash, concluding that the accident resulted from deviations from Standard Operating Procedures (SOPs). They also proposed a new approach for applying FRAM in the pre-analysis of designed operational procedures.

Another significant development involves the integration of Monte Carlo simulation with FRAM, allowing the evaluation of variability in system behavior and the identification of functions most sensitive to resonance through statistical variability measures. This approach was demonstrated in a runway incursion case study, where it enabled the identification of critical relationships between ATC functions and supported the evaluation of system safety under different operational conditions (Patriarca et al, 2017). As in previous studies, time and precision were used to represent potential variability in function performance.

Yang et al. (2017) further extended FRAM by formalizing the method for quantitative safety analysis of ATC systems. In their work, FRAM was combined with formal verification techniques, specifically model checking, to mathematically represent interactions between system functions and analyze how variability propagates throughout the system. This approach enabled a quasi-quantitative evaluation of FRAM functions and demonstrated how relatively small deviations in performance may combine to produce functional resonance that compromises system safety.

Oliveira et al. (2023) proposed a hybrid approach combining FRAM and BBN for the safety assessment of Required Navigation Performance (RNP) approaches. In this framework, FRAM was used to identify functions, their interactions, and potential sources of variability, while BBN enabled the quantitative evaluation of that variability. Similarly, Mohsendokht et al. (2026) combined FRAM and Bayesian Networks to address the inherent qualitative limitations of FRAM and enable a quantitative assessment of performance variability in seaport operations, which represent highly complex socio-technical environments. Their framework was further enhanced through the integration of complementary techniques, including Monte Carlo simulation and canonical probabilistic models, forming a comprehensive approach for modeling uncertainty and systemic variability in complex operational contexts.

Despite the significant number of studies addressing resilience and safety in ATM system, several limitations can be observed in the existing literature. A large portion of the research relies on qualitative approaches, particularly when applying the FRAM method, where the analysis is mainly based on expert judgment and retrospective investigation of past events. Although such studies provide valuable insights into system functioning and variability, they often lack the ability to quantitatively evaluate how variability propagates through the system and influences safety outcomes.

Furthermore, most of the existing studies focus on the analysis of current operational systems or past incidents, while relatively little attention has been given to the proactive assessment of future operational concepts, especially in situations where empirical operational data are not yet available. The increasing level of automation in ATM systems further complicates this issue, as new forms of interaction between human operators and automated tools introduce additional sources of variability that are difficult to capture using purely qualitative methods.

For these reasons, there is a clear need for methodological approaches that combine qualitative system modeling with quantitative techniques, enabling a more comprehensive analysis of variability propagation and its impact on system safety and resilience. Integrating FRAM with probabilistic modeling methods, such as BBN, represents a promising direction for addressing these challenges. Such an approach makes it possible to preserve the systemic perspective of FRAM while introducing quantitative capabilities that allow the evaluation of different scenarios and support the analysis of future ATC system configurations.

3. RESEARCH METHODOLOGY

To date, research on resilience in the ATC system has predominantly been focused on the existing operational environment, most often through retrospective analyses of incidents and accidents. While such approaches provide valuable insight into what went wrong and help identify system vulnerabilities that require mitigation, they are inherently reactive. Given that ATC represents a complex and continuously evolving socio-technical system, shaped by ongoing technological development and increasing levels of automation, a proactive perspective is essential for understanding and strengthening system resilience.

In complex socio-technical systems such as ATC, traditional linear "why–because" approaches to safety analysis frequently reveal important limitations. Accidents rarely result from a single causal factor; rather, they emerge from dynamic interactions among human operators, technologies, procedures, and organizational conditions. At the same time, explaining why systems function successfully under varying and often demanding conditions remains equally challenging, despite the extensive experiential knowledge held by operators (Hirose and Sawaragi, 2020; Aven, 2022). Therefore, resilience analysis must go beyond identifying causes of failure and instead examine how everyday performance variability enables the system to maintain safe and stable operations, even in the presence of disturbances and unexpected situations.

Understanding the future ATC system requires a holistic perspective that considers the integrated interaction of its core elements: people, procedures, technologies, and resources. Only through such an integrated view it is possible to gain meaningful insight into the system's capacity to adapt, absorb variability, and sustain safe performance. This perspective also enables the identification of leverage points through which resilience can be supported and maintained at an appropriate level as automation becomes increasingly embedded in operational processes (Salvendy, 2012).

Accordingly, the objective of the presented methodology is to consider a proactive approach to analyzing a future ATC system in the context of increased automation deployment. The study focuses on the activities of ATCOs to integrate resilience considerations into the design and evaluation of the future system.

The primary objective is to conduct a safety and resilience analysis of ATCO activities before and after the introduction of automation, to identify critical activities, or sets of activities, that contribute most significantly to overall system resilience. To achieve this, the future ATC system scenario is examined, taking into account each activity performed by ATCOs in the execution of their primary task: managing air traffic while maintaining an adequate level of safety.

Figure 9 presents the system functionality representing the scope of the analysis performed in this research. The elements of the system are observed together, that is, through their common interaction during nominal operations. The overlapping parts represent the areas of mutual interaction between system elements and are of crucial importance for analyzing the resilience of the system because in these areas some unforeseen situations can occur

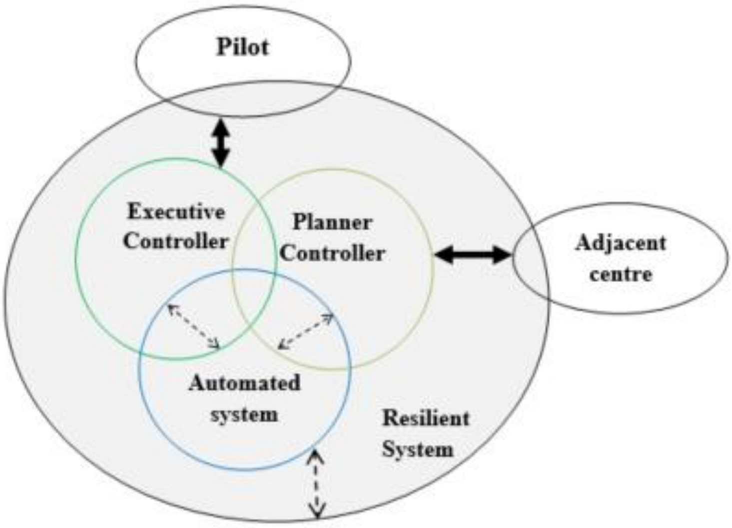


Figure 9. *System functionality*

3.1. THE SELECTION OF METHODS TO CONDUCT RESEARCH

To address and understand all ATCO's activities in a future ATC system, as well as the interrelationships and impacts between system activities, the methodology proposed in this dissertation combines performance variability analysis using the Functional Resonance Analysis Method (FRAM) with the Bayesian Belief Network (BBN) method, which allows quantification of the variability obtained from the FRAM. The FRAM provides the sources for variability for each activity and also the topology for the network (or Direct Acyclic Graph - DAG) with cause–and–effect relations among the activities, which may be difficult to determine when performing a sole BBN analysis (Oliveira et al, 2023). Furthermore, the BBN analysis enables the evaluation of variability and uncertainty previously obtained by the application of FRAM. FRAM identifies qualitative dependencies between complex ATCOs' activities, while BBN quantifies uncertainties enabling risk assessment and resilience measurement, showing which activities are crucial in maintaining safety and resilience (Oliveira et al, 2023). Combining both provides actionable insights for risk mitigation and resilience improvement.

A FRAM model was developed to systematically represent the activities performed by ATCOs in executing their primary responsibility of ATM while maintaining the required level of operational safety. The modelling process involved the identification and structuring of system functions, as well as the mapping of their mutual couplings. Visualization and structural validation of the model were conducted using the FRAM Model Visualizer software[1].

To support the research objective of assessing system resilience and safety in the context of increasing automation, two separate FRAM models were constructed for comparative analysis: one reflecting conventional ATC operations prior to

[1] https://functionalresonance.github.io/FMV_Community_Edition/

automation implementation, and other representing operations following the introduction of automation.

The scope of modelling was limited to activities undertaken by executive and planner ATCOs at their respective working positions. Function identification, descriptions, and subsequent analysis were grounded in empirical and documented evidence derived from the AUTOPACE project (Autopace 2016; Autopace 2017a; Autopace 2017b; Ferreira and Canas, 2019) and from works of Dittman et al (2000), and Wolter and Hollnagel (2008), originally developed on the basis of contemporary ATC operational environments.

By identifying and modelling system functions, the FRAM approach explains functional interdependencies and reveals sources of performance variability inherent to complex and dynamic operational environments. This enables the examination of how variations or deviations in a single activity may propagate across the system and influence overall outcomes (Timotic Petkovic and Netjasov, 2026). However, while FRAM is effective in uncovering functional relationships and potential risk pathways within complex socio-technical systems, the process of function identification and characterization is predominantly grounded in expert judgment. Such reliance introduces subjectivity and may limit methodological consistency and standardization (Guo et al, 2023).

To address these limitations, integration with a BBN model was undertaken. As a probabilistic modelling framework, BBN is well-suited to handling uncertainty and incomplete data, while enabling structured analysis of initiating events and influencing factors. This provides a complementary capability for conducting rapid and resource-efficient risk assessments (Tamburini et al, 2025). Furthermore, BBN supports the incorporation of diverse safety-critical components, including technological innovations and emerging systems, into a quantitative structure appropriate for evaluating low-probability yet high-consequence accident scenarios (Bauranov and Rakas, 2024).

An important advantage of the combined FRAM–BBN approach lies in its capacity to detect system bottlenecks and identify critical functions, thereby supporting proactive safety interventions. In this study, the BBN modelling and analysis were performed using GeNIe Academic 5.0 software[2]. Detailed explanations of both the FRAM and BBN analyses are provided in the following sections.

3.2. CONCEPTUAL FRAMEWORK

Figure 10 illustrates the proposed methodology approach based on integrated application of the FRAM and BBN, forming a unified framework that connects qualitative system understanding with quantitative evidence on system performance. Such a combined approach enables a more holistic and robust assessment of resilience, facilitating not only the identification of potential system vulnerabilities but also the development of informed strategies for enhancing the safety and resilience of future ATC systems.

[2] https://www.bayesfusion.com/genie/

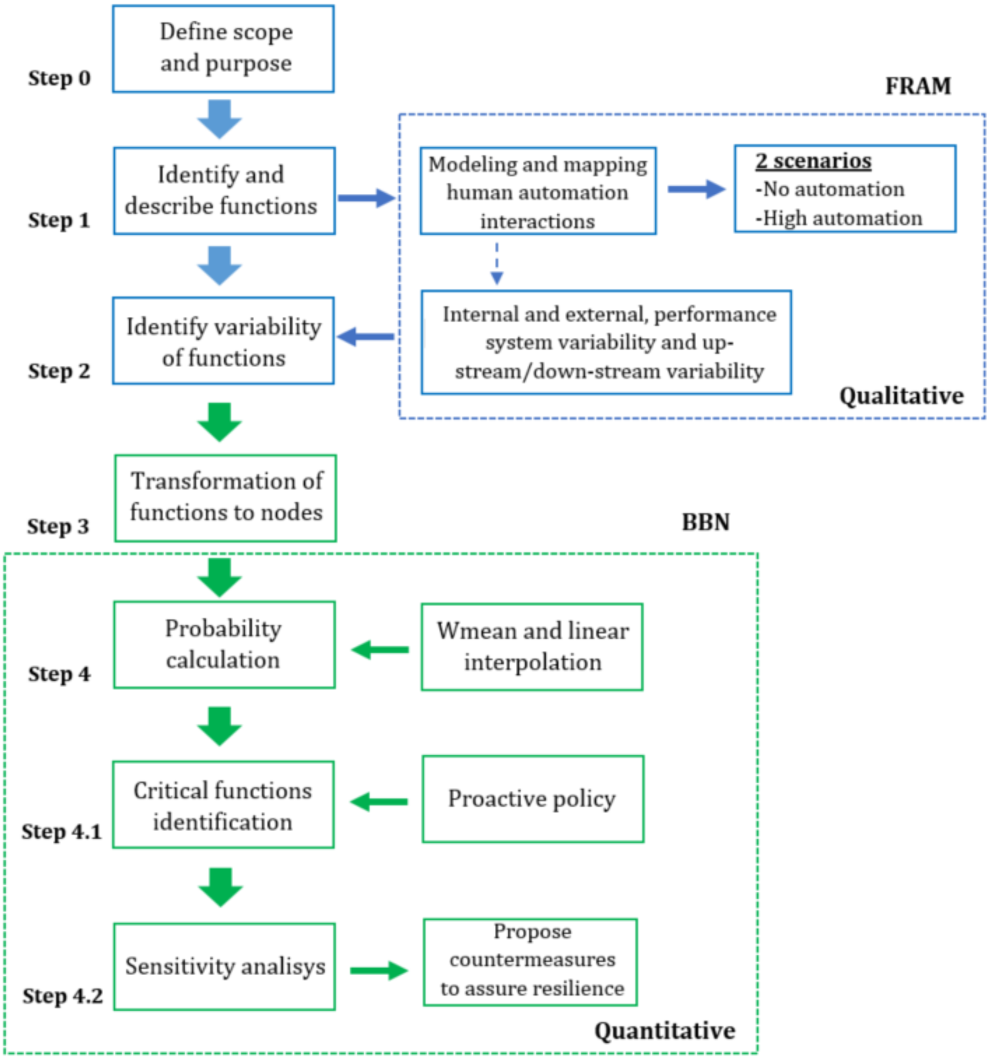


Figure 10. *The proposed methodology approach*

The process begins with *Step 0 – Definition of scope and purpose*, which establishes the analytical boundaries and research objectives. In this study, the focus is placed on examining ATC operational activities in order to support the integration of resilience principles into the design of future, highly automated ATC environments.

In *Step 1 – Identification and description of functions*, the main system functions are defined and structurally described. This phase includes the modelling and mapping of human–automation interactions. To enable comparative assessment, two operational scenarios are defined: one representing operations without automation and another reflecting a high-automation scenario. This functional modelling constitutes the qualitative foundation of the framework.

Step 2 – Identification of variability of functions examines performance variability within and between functions. The analysis considers internal and external sources of variability, including upstream and downstream functional couplings, as well as overall system performance fluctuations. This step remains within the qualitative FRAM domain and captures how variability may resonate across the system.

The transition to quantitative modelling occurs in *Step 3 – Transformation of functions to nodes*, where FRAM functions are systematically translated into BBN nodes, establishing the structural basis for probabilistic analysis.

In *Step 4 – Probability calculation*, quantitative relationships are defined. Conditional probabilities are elicited and computed using approaches such as the weighted mean method and linear interpolation, enabling the quantification of functional dependencies under uncertainty.

Step 4.1 – Critical functions identification uses BBN inference results to detect system bottlenecks and safety-critical functions. Insights from this phase support the formulation of proactive operational or design policies aimed at resilience enhancement.

Finally, *Step 4.2 – Sensitivity analysis* evaluates the influence of individual nodes on overall system outcomes. The most influential nodes can now be identified, which further enables proactive action on these activities within the ATC system in terms of system safety and resilience.

Overall, the framework combines FRAM's strength in capturing functional complexity and variability with BBN's capability for probabilistic reasoning, resulting in an integrated methodology for comprehensive resilience assessment in evolving ATC systems. The subsequent steps of the framework are outlined below and are elaborated in detail in the sections that follow.

4. FUNCTIONAL RESONANCE ANALYSIS METHOD: MODEL DEVELOPMENT AND ANALYTICAL APPROACH

4.1. THE SCOPE AND PURPOSE OF THE ANALYSIS

As previously explained, the first two steps in the conceptual model relate to the formation of the FRAM model (Figure 10). First, it is necessary to define the scope and describe the problem being analyzed, that is, to describe the system that will be the main subject in further analysis (Step 0 in the conceptual framework). Thus, FRAM can be applied to both the analysis of past accidents and prospective risk assessment. Although the overall methodological steps remain the same in both cases, certain details differ depending on the purpose of the analysis. In accident investigations, performance conditions are typically known and can be reconstructed based on available evidence. In contrast, when assessing the risk of potential future events, performance conditions must usually be estimated or assumed, introducing a greater degree of uncertainty into the analysis (Macchi, 2010). In this case, the focus is on the risk assessment for future ATC, and in this respect, the FRAM has been applied.

4.2. DEFINITION OF THE SYSTEM UNDER ANALYSIS

As discussed earlier, the introduction of automation is expected to enhance capacity and efficiency while maintaining the required level of safety. However, it will inevitably affect the role of the ATCO within the ATC system. Although certain responsibilities and tasks are expected to remain with the ATCO across progressively higher levels of automation, their nature and scope will evolve. Even in a foreseeable fully automated scenario, human supervision is anticipated to remain an integral part of system operation (Fereira and Canas, 2019). Consequently, the skills and competencies required of ATCOs will undergo significant transformation and must be carefully managed to keep pace with technological and operational changes.

In developing the FRAM model, it is essential to clearly define the focus of the analysis, that is, to determine which overall system functionality or aspect of performance will constitute the foreground of the study (Macchi, 2010). Following that, the methodology primarily focuses on the core activities of an executive and planer ATCOs within their standard operational environment, including monitoring the traffic situation within a given airspace, preparing inbound and outbound traffic, evaluating traffic conditions, performing conflict detection, making decisions and issuing clearances, communicating with pilots and other ATCOs, coordinating and exchanging information with adjacent controllers, and transferring flights between sectors.

Accordingly, Step 0, in Figure 10, is about examination of ATCO activities to embed system resilience into the design of a future ATC system in which automation is expected to perform all operational tasks, while the ATCO assumes a primarily monitoring role. To enable a systematic comparison and capture potential differences, the analysis includes two scenarios in which one reflects a conventional, non-automated ATC system and the other represents an automated ATC system.

This comparative approach enables an assessment of how the human role evolves with the introduction of automation and to what extent these changes may influence system resilience, safety, and overall ATC performance.

4.3. IDENTIFICATION OF RELEVANT SYSTEM FUNCTIONS

The initial stage of FRAM modelling, focused on the description of functions, allows the abstraction of some specific processes and the diverse conditions under which these functions may be performed, whether in line with formal procedures, informal practices, or context-dependent influences (Timotic Petkovic and Netjasov, 2026). The primary significance is placed on defining functions as activities that must be performed to accomplish a specified operational objective, along with the identification of the aspects that must be provided to each function under real working conditions to ensure its output (Mirkovic et al., 2024).

The FRAM approach decomposes a complex socio-technical system into "functions". A function could be a task or activity that is necessary to achieve a certain outcome (Tian and Caponecchia, 2020). In the context of an ATC system, each function refers to an activity that must be performed to achieve the primary objective of ATC - the safe and efficient flow of air traffic in a designated airspace. The function is not focused exclusively on the execution of a specific task, but is guided by the broader goal of ensuring the functioning of the entire socio-technical system (Macchi, 2010). For this reason, functions should be described without value judgments about the quality or correctness of their outputs, that is, without assessing whether they represent a potential risk.

Functions that precede and can affect other functions are called "upstream" functions, while those that are affected by other elements are "downstream" functions. Also, functions can be divided into two categories: foreground and background. Core functions are foreground functions and form the central part of the analysis and, when possible, require a complete definition of its aspects. Background functions include elements that are not in the immediate focus of the analysis, and for them it is enough to define only the input or output characteristics.

Identification of functions can start from any part of a complex system. Task analysis, and documents such as operating manuals or working procedures are important sources for their recognition. All the information obtained in this way should be integrated with the contribution of the expert in the field. In this research, the functions were identified based on a review of the relevant literature, primarily the results of the AUTOPACE project (AUTOPACE 2016, 2017a, 2017b), the study Integrated Task and Job Analysis of Air Traffic Controllers (ITA) (Ditman et al, 2000), as well as the works of Ferreira and Cañas (Fereira and Canas, 2019), Wolter and Hollnagel (Wolter and Hollnagel, 2008) and Macchi et al (Macchi et al, 2009). The mentioned sources represent a key basis for understanding the activities and responsibilities of en-route ATCOs, since they are based on detailed analyzes of work tasks carried out through interviews, systematic observations and case studies in several air traffic control centers and with different numbers of ATCOs.

The functions defined in the proposed model do not represent a literal transcription of the functions from the mentioned sources, but their adapted interpretation in accordance with the research objectives. They are shaped by integrating findings from the aforementioned literature with the author's professional experience in the field of aviation, whereby the responsibilities and activities of ATCOs are mapped to a functional level suitable for FRAM modeling.

The selection of functions was carried out in accordance with the main objective of the research, which is a comparison of the functioning of the ATC system before and after the introduction of automation. In this context, the model includes key functions that represent the basic tasks of en-route ATCOs, as defined in the aforementioned references, and which are relevant for the analysis of changes in the distribution of functions, responsibilities, and interactions between humans and automated systems.

Within this research, a total of 29 functions were identified (considering both scenarios together), which were included in the analysis of the state of the system before and after the introduction of automation in the ATC system. A description of these functions is given in Table 1.

Table 1. *Function description.*

Name	Description
To monitor the air traffic situation in the given airspace	Monitor to anticipate traffic development.
To monitor flights according to adherence to the flight plan	Monitor all flights regarding the information obtained from the flight plan.
To evaluate the traffic situation	Checking information obtained from the flight plan in case of potential situations that pose a risk to the controlled traffic.
To update flight data	All available changes of trajectory are included in the FDPS.
Conflict detection	Conflict risks are identified between aircraft in the area of responsibility
To issue a warning *(only in the current low automation system)*	To provide early conflict detection.
To issue the Complexity Solution Measures	With the ATC supervision of Local Traffic Management roles in the case of overload situations.
CDM with LTM	In case of an overload situation, the forecast the need for Complexity Solution Measures is obtained from ATC Supervisory or from Local Traffic Management.
Decision Making	Conflict resolution, complexity reduction, and resolving conflicts by using instructions,
To contact pilots	Providing all relevant data to the pilots.
To issue instructions	When decided, the solution is issued further.
To implement the solution	Implementing the solution by the controller.
To coordinate with other controllers	Coordinating with adjacent Controllers/Systems (exit and entry conditions).
To transfer control of the aircraft to the appropriate Controller/Systems	Transferring control of aircraft to the appropriate Controller/Systems when traffic is clear within their area of jurisdiction.
Surveillance data processing (Radar functioning, ADS-B functioning)	Enabling the precise position of aircraft as well as tracking aircraft and collecting information about their location, speed, altitude, and other relevant information. Aircraft position data is automatically sent to air traffic controllers every few seconds.

Flight plans delivery	Delivery flight plans from the ECTRL centre.
Provide MET data	Provide up-to-date weather information relevant to flying.
To provide information on airspace status	Airspace status monitoring (e.g., activation of segregated airspace)
To display data on CWP	All data important for performing the tasks of an air traffic controller is displayed.
To provide an alert	An alert is provided by the system for early conflict detection.
To manage resources	Provide and manage economical, technical, and human resources to enable system functioning.
To manage competence	Provide the controller with the required competence and knowledge about system operations.
To manage procedures	Design, update, and distribute procedures to enable operational activity.
Teamwork	Manage team collaboration (human) and manage automation-human collaboration.
To supervise automation functioning	Controllers oversee automated processes, handling edge cases or anomalies beyond system capabilities
Identify the expected system response	The activity needed to suitably supervise the system
Trust	Manage trust between humans and automation to enable safe and resilient functioning of the new human-automation relationship - leading to safe and resilient operations.
Human - Machine Feedback Loop	Automation continuously learns from controller decisions, and controllers receive feedback on how automation evolves, fostering a symbiotic system. Human decisions train the automation model, while automation suggestions influence future human decisions.
Release traffic	The task loop is done.

According to Hollnagel (2012), there are three types of functions: technological functions, human functions, and organisational functions. Therefore, to examine how the human role changes before and after the implementation of automation in the ATC system, it was necessary to first classify the functions into three groups, depending on whether the system is considered in the pre-automation context (Scenario 1) or in the post-automation context (Scenario 2) (Table 2). The categories are as follows:

1. **Human-performed functions (H):** activities carried out directly by human operators within the ATC system. These functions are essential for decision-making, maintaining effective communication, and managing unexpected or non-routine situations.
2. **Automated functions (A):** activities executed by the automated system in order to support ATC operations. Their role is to alleviate the workload of human operators and enhance precision and consistency in both routine and safety-critical tasks.
3. **Organizational functions (O):** activities and processes established at the organizational level that enable and support both human and automated functions. These include planning, coordination of resources, procedure management, timely training and competence development, as well as

human factors that may significantly affect controllers' judgment and performance. In this study, the organizational functions are further specified and adapted from (Macchi et al, 2009).

Table 2. *Characterization of Functions According to the Analyzed Scenario*

Name	Type	
	Scenario 1	**Scenario 2**
To monitor the air traffic situation in the given airspace	H	A
To monitor flights according to adherence to the flight plan	H	A
To evaluate the traffic situation	H	A
To update flight data	H	A
To issue a warning	H	-
Conflict detection	H	A
CDM with LTM	H	H
To issue the Complexity Solution Measures	H	A
Decision Making	H	A
To issue instructions	H	A
To implement the solution	H	A
To contact pilots	H	A
To coordinate with other controllers	H	A
To transfer control of the aircraft to the appropriate Controller/Systems	H	A
Surveillance data processing (Radar functioning, ADS-B functioning)	A	A
Flight plans delivery	A	A
Provide MET data	A	A
To provide information on airspace status	A	A
To manage resources	O	O
To manage competence	O	O
To manage procedures	O	O
Human factors	O	O
CDM with LTM	H	H
Identify the system's expected response	NA	H
To manage trust	NA	H
Automation supervision	NA	H
To manage teamwork	NA	O
Human-machine feedback loop	NA	H
Release traffic	H	A

**H - human, A - automation, O – organization, NA – not available*

4.4. FUNCTIONAL ASPECTS

Following the function identification and description, the risk assessment proceeds by characterising each function in terms of six aspects, namely: Input (I), Output (O), Time (T), Control (C), Precondition (P), and Resource (R), and visualizing using a hexagon (Figure 11 (Patriarca et al, 2020)).

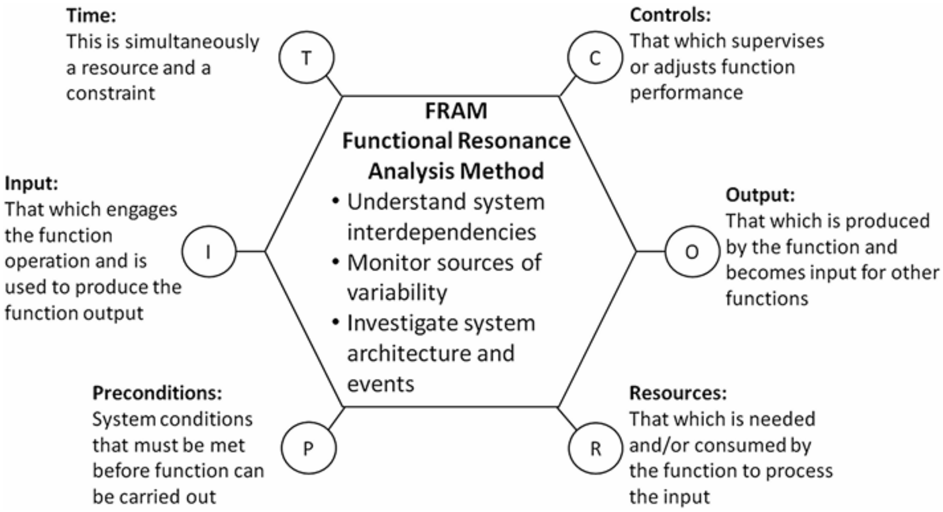


Figure 11. *Depiction of an Activity or Function in the Functional Resonance Analysis Method Through Its Six Defining Aspects.*
Source: Amorin et al, 2015.

According to Hollnagel (2004) the description of the six aspects of a function is as follows:

1. **Input (I):** what the function receives, processes, or transforms, or what initiates its execution.
2. **Output (O):** the outcome produced by the function, which may be a tangible result, a product, or a change of state.
3. **Preconditions (P):** the conditions that must be satisfied before the function can be carried out. Alone, it can not activate the function.
4. **Resources (R):** the means or assets required or consumed by the function to generate its output. Resources will be consumed while the function is executing.
5. **Time (T):** the temporal constraints that influence the function, including its start time, end time, and duration.
6. **Control (C):** the mechanisms or factors that supervise, regulate, or guide the execution of the function.

All aspects are usually presented using a simple table, which then becomes the basis for the future analysis. The six aspects are typically easy to define. However, it is not necessary to specify all of them in every case. Apart from Input and Output, the remaining aspects should be described only when they are clearly applicable to the specific function being analyzed. Regarding Preconditions, a function may have several relevant conditions that need to be taken into account, either collectively or in various combinations, before the function can be performed.

As an illustration, Table 3 presents selected aspects of the function *"Monitor the air traffic situation in the given airspace"* in a non-automated scenario. The inputs to this function comprise the visual display of the current traffic situation within the sector, along with up-to-date information on the airspace status available to ATCOs. These inputs are generated by other functions, such as those performed by surveillance and data presentation systems (e.g., radar and flight data processing systems), as well as through coordination with adjacent sectors and fellow controllers. As it can be observed from the presented example, the function may have more than one input depending on the nature of the function and the context of the problem analysed.

The outputs of the function may consist of an updated understanding of the airspace situation, ongoing assessment of potential risks, and the provision of current flight information, all of which are essential for subsequent operational activities. Note that it is possible to use a single function to produce several different outputs depending on the context of the observed function.

With respect to preconditions, relevant operational instructions must be in place, and the ATCO must be in an appropriate mental and physical state. The Executive and Planner controllers constitute the primary resources required to generate the intended outputs.

The time aspect is closely linked to the traffic context, as monitoring of the air traffic situation is performed continuously and in real time. Due to this continuous execution, the outputs are dynamic and constantly evolving.

Control mechanisms include standard operating procedures (SOPs) related to monitoring, as well as adequate technical training and the competencies of ATCOs.

Table 3*. Identification of function aspects, example of the function: To monitor the air traffic situation in the given airspace for a non-automated scenario.*

Name of Function/Aspects	**F2: To monitor the air traffic situation in the given airspace**
Input	- Visual representation of the traffic situation in the observed airspace - Updated airspace information is available to ATCOs
Output	- Airspace status updated - Risk monitoring provided - The most current flight information is provided
Precondition	- Instruction issued - ATCO is available at the workstation - The ATCO is in an adequate mental and physical condition
Resource	- Executive and Planner ATCOs
Control	- Monitoring procedures - Compliance with technical training requirements
Time	- Performed continuously in real time

The remaining functions, along with their respective aspects for both scenarios, are provided in APPENDIX A. The explanations of the functions, based on their aspects, in this paper are derived from a review of references (Woltjer and Hollnagel, 2008; Macchi et al, 2009; Fereira and Canas, 2019; Autopace 2016; Autopace 2017a; Autopace 2017b; Dittmann et al, 2000) as well as the author's experience.

4.5. FUNCTIONAL COUPLINGS

After all functions have been defined and described through their six aspects, the subsequent step involves identifying the couplings among them. Coupling is the interaction between functions of a system that influences the intensity of the relationship between the two functions and as such their behaviors, which exhibit different effects in the variability propagation. In FRAM, interactions are expressed as relationships between the Output of an upstream function and any of the aspects of a downstream function, so-called upstream–downstream functional couplings (Peng et al., 2023). These connections can be derived systematically from the descriptions provided in the corresponding tables. However, the graphical layout of functions does not imply a temporal order of execution, nor does their visual arrangement indicate linear cause–effect relationships (Macchi, 2010).

The outcome of this process is a specific FRAM instantiation of the system, typically presented in a graphical format. An instantiation represents a specific pattern or sequence of activation of all or selected modeled functions. A function becomes activated when its Input is made available, typically as the Output of an upstream function. At that moment, the coupling between the upstream and downstream functions becomes operational (Fereira and Canas, 2019).

Once the potential links are determined, it becomes possible to examine how variability may propagate across functions, whether it is dampened or amplified (i.e., functional resonance). Moreover, this procedure supports the development of a comprehensive qualitative representation of the system under analysis (Timotic Petkovic and Netjasov, 2026). Figure 12 illustrates two simple cases with four functions. In case (a), the functions are connected sequentially, so that the output of one function is the input for the next function in the chain. In such a configuration, variability is propagates step-by-step, meaning that a deviation in the performance of one upstream function can directly affect the performance of the subsequent downstream function. In contrast, case (b) shows a more complex network of interactions between functions, where in addition to sequential couplings (Function A → Function B→ Function C) there is also a direct connection between functions that are not immediately adjacent. This structure reflects the non-linear and interconnected nature of complex socio-technical systems, where a single function may influence multiple other functions simultaneously (Function A is connected to the Function D by control→output conection). As a result, variability can propagate through multiple patways, potentially amplifying or modifying its effects as it spreads across the system. In accordance with the research topic, the FRAM model was applied to represent a system focused on human-automation interaction. The model maps the functional relationships between human operators and various subsystems and components of the automated system, while additionally including organizational functions that affect the performance of the human operator within the system. (Pent et al, 2023).

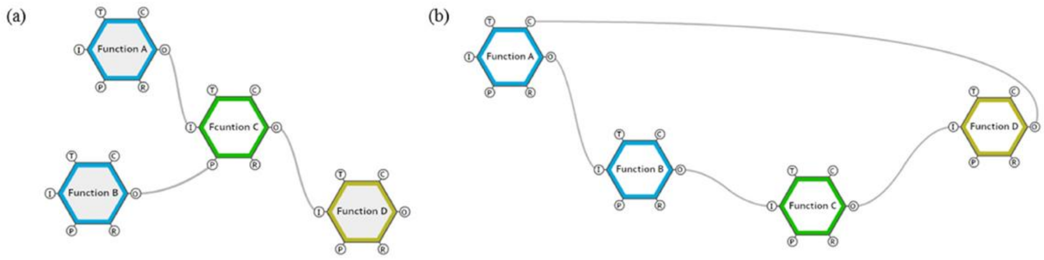


Figure 12. *The FRAM model-graphical visualization*
Source: Peng et al, 2023.

For the context of this research, Tables 4 and 5 summarize the functional couplings identified for the non-automated scenario (25 functions) and the automated scenario (29 functions), respectively. The tables specify which foreground and background functions are connected and clarify how the outputs of certain functions influence, or constitute, specific aspects of subsequent functions within the model. The establishment of these links was guided by findings from the Integrated Task and Job Analysis of Air Traffic Controllers (ITA) (Dittmann et al, 2000) and the AUTOPACE Concept of Operations (ConOps) (AUTOPACE 2017b), further supported by the European ATM Master Plan (SESAR Joint Undertaking, 2025) and A Proposal for the Future Architecture of the European Airspace (SESAR Joint Undertaking, 2019). These references contributed to a more precise understanding of both the current operational structure of the ATC system and its anticipated future development.

Given that the analysis encompasses both the existing and a projected future ATC system, for which comprehensive empirical data are not yet available, it should be noted that the identification of functional couplings is partly based on the author's professional judgment and interpretation of the observed system.

Table 4*. Function type and links: no-automation*

Function	Name	Type	Links
F1	To display data on CWP	Foreground	F1(O)→F2(I), F3(I), F5(I)
F2	To monitor the air traffic situation in the given airspace	Foreground	F2(O)→F3(I), F4(I), F7(I), F8(P), F13(I), F14(I)
F3	To monitor flights according to adherence to the flight plan	Foreground	F3(O)→F4(I), F7(I)
F4	To evaluate the traffic situation	Foreground	F4(O)→F6(I), F9(I), F11(C)
F5	To provide an alert	Foreground	F5(O)→F8(I)
F6	To update flight data	Foreground	F6(O)→F8(I), F9(I)
F7	To issue a warning	Foreground	F7(O)→F8(I)
F8	Conflict detection	Foreground	F8(O)→F9(I), F10(I), F14(I)
F9	To issue the Complexity Solution Measures	Foreground	F9(O)→F10(I)
F10	Decision Making	Foreground	F10(O)→F11(I)
F11	To issue instructions	Foreground	F11(O)→F2(P), F12(I), F14(I), F15(I)
F12	To implement the solution	Foreground	F12(O)→F4(C), F6(C), F10(C), F13(I)
F13	To contact pilots	Foreground	F10(O)→BG10(I)
F14	To coordinate with other controllers	Foreground	F14(O)→F15(I)

F15	To transfer control of the aircraft to the appropriate Controller/Systems	Foreground	F15(O)→BG10(I)
BG1	Surveillance data processing (Radar functioning, ADS-B functioning)	Background	BG1(O)→F1(I)
BG2	Flight plans delivery	Background	BG2(O)→F1(I)
BG3	Provide MET data	Background	BG3(O)→F1(I)
BG4	To provide information on airspace status	Background	BG4(O)→F2(I)
BG5	To manage resources	Background	BG5(O)→F2(P), F3(P), F4(P), F8(P), F10(P), F11(P), F12(P), F14(P), F15(P)
BG6	To manage competence	Background	BG6(O)→F2(C), F3(C), F8(C), F10(C), F14(C), F15(C)
BG7	To manage procedures	Background	BG7(O)→F2(C), F3(C), F4(C), F8(P), F9(C), F10(C), F14(C), F15(C)
BG8	Human factors	Background	BG8(O)→F2(P), F3(P), F4(P), F8(P) F10(P), F14(P), F15(P)
BG9	CDM with LTM	Background	BG9(O)→F9(I)
BG10	Release traffic	Background	-

Table 5. *Function type and links: automation*

Function	Name	Type	Links
F1	To display data on CWP	Foreground	F1(O)→F2(I), F3(I), F5(I)
F2	To monitor the air traffic situation in the given airspace	Foreground	F2(O)→F3(I), F4(I), F7(P), F12(I), F13(I)
F3	To monitor flights according to adherence to the flight plan	Foreground	F3(O)→F4(I)
F4	To evaluate the traffic situation	Foreground	F4(O)→F6(I), F8(I), F10(C), F15(I)
F5	To provide an alert	Foreground	F5(O)→F7(I)
F6	To update flight data	Foreground	F6(O)→F7(I), F8(I)
F7	Conflict detection	Foreground	F7(O)→F8(I), F9(I), F13(I), F15(I)
F8	To issue the Complexity Solution Measures	Foreground	F8(O)→F9(I)
F9	Decision Making	Foreground	F9(O)→F10(I), F15(I)
F10	To issue instructions	Foreground	F10(O)→F2(P), F11(I), F13(I), F14(I)
F11	To implement solutions	Foreground	F11(O)→F4(C), F6(C), F9(C), F12(I)
F12	To contact pilots	Foreground	F12(O)→BG10(I)
F13	To coordinate with other controllers	Foreground	F13(O)→F14(I)
F14	To transfer control of the aircraft to the appropriate Controller/Systems	Foreground	F14(O)→BG10(I)
F15	Identify the system's expected response	Foreground	F15(O)→F17(I), F18(I)
F16	To manage trust	Foreground	F16(O)→F17(P), F18(C), F19(C)
F17	Automation supervision	Foreground	F17(O)→ F18(I), F19(I)
F18	To manage teamwork	Foreground	F18(O)→ F19(I), F12(C)
F19	Human-machine feedback loop	Foreground	F19(O)→ BG10(I)
BG1	Surveillance data processing (Radar functioning, ADS-B functioning)	Background	BG1(O)→F1(I)

BG2	Flight plans delivery	Background	BG2(O)→F1(I)
BG3	Provide MET data	Background	BG3(O)→F1(I)
BG4	To provide information on airspace status	Background	BG4(O)→F2(I)
BG5	To manage resources	Background	BG5(O)→F2(P), F3(P), F4(P), F(5), F6(P), F7(P), F8(P), F9(P), F10(P), F11(P), F12(P), F13(P), F14(P), F15(P), F16(P), F17(P)
BG6	To manage competence	Background	BG6(O)→F2(C), F3(C), F4(C), F8(C), F9(C), F13(C), F14(C), F15(C), F17(C)
BG7	To manage procedures	Background	BG7(O)→F2(C), F3(C), F4(C), F7(C), F8(C), F13(C), F14(C), F16(C), F17(C)
BG8	Human factors	Background	BG8(O)→F2(P), F3(P), F4(P), F7(P) F9(P), F13(P), F14(P), F15(I), F16(I), F17(P), F19(P)
BG9	CDM with LTM	Background	BG9(O)→F9(I)
BG10	Release traffic	Background	-

4.6. FRAM MODELS

The system functions described in the previous step form the FRAM model of the system. A FRAM model is not defined by a diagram or flowchart, but by a detailed verbal description of the functions, including their six aspects. Since the FRAM model does not explicitly show the connections between elements, analysts can generate multiple possible instantiations, illustrating how different working conditions might affect system performance (Macchi, 2010).

Like any model or description, a FRAM model must be both consistent and complete. Since FRAM focuses on describing the interactions between functions, every aspect of each function must be accounted for: be produced as an Output and utilized as an Input, Control, Precondition, Time, or Resource by other functions included in the model. In other words, the model should not contain any "unconnected" or "floating" aspects (Hollnagel, 2012). To ensure this, the description tables must be carefully reviewed for consistency.

The consistency check naturally leads to a completeness check of the model. Since every aspect must be produced by one function and used by at least one other function in the model, completing the consistency check ensures that all necessary functions have been identified, making the FRAM model complete (Macchi, 2010). For each set of foreground functions, it is possible to identify and describe a corresponding set of background functions. Their identification and description are carried out by consistently applying the check rules, starting from the aspects of the foreground functions (Hollnagel, 2012).

As mentioned earlier, two models have been developed: a conventional model that refers to a non-automated ATC system, and a second one that depicts the system after the introduction of automation in ATC. In a traditional, non-automated ATC system, there are two key roles: the executive ATCO and the planning ATCO. The executive ATCO is responsible for the direct control and supervision of flights within his sector. It communicates with pilots, issues course, altitude and speed instructions, and tracks all aircraft in real time. His main function is to ensure the safe and efficient flow of flights through the sector. The planning ATCO, on the other hand, focuses on planning and coordination. He analyzes potential conflicts in advance, prepares solutions, and coordinates with neighboring sectors, providing recommendations to the executive ATCO. In this system, decisions are made mainly based on the knowledge and experience of the ATCO, while information comes from radar data, flight plans and visual surveillance. Therefore, the cognitive load of the ATCO is high, because he has to monitor a large number of flights, evaluate conflicts and manually communicate with other sectors.

The introduction of automation in the ATC changes the distribution of tasks between human and the system. Automation can include automatically anticipating conflicts and proposing solutions, tracking flights and warning of deviations from the flight plan, distributing information about upcoming flights, as well as helping to coordinate with other sectors or ATC centers. Automation reduces the cognitive load of ATCOs, increases safety and efficiency, but at the same time changes the nature of the human role from routine monitoring to supervision and intervention in complex situations. Effective and resilient ATC in such a system requires ATCOs to be able to properly use and monitor automation, as well as to intervene when the system cannot solve a problem on its own.

4.6.1. The FRAM model for a non-automated air traffic control system

The FRAM model shown in Figure 13 represents an integral structure of the functions in a non-automated ATC scenario with an emphasis on the interaction between humans, technical resources and organizational functions. A total of **25** functions were identified, of which **15** are *foreground* functions: primary functions that directly participate in air traffic management and are the focus of the analysis, while the remaining **10** functions are *background* functions (see Table 4), which support the working environment of the system and enable the smooth functioning of basic activities. The color coding reflects both functional role and allocation of responsibility. Blue functions are performed by humans, white are performed by system, while green functions are assigned to the organization. The orange function represents the final node which is in this scenario performed by humans.

Narrative instantiation of the FRAM model for a non-automation scenario

The operational cycle emerges from the interaction between background information-generating functions, controller-centered monitoring and decision-making functions, and coordination and implementation functions that collectively lead to the expected safe system state. It begins with the execution of four basic background functions that represent the primary sources of information in the system (Figure 13):

- Surveillance data processing,
- Flight plans delivery,
- To provide MET data,
- To provide information on airspace status

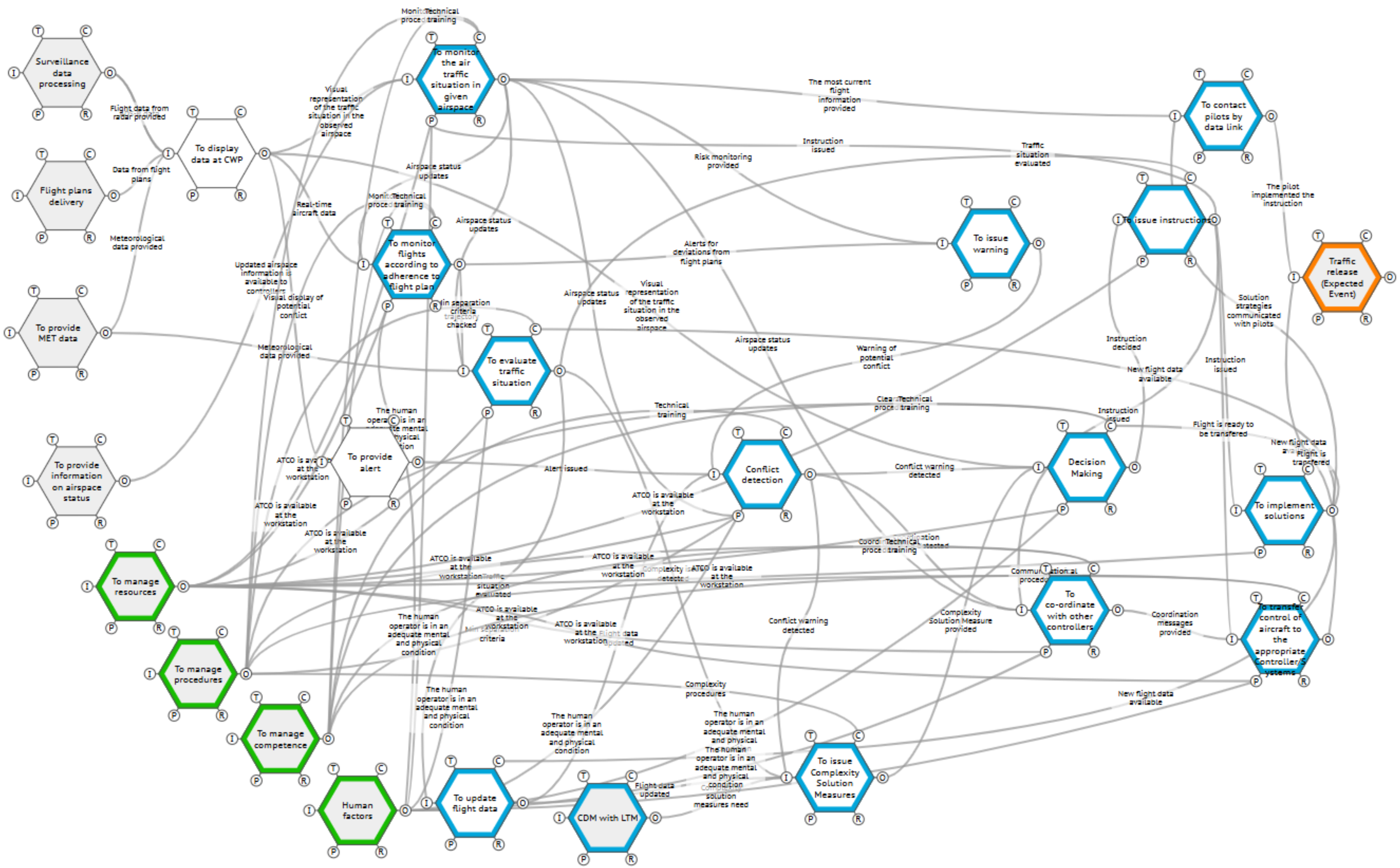


Figure 13. The Functional Resonance Analysis Method (FRAM): Model of Air Traffic Controller Activities at the Working Position (Non-Automation Scenario)

These functions operate continuously and automatically, providing the primary informational inputs to the system. The "*Surveillance data processing*" function provides data on the actual positions and movements of aircraft based on radar and/or ADS-B data. "*Flight plans delivery*" provides reference data on planned routes, flight levels and other relevant elements of accepted flight plans. "*To provide MET data*" generates current meteorological information, while "*To provide information on airspace status*" provides data on the structure and limitations of the airspace, including active restrictions, segregated zones and military activities.

The outputs of the functions "*Surveillance data processing*", "*Flight plans delivery*" and "*To provide MET data*" enter as input into the function "*To display data at CWP*", where they are integrated and visually displayed at the controller's working position (CWP). Airspace status information, however, directly affects the "*To monitor the air traffic situation in given airspace*" function, thus underscoring its immediate operational importance. Variability originating in any of these upstream background functions (e.g., delay, inaccuracy, or incompleteness of data) may propagate downstream by affecting the quality and timing of information available for monitoring. After the data is displayed on the CWP, two related but separate functions are activated:

- To monitor the air traffic situation in given airspace,
- To monitor flights according to the adherence of flight plan.

The first function refers to the global assessment of the traffic situation in the sector, while the second involves checking the compliance of each individual flight with the reference flight plan. Both functions use as input: displayed surveillance data, reference flight plans, meteorological data and airspace status information. Additionally, the monitoring functions are conditioned by several upstream background functions: "*To manage resources", "To manage procedures", "To manage competence", and "Human factors".* These functions do not merely represent static prerequisites but rather, they shape the performance variability of monitoring activities. For example, resource availability, procedural clarity, controller competence, and mental/physical state influence the efficiency, accuracy, and timing of monitoring. Thus, monitoring performance emerges as a product of both informational couplings and performance-shaping couplings.

Monitoring is additionally supported by the automated function "*To provide alert*", which can generate a warning about a potential conflict. In parallel, the controller ATCO through the "*To issue warning*" function can identify and signal a potential problem based on its own assessment of the situation. In this way, deviation detection can come from both automation and human sources. During monitoring, the "*To update flight data*" function can occur, the output of which becomes the key input for the next function which is the "*Conflict detection*" function. The "*Conflict detection*" function depends on the up-to-date flight data, the real traffic picture and the correct operation of the warning system. Variability in earlier functions may amplify at this stage. For example, delayed flight data update may postpone conflict detection, thereby reducing available resolution time.

If a conflict or increased complexity is identified, the system can activate the "*To issue Complexity Solution Measures*" function, which proposes or implements measures to reduce the burden and complexity of the sector. The result of conflict detection and/or complexity assessment is the input for the "*Decision Making*" function. This feature depends on: up-to-date flight information, procedural requirements, minimum separation standards, procedural constrains, coordination requirements and the influence of performance-shaping background functions. Here, variability propagation becomes particularly significant: inaccuracies or delays accumulated upstream may constrain the range of feasible decisions or increase cognitive workload.

After the decision is made, the "*To issue instruction*" function is activated, which generates the appropriate control instruction. The instruction then enters the "*To implement solution*" function, where it is operationalized through a specific change (e.g. altitude, course or speed). At the same time, the "*To coordinate with other controllers*" function can be activated, especially in cases of aircraft transfers or cross-sectoral dependencies. These couplings demonstrate that the system behavior is not linear but network-based and dynamically adaptive. When the instruction has been transmitted to the pilot and implemented, the function "*Transfer aircraft to next sector / ATC unit*" (implicitly shown through the right part of the model) occurs. Finally, the "*Traffic is released*" function (Expected Event) is activated, indicating that the system has reached the desired safe state and that one operational cycle of the ATCO has been successfully completed.

It can be observed that the connections are complex and interdependent, which allows the model to depict the propagation of effects and interaction between functions, rather than just linear information flows. Each function can affect multiple other functions, and the effects can be fed back into the cycle through feedback loops, reflecting the complexity and dynamism of en-route ATCO work. This FRAM model shows that even in a non-automated system there is a complex net of dependencies between people, procedures and technical resources. All functions and their interconnections allow the system to behave flexibly and resiliently, even in unforeseen situations, because each function can adjust its behavior depending on the information and resources it receives from other functions. This approach clearly shows how the FRAM model enables the analysis of complex systems without the limitations of linear diagrams and how the focus is placed on the interactions and performance of the system under real conditions.

4.6.2. The FRAM model for an automated air traffic control system

In the automated scenario, the complete FRAM model is presented in Figure 14. The model comprises a total of **29** functions, of which **19** are classified as foreground and **10** as background functions. The color coding reflects both functional role and allocation of responsibility. Red foreground functions represent activities that were previously performed by humans but are now executed by automation. Blue foreground functions continue to be performed by humans. Two white foreground functions are also automated, while one green foreground function is assigned to the organizational level. Regarding background functions, those colored in green correspond to organizational activities, whereas grey background functions are executed by automation. The final function, marked in orange, is likewise performed by automation and represents a background function associated with the system's overall operational outcome.

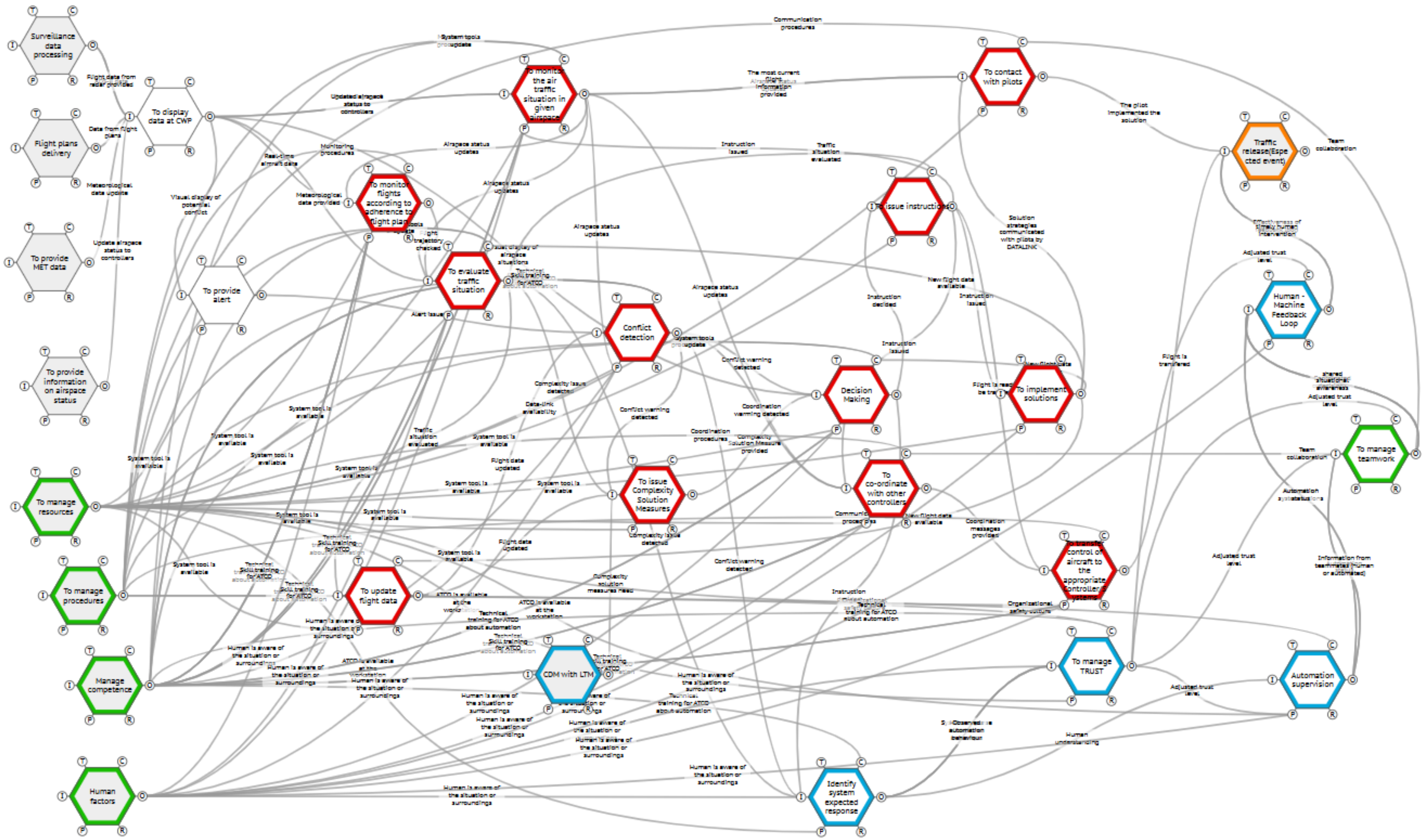


Figure 14. *The Functional Resonance Analysis Method (FRAM): Model of Air Traffic Controller Activities at the Working Position (Automation Scenario)*

In contrast to the non-automated scenario, the function "*To Issue a Warning"* is excluded from this model. In the automated configuration, the human operator no longer directly identifies potential hazards at an early stage. Instead, the detection and signaling of emerging risks are exclusively performed by automation through the function "*To Provide an Alert"*. This modification significantly alters the functional couplings within the monitoring and conflict detection processes, as the early identification of variability is now centralized within the automated subsystem.

To adequately represent the human–automation interaction introduced in this scenario, five additional functions have been incorporated into the model. These newly introduced functions primarily address cognitive and supervisory aspects of automation use and are therefore essential for a comprehensive resilience analysis.

The first added function, "*Identify system expected response"*, refers to the ATCO's ability to correctly interpret and understand what the automated system has generated, proposed, or executed. This function, performed by humans and depicted in blue in Figure 14, is critical for maintaining shared understanding between the operator and the automated system. In FRAM terms, it represents a necessary coupling between automated outputs and human cognitive processing. Variability at this interface may arise from misinterpretation, delayed comprehension, or ambiguity in system feedback.

The function "*To Manage Trust"* represents the ATCO's dynamic calibration of trust in automation and is likewise performed by humans (blue). ATCOs' trust in automation is a key factor in the successful integration of automated systems into the ATC environment. Insufficient trust (undertrust) may lead ATCOs to disregard or underutilize automated support, thereby increasing workload and the likelihood of human error. Conversely, excessive trust (overtrust) can result in overreliance on automation and reduced active supervision, increasing the probability that system errors remain undetected (Eurocontrol, 2003; Timotic and Netjasov, 2022). Achieving an optimal level of calibrated trust is therefore essential to balance the efficiency gains of automation with the need for critical human oversight to ensure system safety. Within the FRAM structure, trust functions as a performance-shaping factor that modulates how strongly automated outputs influence subsequent human decisions.

The function "*Automation Supervision"* refers to the ATCO's capability to oversee automated processes, intervene when necessary, and manage edge cases or anomalous situations that exceed the system's design assumptions or operational boundaries. In the automated model, supervision replaces direct tactical execution as the dominant human contribution. This represents a structural shift in functional roles: variability that previously originated in manual detection and tactical control may now originate in monitoring depth, engagement level, or delayed intervention.

Given that effective operation in highly automated systems depends on coordinated human–automation interaction, the organizational function "*To Manage Teamwork*" has also been introduced (green in Figure 14). This function reflects the principle that complex ATC tasks are best accomplished through complementary capabilities. Automation contributes high processing speed, consistency, and workload reduction, while humans provide contextual reasoning, adaptability, and the ability to manage unforeseen situations. If cooperation is poorly structured, conflicting actions, loss of situational awareness, and degraded resilience may occur. Conversely, well-managed teamwork ensures that the strengths of both human and automated agents are integrated, thereby enhancing overall system safety and resilience. From a FRAM perspective, this function shapes the quality of coordination couplings and influences how variability is either amplified or dampened across human–automation boundaries.

Furthermore, the function "*Human–Machine Feedback Loop*" (blue in Figure 14) has been incorporated to represent the continuous bidirectional exchange of information between the ATCO and the automated system. The existence of such a feedback loop is essential in automated ATC environments, as it enables the ATCO to maintain insight into system logic and operational state, while allowing the automation to receive validation, correction, or override inputs from the human operator. In the absence of an effective feedback loop, situational awareness may deteriorate, trust calibration may become unstable, and either distrust or uncritical reliance may develop. Within the FRAM framework, the feedback loop constitutes a stabilizing coupling mechanism: it enables adaptive adjustment, facilitates early error detection, and supports resilience under dynamic and unpredictable operational conditions.

4.7. VARIABILITY ANALYSIS

The purpose of the variability analysis is to characterise the variability of the functions that constitute the FRAM model. The identification of variability should take into account both everyday, or 'normal' variability and possible cases of unusual 'out of range' variability, and it should take into account both foreground and background functions (Hollnagel, 2012). In the FRAM, the characterisation of performance variability is needed to understand how functions can become coupled and how this can lead to unexpected outcomes. According to Hollnagel (2012), if the Output from a function does not vary even though the function itself varies, then the variability of the function is in principle of no interest. But if the Output from a function varies, then the variability of the function becomes important because it is what determines the quality, hence the variability, of the Output. Within FRAM, the variability of the Output of a function can, in principle, come from three different sources (Hollnagel, 2012):

1. First, variability may be inherent in the function itself. That is, the way a function is executed may naturally oscillate due to its internal characteristics, mechanisms, or constraints. This type of variability is referred to as internal (endogenous) variability, because it originates from the function itself, independent of external influences.

2. Second, the variability of the output may be due to the conditions under which the function is executed. The work environment, available resources, time constraints, organizational factors or contextual requirements can affect the way and quality of the performance of the function. This form is designated as external (exogenous) variability, since it arises from external circumstances and not from the nature of the function itself.

3. Third, output variability can arise as a result of the influence of upstream functions. Since the outputs of these functions represent the inputs, preconditions, resources, control or time, for the observed function, any variability in them can be passed on through the system. Such interdependence is the basis of functional resonance, i.e. upstream-downstream coupling of functions, through which variability can be accumulated, amplified or transformed within the socio-technical system.

Internal and external system variability analysis, performance variability analysis, and upstream-downstream analysis are presented in this section. All analyses were developed in coordination with an expert in the field.

4.7.1. Internal and external system variability

The FRAM methodology is grounded in the assumption that risks emerge from the variability of everyday performance and from the nonlinear interactions among system functions (Macchi et al, 2009). Rather than attributing adverse outcomes solely to component failures, FRAM emphasizes that normal functional variability, when coupled across interconnected functions, may resonate and lead to unintended consequences.

According to Hollnagel (2012), functions within a socio-technical system can be grouped into three main categories: Human, Technology, and Organization. Each category exhibits distinct variability characteristics. Human performance is typically associated with high-frequency and high-amplitude variability. Behavioral adjustments occur rapidly, often influenced by interaction with other actors and contextual factors, reflecting the dynamic nature of the system. The amplitude of variability may also be considerable, meaning that deviations in human performance can be substantial.

Technological functions, in contrast, are designed to be stable, reliable, and predictable. Their variability is generally limited during nominal operation, as technical systems are engineered to minimize fluctuations in performance (Hollnagel, 2012).

Organizational functions occupy an intermediate position. Their variability may be lower than that of human functions, yet organizational factors often exert delayed or indirect effects on human performance, thereby shaping overall system behavior (Hollnagel, 2012).

Given the focus of this research, the variability of all three categories of functions is examined. While it can be anticipated that human functions exhibit greater variability than technological or organizational ones, a comprehensive analysis requires consideration of all sources and types of variability.

Within FRAM, internal variability refers to the likelihood that a function varies due to its own intrinsic characteristics, whereas external variability refers to the likelihood that a function varies as a consequence of its operating conditions, typically influenced by upstream functions (Hollnagel, 2012; Macchi et al, 2009). By analyzing both internal and external variability, it becomes possible to identify the principal sources of variation, estimate their probability of occurrence, and assess their potential impact.

Tables B.1 and B.2 in APPENDIX B present the internal and external variability of the modeled functions. As the model represents general ATCO activities rather than a specific operational event, both functions (first column) and their performers were treated as generalized entities with average characteristics (Oliveira et al, 2023). The second column of the tables specifies the function type (Human, Technology, Organization), the third and fourth columns identify variability sources, and the fifth and sixth columns describe frequency and impact. The variability sources were defined generically, in consultation with a domain expert.

Table B.1 presents the internal and external variability of functions in the non-automated system. The analysis indicates that most human-performed functions have a high probability of generating variability with substantial amplitude. ATCO performance may be influenced by fatigue, workload, stress, temporary loss of situational awareness, and other cognitive or physiological factors. Consequently, variability on the human side represents a significant contributor to overall system dynamics.

Technological functions in the non-automated configuration demonstrate low variability generation under normal conditions. However, when deviations occur, their impact may be considerable, affecting multiple downstream functions. Organizational functions exhibit moderate variability generation, yet when variability manifests, its amplitude can be high, particularly due to its influence on human performance.

In the automation ATC scenario, internal variability analysis focuses on performance fluctuations within the automated system and within the remaining human supervisory role. Internal variability in this context encompasses variations in system performance, timing, accuracy, interface behavior, data integration, and trust dynamics between human and machine (Hollnagel, 2012). Table B.2 presents the variability profile for the automated system. In this scenario, automation performs the majority of operational activities, while the ATCO assumes a supervisory role and may intervene if automation fails. The only function that remains fully human-performed is "*CDM with LTM*". Consequently, internal variability must be examined on both the automation and human sides (Timotic Petkovic and Netjasov, 2026). This distinction is essential, as humans remain a critical component of the socio-technical system. It is particularly important to assess how human variability may change in response to automation malfunctions, especially for functions that were previously performed by humans but are now automated. External variability remains conceptually comparable across both systems, as it arises from inter-functional couplings within the overall system structure.

The variability of automation-performed functions is characterized by low frequency but high impact. Failures or deviations occur rarely, however, when they do occur, their consequences may propagate across multiple coupled functions, potentially affecting the entire ATC system. In contrast, organizational functions maintain variability patterns similar to those observed in the non-automated scenario. For example, teamwork, considered an organizational function, exhibits relatively high frequency but moderate impact. This reflects the ongoing necessity of maintaining effective cooperation between ATCOs and automation.

A thorough understanding of automated system logic, combined with appropriate training and calibrated trust, enables ATCOs to rely on automation effectively while preserving oversight capabilities. In this way, variability within the automated configuration can be managed and absorbed, contributing to overall system resilience rather than undermining it.

4.7.2. Performance variability analysis

The next step in the evaluation of variability involves the analysis of the way in which the variability of the output of one function can be transmitted to the following (downstream) functions, regardless of their own variability characteristics. In other words, it is necessary to consider not only how much the function varies, but also how that variation affects further functional couplings in the system. A simple and operationally applicable approach, proposed by Hollnagel (2012), is based on the characterization of functions through two basic dimensions: time and accuracy. Aspects (Hollnagel, 2012; Oliveira, 2023) can be assigned to each function:

a) in relation to time — not at all, too late, too early, on time, and
b) in relation to accuracy — accurate, acceptable, inaccurate.

By combining the temporal and qualitative dimensions, a spectrum of possible output states is obtained, shown in Figure 15. When it comes to time variability, the category *not at all* can be seen as an extreme form of the *too late* aspect. This means that the output is either not implemented at all, or is implemented so late that it is no longer usable for the next function (Hollnagel, 2012). The time dimension is particularly important in systems like ATC, where a delay can have the same effect as a complete absence of information.

In terms of accuracy, as applied in this research, the output of the function can be *accurate*, *acceptable* or *inaccurate*. It is important to emphasize that accuracy is a relative and not an absolute category, as it is evaluated in the context of functional couplings between upstream and downstream functions. The output is considered *accurate* if it fully meets the needs of the next function and does not contribute to increasing its variability, on the contrary, it can even reduce it. The *acceptable* output is usable, but requires some customization or additional processing before the downstream function can use it. In contrast, *inaccurate* output is incomplete or imprecise to the point that it cannot be used without significant corrections. The consequences of *inaccurate* output are qualitatively similar to those of *acceptable* output, but are more pronounced and with a greater potential for amplification of variability in the system (Hollnagel, 2012).

		Temporal characteristics			
	Aspects	Too early	On time	Too late	Not at all
Accuracy	Accurate	Output to the downstream function is accurate but too early.	Output to the downstream function is accurate and on time.	Output to the downstream function is accurate but delayed, reducing available time.	Output to the downstream function is accurate, but produced too late to be significant or not produced at all.
	Acceptable	Output to the downstream function is acceptable but too early.	Output to the downstream function is acceptable and on time.	Output to the downstream function is acceptable but delayed, reducing available time.	Output to the downstream function is acceptable but produced too late to be significant or not produced at all.
	Inaccurate	Output to the downstream function is inaccurate and too early.	Output to the downstream function is inaccurate but on time.	Output to the downstream function is inaccurate but delayed, reducing available time.	Output to the downstream function is inaccurate and produced too late to be significant or not produced at all.

***Figure 15**. Output characterization*
Source: adapted from (Macchi et al, 2009) in (Timotic Petkovic and Netjasov, 2026)

In this way, the combined analysis of temporal and qualitative dimensions enables a structured monitoring of the way variability is generated and propagated through functional couplings, which is a key step in understanding potential resonance within the socio-technical system.

The possibility of performance variability occurring for the output of each function of the model with respect to time and accuracy is presented in Tables B.3 and B.4 in APPENDIX B for the two observed scenarios. The probabilities will be characterized as typical, likely, possible, and unlikely (highest to least possibility of occurring (Oliveira, 2023)). Possible reasons for this variability were discussed in the previous section (internal and external variability).

4.7.3. Upstream-downstream variability

The variability of the functions in the FRAM arises from their interconnections. The output of the upstream function, which in the downstream function can have the role of input, precondition, resource, control or time limit, can vary in terms of time and accuracy, which directly affects the variability of the following function (Hollnagel, 2012). In this way, the upstream function can act to increase, decrease, or not affect the variability of the downstream function at all (Oliveira, 2023). According to Hollnagel (2012), this relationship can be more precisely explained by a more detailed description of the state of the function and the characteristics of its output. The model functions were evaluated at an overall level, and the results of this variability assessment are presented in Figure 16. In the analysis, the symbol V↑ denotes that variability is expected to increase, V↓ indicates a potential decrease in variability (i.e. a damping effect), while V↔ signifies that variability is likely to remain unchanged (Hollnagel 2012; Oliveira, 2023).

Figure 16 (Oliveira, 2023) illustrates the potential changes in function variability with respect to time and precision, taking into account how the outputs of upstream functions are utilized in downstream functions as inputs, preconditions, resources, controls, or time constraints.

When the outputs of upstream functions are used as inputs to downstream functions, timing and accuracy of information become key factors. If the function is activated earlier than intended, synchronization problems or inefficiencies in information processing may occur. In situations where a certain input directly initiates the activation of the next function, time variability becomes dominant, because premature initiation or delay can disrupt the entire flow of the process. In contrast, when the input is primarily received and processed without an immediate triggering effect, then variability in accuracy is of greater importance. Inaccurate or incomplete data require additional time for verification, correction and integration, thus affecting the efficiency and reliability of further operations (Hollnagel 2012; Oliveira, 2023).

		Input	Precondition	Resource	Control	Time
Time	Too early	V↑ or V↓	V↑	V↑ or V	V↑	V↑
	On time	V↔ or V↓	V↓	V↓	V↔ or V↓	V↔ or V↓
	Too late	V↑	V↑	V↑	V↑	V↑
	Not at all	V↑	V↑	V↑	V↑	V↑
Accuracy	Accurate	V↓	V↓	V↓	V↓	V↓
	Acceptable	V↔	V↔	V↔	V↔	V↔
	Inaccurate	V↑	V↑	V↑	V↑	V↑

***Figure 16**. Upstream-downstream coupling variability*
Source: Oliveira, 2023.

The important notation when performing FRAM analysis is that the function cannot be performed if the preconditions have not been established. If the state of that precondition cannot be determined, then the variability of downstream function can increase. In that case, there is a need to wait until condition is established, or it may be necessary to reconsider the function before, if it is possible, to determine if the condition has already been established (Oliveira, 2023). The both solutions present a waste of time.

When it comes to resources, it represents something that is consumed by function (Hollnagel, 2012). The wrong resources, or the lack of resources can lead to the search for some alternatives and it can increase time and activate delay in the output of a function. If the alternative is not what is needed in that moment, then the output of a function may not be as it should be. Also, when the control of a function is inaccurate, function may vary differently, or it may not occur or occur late if the control is not defined. Under conditions of limited time, performance trade-offs may occur, potentially leading to non-compliance with certain preconditions and increasing variability in terms of both time (synchronisation) and accuracy (inaccurate outputs) (Oliveira, 2023).

In order to carry out such an analysis, it is necessary to instantiate the model and consider possible combinations of functional couplings. An instantiation describes concrete couplings that exist or can exist within a certain scenario or set of conditions and represents the realization of an abstract model in a specific context. It can be said that instantiation represents a concrete manifestation of the model for given (real or assumed) circumstances, whereby it enables a more precise consideration of whether and in what way potential variability can become real variability (Hollnagel, 2012). In this research, however, the evaluation of the previously described FRAM models for two scenarios is carried out using the Bayesian Networks (BBN) method. Thus, the analysis of upstream-downstream coupling and propagation of variability is not only kept at a qualitative level, but is extended to a quantitative assessment of interdependencies and their impact on system performance.

5. BAYESIAN BELIEF NETWORKS: MODEL DEVELOPMENT

Bayesian networks are graphical models based on Directed Acyclic Graphs (DAG), in which nodes represent random variables, and directed branches represent dependencies between them. The structure of the graph shows relationships, often of a causal nature, and allows identification of conditional independence: if the values of the parent nodes are known, the observed variable is independent of the others in the network. These networks are based on Bayes' theorem and the principles of Bayesian inference. Probabilities are updated when new evidence is introduced, with initial assumptions being modified into posterior probabilities based on available data or expert knowledge.

Although the graph defines the dependency structure, the quantitative part of the model consists of tables of conditional probabilities associated with each node. Based on them, it is possible to calculate a priori and posterior probabilities. When evidence is entered into the Bayesian network, the posterior probabilities of connected nodes are automatically updated through probabilistic inference, allowing the analysis of the mutual influences among variables in the system.

The next section is about BBN analysis that has been applied to assess the time aspects (*on time*, *too early, too late or not at all*) and accuracy (*accurate, acceptable,* and *inaccurate*) of the outputs of the functions defined in the FRAM model. In accordance with the variability analysis from the previous chapter, the accuracy assessment was carried out for organizational functions, while the time analysis included all other functions. First, it was necessary to transform the FRAM functions into nodes suitable for use in the BBN model, while a priori and posterior probabilities are calculated next to obtain numerical evidence. Then, sensitivity analysis should be performed to identify critical nodes and critical paths in the presented model. A detailed description of the BBN analysis is given below step by step.

5.1. FUNCTIONS TO NODES TRANSFORMATION

Given that the BBN model works with random variables represented through parent and child nodes, it was necessary to first transform the FRAM functions into nodes before the actual quantification. Also, bearing in mind that the complexity of quantification increases with the number of nodes in the network, a certain reduction in the number of functions was performed during their transformation. The following functions have been reshaped as follows:

- A new node "*Data Acquisition*" was introduced, which combines inputs from the functions "*Surveillance data processing*", "*Flight plan delivery*", "*Provision of meteorological data*" and "*Provision of airspace information*", which are defined as background functions in the FRAM model.
- The "*To display data at CWP*" function has been renamed to the "*Data presentation*" node.

- The functions "*To monitor air traffic situation in a given airspace*" and "*To monitor flights according to adherence to flight plan*" are combined into the "*Monitoring*" node.
- The "*To issue Complexity Solution Measures*" function is modeled through the "*Decision support*" node.
- The "*To implement solution*" function is included in the "*Decision making*" node.
- The "*To communicate with pilots*" function has been renamed to the "*Pilot actions*" node.

The other nodes remained unchanged by name from the FRAM model. The BBN qualitative illustrations of non-automated and automated ATC systems are presented in Figures 17 and 18.

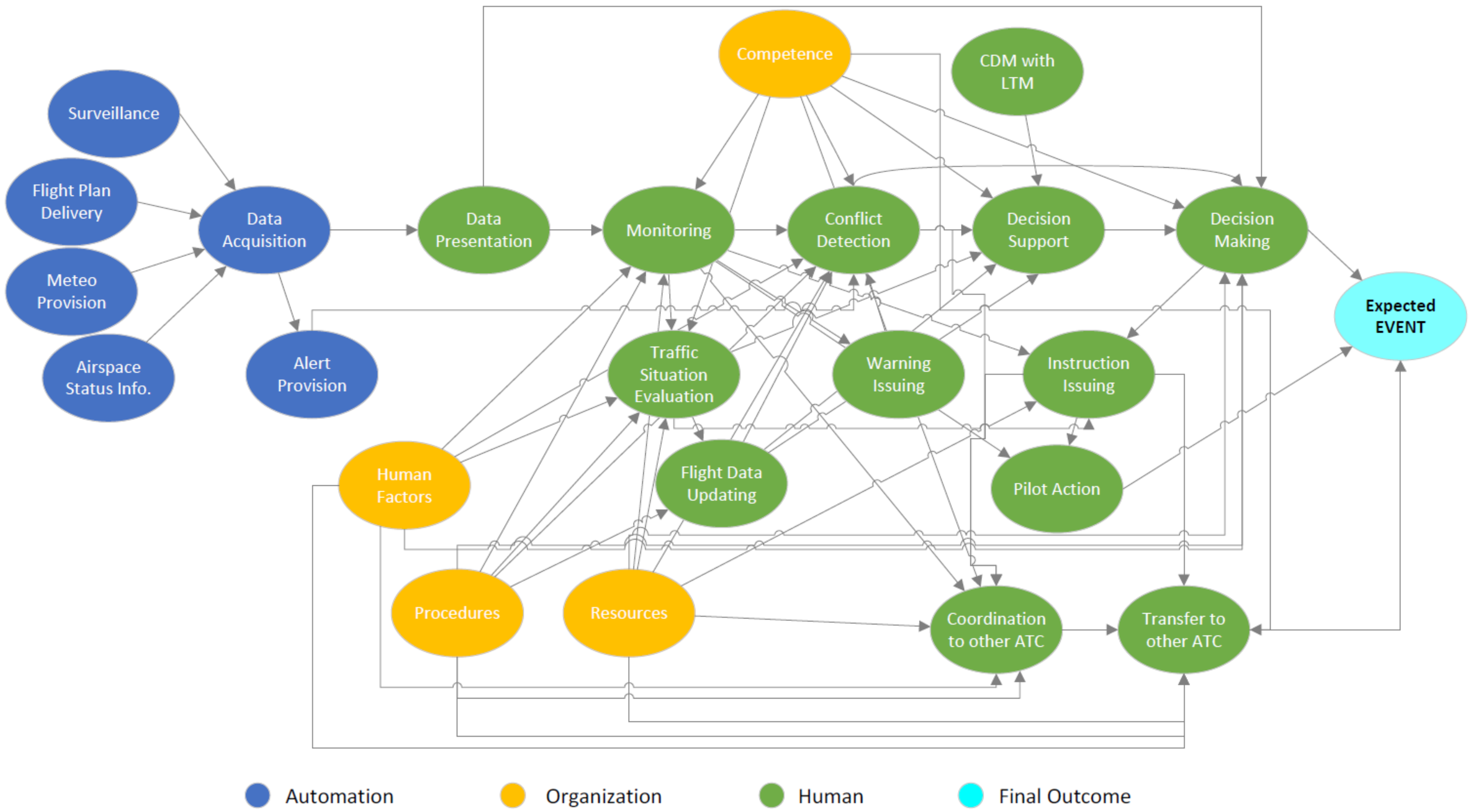


Figure 17*. Qualitative Illustration of the Bayesian Belief Network for a Non-Automated Air Traffic Control System Scenario*

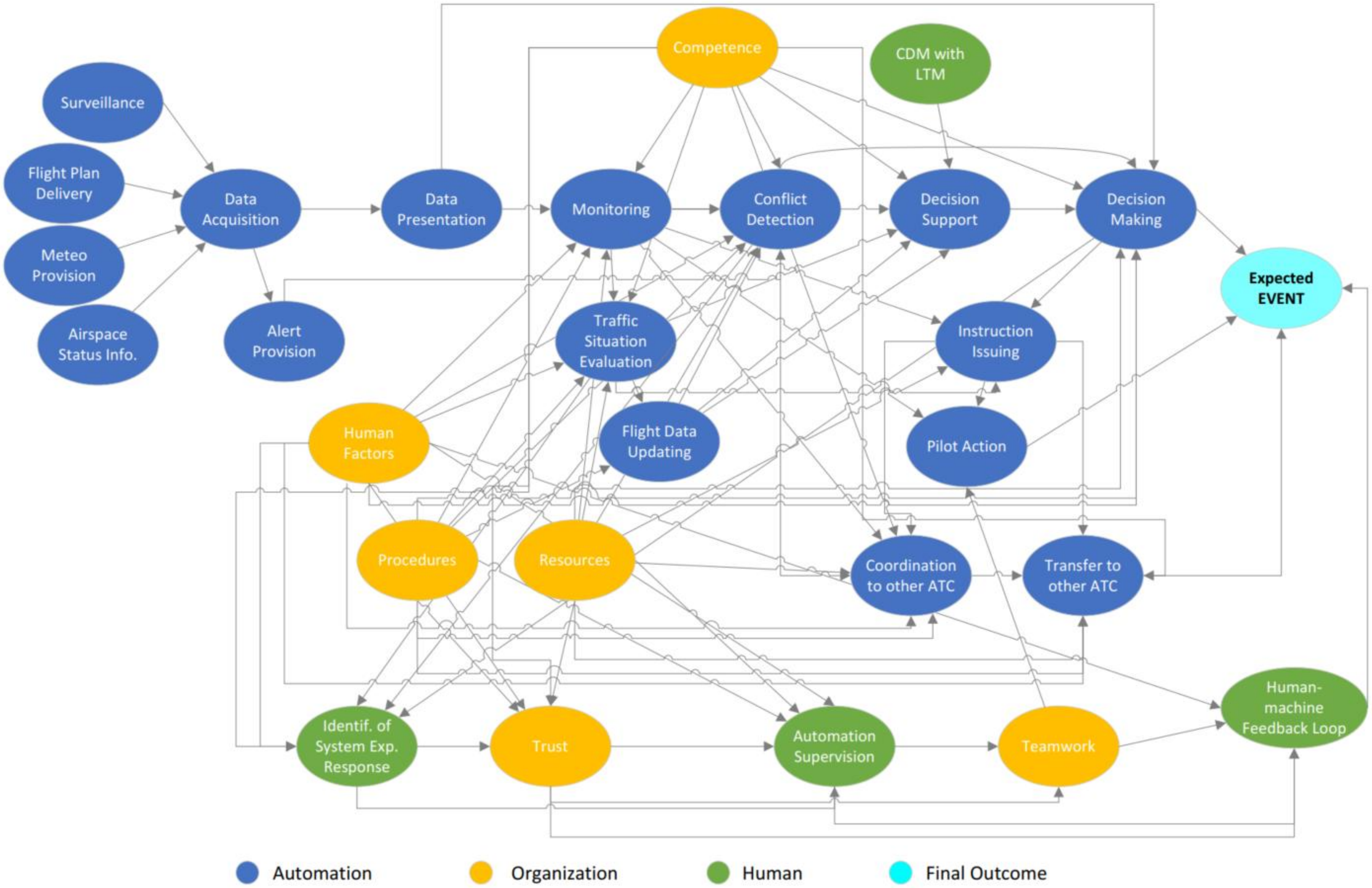


Figure 18. *Qualitative Illustration of the Bayesian Belief Network for an Automated Air Traffic Control System Scenario*

5.2. THE FORMATION OF CONDITIONAL PROBABILITY TABLES

In Bayesian networks, each node is modeled as a random variable representing, for example, an influencing factor or a causal element, while directed edges indicate conditional or causal relationships from parent nodes to their respective child nodes. The DAG structure ensures consistent probability propagation across the network (Chen et al., 2024). For discrete nodes, the defined states are mutually exclusive and collectively exhaustive, meaning that all possible outcomes are fully represented and no overlap exists among them (Kammouh et al, 2020). Nodes without incoming edges are referred to as root nodes and correspond to variables that are not conditioned on other variables in the model. Conversely, nodes without outgoing edges are termed leaf nodes and typically represent final or observed outcomes (Tamburini et al, 2025).

A fundamental element of a Bayesian network is the conditional probability table (CPT) assigned to each node. The CPT quantifies the strength and nature of the dependencies between a node and its parent nodes, thereby formally capturing the degree of influence within the modeled relationships (Chen et al, 2024; Ruiz-Tagle et al, 2022; Tamburini et al, 2025).

Before calculating the CPTs, it is necessary to point out the principle on which Bayesian networks are based. So, the calculation of Bayesian inference is referred to Bayesian rule. The joint probability distribution (JPD) of the network comprised of n variables A_1, A_2, A_3,.... A_n, can be calculated as:

$$P(A_{1,}A_{2,}\, A_{3,}\, \dots, A_n) = P(A_1 |\, A_{2,}\, \dots., A_n) \cdot\ P(A_2 |\, A_{3,}\, \dots., A_n) \cdot\ P(A_{n-1} |\, A_n\,) \cdot P(A_n) \tag{1}$$

Further, Equation 1 can be written as:

$$P(A_{1,}A_{2,}\, A_{3,}\, \dots, A_n) = \prod_{i=1}^{n} P(A_i |\, A_{i+1,}\, A_{i+2,}\, \dots., A_n) = \prod_{i=1}^{n} P(A_i | Parents(A_i)) \tag{2}$$

Also, the calculation of the marginal distribution of individual nodes in the network can be achieved by the process of marginalization, a distributive operation on combinations (Fenton and Neil, 2018 in Wang et al). The global joint probability distribution can be further marginalized by marginalizing the CPTs of the nodes.

In the BBN model, CPTs form the quantitative basis of the network, as they define the probability distribution of each node's state depending on its parent nodes. For orphaned nodes, the CPT contains a priori probabilities that describe the expected state distribution in the absence of other influences. For nodes with one or more parents, CPT includes the conditional probabilities for each combination of states of the parent nodes, taking into account dependencies and causal relationships in the network (Jensen & Nielsen, 2007; Kjaerulff & Madsen, 2013).

Defining probabilities can be based on empirical, statistical or historical data, as well as on expert assessment, and in situations where data are not available, expert opinion is most often applied (Cain, 2001).

Since the research focuses on the conceptual design of a future system for which empirical data are not yet available, it was necessary to establish an appropriate approach for assigning probabilities to the defined nodes. Furthermore, bearing in mind the functional variability identified through the FRAM analysis, each node is characterized by multiple states. Organizational nodes are described by three states (*accurate, acceptable, inaccurate*), whereas the remaining nodes are defined by four states (*on time, too early, too late, not at all*).

In addition to the multi-state structure, most nodes (except root nodes) are influenced by multiple parent nodes, which further increase the complexity of constructing the corresponding CPTs. Following comprehensive analysis and consultations with domain experts, the Weighted Average method was selected as a suitable approach for probability elicitation. The weighted average approach represents a straightforward and commonly used technique for modeling causal relationships between nodes (Wang et al, 2023). The mathematical formulation of the weighted average method is provided in Equation 3:

$$\boldsymbol{WMEAN} = \sum w_i \cdot X_i, i = 1,2, \dots, n; \;\; 0 < w_i < 1; \sum w_i = 1 \tag{3}$$

In accordance with Equation (3), the probability distribution of a child node is obtained as the weighted average of the probabilities of its parent nodes. In this formulation, i represents the number of parent nodes directly connected to the child node, while w_i represents the weight assigned to the i_{th} parent node. These weights are defined based on expert judgment and express the relative influence of each parent on the state of the child node. This aspect is particularly significant in systems such as automated ATC system, where certain information sources may have a more dominant impact on the final outcome.

The $WMEAN$ method provides an initial set of probabilities that are logically consistent, but it does not inherently define all intermediate combinations of parent states, especially in cases where parent nodes have more than two possible states. Assuming linear relationships between nodes (as a model assumption), linear interpolation can be applied to calculate probabilities for all combinations of parent states that are not explicitly specified. By using linear interpolation, the resulting child-node probabilities change gradually and consistently between defined extreme points, thereby supporting a more realistic representation of system behavior. The linear interpolation procedure is described by Equation (4):

$$\boldsymbol{P} = P_1 + \alpha \cdot (P_2 - P_1), \tag{4}$$

$$\boldsymbol{\alpha} = \frac{x - x_1}{x_{2-} x_1}, \tag{5}$$

P_1	–	the probability of the child node at the initial or lower point (extreme state of the parent),
P_2	–	the probability at the final or upper point,
α	–	the relative position within the segment between the two reference points, $\alpha \in [0,1]$,
x	–	the WMEAN value,
x_1	–	the lower point,
x_2	–	the upper point.

If the value $\alpha = 0$, the interpolated probability P is equal to P_1, but if the value $\alpha = 1$ then $P = P_2$. If nodes have multiple states, then α is calculated proportionally to the position of the state within the interval (Timotic Petkovic and Netjasov, 2026). This combined approach enables the completion of all CPT entries in a consistent and logically structured manner, even in the absence of empirical data, by effectively integrating expert judgment with mathematical rigor and internal model coherence.

5.3. PROBABILITY CALCULATION: THE STEP BY STEP EXPLANATION

The procedure for probability calculation and CPT construction is presented in the following chapter through an illustrative example drawn from the non-automated ATC system scenario. Specifically, the function “Pilot actions” was selected to demonstrate the applied methodology.

STEP 1

First, the states need to be converted into scores using the performance variability analysis presented in chapter 4.7.2. All functions are defined through four states such as: *on time, too early, too late*, and *not at all*. Each parent state can be converted into a score in the following way:

Not at all – score 0, the pilot fails to execute the required action. Such a situation may generate serious safety risks due to the complete absence of the expected response.

Too late – score 1, the pilot performs the action, but with a considerable delay. This may lead to potential conflicts or increased workload for the ATCO, as the action is not carried out within the appropriate timeframe.

Too early – score 2, the pilot acts prematurely. Although the instruction is correctly understood, it is executed earlier than intended. This condition is generally less critical than a delayed response, since there is still sufficient time to adjust and ensure safe operation.

On time – score 3, the pilot performs the action fully in accordance with the given instructions and procedures. This state supports optimal information flow and operational safety, representing the desired and expected behavior.

The linear scale (0-3) was applied in the calculation especially due to transparency and simplicity with the assumption of equal differences between conditions. However, the important notation is that this assumption may not reflect the actual non-linear relationships, but it enables model iteration and further adjustment through expert judgement.

STEP 2

The appropriate weights are assigned to each parent indicating the importance of its influence on the child node (Timotic Petkovic and Netjasov, 2026). According to model assumption and expert judgement, in the non-automated system, the pilot’s actions are influenced by following nodes: “*Instruction issuing*” and “*Monitoring*”. The “*Instruction issuing*” node represents direct instructions given by an ATCO to the pilot and has more influence because it is the primary source of information and instructions for performing actions. On the other hand, the “*Monitoring*” node involves monitoring the situation by the ATCO and checking that the pilot is carrying out the instructions correctly.

According to the assumption of an expert in a field, the following weights are given to the mentioned parent nodes:

Instruction issuing - weight 0.6,

Monitoring - weight 0.4.

STEP 3

The Step 3 includes the calculation of the $WMEAN$ value using the Equation 1, by multiplying the score assigned to each parent state by its corresponding weight and then summing the obtained values.

For the “*Pilot actions*” node, the $WMEAN$ is computed for all possible combinations of parent states, meaning that each state score is multiplied by the appropriate weight and aggregated accordingly. Given that this node has two parent nodes, each defined by four states, the CPT must contain sixteen rows, representing all possible state combinations (4 × 4). An illustrative example of the $WMEAN$ calculation for one specific combination of parent states is provided in Equation (6).

$$\boldsymbol{WMEAN} = (X'\text{instruction issuing'} =< too\ late >* w\ 'instruction\ \text{issuing}') + (\text{X}'\text{monitoring}' =< on\ time >* w'\text{monitoring}') = (1*0.6) + (3*0.4) = \mathbf{1.8} \tag{6}$$

STEP 4

Next step is to map the $WMEAN$ value into predefined probability intervals. These intervals are defined according to author’s and expert’s judgement and presented in Table 6. Each $WMEAN$ value interval corresponds to a specific probability distribution for the states of the observed node. For example, if the WMEAN value belongs to the interval [0.00-0.75), the highest probability is assigned to the *not at all* state. However, if the WMEAN value is in the interval [2.25-3.00) then the highest probability is assigned to the *on time* state. This should be done for all obtained $WMEAN$ values according to all combinations of parents’ states

Table 6*. The predefined probability intervals – expert judgement*

Weighted score range	Expected child state	Probability reasoning
[0.0 to 0.75]	Not at all	Most parents’ score very low; the child's state is most likely *not at all*.
[0.75 to 1.5]	Too late	The score indicates lateness; the child's state is likely *too late*.
[1.50 to 2.25]	Too early	The parents' score is early; the child's state is likely *too early*.
[2.25 to 3.0]	On time	Most parents’ state *on time*; the child state very likely to be *on time*.

In the case of the illustrative example, the $WMEAN$ is 1.8 and belongs to the interval *Too early* with the weighted score range [1.50 to 2.25). The further calculation is as follows:

for $X_1 = \mathbf{1.50}$: $P_1 = [P(0), P(1), P(2), P(3)] = [0.0, 0.2, 0.7, 0.1]$

for $X_2 = \mathbf{2.25}$: $P_2 = [P(0), P(1), P(2), P(3)] = [0.0, 0.0, 0.3, 0.7]$,

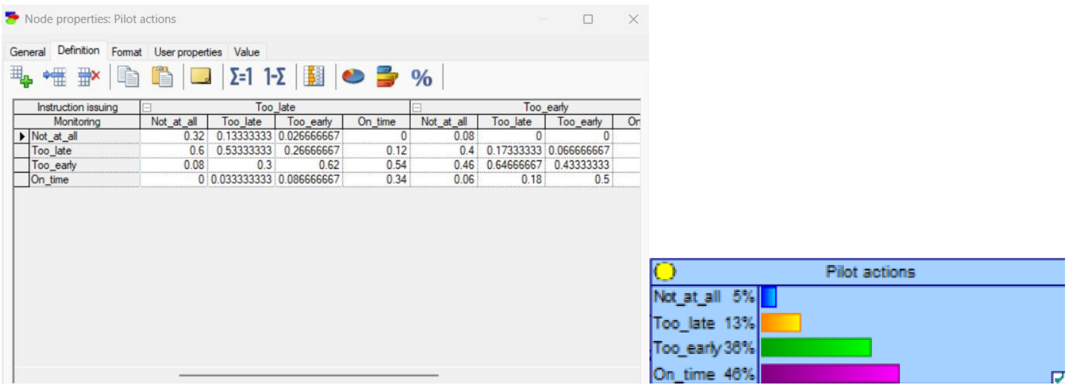
1. **To calculate the α value**:

$$\alpha = \frac{x - x_1}{x_2 - x_1} = \frac{1.8 - 1.5}{2.25 - 1.5} = \frac{0.3}{0.75} = 0.4,$$

2. **To interpolate for every state to calculate the probability of the child state for CPT**:

$$P(0) = 0.0 + 0.4 \cdot (0.0 - 0.0) = 0.0,$$
$$P(1) = 0.2 + 0.4 \cdot (0.0 - 0.2) = 0.12,$$
$$P(2) = 0.7 + 0.4 \cdot (0.3 - 0.7) = 0.54,$$
$$P(3) = 0.1 + 0.4 \cdot (0.7 - 0.1) = 0.34.$$

The required probabilities for one row in the CPT are defined, and the process should be repeated for all others combinations of the parent's nodes states. Appendix C provides an extract from an Excel file in which probability calculations were performed for all rows within a node. In this way, probabilities were also calculated for the other nodes required for the formation of CPTs. The important notation is that the sum of probabilities for each row have to be one. The final CPT for the "*Pilot actions*" node is presented in Figure 19 (a).



Instruction issuing	Too_late				Too_early			
Monitoring	Not_at_all	Too_late	Too_early	On_time	Not_at_all	Too_late	Too_early	On
Not_at_all	0.32	0.13333333	0.026666667	0	0.08	0	0	
Too_late	0.6	0.53333333	0.26666667	0.12	0.4	0.17333333	0.066666667	
Too_early	0.08	0.3	0.62	0.54	0.46	0.64666667	0.43333333	
On_time	0	0.033333333	0.086666667	0.34	0.06	0.18	0.5	

***Figure 19**. a) Conditional Probability Table (CPT) for the "Pilot Actions" Node and (b) Posterior Probability Distribution of the "Pilot Actions" Node*

Source: GeNIe Academic 5.0 software

STEP 5

After the CPT has been established, it becomes possible to calculate the posterior probability distribution of the selected node. The resulting probability distribution for the observed node, influenced by the two previously described parent nodes, is presented in Figure 19 (b). These probabilities are derived directly from the defined CPT in combination with the overall network structure.

The highest probability corresponds to the state *on time* (45.6%), followed by *too early* (36.2%), whereas the states *too late* (13.1%) and n*ot at all* (5.1%) exhibit considerably lower likelihoods. Such results suggest that, in the majority of cases, the pilot responds appropriately and within the expected timeframe, thereby contributing positively to system safety and resilience.

Although there is a relatively high probability of early action, this outcome can typically be adjusted or managed in a way that does not significantly compromise operational safety or resilience. In contrast, delayed or missing responses occur with much lower probability. Overall, despite inherent variability, the system demonstrates a tendency to favor outcomes that pose minimal risk to operational safety and stability, thereby supporting its resilient performance.

5.4. BAYESIAN BELIEF NETWORK MODELS

As explained earlier, the BBN method was applied to develop the quantitative ATC model. This approach has proven to be both consistent and well suited for representing uncertainty, particularly in situations where certain variables cannot be directly observed and must instead be described through hypothetical variability. In addition, BBNs provide a clear framework for modeling causal relationships and influences among system elements.

A key advantage of the method lies in its ability to propagate uncertainty throughout the network and to update probability distributions as new evidence becomes available. This makes it especially appropriate for complex systems, where numerous interdependencies exist. By offering an intuitive graphical structure combined with a rigorous probabilistic foundation, BBNs simplify the representation and analysis of such systems.

Importantly, BBN is a probabilistic approach widely used in safety assessment. In the context of this research, it plays a central role in complementing the qualitative FRAM model with a quantitative representation. While FRAM enables the identification and description of functional variability, the BBN framework translates these qualitative insights into measurable probabilistic relationships. Through this integration, it becomes possible to systematically analyze both the resilience and the safety of the ATC system.

Overall, the BBN method represents a powerful tool for analyzing systems characterized by numerous interconnected elements, particularly when relationships are uncertain, partially known, or supported by limited data. This is especially relevant for the future ATC system, where not all structural and operational details are yet fully defined. So, after transforming functions into nodes, defining the connections between them, and calculating prior and posterior probabilities, it is possible to form two BBN models.

The BBN model for a non-automated ATC system is presented in Figure 20. In the given figure, the blue nodes represent activities performed by ATCOs, the white nodes are activities performed by the system and that are directly automated, the green nodes refer to organizational activities, while the last node, which relates to the resilience and safety of the system, is shown in orange. In the case of the non-automated ATC system, the obtained results indicate that the network predicts an on-time realization of the event in nearly half of all cases. In an additional 36% of cases, the event occurs earlier than planned, which can still be considered acceptable since it does not jeopardize safety. Together, these findings suggest that the system possesses an inherent capacity to absorb variability and preserve operational stability.

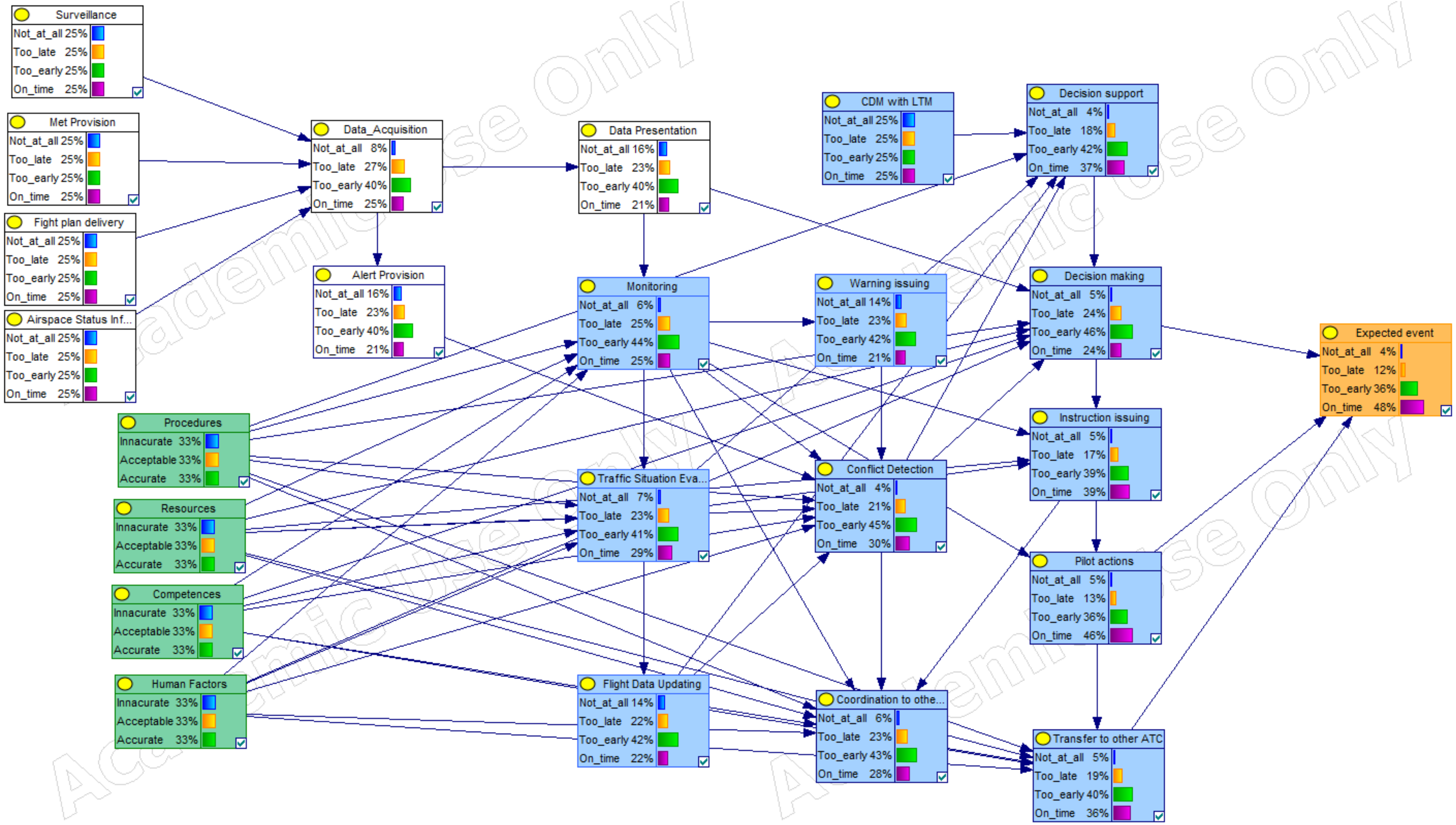


Figure 20. *Bayesian Belief Network Model for a Non-Automated Air Traffic Control System Scenario*

An early execution can be interpreted as a manifestation of variability that does not significantly disrupt system performance. In such situations, the system continues to function efficiently, although minor adjustments may be required.

Conversely, the relatively low probability assigned to the most critical states further highlights the system's resilience. While deviations such as delays or errors remain possible, their likelihood and overall impact are limited. The results demonstrate that multiple interdependent functions collectively contribute to maintaining stability, even when input variability is present.

Notably, the network captures the damping effect of variability propagation. Although key input functions (e.g., "*Meteorological provision*" and "*Surveillance*") are initially modeled with equal prior probabilities across all states (25% each), the interactions within the network lead to an increased probability of the final event occurring on time. This indicates that the modeled system structure does not merely transmit variability, but actively moderates its effects through functional interdependencies.

The BBN model representing the automated ATC system is presented in Figure 21. In the case of automated system, the colour scheme is similar as the previous one: the white nodes are activities performed by automation, blue ones are activities performed by ATCOs, green ones are organizational, while the orange one is the same as in case of non-automated system. However, the results reveal a markedly different probability distribution compared to the non-automated scenario. In this case, the most likely outcomes of the final node, "*Expected Event*," are *too late* (41%) and *too early* (42%), while the probability of the *on time* state drops to only 7%. This distribution indicates that, although the system continues to respond, its performance is no longer optimal. Instead of attenuating variability, the automated configuration appears to amplify or redistribute it, thereby introducing new sources of deviation. The pronounced dominance of premature and delayed outcomes suggests a loss of temporal precision and coordination within the system.

Moreover, the probability of the most critical state, *not at all* (10%), is considerably higher than in the non-automated model. This implies a tangible risk that a key event may fail to occur entirely, for example due to automation malfunction, inadequate feedback mechanisms, or issues related to trust. From a resilience perspective, this represents a serious concern, as it points to the potential for systemic breakdown without sufficiently robust recovery or mitigation mechanisms.

An examination of the additional nodes introduced in the automated model further clarifies these findings. In particular, the "*Human–automation feedback loop*" and "*To manage trust*" nodes exert a strong influence on overall system behavior. Their robustness largely determines whether the system can effectively adapt to and recover from deviations. If these mechanisms are insufficiently developed, the system tends to oscillate between premature and delayed actions, rather than stabilizing around the desired on-time performance.

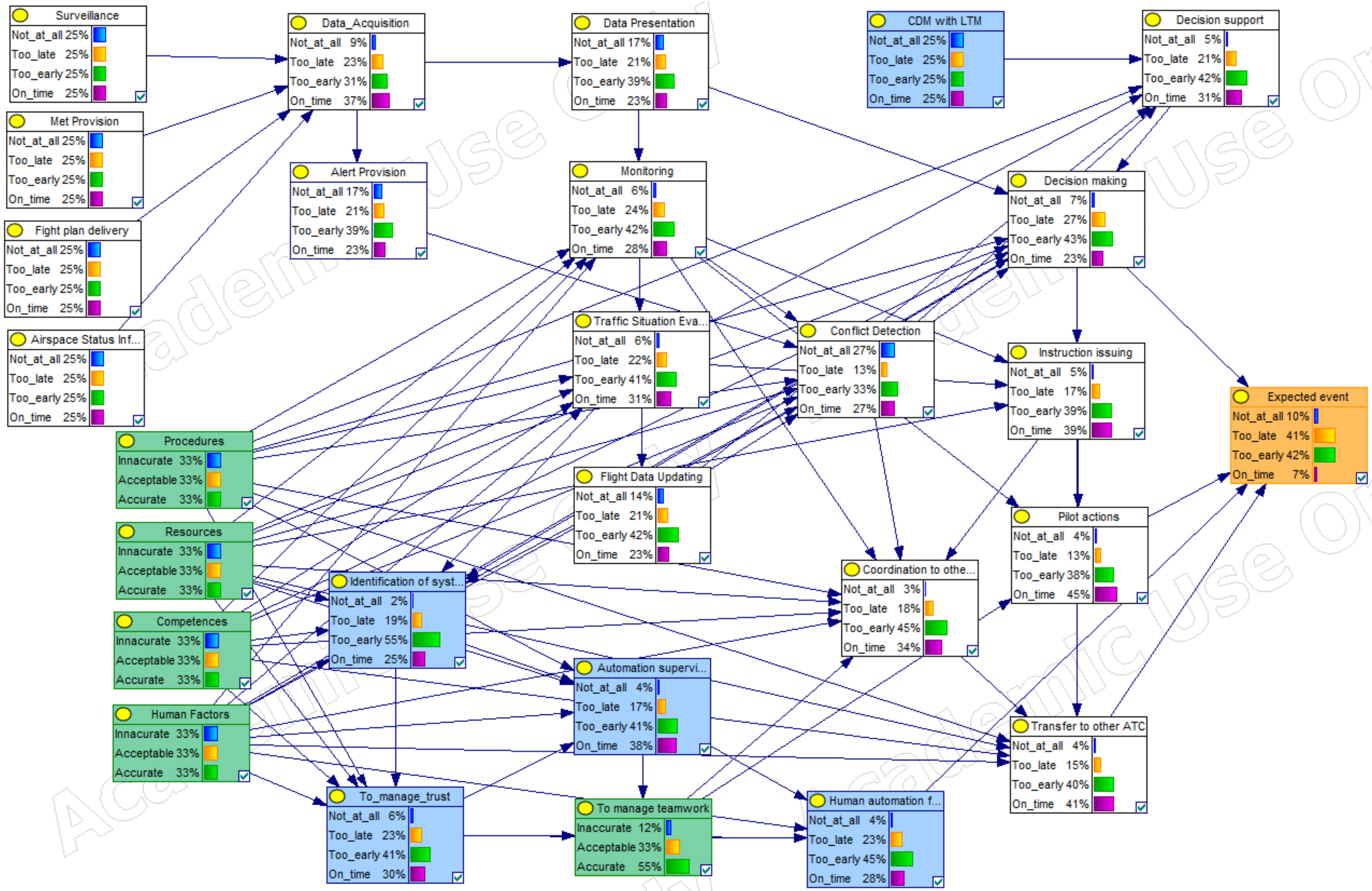


***Figure 21**. Bayesian Belief Network Model for an Automated Air Traffic Control System Scenario*

6. SENSITIVITY ANALYSIS

In order to identify the activities that most strongly influence the resilience of the future ATC system, sensitivity analysis was performed. Sensitivity analysis is a mathematical method used to examine how variations in input variables affect the outputs results of a model. More specifically, it enables the identification of those inputs that have the greatest impact on overall system behavior.

This technique can be applied to both linear and nonlinear models, with the primary objective of understanding how even small changes in input parameters may influence the final outcome. It is particularly valuable in situations characterized by uncertainty in the input data or when the modeled system is complex and difficult to interpret.

In the context of this research, sensitivity analysis serves as an effective tool for identifying the most influential factors, namely, specific ATCO's activities that affect the resilience of the future ATC system under conditions of change. These changes refer to the introduction of automation into ATC operations. By determining which activities exert the strongest influence on system performance, it becomes possible to proactively evaluate and adjust the system design, thereby preserving and enhancing the resilience and safety of the future ATC system.

For the purposes of this research, sensitivity analysis was performed in GENIE Academic software. A probabilistic inference within the BBN model was performed using the Kjaerulff junction tree algorithm, which enables exact propagation of probabilities and efficient computation of posterior distributions and sensitivity measures. The algorithm is based on the principle of selecting a target node, which is actually a node within the BBN model for which a sensitivity analysis needs to be performed. Next, the algorithm calculates the partial derivatives of the posterior probability distribution for each target node depending on each input variable available in the network. These derivatives allow measuring the sensitivity of the target node to changes in the input variables (Kjaerulff and van der Gaag, 2000).

In order to systematically evaluate the influence of different factors on the resilience of the modeled ATC system, three complementary types of analyses were performed within the BBN framework: Tornado analysis, backward analysis and forward analysis. Although all three approaches are based on probabilistic inference, they differ in their logical direction, purpose, and interpretation. Backward and forward analysis belong to "sensitivity-to-evidence" methodology with the aim to see how the probability change of some node (evidence) may influence the target node, while Tornado analysis is "sensitivity-to-parameters" methodology where it can be observed how much the target node is sensitive to change of numerical values from CPTs (Kjaerulff and van der Gaag, 2000).

6.1. TORNADO ANALYSIS

Tornado analysis is the part of the sensitivity analysis widely used in risk assessment or decision-making processes due to its role in identifying the most important variables or parameters that contribute the most to the uncertainty of the outcome. The analysis primarily ranks inputs by importance, providing a clear picture of which variables have the most impact on the realization of the final output. This analysis is based on a series of model runs where, in each run, one input is varied while the others are held constant. The resulting output from each run is then plotted on a Tornado diagram, where the most significant inputs are presented on the top of the diagram, while the least influential ones are at the bottom (Homma and Salteli, 1996).

Tornado analysis is used to identify the parameters that have the greatest influence on the probability of a selected target node. In this analysis it is important to define which node is the target node, and then, the method evaluates how sensitive the posterior probability of that target node is to variations in the numerical parameters of the network which are actually the values defined in the CPTs (Homma and Saltelli, 1996). Unlike forward and backward analyses, tornado analysis does not investigate a specific evidence scenario but rather ranks the variables according to their relative influence within the network structure.

In the context of research into the resilience of ATC systems, this analysis enables the identification of activities that have the greatest potential impact on the resilience and safety of the system.

Tornado analysis was conducted for both the non-automated and automated ATC scenarios in order to assess the structural distribution of influence within each system configuration. Tornado analysis evaluates the sensitivity of the target node to variations in individual model parameters, thereby identifying the most influential elements in the network structure. In the non-automated model, this analysis provides a baseline representation of how resilience-related influence is distributed across human and organizational functions. In the automated model, it reveals whether newly introduced mechanisms, such as trust management, human–automation feedback loops, and automation reliability become dominant determinants of system performance. Comparing the two models enables the assess whether automation redistributes influence or concentrates it within a smaller set of nodes, which has direct implications on structural robustness and resilience. A more balanced distribution of influence suggests greater systemic robustness, whereas increased concentration may indicate heightened structural vulnerability. Thus, tornado analysis plays a crucial role in evaluating how automation reshapes the underlying sensitivity structure of the ATC system.

The diagram, as a result of Tornado analysis, shows the most sensitive parameters for a selected state of the target node sorted from the most to least sensitive. For each parameter, it is possible to see its precise location in the model (node and its state conditional on the parents and their states). Each bar represents the range of variation in the probability of the target state caused by a change in the corresponding network parameter within a predefined interval, in this case ±10% of its current value. Parameters associated with longer bars indicate a stronger influence on the target node. The left and right sides of the bar represent the minimum and maximum probability values obtained within the analyzed range. Also, Tornado analysis can isolate one most influential factor, or a combination of several most influential factors. Note that the Tornado diagram allows for the extraction of ten or more nodes with specific states that most influence the final outcome. In the case of both scenarios developed in this paper, the Tornado diagram shows the ten most influential nodes. Also, Tornado analysis does not represent a direct cause-and-effect interpretation, but shows how sensitive the probability of the target event is to changes in certain model parameters.

6.1.1. Tornado analysis for a non-automated air traffic control system

The first step in this analysis was to identify the activities that exert the greatest influence within the network structure. To conduct this assessment, it is necessary to define at least one node as the target of the analysis. Given that the primary objective of this study is to determine which activities, or combinations of activities, most strongly affect the realization of the "*Expected Event*" and consequently the resilience and safety of the system through the timely completion of all operational tasks, the final node of the network, labeled "*Expected Event*," was selected as the target node.

After defining the target, the sensitivity analysis enables the computation of how variations in individual network parameters influence the posterior probability of the target state. This procedure makes it possible to systematically identify the nodes with the strongest impact on the final system outcome. As explained earlier, the procedure was done in the GeNIE Academic software.

As shown in Figure 22, which presents the activity network of the non-automated ATC system, the nodes highlighted in red represent parameters that exert a significant influence on the posterior probability of the target node (a more intense red coloration indicates a stronger structural impact) being realized. By identifying the nodes with the highest intensity, it becomes possible to determine which activities are most sensitive to variation and therefore most critical to overall system performance. Note, the color scheme is automatically generated by the software after a sensitivity analysis is performed. In the non-automated ATC system, the most influential parameters belong to the following categories:

- **Organizational functions:** Procedures, Resources, Competences, and Human Factors;
- **Human functions:**
    - Highest impact: Pilot actions and CDM with LTM;
    - Moderate but still relevant impact: Flight data updating, Instruction issuing, and Warning issuing;
- **Technological functions:**
    - Highest impact: Surveillance, Meteorological provision, and Flight plan delivery and Data presentation;
    - Moderate impact: Airspace status information and Alert provision.

The prominence of these parameters in the sensitivity analysis suggests that they have the strongest influence on the probability of the final node, highlighting their critical role in shaping system performance and maintaining operational stability in a non-automated ATC environment. Resilience primarily depends on procedural robustness, resource adequacy, operator competence, and effective coordination. Human functions such as pilot actions and collaborative decision-making exert the strongest structural influence because they directly determine whether operational activities are completed on time.

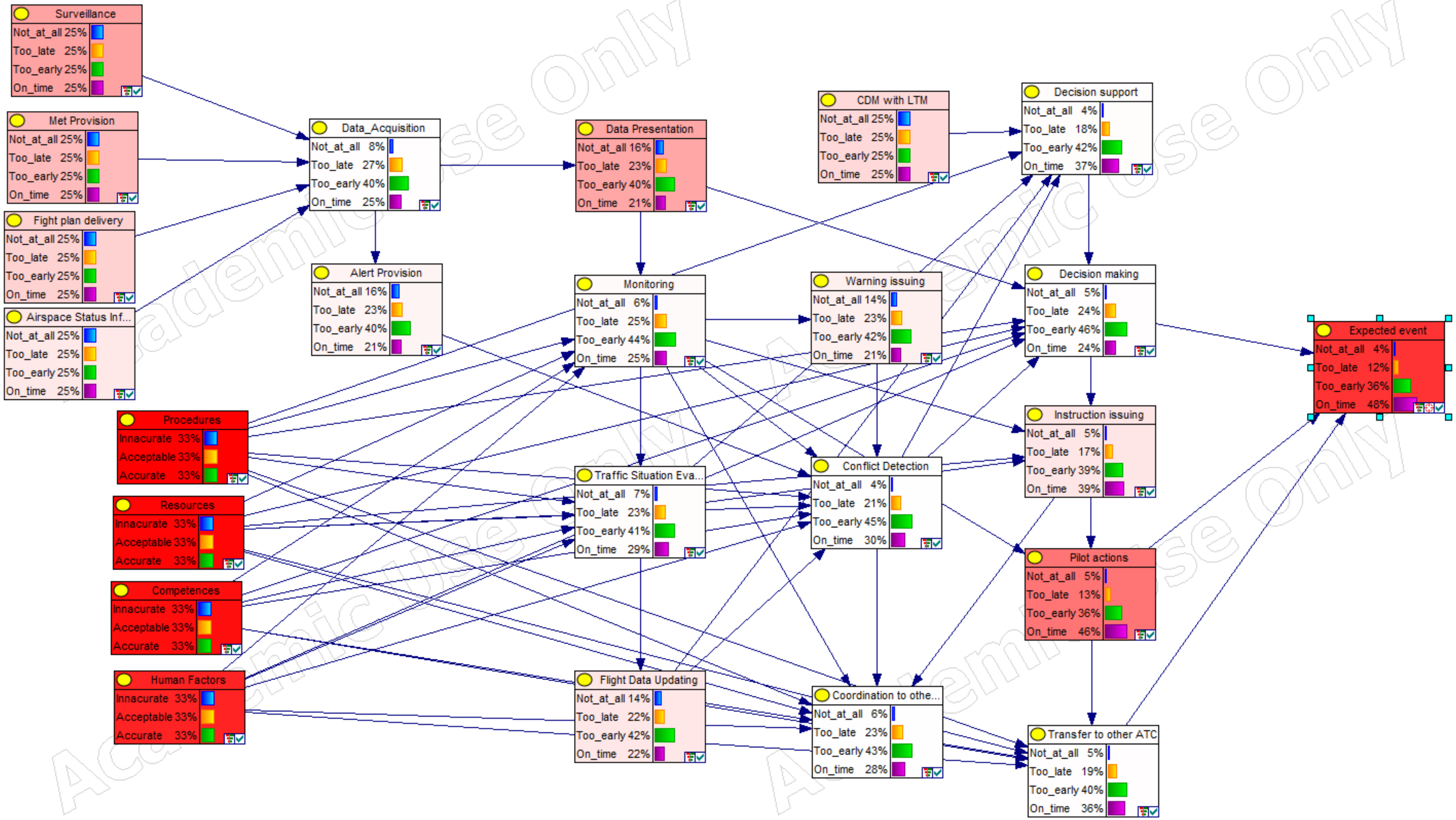


Figure 22*. The most significant nodes in the network: a non-automated scenario*

Technological functions, particularly surveillance, meteorological provision, and flight plan delivery, also play a significant role by shaping the informational foundation upon which decisions are made. Together, these findings indicate that resilience in the non-automated system is largely distributed across human and organizational mechanisms, with technology serving as a critical but supportive component rather than an autonomous stabilizing force.

Accordingly, a Tornado analysis was performed in order to identify the most influential activities or combination of them affecting the realization of the final outcome, represented by the "*Expected event*" node, in the scenario where all activities are performed by a human operator. In other words, Tornado analysis answers the question: *which activities have the greatest influence on whether the "Expected event" will be realized on time, too early, too late or not at all.* **Target outcome: "Expected event" = On time**

Figure 23 shows the Tornado diagram obtained when the "*Expected event*" node is set to the state o*n time* realization. The diagram provides the numerical sensitivity values, highlighting the states for ten variables that have the greatest influence on the output variable. As illustrated in Figure 23, some influences correspond to a single state of an individual variable, while others represent combinations of several states across different variables.

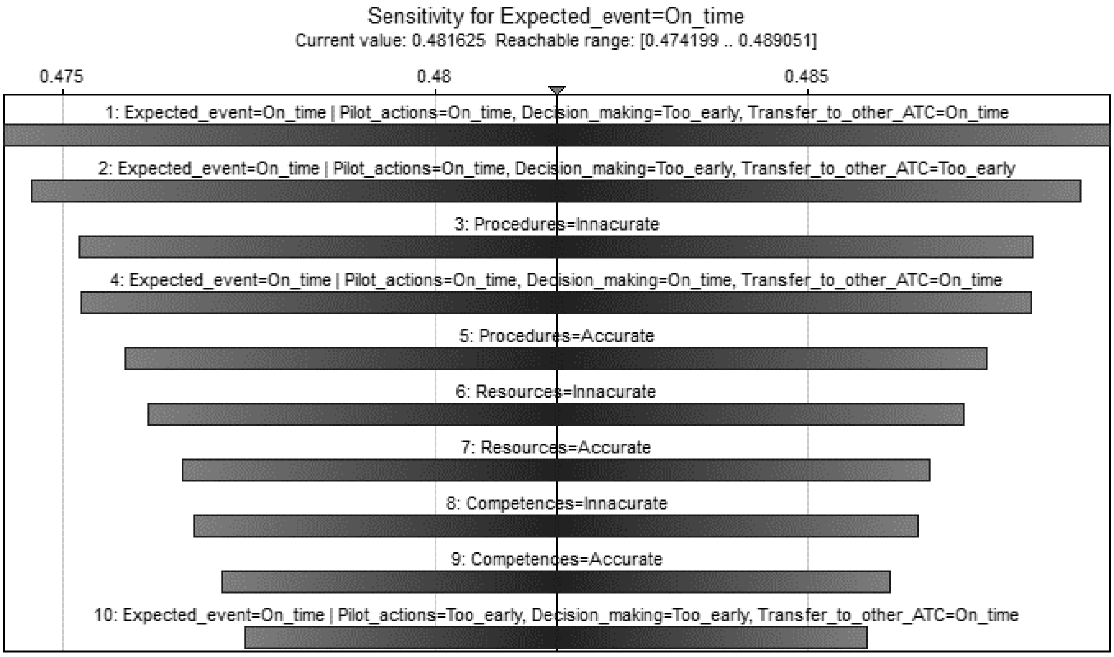


Figure 23. *Tornado diagram for the "Expected Event" node - on time realization in a non-automated air traffic control system*

From the Tornado diagram, presented in Figure 23, it can be observed that in the baseline model the probability of the "*Expected Event*" occurring in the state *on time* is approximately 48%. The Tornado analysis illustrates the sensitivity of this probability to changes in the states of other nodes within the Bayesian network. In this case, the reachable range is between [0.474 and 0.489], indicating that variations in the most influential factors can shift the probability of timely event realization from approximately 47.4% to 48.9%. The range of target values indicates minimum and maximum posterior probability values for the selected target outcome. The relatively narrow range of variation suggests that the modeled system exhibits a certain degree of stability, although specific operational and organizational factors can still influence the likelihood of the event being realized on time.

As previously explained, each bar in the Tornado diagram corresponds to the state of a single variable or to a combination of several states within the network. In this case, the left side of the bar indicates a decrease in the probability of the *on time* realization, while the right side represents an increase in this probability. The length of the bar reflects the magnitude of the influence, with longer bars indicating stronger sensitivity of the target node to the corresponding factor.

The most influential entry in the diagram represents a combination of three operational nodes: "*Pilot actions = on time*", "*Decision making = too early*", and "*Transfer to other ATC = on time*". This combination produces the largest variation in the probability of the expected event being realized on time. The result highlights the importance of the temporal coordination of key operational activities within the ATC. In particular, the interaction between pilot actions, ATCO decision-making, and sector transfer procedures plays a critical role in ensuring the timely realization of operational events. These findings indicate that the performance of the non-automated ATC system is strongly influenced by the synchronization of human-driven operational processes, emphasizing the central role of human coordination and timing in maintaining efficient system performance.

The second most influential case corresponds to the combination of states "*Pilot actions = on time*", "*Decision making = too early*", and "T*ransfer to other ATC = too early*". This result indicates that performing the sector transfer earlier than expected, in addition to earlier decision making, can significantly affect the probability of the event being realized on time. Such a finding highlights the importance of temporal alignment between different operational activities. In particular, it suggests that the discrepancy in the time execution of certain activities can lead to changes in the operational outcome, even when other key actions were performed in a timely manner.

In addition to these operational activities, several organizational functions also appear among the influential factors affecting the timely realization of the event. For example, the analysis shows that inaccurate procedures can significantly reduce the probability of the event being realized on time, indicating that the quality and clarity of operational procedures directly influence the efficiency of task execution within the ATC system. Similarly, inadequate resources, such as insufficient personnel, equipment, or information availability, may negatively affect operational performance and reduce the likelihood of timely event realization. Finally, the competences of the ATCO also play an important role, further emphasizing the significance of the human factor in the overall performance and reliability of the system.

Target outcome: “Expected event” = Too early

The Tornado diagram presented in Figure 24 illustrates the sensitivity of the probability of the *too early* realization of the “*Expected event*” in the non-automated ATC system. The baseline probability of this state is approximately 36%, while the sensitivity analysis indicates that this value may vary within the range of approximately 35% to 37% depending on the states of the most influential variables.

And in this case, the most influential variables stand out as "*Pilot actions*", "*Decision making*" and "*Transfer to other ATC*" in combination with different states. The results indicate that early decision-making and early execution of operational actions can increase the likelihood of premature event realization.

These findings highlight the importance of temporal coordination between operational functions, suggesting that mismatches in the timing of key activities may lead to early realization of operational events within the ATC process.

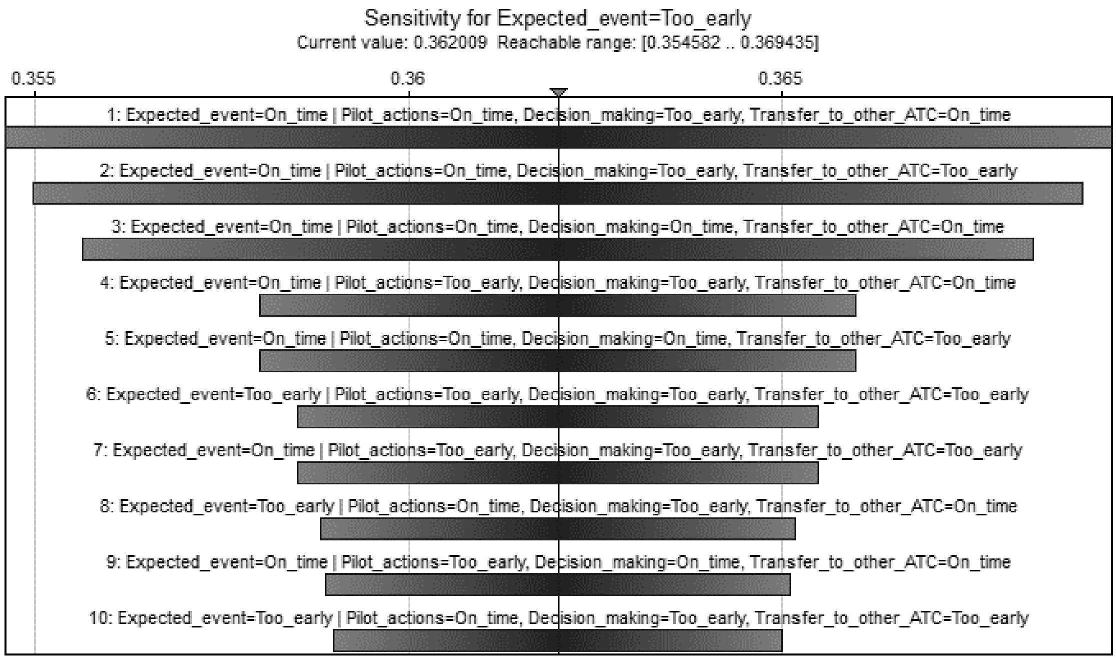


***Figure 24**. Tornado diagram for the “Expected Event” node - too early realization in a non-automated air traffic control system*

Target outcome: “Expected event” = Too late

The Tornado diagram presented in Figure 25 illustrates the sensitivity of the probability of the “*Too late*” realization of the “*Expected event*” in the non-automated ATC system. The baseline probability of this state is approximately 12%, while the sensitivity analysis shows that this value may vary within the range of approximately 11% to 12% depending on the states of the most influential variables.

The most influential parameter is “*Procedures = inaccurate*”. This result shows that imprecise or inadequate procedures significantly increase the probability of an event being realized late. In other words, the quality of operational procedures plays a key role in maintaining the timely execution of activities in the ATC system.

The second most influential is the node "*Resources = inaccurate*". This indicates that insufficient or inadequate resources, such as a lack of staff, equipment or information, may increase the likelihood of delays in event delivery. Similarly, the factors "*Competences*" and "*Human factors*" appear, which shows that the human and organizational aspects of the system have a significant impact on the occurrence of delays in operations. For example: "*Competences = inaccurate*" increases the probability of delays, while "*Human factors = inaccurate*" also contributes to increasing the probability of late realization of events. These results emphasize the importance of controller competencies, work organization and human performance in maintaining system efficiency.

Unlike the previous diagrams (*on time* and *too early*), where operational activities dominated, here they appear only in the lower part of the diagram, as a combination: "*Pilot actions*", "*Decision making*", "*Transfer to other ATC*", especially in cases where all these activities were implemented late. This means that delay can occur when multiple operational functions are late at the same time, but their impact is minor compared to organizational factors such as procedures and resources.

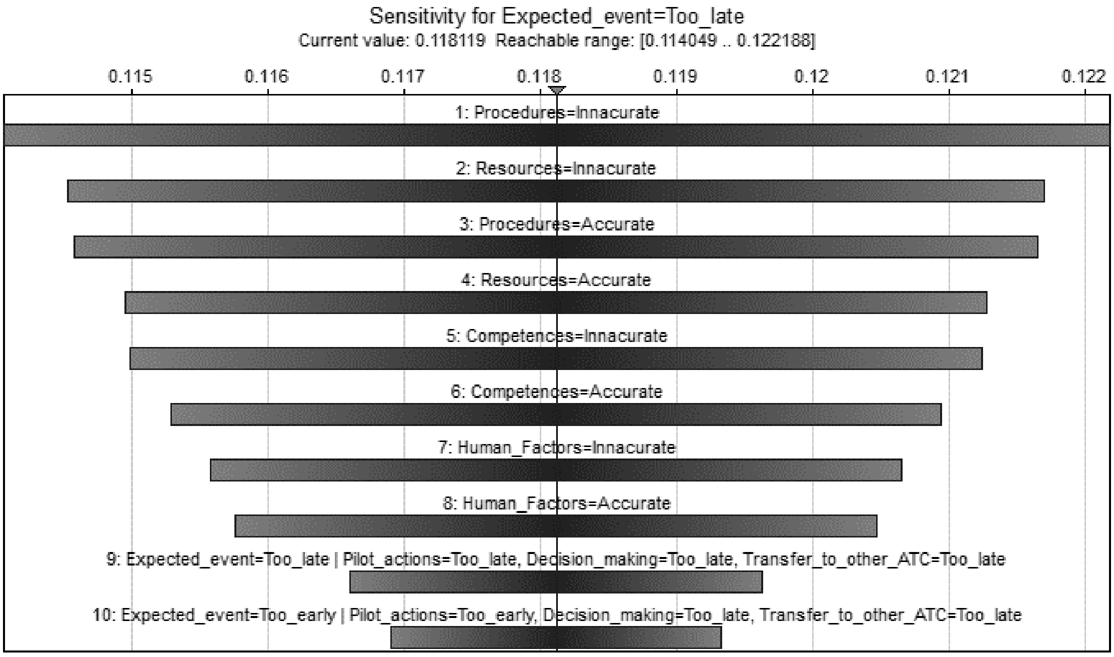


Figure 25. *Tornado diagram for the "Expected Event" node - too late realization in a non-automated air traffic control system*

Target outcome: "Expected event" = Not at all

The Tornado diagram presented in Figure 26 illustrates the sensitivity of the probability of the *not at all* realization of the "*Expected event*" in the non-automated ATC system. The baseline probability of this state is approximately 4%, while the sensitivity analysis indicates that this value may vary between approximately 3% and 4% depending on the states of the most influential variables.

The most significant impact is associated with organizational and human-related factors, particularly the accuracy of procedures and the availability of resources. Inaccurate procedures and inadequate resources increase the likelihood that the expected event will not be realized. In addition, ATCO's competences and human factors also influence the probability of this outcome. Operational activities such as "*Pilot actions*", "*Decision making*", "*Transfer to other ATC*" sector appear lower in the diagram, suggesting that the complete failure of event realization is more strongly related to systemic and organizational conditions than to the timing of individual operational actions.

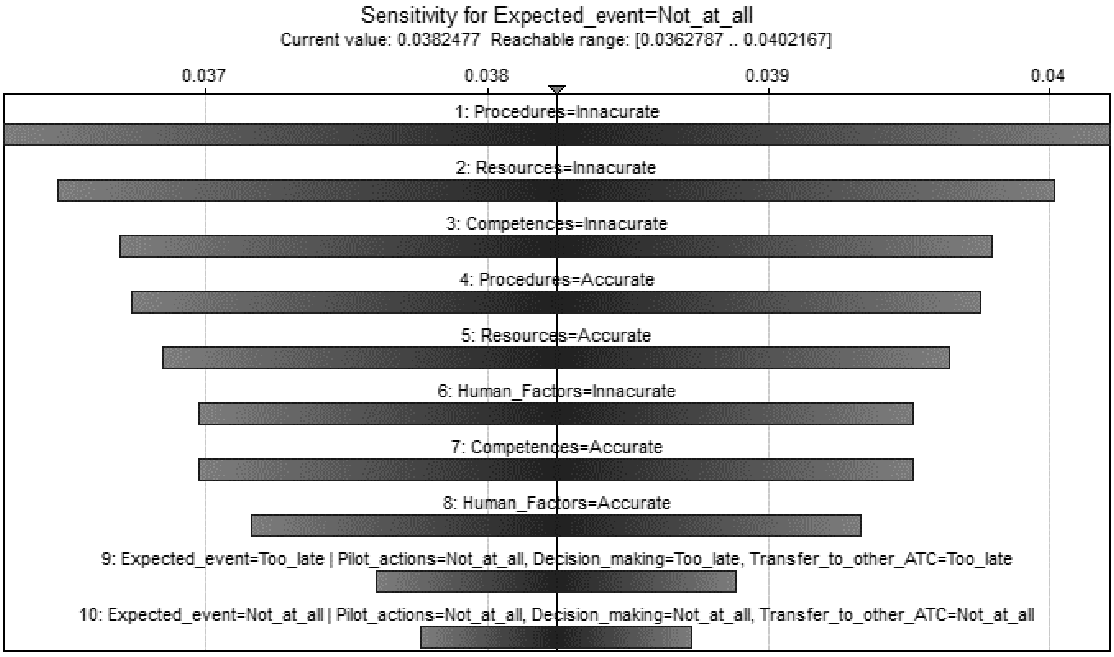


Figure 26. Tornado diagram for the "Expected Event" node - not at all realization in a non-automated air traffic control system

6.1.2. Tornado analysis for an automated air traffic control system

As for the non-automated system, for the case where automation is introduced into the ATC system, it is necessary to set the last node, the "*Expected Event*" as the target. In this way, it is possible to identify the most influential activities on the final outcome and the analysis procedure is the same as for the previous scenario. A visual representation of the most significant activities within the automated ATC system is given in Figure 27. Note, the color scheme is automatically generated by the software after a sensitivity analysis is performed: the most influential activities are given in a stronger red color.

In the automated ATC system, the most influential parameters belong to the following categories:

- **Organizational functions:**
  - Highest impact: *Human factors*
  - Moderate but still relevant impact: *Competences*, *Resources* and *Procedures*

- **Human functions:** *To manage teamwork* and *Human-automation feedback loop*
- **Technological functions:**

- Highest impact: *Pilots actions*, *Data presentation*, *Surveillance*, and *Meteorological provision*.
- Moderate impact: *Airspace status information* and *Flight plan delivery*

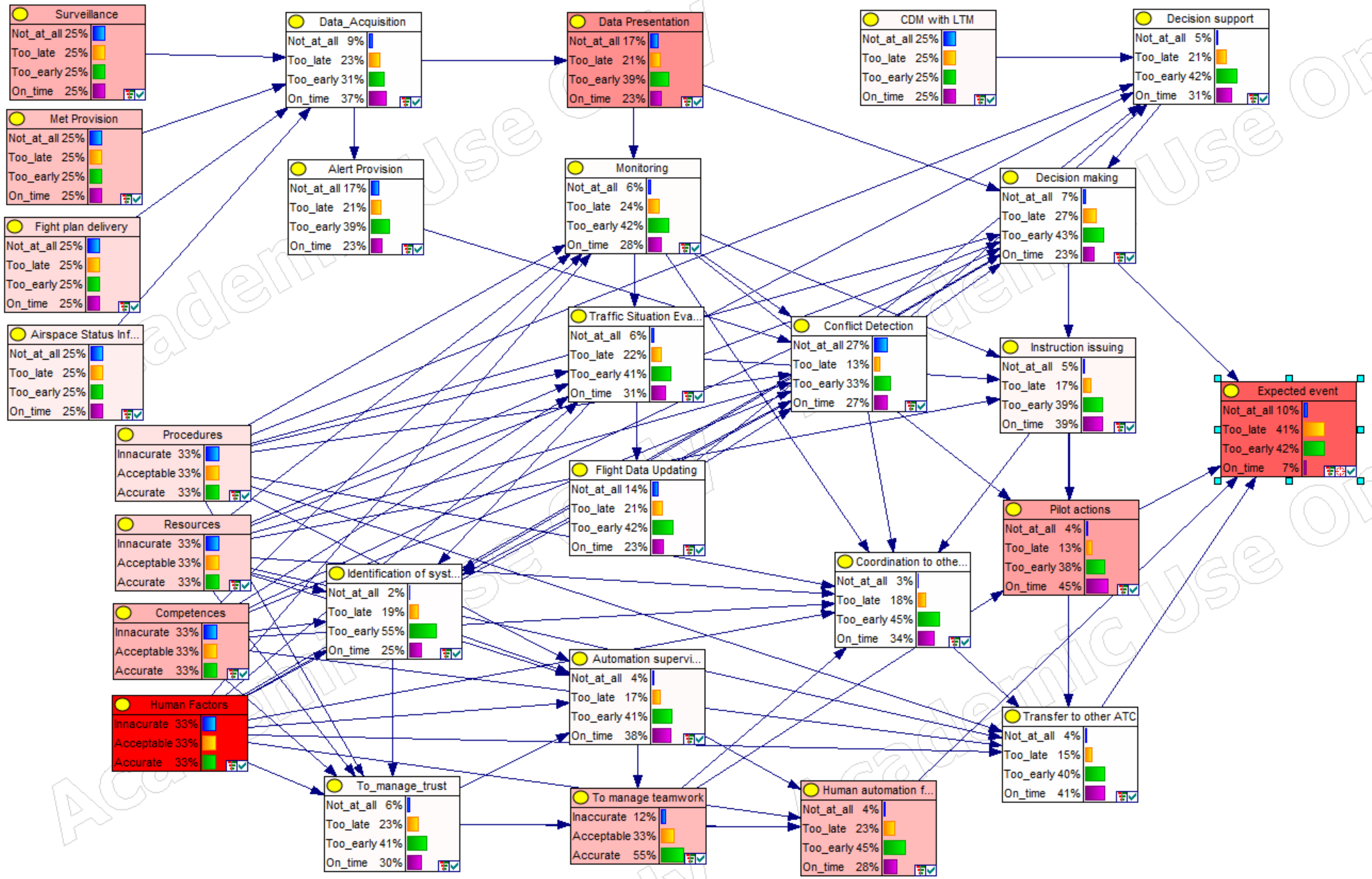


Figure 27. *The most significant nodes in the network: an automated scenario*

In this scenario, a redistribution of structural influence can be observed compared to the non-automated configuration. The most influential parameter becomes “*Human factors*”, indicating that, despite the introduction of advanced technological support, the human operator remains the critical safety barrier. In automated environments, ATCOs assume a supervisory role, which increases the importance of cognitive workload management, situation awareness maintenance, and the ability to detect and override potential automation failures. Consequently, system resilience becomes strongly dependent on the quality of human–automation interaction.

Functions such as “*Competences*”, “*Resources*”, and “*Procedures*” retain moderate influence, reflecting the need for adapted training in relation to automation introduction, robust organizational support, and clearly defined fallback strategies in highly automated contexts. Human functions shift toward managing teamwork and maintaining an effective human–automation feedback loop, emphasizing that resilience in automated systems emerges from coordinated socio-technical interaction rather than from isolated human actions.

Among technological functions, “*Pilot actions*”, “*Data presentation*”, “*Surveillance*”, and “*Meteorological provision*” exhibit the highest impact. Automation increases dependence on the accuracy and reliability of input data and on the clarity of information presentation. Inaccurate surveillance or meteorological data may propagate through automated decision-support algorithms, amplifying their systemic effect. Therefore, resilience in the automated ATC system is shaped not only by technological reliability but by the transparency, interpretability, and adaptability of the entire socio-technical network

As for the previous scenario, Tornado analysis was conducted for the "*Expected Event*" and the analysis of the most influential factors on the realization of the states of this event in the case when the system is fully automated, i.e. when all activities are performed by automation.

Target outcome: “Expected event” = On time

The Tornado diagram depicts the most influential activities for a selected state of the output node in Figure 28. These activities are arranged in descending order of sensitivity. It can be observed that in the baseline model the probability of the “*Expected Event*” occurring in the state *on time* is approximately 6.9%. In this case, the reachable range is between 0.0678 and 0.0703, indicating that variations in the most influential factors can shift the probability of timely event realization from approximately 6.8% to 7.0%. The range of target values indicates minimum and maximum posterior probability values for the selected target outcome. It can be observed that the range of change is very small, which indicates that the system is extremely stable in relation to changes in individual factors.

In Figure 28 ten most influential nodes with their states are presented. The first two entries in the Tornado diagram in Figure 28 correspond to the states of the “*Human factors”* node. The results show that favorable human factors, representing adequate mental condition, alertness, and situational awareness of the ATCO, increase the probability of timely event realization (right side of the diagram). Conversely, unfavorable human factors reduce this probability (left side of the diagram). This finding highlights the importance of the ATCO's cognitive state in automated environments, where operators primarily monitor automated processes and must intervene rapidly when necessary.

In contrast to the non-automated system, the automated model introduces the node "*Human–automation feedback loop*", which appears in combination with operational activities such as "*Pilot actions*", "*Decision making*", and "*Transfer to other ATC*". The results indicate that the timely exchange of information between human operators and the automated system has a significant influence on the timely realization of operational events. In automated environments, ATCOs often perform a monitoring role, supervising the actions of automated tools and intervening when necessary. Therefore, maintaining adequate levels of attention and situational awareness is essential to ensure that ATCOs can react quickly and effectively if the automated system fails or behaves unexpectedly.

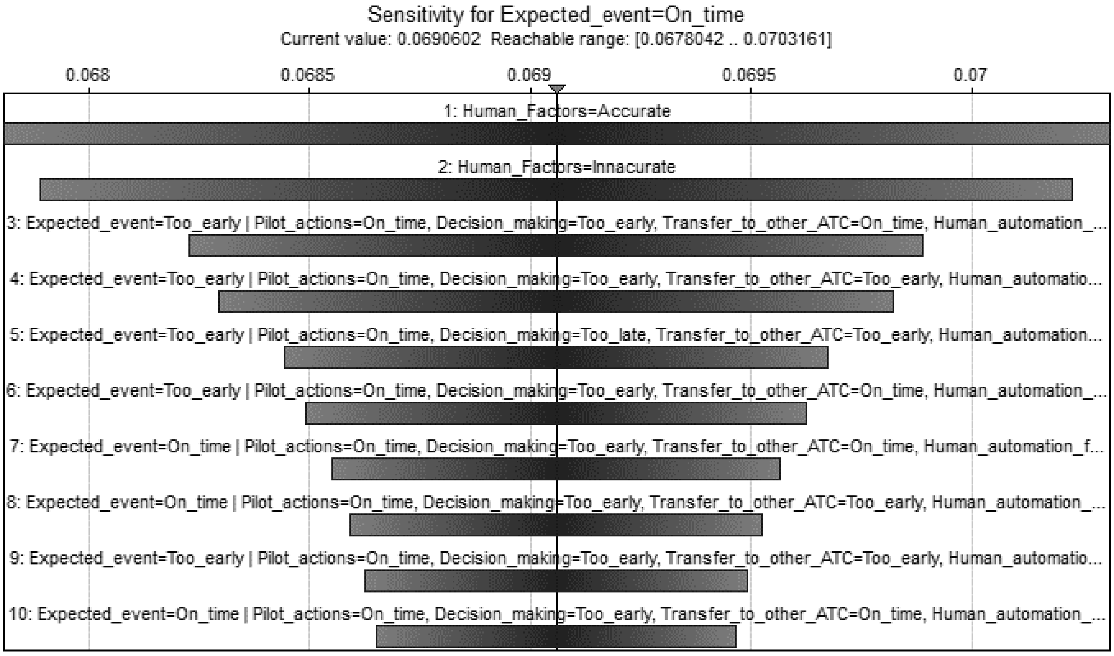


Figure 28. Tornado diagram for the "Expected Event" node - on time realization in an automated air traffic control system

Target outcome: "Expected event" = too early

The Tornado diagram presented in Figure 29 illustrates the sensitivity of the probability of the *too early* realization of the "*Expected event*" in the automated ATC system. The baseline probability of this state is approximately 41.9%, while the sensitivity analysis indicates that this value may vary within the range of approximately 41.5% to 42.3% depending on the states of the most influential variables.

The results show that human-related factors have the strongest influence on this outcome. In particular, favorable human factors, representing adequate mental condition, alertness, and situational awareness of the ATCO, reduce the probability of premature event realization, while unfavorable human factors increase this probability.

In addition, the "*Human–automation feedback loop*" implies as an important element influencing system behavior. The results suggest that premature realization of operational events may occur when the interaction between the ATCO and the automated system is not optimally synchronized. Therefore, the timely and effective exchange of information between human operators and automated support systems is essential for maintaining stable system performance. In the correlation with the other important nodes such as "*Pilot actions*", "*Decision making*" and "*Transfer to other ATC*", the "*Human–automation feedback loop*" plays important role of realizing ATCO activities without some premature reactions.

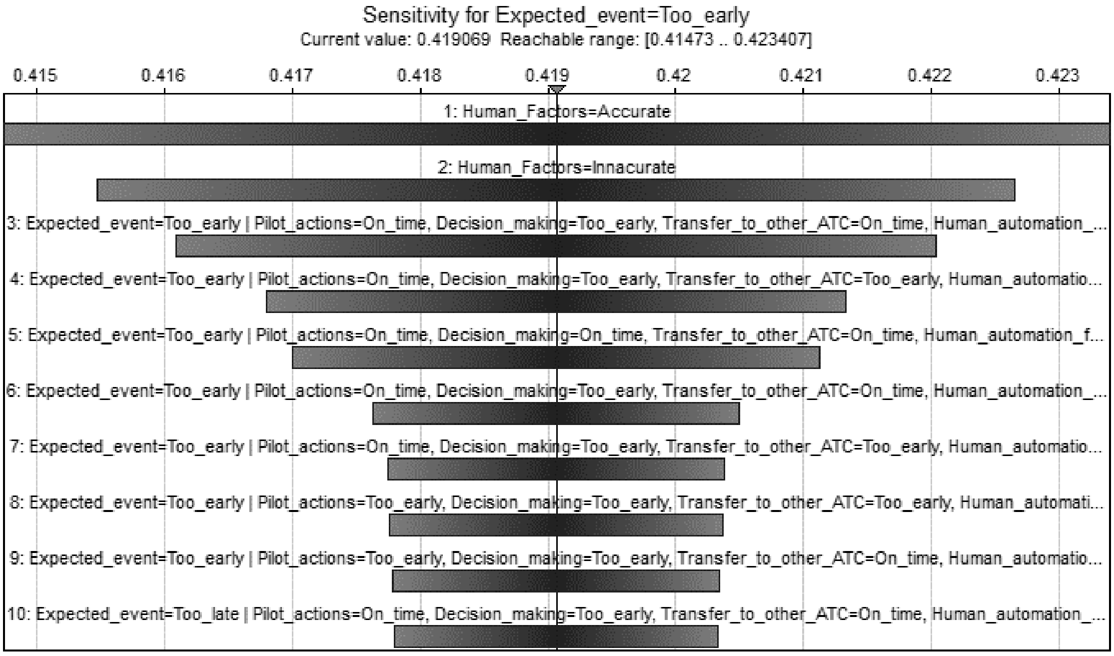


Figure 29. *Tornado diagram for the "Expected Event" node - too early realization in an automated air traffic control system*

Target outcome: "Expected event" = too late

The Tornado diagram presented in Figure 30 illustrates the sensitivity of the probability of the *too late* realization of the "*Expected event*" in the automated ATC system. The baseline probability of this state is approximately 41.3%, while the sensitivity analysis indicates that this value may vary within the range of approximately 40.9% to 41.7% depending on the states of the most influential variables. The range of change is relatively small, which again indicates that the model shows a certain level of stability, although certain factors may affect the probability of late realization of the event.

As shown in Figure 30, the first two bars correspond to the **"***Human factors***"** variable, as was also observed in the analysis of the previous two states, although their interpretation differs depending on the target outcome. When the node **"***Human factors = accurate***"**, the left side of the bar represents a scenario in which the human factors are favorable, meaning that the ATCO is in a good mental condition, maintains adequate alertness, and possesses a high level of situational awareness. Under such conditions, the probability of the *too late* realization decreases, contributing to more stable system performance. Conversely, the right side of the bar indicates that deviations in human factors such as fatigue, reduced attention, or loss of situational awareness may increase the likelihood of delayed realization of the expected event.

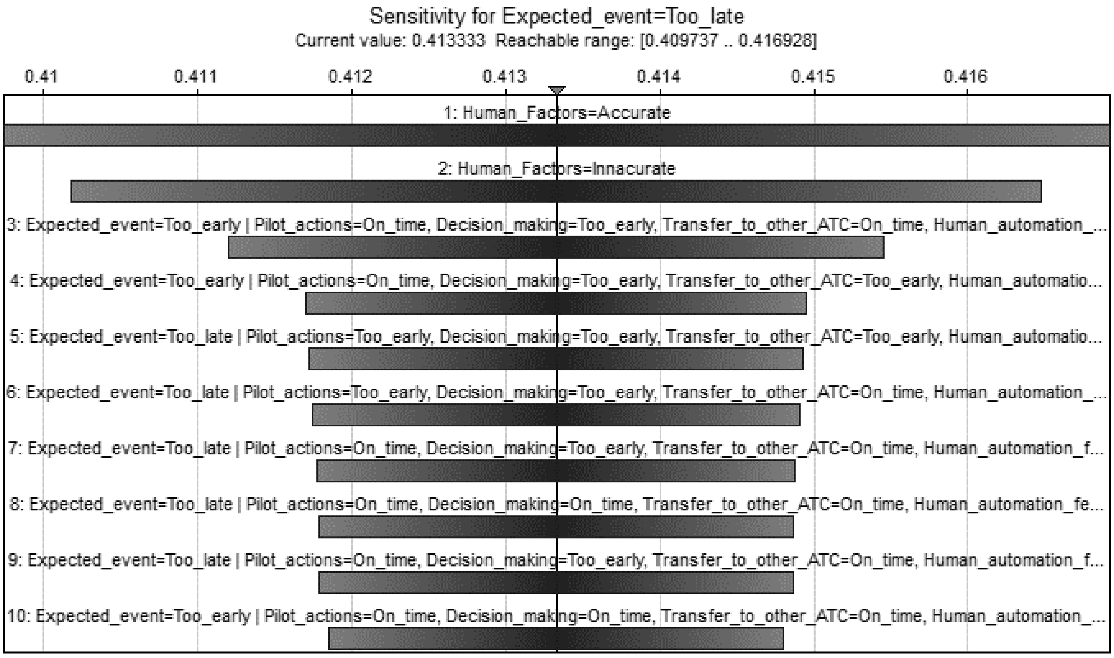


Figure 30. Tornado diagram for the "Expected Event" node - too late realization in an automated air traffic control system

Similarly, when the node **"***Human factors = inaccurate***"**, unfavorable human factors increase the probability of delayed event realization, while improvements in human factors reduce this probability. These results emphasize that the ATCO's cognitive state plays a crucial role in maintaining timely system performance even in an automated operational environment.

The *"Human–automation feedback loop"* node appears again as an important element influencing system behavior. The results suggest that delays may occur when the interaction between the ATCO and the automated system is not optimally synchronized, which is consistent with the observations made for the previously analyzed states. Therefore, the effectiveness of human–automation coordination plays a crucial role in maintaining stable and timely system performance.

Other important nodes that also appear in the diagram are "*Pilot actions*", "*Decision making*" and "*Transfer to other ATC*". These nodes appear in combination with the "*Human-automation loop*" node, and since they are performed by automation in this scenario, it can be seen that the knowledge of the automated system and the feedback of the system to the human and vice versa, is an essential feature in executing the final event without delay.

Target outcome: "Expected event" = not at all

The Tornado diagram presented in Figure 31 illustrates the sensitivity of the probability of the "*Not at all*" realization of the "*Expected event*" in the automated ATC system. The baseline probability of this state is approximately 9.9%, while the sensitivity analysis indicates that this value may vary within the range of approximately 9.65% to 10.5% depending on the states of the most influential variables. The range of change is relatively small, which again indicates that the model shows a certain level of stability, although certain factors may affect the probability of late realization of the event.

The tornado sensitivity analysis for the automated ATC system indicates that the probability of the target state *Expected event = not at all* is most strongly influenced by parameters related to human factors. The states *Human factors = accurate* and *Human factors = inaccurate* appear as the most influential parameters, indicating that even in an automated operational environment, system performance remains highly dependent on human-related characteristics.

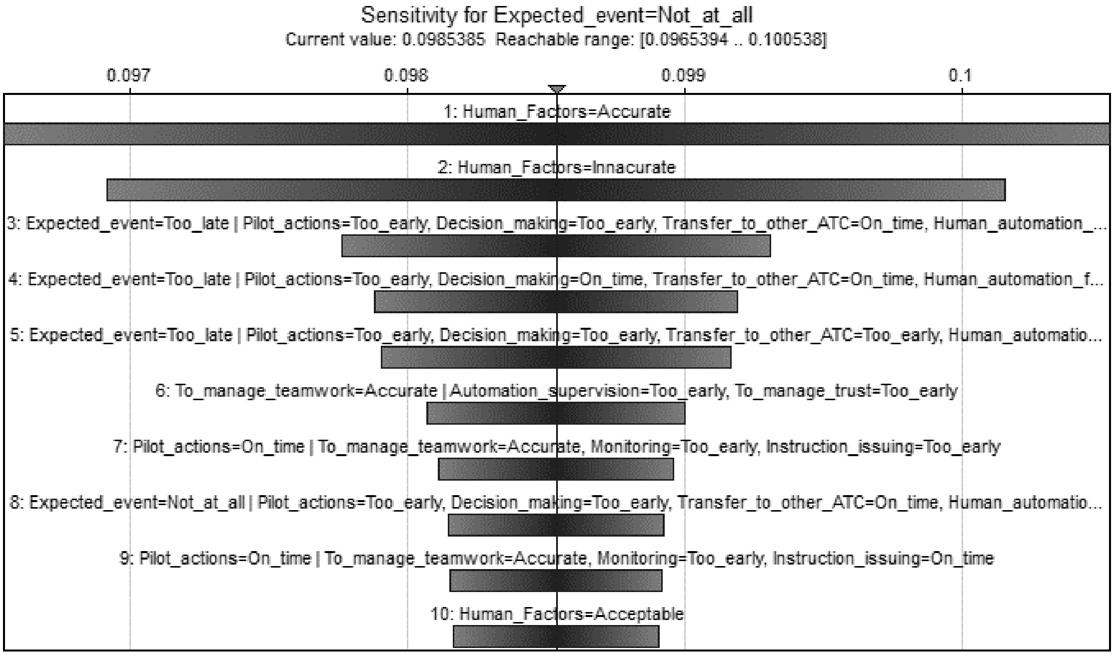


Figure 31. Tornado diagram for the "Expected Event" node - not at all realization in an automated air traffic control system

In addition to the previously discussed variables, the Tornado diagram (Figure 31) also highlights the influence of two functions that are performed by humans such as "*Automation supervision" and* "*To manage teamwork*", and one performed by automation such as "*Instruction issuing*". These functions represent important aspects of ATCO's activities in an automated ATC environment. Automation supervision refers to the monitoring of automated system functions and the ATCO's ability to detect and respond to potential system deviations. The function "*To manage teamwork"* reflects the coordination between ATCOs and mainly the automation, which is essential for maintaining a consistent flow of information and decisions within the system. Finally, the function "*Instruction issuing"* represents the communication of operational instructions to pilots, which directly enables the execution of planned actions. Since this function is performed by automation, the correlation with the two previously mentioned human functions indicates how important it is for humans and automation to be in good coordination while performing tasks. Thus, the presence of these functions in the Tornado diagram indicates that, even in an automated environment, effective coordination, supervision of automated tools, and timely communication remain critical elements influencing system performance.

6.2. BACKWARD ANALYSIS

Backward analysis is based on diagnostic reasoning and involves setting evidence on the target (output) node and observing how this evidence influences the posterior probability distributions of upstream nodes (Wang et al, 2023). In other words, instead of examining how causes affect consequences, backward analysis investigates which combinations of causes are most consistent with a given outcome. This approach answers the question: "Given that a particular system outcome has occurred, which factors most likely contributed to it?"

Backward analysis is particularly useful for identifying critical paths, diagnosing system vulnerabilities, and understanding how unfavorable outcomes may emerge from interactions among multiple interdependent functions. In resilience studies, it enables the detection of structural weaknesses that may not be immediately visible through forward (predictive) analysis.

The essential step in this procedure is to assign a 100% probability to a selected state of the target node, which represents the key performance indicator for assessing system resilience (Oliveira et al, 2023). By fixing the target outcome in this way, it becomes possible to observe how the posterior probabilities of its parent and upstream nodes adjust, thereby identifying those factors that most strongly contribute to the specified outcome. The model actually computes the following:

$$P(Cause|Consequence)$$

This approach not only highlights the nodes with the greatest influence, but also reveals the specific states in which these nodes need to be in order for the final expected event to occur on time. In the context of this study, this corresponds to the successful and timely completion of the entire loop of ATCO activities.

Furthermore, the same analytical procedure can be applied to alternative states of the target node. By doing so, different causal configurations and pathways leading to other system outcomes can be identified, enabling a comprehensive understanding of the structural conditions associated with both desirable and undesirable performance states.

In order to perform backward analysis, the target node "*Expected Event*" was set to record with a 100% probability for the desired state (*on time*, *not at all*, *too late* and *too early*), whereby this information is propagated backwards through the network to the parent and dependent nodes. In this way, it is possible to determine which nodes and states have the greatest contribution to specific outcome.

In this way, a set of activities can be determined that will represent the "critical path" in the realization of the final event set on desired state. In this case, as already explained in one of the previous chapters, the final outcome refers to the realization of the ATCOs activities depending on selected state in order to preserve the resilience and safety of the system. That is why it is very important to examine which activities should be acted on in advance in order to avoid some undesirable effects and situations. One important notation when defining the "critical path" of activities is that with this analysis, it is not identified deterministically, but rather represents a set of variables with the largest posterior contribution to a given goal.

6.2.1. Backward analysis for a non-automated air traffic control system

The following text presents the results of a backward sensitivity analysis when the states of the "*Expected Event*" node are set to 100% realization for the non-automation scenario.

Back-propagation with output accuracy 100% on time – Best case

Figure 32 presents the BBN when the state of the final node, "*Expected event*", is set to 100% *on time* realization. The results indicate that system resilience emerges from the distributed flexibility of multiple operational functions that can adapt to variability and compensate for deviations occurring during the operational process. In this configuration, resilience is not associated with a single critical activity but rather with the collective contribution of several interconnected functions. Responsibility for maintaining system performance is distributed across functions such as decision making, monitoring, coordination, and operational execution, allowing deviations in one activity to be mitigated by adjustments in others. Consequently, the system demonstrates a high capacity to absorb variability, primarily due to a human adaptability and effective coordination among operational actors.

Table 7 presents the probabilities of the most influential nodes and their respective states that contribute to the realization of the "*Expected event*" as *on time* when the final node is fixed at 100% *on time*. The results show that the strongest influence is associated with the node "*Pilot actions*", which are performed on time in 63% of the cases. This is followed by "*Transfer to other ATC*", which occurs on time in 49% of the cases, and "*Decision making*", which is realized on time in 35% of the cases. Although the proportion of *too early* outcomes in the "*Decision making*" node remains relatively high, the interaction with other ATCO activities allows these deviations to be compensated. As a result, the overall sequence of operations may still lead to the successful and timely realization of the final event.

The critical operational path identified in this model, which highlights human flexibility and coordination as the primary contributors to resilience in the non-automated system, is shown in Figure 32 and can be described as follows:

Monitoring → Conflict detection → Decision making → Instruction issuing → Pilot actions → Transfer to other ATC → Expected event.

In addition to this main path, it is also important to consider the supporting sequence (Figure 32):

Monitoring → Traffic situation evaluation → Conflict detection → Coordination to other ATC → Transfer to other ATC → Expected event.

This supporting path emphasizes the importance of early situation awareness. When the system is able to recognize traffic conditions and potential conflicts in a timely manner, it enables subsequent operational functions to be performed at the appropriate moment, thereby increasing the likelihood of the final event being realized on time.

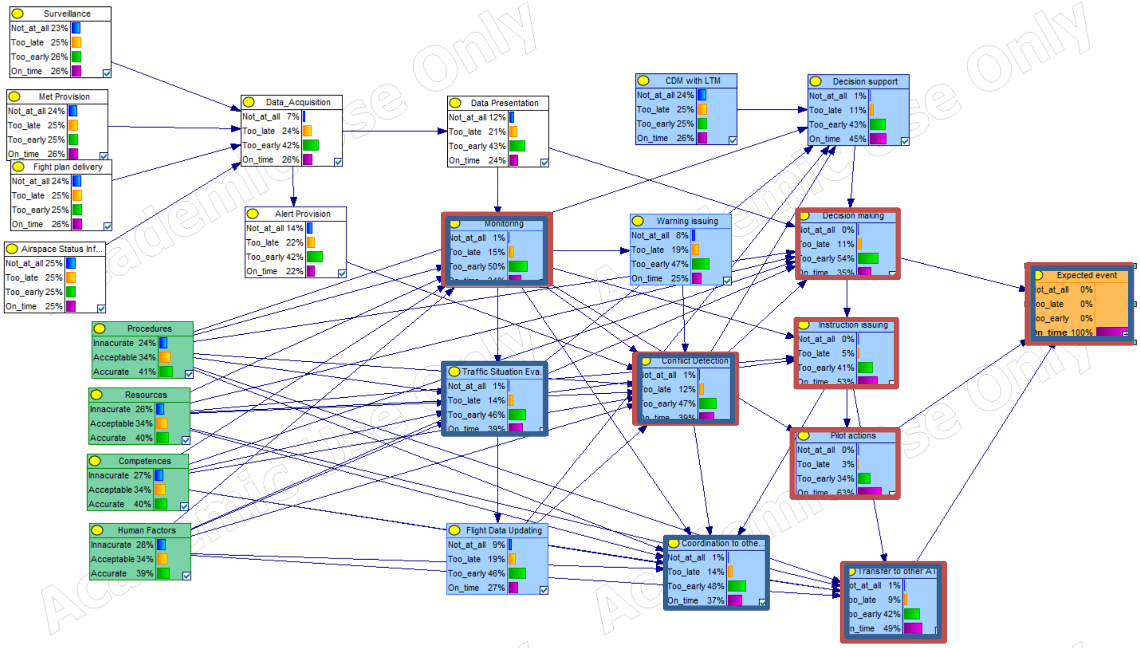


Figure 32. *Bayesian Belief Network with 100% "on time" Expected Event Realization in a Non-Automated System*

Table 7. *Nodes that form the critical path in the case of 100% "on time" Realization of the Final Event in a Non-Automated Air Traffic Control System*

	On Time	Too early	Too late	Not at All
Decision Making	35%	54%	11%	0%
Instruction Issuing	53%	41%	5%	0%
Pilot Actions	63%	34%	3%	0%
Transfer to other ATC	49%	42%	9%	1%
Conflict Detection	39%	47%	12%	1%
Monitoring	34%	50%	15%	1%

Back-propagation with output accuracy 100% Not at all – Worst case

A back-propagation analysis was conducted under the assumption that the "*Expected event*" did not occur in 100% of cases. Figure 33 illustrates this scenario within a non-automated system where the desired outcome is completely absent. The results show that the majority of key functions such as "*Monitoring*", "*Conflict Detection*", "*Traffic Situation Evaluation*", "*Coordination*", "*Pilot Actions*", and "*Transfer to Other ATC*" are highly unlikely to be performed on time.

The probability distributions are predominantly concentrated in the "*Not at all"* and "*Too late"* states, while the likelihood of the *on time* state is almost negligible. For instance, the probabilities of performing "*Conflict Detection*" *on time*, "*Decision*

Making" *on time*, and "*Instruction Issuing*" *on time* amounts to 2%, 0%, and 0%, respectively. Similarly, "*Coordination*" (1%) and "*Pilot Actions*" (0%) show extremely low probabilities of timely execution.

At the same time, upstream factors such as "*Procedures*," "*Resources*," "*Competencies*," and "*Human Factors*" predominantly shift toward the *inaccurate* state. This overall pattern suggests that a system relying exclusively on human performance lacks sufficient capacity to complete the full chain of activities within the required timeframe. Consequently, resilience is significantly reduced, and the system remains without an effective protective mechanism when exposed to disturbances.

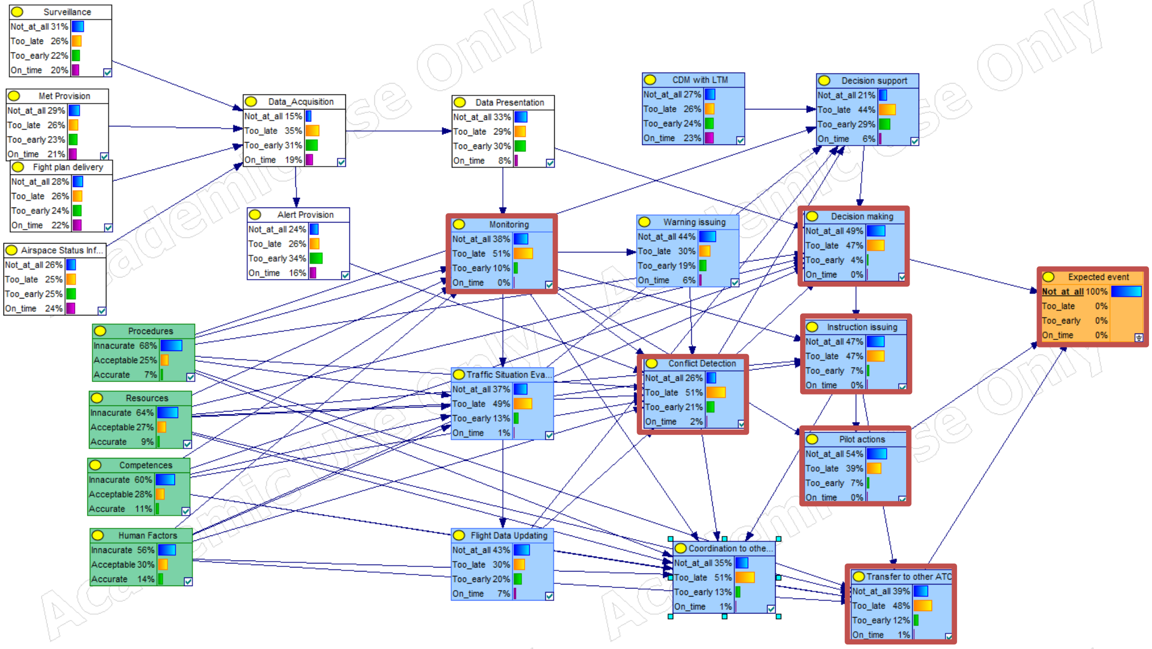


***Figure 33**. Bayesian Belief Network Back-Propagation with 100% "not at all" Outcome in the Expected Event Node for a Non-Automated Air Traffic Control System*

In this case, a critical path is consisting of functions that are crucial to the realization of the final event *on time*, but can barely be realized *on time*, namely (Figure 33):

Monitoring → Conflict detection → Decision making → Instruction issuing → Pilot actions → Transfer to other ATC → Expected event.

Back-propagation with output accuracy 100% Too early

The back-propagation analysis was conducted for the scenario in which the final node "*Expected event*" was set to the state *too early* with 100% probability. This configuration allows the identification of the most probable upstream conditions that could lead to a premature realization of the expected event in a non-automated ATC system. This back-propagation analysis is presented in Figure 34.

The results indicate that the human-performed functions, given in blue nodes, such as "*Monitoring*", "*Conflict Detection*", "*Decision Making*", "*Instruction Issuing*", "*Pilot Actions*", "*Coordination*", and "*Transfer to Other ATC*", exhibit a dominant shift toward the *too early* state. The model redistributes probabilities across key functions, while the likelihood of *on time* decreases and the *not at all* state remains comparatively low. This pattern suggests that, in a non-automated environment where operational functions are executed exclusively by humans, premature actions across multiple stages of the operational chain are the most probable contributors to the early occurrence of the expected event.

Importantly, the functions performed by system (white nodes) do not indicate structural failure but rather reflect altered timing dynamics. The system remains operational. However, the temporal alignment between functions is disrupted. The organizational factors such as "*Procedures*", "*Resources*", "*Competences*", and "*Human Factors*", do not predominantly transition into the "*Inaccurate"* state, which would indicate systemic degradation. Instead, their distributions suggest that the early realization of the event is not primarily caused by organizational breakdown, but rather by cumulative temporal deviations in human-executed processes.

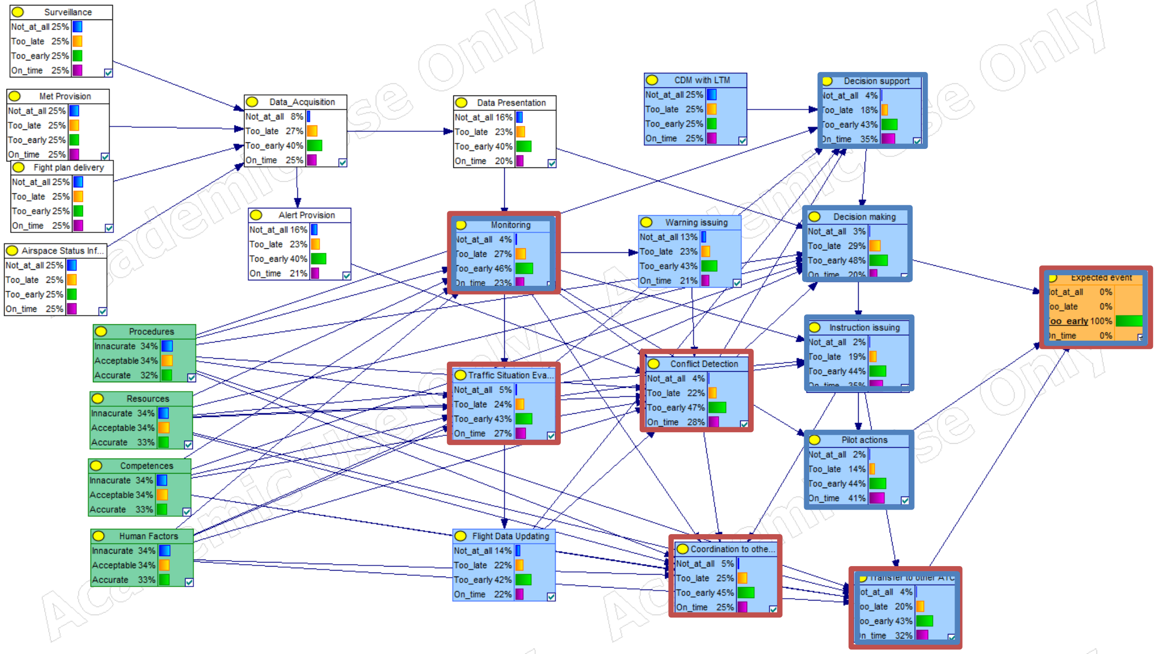


Figure 34*. Bayesian Belief Network Back-Propagation with 100% "too early" Outcome in the Expected Event Node for a Non-Automated Air Traffic Control System*

In this case (Figure 34), two critical paths can be defined:

Monitoring → Traffic Situation Evaluation → Conflict detection → Coordination → Transfer to other ATC → Expected event, and

Monitoring → Decision support → Decision making → Instruction issuing →Pilots actions → Transfer to other ATC → Expected event.

Back-propagation with output accuracy 100% Too late

Backward analysis was performed for a scenario in which the final node "*Expected event*" is set to the state *too late* with a probability of 100%, within a non-automated air traffic control system (Figure 35). The results show a pronounced shift of most human functions towards the *too late* state, with almost negligible values for the *on* *time* state. Functions such as "*Monitoring*", "*Conflict Detection*", "*Decision Making*", "*Instruction Issuing*", "*Pilot Actions*", "*Coordination*" and "*Transfer to Other ATC*" show dominant delay probabilities, indicating the existence of a chain structure of time displacement along the entire operational flow. The delay in the early stages ("*Monitoring*" with only 3% *on time* and 51% *too late* realization, and "*Conflict Detection*" with 7% *on time*, and 44% *too late* realization) generates a domino effect that is transmitted to the decision-making, issuing of instructions and execution of actions.

Unlike the scenario of premature realization of the event, in this case the organizational factors ("*Procedures*", "*Resources*", "*Competences*" and "*Human Factors*") dominantly move to the *inaccurate* state (56%, 54%, 51% and 48% respectively), which indicates that the cause of the delay is not exclusively of an individual nature, but is a consequence of the systemic weakening of support for human functions. Although the system does not show a complete collapse of activity, the loss of temporal stability and the ability to respond in a timely manner is evident, which significantly impairs its resilience.

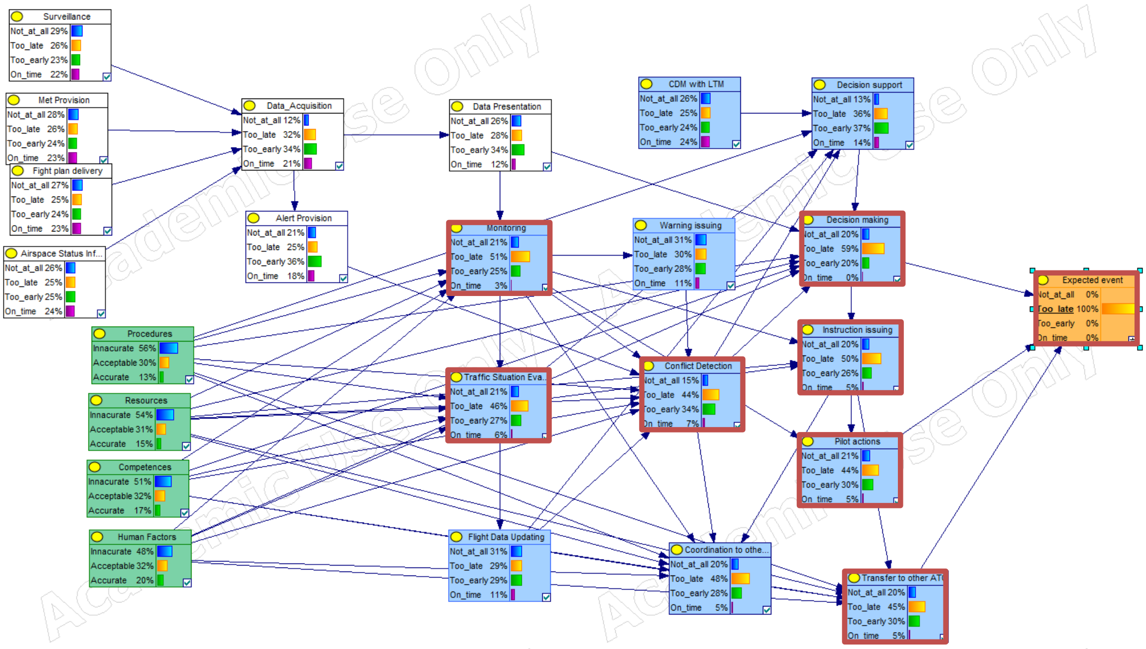


Figure 35. *Bayesian Belief Network Back-Propagation with 100% "too late" Outcome in the Expected Event Node for a Non-Automated Air Traffic Control System*

In this case, a critical path is consisting of functions that are crucial to the realization of the final event *too late*, namely (Figure 35):

Monitoring → Traffic situation evaluation → Conflict detection → Decision making → Instruction issuing → Pilot actions → Transfer to other ATC → Expected event.

6.2.2. Backward analysis for an automated air traffic control system

Back-propagation with output accuracy 100% on time – Best case

In the automated system scenario, the BBN configuration in which the "*Expected event*" is set to 100% *on time* is shown in Figure 36. The results indicate that the system exhibits reduced flexibility compared to the non-automated case, primarily because human operators are no longer directly engaged in all operational functions, but are instead limited to supervisory and intervention roles. In this configuration, resilience largely depends on a smaller number of critical nodes, particularly "*Human–automation feedback*" and "*Automated supervision*".

The findings suggest that the automated system achieves higher efficiency under nominal conditions, provided that all components function as intended. However, this efficiency is accompanied by increased structural sensitivity: a malfunction or degradation in one of the key nodes can significantly diminish the likelihood of timely realization of the final event. This implies that the introduction of automation in future ATC systems must be accompanied by carefully designed redundant and transparent feedback mechanisms to preserve overall system resilience.

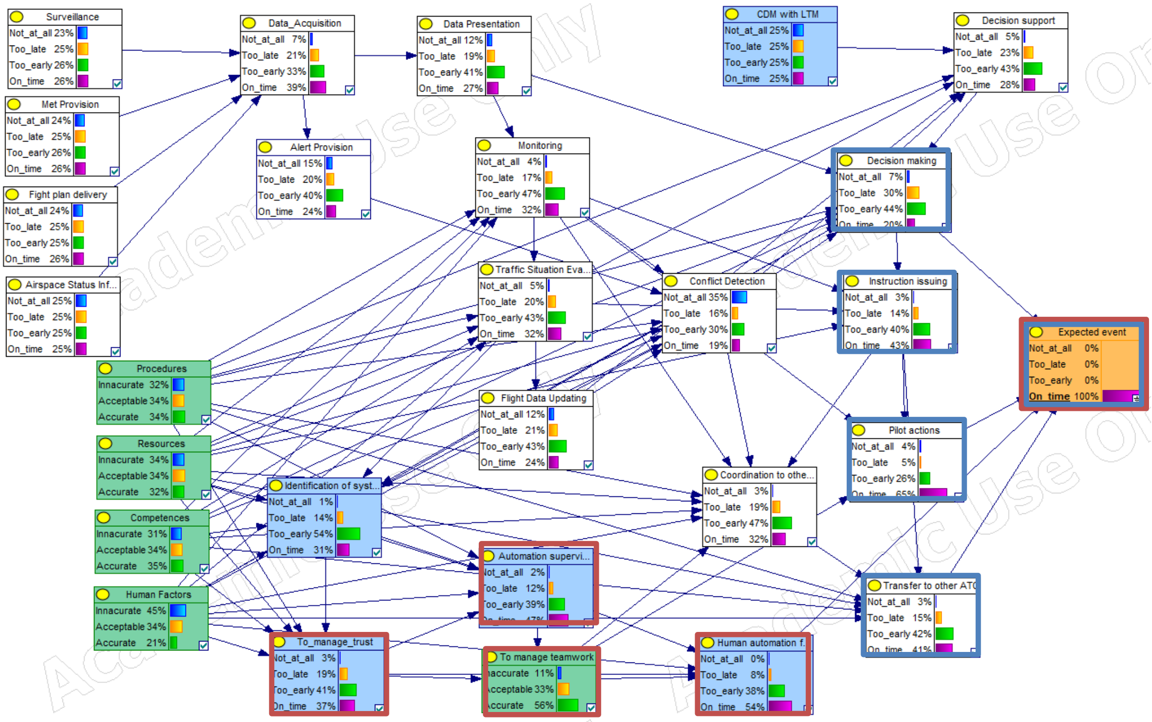


Figure 36. *Bayesian Belief Network with 100% on Time Expected Event Realization in an Automated System*

Table 8 presents the probability distributions of the nodes most strongly associated with the timely realization of the final event when the final node is fixed at 100% *on time* in the automated configuration. The results show that the strongest contributor to timely task execution is "*Pilot activities*", which are performed *on time* in 65% of cases, followed by the "*Human–automation feedback loop*", realized *on time* in 54% of cases. Although the nodes "*Decision Making*", "*Transfer to other ATC*", "*Coordination*", and "*To manage trust*" still display a slightly higher tendency toward *too early* realization, the presence of an effective feedback loop between automation and the ATCO enables these premature actions to be detected, adjusted, and compensated. As a result, their early execution does not substantially compromise the timely achievement of the final operational objective.

Table 8. *Most Influential Nodes under 100% "on time" Realization of the Final Event in an Automated Air Traffic Control System*

	On Time	**Too early**	**Too late**	**Not at All**
Human-automation feedback loop	54%	38%	8%	0%
Automation Supervision	47%	39%	12%	2%
To manage Trust	37%	41%	19%	3%
Decision Making	20%	44%	30%	7%
Pilot Actions	65%	26%	5%	4%
Coordination	32%	47%	19%	3%
Transfer to other ATC	41%	42%	15%	3%
	Accurate	**Acceptable**	**Inaccurate**	
To manage Teamwork	56%	33%	11%	

In this case, two critical paths can be observed that contribute to the realization of the "*Expected event*" *on time*, namely (Figure 36):

To Manage Trust→ Automation supervision →To Manage Teamwork → Human–automation feedback loop → Expected Event, and

Decision making → Instruction issuing → Pilot actions → Transfer to ATC→ Expected Event.

Back-propagation with output accuracy 100% Not at all – Worst case

In the automated system configuration (Figure 37), imposing the same condition produces a markedly different probability distribution. Key operational functions show a substantially higher likelihood of being executed on time: conflicts are detected on time in 35% of cases, instructions are issued on time in 35% as well, pilot reactions occur on time in 27%, and transfer to another ATC unit is completed promptly in 41% of cases.

Organizational factors also demonstrate improved performance compared to the non-automated scenario. The "*Human Factors*" is in the "*Accurate*" state in 47% of cases, "*Competencies*" in 31%, while "*Procedures*" and "*Resources*" are accurate in 33% and 34% of cases, respectively. Furthermore, nodes specific to the automated architecture, such as "*Automation Supervision*" and the "*Human–Automation Feedback Loop*" contribute significantly to the "*On time*" and "*Accurate*" states, reinforcing overall system performance.

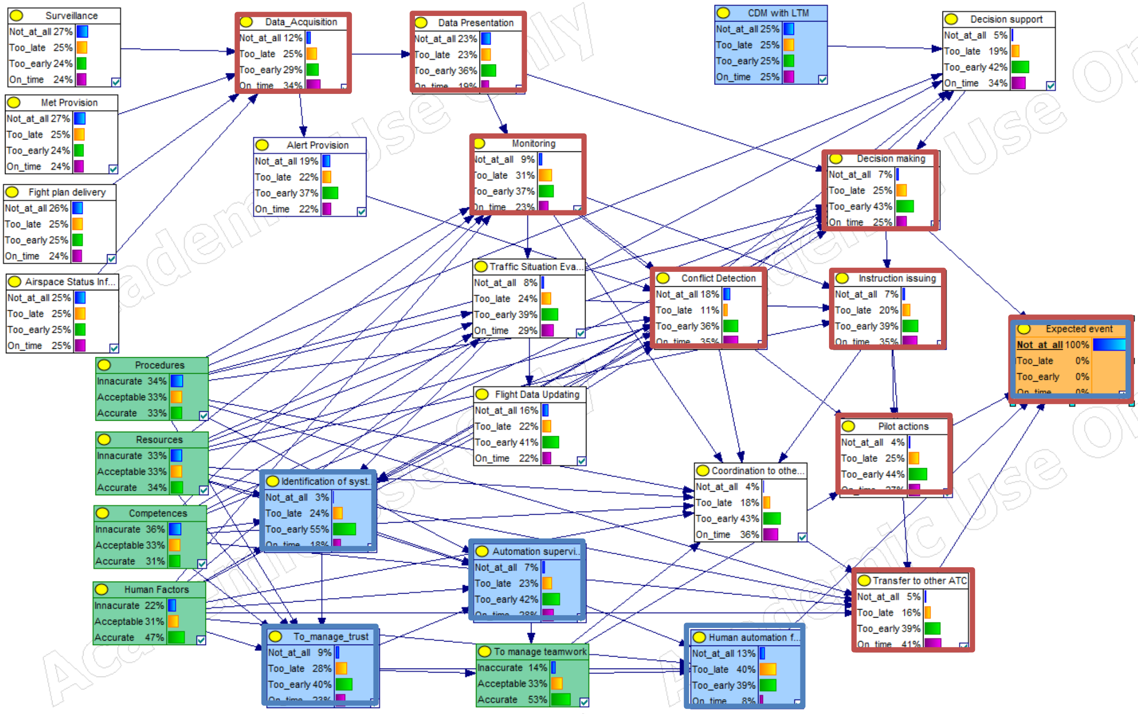


Figure 37. *Bayesian Belief Network Back-Propagation with 100% "not at all" Outcome in the "Expected Event" Node for an Automated Air Traffic Control System*

In this case, two critical paths can be observed, namely (Figure 37):

Data Acquisition → Data Presentation →Monitoring → Conflict Detection → Decision Making → Instruction Issuing → Pilot Actions → Transfer to Other ATC → Expected Event, and

Identification of system expected response → To Manage Trust → Automation Supervision → Human Automation Feedback → Expected Event.

Back-propagation with output accuracy 100% Too early

Backward analysis of the automated ATC system was performed for a scenario where the "*Expected event*" node is set to the state "*Too early*" with a probability of 100% (Figure 38). The results show that the premature realization of the event does not lead to system degradation, but to a marked shift in the temporal dynamics of operational functions. Human functions, such as "*Monitoring*", "*Decision Making*" and "*Pilot Actions*", show a dominant tendency towards the "*Too early*" state, but at the same time retain a significant percentage of "*On time*" realization, which indicates the preserved operational capability of the system.

Automated functions, including "*Conflict Detection*", "*Instruction Issuing*", and "*Automation Supervision*", show a relatively balanced distribution between "*On time*" and "*Too early*" states, without transitioning into critical states.

Organizational functions do not show a significant shift towards the "*Inaccurate*" state, which confirms that the premature realization of the event is not a consequence of organizational disruption, but rather a change in the dynamics of human-automation interaction.

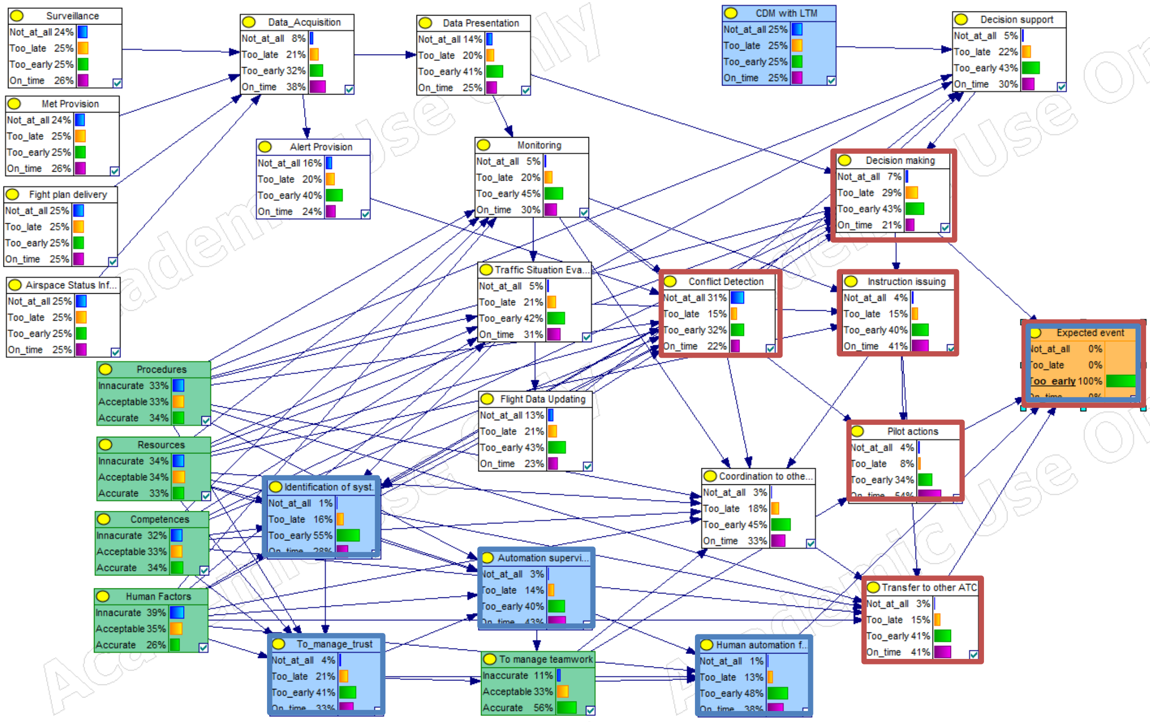


Figure 38. *Bayesian Belief Network Back-Propagation with 100% "too early" Outcome in the "Expected Event" Node for an Automated Air Traffic Control System*

Two dominant critical pathways can be identified in this case. The first corresponds to the core operational chain of the ATC process, consisting of the sequence:

Conflict detection → Decision making → Instruction issuing → Pilot actions → Transfer to other ATC unit → Expected event.

The second critical pathway is related to human–automation interaction and includes the sequence:

Identification of system state → To manage trust → Automation supervision → Human–automation feedback loop → Expected event.

Back-propagation with output accuracy 100% Too late

Backward analysis of the automated ATC in case of a scenario where the "*Expected event*" end node is set to the "*Too late*" state with a probability of 100% is presented in Figure 39. The results show that, in contrast to the non-automated system, there is no global degradation of functions. Most operational nodes, including "*Conflict Detection*", "*Instruction Issuing*", "*Pilot Actions*" and "*Transfer to Other ATC*", retain a significant percentage of realization in the "*On time*" and "*Too early*" states, while the "*Too late*" state is dominant only in the final outcome.

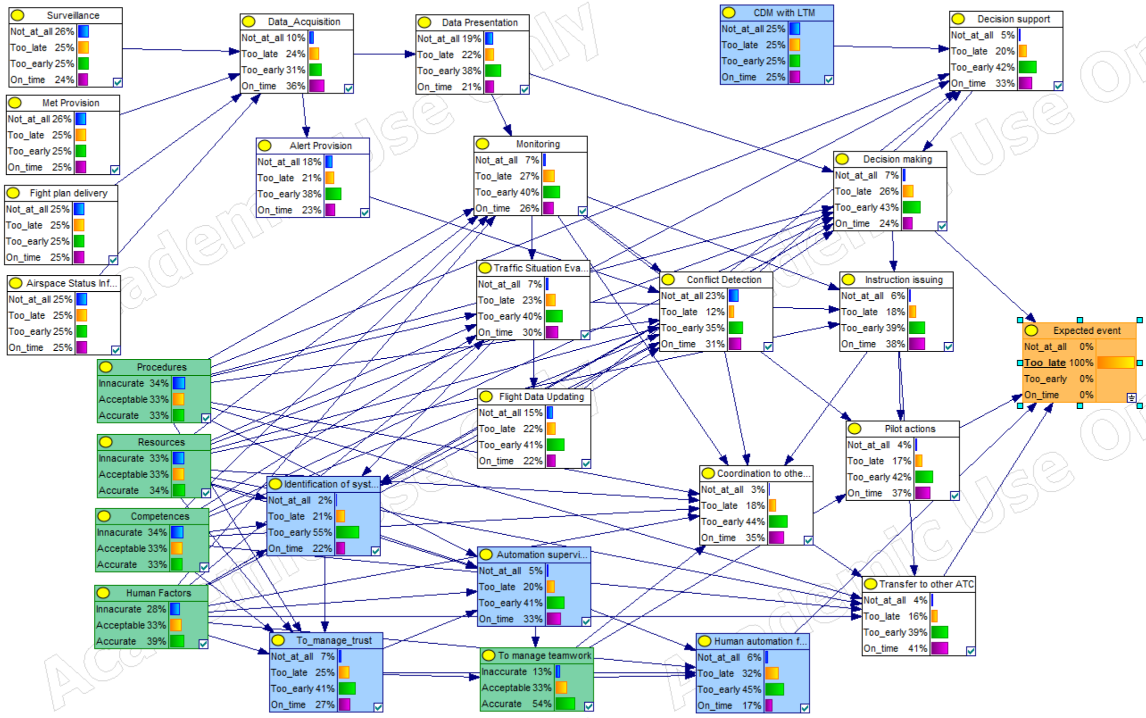


***Figure 39**. Bayesian Belief Network Back-Propagation with 100% "too late" Outcome in the "Expected Event" Node for an Automated Air Traffic Control System*

Organizational functions do not transition to the "*Inaccurate*" state, indicating that the cause of the delay is not a systemic collapse or a decline in organizational support. The analysis shows that the delay is most pronounced in the nodes representing automation interaction and supervision, especially in the functions "*Human–Automation Feedback*" and "*Automation Supervision*". This indicates that the system is functionally stable, but sensitive to disturbances in the coordination between humans and automated processes. Automation maintains the continuity of the execution of routine tasks, but the final failure can occur as a result of disruptions in the integration and synchronization of key control mechanisms, thus shifting the resilience of the system from the operational to the level of management and supervision.It should be noted that in this case no dominant critical pathway can be identified, since the probability of the *too late* state remains lower than the probabilities of the other states throughout the analysed nodes.

6.3. FORWARD ANALYSIS

Forward analysis is a type of probabilistic analysis that allows the analysis of the influence of an input node on the output of a network. In this approach, a probability distribution is associated with the input nodes, while the final probability distribution of the target node is actually calculated by propagating uncertainty through the network. The analysis is conducted with the aim of examining how uncertainties in the input nodes can affect the probability of the final node. This analysis is essentially cause-to-effect analysis in which the marginal distribution of ancestor nodes measure their influence on connected descendant nodes (Wang et al, 2023), and it can be written as follows:

$$P(Consequence|Cause)$$

This analysis is particularly useful for evaluating the effects of introducing automation and for predicting system behavior under different scenarios. This approach enables evaluation of the impact of different inputs on the network output and helps identifying the input nodes with the highest effect on the output (Delgado-Aguilera Jurado et al, 2022).

Forward analysis therefore enables the assessment of how variability propagates within the modified system and whether the automated configuration dampens or amplifies disturbances. After identifying the most influential factors through the Tornado analysis and determining the critical operational path using the backward analysis, a forward analysis was performed in order to examine how variations in the key parameters propagate through the system. This approach enables the evaluation of how variability in critical functions affects the overall system behavior and the realization of the "*Expected event*", particularly in the automated system where operational functions are transferred from the human operator to automated components.

Forward analysis was primarily conducted for the automated ATC system, as this configuration introduces significant structural changes in the distribution of functions between the human operator and the automated system, and it is important to evaluate resilience under these conditions of structural change. While the non-automated system serves as a baseline reference with already established operational behavior, the introduction of automation fundamentally alters system architecture by adding new interaction mechanisms, such as human–automation feedback loops, trust management, and automation reliability. These elements introduce additional sources of variability and nonlinear interdependencies, whose effects cannot be directly inferred without simulation.

Therefore, the forward analysis focused on key nodes related to human–automation interaction and supervision of automation, such as "*Human factors*", "*Human–automation feedback loop*", "*Automation supervision",* and *"To manage trust"*. By setting evidence on these nodes, several operational scenarios were simulated in order to examine how deviations in these functions influence downstream processes and the realization of the expected event. This approach provides additional insight into the resilience of the automated system and the mechanisms through which variability may affect overall system performance. The mentioned scenarios for selected nodes are explained further.

1. Degraded human factor

The first analyzed scenario refers to degraded human factors where the evidence is set to "*Human factors = inaccurate"*. In this case, the analysis includes how basic activities, previously performed by ATCOs, are changing and now are being performed by automation. The main goal of this scenario is to show how ATCO's fatigue, loss of situational awareness, poor mental state, reduced ability to monitor automation, and other related factors can affect the realization of the final event. Although it is an automated system, previous analyses have shown that this node is of exceptional importance for the resilience of the future ATC system, primarily because it affects the quality of the ATCO's reaction in situations when it is needed. Forward analysis for this node is presented in Figure 40.

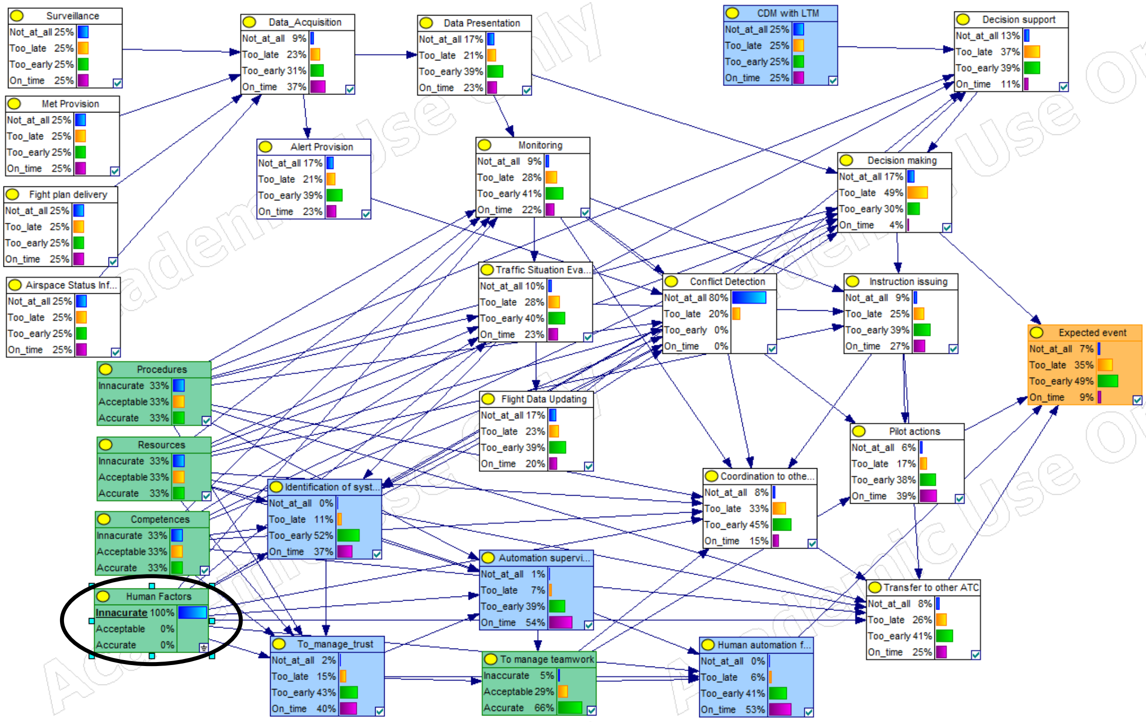


Figure 40. Forward analysis – "Human factors" = Inaccurate

The results of the forward analysis (Figure 40) show noticeable changes in the probability distribution across several nodes in the network. In particular, the probability of the state *too late* in the "*Decision making"* node increases significantly (from 27% to 49%), while the probability of the *on time* state decreases (from 23% to 4%). This indicates that degraded situational awareness and reduced ATCO attention may lead to delayed decision-making processes. In addition, significant changes are observed in the "*Conflict detection"* node ("*not at all*" increase from 27% to 80%), suggesting that insufficient monitoring of automated processes may reduce the likelihood of timely conflict identification. These changes propagate further through the network and ultimately affect the probability distribution of the "*Expected event"*. However, the changes in the final node are not drastic despite the degradation of human performance. Such behavior suggests a certain level of robustness within the system structure.

Note that these changes do not imply that automation itself performs worse, but rather that degraded human supervision and interpretation of automated information may influence how automated outputs are used within the operational process. This illustrates that even in highly automated systems the human operator remains an essential component of system performance and resilience.

2. Automation supervision problem

In this scenario, the "*Automation supervision*" node is set to the *too late* state to examine what happens in situations where the ATCO does not notice the existence of an automation problem in time.

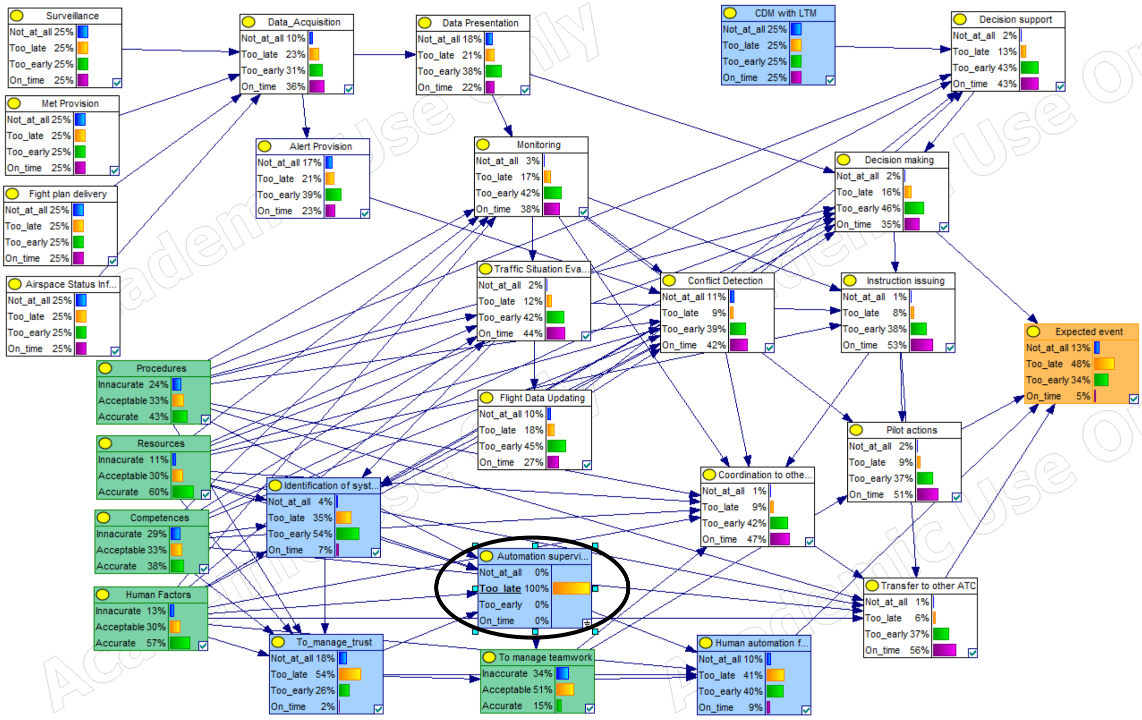


Figure 41. Forward analysis – "Automation supervision" = Too late

The results (Figure 41) show noticeable changes in several nodes related to human–automation interaction. First of all, a change is observed in the node that is actually an influential node to the node being analyzed, which is the node "*To manage trust*". It can be observed that it shifts predominantly to the state *too late*, reaching a probability of 54% (23% in baseline scenario), while the probabilities of the states *too early*, *not at all*, and *on time* are 26%, 18%, and 2%, respectively (41%, 6% and 30% in baseline scenario, respectively). In addition, the node "*Human–automation feedback loop"* exhibits significant temporal variability, with probabilities of 41% for *too late*, 40% for *too early*, 10% for *not at all,* and only 9% for *on time* (23%, 45%, 4%, and 28% in baseline scenario, respectively).

Ultimately, these changes influence the final node "*Expected event*", where the probability of the *too late* realization becomes dominant at 48%, followed by 34% for *too early*, 13% for *not at all*, and only 5% for the *on time* realization (41%, 42%, 10%, 7% in baseline scenario, respectively). This indicates that delayed supervision of automated processes primarily shifts the system toward delayed operational outcomes, highlighting the critical role of timely human oversight in maintaining the performance and resilience of automated air traffic control systems.

3. Poor interaction between humans and automation

In order to examine the impact of delayed information from automation or late ATCO reaction due to incomplete or incorrect information from automation on the final outcome, the "*Human-automation feedback loop*" node was set to the *too late* state (Figure 42).

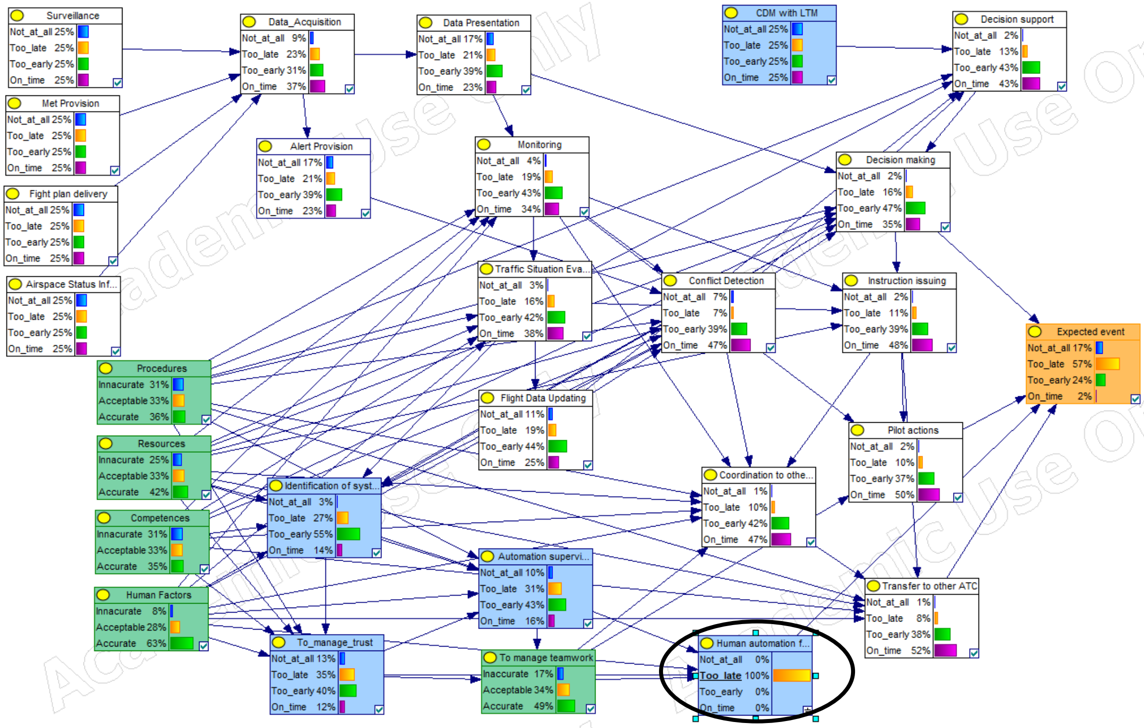


Figure 42. Forward analysis – "Human-automation feedback loop" = too late

The effects of the delayed human–automation interaction are clearly reflected in the final node "*Expected event*", where the probability of the *too late* realization becomes dominant at 57% (41% in baseline scenario), followed by 24% for *too early* (42% in baseline scenario), 17% for *not at all* (10% in baseline scenario), and only 2% for the *on time* realization (7% in baseline scenario). These results indicate that delays in the human–automation feedback loop may significantly shift system performance toward delayed operational outcomes.

Further on, from Figure 42, it can be seen that a change in the analyzed node propagates through the network and leads to changes in probabilities within nodes to which it is not directly connected. Practically, the node "*Decision making*" shifts toward earlier decisions, with the probability of the state *too early* reaching 47% (43% in baseline scenario), while the probabilities of the states *on time* and *too late* become 35% and 16% (23 and 27% in baseline scenario), respectively.

In the node "*Conflict detection*", the probability of the *on time* state remains relatively high at 47% (27% in baseline scenario), followed by 39% for the *too early* state (33% in baseline scenario), indicating that the automated detection process remains relatively stable despite the delayed feedback.

However, the node "*Instruction issuing*" shows increased temporal variability, with probabilities of 48% for *on time* (39% in baseline scenario), 39% for *too early* (identical as in baseline scenario), and 11% for *too late* (17% in baseline scenario).

4. Problems with ATCO' trust in automation

The node “*To manage trust”* represents the timing of the ATCO’s trust calibration in relation to the automated system. When trust is managed *on time*, the ATCO appropriately balances reliance on automation with active supervision, which supports stable system performance. If trust is established *too early*, the ATCO may rely excessively on automated recommendations, leading to reduced monitoring of the system, which may increase the risk of delayed or unsuccessful event realization. Conversely, when trust is established *too late*, the ATCO may hesitate to rely on automation, potentially delaying decision-making and operational actions. Finally, the state *not at all* represents the absence of trust in automation, where automated support is largely disregarded.

“To manage trust” = too early

When the node “*To manage trust”* is set to the state *too early* (Figure 43), the results indicate the effects of premature trust in automation. This situation represents a scenario in which the ATCO relies on automated recommendations earlier than appropriate, which may reduce the level of active supervision. This situation may indicate an over-trust in automation. In such situations, operators may accept system outputs without sufficient verification, potentially reducing active monitoring of the system. If the automation provides inaccurate or incomplete information, this excessive reliance may increase the likelihood of unexpected operational events and negatively affect overall system resilience (Timotic and Netjasov, 2022).

The changes are first observed in the nodes directly connected to “*To manage trust”*. In the node “*Automation supervision”*, the probability of the *too early* state increases to 50% (41% in baseline scenario), followed by 39% for *on time* (38% in baseline scenario) and 17% for *too late*, indicating that the operator may prematurely rely on automation and reduce monitoring of its performance. A similar tendency appears in the node “*Human–automation feedback loop”*, where the probabilities become 48% for *too early* (45% in baseline scenario), 26% for *on time* (28% in baseline scenario), and 22% for *too late* (23% in baseline scenario), suggesting earlier but less stable interaction between the human operator and automated functions.

The probability distribution of the final node “*Expected event”* remains unchanged. This indicates that premature trust in automation does not significantly alter the overall distribution of the final outcomes in the model. The reason for this lies in the distributed structure of the system, where the final event depends on the interaction of several operational functions rather than on a single node.

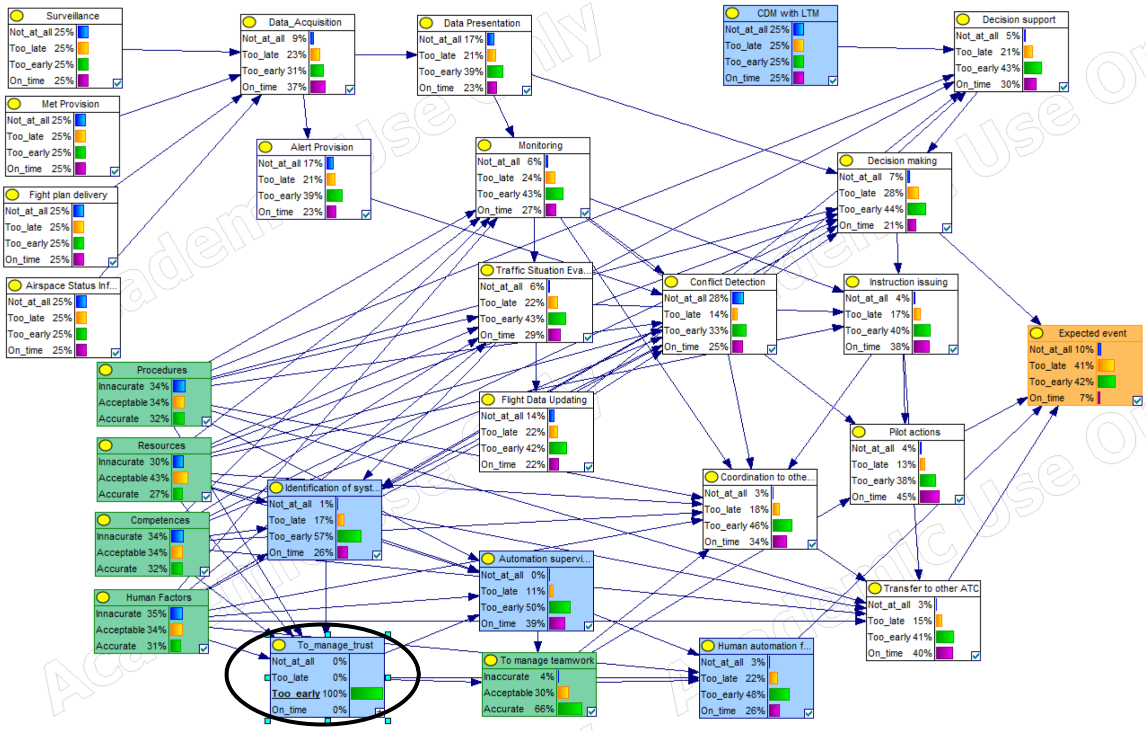


Figure 43. Forward analysis – "To manage trust" = Too early

"To manage trust" = too late

A forward analysis (Figure 44) was performed by setting the node "*To manage trust*" to the "too late" state to examine the effects of delayed trust in automation. This scenario represents a situation in which the ATCO develops trust in the automated system later than appropriate, leading to excessive verification of automated recommendations. This situation indicates the under-trust in the system automation. When automated support is not utilized fully and additional verification steps delay operational decisions, such behaviour can reduce the efficiency of the automated system and increase the probability of delayed operational outcomes (Timotic and Netjasov, 2022).

In the node "*Automation supervision*", the probabilities become 44% for *too early*, 40% for *too late*, 9% for *not at all*, and only 8% for *on time* (41%, 17%, 4%, and 38% in baseline scenario, respectively), indicating unstable supervision of automated processes.

In the node "*Human–automation feedback loop*", the probabilities shift to 44% for *too early*, 34% for *too late*, 14% for *on time*, and 8% for *not at all* (45%, 23%, 28% and 4% in baseline scenario, respectively), suggesting temporal misalignment in the interaction between the human operator and the automated system.

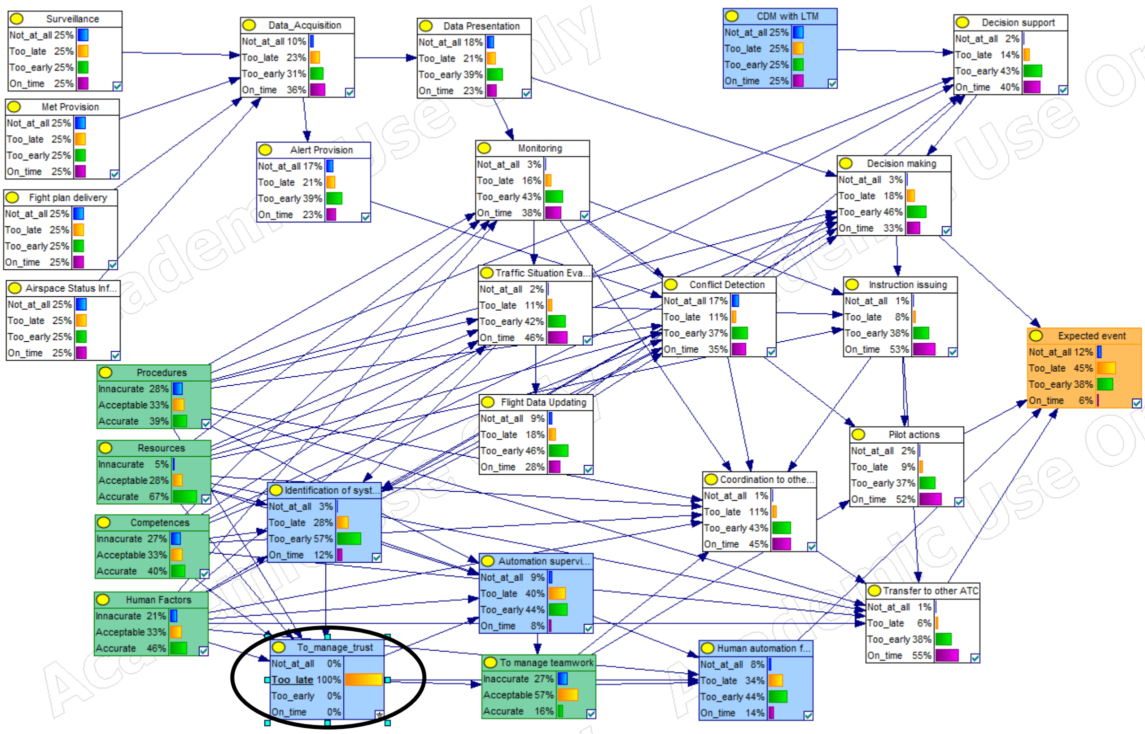


Figure 44. Forward analysis – "To manage trust" = Too late

In the node "*Human–automation feedback loop*", the probabilities shift to 44% for *too early*, 34% for *too late*, 14% for *on time*, and 8% for *not at all* (45%, 23%, 28% and 4% in baseline scenario, respectively), suggesting temporal misalignment in the interaction between the human operator and the automated system.

The node "*To manage teamwork*" also shows changes, with 57% for *acceptable*, 27% for *inaccurate*, and 16% for *accurate* (33%, 12%, and 55% in baseline scenario, respectively), indicating reduced efficiency in human–automation collaboration. These changes propagate further through the operational nodes. The cumulative effect of these changes is reflected in the final node "*Expected event*", where the probability of the *too late* realization becomes dominant at 45% (41% in baseline scenario), followed by 38% for *too early*, 12% for *not at all*, and 6% for *on time* (42%, 10% and 7% in baseline scenario, respectively). These results suggest that delayed trust in automation may introduce instability in the timing of operational processes and increase the likelihood of delayed system outcomes.

"To manage trust" = on time

A forward analysis was performed by setting the node "*To manage trust*" to the state *on time* (Figure 45) in order to examine the effects of appropriately calibrated trust in automation. This scenario represents a situation in which the ATCO develops trust in the automated system at the appropriate moment, allowing the operator to rely on automation while maintaining adequate supervision.

According to the results of the analysis, in the node "*Automation supervision*", the probability of the *on time* state increases to 67%, followed by 32% for *too early* and 1% for *too late* (38%, 41% and 17% in baseline scenario, respectively), indicating stable and timely supervision of automated processes.

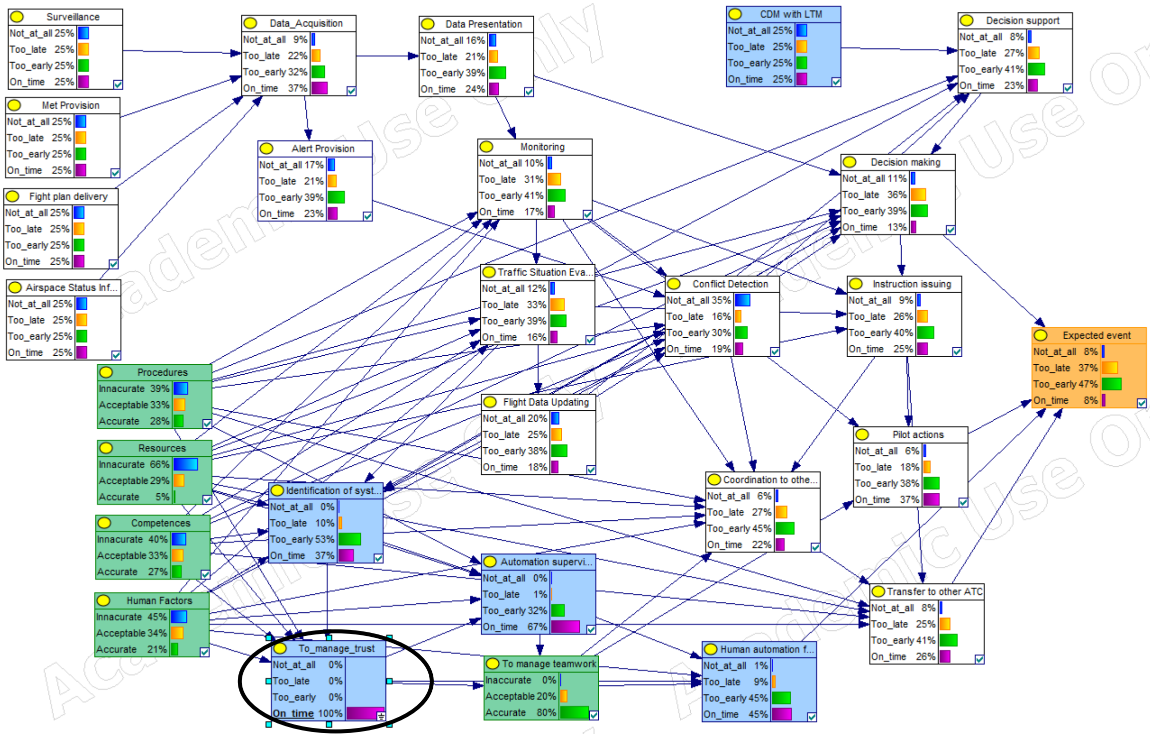


Figure 45. Forward analysis – "To manage trust" = on time

In the node "*Human–automation feedback loop*", the probabilities that are changed are 45% for *on time* (28% in baseline scenario), 9% for *too late (*23% in baseline scenario), and 1% for *not at all* (4% in baseline scenario) while the percentage of too early realisation didn't changed (45% in both scenarios). This suggests, relatively balanced interaction between the human operator and automated functions.

Furthermore, the node "*To manage teamwork*" shows a dominant *accurate* state of 80% (55% in baseline scenario), followed by 20% for *acceptable* (33% in baseline scenario), while the *inaccurate* state disappears entirely, indicating improved human–automation coordination.

These changes propagate through the network affecting the operational nodes. In the node "*Decision making*", the probabilities become 39% for *too early*, 36% for *too late*, 13% for *on time*, and 11% for *not at all* (43%, 27%, 23% and 7% in baseline scenario, respectively), indicating moderate temporal variability in decision processes.

Finally, the node "*Expected event*" shows 47% for *too early*, 37% for *too lat*e, 8% for *on time*, and 8% for *not at all* (42%, 41%, 7% and 10% in baseline scenario, respectively), suggesting that although appropriately calibrated trust supports stable system behavior, the overall variability of the operational process remains present.

"To manage trust" = not at all

This scenario represents an extreme case in which the ATCO does not develop trust in the automation at all (Figure 46). This means that the operator constantly checks the system, does not rely on its recommendations and retains full control over the decision-making process. This scenario can be interpreted as a complete lack of trust in the automated system, which can lead to increased operator workload and disruption in human-automation interaction.

In the node "*Automation supervision*", the probability of the *too late* state becomes dominant at 53% (17% in baseline scenario) while only 1% for *on time* (38% in baseline scenario), indicating inefficient supervision of automated processes. In the node "*Human–automation feedback loop*", the probabilities become 49% for *too late* (23% in baseline scenario), and just 6% for *on time* (28% in baseline scenario), suggesting a significant temporal misalignment in the interaction between the human operator and the automated system. Furthermore, the node "*To manage teamwork*" shifts predominantly to the *inaccurate* state with a probability of 72% (12% in baseline scenario), and only 3% for accurate (55% in baseline scenario), indicating deteriorated collaboration between the human operator and automated functions.

Ultimately, the effects of these changes appear in the final node "*Expected event*", where the probability of the *too late* realization becomes dominant at 50% (41% in baseline scenario), followed by 31% for *too early*, 15% for *not at all*, and 4% for the *on time* realization (42%, 10% and 7% in baseline scenario, respectively), indicating that the absence of trust in automation may lead to delayed system performance.

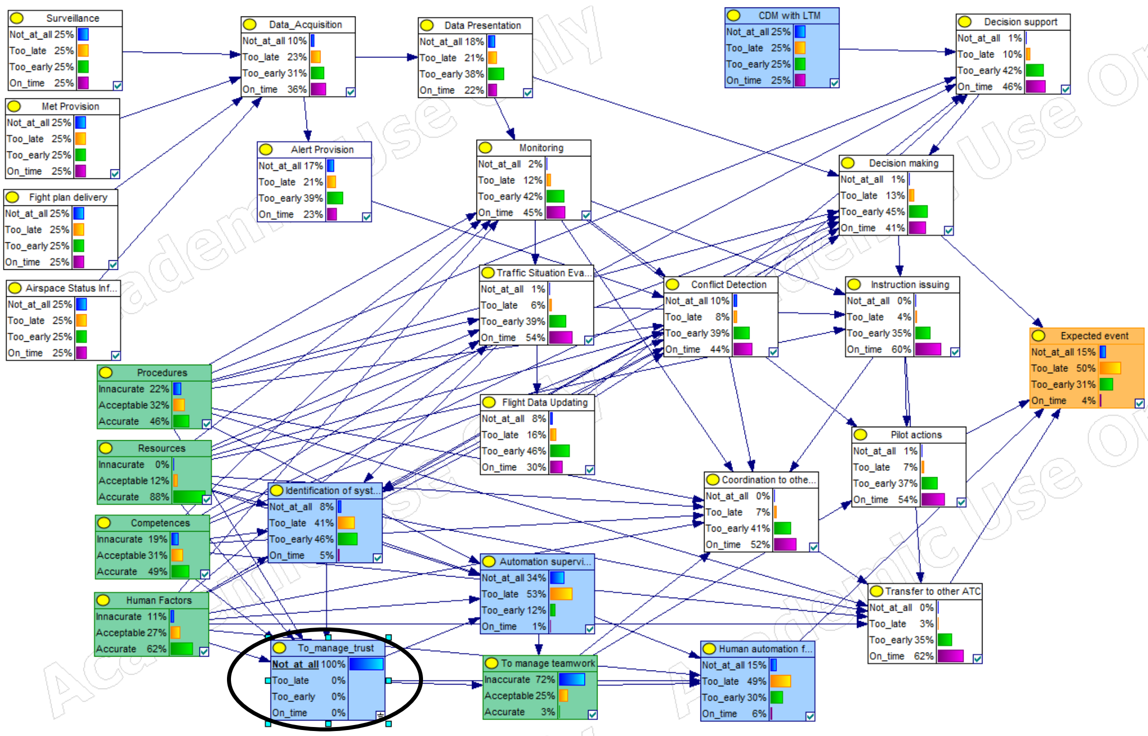


Figure 46*. Forward analysis – "To manage trust" = not at all*

The overall analysis of the influence of different trust states on the realization of "Expected event"

Figure 47 shows the influence of different trust states on the probability distribution of the "*Expected event*" node. The results were obtained through backward analysis, where the node "*To manage trust*" was fixed in different states in order to observe how variations in trust calibration influence the final system outcome. The results indicate that trust calibration significantly affects the temporal distribution of operational outcomes, particularly the balance between delayed and premature realizations of the expected event.

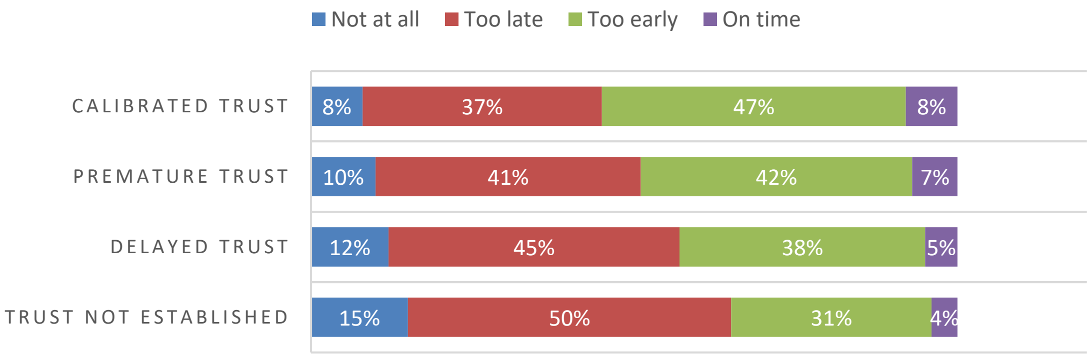


Figure 47. Influence of trust calibration on the probability distribution of the Expected event node

When trust is not established, the probability of the *too late* realization reaches the highest value of 50%, while the probability of *too early* realization is 31%, and *on time* realization remains very low (4%). This suggests that insufficient trust in automation may lead to delayed system responses, as operators tend to verify automated outputs or hesitate to rely on automated support. When trust is delayed, the probability of *too late* realization slightly decreases to 45% relative to trust not established, while the probability of *too early* realization increases to 38%, indicating a gradual shift in system behaviour as trust begins to develop.

In the case of premature trust, representing a situation of potential over-trust in automation, the probability of *too early* realization is 42%, while the probability of *too late* is 41%. This suggests that excessive reliance on automation may cause the system to react earlier than necessary. Finally, when trust is calibrated appropriately, the distribution becomes more balanced. The probability of *too early* realization reaches 47%, while the probability of *too late* realization decreases to 37%, and the probability of *on time* realization increases to 8%, which is the highest among the analysed scenarios. This indicates that appropriate trust calibration improves the temporal coordination of system functions and contributes to more stable system behaviour.

Overall, the results show that trust calibration acts as a regulatory mechanism that shifts system behaviour between delayed and premature responses. While insufficient trust leads to delayed outcomes, excessive trust tends to push system behaviour toward premature actions. Balanced trust supports more stable system performance, although the probability of perfectly *on time* outcomes remains relatively limited due to the inherent variability of complex socio-technical functions in ATC system.

7. CONCLUSION

The introduction of advanced automated tools, machine learning methods and artificial intelligence into the ATC system is expected to contribute to more efficient execution of operational tasks and improve the management of complex and dynamic operational situations. These technological innovations represent significant potential for improving the overall performance of ATM system, while simultaneously increasing airspace capacity and providing additional support to ATCOs in dealing with increasing operational demands.

In such an environment, safety remains a basic system requirement, while resilience is increasingly recognized as a key feature that needs to be systematically considered during all phases of system development and modernization. The increase in the level of automation inevitably affects the change in the role and position of ATCOs within the human-machine system. Accordingly, the main motive for choosing this research topic results from the significant impact that the introduction of automation has on the role and position of the human operator within the human-machine system. As automated systems take over an increasing share of operational functions, the nature of human participation in the management process is also changing from the immediate execution of tasks to the monitoring of system operation, timely intervention and system recovery in the event of a disruption. Such a transformation requires careful consideration of the relationship between the efficiency brought by automation and the specific capabilities of human operators, especially in non-nominal or degraded operating conditions, when the ability to adapt and recover the system becomes crucial.

Also, trust represents one of the key elements of the relationship between humans and automation, and an additional motive for conducting this research is the need to establish an appropriate level of trust in the newly introduced automated systems. For ATCOs, trust in system functionality plays a significant role in achieving effective and balanced interaction between humans and automated tools. An environment in which trust in automation is properly calibrated with avoiding both uncritical reliance on the system and excessive suspicion of its operation is essential for automation to be applied in a safe, adequate and effective manner.

Therefore, the basic idea of this research is a proactive consideration of the future ATC system for which there is still no available empirical operational data. The goal is to assess the safety and resilience of the system, both in its current state and after the introduction of automation. This proactive approach enables early recognition of potential system vulnerabilities, changes in the distribution of roles within the system, as well as the appearance of new forms of variability in performance. In this way, support is provided for making informed decisions during the process of designing and implementing future system solutions.

The research was conducted through the creation of two scenarios: a non-automated ATC system, in which activities are mostly performed by a human, and an automated ATC system in which automation takes over the main function of the activity performer, while a human is responsible for monitoring and intervening as necessary.

The research methodology included several steps: first, it was necessary to define the purpose and scope of the research, and then to choose how to conduct a qualitative and quantitative analysis of the aforementioned scenarios. Given that the ATC system represents a socio-technical environment composed of human, technological, and organizational elements that continuously interact with each other, it was necessary to select analytical methods capable of addressing such systemic complexity. An additional challenge in this research was the absence of empirical operational data, as the study considers a future system for which real-world data are not yet available. Consequently, the research relied on insights drawn from relevant scientific literature, findings from previously completed projects addressing similar topics, and consultations with domain experts in order to support the analysis and methodological approach.

Consequently, two complementary methods were applied in the analysis. For the qualitative part of the study, the FRAM method was employed to model system functions/activities and their interactions. Two FRAM models were developed in FRAM Model Visualizer software: the first representing a non-automated system consisting of 25 functions, each corresponding to activities within the ATC system performed by humans, technological systems, or organizational structures, and the second, representing an automated system comprising 29 functions. The latter model includes the functions from the previous model with modified executors, as well as additional functions primarily related to human–automation interaction.

The FRAM method enables a comprehensive representation of the activities performed by an ATCO during operational work and captures the relationships between these activities. It also allows the examination of how performance variability may arise during the execution of these functions and how such variability can propagate throughout the system. Once the main functions are identified, their couplings and potential variability can be further analyzed based on expert judgment. After the FRAM models were developed, the variability of the functions was identified through internal and external performance variability analysis, as well as through upstream–downstream variability analysis.

Following this qualitative assessment, it was necessary to define an appropriate method for the potential quantification of the previously established FRAM models. Since the main objective of this research is the analysis of both resilience and safety in a future ATC system, the BBN method was selected for the quantification phase. BBN represents a probabilistic approach that, based on expert judgment and prior knowledge, enables quantitative inference and supports proactive system analysis. The combined application of FRAM and BBN methods enables a more comprehensive analysis of complex socio-technical systems, because FRAM provides insight into the system structure, function interdependencies and potential performance variability, while BBN enables the quantification of those relationships and the analysis of their impact on system safety and resilience.

Prior to the quantification process, the FRAM functions were transformed into nodes within the BBN structure followed by the definition of the corresponding probabilities and the construction of CPTs. Considering the functional variability identified through the FRAM analysis, each node was characterized by multiple states: organizational nodes were defined by three states (accurate, acceptable, inaccurate), while the remaining nodes were described by four states (on time, too early, too late, not at all). Following a comprehensive analysis and consultations with domain experts, the WMEAN method was selected as an appropriate approach for probability elicitation providing an initial set of logically consistent probabilities, but without inherently definition of all intermediate combinations of parent node states, particularly when parent nodes contain more than two possible states. Under the assumption of linear relationships between nodes, linear interpolation was applied to estimate probabilities for combinations of parent states that were not explicitly defined. Through the use of linear interpolation, the resulting child-node probabilities change gradually and consistently between defined extreme points, enabling a more realistic representation of system behavior.

On the basis of the formed quantified models, the probabilities of realization of the final node were calculated. In the case of a non-automated system, the results show that the "*Expected event*" is realized *on time* in almost half of the cases, while in about 36% of cases it is realized earlier, which can still be considered acceptable because it does not threaten the safety of the system. This distribution indicates the ability of the system to mitigate variability and maintain stability of operations.

On the other hand, the results of the BBN model for the automated system show a significantly different distribution. The most likely outcomes are *too early* (41.9%) and *too late* (41.3%), while the realization *on time* is much less common (6.9%). This indicates a loss of temporal precision and coordination in the system, which can lead to a decrease in its resilience. Also, the increased probability of the state *not at all* (9.9%) indicates the risk that a key event is not realized, for example due to problems in the operation of the automation, insufficient feedback or an inadequate level of trust in the system. The nodes "Human–automation feedback loop" and "To manage Trust" play a key role in preserving the resilience of the system, because they affect the ability of the system to adapt and recover from deviations and are especially highlighted in this analysis.

In order to identify the activities that affect the resilience of the future ATC system the most, a sensitivity analysis was conducted. The analysis was carried out in the GeNIE Academic software, using three complementary methods within the BBN framework: Tornado analysis, backward analysis and forward analysis. Although all three methods are based on probabilistic reasoning, they differ in the logical direction of the analysis, the purpose and the method of interpretation of the results: backward and forward analysis belong to the "sensitivity-to-evidence" approach, which examines how a change in the probability of a certain node (evidence) affects the target node, while Tornado analysis represents a "sensitivity-to-parameters" approach, which evaluates the sensitivity of the target node to changes in numerical values in CPT.

Accordingly, the main conclusions and contributions that can be drawn from the present research are as follows:

- A non-automated system exhibits greater flexibility because it relies on human adaptation and coordination. Multiple functions, such as monitoring, conflict detection, decision making and pilot activities, can mutually compensate for deviations, thus contributing to system stability and resilience.

- An automated system reduces variability in routine tasks, but at the same time loses precision in time coordination. In this way, instead of amortizing variability, the system can generate new deviations. Therefore, it is necessary to improve the detection of system reactions, properly calibrate the trust between humans and automation, optimize feedback (clear, fast and unambiguous information) and define procedures for dealing with situations when automation does not respond.

- The results of the sensitivity analysis show that the resilience of the non-automated system primarily results from human adaptation, coordination and organizational stability. Organizational factors have a key influence, as well as pilot activities and decision-making, while technology plays an important, but above all supporting role by providing information for operational decision-making.

- In an automated system, the distribution of impacts changes, with human factors becoming the most critical element of resilience. Despite the greater degree of automation, the stability of the system depends to a large extent on the quality of interaction between humans and automation, as well as on the reliability and accuracy of the information on which the automated systems base their decisions.

- In a non-automated system, the key resilience path includes nodes such as Monitoring, Conflict Detection, Decision Making, Instruction Issuing, Pilot Actions, Transfer to ATC, and Expected Event.

- In an automated system, the two key paths include nodes such as: a) To Manage Trust, Automation Supervision, To Manage Teamwork, Human–Automation Feedback Loop to Expected Event, and b) Decision Making, Instruction Issuing, Pilot Actions, Coordination, and Transfer to ATC for the Expected Event.

- In both scenarios, certain functions can compensate for the variability of other, but in the automated system overall performance becomes more dependent on a smaller set of key ATCO supervisory activities.

- In the non-automated system, resilience emerges from the distribution of responsibilities across multiple interconnected human-driven functions, while in the automated system resilience depends on fewer critical nodes, increasing efficiency in nominal conditions but also vulnerability in case of disruptions.

- The non-automated system tends to fail because most functions struggle to achieve the *on time* state, whereas the automated system maintains higher reliability in routine tasks even when the final event is not realized.

- Consequently, automated systems require carefully designed redundancy, transparent human–automation feedback mechanisms, proper trust calibration, and clearly defined fallback procedures to maintain system resilience.

- In automated system, degradation of human factors (fatigue, loss of situational awareness, reduced attention) significantly affects operational functions such as decision-making and conflict detection. In particular, there is an increase in the probability of delays in decision-making and a reduced probability of timely conflict detection. Although automation can mitigate some of the consequences, the results show that the quality of human supervision still plays a key role in maintaining system resilience.

- A delay in the supervision of automated processes leads to a shift in the system towards a delay in the realization of operational outcomes. This scenario clearly shows that automated systems require continuous and timely human supervision to maintain the stability and efficiency of operations.

- A delay in the interaction between the ATCO and the automated system significantly increases the likelihood of the final event being delayed. Although automated processes, such as conflict detection, can remain relatively stable, the lack of timely information exchange between human and system negatively affects the coordination of operational activities.

- The results show that both under-trust and over-trust can negatively affect system performance in automated system. Under-confidence leads to delays in operations due to additional checks and reduced use of automation, while over-confidence can reduce the level of oversight of the system. The most stable behavior of the system is achieved when trust is properly calibrated, because then there is a balanced cooperation between human and automation.

- The stability of the system does not depend exclusively on the reliability of the technology, but on the coordinated functioning of human, organizational and technological elements, whereby human supervision, the quality of the feedback loop and the correct calibration of trust are key factors in preserving resilience.

Based on the conducted analysis, it can be concluded that the combined application of FRAM and BBN methods enables a comprehensive analysis of the ATC system. While FRAM provides insight into the structure of the system, the interdependencies of functions and the variability of their execution, BBN enables the quantification of those relationships and the assessment of their impact on final outcomes through probabilistic inference. This approach enables proactive risk management, identification of strategies to increase system resilience, as well as the implementation of reliable safety analysis, which contributes to the development of effective and proactive policies in ATC.

Finally, future research directions may include the following:

- Extending the model to different levels of automation - future research could analyze different levels of automation in ATC systems where automation has begun to be introduced, and examine how changes in the distribution of functions between humans and automation affect the safety and resilience of the system.

- A more detailed analysis of trust in automation - one direction of further research may be the development of more detailed models for the assessment and calibration of trust in automation, including psychological, organizational and operational factors that influence the formation of trust in ATCOs.

- Analysis of extreme or crisis operational scenarios - the model could be further extended by analyzing non-nominal situations, such as technical failures, loss of communication or sudden increase in traffic, in order to assess the resilience of the system under critical conditions.

- Integration with other methods for resilience analysis - further research may consider combining the FRAM–BBN approach e.g agent-based modeling or simulation models, to obtain an even more complete picture of system behavior.

To conclude, the results of this research indicate that a sustainable transformation towards a highly automated ATM system requires careful balancing between the technological possibilities of automation and the adaptive abilities of human operators, because their integration is a key prerequisite for preserving the safety and resilience of future systems.

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APPENDIX A

***Table A 1**. Function aspects description – non-automation scenario*

Name of Function/Aspects	***F1: To display data at CWP***
Input	Meteorological data provided
	Flight data from the radar was provided
	ADS-B data
	Data from flight plans
Output	Visual representation of the traffic situation in the observed airspace
	Visual display of potential conflict
	Real-time aircraft data
Precondition	n/a
Resource	n/a
Control	n/a
Time	Performed continuously in real time
Name of Function/Aspects	***F3: To monitor flights according to adherence to the flight plan***
Input	Airspace status updates
	Real-time aircraft data
Output	Flight trajectory checked
	Alerts for deviations from flight plans
Precondition	The human operator is in an adequate mental and physical condition
	ATCO is available at the workstation
Resource	Executive and Planner Controllers
Control	Monitoring procedures
	Compliance with technical training requirements
Time	Performed continuously in real time
Name of Function/Aspects	***F4: To evaluate the traffic situation***
Input	Flight trajectory checked
	Meteorological data provided
	Airspace status updates
Output	Traffic situation evaluated
	Complexity issue detected
Precondition	The human operator is in an adequate mental and physical condition
	ATCO is available at the workstation
Resource	Executive and Planner Controllers
Control	New flight data available
	Minimum separation criteria
Time	Performed continuously in real time
Name of Function/Aspects	***F5: To provide alert***
Input	Visual display of potential conflict
Output	Alert issued
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F6: To update flight data***
Input	Traffic situation evaluated
Output	Flight data updated
Precondition	n/a
Resource	n/a
Control	New flight data available
Time	n/a
Name of Function/Aspects	***F7: To issue a warning***
Input	Risk monitoring provided
	Alerts for deviations from flight plans
Output	Warning of potential conflict

Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F8: Conflict detection***
Input	Alert issued
	Flight data updated
	Warning of potential conflict
Output	Conflict warning detected
	Coordination warming detected
Precondition	Airspace status updates
	The human operator is in an adequate mental and physical condition
	Minimum separation criteria
	ATCO is available at the workstation
Resource	Executive and Planner Controllers
Control	Compliance with technical training requirements
Time	n/a
Name of Function/Aspects	***F9: To issue Complexity Solution Measures***
Input	Flight data updated
	Complexity issue detected
	Conflict warning detected
	Complexity solution measures need
Output	Complexity Solution Measure provided
Precondition	n/a
Resource	n/a
Control	Complexity procedures
Time	n/a
Name of Function/Aspects	***F10: Decision Making***
Input	Conflict warning detected
	Complexity Solution Measure provided
	Visual representation of the traffic situation in the observed airspace
Output	Instruction decided
Precondition	The human operator is in an adequate mental and physical condition
	ATCO is available at the workstation
Resource	Executive and Planner Controllers
Control	New flight data available
	Clearance procedures
	Compliance with technical training requirements
Time	n/a
Name of Function/Aspects	***F11: To issue instructions***
Input	Instruction decided
Output	Instruction issued
	Flight is ready to be transferred
Precondition	ATCO is available at the workstation
Resource	n/a
Control	Traffic situation evaluated
Time	n/a
Name of Function/Aspects	***F12: To implement solutions***
Input	Instruction issued
Output	Solution strategies were communicated to pilots
	New flight data available
Precondition	ATCO is available at the workstation
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F13: To contact pilots***
Input	The most current flight information is provided

	Solution strategies were communicated to pilots
Output	The pilot implemented the instruction
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F14: To co-ordinate with other controllers***
Input	Coordination warming detected
	Instruction issued
	Airspace status updates
Output	Coordination messages provided
Precondition	The human operator is in an adequate mental and physical condition
	ATCO is available at the workstation
Resource	Executive and Planner Controllers
Control	Coordination procedures
	Compliance with technical training requirements
Time	n/a
Name of Function/Aspects	***F15: To transfer control of aircraft to the appropriate Controller/Systems***
Input	Coordination messages provided
	Flight is ready to be transferred
Output	Flight is transferred
Precondition	The human operator is in an adequate mental and physical condition
	ATCO is available at the workstation
Resource	Executive and Planner Controllers
Control	Communication procedures
	Compliance with technical training requirements
Time	n/a
Name of Function/Aspects	***BG1: Surveillance data processing***
Input	n/a
Output	ADS-B data
	Flight data from radar was provided
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG2: Flight plans delivery***
Input	n/a
Output	Data from flight plans
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG3: To provide MET data***
Input	n/a
Output	Meteorological data provided
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG4: To provide information on airspace status***
Input	n/a
Output	Updated airspace information is available to controllers
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a

Name of Function/Aspects	***BG5: To manage resources***
Input	n/a
Output	ATCO is available at the workstation
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG6: To manage competence***
Input	n/a
Output	Compliance with technical training requirements
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG7: To manage procedures***
Input	n/a
Output	Monitoring procedures
	Coordination procedures
	Clearance procedures
	Min separation criteria
	Complexity procedures
	Communication procedures
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG8: Human factors***
Input	n/a
Output	The human operator is in an adequate mental and physical condition
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG9: CDM with LTM***
Input	n/a
Output	Complexity solution measures need
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG10: Traffic release (Expected Event)***
Input	The pilot implemented the instruction
	Flight is transferred
Output	n/a
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a

Table A 2. *Function aspects description - automation scenario*

Name of Function/Aspects	***F1: To display data at CWP***
Input	Flight data from the radar was provided
	ADS-B data
	Data from flight plans
	Update airspace status to controllers
	Meteorological data update
Output	Visual display of airspace situations
	Visual display of potential conflict
	Real-time aircraft data
	Updated airspace status to controllers
	Meteorological data provided
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F2: To monitor the air traffic situation in the given airspace***
Input	Visual display of airspace situations
	Updated airspace status to controllers
Output	Airspace status updates
	The most current flight information is provided
Precondition	Instruction issued
	System tool is available
	Humans are aware of the situation or surroundings
Resource	System tools
Control	Monitoring procedures
	Technical training for ATCO on automation
	Skill training for ATCO
	System tools update
Time	Performed continuously in real time
Name of Function/Aspects	***F3: To monitor flights according to adherence to the flight plan***
Input	Airspace status updates
	Real-time aircraft data
Output	Flight trajectory checked
Precondition	System tools update
	System tool is available
	Humans are aware of the situation or surroundings
Resource	System tools
Control	Technical training for ATCO on automation
	Skill training for ATCO
	Monitoring procedures
Time	Performed continuously in real time
Name of Function/Aspects	***F4: To evaluate the traffic situation***
Input	Flight trajectory checked
	Airspace status updates
	Meteorological data provided
Output	Traffic situation evaluated
	Complexity issue detected
Precondition	System tool is available
	Humans are aware of the situation or surroundings
Resource	System tools
Control	New flight data available
	Technical training for ATCO about automation
	Skill training for ATCO
	System tools update
	Minimum separation criteria
Time	Performed continuously in real time
Name of Function/Aspects	***F5: To provide alert***

Input	Visual display of potential conflict
Output	Alert issued
Precondition	System tool is available
Resource	System tools
Control	n/a
Time	n/a
Name of Function/Aspects	***F6: To update flight data***
Input	Traffic situation evaluated
Output	Flight data updated
Precondition	System tool is available
Resource	n/a
Control	New flight data available
Time	n/a
Name of Function/Aspects	***F7: Conflict detection***
Input	Alert issued
	Flight data updated
Output	Conflict warning detected
	Coordination warming detected
Precondition	Airspace status updates
	System tool is available
	System tools update
	Humans are aware of the situation or surroundings
Resource	System tools
Control	Separation standards
	Skill training for ATCO
	Technical training for ATCO on automation
Time	n/a
Name of Function/Aspects	***F8: To issue Complexity Solution Measures***
Input	Flight data updated
	Complexity issue detected
	Conflict warning detected
	Complexity solution measures need
Output	Complexity Solution Measure provided
Precondition	System tool is available
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F9: Decision Making***
Input	Conflict warning detected
	Complexity Solution Measure provided
	Visual display of airspace situations
Output	Instruction decided
Precondition	System tool is available
	Humans are aware of the situation or surroundings
Resource	System tools
Control	New flight data available
	Technical training for ATCO on automation
	Technical training for ATCO on automation
	System tools update
	Clearance procedures
Time	n/a
Name of Function/Aspects	***F10: To issue instructions***
Input	Instruction decided
Output	Instruction issued
	Flight is ready to be transferred
Precondition	System tool is available
Resource	n/a

Control	Traffic situation evaluated
Time	n/a
Name of Function/Aspects	***F11: To implement solutions***
Input	Instruction issued
Output	Solution strategies were communicated to pilots by Data-link
	New flight data available
Precondition	System tool is available
	Human is aware of the situation or surroundings
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***F12: To contact pilots***
Input	The most current flight information is provided
	Solution strategies were communicated to pilots by Data-link
	Airspace status updates
Output	The pilot implemented the solution
Precondition	Data-link available
Resource	n/a
Control	Team Collaboration
	Communication procedures
Time	n/a
Name of Function/Aspects	***F13: To co-ordinate with other controllers***
Input	Coordination warming detected
	Instruction issued
	Airspace status updates
Output	Coordination messages provided
Precondition	Humans are aware of the situation or surroundings
	System tool is available
Resource	System tools
Control	Coordination procedures
	Team collaboration
	Skill training for ATCO
	Technical training for ATCO about automation
Time	n/a
Name of Function/Aspects	***F14: To transfer control of aircraft to the appropriate Controller/Systems***
Input	Coordination messages provided
	Flight is ready to be transferred
Output	Flight is transferred
Precondition	Humans are aware of the situation or surroundings
	System tool is available
Resource	System tools
Control	Communication procedures
	Skill training for ATCO
	Technical training for ATCO on automation
Time	n/a
Name of Function/Aspects	***F15: Identify system expected response***
Input	Instruction decided
	Conflict warning detected
	Complexity issue detected
	Humans are aware of the situation or surroundings
Output	System response is obtained clearly
	Human has situational awareness
	Human understanding
	Observed automation behavior
Precondition	ATCO is available at the workstation
Resource	Executive and planner ATCO
Control	Technical training for ATCO on automation

Time	n/a
Name of Function/Aspects	***F16: To manage TRUST***
Input	System response is obtained clearly
	Observed automation behavior
	Humans are aware of the situation or surroundings
	Humans have situational awareness
Output	Adjusted trust level
Precondition	ATCO is available at the workstation
Resource	Executive and planner ATCO
Control	Technical training for ATCO about automation
	Organizational safety culture
Time	n/a
Name of Function/Aspects	***F17: Automation supervision***
Input	Human understanding
Output	Analysis of system actions
	Automation status
	Information from teammates (human or automated)
Precondition	Adjusted trust level
	ATCO is available at the workstation
	Humans are aware of the situation or surroundings
Resource	Executive and planner Controllers
Control	Organizational safety culture
	Technical training for ATCO on automation
Time	n/a
Name of Function/Aspects	***F18: To manage teamwork***
Input	Adjusted trust level
	Information from teammates (human or automated)
	Automation status
Output	Team collaboration
	Coordinated decisions
	Shared situational awareness
Precondition	n/a
Resource	n/a
Control	Adjusted trust level
Time	n/a
Name of Function/Aspects	***F19: Human - Machine Feedback Loop***
Input	Analysis of system actions
	Team collaboration
	Automation status
	Coordinated decisions
	Shared situational awareness
Output	Effectiveness of the feedback loop
	Tmely human intervention
Precondition	Humans are aware of the situation or surroundings
Resource	Executive and planner Controllers
Control	Adjusted trust level
Name of Function/Aspects	***BG1: Surveillance data processing***
Input	n/a
Output	ADS-B data
	Flight data from radar was provided
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG2: Flight plans delivery***
Input	n/a

Output	Data from flight plans
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG3: To provide MET data***
Input	n/a
Output	Meteorological data provided
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG4: To provide information on airspace status***
Input	n/a
Output	Updated airspace information is available to controllers
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG5: To manage resources***
Input	n/a
Output	System tool is available
	Data-link availability
	ATCO is available at workstation
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG6: To manage competence***
Input	n/a
Output	Technical training for ATCO about automation
	Skill training for ATCO
	System tool update
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG7: To manage procedures***
Input	n/a
Output	Monitoring procedures
	Coordination procedures
	Clearance procedures
	Minimum separation criteria
	Separation standards
	Communication procedures
	Organizational safety culture
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG8: Human factors***
Input	n/a
Output	Humans are aware of the situation or surroundings
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a

Name of Function/Aspects	***BG9: CDM with LTM***
Input	n/a
Output	Complexity solution measures need
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a
Name of Function/Aspects	***BG10: Traffic release (Expected Event)***
Input	The pilot implemented the instruction
	Flight is transferred
	Effectiveness of the feedback loop
	Timely human intervention
Output	n/a
Precondition	n/a
Resource	n/a
Control	n/a
Time	n/a

APPENDIX B

***Table B 1**. Internal and external variability – non–automation scenario*

Function	Type of a function	Source of internal variability	Source of external variability	Uncertainty (frequency)	Amplitude
To monitor the air traffic situation in the given airspace	H	Workload, fatigue, stress due to high traffic, psychological factors, and circadian rhythm. Situational awareness, attention, and focus, personal training.	High traffic demand, norms and policies, pressure, and shortage of available controllers. Wrong interpretation of information.	High	High
To monitor flights according to adherence to the flight plan	H	Workload, fatigue, stress due to high traffic, psychological factors, and circadian rhythm. Situational awareness, attention, and focus, personal training.	High traffic demand, norms and policies, pressure, and shortage of available controllers. Wrong interpretation of information. Slower detection of deviations from flight paths.	High	High
To evaluate the traffic situation	H	Workload, fatigue, stress due to high traffic, psychological factors, and circadian rhythm. Situational awareness, attention and focus, personal factors, training.	Traffic unpredictability can render pre-emptive flow control measures ineffective, requiring rapid human intervention. High cognitive load in complex airspace conditions.	High	High
To update flight data	H	Workload, fatigue, stress due to high traffic, Psychological factors, and circadian rhythm.	Manual updates increase the risk of data errors. Technology malfunction.	High	High
Conflict detection	H	Workload, fatigue, stress due to high traffic, psychological factors, and circadian rhythm. Situational awareness, attention and focus, personal factors, and training.	Weather conditions, pilot behaviour and aircraft performance, surveillance inaccuracies, navigation uncertainties, communication delays. Shortage of available controllers.	High	High
To issue a warning *(only in the current low*	H	Overwork (or high task load) leads to fatigue and increased workload,	Weather conditions, pilot behaviour and aircraft performance,	High	High

automation system)		which can lead to late or missed recognition of conflict or a situation of risk. Delays due to manual assessment before issuing warnings.	surveillance inaccuracies, navigation uncertainties, communication delays. Shortage of available ATCOs.		
To issue the Complexity Solution Measures	H	Workload, fatigue, stress due to high traffic, psychological factors, and circadian rhythm.	Technology effects (interpretation of information and usability of equipment); Intense air traffic requiring a high concentration of ATCOs.	High	High
CDM with LTM	H	More time-consuming without automated decision aids. Workload, fatigue, stress due to high traffic, psychological factors, and circadian rhythm.	Technology effects (interpretation of information and usability of equipment); Intense air traffic requiring a high concentration of ATCOs.	High	High
Decision Making	H	Workload, time pressure, individual experience and expertise, situational awareness, attention and focus, personal factors, training.	Weather conditions, high traffic volume, system or equipment issues, procedural constraints, technological interface, and team communication.	High	High
To contact pilots	H	Problem in communication with pilots, different language-misunderstanding.	Problem with radio contact.	Medium	High
To issue instructions	H	Workload, time pressure, individual experience and expertise, situational awareness, attention, and focus.	Slower command execution due to manual assessment. Technological interface.	High	High
To implement the solution	H	Workload, time pressure, individual experience and expertise, situational	Slower command execution due to manual assessment.	High	High

		awareness, attention, and focus.	Technological interface.		
To coordinate with other controllers	H	Miscommunication or incomplete data during handover could result in aircraft not being adequately tracked or managed by the next controller, leading to separation errors. Workload, stress and fatigue, attention, and understanding of sector boundaries and procedures	Unexpected traffic changes, poor communication tools, high traffic, sector overlap, and different work styles.	High	High
To transfer control of the aircraft to the appropriate Controller/Systems	H	Early or late handoffs can affect safety and workload. Awareness of neighbouring sector, miscommunication can cause loss of separation or delay in service, multitasking ability.	Communication delays or failures, traffic density at handoff point, system interface issues, differences in procedures between centres, or regular action differences when transferring across borders.	High	High
Surveillance data processing (Radar functioning, ADS-B functioning)	T	Requires manual interpretation of raw radar data; Risk of missing critical aircraft movements.	Radar or ADS-B failure due to external conditions; Improper maintenance.	Low	High
Flight plans delivery	T	Errors in flight plan delivery can lead to discrepancies in FDPS, potentially causing conflicts or delays in processing.	Software and hardware malfunction. Late delivery.	Low	High
Provide MET data	T	Weather forecasting errors or delays in real-time updates.	Software and hardware malfunction.	Low	High
To provide information on airspace status	T	Operators must manually cross-check restricted airspace updates.	Late provision of information.	Low	High
To display data on CWP	T	A lag in data processing or issues with the CWP interface could hinder a controller's ability to monitor and respond to air	Software and hardware malfunction. Loss of image due to a power failure.	Low	High

		traffic changes in real time. Manual adjustments needed, increasing workload.			
To provide an alert	T	A lag in data processing or issues with the CWP interface.	Automation support may fail or give a false alarm.	Low	High
To manage resources	O	Organisational memory, organisational culture.	Insufficient resources to complete tasks.	Medium	High
To manage competence	O	Effectiveness of communication, authority gradient, organisational memory, organisational culture, training.	Availability of training, training frequency.	Medium	High
To manage procedures	O	Effectiveness of communication, authority gradient, organisational memory, organisational culture.	Availability of procedures, number of procedures.	Medium	High
Release traffic	H	Traffic may not be released on time due to the variability of other functions.	Traffic may not be released on time due to the variability of other functions.	High	High

H-Human, T-Technology, O-Organization

Table B 2. *Internal and external variability – automation scenario*

Function	Type of a function	Source of internal variability	Source of external variability	Uncertainty (frequency)	Amplitude
To monitor the air traffic situation in the given airspace	T	Reduced vigilance due to automation complacency. Overtrust, loss of situational awareness/Accuracy of data, refresh rates, system lag, sensor integration errors.	Incomplete picture from sensor/data fusion errors.	High/Low	High
To monitor flights according to adherence to the flight plan	T	Delayed reaction to deviations, overtrust, loss of situational awareness/Latency in receiving flight plan updates; inconsistency in	Incorrect or outdated flight plan data.	High/Low	High

		trajectory prediction models.			
To evaluate the traffic situation	T	Incorrect judgment due to skill degradation, trust, and loss of situational awareness,/ System modelling accuracy, and computational delays.	Dependence on AI decision accuracy and inaccurate traffic prediction by the system.	High/Low	High
To update flight data	T	Delay or error in manual input override due to loss of situational awareness or trust in automation (when automation fails, humans must intervene, and this can happen)/ Update frequency, synchronization errors between subsystems, format mismatches.	Software glitches could result in incorrect data.	High/Low	High
Conflict detection	T	Over-reliance on automation, missing manual cross-checks, skill degradation,/ Sensitivity of detection algorithms, and prediction uncertainties.	False positives or negatives from automation algorithms.	High/Low	High
To issue the Complexity Solution Measures	T	Delayed decision due to uncertainty/ Choice of solutions based on algorithm heuristics; Solution conflicts with other actions.	Limited flexibility in system-generated solutions.	High/Low	High
CDM with LTM	H	Communication delays or misunderstandings.	Integration errors between systems.	High	High
Decision Making	T	Overtrust, loss of situational awareness, skill degradation,/Algorithm biases, decision thresholds, and limited adaptability to unexpected scenarios.	Insufficient or ambiguous data.	High/Medium	High
To contact pilots	T	Communication errors or delays in issuing messages/ Delay in	Radio/intercom malfunction, poor signal.	High/Medium	High

		communication dispatch, message clarity, translation errors if text-to-speech used.			
To issue instructions	T	Missing critical updates due to distractions or due to previously performed by automation,/ Timing of instruction, formatting, conflicts with other instructions or goals.	Miscommunication due to poor interface.	High/Mediu m	High
To implement the solution	T	Delayed execution due to doubt,/ Execution timing, sequencing issues, and resource constraints.	Automation misapplication, technical limitations.	High/Mediu m	High
To coordinate with other controllers	T	Miscommunication or missed coordination,/ Message timing, protocol mismatches, inconsistent interfaces, and handoff delays.	Interface mismatch, communication tool lag.	High/Low	High
To transfer control of the aircraft to the appropriate Controller/S ystems	T	Missed or incorrect handoff./ Handoff lag, sector boundary alignment, system coordination errors.	System routing failure, timing mismatch.	High/Low	High
Surveillance data processing (Radar functioning, ADS-B functioning)	T	Misinterpretation of data displayed; overtrust or undertrust in automation.	Data latency, dropouts, and hardware/software malfunctions.	Low	High
Flight plans delivery	T	Delay in verifying or updating due to cognitive overload.	Delayed or corrupted transmission, system syncing issues.	Low	High
Provide MET data	T	Misinterpretation of automated weather alerts.	Inaccurate or outdated weather data; sensor failure.	Low	Medium
To provide information on airspace status	T	Failure to detect restrictions or updates due to inattentiveness.	Delay in updating restrictions, data source errors.	Low	High

To display data on CWP	T	Misinterpretation of displayed information due to mental fatigue or loss of situational awareness.	System errors could cause airspace mismanagement, display lag.	Low	High
To provide an alert	T	Alert fatigue, misinterpretation.	False alarms, delayed alerts.	Low	High
To manage resources	O	Misallocation due to workload misjudgement (if the automation fails and the ATS is not ready for that).	Resource tracking system limitations	Medium	High
To manage competence	O	Lack of training or experience with automated systems.	Inadequate training tools or SOPs.	Medium	High
To manage procedures	O	Misapplication or skipping steps (if the automation fails, skill degradation due to inadequate and infrequent training or knowledge refresher)	Outdated procedures are not aligned with current systems.	Medium	High
Teamwork	O	Poor collaboration, misunderstandings, ATCO doesn't have available knowledge of how automation works, and the human is not familiar with how the automated system is designed	Tools not supporting collaboration effectively, and a lack of transparency in automation work.	High	Medium
To supervise automation functioning	H	Complacency, inattention, or lack of understanding.	Hidden system errors, lack of transparency.	High	High
Identify the expected system response	H	Incorrect mental model of automation, inadequate knowledge about automation design, and its actions	Poor documentation or feedback from the system.	High	High
Trust	H	Overtrust or distrust in automation.	Inconsistent system performance.	High	High
Human - Machine Feedback Loop	H	Failure to notice system cues or respond appropriately.	Delayed or unclear system feedback.	High	High
Release traffic	T	Determining optimal timing, sequencing	Trust in automation is crucial for	Low	High

	conflicts, and resource availability	operational flow. System misclassification of ready traffic	

H-Human, T-Technology, O-Organization

Table B 3. *Functional Resonance Analysis Method Functions under Non-Automation Scenario - Performance Variability*

Function	Possibility of occurring performance variability – time				Possibility of occurring performance variability – accuracy		
	Too early	**On time**	**Too late**	**Not at all**	**Accurate**	**Acceptable**	**Inaccurate**
Surveillance data processing (Radar functioning ADS-B functioning)	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
Flight plans delivery	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
Provide MET data	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
To display data on CWP	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
To provide information on airspace status	Unlikely	Typical	Possible	Possible*	Likely	Typical	Possible
To monitor the air situation picture	Possible	Typical	Possible	Unlikely	Typical	Likely	Possible
To monitor flights according to adherence to flight plan	Likely	Typical	Possible	Unlikely	Typical	Likely	Unlikely
To evaluate traffic situation	Likely	Typical	Possible	Unlikely	Typical	Likely	Unlikely
To update flight data	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
Conflict detection	Likely	Typical	Possible	Unlikely	Typical	Likely	Unlikely
To provide alert	Likely	Typical	Possible	Unlikely	Typical	Likely	Unlikely
To issue warning *(only in current – low automation system*	Likely	Typical	Possible	Possible*	Typical	Likely	Unlikely
To issue Complexity Solution Measures	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
CDM with LTM	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
Decision Making	Possible	Typical	Possible	Unlikely	Typical	Likely	Unlikely

To contact with pilots	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
To issue instruction	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
To co-ordinate with other controllers	Likely	Typical	Possible	Unlikely	Typical	Likely	Unlikely
To transfer control of aircraft to the appropriate Controller/Systems	Likely	Typical	Possible	Unlikely	Typical	Likely	Unlikely
To manage resources	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
To manage competence	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
To manage procedures	Unlikely	Typical	Possible	Possible*	Typical	Likely	Unlikely
Manage teamwork	Possible	Typical	Likely	Possible*	Typical	Likely	Unlikely
Release traffic	Unlikely	Typical	Possible	Unlikely	Typical	Likely	Unlikely

*Possible - only in the case of total breakdown

Table B 4. *Functional Resonance Analysis Method Functions under Automation Scenario - Performance Variability*

Function	**Possibility of occurring performance variability – time**				**Possibility of occurring performance variability – accuracy**		
	Too early	**On time**	**Too late**	**Not at all**	**Accurate**	**Acceptable**	**Inaccurate**
Surveillance data processing (Radar functioning ADS-B functioning)	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
Flight plans delivery	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
Provide MET data	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
To display data on CWP	Unlikely	Typical	Possible	Possible*	Typical	Unlikely	Unlikely
To provide information on airspace status	Possible	Typical	Possible	Unlikely	Typical	Possible	Unlikely
To monitor the air situation picture	Possible	Typical	Possible	Possible*	Typical	Possible	Possible

To monitor flights according to adherence to flight plan	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
To evaluate traffic situation	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
To update flight data	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
Conflict detection	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
To provide alert	Possible	Typical	Possible	Possible*	Typical	Likely	Possible
To issue Complexity Solution Measures	Unlikely	Typical	Possible	Possible*	Typical	Likely	Possible
CDM with LTM	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
Decision Making	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
To contact with pilots	Possible	Typical	Possible	Possible*	Typical	Possible	Unlikely
To issue instruction	Possible	Typical	Possible	Possible*	Typical	Possible	Possible
To co-ordinate with other controllers	Possible	Typical	Possible	Possible*	Typical	Possible	Possible
To transfer control of aircraft to the appropriate Controller/Systems	Possible	Typical	Possible	Possible*	Typical	Possible	Possible
To manage resources	Unlikely	Typical	Likely	Possible*	Typical	Possible	Possible
To manage competence	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
To manage procedures	Unlikely	Typical	Possible	Possible*	Typical	Possible	Possible
Manage teamwork	Possible	Likely	Possible	Possible*	Typical	Possible	Possible
Supervise Automation Functioning	Possible	Likely	Possible	Possible*	Typical	Possible	Possible
Identify Expected System Response	Unlikely	Likely	Possible	Possible*	Typical	Possible	Possible

Trust	Possible	Likely	Possible	Possible*	Typical	Possible	Possible
Human-machine feedback loop	Possible	Typical	Likely	Possible*	Typical	Possible	Likely
Release traffic	Unlikely	Typical	Possible	Possible*	Typical	Possible	Unlikely

*Possible - only in the case of total breakdown

APPENDIX C

Instruction Issuing	Decision making	Weighted Mean	alfa	P(0)	P(1)	P(2)	P(3)
0	0	0	0.00	0.80	0.20	0.00	0.00
0	1	0.4	0.53	0.48	0.47	0.05	0.00
0	2	0.8	0.07	0.19	0.67	0.14	0.01
0	3	1.2	0.60	0.08	0.40	0.46	0.06
1	0	0.6	0.80	0.32	0.60	0.08	0.00
1	1	1	0.33	0.13	0.53	0.30	0.03
1	2	1.4	0.87	0.03	0.27	0.62	0.09
1	3	1.8	0.40	0.00	0.12	0.54	0.34
2	0	1.2	0.60	0.08	0.40	0.46	0.06
2	1	1.6	0.13	0.00	0.17	0.65	0.18
2	2	2	0.67	0.00	0.07	0.43	0.50
2	3	2.4	0.20	0.00	0.00	0.30	0.70
3	0	1.8	0.40	0.00	0.12	0.54	0.34
3	1	2.2	0.93	0.00	0.01	0.33	0.66
3	2	2.6	0.47	0.00	0.00	0.30	0.70
3	3	3	1.00	0.00	0.00	0.30	0.70

Node/State	Too Early	On Time	Too Late	Not at all	Weight
Instruction Issuing	2	3	1	0	0.6
Monitoring	2	3	1	0	0.4

Weighted Score Range	Intuition	Child State
0.0 to 0.75	Mostly not at all	Not at all
0.75 to 1.5	Mostly late	Too late
1.5 to 2.25	Mostly early	Too early
2.25 to 3.0	Mostly on time	On time

			not at all	too late	too early	on time
Range Label	Lower	Upper	P(0)	P(1)	P(2)	P(3)
Not at all	0	0.75	0.8	0.2	0	0
Too late	0.75	1.5	0.2	0.7	0.1	0
Too early	1.5	2.25	0	0.2	0.7	0.1
On time	2.25	3	0	0	0.3	0.7

Figure C1. *An extract from an Excel file for the probability calculation for "Pilots action" node in non-automated system*

AUTHOR'S BIOGRAPHY

Doroteja Timotić Petković was born on **July 4, 1994**, in Valjevo, Republic of Serbia. She completed her primary education at "Milovan Glišić" Primary School in 2008, achieving excellent academic results and earning the Vuk Diploma as the top student of her generation. She completed her secondary education at Valjevo Gymnasium in 2013, also with outstanding academic performance.

In the academic year 2013/2014, she enrolled in the Air Transport and Traffic study module at the Faculty of Transport and Traffic Engineering, University of Belgrade. She graduated on September 22, 2017, completing her undergraduate academic studies (240 ECTS credits) with an average grade of 8.98/10. Her Bachelor's thesis, titled "Wave System at a Hub Airport: Impact on Flight Schedule and Network Connectivity", supervised by Prof. Danica Babić, PhD, was defended with the highest grade (10), thereby earning the title of **BSc in Traffic and Transport Engineering.**

In the academic year 2017/2018, she enrolled in Master's academic studies (60 ECTS credits) at the same faculty and study module. She completed her Master's studies on September 25, 2018, with an average grade of 9.63/10. Her Master's thesis, titled "Modeling the Causes of Runway Excursions Using Bayesian Networks", supervised by Prof. Feđa Netjasov, PhD, was defended with the highest grade (10), earning her the title of **MSc in Traffic and Transport Engineering**.

In the academic year 2018/2019, she enrolled in PhD academic studies (180 ECTS credits) at the **Faculty of Transport and Traffic Engineering**, University of Belgrade. To date, she has completed all coursework предусмотрed by the study program with a perfect average grade (10/10) and has defended her annual seminar paper.

During her studies, based on her academic excellence, she was awarded the "Scholarship for Encouraging the Education and Development of Gifted Pupils and Students" by the City of Valjevo for two consecutive academic years (2016/2017 and 2017/2018).

From June to December 2018, she completed a six-month professional traineeship at EUROCONTROL in Brussels, within the Network Manager Directorate, Office of the Director. Before that, she gained practical experience through internships at the Civil Aviation Directorate of the Republic of Serbia (Air Traffic Management Department), SMATSA LLC, Belgrade (Aeronautical Information Services Department), and AirSERBIA (Cargo Department).

Since January 2019, she has been employed at the **Faculty of Transport and Traffic Engineering**, University of Belgrade, initially as a **junior research assistant** (2019–2021), and subsequently as a **research assistant**, a position she currently holds. During this period, she has participated in the national research project "Support for Sustainable Development of Air Transport in the Republic of Serbia" (Project No. 36033), as well as in the international project "saFety And Resilience guidelines for aviatiOn (FARO)." She has also actively participated in numerous national and international scientific conferences, seminars, workshops, and summer schools. In addition, she has been engaged in undergraduate teaching within the course Air Navigation.

The candidate has published the results of her research through a total of **16 scientific publications**. This includes **one paper** published in an international journal of exceptional importance (M21a+), **one paper** in an international journal of significance (M21), **eleven papers** in proceedings of international scientific conferences (M33), **two papers** in proceedings of international scientific meetings (M34), and **one paper** in a national journal (M53).

Furthermore, she has attended several professional and scientific training programs and workshops, including those organized by EUROCONTROL and academic institutions, covering topics such as airport capacity, safety, human factors, and resilience in aviation systems, such as:

- “Airport Capacity Imbalance” (EUROCONTROL, 2021),
- “Safety and Human Factors Webinar – Costa Concordia Case” (EUROCONTROL, 2020–2021),
- “Just Culture Across Industries” (EUROCONTROL, 2020),
- “Engage Summer School 2020” (University of Belgrade),
- “Engage Winter School 2025” (Belgrade),
- ATC Intro Course at EUROCONTROL ALC (Luxembourg, 2025), and many others.

She is fluent in English, married, and a mother of two children.

БИОГРАФИЈА АУТОРА

Доротеја Тимотић Петковић је рођена **4.7.1994.** године у Ваљеву. Основну школу „Милован Глишић“ завршила је 2008. године са одличним успехом, као носилац Вукове дипломе и као најбољи ђак генерације. Средњу школу, Ваљевску Гимназију, завршила је 2013. године, такође са одличним успехом.

Саобраћајни факултет Универзитета у Београду уписала је школске 2013/2014. године, а дана 22. 09. 2017. године завршила је основне академске студије, првог степена, обима 240 (двеста четрдесет) бодова ЕСПБ, на модулу за Ваздушни саобраћај и транспорт, са просечном оценом 8,98 (осам и 98/100). Завршни рад на тему „СИСТЕМ ТАЛАСА У ХАБ АЕРОДРОМУ: УТИЦАЈ НА РЕД ЛЕТЕЊА И ПОВЕЗАНОСТ МРЕЖЕ ЛИНИЈА“ под менторством проф. др Данице Бабић, је одбранила са оценом 10 (десет) и тиме стекла звање: **Дипломирани инжењер саобраћаја**.

Мастер академске студије, другог степена, на Саобраћајном факултету Универзитета у Београду, обима 60 (шездесет) бодова ЕСПБ, на модулу Ваздушни саобраћај и транспорт уписала је школске 2017/2018. године. Мастер академске студије завршила је 25. 09. 2018. године са просечном оценом 9,63 (девет и 63/100). Мастер рад на тему „МОДЕЛИРАЊЕ УЗРОКА ИЗЛЕТАЊА СА ПОЛЕТНО-СЛЕТНИХ СТАЗА ПРИМЕНОМ БАЈЕСОВИХ МРЕЖА“ под менторством проф. др Феђе Нетјасов, одбранила је са оценом 10 (десет) и тиме стекла звање: **Мастер инжењер саобраћаја**.

Докторске академске студије, трећег степена, на Саобраћајном факултету Универзитета у Београду, обима 180 (сто осамдесет) бодова ЕСПБ, на студијском програму Саобраћај уписала је текуће школске 2018/2019. године. До сада је положила све испите предвиђене наведеним студијским програмом, са просечном оценом 10 (десет) и одбранила годишњи рад на семинару.

Током студија, а на основу успеха на претходним нивоима студија, била је две године прималац „Стипендије за подстицање образовања и усавршавања надарених ученика и студената“, коју додељује град Ваљево, почевши од школске 2016/17, а закључно са школском 2017/18. Годином.

Од јуна до децмбра 2018. године, кандидаткиња је боравила у Бриселу на стручној пракси у Еуроконтолу са седиштем у Бриселу, Белгија. Стручну праксу обавила је у одсеку под називом Network Manager Directorate/Office of the Director у трајању од шест месеци. Пре тога је обавила следеће стучне праксе: Директорат Цивилног Ваздухопловства Републике Србије, одсек за управљање ваздушним саобраћајем, лиценцирање контролора летења, ваздухопловну метеорологију и ваздухопловно информисање (фебруар 2018. године), Контрола летења Србије и Црне Горе SMATSA ДОО Београд, одсек за ваздухопловно информисање (јул 2017. године) и AirSERBIA, одсек за робни транспорт (април-мај 2017. године).

Од јануара 2019. године запослена је на **Саобраћајном факултету Универзитета у Београду**, прво као **истраживач-приправник** у периоду од јануара 2019. године до децембра 2021. године када бива изабрана у звање **истраживач-сарадник** које има и дан данас. Током студија, била је ангажована је на пројекту Министарства Науке и Технолошког развоја за Подршку одрживог развоја ваздушног саобраћаја у Републици Србији (број пројекта 36033), као и на међународном пројекту под називом „saFety And Resilience guidelines for aviatiOn-FARO". У току овог периода била је учесник више домаћих и међународних конференција, семинара, радионица и летњих школа. Поред тога, кандидаткиња је у току свог радног ангажмана на Саобраћајном факултету учествовала у настави на основним студијама у оквиру предмета Ваздухопловна навигација.

Резултате свог научноистраживачког рада кандидаткиња је публиковала кроз укупно **16 научних радова**. Од наведеног броја, **један рад** објављен је у међународном часопису изузетног значаја (М21а+), **један рад** у међународном часопису од значаја (М21), **једанаест радова** у зборницима радова са међународних научних конференција (М33), **два рада** у зборницима међународних научних скупова (М34), док је **један рад** објављен у националном часопису (М53).

Кандидаткиња је похађала неколико стручних и научних курсева и радионица од којих се могу издвојити следеће: „*Airport capacity Imbalance*" у организацији Европске организације за безбедност ваздушне пловидбе- ЕУРОКОНТРОЛ, одржаног 25. Марта 2021 у виртуелном формату, „*Safety and Human factors Webinar*" случај Коста Конкордиа, у организацији Европске организације за безбедност ваздушне пловидбе - ЕУРОКОНТРОЛ (одсек за безбедност), одржаног у пет семинара у периоду септембар 2020-фебруар 2021 у виртуелном формату, „*Just culture across industries: Continuing to learn from each other*" у организацији Европске организације за безбедност ваздушне пловидбе – ЕУРОКОНТРОЛ, одржаног у четири семинара у периоду октобар-новембар 2020. у виртуелном формату, „*Engage summer school 2020*", у организацији Катедре за аеродроме и безбедност ваздушне пловидбе (Саобраћајни факултет Универзитета у Београду), члана Engage конзорцијума уз подршку осталих чланова конзорцијума, одржане 21-25. септембра у виртуелном формату, „*Engage summer school 2025*", у организацији Катедре за аеродроме и безбедност ваздушне пловидбе (Саобраћајни факултет Универзитета у Београду), члана Engage конзорцијума уз подршку осталих чланова конзорцијума, одржане 27-31. јануара у Београду, *ATC-Intro course at EUROCONTROL-ALC*, одржаног у Луксембургу у јуну 2025. године уз подршку Engage 2 пројекта, као и многе друге.

Говори енглески језик, удата је и мајка је двоје деце.

ИЗЈАВА О АУТОРСТВУ

Име и презиме аутора **Доротеја Д. Тимотић Петковић**

Број индекса **ДС18Д004**

Изајвљујем

да је докторска дисертације под насловом

МОДЕЛОВАЊЕ УТИЦАЈА ПОВЕЋАЊА НИВОА АУТОМАТИЗАЦИЈЕ НА БЕЗБЕДНОСТ И РЕЗИЛИЈЕНТОСТ СИСТЕМА КОНТРОЛЕ ЛЕТЕЊА

- резултат сопственог истраживачког рада;
- да дисертација у целини ни у деловима није била предложена за стицање друге дипломе према студијским програмима других високошколских установа;
- да су резултати коректно наведени и
- да нисам кршила ауторска права и користила интелектуалну својину других лица.

У Београду, **Потпис аутора**

20.03.2026.

ИЗЈАВА О ИСТОВЕТНОСТИ ШТАМПАНЕ И ЕЛЕКТРОНСКЕ ВЕРЗИЈЕ ДОКТОРСКОГ РАДА

Име и презиме аутора	**Доротеја Тимотић Петковић**
Број индекса	**ДС18Д004**
Студијски програм	**Саобраћај**
Наслов рада	**МОДЕЛОВАЊЕ УТИЦАЈА ПОВЕЋАЊА НИВОА АУТОМАТИЗАЦИЈЕ НА БЕЗБЕДНОСТ И РЕЗИЛИЈЕНТОСТ СИСТЕМА КОНТРОЛЕ ЛЕТЕЊА**
Ментор	**др Фeђа Нетјасов, редовни професор** **Универзитет у Београду – Саобраћајни факултет**

Изјављујем да је штампана верзија мог докторског рада истоветна електронској верзији коју сам предао ради похрањивања у **Дигиталном репозиторијуму Универзитета у Београду**.

Дозвољавам да се објаве моји лични подаци везани за добијање академског назива доктора наука, као што су име и презиме, година и место рођења и датум одбране рада.

Ови лични подаци могу се објавити на мрежним страницама дигиталне библиотеке, у електронском каталогу и у публикацијама Универзитета у Београду.

У Београду, **Потпис аутора**

20.03.2026.

ИЗЈАВА О КОРИШЋЕЊУ

Овлашћујем Универзитетску библиотеку „Светозар Марковић“ да у Дигитални репозиторијум Универзитета у Београду унесе моју докторску дисертацију под насловом:

МОДЕЛОВАЊЕ УТИЦАЈА ПОВЕЋАЊА НИВОА АУТОМАТИЗАЦИЈЕ НА БЕЗБЕДНОСТ И РЕЗИЛИЈЕНТОСТ СИСТЕМА КОНТРОЛЕ ЛЕТЕЊА

која је моје ауторско дело.

Дисертацију са свим прилозима предала сам у електронском формату погодном за трајно архивирање.

Моју докторску дисертацију похрањену у Дигиталном репозиторијуму Универзитета у Београду и доступну у отвореном приступу могу да користе сви који поштују одредбе садржане у одабраном типу лиценце Креативне заједнице (Creative Commons) за коју сам се одлучио.

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(Молимо да заокружите само једну од шест понуђених лиценци.
Кратак опис лиценци је саставни део ове изјаве).

У Београду,

20.03.2026.

Потпис аутора

1. **Ауторство**. Дозвољавате умножавање, дистрибуцију и јавно саопштавање дела, и прераде, ако се наведе име аутора на начин одређен од стране аутора или даваоца лиценце, чак и у комерцијалне сврхе. Ово је најслободнија од свих лиценци.

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3. **Ауторство – некомерцијално – без прерада**. Дозвољавате умножавање, дистрибуцију и јавно саопштавање дела, без промена, преобликовања или употребе дела у свом делу, ако се наведе име аутора на начин одређен од стране аутора или даваоца лиценце. Ова лиценца не дозвољава комерцијалну употребу дела. У односу на све остале лиценце, овом лиценцом се ограничава највећи обим права коришћења дела.

4. **Ауторство – некомерцијално – делити под истим условима**. Дозвољавате умножавање, дистрибуцију и јавно саопштавање дела, и прераде, ако се наведе име аутора на начин одређен од стране аутора или даваоца лиценце и ако се прерада дистрибуира под истом или сличном лиценцом. Ова лиценца не дозвољава комерцијалну употребу дела и прерада.

5. **Ауторство – без прерада**. Дозвољавате умножавање, дистрибуцију и јавно саопштавање дела, без промена, преобликовања или употребе дела у свом делу, ако се наведе име аутора на начин одређен од стране аутора или даваоца лиценце. Ова лиценца дозвољава комерцијалну употребу дела.

6. **Ауторство – делити под истим условима**. Дозвољавате умножавање, дистрибуцију и јавно саопштавање дела, и прераде, ако се наведе име аутора на начин одређен од стране аутора или даваоца лиценце и ако се прерада дистрибуира под истом или сличном лиценцом. Ова лиценца дозвољава комерцијалну употребу дела и прерада. Слична је софтверским лиценцама, односно лиценцама отвореног кода