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Review

A Review of Machine Learning Applications in Aviation Engineering

Parankush Koul *

Department of Mechanical and Aerospace Engineering, Illinois Institute of Technology, 60616 Chicago, Illinois, United States of America

* Correspondence: pkoul2.iit@gmail.com

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Abstract

This review paper investigates how machine learning (ML) has transformed multiple facets of aviation engineering. The work demonstrates substantial progress in flight operations and air traffic management (ATM) optimization through frameworks such as Reinforcement-Learning-Informed Prescriptive Analytics (RLIPA) and deep reinforcement learning (DRL) techniques applied to conflict resolution. The study highlights how ML contributes to operational efficiency through faster computational processes and better decision-making abilities for those who control air traffic. The paper examines how leading firms such as SpaceX and Raytheon use ML technology to enhance manufacturing processes, including predictive maintenance (PdM) and autonomous systems development. The paper discusses ML implementation obstacles, including model interpretability, and highlights further research requirements for adapting to real-world issues such as changing traffic volumes and weather variations. Overall, the study demonstrates how ML technology can transform aviation engineering through enhancements in safety standards as well as operational and process efficiency.

Keywords: machine learning, aviation engineering, predictive maintenance, air traffic management, integration

Abbreviations

ADS-B	Automatic Dependent Surveillance-Broadcast
AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ATCO	Air Traffic Control Operator
ATFM	Air Traffic Flow Management
ATFSTNP	Air Traffic Flow Spatial-Temporal Network Prediction
ATM	Air Traffic Management
BIT	Blade Inspection Tool
BP	Back Propagation
BαPVWVD	Buffered α-Predicted-Vector Weighted Voronoi Diagram
CDDR	Collaborative Digital Departure Reroute
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Network
DPHM	Diagnosis, Prognosis, and Health Management
DQN	Deep Q Network
DRL	Deep Reinforcement Learning
EAI	Explainable Artificial Intelligence
MLR	Multiple Linear Regression
ECS	Environmental Control Systems
ESA	European Space Agency
FFT	Fast Fourier Transform
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GCN	Graph Convolutional Network
GDP	Ground Delay Program
GPR	Gaussian Process Regression
GS	Ground Stops
HIM	Horizontal Interdependency Matrix
IoT	Internet of Things
JDA	Joint Distribution Alignment
KNN	K-nearest Neighbors
LIME	Local Interpretable Model-Agnostic Explanations
LST-SATM-Net	Lightweight Spatial-Temporal Model Fusion Self-Attention Mechanism
LSTM	Long Short-Term Memory
MADRL	Multi-Agent Deep Reinforcement Learning
MAE	Mean Absolute Error
MDP	Markov Decision Process
ML	Machine Learning
MLP	Multilayer Perceptron
RSF	Random Survival Forest

MLT	ML Technique	RT	Regression Tree
NAS	National Airspace System	RUL	Remaining Useful Life
NLP	Natural Language Processing	RVM	Relevance Vector Machine
OoD	Out-of-Distribution	SAC	Soft Actor-Critic
PdM	Predictive Maintenance	SATM	Spatial Attention Mechanism
PHM	Prognostics and Health Management	SERL	Safety-Informed Evolutionary Reinforcement Learning
PPO	Proximal Policy Optimization		
PRSOV	Pressure Regulated Shutoff Valves	SHAP	Shapley Additive Explanation
PSO-BP	Particle Swarm Optimization-Back Propagation	SVM	Support Vector Machine
		TCA	Transfer Component Analysis
RBF	Radial Basis Function	TCS	Tactical Conflict Solver
RL	Reinforcement Learning	TMI	Traffic Management Initiative
RLIPA	Reinforcement-Learning-Informed Prescriptive Analytics	TSSAC	Transfer-Safe Soft Actor-Critic
		UAM	Urban Air Mobility
RMSE	Root Mean Squared Error	UAS	Unmanned Aircraft Systems
RM-IMM	Residual-Mean Interacting Multiple Models	UAV	Unmanned Aerial Vehicle

1. Introduction

ML stands as a transformative technology in aviation engineering because it finds application throughout different industry sectors. As more industries adopt data-driven decision-making systems, ML becomes central to applications that boost PdM capabilities along with safety monitoring, performance optimization, and operational efficiency. ML methods solve intricate aviation problems, including fault detection and ATM, while boosting security measures, which results in higher safety standards and system reliability (Shuaia et al., 2023; Karaoğlu et al., 2023).

There are no industries as regulatory and operational as the aviation industry, and so there are new and unique challenges that can be met with ML. ML algorithms can mine vast volumes of data that are generated from airplanes and detect patterns and make predictions that reduce human labor and optimize various operations (Garcia et al., 2021). In addition, the coupling of ML with other new technologies, including the Internet of Things (IoT) and big data analytics, opened the possibility for the analysis and decision-making of data in real time and eased the operation and maintenance of airplanes (Murthy et al., 2023; Timjerdine et al., 2024).

PdM is one application of ML in aviation engineering. Predicting what will fail using historical information of aircraft performance and history of maintenance helps ML models to take predictive action in order to make aircraft reliable and minimize maintenance. Preventive maintenance measures like these have become more and more important for airlines who want to minimize downtime and maximize flights (Karaoğlu et al., 2023; Wade et al., 2017). Additionally, ML can help build advanced flight management systems that leverage real-time information to control air traffic and find flight routes, which saves fuel and emissions (Garcia et al., 2021; Timjerdine et al., 2024).

ML also addresses major safety issues during flights. Stakeholders can monitor aircraft systems for anomaly trends that signal potential failure or cybersecurity threats with anomaly detection systems powered by ML. With the evolution of the aviation industry, artificial intelligence and ML are expected to grow even more significant in the future of aviation engineering and change the way the industry operates (Shuaia et al., 2023; Luettig et al., 2024).

Overall, this overview of ML in aviation engineering shows how massive the potential is of these technologies to change the face of processes, increasing safety, efficiency, and reliability. As the market develops in this space, further studies will be needed to optimize methods and resolve the challenges of the certification and deployment of ML systems in aviation (Wade et al., 2017; Luettig et al., 2024).

2. Review methodology

This paper uses a systematic method to analyze current literature about ML applications in the aviation industry. Here are the key components of the review methodology:

- Literature selection
  Time frame: The review examines scholarly articles published between 2019 and 2024 to stay current with the latest developments in ML applications for aviation engineering.
- Comparative analysis

Categorization: The analyzed research papers have been organized according to distinct ML applications, which include:
- Optimization of flight operations and ATM,
- Enhancement of autonomous flight systems and safety,
- PdM and fault diagnosis in aircraft systems.

Tables for comparison: The paper presents comparison tables that detail the reviewed articles. These tables highlight:
- Focus areas of each study,
- Methodologies employed,
- Key discoveries and outstanding issues regarding the application of ML in every category.

- Identification of gaps
  Unresolved Challenges: The review documents unresolved challenges encountered during the application of ML across various domains within aviation engineering, which include problems of model interpretability and system integration as well as real-time applicability in dynamic environments.
- Conclusion synthesis
  Summary of Findings: The paper ends with a summary of how machine learning can revolutionize aviation engineering while highlighting the necessity for further research to tackle present issues and investigate new applications.

The review methodology delivers comprehensive results through systematic literature selection and comparative analysis, which identifies gaps and synthesizes research findings to present current ML applications and future directions in aviation engineering.

3. Methodologies to implement ML in aviation engineering

ML integration into aviation engineering uses a systematic method to improve industry performance together with safety and efficiency. Advanced algorithms and statistical models enable ML to process large volumes of aviation data, which supports PdM practices as well as fatigue management and mission planning with operational optimization. A well-defined methodology with multiple critical stages needs to be followed for successful ML integration into aviation systems. The major elements of the methodology include data collection and preprocessing along with model selection and training/testing before system integration and human factor considerations. The following subsections outline these key steps in the ML implementation process, highlighting their significance in advancing aviation engineering:

- Data collection and preprocessing: implementing ML in aviation engineering begins with data collection and preprocessing (Kabashkin et al., 2023). Effective ML models require comprehensive datasets. Operational aircraft sensor data, maintenance records, and environmental conditions make up these datasets. The data preprocessing stage remains crucial to maintaining high-quality datasets because it consists of cleaning activities along with normalization and transformation procedures that boost model performance. Outlier detection with missing value imputation and noise reduction methods enhances data integrity during data preprocessing (Ahmadi et al., 2017).
- Selection of models: Choosing appropriate ML models is essential to attain successful results in aviation applications. Several ML algorithms are suitable for use in different contexts, including supervised learning models along with unsupervised learning techniques and reinforcement learning (RL) approaches. Supervised learning methods such as decision trees and neural networks frequently serve as tools for PdM because they help predict possible machine failures (Hasan et al., 2022). Clustering as an unsupervised learning method enables pattern recognition within unlabeled data, which proves useful for detecting anomalies and optimizing operations (Jacko, 2009). The choice of the right model relies on its application purpose in aviation engineering and the characteristics of the collected data.
- Training and testing: After models are selected, training and testing models on the current datasets is done. It involves reworking the data into training and testing sets in order to check the performance of the model (STP, 2021). In training, the model can learn from the data patterns, and in testing, it can be tested on unobserved data. There are performance metrics, such as accuracy, precision, recall, and F1-score, used to calculate the predictive performance of the

model. To achieve optimal performance, iterative model tuning might be required, which includes methods such as cross-validation combined with hyperparameter optimization (Ahmadi et al., 2017).

- Integration into aviation systems: ML applications are only effective when the models are integrated into current airplane systems. In this step, the models are deployed to in-house software for flight operations, maintenance schedule, or safety analysis (Lüdtke & Möbus, 2005). Integration will require working with software engineers and aviation professionals to make sure the ML models are compatible with practical operational requirements and regulatory requirements. Also, continuous monitoring and updates of the models to take account of changes in the working environment and to make the models accurate as the years pass.
- Human factors and ML: When it comes to ML in aviation, human factors come into play. ML algorithms should complement, not supersede, human judgment. Interface design and comprehensibility of model output are important issues in order to make it easy for aviation experts to apply the knowledge generated by ML models (Jacko, 2009). The aviation industry can also adopt these systems by learning how to use them.

4. Benefits and applications of ML in aviation engineering

ML is transforming aviation engineering through improvements in efficiency and safety while upgrading decision-making processes throughout multiple industry areas. ML-driven solutions use large volumes of data to boost performance and minimize risks across flight operations optimization and PdM and cyber-security. ML analysis of live sensor streams and failure predictions teamed with automated air traffic control integration positions it as an essential aviation technology. The following subsections highlight the key benefits and diverse applications of ML in the aviation industry.

4.1. Benefits of ML in aviation engineering

ML contributes to aviation engineering through its ability to boost safety standards alongside operational efficiency. The foremost advantage of this ability lies in its capability to examine extensive datasets, which proves essential in an industry that requires decision-making based on intricate and changing information. ML algorithms function to identify irregularities in aircraft sensor data streams that serve as a critical component of PdM programs. ML enables equipment failure predictions that reduce maintenance expenses and downtime while increasing operational safety (Shuaia et al., 2023).

Moreover, ML makes ATM more automated. Advanced algorithms can predict flight routes, save fuel, and delay if necessary (Morales et al., 2017). When ML is coupled with current systems, it is easier to make decisions when uncertain, especially in the face of weather patterns and more passengers. The result is cleaner and more efficient air traffic (Garcia et al., 2021).

Moreover, ML accelerates the monitoring and analysis in the air traffic control system. It helps in the validation of safety processes by searching for patterns in incident reports and operational records that are not readily visible (Shuaia et al., 2023).

4.2. Applications of ML in aviation engineering

There are several examples of ML applications in aviation engineering, which serve different use cases and problems.

- PdM: It is the most effective use case of ML algorithms to prevent component failures in aircraft. Historical and current sensor information can be analyzed by ML to detect the possibility of failures and so maintain it before any problems arise (Brown et al., 2021).
- Flight operations optimization: ML is the engine behind flight operations optimization to forecast air traffic and adjust the flight times. The algorithms take the inputs, like weather conditions, air traffic density, and aircraft performance, and recommend the best flight paths and altitudes, which will lead to improved fuel efficiency and delays (Morales et al., 2017).
- Anomaly detection in aviation cybersecurity: With its reliance on technology, cybersecurity has never been more important. They also apply ML to spot and respond to problems in avionics equipment, which protects against cyber-attacks. Such as monitoring the data communications channels in real-time to flag suspicious activity (Garcia et al., 2021).

- Human factors assessment: ML use cases extend to human factors assessment in the aerospace industry, pilot performance, and workload management. ML models can inform training program optimization and pilot decision-making by using data from the simulator and real-world flight conditions.
- Air traffic control: ML is applied to make air traffic control processes efficient by automating operations and offering decision-support algorithms to controllers for managing the flow of air traffic. This makes the work of human operators less cognitive and safer (Garcia et al., 2021).
- Aircraft design and testing: ML is also used in the designing and testing of the aircraft. When design engineers use ML algorithms to look at simulation and prototype performance data, they can make safer and more effective design decisions (Brown et al., 2021).

5. Past projects in manufacturing companies implementing ML in aviation engineering

Leading aviation industry players, together with new aerospace firms, are pushing the application of ML in aviation engineering to boost operational efficiency and innovation while improving safety standards. The aviation and aerospace industries use ML to improve manufacturing processes along with PdM and autonomous operations through real-time data analytics. The practical applications of ML in aviation engineering are illustrated through the analysis of previous manufacturing projects while showing how industry progress benefits field development. By incorporating several companies, this study delivers diverse viewpoints about ML utilization, which covers commercial aviation alongside defense and space exploration activities.

Boeing uses ML in various projects, including improving procurements with AI-driven solutions. The company has leveraged generative artificial intelligence (AI) to learn what shoppers spend and to process sourcing, which is particularly helpful for lower-value, higher-volume transactions. Similarly, Boeing also uses predictive data models to increase safety by anticipating risks before they become serious (Pahuja, 2024).

Airbus is using ML to boost the efficiency and operations of manufacturing with their Project ADAM, which attempts to include ML in design and production. The project increases productivity by automating those processes that have traditionally been performed by humans so that engineers can be more involved in development (ADAM, 2020).

Rolls-Royce applies ML with its AI-powered Aletheia Framework, which continuously processes the data from jet engines on the road. The AI-powered system helps engineers identify troublesome potential faults and operational irregularities, making maintenance scheduling and unexpected downtime much easier. Rolls-Royce's advanced analytics system analyzes engine data in real time and flags anomalies for human inspection (Pearce, 2024).

GE Aviation uses ML to reduce engine maintenance costs and boost efficiency. They apply AI in devices like the Blade Inspection Tool (BIT), which helps technicians check the components more quickly and precisely, thus increasing the reliability of engines (Noon, 2024; ANI, 2024). They have been focusing on ML, which has made them one of the major AI patent holders in the aerospace space and is incorporating the technologies in multiple applications (Noon, 2024).

Pratt & Whitney uses ML extensively in oil analysis systems to prevent engine problems before they occur. Using micro-traces of metal in the oil samples, their ML-based system predicts maintenance requirements for proactive decision-making and cost reductions for customers (Pratt & Whitney Customer Service, 2022; Pratt & Whitney, 2022). They also recently partnered with a startup to build an AI-driven aircraft engine inspection tool called Percept that automates inspections and saves hours of turnaround time (Pratt & Whitney, 2023; Phadnis, 2023).

Honeywell also uses ML on its Honeywell Forge Performance+ platform for aerospace manufacturing and maintenance organizations for PdM. These capabilities ensure higher operational efficiencies and the accurate detection of repair requirements in time to increase safety and lower costs (Rainey, 2024; Melin, n.d.). Their AI systems enable them to automate processes and maximize the utilization of assets for various aerospace use cases (Rainey, 2024).

Northrop Grumman implements ML-based systems in defense and aerospace, particularly in autonomous operations and real-time data processing. Their AIs support situational awareness by analyzing huge amounts of data fast, which is important for military applications and autonomous systems

(Northrop Grumman, 2023; Madhavan, 2019). AI adoption in unmanned aerial and ground systems demonstrates their commitment to advanced technology in aviation engineering (Madhavan, 2019).

Raytheon Technologies applies ML to optimize aircraft design and maintenance procedures to increase efficiency and safety. Their advanced materials studies leverage AI to discover new materials with improved performance in many areas of aerospace and defense. Raytheon's emphasis on mutual autonomy ensures that AI serves multi-domain missions well (RTX, n.d.).

Lockheed Martin's ML applications help augment modeling and simulation tools for defense systems. AI is used in agile missions by initiatives such as the DARPA AIR project, providing predictive analytics to aircraft and military assets through the use of big data modeling (Lockheed Martin, 2024a; 2024b). They invest in AI in an effort to keep an advantage in aerospace technologies (Lockheed Martin, 2024a).

SpaceX also leverages ML at every level, from the way it optimizes its flight paths to the prediction of repairs for spacecraft systems. They use AI-powered autopilot systems to autonomously land rockets and ML algorithms to improve mission performance by using real-time data to make operational decisions (Malik, 2024; Saitata, 2023). The company's adoption of AI on Starlink reflects its investment in technology innovation and effectiveness in space (Malik, 2024).

Blue Origin uses ML to enhance navigation and control for its spacecraft. With artificial intelligence algorithms for self-driving operations, Blue Origin will ensure its missions are safer and more efficient, continuing an increasing effort to include AI in aerospace engineering. They also invest in AI talent to emphasize their mission to transform space travel and exploration with cutting-edge technology (Do-Han, 2024).

NASA is harnessing ML to support air traffic control and space operations. Their Collaborative Digital Departure Reroute (CDDR) software uses ML algorithms to forecast traffic patterns, improving runway management and reducing fuel use at large airports. These innovations reflect NASA's continued commitment to using AI to make aircraft sustainable and efficient (Smith, 2023).

Virgin Galactic also incorporates ML in its operation to help with microgravity experiments. Currently working on its SpaceShipTwo rocket for experiments, the company uses AI to plan and execute experiments in an efficient way, making it one of the leaders in the burgeoning space research market. Their method emphasizes the interoperability of space platforms, promoting commercial spaceflight innovation (Reim & Norris, 2023).

Finally, the European Space Agency (ESA) uses ML to build performance prediction models for satellite navigation systems such as EGNOS. Researchers are using ML to predict performance more accurately, and it's affecting industries such as aviation by assisting in the navigational processes. The ongoing research is another example of ESA's dedication to space technology via AI (Gutierrez, 2024).

6. Overview of past research on ML applications in aviation engineering

Over the last half-decade, aviation engineering has embraced ML while researchers investigated its capabilities in multiple areas, including flight operations and autonomous systems, alongside PdM. This section employs a systematic literature review approach to present a structured and detailed overview of recent advancements. Figure 1 presents a quantitative breakdown of the reviewed articles, categorized into three primary ML applications: optimization of flight operations and ATM, enhancement of autonomous flight systems and safety, and PdM and fault diagnosis in aircraft systems.

The reviewed articles' distribution shows a progressive pattern that keeps study representation balanced across all categories over time. The number of selected articles published annually rose to show expanding research interest in ML applications for aviation. The publication pattern increased from one article per category in 2019 to two in 2020 and three in 2021 and continued this growth until six articles per category were reached by 2024. Recent developments receive adequate representation through this structured selection process while maintaining balanced evaluations across multiple ML applications. The growing volume of publications over time demonstrates how ML's application in aviation engineering is spreading as researchers become more involved in this domain.

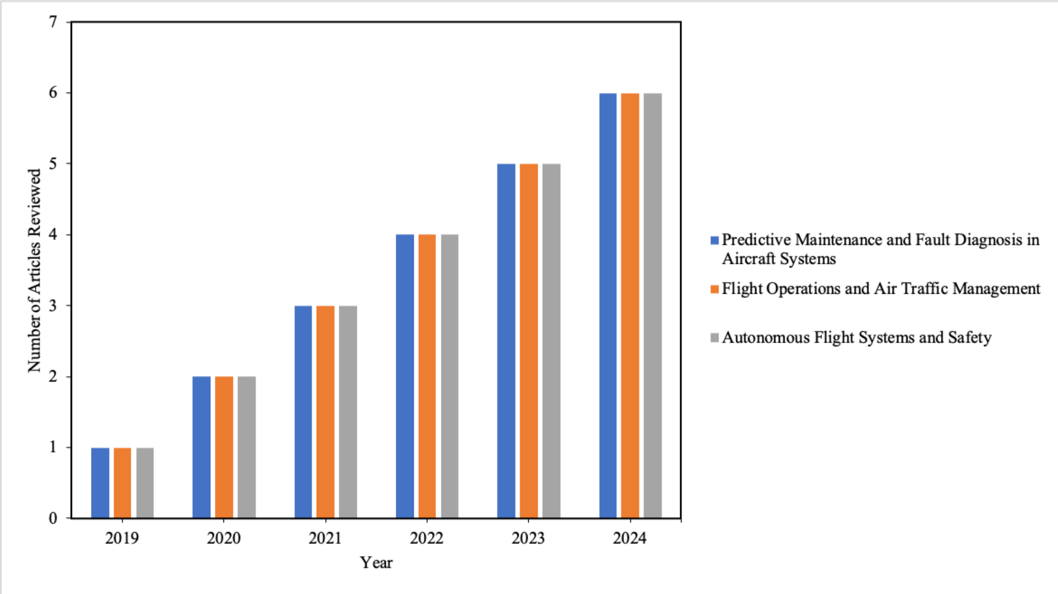

Fig. 1. Number of articles on ML applications in aviation engineering *vs.* year.

6.1. ML in PdM and fault diagnosis in aircraft systems

Table 1 below shows a quantitative distribution by publisher of the number of articles related to the applications of ML in PdM and fault diagnosis in aircraft systems.

Table 1. Number of articles from different publishers reviewed on the applications of ML in PdM and fault diagnosis in aircraft systems.

Publisher	Number of articles reviewed
IEEE	6
Elsevier	2
SPIE Digital Library	2
Springer	2
EDP Sciences	1
IGI Global Scientific Publishing	1
IOP Publishing	1
MDPI	1
SBC Digital Library	1
SciELO	1
Shodh Sagar International Publications	1
SSRN	1
Wiley	1
Total	**21**

Zhou et al. (2019) developed a fault diagnosis algorithm for aircraft engine fuel regulators by employing a Relevance Vector Machine (RVM) to create an engine inverse model that overcomes the nonlinearities of fuel system modeling. Their system found faults using hardware-in-the-loop simulations that proved high estimation accuracy and improved system performance. Hermawan et al. (2020) developed a maintenance algorithm that used a mixture of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to compute Remaining Useful Life (RUL). This technique proved to be more accurate and efficient in simulations, which allowed accurate maintenance scheduling in real-time. Dangut et al. (2020) fixed data unbalance in PdM using soft mixed Gaussian techniques and the Expectation-Maximization approach. With a seven-year heterogeneous dataset, they were far more accurate than a standard random forest algorithm in their recall of rare faults, thus better predicting the failures of critical parts.

Li (2021) compared Support Vector Machine (SVM), Random Forest, and Particle Swarm Optimization-Back Propagation (PSO-BP) algorithms for aircraft engine fault diagnosis and showed that the PSO-BP algorithm performed better (98.3% accuracy and shortest recognition time). This highlighted its value in detecting faults early and providing safer flights. Caricato et al. (2021) devoted to RUL estimation for aeroengines through Tree Regression, Gaussian Process Regression (GPR), and Multilayer Perceptron (MLP). The MLP model with a defined architecture was best at prediction performance, maintaining lower maintenance and improving asset availability. Dangut et al. (2021) dealt with the problem of prognostication of rare failure by using a hybrid combination of Natural Language Processing (NLP) and ensemble learning. Their model did a pretty decent job in terms of overcoming data imbalance problems, increasing predictive power by about 10% over the previous methods.

Ingole et al. (2022) explored the use of various regression models, particularly Random Survival Forest (RSF), to enhance PdM strategies for aircraft engines. Their work showed that RSF was superior to the other algorithms for explained variance and absolute error, making it a more accurate approach for failure detection and maintenance decision-making. Sano and Berton (2022) applied deep learning (DL) algorithms, such as CNNs and MLPs, to aircraft maintenance for fault finding in Pressure Regulated Shutoff Valves (PRSOV). They demonstrated an improvement of classification efficiency over the standard approach, and the MLP and CNN models have 99.62% and 99.37% accuracy, respectively, which clearly indicate that DL can be used to improve fault detection. Liu et al. (2022) dedicated themselves to using data-driven Prognostics and Health Management (PHM) technology to diagnose failures of the aviation electromechanical systems. With ML algorithms, using hydraulic test data, they could efficiently detect fault conditions, identify patterns, and inform maintenance decision support, which made aircraft safer to fly.

Jia et al. (2022) developed a multi-data fusion hybrid deep fault diagnostics for aircraft sensor systems to enhance fault detection by converting sensor data to time-frequency models. Their approach, using DL to characterize and locate faults in aircraft attitude sensors, trumped existing diagnostic systems and made flights safer by correctly identifying sensor failures. Liu et al. (2023) focused on a ML clustering method for the diagnosis of multi-component degradation in aircraft fuel systems. With a new test rig and temporal and frequency-domain clustering features, they had greater than 99% fault detection and near-perfect severity detection. This method was remarkably reliable for identifying component degradation rates and was extremely useful for PdM in high-dimensional systems such as fuel tanks. Jia et al. (2023) used transfer learning to resolve cross-condition fault detection for aircraft Environmental Control Systems (ECS). They employed Transfer Component Analysis (TCA) and Joint Distribution Alignment (JDA), which resulted in predictive performance of 95.22% on average with unlabeled data and was very useful in fault diagnosis under different operating scenarios.

Saxena and Ak (2023) studied early-warning systems for airplanes that use ML classification models to find failures before they happen by turning data on RUL into binary classifications. Their solution showed a strong potential for early failure detection to allow for proactive maintenance and increase safety in operation. Rahamathunnisa et al. (2023) extended ML and DL into small aircraft systems, elaborating on their inclusion in autopilot, navigation, fault detection, and pilot aids. Their work focused on the generalizability of intelligent systems in the pursuit of safety, efficiency, and reliability, and it was backed by examples from the field and insight into implementation challenges. Yang et al. (2023) developed the Lightweight Spatial-Temporal Model Fusion Self-Attention Mechanism (LST-SATM-Net) model, which combined LSTM networks with spatial attention algorithms to identify failures in aero-engine hydraulic systems. Their model performed much better than other systems in diagnostic quality and effectiveness, showing the utility of high-end DL architectures in complex aircraft.

Lv et al. (2024) proposed an encapsulated approach involving DL for feature extraction and Markov models for state transition for fault diagnosis and prediction. Their approach, tested on real aircraft data, showed robust accuracy, recall, and F1 score increases, proving the strength and practicality of their methodology to augment aircraft safety and maintenance productivity. Dube (2024) was interested in the use of DL for PdM of aircraft engines, with a focus on how it can process big data, improve maintenance time, and minimize downtime. This research, through the application of DL algorithms, was proven to have better reliability and performance than traditional reactive and preventative maintenance approaches to address important safety and financial issues in aviation. Stanton et al. (2024) resolved the challenge of lack of available proprietary data by using the DoppelGANger model to produce synthetic time-series datasets for landing gear systems of aircraft. These datasets, validated through fidelity metrics, allowed for more research and allowed new PdM models to be constructed without losing proprietary data.

Zhang and Du (2024) solved the problem of unbalanced operational data for aeroengines by combining LSTM networks and generative adversarial networks (GANs) with human-machine interaction in order to detect dynamic features and minimize false alarms and missed alarms. Their approach also made significant diagnostic gains by simply adding dynamic mode data. Chu and Yin (2024), however, worked on fault diagnosis of today's modern aircraft and showed that fusion approaches (including rough set theory with Back Propagation (BP) networks) were better than single diagnostics in pinpointing the location of faults, underscoring the value of hybrid solutions. Shen et al. (2024) took it further to fault diagnosis, prognosis, and health management (DPHM) using a hybrid model combining nonlinear filtering, deep neural networks (DNNs), and mixed learning methods. Their solutions enabled predictive, self-contained health monitoring, which was more reliable and minimized maintenance costs and downtime.

Table 2 provides a comparative analysis of the articles reviewed above, highlighting their focus areas, methodologies, key findings, and unresolved challenges in the application of ML for PdM and fault diagnosis in aircraft systems between 2019 and 2024.

Table 2. Comparison of reviewed articles (2019–2024) on ML applications in PdM and fault diagnosis for aircraft systems.

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Zhou et al., 2019)	Fault diagnosis for fuel regulators in aircraft engines using RVM.	Developed an engine inverse model using RVM, validated through hardware-in-the-loop simulation tests.	High estimation accuracy and effective fault diagnosis, improving system reliability and enabling PdM.	Complexity in modeling due to the strong nonlinearity of engine structures remains a challenge.
(Hermawan et al., 2020)	PdM of aircraft engines using DL techniques (CNN + LSTM).	Utilized CNN and LSTM for feature extraction and sequence learning. Simulations tested RUL prediction accuracy.	Improved RUL estimation accuracy and reduced computational time compared to earlier methods.	Further optimization of hybrid DL techniques for real-time applications is needed.
(Dangut et al., 2020)	Aircraft PdM modeling addressing data imbalance in heterogeneous datasets.	Hybrid approach using soft mixed Gaussian processes and Expectation-Maximization, with seven years of real-world data.	Outperformed baseline methods (RF algorithm), achieving >80% accuracy in predicting rare faults.	Addressing extreme imbalance ratios and testing the method on larger datasets with broader systems.
(Li, 2021)	Comparison of ML algorithms for aircraft engine fault diagnosis.	SVM, Random Forest, PSO-BP algorithms; Artificial and real fault datasets with 780 training samples and 520 testing samples.	PSO-BP achieved 98.3% accuracy, Random Forest 85.7%, and SVM 79.2%. PSO-BP was faster than SVM.	Lack of testing on a broader range of engine types and real-world conditions.
(Caricato et al., 2021)	Prognostic techniques for aeroengine health assessment and RUL estimation.	Tree Regression, GPR, MLP using NASA's Prognostics Center of Excellence datasets (FD001, FD002).	MLP with 1 hidden layer and 5 nodes had RMSE of 17.38 and Mean Absolute Error (MAE) of 12.50. Performance consistent with existing literature.	Need for further optimization in GPR models and testing on larger datasets.
(Dangut et al., 2021)	Hybrid ML model for rare failure prognostics in aircraft components.	NLP + Ensemble Learning using real aircraft log-based dataset with rare unscheduled component replacements.	Hybrid model improved performance by 10% in precision, recall, and F1-score compared to synthetic minority oversampling techniques.	Further research on improving data imbalance handling and real-time implementation in aircraft systems.
(Ingole et al., 2022)	Investigation of Different Regression Models For The PdM of Aircraft's Engine.	Data-driven approach using RSF for PdM. Various ML algorithms were tested.	Random Forest outperformed other algorithms with the highest explained variance and the lowest absolute error. Confidence bands were added for reliability in maintenance decisions.	Further exploration of other algorithms for additional predictive accuracy and integrating the model into real-time maintenance systems.
(Sano & Berton, 2022)	Application of DL Models for Aircraft Maintenance.	DL models, specifically CNN and MLP, were used for fault detection in PRSOV.	CNN and MLP showed significant accuracy improvements over baseline models: MLP = 0.9962, CNN = 0.9937, Baseline K-nearest neighbors (KNN) = 0.8788.	Expanding the study to include more components and scenarios to assess the generalizability of the models.
(Liu et al., 2022)	Application of Data-Driven PHM Technology in Aviation Electromechanical Systems.	ML algorithms were used for fault diagnosis in electromechanical systems, analyzing hydraulic test data.	The developed models effectively identified abnormal trends, improving maintenance decision-making. The framework enhanced operational safety.	Additional work on real-time data analysis and improving the scalability of the approach to different subsystems.

Table 2. *Cont.*

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Jia et al., 2022)	Hybrid deep fault diagnosis model for aircraft sensor systems, focusing on PdM and flight safety.	Data from residual timing signals transformed into frequency and time-frequency domain representations using Fast Fourier transform (FFT) and S-transform techniques. The DL model processes three inputs and uses a classifier for fault diagnosis.	The hybrid model outperforms traditional methods, offering improved accuracy and reliability in fault identification. Specific performance metrics not provided but noted as superior to traditional methods.	Need for more detailed metrics and performance comparison across various fault types.
(Liu et al., 2023)	ML-based clustering approach for diagnosing multi-component degradation in aircraft fuel systems.	A new test rig simulating multi-component degradation with data analyzed in both time and frequency domains for fault detection and severity classification.	Achieved over 99% accuracy in fault detection and nearly 100% in severity identification. The degradation levels correlated well with an R-square value exceeding 0.9.	Possible expansion to other systems and real-world validation beyond the case study.
(Jia et al., 2023)	Fault diagnosis of aircraft ECS using transfer learning, focusing on cross-condition scenarios.	TCA and JDA transfer learning techniques applied to unlabeled ECS data from different operating conditions to assess fault diagnosis performance.	The TCA method achieved 95.22% predictive accuracy in diagnosing faults from unlabeled data under different conditions, outperforming traditional methods.	Exploration of more transfer learning techniques and their application to different aviation systems.
(Saxena & Ak, 2023)	Testing of aircraft failure using ML algorithms.	ML classification models for PdM in aircraft systems. The dataset consists of maintenance and failure data of aircraft equipment collected over a two-year period.	The model effectively predicts aircraft system malfunctions, enabling timely warnings before failures. It shows potential for improving safety and maintenance efficiency in aviation.	Need for more diverse datasets for broader applicability and improvements in model generalization.
(Rahamathunnisa et al., 2023)	ML and DL for Intelligent Systems in Small Aircraft Applications.	Integration of ML and DL technologies for fault detection and PdM in small aircraft. Data involves real-world case studies from aircraft operations.	Enhanced safety, efficiency, and performance of small aircraft through intelligent systems. Successful real-world implementation of ML/DL for fault detection and pilot support systems.	Challenges in data robustness and technical limitations in implementing intelligent systems.
(Yang et al., 2023)	The LST-SATM-net: A new deep feature learning framework for aero-engine hydraulic pipeline systems intelligent faults diagnosis.	LST-SATM-net framework integrating LSTM networks with Spatial Attention Mechanism (SATM) for fault diagnosis. The dataset consists of various operational conditions and fault scenarios.	The framework outperforms traditional fault diagnosis methods with high accuracy, reducing diagnosis time and enhancing reliability in aero-engine hydraulic systems.	Further optimization needed for real-time application and broader validation across different operational contexts.
(Lv et al., 2024)	Aircraft Fault Diagnosis and Prediction Algorithm Based on DL and Markov Model.	DL for feature extraction and Markov model for state transitions. Integration algorithm tested on actual aircraft data.	Significant improvements in accuracy, recall, and F1 score compared to single models. Enhanced fault diagnosis and prediction in aircraft systems.	Further testing with diverse datasets and systems. Optimization of the integration algorithm for other applications.
(Dube, 2024)	Application of DL in PdM of Aircraft Engines.	DL models analyzing large datasets and optimizing maintenance schedules for aircraft engines.	Improved reliability and efficiency through PdM. Reduced downtime and cost savings for airlines.	Exploration of specific DL models for various engine types and broader application.
(Stanton et al., 2024)	Data Augmentation for PdM: Synthesizing Aircraft Landing Gear Datasets.	Utilization of the DoppelGANger model to generate synthetic time-series datasets for PdM.	Successfully generated synthetic data that mimics real-world datasets, improving accessibility for research. Datasets are publicly available for further use.	Limited to Airbus landing gear data, expanding to other systems would improve applicability.

Table 2. *Cont.*

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Zhang & Du, 2024)	Fault diagnosis methods for civil aircraft, focusing on enhancing data for aeroengines using LSTM networks and GANs.	LSTM networks, GANs for data enhancement, human-machine interaction to address data imbalance in aircraft systems.	LSTM and GAN model successfully captured dynamic characteristics, reduced false alarms, and improved PdM for civil aircraft engines.	The study didn't address scalability issues for larger aircraft systems or how to apply the method to other engine types.
(Chu & Yin, 2024)	Intelligent fault diagnosis for aircraft systems, specifically focusing on fusion methods combining rough set theory and BP networks for improved fault location accuracy.	Hybrid fusion of rough set theory and BP networks; testing with actual aircraft fault data.	Fusion method outperformed single methods in fault location accuracy. The hybrid approach combining rough set theory and BP network demonstrated the best accuracy in fault diagnosis.	Future research could explore further automation of fault diagnosis in diverse aircraft systems and its integration into real-time systems.
(Shen et al., 2024)	Hybrid ML methodologies for fault DPHM in aircraft, focusing on integrating nonlinear filtering, DNNs, etc.	Hybrid ML approaches, nonlinear filtering algorithms, DNNs, supervised and unsupervised learning algorithms, model-based methods.	The hybrid methodologies led to autonomous, intelligent fault diagnosis and health management, improving fleet-wide monitoring capabilities, maintenance practices, and reducing downtime.	The paper did not focus on the challenges of integrating these methods into existing industrial infrastructure and their real-time applicability in highly dynamic environments.

6.2. ML in optimization of flight operations and ATM

Table 3 shows a quantitative distribution by publisher of the number of articles related to the applications of ML in optimization of flight operations and ATM.

Table 3. Number of articles on the applications of ML in optimization of flight operations and ATM by Publisher.

Publisher	Number of articles reviewed
Elsevier	4
IEEE	4
ARC (Aerospace Research Central)	4
MDPI	3
EWA Publishing	1
Vilnius Tech	1
arXiv (Cornell University)	1
SPIE Digital Library	1
Institute for Operations Research and the Management Sciences	1
The Japan Society for Aeronautical and Space Sciences	1
Total	**21**

Gallego et al. (2019) concerned probabilistic horizontal interdependencies between planes as a part of trajectory prediction to improve the accuracy of the descent phase by setting air traffic in context. They found that including interdependencies made a huge difference to trajectory prediction and aided trajectory-based computations by foreseeing conflicts. Gui et al. (2020) focused on aviation big data analysis with ML techniques (MLT) and LSTM networks for managing the flow of air traffic. They were more accurate at forecasting traffic flow along major roads and recognized periodic patterns that guided scheduling and airspace use decisions. Sridhar et al. (2020) provided a general discussion of ML use in ATM, which stressed on the data quality, feature selection and context. In case studies, they also described the way ML applications had grown to solve multi-objective problems and operational kinks.

Xie et al. (2021) focused on applying ML and explainable artificial intelligence (XAI) to anomaly detection, risk assessment, and ATM operation monitoring. The algorithm, implemented with XGBoost and explainability methods Shapley Additive Explanation (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), improved the interaction between human and machine by helping air traffic control operators (ATCOs) trust and comprehend system recommendations. Choi et al. (2021) handled trajectory forecasting in terminal airspace with a combination of ML and the Residual-Mean Interacting Multiple Models (RM-IMM) algorithm. This approach improved precision through historical data and real-time physics-based updates, which made significant improvements for conflict detection and scheduling. Meanwhile, Dalmau et al. (2021) used explainable ML to correct take-off times and used SHAP to learn important considerations such as weather and air traffic. Their model was better than the old style, and it provided real-world information to allocate and schedule resources.

Zang et al. (2022) built the Air Traffic Flow Spatial-Temporal Network Prediction (ATFSTNP) model that combined ResNet, Graph Convolutional Network (GCN), and LSTM to predict airport flight patterns using environmental considerations. Their model was much more accurate and robust at predicting flight flow and proved useful for reallocating airport resources. Wild et al. (2022) compared various ML algorithms like Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN), and SVM to predict air transport demand. ANFIS performed better than other models, such as multiple linear regression (MLR), and was the best at forecasting demand, which is essential for planning operations and making economic decisions in airlines. Xie et al. (2022) developed a hybrid AI-based rerouting approach with the Tabu search algorithm to manage the unmanned aircraft systems (UAS) traffic efficiently. The work combined metaheuristic algorithms with ML to make the decisions in real time and developed a flexible, uncertainty-tolerant model of low-altitude traffic that was highly effective.

Dhief et al. (2022) have created a ML go-around prediction system using pilot-in-the-loop simulations to model go-around probability on approach. Their model was able to predict go-arounds accurately and quickly, helping ATCOs plan for the best re-sequencing arrival flights. Their findings indicated that the model predicted more than 93% of go-around events, and that chances of landing were very low. Cai (2023) did a brief analysis on ML in ATM and the ways it could be leveraged to improve the flow of air traffic, the services, and the airspace management. This paper was very much focused on ML for anticipating delays, traffic, and decision-making but highlighted issues of models' comprehensibility. Cai's work urged further investigation of practical complexity, like traffic flows and weather. Sui et al. (2023a) focused on conflict resolution within ATM, which used a DRL-based technique to handle the air traffic conflict. Their system was based on a Markov Decision Process (MDP) and involved a Deep Q Network (DQN) algorithm to tune flight directions using altitude, speed, and heading control. Its application to simulations proved that the model could help with both flight safety and conflict resolution laws.

Wang et al. (2023) proposed a new system, RLIPA, for Air Traffic Flow Management (ATFM). They worked on combining RL for reward forecasts and predictive analytics for hard constraints. They showed that their results provided computational efficiency that was more than 10 times higher than that achieved by a reference approach while maintaining or improving optimal ATFM operations. It turned out that this methodology can also be generalized to other highly specialized multi-agent systems like ride-hailing or meal delivery. In contrast, Sui et al. (2023b) built a DRL tactical conflict solver (TCS) for air traffic controllers to solve tactical conflict. The TCS achieved a rate of 87.1% conflict resolution under normal traffic, but the rate dropped a bit under dense airspace. They demonstrated that DRL can help air traffic controllers make better decisions and burden less work, thereby increasing safety and efficiency. Park et al. (2023) proposed a Multi-Agent Deep Reinforcement Learning (MADRL) algorithm for collaborative air transport services in Urban Air Mobility (UAM) systems. Their algorithm using CommNet (centralized training and distributed execution) ensured the best cooperation between many UAM cars. As the simulation showed, their system was way better than other systems in terms of service quality with equal outcomes across agents as the vehicles increased. They proved how critical communication can be in multi-agent systems and offered a solution to autonomous air transport in cities.

Vaidyanathan et al. (2024) focused on ML-based optimization of flight planning, predicting acceptability of flight plans, and picking favorite routes. They used both supervised and unsupervised learning, and the data was able to show reductions in human effort, time, and expense and could provide a major enhancement to flight planning and operation. De Giovanni et al. (2024) used a data-driven optimization of ATFM based on trajectory preferences based on traffic data. Through clustering, classification, and mathematical programming, they were able to address ATFM problems on a massive scale, with a minimum of waste in terms of airspace and capacity while still keeping user preferences at the center. It revealed a trade-off between delays and preference prioritization that can be used to understand how airspace management works in practice. Taylor et al. (2024) implemented RL to build a decision support system for flow manager air traffic with strategy stability through dynamic constraints and performance thresholds. They noted that they needed to ensure consistent recommendations over time and that more rigid constraints resulted in better strategy stability (although sometimes this was in tension with delay reduction).

Al-Ghzawi and El-Rayes (2024) worked on ML models for forecasting the impact of construction work during airport expansion on air traffic. They used several ML algorithms to compare different phasing of construction plans and show how these could effectively reduce flight times and improve airport operations through a fast analysis of alternative building plans. In contrast, Agrawal et al. (2024) focused on estimating Terminal Traffic Management Initiatives (TMIs) such as Ground Stops (GS) and Ground Delay Programs (GDP) by applying various supervised learning models, such as Logistic Regression and LSTM networks. They observed that LSTM networks outperformed other models in the prediction of particular TMI types and were better prepared for air traffic control in the event of weather or capacity outages. Andreeva-Mori and Onji (2024), on the other hand, tapped into the weaknesses of ATFM with ML in adjusting airborne delay buffers. They found through GPR and high-fidelity traffic simulations that dynamically changing delay buffers could minimize ground delays and capacity loss without accounting for the trade-off between airborne delays and other costs. ML can be used to improve buffer estimation, which they also observed, although it needed to be improved.

Table 4 provides a detailed comparison of the articles reviewed above, highlighting their focus, methodologies, key findings, and unresolved issues in the application of ML for flight operations optimization and ATM between 2019 and 2024.

Table 4. Comparison of articles published between 2019 and 2024 on ML applications in flight operations optimization and ATM.

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Gallego et al., 2019)	ML approach to model air traffic interdependencies for trajectory prediction, enhancing flight operations and ATM during descent phase.	Developed a probabilistic horizontal interdependency measure between aircraft. Used ML algorithms to analyze time separations and vertical profiles of flight trajectories. Utilized a horizontal interdependency matrix (HIM) to quantify interdependencies between pairs of aircraft.	The interdependency measure identified potential conflicts between aircraft in advance, validated by air traffic control actions. Including surrounding air traffic as a factor significantly affected the location of the top of descent.	Future research could focus on improving the framework for more complex air traffic scenarios and operational contexts.
(Gui et al., 2020)	ML for enhancing ATFM, optimizing flight scheduling strategies, and improving airspace utilization through aviation big data analysis.	Created an aviation big data platform integrating automatic dependent surveillance-broadcast (ADS-B) data for real-time air traffic monitoring. Employed LSTM networks to predict air traffic flow, considering abnormal factors in traffic control. Dataset included air traffic from routes like Beijing-Wuhan, Shanghai-Tianjin, Nanjing-Beijing, and Guangzhou-Shanghai.	LSTM-based model outperformed traditional methods in predicting traffic flow. Identified periodic patterns in air traffic, with clear peaks and valleys throughout the day.	Future work could explore more advanced models for predicting abnormal air traffic flow and better integrate different models to enhance prediction accuracy.
(Sridhar et al., 2020)	Application of MLT in ATM to enhance decision-making and multi-objective scenario handling.	Review of case studies from the authors' experience over three decades. Focused on data and feature selection in ATM applications of MLT. Discussed challenges in data quality and understanding physical aviation operations for successful implementation.	MLT can enhance operational efficiency and decision-making in ATM, but depends on high-quality data, appropriate feature selection, and understanding of physical aviation contexts.	Challenges in data quality, feature selection, and complex operational contexts need further exploration to fully unlock the potential of MLT in ATM.
(Xie et al., 2021)	Explanation of ML solutions in ATM, focusing on anomaly detection, risk prediction, and operational risk monitoring using XGBoost. Emphasis on XAI.	XGBoost algorithm for ML-based risk prediction, SHAP and LIME for explainability techniques. Aviation occurrences and meteorological databases used for training the model.	ML-based risk-prediction tool for ATM with explainable AI enhances ATCOs' trust in the system. The study highlighted the potential for XAI in improving human-machine interaction and its broader applications in performance-driven autonomy.	Potential for further research on improving integration of XAI for fully autonomous systems in ATM.

Table 4. *Cont.*

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Choi et al., 2021)	Hybrid ML and estimation-based flight trajectory prediction for improving ATM in terminal airspace.	Combination of ML (using historical surveillance data) and physics-based estimation (RM-IMM algorithm) for trajectory prediction. Real air traffic surveillance data used for testing.	Hybrid approach significantly improves trajectory prediction accuracy compared to existing ML algorithms. The framework enhances the safety and efficiency of air traffic operations in terminal airspace.	Potential application in non-terminal airspace and real-time implementation.
(Dalmau et al., 2021)	Explainable ML approach to improve take-off time predictions for optimized flight operations and ATM. Various ML algorithms (decision trees, ensemble methods) applied to historical flight data. SHAP for explainability. Dataset included numerous flights with factors like weather, air traffic, and aircraft characteristics.	Various ML algorithms (decision trees, ensemble methods) applied to historical flight data. SHAP for explainability. Dataset included numerous flights with factors like weather, air traffic, and aircraft characteristics.	Significant improvement in predicting take-off times with enhanced accuracy. SHAP-based explainability provides insights into the factors influencing predictions, which aids in trust and decision-making. Results contribute to optimized scheduling and resource allocation in airport operations.	Need for extending the approach to other areas of flight scheduling beyond take-off times.
(Zang et al., 2022)	Flight flow prediction in airport networks, optimizing operations and ATM.	DL model (ATFSTNP), integrating ResNet, GCN, and LSTM.	ATFSTNP model outperformed traditional models, especially under varying weather conditions. Demonstrated strong robustness and accuracy in predicting flight flow.	Limited generalization to non-Chinese airports; further testing required in diverse real-world environments.
(Wild et al., 2022)	ML for air transport demand forecasting and operational planning.	Evaluation of ANN, ANFIS, Genetic Algorithm (GA), SVM, Regression Tree (RT), and MLR using Root Mean Squared Error (RMSE) and R^2 metrics.	ANFIS performed best with the lowest RMSE. ANN followed closely. RT model showed poor performance.	Need for more real-world data for validation; potential improvement in models for longer-term forecasting.
(Xie et al., 2022)	Hybrid AI-based dynamic rerouting method for low-altitude air traffic operations, focusing on UAM and UAS.	Hybrid approach using Tabu-search algorithm for rerouting and ML for real-time optimization.	Uncertainty-resilient framework improved Demand-Capacity Balancing (DCB) and traffic management. Promising for UAM integration.	Scalability in highly congested airspaces; integration with existing air traffic control systems still requires refinement.
(Dhief et al., 2022)	ML model for predicting go-around probabilities to enhance ATM.	Pilot-operated flight simulator for data collection under varying visibility conditions; real-time go-around probability prediction model.	The model's predictions closely matched computed probabilities, showing >93% go-around likelihood when initiated and accurate prediction of low go-around chances during successful landings.	Limited focus on varying air traffic conditions and non-visibility-related factors that may affect go-around events.
(Cai, 2023)	Overview of ML applications in ATM, including delay prediction, traffic flow analysis, and decision-making improvement.	Review of existing ML research and algorithms like random forests and SVMs.	ML has substantial potential for improving ATM by optimizing traffic flow, enhancing safety, and increasing efficiency. Identified research areas include ATFM, Air Traffic Services, and Airspace Management.	Need for more research into model interpretability ("black box" nature of ML) and incorporating real-world factors like weather and pilot skills.
(Sui et al., 2023a)	Conflict resolution strategy in ATM using DRL for altitude, speed, and heading adjustments.	MDP framework; DQN algorithm for agent training.	DRL-based approach effectively resolved conflicts with accurate decision-making for altitude, speed, and heading adjustments, enhancing flight safety. Results were aligned with air traffic control regulations.	Future work needed to explore scalability and real-time adaptation in complex airspace environments.

Table 4. *Cont.*

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Wang et al., 2023)	RLIPA for ATFM	Integrated RL with prescriptive analytics for decision-making. Numerical experiments and a real case study for validation.	RLIPA improved computational efficiency by over 10 times and maintained or improved optimality in ATFM.	General applicability across multiple agent-based systems (ride-hailing, food delivery).
(Sui et al., 2023b)	TCS for Air Traffic Controllers Using DRL.	DRL-based TCS using actor-critic approach. Simulated conflict scenarios with ATCO input for conflict resolution.	Conflict resolution rate of 87.1%, reduced to 81.2% with 1.4x increased airspace density.	Impact of increased airspace density on performance, scalability of TCS in larger systems.
(Park et al., 2023)	Multi-Agent DRL for Cooperative Air Transportation in Autonomous UAM.	Multi-agent DRL with CommNet for cooperative decision-making. Data-intensive simulations using vertiport maps and UAM specifications.	Algorithm outperformed existing methods in service quality, ensuring equitable performance among agents.	Scalability and real-world deployment of MADRL in larger, more dynamic systems.
(Vaidyanathan et al., 2024)	Enhancing flight planning efficiency through ML by predicting flight plan acceptance and identifying preferred routes.	MLT, including supervised and unsupervised learning. The study uses operational flight planning data for model development.	Reduction in human effort, cost, and time in generating flight plans. The ML models are expected to optimize flight operations and ATM.	Models to be deployed in operational environments, potentially improving flight plan acceptance rates.
(De Giovanni et al., 2024)	Data-driven optimization for ATFM, focusing on trajectory preferences and resolving demand-capacity imbalances through ML.	ML clustering and classification techniques. The dataset used is from Eurocontrol, involving over 32,000 flights. A mathematical programming model was used to resolve demand-capacity imbalances.	Successfully solved the largest ATFM instances with short computational times. The trade-off between user preferences and delays was identified, providing insights into optimizing ATM.	Further exploration of the trade-offs between user preferences and delays, and the practical deployment of the proposed models in real-world ATM systems.
(Taylor et al., 2024)	Using RL for ATFM, focusing on strategy stability, delay reduction, and flight predictability in managing air traffic.	The research proposes a decision support system using RL with dynamic constraints and performance thresholds. Evaluation was done using an agent's reward function and stability measures.	The more restrictive set of constraints improved strategy stability and reduced delays. The performance improvement threshold did not significantly impact delay reduction but enhanced strategy stability. A trade-off between optimizing for delay and ensuring predictability was observed.	Further refinement of the constraints and thresholds, and a deeper understanding of their impact under varying conditions (e.g., different traffic volumes or operational scenarios).
(Al-Ghzawi & El-Rayes, 2024)	ML for predicting the impact of construction activities on air traffic operations during airport expansion projects. The research focuses on optimizing flight operations and ATM during airport expansions.	Data collection and preprocessing; 5 ML models were developed to predict the impact of construction on flight ground movement times.	Five models were developed, compared, and evaluated to accurately predict the impact of construction activities on airport operations. It helps in evaluating alternative construction phasing plans to minimize delays.	There is room to further improve the models and explore additional construction scenarios or airport conditions.
(Agrawal et al., 2024)	Predicting Terminal TMIs using ML to optimize ATM efficiency based on weather and airport conditions.	Logistic Regression, Random Forest, XGBoost, and LSTM networks were applied using three years of historical data from Newark airport.	Random Forest and XGBoost are effective for predicting TMI necessity, while LSTM outperforms them in predicting specific TMI types due to its sequence learning capability.	Future studies could explore other predictive models and improve the TMI prediction accuracy with better feature engineering.
(Andreeva-Mori & Onji, 2024)	Optimizing airborne delay buffers in ATFM under uncertainties using ML to select dynamic buffers for improved efficiency.	High-fidelity traffic simulations for 162 days of traffic data. The GPR model predicted delays based on projected traffic.	The optimal buffer reduces ground delay and capacity loss while increasing airborne delay. The optimal buffer varies based on the weight of capacity loss, with an ideal buffer range between 5 to 8 minutes.	The challenge in achieving optimality and estimation accuracy with ML for dynamic buffer selection.

6.3. ML in enhancement of autonomous flight systems and safety

Table 5 shows a quantitative distribution by publisher of the number of articles related to the applications of ML in enhancement of autonomous flight systems and safety.

Table 5. Number of articles on the applications of ML in enhancement of autonomous flight systems and safety by Publisher.

Publisher	Number of articles reviewed
IEEE	5
Springer	4
arXiv (Cornell University)	2
IOP Publishing	2
AnaPub Publications	1
ARC (Aerospace Research Central)	1
Elsevier	1
Francis Press	1
Frontiers	1
Preprints.org	1
River Publishers	1
Vertical Flight Society	1
Total	**21**

Bati and Withington (2019) came up with a fully-fledged risk metric for the National Airspace System (NAS), employing MLT for the airport surface environment. Their study showed that traditional safety indicators were not enough and that incorporating severity in incident analysis could give a broader picture of aviation risks and, therefore, be a more valuable safety surveillance tool. Fremont et al. (2020) addressed the reliability of autonomous aircraft taxiing systems by applying the VerifAI toolkit for formal analysis and retraining of neural networks. They have an industrial case study with Boeing's autonomous taxiing system, proving that ML systems could be falsified and debugged extensively to improve the system's reliability and effectiveness in the field. Puranik et al. (2020), which was focused on ML prediction of safety-relevant landing parameters in approach. With an offline-online approach, they were able to accurately predict the actual airspeed and ground speed far better than previously known, and this allowed real-time decision-making and risk identification during key flight phases.

Jagannath et al. (2021) emphasized the combination of DL and RL for increased autonomy of UAS. They investigated how to use DL for computer vision tasks such as object detection and navigation and RL for real-time decision-making to allow UAS to perform better in situations where wireless connectivity is unreliable. The work proved useful for navigating obstacles in tactical and rescue missions, although it recognized the continuing problems with safety, technical constraints, and regulatory issues. Lee et al. (2021) focused on improving aviation safety by developing a data-driven system for real-time health monitoring of commercial aircraft using deep autoencoders. They scoured for flight disruptions and aircraft upsets, which were early warning signs of crash. Through historical flight data, the system sent out early warnings for pilot status and for better flight management. The experiments confirmed that the autoencoder-based approach was significantly better than the conventional statistical detection, making it a useful piece of equipment in the wider aviation safety domain. In contrast, Arnez et al. (2021) improved the strength of DNNs for aerial navigation using input uncertainty in Bayesian DL. Their approach centered around uncertainty-as-input processing (a key requirement when working with Out-of-Distribution (OoD) data and robust system performance in safety-critical workloads). They found through experiment that this strategy improved navigation policies, particularly in the presence of uncertainty, and demonstrated that it can improve the safety and stability of autonomous flight systems.

Wang et al. (2022) proposed a DRL system for better explainability and safety in self-driving air travel, especially in hostile environments. Their distributed model, which based safety awareness on the separation of decision-making efficiency, led to better simulation conflict resolution and an open DRL controller. In contrast, Cofer et al. (2022) focused on a neural network-based collision avoidance system built into Boeing's testbed planes. They used run-time guarantees and formal procedures to monitor for safety compliance, and they finally carried out a flight test to validate the system's ability to intervene in cases of safety breaches. Salvador (2022) described how it was difficult to make ML compliant and safe for eVTOL aircraft. The research emphasized ML's capabilities to process large quantities of data, predict failures, and reduce human error in favor of fully autonomous functions, backed by such technology as digital twins and advanced networks.

Mohammed et al. (2022) looked at various ML solutions in aerospace, including PdM, fuel savings, and autonomous air vehicles, with safety and reliability as top priorities. They showed how ML could increase productivity (especially in the context of COVID-19) and how AI-based data analytics helped boost the resilience of the industry. Yue et al. (2023) focused on RL for multi-unmanned aerial vehicle (UAV) autonomous decisions and proposed the Transfer-Safe Soft Actor-Critic (TSSAC) algorithm. They found that TSSAC was very successful (96%) and kept to safety parameters, which, compared with older algorithms such as Soft Actor-Critic (SAC) and Proximal Policy Optimization (PPO), is better on both sides of the fence. Katta and Viegas (2023) developed a small ML-based onboard fault detection system for drones with a 0.4% false positive rate and a 43% reduction in computation cost. This work showed up reliably identifying physical faults while alerting model unreliability to operators for intervention.

Luo and Chen (2023) specialized in using LSTM networks for monitoring and correcting errors onboard an aircraft in real time and automated warnings to support pilot decision-making and safety in flight. Their system included a real-time flight data processing module, and this helped with adaptive decision-making, demonstrating the possibilities of LSTM networks for pilot support and drones. In contrast, Haughn et al. (2023) used DRL for gust mitigation on UAVs, reducing gust impact by 84%. Their experiment demonstrated sensor efficiency (decreasing the sensor dependence at no loss of performance), proving that RL can be used for UAV operational safety in adverse environments. Helgo (2023) extended ML to PdM and flight data processing with LSTMs, CNNs, autoencoders, and more for diagnostic accuracy and efficiency. Her research underscored the importance of feature selection and flight data tracking to optimize safety and maintenance.

Chen et al. (2024) involved obstacle avoidance in UAVs with a DRL algorithm coupled to depth camera information and Voronoi diagrams for streamlined path planning and dynamic obstacle detection. The approach proved more efficient in choosing a course, flight time, and safety by minimizing obstacle detection. Gavra and Kampen (2024) introduced a hybrid Safety-informed Evolutionary Reinforcement Learning (SERL) algorithm for fault-tolerant flight control. Combining DRL and neuro-evolution, they crafted more efficient control policies, achieved better tracking under all test conditions, and were robust against faults and changing conditions that underpinned smoother, more stable autonomous behavior. Khelifi et al. (2024) dealt with rotorcraft safety using a low-cost DL system that automated cockpit data collection using standard cameras. Their solution made real-time gauge detection, classification, and reading inference possible, supporting data-driven safety and cost-effective monitoring.

Jin et al. (2024) devoted to the use of AI in tandem with human-computer interaction to track pilot fatigue and prevent accidents through the design of a flexible system that adapts to cognitive load. The paper emphasized AI for better human-machine cooperation and error-minimizing under pressure. Liu et al. (2024) tested SVM-based hazardous flight weather prediction based on weather forecasting (based on the weather data), such as storms and turbulence. Their model was very accurate, and this increased early warning that is so important to flight safety as air transport becomes increasingly sophisticated. Lastly, Hu et al. (2024) used BP neural networks to estimate horizontal tail flight loads in large UAVs and emphasized reliable load prediction for reliability and safety. The scientists gained high accuracy through the data quality improvement, model tuning, and validation.

Table 6 provides a comparative analysis of the articles reviewed above, highlighting their study focus, methodologies, key findings, and the unresolved challenges in applying MLT to enhance autonomous flight systems and safety.

Table 6. Comparative analysis of articles published between 2019 and 2024 on ML applications in enhancing autonomous flight systems and safety.

Author(s) and year	**Study focus and application**	**Methodology and dataset**	**Key findings and metrics**	**Unresolved issues/gaps**
(Bati & Withington, 2019)	Development of a ML-based risk metric for safety performance in the NAS.	Utilized MLT to analyze data on airport surface incidents and accidents; severity measures incorporated.	The new metric offers a more holistic assessment of safety, providing insights beyond traditional incident-focused metrics.	Further validation across different airport environments and integration with real-time safety systems.
(Fremont et al., 2020)	Enhancing autonomous flight system safety and performance using the VerifAI toolkit for formal analysis of neural networks.	The VerifAI toolkit used for formal analysis; industrial case study of autonomous aircraft taxiing system by Boeing; falsification and retraining processes.	Improved the reliability of the autonomous taxiing system by identifying failure cases and retraining the neural network.	Further exploration of edge cases and integration with other autonomous flight system components.

Table 6. *Cont.*

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Puranik et al., 2020)	Prediction of safety-critical landing metrics (airspeed and ground speed) during the approach phase in aviation.	Data from on-board recorders; Random Forest regression algorithm for predicting landing metrics; offline-online Framework.	Achieved robust predictive performance, with root mean square errors of 2.62 knots (airspeed) and 2.98 knots (ground speed).	Potential adaptation to more diverse aircraft and operating conditions for broader applicability.
(Jagannath et al., 2021)	Enhancing autonomy in UAS through DL and RL.	DL and RL for computer vision, simulation, and prototyping.	UAS autonomy improved through ML; DL used for object detection, RL for control; simulation platforms suggested.	Technical hurdles, safety concerns, regulatory issues, real-world deployment.
(Lee et al., 2021)	Data-driven aircraft health monitoring for detecting off-nominal flight operations.	Deep autoencoder for real-time detection, using historical flight datasets.	Early alerts for upset precursors improve pilots' situational awareness and flight safety; real-time detection tested with accident scenario.	Need for broader dataset application, further refinement of the monitoring system.
(Arnez et al., 2021)	Incorporating input uncertainty in Bayesian DL for aerial navigation.	Bayesian DL method to incorporate input uncertainty, experimental trias.	Improved robustness in navigation policies when handling OoD scen arios.	Need for further testing in diverse real-world applications.
(Wang et al., 2022)	Focus on improving autonomous flight systems by enhancing conflict resolution, explainability, and safety in air traffic control designs, particularly under adversarial attacks.	Developed a DRL controller with a safety-awareness and efficiency framework; simulated experiments were conducted.	Results showed significant improvements in performance for free-flight tasks and enhanced explainability in decision-making. Introduced an adversarial attack strategy revealing DRL's safety limitations.	Further exploration of DRL's limitations under adversarial conditions, scalability of decentralized systems.
(Cofer et al., 2022)	Integration of ML in safety-critical systems, specifically for collision avoidance in autonomous aircraft.	Neural network-based collision avoidance system integrated with Boeing's Autonomy Testbed Aircraft; real-time monitoring and flight test demonstration.	Successful flight test demonstrated real-time monitoring of the neural network, ensuring compliance with safety protocols. Run-time assurance enabled effective safety interventions.	Scalability and adaptability to various aircraft systems and real-time operation under varying conditions.
(Salvador, 2022)	Enhancing the reliability and safety of eVTOL aircraft through ML to predict system failures and reduce human error.	ML applied to data generated by eVTOL systems; explored integration with Digital Twins and 6G networks.	ML enhances reliability by predicting system failures and reducing human error in eVTOLs. The potential for fully autonomous operations in the future was highlighted.	Challenges in integrating ML with emerging technologies, dealing with increased air traffic in urban environments.
(Mohammed et al., 2022)	Application of AI/ML in aerospace, focusing on autonomous flight systems, fuel efficiency, smart maintenance, ATM, pilot training, passenger and threat identification, remote sensing, autonomous aerial vehicles, and safety in aerospace.	Review of various AI/ML applications in aerospace.	AI/ML enhances safety, fuel efficiency, ATM, and pilot training; improves autonomous aerial vehicle systems; plays a critical role in safety.	Limited research on fully autonomous drones and aircraft; potential concerns over integration challenges.
(Yue et al., 2023)	Safe decision-making in multi-UAV systems using RL to improve safety and training efficiency in decision-making processes.	Developed TSSAC algorithm, integrating constrained MDPs. Simulated with UAVs performing different roles.	TSSAC demonstrated a 96% success rate while maintaining safety; better than PPO, SAC, and other algorithms in balancing safety and success.	Further exploration of TSSAC's adaptability in real-world scenarios; integration of more diverse UAV types.
(Katta & Viegas, 2023)	Onboard fault detection in autonomous UAVs using ML to enhance safety with minimal processing.	Feature selection and classification assessment using a multi-view rationale for UAV sensors. Tested on a real quadcopter UAV.	Reduced false-positive rate to 0.4%; computational costs reduced by 43%; system alerted operators when model was unreliable.	Need for testing with a wider range of UAVs; more diverse fault scenarios for comprehensive validation.

Table 6. *Cont.*

Author(s) and year	Study focus and application	Methodology and dataset	Key findings and metrics	Unresolved issues/gaps
(Luo & Chen, 2023)	Enhancing aircraft safety and autonomous flight assistance using DL, specifically LSTM networks.	LSTM network for real-time monitoring of aircraft status, error correction, and autopilot functions. Real-time flight data processing module.	Automated early warning, error correction, and assisted driving features developed. Improved decision-making and flight safety.	Need for broader validation in diverse flight conditions and more comprehensive data integration.
(Haughn et al., 2023)	Enhancing gust alleviation in UAVs using DRL, enabling operation with fewer sensors in urban areas.	DRL to develop an autonomous gust alleviation controller for a camber-morphing wing. Real-time pressure signal analysis.	84% reduction in gust impact, fewer sensors needed without compromising performance, increased UAV operational efficiency.	Further exploration of sensor efficiency and robustness in highly variable urban environments.
(Helgo, 2023)	Enhancing aircraft maintenance and flight data analysis using ML and DL algorithms.	Deep Autoencoders, Deep Belief Networks, LSTMs, CNNs for feature extraction, PdM, and flight data monitoring.	Improved aircraft safety and operational efficiency through PdM, better feature selection, and unsafe behavior detection.	Integration of various DL architectures for complex, real-world scenarios in aviation.
(Chen et al., 2024)	Obstacle Avoidance for UAV Flight Safety.	DRL, Buffered α-Predicted-Vector Weighted Voronoi Diagram (BαPVWVD), Dynamic Graph Generation.	Improved obstacle avoidance, optimized flight distance, safer path selection.	Integration of more complex environments and real-time dynamic changes.
(Gavra & Kampen, 2024)	Evolutionary RL for Fault-Tolerant Flight Control.	SERL, High-fidelity Nonlinear Aircraft Model.	Better tracking performance, robust fault tolerance, smoother agent action.	Real-world applicability in highly variable conditions, further refinement of hybrid methods.
(Khelifi et al., 2024)	Rotorcraft Flight Data Monitoring with DL.	DL Framework, Curated Dataset for Rotorcraft Cockpits.	Improved safety through automated flight data analysis, enhanced gauge detection and reading inference.	Further dataset validation, application to different aircraft types.
(Jin et al., 2024)	Integration of AI in flight safety for fatigue monitoring and risk mitigation in autonomous flight systems. Focus on cognitive load and decision-making improvements.	Human-machine interaction, cognitive load management, adaptive intelligent cabin systems, and human factors consideration. No specific dataset provided.	Improved safety through better human-machine interaction, cognitive load management, adaptive systems, and AI to reduce human error.	Need for further integration of human factors throughout system design; Real-time AI system development for complex flight operations.
(Liu et al., 2024)	Prediction of dangerous flight weather using ML, specifically SVMs, for aviation safety.	SVM models with radial basis function (RBF) as kernel; Historical meteorological data such as temperature, humidity, wind speed, and direction from weather stations.	Successfully predicted hazardous flight weather conditions. Enhanced safety through early warning systems for dangerous weather conditions.	Further exploration of other MLT for improving prediction accuracy in complex meteorological environments.
(Hu et al., 2024)	Prediction of flight loads in large UAVs using ML, focusing on improving flight safety and reliability in autonomous flight systems.	BP neural networks to predict shear, bending moment, and torque based on flight parameters. Data processing and optimization through error analysis. Dataset not provided.	Accurate prediction of flight loads, optimization of BP neural network, error analysis, and validation through test and training sets.	Model performance in real-world applications beyond the training/test set; Potential for further optimization in large UAV systems.

7. Conclusions

In the article based on the ML applications for aviation engineering, there are some of the major conclusions and lessons for the sector. ML also has the capability to assist in making decisions better, such as in ATM. Through various ML models, scientists were able to perform better flight operations, better control air traffic, and have less delay, essential to keep aircraft safe and efficient. It is a breakthrough that ML can anticipate delays and traffic congestion. There are also studies showing high success in forecasting go-arounds and terminal traffic control programs, which can greatly assist air traffic controllers. With the addition of ML to the processing of air traffic flow control, computational efficiency improved to greater than a factor of 10 (for some methods). Not only does this efficiency increase the capability of the aircraft, it reduces pressure on the controllers and ultimately increases safety. Even with the progress, there are still issues such as ML models being interpretable and adapting to real-world circumstances like traffic patterns and weather conditions. These issues need to be investigated, and ML in the aviation system needs further investigation. As these results of this review show, ML could not only be used for air traffic control but also for other fields of aviation engineering like PdM and fault identification in aircraft systems. That looks like an opportunity for the future of ML use in the aviation industry. The paper summarizes the profound changes that ML can make to aviation engineering, both in terms of increasing the efficiency, safety, and decision-making and in terms of the research work required to overcome the existing issues.

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Przegląd Zastosowań Uczenia Maszynowego w Inżynierii Lotniczej

Streszczenie

W niniejszym artykule przeglądowym przedstawiono w jaki sposób uczenie maszynowe (ang. machine learning - ML) przekształciło wiele aspektów inżynierii lotniczej. Artykuł przedstawia znaczny postęp w optymalizacji operacji lotniczych i zarządzania ruchem lotniczym poprzez preskryptywną analizę opartą na uczeniu się przez wzmacnianie i techniki głębokiego uczenia się ze wzmocnieniem stosowane do rozwiązywania konfliktów. Badanie podkreśla w jaki sposób ML decyduje o wydajności operacyjnej poprzez szybsze procesy obliczeniowe i lepsze zdolności podejmowania decyzji przez osoby kontrolujące ruch lotniczy. Artykuł analizuje, w jaki sposób wiodące firmy, takie jak SpaceX i Raytheon, wykorzystują technologię ML do ulepszania procesów produkcyjnych, w tym utrzymania predykcyjnego i rozwoju systemów autonomicznych. Omówiono również przeszkody we wdrażaniu ML, w tym interpretowalność modelu, oraz wskazano dalsze wymagania badawcze dotyczące dostosowywania się ML do rzeczywistych problemów, takich jak zmieniające się natężenie ruchu i wahania pogody. Ogólnie rzecz biorąc, wyniki badań omówione w artykule przedstawiają w jaki sposób technologia ML może wspomagać inżynierię lotniczą poprzez udoskonalenie norm bezpieczeństwa, a także wydajność operacyjną i procesową.

Słowa kluczowe: uczenie maszynowe, inżynieria lotnicza, utrzymanie predykcyjne, zarządzanie ruchem lotniczym, integracja