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An Algorithmic Model for Assessing and Improving the Compliance of Air Traffic Control Operations with Regulatory Standards

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Abstract

Air Traffic Control (ATC) operations must comply with international and European regulatory standards to ensure the safety, efficiency, and reliability of air traffic management systems. Increasing operational complexity and growing performance requirements have made regulatory compliance a critical challenge for air navigation service providers. Deviations between operational practices and regulatory requirements may introduce safety risks and negatively affect system performance. This study proposes an algorithmic model for assessing and improving the compliance of ATC operations with regulatory standards established by the International Civil Aviation Organization (ICAO), the European Union Aviation Safety Agency (EASA) and EUROCONTROL. The research methodology is based on an analysis of the existing regulatory framework, the identification of key operational and regulatory factors and the development of an algorithmic structure capable of objectively measuring compliance levels. This research provides both a theoretical and practical contribution to the field of air traffic management by offering regulatory authorities and air navigation service providers a structured tool for strengthening compliance, improving safety performance and supporting the continuous enhancement of ATC operations.

Keywords

Air Traffic Control, Regulatory Compliance, ICAO, EASA, EUROCONTROL, Algorithmic Model, Air Traffic Management, Aviation Safety

1. Introduction

The aviation industry represents one of the most complex and regulated sectors globally, where safety, efficiency and operational reliability are essential elements for its operation. The continuous growth of air traffic, technological development and ever higher performance requirements have significantly increased the complexity of air traffic management. In this context, Air Traffic Control (ATC) plays a key role in guaranteeing the safe, orderly and efficient movement of aircraft, contributing directly to maintaining the safety of civil aviation and optimizing the use of airspace [1]-[3].

The effective functioning of ATC operations is based on compliance with standards and procedures established by International and European aviation bodies. The International Civil Aviation Organization (ICAO), the European Aviation Safety Agency (EASA) and EUROCONTROL have developed a broad regulatory framework aimed at harmonizing air traffic services, increasing operational safety and improving the performance of the air traffic management system [2] [4] [5]. Compliance with these standards is considered an essential factor in ensuring the safety and continuity of operations in modern aviation environments.

However, the continuous development of technologies, operational procedures and regulatory requirements presents significant challenges for organizations providing air navigation services. In practice, deviations from standards may stem from technical factors, human factors, procedural deficiencies or organizational limitations. These inconsistencies can negatively affect operational performance and increase the level of risk in the air traffic management system [3] [4] [6].

Traditional conformity assessment methods rely mainly on audits, inspections, safety reports and expert assessments. Although these mechanisms remain indispensable for monitoring operations, they are often characterized by lengthy evaluation processes and difficulties in integrating a large number of operational factors into a single, objective analysis. As a result, there is a growing need for the use of computational and algorithmic methods that can support decision-making and provide more transparent and standardized assessments of the level of regulatory compliance.

Unlike studies that focus mainly on the theoretical analysis of regulatory requirements, this study is based on the development of an algorithmic model for the assessment of operational compliance in Air Traffic Control. At the center of the research is the use of fuzzy logic (Fuzzy Logic), which enables the handling of uncertainties and complexities that characterize the operational environment of air traffic. Previous studies have shown that systems based on fuzzy logic can be successfully used for decision support, risk analysis and evaluation of operational processes in Air Traffic Control environments, providing more flexible results and closer to real operational conditions [7] [8].

The purpose of this study is to develop and evaluate an algorithmic model for measuring and improving the compliance of Air Traffic Control operations with the regulatory standards set by ICAO, EASA and EUROCONTROL.

The main contribution of this research lies in the construction of an algorithmic framework that transforms operational indicators into measurable levels of compliance. By combining regulatory requirements with fuzzy inference mechanisms, the model aims to provide a more objective, transparent and effective approach to assessing operational compliance in Air Traffic Control, contributing to improving the safety and performance of the air traffic management system [7] [8].

2. Methodology

This study is based on a research approach oriented towards the development of an algorithmic model for assessing the compliance of Air Traffic Control (ATC) operations with international and European regulatory standards. The methodology combines the analysis of the regulatory framework with computer modeling, with the aim of creating an objective and structured mechanism for assessing operational conditions in the air traffic environment [2] [4] [5].

In the first phase of the study, an analysis of documents and standards published by the International Civil Aviation Organization (ICAO), the European Union Aviation Safety Agency (EASA) and EUROCONTROL was carried out, as well as a review of the scientific literature on operational safety, air traffic management and the use of intelligent methods in decision-making [2] [3] [5]. This analysis served to identify the main elements that affect the performance and safety of ATC operations.

In the second phase, an algorithmic model based on fuzzy logic was developed, which was selected for its ability to handle the uncertainty and complexity that characterize real air traffic control operations. The Runway Visual Range (RVR), Traffic and Delay parameters, were used as input variables to build the model, which represent operational elements with a direct impact on the operating conditions of the ATC system. These parameters were classified into linguistic levels and integrated into the fuzzy inference system to represent different operational compliance.

Based on the input variables, a set of fuzzy rules was built, which enable the combination of parameters and the generation of an overall assessment of the operational compliance. The fuzzy inference process transforms the input information into a final result that reflects the level of compliance of operations with the defined requirements and standards [7] [8].

To evaluate the model's performance, four representative operational scenarios were conducted, testing different combinations of input parameter values. The results generated by the model were analyzed to assess its ability to identify operational deviations, support risk analysis and provide a more objective mechanism for monitoring regulatory compliance [7] [8].

This methodology aims to demonstrate that the use of an algorithmic approach based on fuzzy logic can provide an effective tool for the systematic evaluation of ATC operations and for supporting processes of continuous improvement of safety and operational performance [7] [8].

3. Algorithmic Model Development

The model proposed in this study has been developed to enable a structured and objective assessment of operational conditions that affect the performance of Air Traffic Control operations. Due to the complex nature of the ATC environment, where many factors cannot be described in an absolute manner, as acceptable or unacceptable, the use of fuzzy logic was chosen as the main mechanism for modeling and analyzing operational data [7] [8].

Fuzzy logic offers the possibility of dealing with situations characterized by uncertainty and gradual assessments, making it suitable for applications in complex aviation environments. Instead of using binary classifications, this approach enables the representation of different levels of operational compliance and provides a more realistic interpretation of the conditions that affect air traffic management processes [7] [8].

The model is built on a fuzzy inference system (Fuzzy Inference System, FIS), which uses Runway Visual Range (RVR), Traffic and Delay parameters as input variables. These variables have been selected because of their direct impact on air traffic operating conditions and on the system's ability to ensure safety and operational efficiency [1] [7]-[9].

3.1. Regulatory Basis of Model Inputs

The selection of the input variables was based on operational factors that are directly associated with aviation safety, air traffic management performance and operational procedures established by international and national aviation frameworks. The proposed model does not evaluate legal compliance with individual regulatory provisions. Instead, it assesses the degree to which operational conditions remain aligned with recognized safety and performance objectives defined by ICAO, EUROCONTROL, EASA and national air navigation service procedures.

Runway Visual Range (RVR) was selected as an input parameter because visibility conditions have a direct influence on aircraft take-off and landing operations and are closely associated with operational restrictions and low-visibility procedures. Information related to runway visibility constitutes an important component of aeronautical information management and operational decision-making processes in aviation environments, particularly under reduced visibility conditions [5] [9].

Traffic was included as an indicator of operational workload and airspace complexity. Increasing traffic density requires greater coordination, communication and monitoring effort from air traffic controllers, directly affecting the ability of Air Traffic Control services to maintain safe, orderly and efficient operations. Consequently, traffic levels represent an important operational factor in evaluating ATC performance and operational effectiveness [1] [2].

Delay was selected as a performance-related indicator because operational delays are commonly used in air traffic management to assess operational efficiency, capacity utilization and service performance. Increased delays may indicate congestion, reduced operational efficiency or operational constraints that can affect the overall effectiveness of ATC operations [2] [10].

Based on these considerations, operational compliance is defined in this study as the degree to which operational conditions remain within acceptable safety and performance limits derived from recognized aviation operational frameworks. Therefore, the proposed model evaluates operational compliance through representative operational indicators rather than through direct verification of individual regulatory provisions.

The membership-function ranges, fuzzy rules and output classifications were developed as part of the proposed research model and were not adopted directly from a specific ICAO, EASA, EUROCONTROL or national regulatory document. However, the selection of the input variables was based on operational factors consistently recognized across aviation safety and air traffic management frameworks.

As shown in **Table 1**, the selected input variables were chosen because they represent operational factors commonly recognized within aviation safety and air traffic management frameworks. The proposed model evaluates operational compliance through these representative indicators rather than through direct verification of individual regulatory provision.

Table 1. Regulatory and operational basis of the model inputs.

Input Variable	Operational Role in the Model	Regulatory/Operational Basis
RVR (Runway Visual Range)	Represents visibility conditions affecting aircraft take-off, landing and ATC operations	Visibility-related operational procedures and aeronautical information requirements (ICAO Annex 15; AIP Albania)
Traffic	Represents air traffic density and controller workload	Air traffic management performance and operational complexity indicators (Albcontrol ATM; EUROCONTROL)
Delay	Represents operational efficiency and service performance	ATM performance monitoring and operational efficiency assessment (EUROCONTROL; EUROCONTROL Guidelines)

As shown in **Figure 1**, the model takes as input regulatory standards and operational data, which go through the process of normalization, fuzzy inference and defuzzification. Finally, a numerical output is generated that can be used to assess the level of compliance, identify operational risk and support corrective actions.

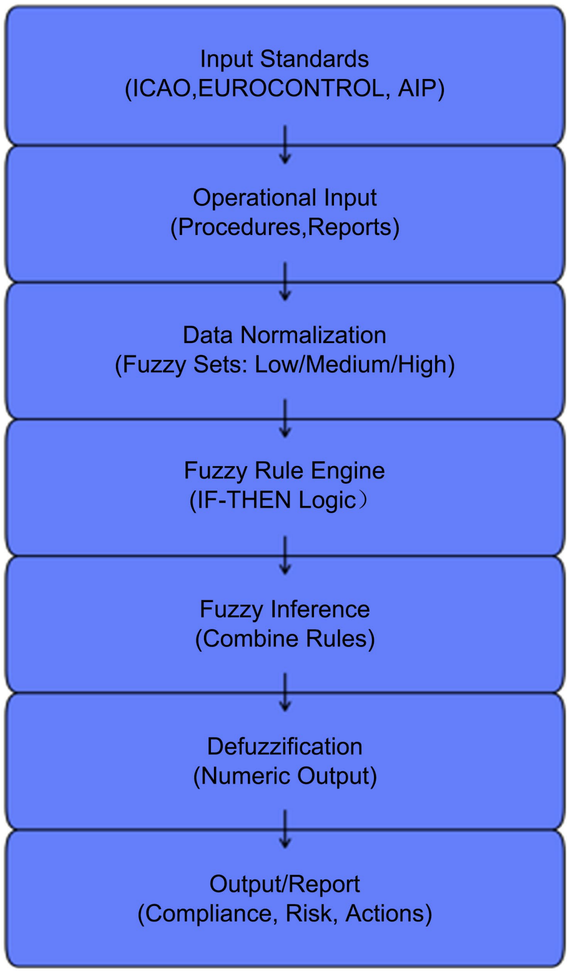

Figure 1. Architecture of the proposed algorithmic model for assessing operational compliance in ATC.

RVR (Runway Visual Range) represents the level of visibility on the runway and is considered a critical factor in aircraft take-off and landing operations. Lower RVR values create more challenging operational conditions and require more rigorous procedures to ensure safety [5] [9].

Traffic represents the level of air traffic load. Increased traffic density is associated with higher demands for coordination, monitoring and decision-making by air traffic controllers, directly affecting operational complexity [1] [2].

Delay represents the level of operational delays that occur during air traffic management. Delays are considered an important indicator of system performance and may reflect operational limitations or challenges in traffic flow management.

After defining the input variables, each of them was modeled through fuzzy membership functions, which enable the gradual representation of different operational levels. This approach allows the changes between operational conditions to be treated continuously and not through rigid numerical boundaries.

The core of the model consists of a set of fuzzy rules built on the relationships between the input parameters. These rules simulate the decision-making logic of experts in the field and enable the interpretation of different combinations of operational values. In this way, the system is able to evaluate the simultaneous impact of visibility conditions, traffic load and delays on the final analysis result.

The model operation process includes three main phases. In the first phase, the input data is fuzzified, where numerical values are transformed into linguistic terms. In the second phase, fuzzy inference rules are activated, which combine the information obtained from the input variables. In the third phase, defuzzification is performed, a process through which the fuzzy result is converted into a numerical value interpreted as an indicator of the operational compliance [7] [8].

The proposed architecture aims to provide a transparent and standardized mechanism for the analysis of operational conditions in Air Traffic Control. By integrating the main operational parameters into a single computational structure, the model enables the identification of situations with high operational impact and supports the processes of evaluation, monitoring and improvement of the system's performance [7] [8].

3.2. Fuzzy System Specification

The proposed model was implemented using a Mamdani Fuzzy Inference System (FIS). The model uses three input variables: Runway Visual Range (RVR), Traffic and Delay, and generates two output variables: Operational Compliance and Operational Risk.

Triangular and trapezoidal membership functions were used to represent the linguistic categories Low, Medium and High. The Mamdani minimum operator was applied for the fuzzy AND operation, while the maximum operator was used for rule aggregation. Centroid defuzzification was employed to transform the aggregated fuzzy outputs into crisp numerical values.

The output variables Operational Compliance and Operational Risk were defined on a scale from 0% to 100%. All fuzzy rules were assigned equal weights and evaluated using the same inference mechanism. Although both outputs are expressed on a scale from 0% to 100%, Operational Compliance and Operational Risk are evaluated as independent fuzzy outputs. Consequently, the two indicators are not complementary and are not expected to sum to 100%. High compliance does not necessarily correspond to proportionally low risk, since each output is generated through a separate fuzzy evaluation process.

Table 2 summarizes the membership function parameters used for the input variables of the Mamdani Fuzzy Inference System. Triangular and trapezoidal membership functions were employed to represent the linguistic categories Low, Medium and High for each input variable.

Table 3 presents the membership function parameters used for the output variables Operational Compliance and Operational Risk. The output variables were defined on a scale from 0% to 100% and represented through three linguistic levels: Low, Medium and High.

Table 2. Input membership function parameters.

Variable	Low	Medium	High
RVR (m)	TrapMF (0, 0, 400, 600)	TriMF (400, 750, 1100)	TrapMF (900, 1100, 1500, 1500)
Traffic	TrapMF (1.8, 2.5, 5, 5)	TriMF (0.8, 1.5, 2.5)	TrapMF (0, 0, 0.8, 1.2)
Delay (min)	TrapMF (5, 7, 15, 15)	TriMF (1, 3.5, 6)	TrapMF (0, 0, 0.5, 1.5)

Table 3. Output membership functions.

Output Variables	Low	Medium	High
Compliance (%)	TrapMF (0, 0, 15, 40)	TriMF (25, 55, 80)	TrapMF (65, 88, 100, 100)
Risk (%)	TrapMF (0, 0, 12, 30)	TriMF (20, 50, 78)	TrapMF (65, 88, 100, 100)

Table 4 presents the fuzzy rule base used in the proposed model. The rules were designed to represent the relationships between operational conditions and the resulting levels of operational compliance and operational risk.

Table 4. Fuzzy rule base.

IF Condition	THEN Result
IF RVR is Low	Compliance is Low AND Risk is High
IF RVR is Medium	Compliance is Medium AND Risk is Medium
IF RVR is High	Compliance is High AND Risk is Low
IF Traffic is High	Compliance is Low AND Risk is High
IF Traffic is Medium	Compliance is Medium AND Risk is Medium
IF Traffic is Low	Compliance is High AND Risk is Low
IF Delay is High	Compliance is Low AND Risk is High
IF Delay is Medium	Compliance is Medium AND Risk is Medium
IF Delay is Low	Compliance is High AND Risk is Low
IF RVR is Low AND Traffic is High	Compliance is Low AND Risk is High
IF RVR is Medium AND Delay is High	Compliance is Low AND Risk is High

4. Results and Analysis

4.1. Model Implementation

After developing the architecture of the algorithmic model, its implementation was carried out in the fuzzy logic environment to test the functioning of the system and analyze its behavior under different operating conditions. The model was built using three input variables, namely RVR, Traffic and Delay, which were represented through fuzzy membership functions. Based on these variables, inference rules were defined that describe the relationships between the operating conditions and the final result of the model. The implementation enabled the visualization of membership functions, the execution of fuzzy rules and the analysis of the interaction between input parameters. The system also offered the possibility of generating response surfaces (surface plots), which represent the impact of different combinations of parameters on the result produced by the model [7] [8].

Figure 2 shows the membership functions used in the model. Each variable is divided into linguistic categories that represent different operational conditions used in the compliance assessment process. These functions serve as the basis for the fuzzification process and enable the transformation of numerical values into fuzzy terms for use in the inference system. For the RVR variable, membership functions were defined at three levels: low (0 - 550 m), medium (500 - 1000 m) and high (1000 - 1500 m). Similarly, the traffic variable was classified into the intervals 0 - 1, 1 - 3 and 3 - 6 aircraft, while the delay variable was classified into the intervals 0 - 1, 1 - 3 and 3 - 10 minutes. These intervals were chosen to represent different operational air traffic conditions and to enable a gradual assessment of operational situations.

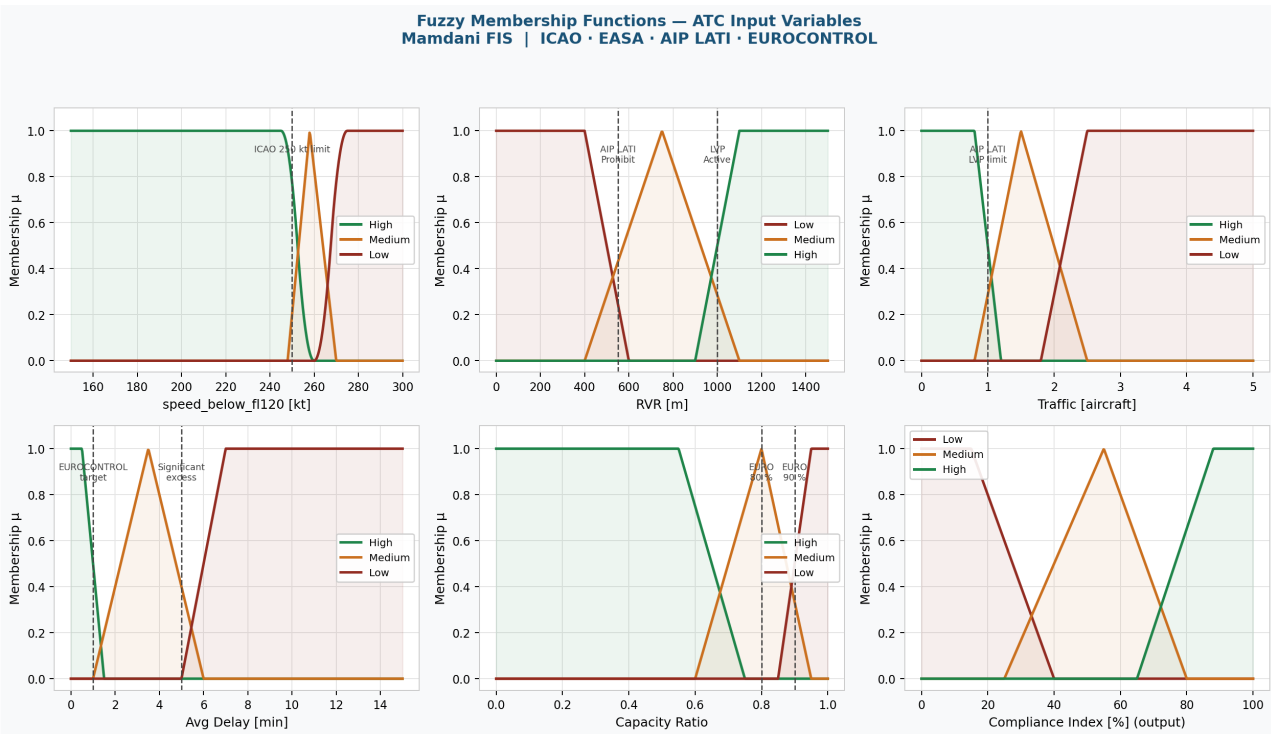

Figure 2. Membership functions for input and output variables in the ATC fuzzy system.

4.2. Analysis of Results

The results generated by the model showed that changes in the input parameters directly affect the assessment of the operational compliance. In scenarios where RVR values were high and traffic and delay levels were low, the model produced results corresponding to favorable operational conditions. In these cases, the system evidenced a high level of operational compliance and a relatively low exposure to risk factors.

On the other hand, combinations of reduced visibility, heavy traffic and significant delays resulted in more critical output values. This shows that the model is capable of identifying operational situations with high complexity and reflecting the simultaneous influence of factors that may impair the efficiency of ATC operations.

The analysis of the response surfaces also showed that the relationship between the variables is not linear. The influence of a parameter varies depending on the values of other parameters, which justifies the use of fuzzy logic as a more suitable method compared to traditional linear models.

Figure 3 shows the result generated by the fuzzy model for a normal operational scenario. The system produced a compliance index of 74.9% and a risk level of 26.5%. The result shows that the operations are considered Mostly Compliant with the defined requirements, approaching the target compliance threshold of 75%. At the same time, the risk level remains below the warning limit of 30%, indicating that the operational conditions are within acceptable performance and safety limits. The compliance and risk outputs should be interpreted as independent indicators generated by separate fuzzy evaluations. Therefore, the two values are not complementary and do not necessarily add to 100%.

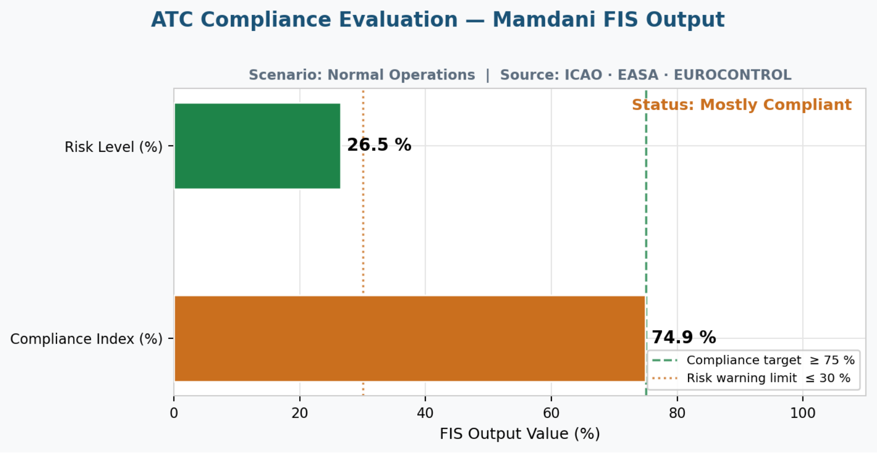

Figure 3. Assessment of compliance and risk level in ATC operations under normal conditions.

Figure 4 presents the results of the fuzzy model for four different operational scenarios: normal operations, reduced visibility (Low RVR), high traffic and high operational delays. For each scenario, the compliance index and the operational risk level generated by the Mamdani FIS system are presented.

The results show that the normal operations scenario presents the best performance, with a compliance index of 74.9% and a risk level of 26.5%, staying very close to the target of 75% and within the acceptable risk limit of 30%. In the reduced visibility (Low RVR) scenario, compliance drops to 52.3%, while the risk increases to 47.9%. This shows the significant impact that limited visibility conditions have on the safety and performance of ATC operations.

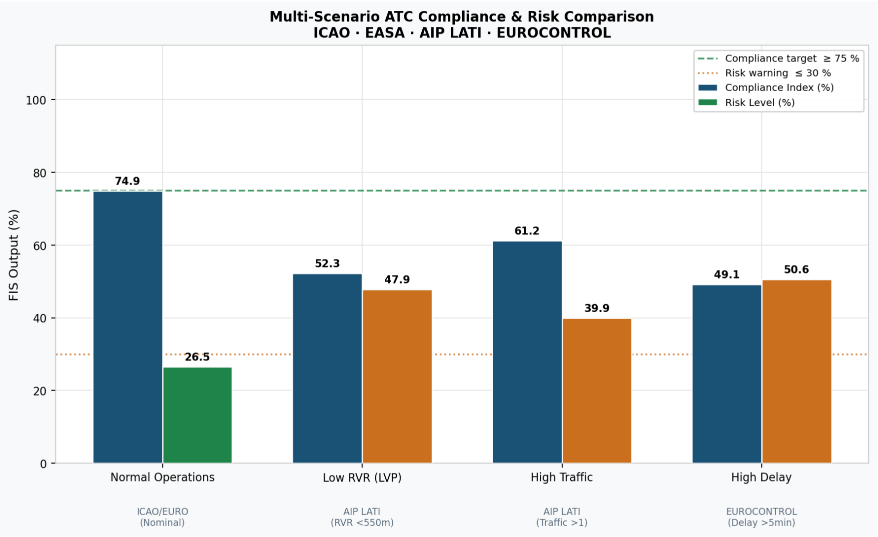

Figure 4. Comparison of compliance and risk level in different operational scenarios in ATC.

The High Traffic scenario generates a compliance index of 61.2% and a risk level of 39.9%. Although the impact is more moderate compared to the low visibility case, the results show that the increase in traffic load, negatively affects operational efficiency.

The most critical values are observed in the High Delay scenario, where the compliance index drops to 49.1%, while the risk level reaches 50.6%. This suggests that operational delays constitute one of the factors with the greatest impact on the degradation of system performance and the increase in exposure to operational risk.

Overall, the results confirm the ability of the fuzzy model to distinguish different levels of operational performance and to identify the factors that contribute most to the reduction of compliance and the increase in risk. The analysis shows that adverse operational conditions significantly affect the system results, while normal operations remain within acceptable performance and safety limits.

Figure 5 presents the impact of Runway Visual Range (RVR) on the compliance index generated by the fuzzy model. The results show that an increase in the RVR value is associated with a gradual improvement in the level of operational compliance. In conditions where the RVR is below 550 m, the compliance level remains relatively low due to operational limitations and special procedures applicable under reduced visibility conditions. As the RVR increases above this threshold, the compliance index shows a positive trend, reaching values close to the defined target of 75%. The graph can be interpreted with reference to two important operational thresholds. The first threshold is related to the limit of 550 m, where significant operational limitations apply, while the second threshold is associated with

Low Visibility Procedures (LVP), which may be activated for RVR values below 1000 m. The results indicate that improved visibility conditions have a direct positive effect on the operational compliance of Air Traffic Control operations.

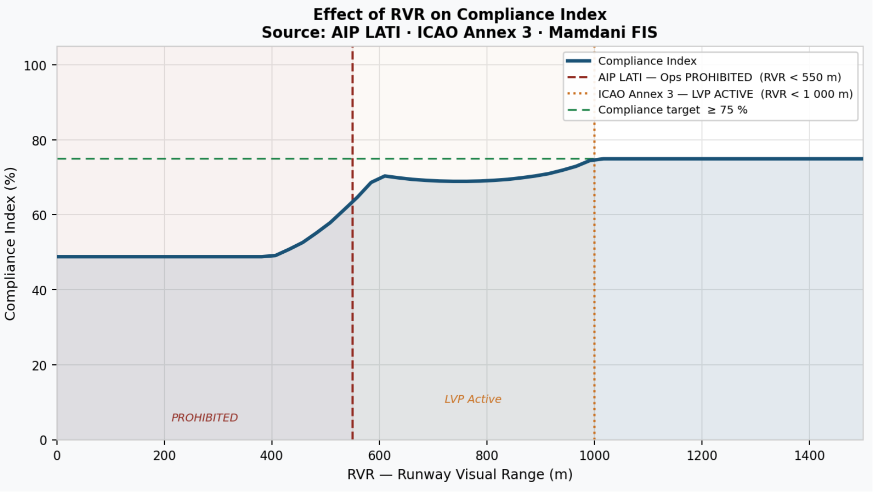

Figure 5. Impact of visibility (RVR) on operational compliance in ATC systems.

Figure 6 presents the fuzzy aggregation and defuzzification process for the normal operations scenario. After activating the fuzzy rules, the membership functions are combined to generate a fuzzy aggregate set, which represents the overall result of the system. Then, the centroid of gravity (CoG) method is applied, which is used to transform the fuzzy result into a final numerical value.

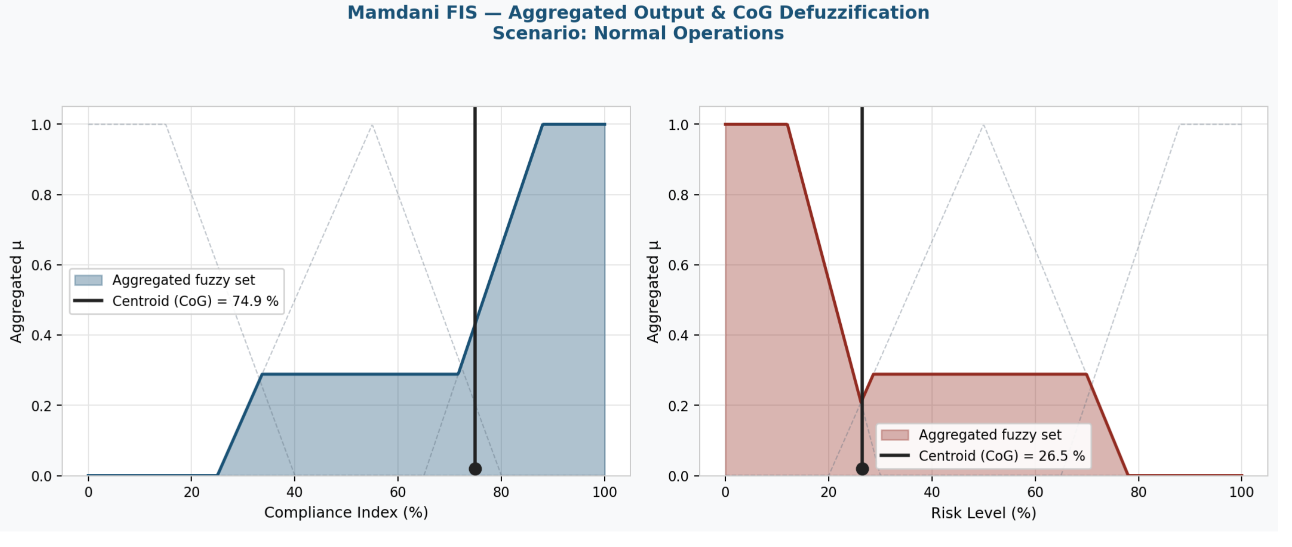

Figure 6. Fuzzy aggregation and defuzzification (Centroid) results for compliance and risk level in the Mamdani FIS model.

The results show that the compliance index reaches a value of 74.9%, while the operational risk level is estimated at 26.5%. These values indicate that the operations are analyzed as generally in compliance with the defined requirements and that the operational risk remains within acceptable limits. The defuzzification process enables the practical interpretation of the model results, transforming the information obtained from the fuzzy rules into numerical indicators usable for operational monitoring and decision-making support. This phase represents the last step of the algorithm and provides the link between the fuzzy analysis and the practical application of the results in the air traffic control environment.

Figure 7 presents the impact of average operational delays on the compliance index generated by the fuzzy model. The results show that, for low levels of delays, operational compliance remains at high levels and close to the set target of 75%. This indicates that the system operates under stable conditions and within acceptable operational parameters.

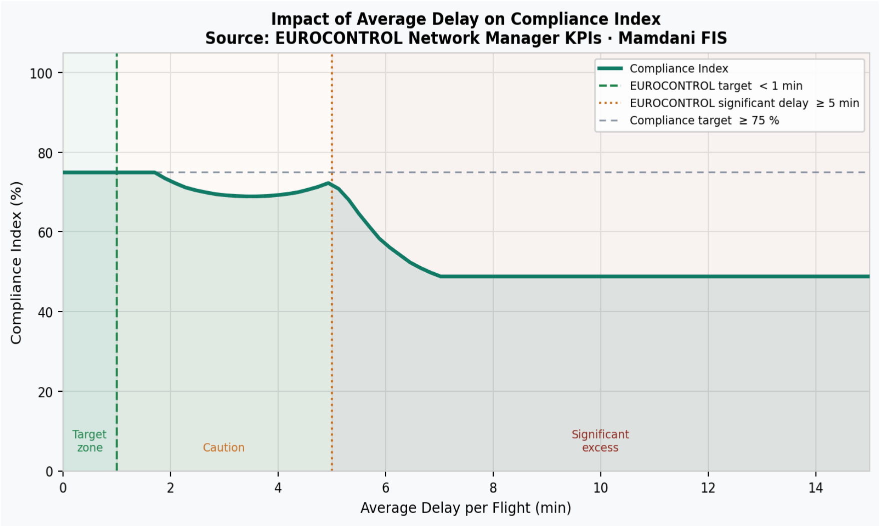

Figure 7. Relationship between operational delays and compliance in the ATC system.

As the average delays increase, a progressive decrease in the compliance index is observed. In the interval between 1 and 5 minutes, the system enters a caution zone, where operational performance begins to be affected by capacity constraints or air traffic complexity.

After the 5-minute threshold, considered as a significant operational delay, the model evidences a more significant decrease in compliance. In this zone, the effect of delays becomes more evident on the efficiency of ATC operations, negatively affecting the overall performance of the system.

The results confirm that operational delays constitute one of the most important performance indicators in air traffic management. The model is able to identify their impact on the level of compliance and to highlight the limits above which corrective measures are required to maintain operational standards.

4.3. Model Performance

Evaluation of the tests performed showed that the model is able to process different combinations of operational conditions and provide consistent results. The operation of the system, demonstrated the ability to integrate information from different operational sources and transform it into a single assessment, easily interpreted by the user.

An important advantage of the model is the transparency of the decision-making process. Because the results are based on clearly defined rules and known membership functions, users can understand the reasoning leading to the final result. This makes the model potentially useful as a supporting tool for operational monitoring and performance analysis in ATC environments.

The proposed model was evaluated through four representative simulation scenarios designed to reflect different operational conditions, including normal operations, reduced visibility, high traffic and high delay conditions. Validation using real operational ATC datasets was beyond the scope of the present study and represents an important direction for future research. Future work may include the use of historical ATC operational data to further assess the accuracy, robustness and practical applicability of the proposed model.

Overall, the results obtained show that the fuzzy logic-based approach provides an effective mechanism for analyzing operational conditions and identifying situations that require increased attention or remedial measures. The model demonstrates potential for use as a supporting tool in the processes of operational evaluation and continuous improvement of the performance of air traffic control systems.

5. Conclusion

This study presented an algorithmic model based on fuzzy logic for assessing compliance and risk level in Air Traffic Control (ATC) operations. The proposed approach aims to provide a more objective and structured method for analyzing operational conditions, integrating into a single framework the main parameters that affect system performance. The model was built on three input variables, namely Runway Visual Range (RVR), Traffic and Delay, which were processed through a Mamdani FIS inferential system. The results showed that the model is able to effectively assess the impact of each parameter on the level of compliance and operational risk, reflecting the behavior of the system under different operational conditions. The analysis of the tested scenarios revealed that normal operations generate the highest level of compliance and the lowest level of risk, while conditions of reduced visibility, high traffic and operational delays negatively affect operational compliance and increase operational risk. In particular, high delays resulted as the factor with the greatest impact on reducing compliance and increasing exposure to operational risk. One of the main contributions of this study lies in the application of fuzzy logic to the modeling of a complex decision-making process in the ATC environment. Compared to traditional approaches based on rigid boundaries and binary classifications, the proposed model enables the handling of uncertainty and provides results that are more flexible, more transparent and closer to operational reality. The results obtained confirm that the model can serve as a supporting tool for monitoring operational performance, identifying deviations, analyzing risk and supporting decision-making processes in the field of air traffic management. Furthermore, the proposed approach can contribute to the continuous improvement of safety, efficiency and compliance with ICAO, EASA and EUROCONTROL standards. In the future, the model can be expanded by integrating additional operational, meteorological and human performance parameters, as well as being validated with real operational data. This would enable further increase in its accuracy, reliability and applicability in modern air traffic management systems.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Albcontrol (2026) Air Traffic Management. https://www.albcontrol.al/air-traffic-management

[2] EUROCONTROL (2026) https://www.eurocontrol.int

[3] International Civil Aviation Organization (ICAO) (2018) Safety Management Manual (Doc 9859). ICAO.

[4] European Union Aviation Safety Agency (EASA) (2026) https://www.easa.europa.eu

[5] International Civil Aviation Organization (ICAO) (2018) Annex 15: Aeronautical Information Services. ICAO.

[6] Albcontrol (2026) Integrated Management System. https://www.albcontrol.al/integrated-management-system

[7] Mulligan, D. and Cohen, K. (2023) Air Traffic Control Using Fuzzy Logic. In: *Lecture Notes in Networks and Systems*, Springer, 25-35. https://doi.org/10.1007/978-3-031-46778-3_3

[8] Yeşil, G. and Şahin, Ö. (2025) Aircraft Sequencing with Fuzzy Logic Method. *Eskişehir Technical University Journal of Science and Technology A—Applied Sciences and Engineering*, **26**, 161-178. https://doi.org/10.18038/estubtda.1674259

[9] Aeronautical Information Publication (AIP) Albania. https://www.albcontrol.al/aip

[10] EUROCONTROL (2025) Guidelines for Harmonized AIP Publication and Data Set Provision (Edition 2.2). EUROCONTROL. https://www.eurocontrol.int/publication/eurocontrol-guidelines-harmonised-aip-publication-and-data-set-provision