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MACHINE LEARNING-BASED APPROACH IN AIR TRAFFIC MANAGEMENT

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Air traffic management, Machine learning, Database networks

Abstract

With the increasing demand for air transportation, the volume of air traffic has also grown significantly. This rise in air traffic directly affects safety, operational efficiency, and environmental impacts. Traditional methods have proven inadequate in addressing the complex and challenging problems of air traffic management (ATM), leading to the adoption of machine learning (ML) techniques, which offer higher accuracy and practical applicability.

This study presents a comprehensive investigation into the use of machine learning models in air traffic management. It evaluates ML applications in various critical ATM areas, including flight trajectory prediction, conflict and collision avoidance, traffic flow and capacity prediction, weather forecasting, and environmental impact assessment, through examples from existing literature. The study highlights the strategic importance of ML-supported systems in the modernization of ATM.

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MMO YAYIN

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HAVA TRAFİK YÖNETİMİNDE MAKİNE ÖĞRENMESİ YAKLAŞIMI

Anahtar Kelimeler

Hava trafik yönetimi, Makine öğrenmesi, Veri tabanı ağları

Öz

Günümüzde hava taşımacılığına olan talebin artması ile hava trafik sayısı da önemli ölçüde artmaktadır. Artan hava trafik sayısı; emniyeti, operasyonel verimliliği ve çevresel etkileri doğrudan etkilemektedir. Hava trafik yönetiminde karmaşık zorlu problem çözümlerinde geleneksel yöntemlerin yetersiz kalması nedeni ile bu problemlerin çözümünde makine öğrenmesi (ML) kullanılarak daha yüksek doğruluk ve uygulanabilirlik sağlamaktadır.

Bu çalışma, hava trafik yönetimi (ATM)'inde makine öğrenmesi modellerinin kullanılmasına ilişkin kapsamlı bir araştırma sunmaktadır. Hava trafik yönetiminde karşılaşılan uçuş yörünge tahmini, çatışma/çarpışma önleme, trafik akış ve kapasite tahmini, hava durumu tahmini ve çevresel etkiler gibi alanlar için makine öğrenmesi modelleri literatürden örneklerle değerlendirilmiştir. Çalışma, ATM'nin modernizasyonunda makine öğrenmesi destekli sistemlerin stratejik önemine dikkat çekmektedir.

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Extended Abstract

1. Introduction

With the steadily increasing demand for air transportation, the number of flight operations within the airspace has also risen. This growing density in the airspace leads to negative outcomes such as delays and operational inefficiencies in resolving traffic conflicts. It has become evident that traditional methods are insufficient to address the complexity created by the rising traffic. For decades, research on artificial intelligence has been conducted to enhance airspace traffic capacity and efficiency; however, due to the limitations of data processing technologies, adequate solutions could not be achieved (Gosling, G. D., 1987). Machine learning, which stands out with its capabilities in processing and forecasting large-scale data, has begun to be utilized in addressing challenges encountered in air traffic control, such as preventing collisions between aircraft or with other obstacles, producing more accurate trajectory predictions, and forecasting meteorological conditions. It possesses the potential to deliver more precise, reliable, and innovative solutions in this field.

As a technology that automates and enhances decision-making, machine learning offers adaptive and scalable solutions to complex problems that are difficult to solve using traditional approaches (such as metaheuristic algorithms or optimization methods), by learning from available data. It has facilitated the development of data-driven strategies particularly in areas such as finance, healthcare, and engineering.

In air traffic management, machine learning is playing an increasingly vital role in improving efficiency, ensuring safety, and optimizing airspace capacity. Large volumes of flight data, weather information, and traffic flow data are collected and processed, enabling air traffic to be managed in a more intelligent and predictable manner.

Machine learning algorithms enhance many critical processes in air traffic management. For instance, in air traffic flow management, historical flight data can be analyzed to predict potential delays in advance and allow for necessary adjustments. Moreover, machine learning–based solutions strengthen decision-support systems in areas such as the dynamic allocation of airspace, route optimization, and collision avoidance systems, thereby ensuring safer and more efficient air traffic management.

In air traffic management, various methods such as metaheuristic algorithms, linear and nonlinear optimization techniques, multi-criteria decision-making (MCDM), and simulation-based approaches have previously been employed to address emerging challenges. However, with the increasing volume of air traffic, these problems have become more complex. Therefore, the application of machine learning methods—which are widely used today to solve a broad range of problems—is expected to enhance efficiency in this domain. The comparative analysis conducted by Wild, Baxter, Srisaeng, and Richardson (2022) demonstrates that machine learning techniques outperform classical regression and highlights the growing prevalence of data-driven approaches. Table 1 presents several air traffic management problems and the solution methods applied between the years 2010 and 2024.

Table 1. Literature Review on Problems Encountered in Air Traffic Control and Corresponding Solution Methods

Year	**Title**	Air Traffic Control Problem	Applied Method	Reference
2010	**A Mixed-Integer Linear Programming Model for Air Traffic Flow Management**	Aircraft Conflict Detection	Mixed Integer Linear Programming (MILP)	Çeçen, R. K. (2021)
2010	**Stochastic programming approaches to air traffic flow management under the uncertainty of weather**	Inter-route capacity constraints in air traffic flow management	Stochastic Programming and Lagrangian Relaxation with Subgradient Method	Chang, Y. H. (2010)
2011	**A benders decomposition approach for an integrated airline schedule design and fleet assignment problem with flight retiming, schedule balance, and demand recapture**	Flight Planning	Benders Decomposition Method	Sherali, H.D., Bae, KH. and Haouari, M.
2012	**A Hybrid Optimization Approach to Air Traffic Management for Metroplex Operations**	Route Assignment and Sequencing Problem	Linear Programming and Genetic Algorithm	Capozzi B. and Atkins S., (2010)
2014	**Optimal large-scale air traffic flow management**	Large-Scale Air Traffic Flow Management	Integer Programming	Balakrishnan, H., and Chandran, B.G. (2014).
2015	**A dynamic programming approach for the aircraft landing problem with aircraft classes**	Airport Capacity	Dynamic Programming	Lieder, A., Briskorn, D., and Stolletz, R. (2015)
2016	**Dynamic airspace sectorization using controller task load**	Dynamic Airspace Sectorization	Controller Workload and Fuzzy Clustering	Gerdes, I., Temme, A., and Schultz, M. (2016).
2016	**En-route aırspace capacıty and traffıc flow enhancement usıng genetıc algorıthms**	Airspace Capacity and Traffic Flow	Genetic Algorithm	Çetek, C., and Çeçen, R. K. (2017)
2017	**A robust optimization approach for airport departure metering under uncertain taxi-out time predictions**	Aircraft Departure Time under Uncertainty in Taxi Time	Robust Optimization	Murça, M. C. R. (2017)
2018	**A hybrid metaheuristic approach for air traffic flow management with uncertainty**	Aircraft 4D-Trajectory Problem	Genetic Algorithm and Simulated Annealing	Chaimatanan, S., Delahaye, D., and Mongeau, M. (2018)
2018	**A fuzzy cluster based genetic algorithm approach for the aircraft landing scheduling problem**	Scheduling of Aircraft Landing Times	Fuzzy Set-Based Genetic Algorithm Approach	Çelikbilek, Y. (2018)
2019	**Applied game theory to enhance air traffic control training**	Conflict Detection	Game Theory	Rangrazjeddi, A., González, A. D., and Barker, K. (2023)
2020	**Optimal sector modelling of airspace based on optimization algorithms**	Optimization of Air Traffic Control Sector Boundaries	Mathematical Optimization Method	Todorov, T. D., and Simeonov, S. (2020)
2021	**Particle swarm optimization for airlines fleet assignment**	Airline Fleet Assignment	Particle Swarm Optimization	Abouzeid, A. A., Eldin, M. M. and Razek, M. A. (2021).

2021	**A Scenario Optimization Approach for Air Traffic Flow Management with Sector Capacity Uncertainty**	Air Traffic Flow and Capacity Management	Scenario Optimization and Chance-Constrained Optimization Method	Fadil, A., Cai, K., Yang, Y., and Hao, B. (2021)
2023	**Conflict assessment and resolution of climate-optimal aircraft trajectories at network scale**	Conflict Resolution and CO_2 Pollution	Speed Variation and Trajectory Optimization	Baneshi, F., Soler, M., and Simorgh, A. (2023).
2024	**Runway assignment optimisation model for Istanbul Airport considering multiple parallel runway operations**	Aircraft Landing Sequencing and Runway Assignments	Mixed Integer Linear Programming	Güven, A., Cetek, F. A., and Cecen, R. K. (2024).
2024	**Concept of robust climate-friendly flight planning under multiple climate impact estimates**	Designing Climate-Optimal Trajectories, CO_2 Emissions	Robust Optimization, Trajectory Optimization	Simorgh, A., Soler, M., Castino, F., Yin, F., and Cerezo-Magaña, M. (2024).
2024	**Multi-objective air traffic flow management through lexicographic optimisation**	Air Traffic Flow Management	Multi-objective Optimization, Lexicographic Optimization	Dalmau, R., Gawinowski, G., and Kopec, J. (2024)

This study will primarily provide a detailed explanation of machine learning methods. In addition, it addresses issues such as regulatory requirements, human–machine interaction, operational feasibility, and environmental sustainability. The reviewed studies were examined through the steps of title–abstract screening → full-text evaluation → qualitative synthesis. The subsequent section aims to present the advantages and challenges of applying machine learning to commonly encountered problems in air traffic management and to discuss potential future areas of development.

2. Machine Learning Models and Techniques

Machine learning enhances operational decision-making mechanisms in air traffic management by analyzing various types of data. The learning model stages of machine learning involve enabling a program to learn general patterns from large amounts of data, constructing a model, and attempting to predict a target value; then continuing through trial and error by comparing the predicted and actual values, iterating and optimizing, and ultimately producing a highly accurate model. Figure 2.1 schematically illustrates the fundamental stages of machine learning.

Figure 2.1 Fundamental stages of machine learning required for modeling

2.1. Dataset Construction

Developing a reliable machine learning model requires a large and high-quality dataset. Typically, several stages are involved in constructing such a dataset. First, data are mostly collected from published research studies, internal data sources of relevant regulatory agencies, and publicly available datasets. In cases where data are insufficient, new datasets may be generated for machine learning mapping purposes using ADS-B messaging systems and air traffic control (ATC) communication records. Once these steps are completed, key variables for the models such as aircraft position, speed, heading, and altitude—are identified based on the nature of the study and defined as input features. In the final stage, the output variables to be calculated or predicted in line with the objectives of the study are determined.

Table 2. Commonly used database networks in air traffic (Cai, Z., 2023)

Database Name	Database Website	Description
OpenSky Network	https://opensky-network.org	An open-source air traffic database collecting ADS-B, Mode S, TCAS, and FLARM data from around the world.
OPSNET	https://aspm.faa.gov/opsnet/sys/Main.asp	An official open-source database containing FAA air traffic operations and delay data..
TrajAir	https://theairlab.org/trajair	Route and weather data recorded during flight operations at Pittsburgh-Butler Regional Airport.
LiveATC	https://www.liveatc.net	A live streaming platform providing real air traffic control (ATC) communications at airports
ATCSpeech	https://github.com/sculyi/ASR-Corpus	A multilingual speech dataset collected from ATC systems (e.g., Mandarin, accented English, etc.)
EUROCONTROL Data	https://www.eurocontrol.int	A platform offering operational and strategic data related to European air traffic management.
AviationDB	https://aviationdb.net	A comprehensive aviation database including airline, flight, airport, and pilot information.
FlightAware	https://www.flightaware.com	A commercial platform providing real-time and historical flight tracking data.
Flightradar24	https://www.flightradar24.com	A data platform enabling real-time tracking of aircraft around the world..
FAA Data ve Research	https://www.faa.gov/data_research	Air traffic, airport, and flight safety data provided by the U.S. Federal Aviation Administration.
Global ADS-B Exchange	https://www.adsbexchange.com	An independent flight tracking network that publicly shares ADS-B data.

2.2. Data Preprocessing Process

In the process of constructing the dataset, it is often not feasible to apply raw data directly to the model. Missing or inconsistent data can adversely affect the model's accuracy. Therefore, the data preprocessing stage is critically important. At this stage, if there are features with a large number of missing values, these features are removed, as such data can reduce the model's reliability. If there are only a few missing values but some feature values are anomalous, these values can either be removed from the dataset or corrected using appropriate techniques.

Additionally, when some variables have large magnitude values, they can influence the model's outcomes and disrupt the learning process. To prevent this, scaling or normalization methods are applied to keep the variables within a specific range.

2.3 Model Selection and Development

Machine learning models are typically used for classification and regression prediction tasks. While classification models categorize discrete data into specific classes, regression models are employed to predict continuous variables. Common algorithms such as decision trees, random forests, support vector machines, artificial neural networks, and XGBoost can be applied to both classification and regression problems. However, Naive Bayes and k-Nearest Neighbor algorithms are suitable only for classification, whereas multiple linear regression is exclusively used for regression prediction. In the context of air traffic control, classification models are used to determine whether traffic conditions will cause delays, while regression models predict the flow of air traffic over time.

In the model development process, the dataset to be processed is generally divided into three parts: training, validation, and testing. Typically, 70% of the data is allocated for training, 20% for validation, and 10% for testing. The training set enables the model to learn, while the validation set is used to optimize the model's hyperparameters. Adjustments in hyperparameters are made using methods such as GridSearchCV to improve model performance. The test set is employed to assess the model's generalizability. Alternatively, k-fold cross-validation is used to evaluate the consistency of the model across different data subsets, with ten-fold cross-validation being the most commonly applied approach currently.

The success of the selected model is evaluated using different metrics depending on the type of the target variable. For regression models, common criteria include the coefficient of determination (R^2) and root mean squared error (RMSE). Classification models are analyzed using metrics such as accuracy, precision, recall, and receiver operating characteristic (ROC) curve. The area under the ROC curve (AUC) is considered an important criterion for determining the overall performance of classification models.

2.4 Model Analysis

Machine learning models can make highly accurate predictions; however, their internal workings are often not fully transparent, making them difficult to interpret completely. Therefore, it is crucial to examine how models make decisions and to assess their reliability. This transparency is especially important in critical domains such as air traffic control. Methods such as feature importance ranking can be used to understand the extent to which variables influence model predictions. This ranking can be directly obtained from algorithms like random forests, while more complex models require approaches such as SHAP and LIME (Xie, Pongsakornsathien, Gardi, and Sabatini, 2021).

Additionally, sensitivity analysis can be conducted to measure the model's responsiveness to specific inputs. This analysis helps identify which variables the model is overly dependent on and where errors occur within the model. Over- or under-predictions can be evaluated by comparing training and testing errors. For classification models, false positive and false negative rates can be analyzed to determine whether the model is biased toward a particular class. Such analyses are essential for improving model reliability and evaluating its performance in real-world applications.

3. Machine Learning Techniques in ATM

The machine learning techniques predominantly used in ATM systems are as follows:

- **Supervised Learning**: This method, which learns from labeled data, can be utilized to enhance the performance of air traffic control systems by using historical flight data and labeled anomaly records. For example, it is possible to predict whether delays will occur under certain meteorological conditions or to classify risky situations in terms of flight safety in advance.

- **Unsupervised Learning:** Effective in identifying anomalies and unusual movements in traffic flow. Clustering algorithms such as K-Means and DBSCAN detect abnormal flight patterns in the airspace, providing early warnings to air traffic control systems (Boyrazlı and Çınar, 2021).

- **Reinforcement Learning:** Can be applied to dynamic allocation of airspace and autonomous vehicle decision-making. Deep reinforcement learning (Deep RL) models are used to optimize air traffic by determining the most suitable routes for autonomous aircraft.

Additionally, deep learning techniques are increasingly employed in air traffic management. In particular Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are used to analyze air traffic data and make long-term forecasts.

3.1. Research on Machine Learning Applications in Air Traffic Management

The foundation of machine learning techniques in air traffic management lies in predicting conflict/collision probabilities and ensuring safe separation. In their study, Paielli and Erzberger (1997) modeled conflict probabilities within the free flight concept and introduced the idea of automated conflict resolution. Supported by NASA and the FAA, the work of Erzberger (2004) is considered one of the most influential studies on full automation in air traffic control.

In this study, the problems encountered in air traffic management are examined in detail under the following topics: air traffic services, air traffic flow and capacity management, collision avoidance and conflict resolution systems, weather forecasting, noise, and environmental impacts.

1.1.1. Air Traffic Services (ATS)

Air traffic services include air traffic control (ATC), flight information services (FIS), and alerting services aimed at ensuring flight safety. Deep learning-based prediction models play a critical role in air traffic control processes. In particular, LSTM-based models are used for flight trajectory prediction and decision support systems for air traffic controllers. Additionally, automatic speech recognition (ASR) systems analyze controllers' commands to reduce operational errors.

Dhariwal (2020) focuses on big data analytics and machine learning techniques to meet the increasing demands of air traffic management. Machine learning (ML) and big data technologies have been utilized to improve air traffic management processes, and a recommendation mechanism for air traffic controllers was developed along with an Android-based application. The Hive and Hadoop ecosystem were used to process large datasets in a distributed environment. It was observed that Hive is more efficient than traditional databases in terms of both time and data volume. Data collected from various Indian airlines were analyzed using Hive, and machine learning algorithms were applied in Python. The results demonstrated that big data and machine learning techniques play a significant role in optimizing air traffic management and developing decision support systems.

Agrawal, Memarzadeh, Kalyanam, Mulholland, and Tan (2024) investigate machine learning methods to predict airport traffic management initiatives (TMI) such as aircraft gate positions (GS) and ground delay programs (GDP), which depend on meteorological conditions and airport situations. The models were developed using logistic regression, k-nearest neighbors, random forest, XGBoost, and Long Short-Term Memory (LSTM) networks with three years of data from Newark Airport. While random forest and XGBoost algorithms accurately predicted TMI needs, LSTM models showed superior performance by learning from previous TMI sequences to forecast the type of program to be implemented. This study paves the way for more advanced modeling techniques to predict future TMI. TMI forecasts will enable more efficient traffic management for air traffic controllers.

Zuluaga-Gomez, Motlicek, Zhan, Vesely, and Braun (2020) designed an ASR-based platform in the CleanSky EC-H2020 ATCO2 project, using machine learning methods to automatically process and organize controllers' speech data. The study evaluates the performance of a model employing deep learning and text processing techniques such as TDNNF (factorized time-delay neural networks) and Byte-Pair Encoding. Results indicate that errors caused by speaker accents decrease as data volume increases, and the system performs more efficiently in the air traffic control environment. The developed ASR system achieved an average Word Error Rate (WER) of 7.75% across four different datasets, with Byte-Pair Encoding providing a 35% improvement in WER. This study highlights machine learning as a powerful tool to reduce operational errors in air traffic control.

Additionally, Artificial Neural Networks (ANN) have been used to predict aircraft taxi times (Wang, Brownlee, Woodward, Weiszer, Mahfouf, and Chen, 2021); while prominent algorithms for trajectory prediction include random forest (Pham, 2019) and LSTM (Shi, Xu, and Pan, 2020; Ma and Tian, 2020; Shi, Xu, Pan, Yan, and Zhang, 2018; Zhang and Mahadevan, 2020).

1.1.2. Prediction Models for Air Traffic Flow and Capacity Management (ATFCM)

Machine learning is employed for forecasting air traffic flow and mitigating congestion. By analyzing historical data, congestion levels at specific times can be predicted, enabling optimized traffic management. Marcos et al. (2018) were among the first to directly apply machine learning to route preferences. They systematically examined route choice models using ML and laid the groundwork for subsequent prediction studies. LSTM-based time series analysis models are among the most commonly used methods for forecasting air traffic density. Additionally, algorithms such as XGBoost and Random Forest analyze past data to predict delays in air traffic. Airspace allocation is generally based on static rules; however, machine learning-based approaches enable dynamic allocation of airspace.

Keerthana and Priya (2022) analyze machine learning and regression techniques for air traffic flow control. With the increase in unmanned aerial vehicles and general aviation aircraft, air traffic has become more complex. ADS-B technology allows high-precision tracking of aircraft. The aim of Keerthana and Priya's (2022) study is to predict intercity air traffic using analyzed databases and route maps. The system creates an intelligent civil aviation management model by evaluating air traffic control radar data and navigation data. Simulation results demonstrate the model's ability to manage air traffic control processes. During testing, the Random Forest model achieved a Mean Absolute Error (MAE) of 4.7832, while the LSTM model's MAE was approximately 3000. These results indicate that air traffic control may be utilized more effectively as a management technique in the future.

Marcos, García-Cantú, and Herranz (2018) propose machine learning methods for route prediction in Air Traffic Flow and Capacity Management (ATFCM). The study aims to forecast routes during the pre-tactical phase—when flight plans are limited or unavailable—using multinomial logistic regression and decision tree models. The models were calibrated with historical traffic data to assess their ability to predict traffic volumes in congested regions. Although the proposed approach improved traffic prediction before departure, the exclusion of factors affecting route operational suitability (e.g., military airspace access) led to misleading results. This limitation highlights the need to incorporate route feasibility into future models to obtain more accurate forecasts.

Wang, Yang, Duan, and Li (2023) developed the CWTAC model to assess the impact of convective weather on terminal airspace capacity, utilizing SVR, RF, and ANN algorithms. Tests conducted with data from Guangzhou and Wuhan terminal areas showed that ANN provided the highest prediction accuracy. The results indicate that the model's forecasts align well with actual flight counts. Future work should explore the uncertainty of weather forecasts and consider additional dynamic factors.

A review of the literature reveals studies employing ANN for airport capacity estimation (Hosoz and Ertunc, 2006; Choi and Kim, 2021), airport traffic volume prediction (Yang, Lee, Jou, Chung, and Lin, 2023), passenger demand forecasting (Anguita and Olariaga, 2022), and air cargo demand forecasting (Anguita and Olariaga, 2023; İlgün and Alptekin, 2022).

Random Forest algorithms have been used with notable success in capacity estimation (Andy, Alam, Piplani, Lilith and Dhief, 2021; Zhang, Liu, Wang, Song, and Liu, 2020), flight delay prediction (Bardach, Gringinger, Schrefl, and Schuetz, 2020; Guo, Yu, Hao, Wang, Jiang, and Zong, 2021; Rebollo and Balakrishnan, 2014), on-time performance analysis (Setiawan, 2023), and taxi-out time estimation (Kim and Baik, 2021).

Support Vector Machine (SVM) algorithms are also frequently used in the literature for air traffic flow management (Zhao, Yuan, and Chen, 2023; Gui, Zhou, Wang, Liu, and Sun, 2020), ground delay problems (Liu, Hansen, Pozdnukhov, and Zhang, 2019), terminal area congestion (Zhang, J ang, and Yang, 2016), traffic volume analysis (Yang, Lee, Jou, Chung, and Lin, 2023), and passenger traffic analysis using various algorithms (Stanulov and Yassine, 2024).

The majority of existing studies have been conducted based on a single variable (e.g., capacity or delay time). However, in real operational environments, factors such as weather conditions, traffic density, and human factors are also present. Moreover, the models used in these studies were mostly trained on limited airspace, making it uncertain how they would perform under changes in airspace structure. It is of great importance for future studies to also consider new types of traffic, such as unmanned aerial vehicles (UAVs) and eVTOLs.

1.1.3. Collision Avoidance and Conflict Resolution Systems

Active traffic collision avoidance systems (TCAS) used in aircraft are air-based systems designed to prevent potential collisions by instructing one aircraft to descend while the other ascends. This system is constructed using “if–then–else” rule statements (Button, K., 2017). With the advancement of machine learning and artificial intelligence, the Federal Aviation Administration (FAA) continues its work on the airborne collision avoidance system (ACAS X). The ACAS X standard came into effect in 2020, although the certification process has not yet been completed (FAA, 2023). Meanwhile, the European Union Aviation Safety Agency (EASA) has proposed new guidelines for the use of ACAS X within the SESAR framework (EASA, 2023). Unlike rule-based systems, the ACAS X collision avoidance system has been developed using both deep neural networks and machine learning techniques. Machine learning can analyze an aircraft’s trajectory and its distance from other aircraft to identify potential conflict scenarios. Deep learning–based systems can process information obtained from radars and ADS-B data to minimize collision risks. Deep reinforcement learning (Deep RL) algorithms provide decision-support to air traffic controllers by offering alternative solutions to prevent collisions. In addition, graph-based deep learning methods hold significant potential for analyzing and managing air traffic networks.

Machine learning algorithms can also analyze radar and ADS-B data to detect abnormal aircraft movements, enabling earlier identification of potentially hazardous situations and allowing for faster intervention. Anomaly detection algorithms enhance safety by identifying unusual flight patterns within the airspace. Autoencoder-based neural networks are widely used to distinguish between normal and abnormal behaviors in flight data.

Kuchar and Yang (2000) classified 68 different methods aimed at conflict resolution in their study. They highlighted the strengths and weaknesses of the fundamental assumptions underlying these methods. This review provided a comprehensive overview of the research accumulated up to that time, serving as a reference for machine learning techniques developed in subsequent years.

In the study by Vouros, Papadopoulos, Bastas, Cordero, and Rodriguez (2022), the proposed graph convolutional reinforcement learning (DGN) method aims to support air traffic controllers (ATCos) in resolving conflicts between flights. The proposed model performs conflict detection and resolution tasks in a multi-agent environment where each flight acts as an individual agent. The method delivers high-quality solutions and meets the operational integrity and transparency expectations of ATCos. The system has demonstrated strong performance not only in the Barcelona airspace, where it was trained, but also in other airspaces. Future work includes testing the system in simulated real-life scenarios, training it across a broader range of scenarios to enhance safety, and developing disclosure mechanisms. These advancements are expected to support the use of automation and the integration of AI-based systems in ATC.

Xia, Zhou, and Ahmad (2025) developed a machine learning model to detect and predict commercial aircraft accidents. Data labeling was conducted based on rules established by the International Civil Aviation Organization (ICAO) for business jets and was validated by expert pilots. The best predictive model was identified as a linear dipole test with 93% accuracy, and the model's "good fit" was confirmed with anomaly detection achieving 0.97 AUC and daily detection rates of 0.96 AUC. The study aims to predict abnormal flight behaviors by analyzing altitude, heading, and speed parameters from ADS-B data.

Collision avoidance is one of the most critical aspects of air traffic management. Prediction studies in this area occupy a significant place in the literature. Conflict resolution methods have been developed using SVM (Jiang, Wen, Wu, Wang, & Qiu, 2018; Zheng, Le, Huanquan, Junhao, XuGuang, Chuanjiang, & Wei, 2024) as well as combining SVM with other techniques (Chen, Sun, Wang, & Peng, 2022). Xie, Wu, Wen, Chen, Zhang, and Sun (2024) conducted a study on SVM-based conflict detection algorithms using speed limitation methods. Alternatively, conflict resolution has also been approached using ANN (Zhaoning, Haiyang, & Qingyu, 2021; Chen, 2011). LSTM applications are also preferred for collision prevention solutions (Eagleton, Smith, & Nakashima, 2024). Another method used for conflict prediction and trajectory forecasting is the Deep Q-Learning algorithm, a reinforcement learning approach (Pham, 2019).

Although the existing studies appear quite promising, the models have been tested only in simulation environments or on a limited number of scenarios; therefore, their performance should be evaluated in more complex airspace settings.

1.1.4. Weather Forecasting and Mitigation of Noise and Environmental Impacts

Machine learning assists in analyzing weather models to minimize the effects of storms, turbulence, and other meteorological phenomena. This enables the re-planning of flight routes, thereby enhancing both safety and efficiency. Convolutional Neural Networks (CNN) analyze weather forecast data to enable timely responses to sudden weather changes. Likewise, Recurrent Neural Networks (RNN) models work on temporal data to provide long-term weather predictions.

Simorgh, Soler, Castino, Yin, and Cerezo-Magaña (2022) examine the impact of aviation on climate change and investigate operational strategies to reduce this impact. Aviation contributes to climate change through both CO_2 and non-CO_2 emissions, with the effect of non-CO_2 emissions varying significantly depending on factors such as geographic location, altitude, and emission timing. Hence, intelligent route planning is a critical strategy for mitigating aviation's environmental footprint. The study classifies operational solutions proposed in the literature based on methodology, climate parameters, reliability, and feasibility. The analyses assess the effectiveness of different strategies and provide recommendations for future research. The findings suggest that operational strategies can play a significant role in reducing aviation's climate impact, highlighting the need for further investigation in this field.

Feng, Zhou, Ding, Zeng, and Guo (2023) evaluate the effectiveness of machine learning methods for predicting aircraft noise beyond the current best practices and scientific models. Multiple Linear Regression (MLR) and Random Forest (RF) models were applied using data from the Seattle-Tacoma International Airport during the summer periods of 2020-2022. Experimental results indicate that the RF model outperforms the MLR model in noise prediction accuracy. The RF model achieved an R^2 value of 74.469%, which is 5.361% higher than the MLR model. Additionally, the RF model's RMSE value of 0.814 is 0.106 lower than that of the MLR model.

Furthermore, numerous studies employing Artificial Neural Networks (ANN) have been conducted on wind direction and intensity forecasting (Lawrence, Garba, Malgwi, and Hambali, 2022), air pollution prediction (Kamsing, Cao, Boonpook, Boonprong, Xu, and Boonsrimuang, 2025), weather forecasting (Zemnazi, El Filali, and Ouahabi, 2024), and turbulence prediction in aviation using Random Forest algorithms (Williams, 2014; Muñoz-Esparza, Sharman, and Deierling, 2020). Weather prediction studies also utilize Random Forest (Singh, Chaturvedi, and Akhter, 2019), while aircraft noise prediction based on aircraft characteristics has been explored (Toraman, Dursun, and Aygun, 2025). Wind forecasting for flight path planning using SVM has been addressed by Kim, Zhang, Briceno, and Mavris (2021), alongside studies on turbulence prediction (Mizuno, Ohba, and Ito, 2022). Additionally, Singh, Pawar, Afnan, Hegde, and Kannadaguli (2024) compared SVM, Logistic Regression, Naive Bayes, and Decision Trees for an application named "Silent Skies," achieving highly successful results with each technique.

Although machine learning techniques have demonstrated successful results in short-term weather forecasting, uncertainties remain in long-term predictions, which reduces their reliability. Another area lacking operational suitability is the study of environmental impacts. Current models are not sufficiently advanced to be directly implemented. Therefore, future research should focus on utilizing larger datasets and modeling long-term environmental effects.

4. Challenges Faced in Air Traffic Management for Machine Learning

Air traffic management is becoming increasingly complex due to rising air traffic volumes and safety requirements. In recent years, machine learning has made significant contributions to areas such as air traffic management and decision support systems. The literature review clearly indicates that the results are promising. However, a considerable portion of the studies has been conducted using limited datasets and in restricted simulation environments, and their applicability to current operational conditions has generally not been tested. The integration of these technologies into ATM processes presents a range of technical, operational, and regulatory challenges. This section outlines the main challenges faced by researchers applying machine learning in ATM.

4.1 Data Limitations and Quality

The accuracy and size of datasets play a critical role in the success of any model. However, collecting data for ATM studies, as well as sharing and processing this data, is subject to various restrictions. Data used in air traffic control is critical for operational and national security purposes. Therefore, real-time control data is not publicly available. Limited access to data adversely affects the model development process. Likewise, datasets that are incomplete, inaccurate, or erroneous negatively impact model performance.

Another challenge arises from data imbalance. Since critical events such as air traffic accidents occur rarely, datasets containing such events are limited. This scarcity makes it difficult for models to accurately predict rare events. To overcome these challenges, it is essential to promote open data policies in ATM, generate synthetic data in simulation environments, and employ advanced data cleaning techniques.

4.2 Real-Time Processing and Computational Requirements

Decisions made in air traffic management must be highly precise and executed in real time. Machine learning models trained on large datasets often entail high computational costs. Deep learning (DL), Long Short-Term Memory (LSTM), and transformer-based networks require substantial processing power. However, ATM systems demand decisions within seconds, making it challenging to optimize models for real-time operation. Furthermore, machine learning models deployed in ATM must maintain low response times. Latency arising from CPU or GPU processing can be unacceptable for conflict detection and flight path optimization.

Efficiency of real-time machine learning models can be improved through techniques such as model compression, hardware acceleration, and quantization.

4.3. Model Transparency and Explainability

For machine learning models to be utilized effectively in ATM processes, they must not only produce accurate predictions but also provide explanations for their decision-making processes. However, many deep learning models are considered “black boxes.” Explainable Artificial Intelligence (XAI) techniques can make these decision processes more transparent. Examples of such techniques include LIME, SHAP, and Partial Dependence Plots. These methods enable visualization of the features the model considers and clarify why certain outputs are generated.

Air traffic controllers need to trust machine learning-supported systems. Opaque models may lead to skepticism towards predictions, reducing system effectiveness. The use of XAI techniques represents an important step towards enhancing human-machine collaboration.

4.4 Safety Standards

The implementation of machine learning models in ATM requires compliance with regulations established by international aviation authorities such as the FAA, ICAO, and EASA. These bodies must approve the use of ML models; however, there are currently no specific regulations tailored to machine learning models. The safety compliance of ML models must be thoroughly tested, and operational risks minimized before deployment. Nevertheless, the non-deterministic nature of machine learning systems poses challenges during testing procedures.

Developing new regulatory frameworks and auditing mechanisms to improve model reliability is essential for successful integration.

4.5 Human-Machine Interaction and Training

Effective human-machine interaction is critical for the successful adoption of machine learning models. Controllers and pilots must be adequately trained to understand and operate these systems correctly. Additionally, machine learning-enabled air traffic management systems should feature user-friendly interfaces to facilitate acceptance and ease of use.

5. Conclusion

This study provides a comprehensive evaluation of the increasing importance and potential contributions of machine learning (ML) models in the field of air traffic management (ATM). The literature has evolved from early optimization methods toward data-driven models. Literature reviews and application examples indicate that ML-based models offer higher accuracy, scalability, and flexibility compared to traditional optimization methods, metaheuristic algorithms, and multi-criteria decision-making approaches.

In particular, algorithms such as long short-term memory (LSTM), random forests, XGBoost, and deep reinforcement learning have demonstrated successful results in critical processes, including flight trajectory prediction, conflict detection and resolution, air traffic management, and weather forecasting. Nevertheless, the generalizability, interpretability, and transparency of the models used remain fundamental challenges for practical implementation in this field.

The integration of machine learning (ML) technologies into air traffic management (ATM) has been examined in detail, demonstrating enhanced operational efficiency, reduced conflict resolution time, and more effective utilization of airspace resources. For instance, LSTM-based time series models accurately predict traffic density using historical weather data, while deep learning algorithms focused on reinforcement learning offer innovative solutions for dynamic route optimization and autonomous systems. Additionally, algorithms such as random forests and XGBoost, which show high efficiency in delay prediction and capacity assessment, strengthen the decision-making process of air traffic controllers. Deep learning methods, including convolutional neural networks (CNN) and recurrent neural networks (RNN), have proven effective in weather forecasting and mitigating environmental impacts.

However, integrating ML technology into ATMs faces numerous technical, operational, and regulatory challenges. First, accessibility and data quality pose significant limitations. Access to most ATM data is restricted due to operational confidentiality and national security considerations, which reduces the diversity of data required for model training. In particular, access to rare event data, such as aircraft accidents, is limited, hindering the model's ability to accurately predict such scenarios. To address this issue, various solutions have been proposed, including promoting open data policies, generating simulation-based synthetic data, and developing algorithms capable of handling incomplete or imbalanced datasets. For example, anomaly monitoring and detection algorithms can provide resilience against such data processing constraints.

Second, real-time processing requirements complicate the implementation of ML models in ATM. Deep learning models incur high computational costs, making it difficult to achieve low response times. Model compression, quantization, and hardware acceleration are crucial for mitigating this challenge. Third, the transparency of ML models—particularly the "black box" nature of deep learning—limits air traffic controllers' trust in the system. Explainable AI (XAI) technologies, such as LIME and SHAP, can enhance transparency by making the model's decision-making process accessible, thereby strengthening human–machine collaboration.

Compliance with international aviation regulations (e.g., FAA, ICAO, EASA) constitutes another major constraint to the integration of ML models into ATM. Current regulations cannot fully accommodate the uncertainties inherent in ML-based systems. Therefore, developing new regulatory frameworks and establishing standardized control mechanisms to validate model reliability are essential. Furthermore, human–machine interaction plays a critical role in the success of ML-based systems. User-friendly interfaces and comprehensive training programs can increase air traffic controllers' and pilots' trust in and adherence to these systems.

Future research should focus on several key areas to enhance the potential of ML techniques in ATM. First, innovative algorithms capable of handling incomplete or imbalanced datasets should be developed, which can be facilitated through methods such as synthetic data generation, transfer learning, or collective learning. Second, broader integration of XAI techniques will improve model transparency, thereby reinforcing operational reliability. Third, ML-based solutions aimed at mitigating environmental impacts, such as route optimization and noise prediction, should be explored in greater detail. Techniques such as cloud computing and edge computing may prove effective in meeting real-time processing requirements.

Finally, studies could incorporate next-generation aircraft such as UAVs and eVTOLs, and joint airspace operations could be conducted to address conflict and traffic flow management.

In summary, machine learning offers transformative potential for air traffic management in achieving safety, efficiency, and sustainability objectives. However, fully realizing this potential requires a systematic approach to multidimensional issues such as data accessibility, model transparency, regulation, and human–machine interaction. In this context, interdisciplinary research focused on technological innovation and operational sustainability will play a crucial role in the future of ATM. Machine learning–based systems should occupy a central position in the modernization of air traffic control.

Ethical Statement: This study was conducted in accordance with research and publication ethics. The authors declare that there is no conflict of interest regarding this study.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used AI to assist in improving the readability and language of the text. After employing this tool, the authors thoroughly reviewed and edited the content as needed and take full responsibility for the final version.

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