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Artificial Intelligence in the Aviation Operations: A State of the Art

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Artificial Intelligence in the Aviation Operations: A State of the Art

Abstract: In recent years, the use of artificial intelligence (AI) has grown significantly, largely driven by the expansion of Industry 4.0 and the increasing generation of data across various sectors. The aviation industry has been no exception to this technological advancement, with numerous studies exploring AI applications in this field. This study aims to provide a comprehensive and up-to-date analysis of AI usage in air operations, with a particular focus on flight planning, trajectory prediction, and resource optimization. Through this analysis, we seek to delve into the latest advancements and methodologies employed in the industry, identifying key algorithms and techniques used. Additionally, the study offers an integrated view of AI applications in aviation, highlighting its potential to enhance operational efficiency, safety, and decision-making. Finally, we aim to identify the most promising areas for research and development to support ongoing innovation in this ever-evolving field.

Keywords: Aviation; artificial intelligence; machine learning; trajectories.

Inteligencia artificial en las operaciones aéreas: un estado del arte

Resumen: En los últimos años, el uso de la inteligencia artificial (IA) ha crecido significativamente, impulsado en gran medida por la expansión de la Industria 4.0 y la creciente generación de datos en diversos sectores. La industria aeronáutica no ha sido la excepción en este avance tecnológico, y numerosos estudios han explorado las aplicaciones de la IA en este campo. Este estudio tiene como objetivo ofrecer un análisis exhaustivo y actualizado sobre el uso de la IA en las operaciones aéreas, con un enfoque particular en la planificación de vuelos, la predicción de trayectorias y la optimización de recursos. A través de este análisis, buscamos profundizar en los últimos avances y metodologías empleadas en el sector, identificando los principales algoritmos y técnicas utilizados. Además, el estudio proporciona una visión integral de las aplicaciones de la IA en la aviación, destacando su potencial para mejorar la eficiencia operativa, la seguridad y la toma de decisiones. Finalmente, esperamos identificar las áreas de investigación y desarrollo más prometedoras para contribuir al progreso e innovación en este campo en constante evolución.

Palabras clave: aviación; inteligencia artificial; *machine learning*; trayectorias.

Inteligência artificial nas operações de aviação: Um estado da arte

Resumo: Nos últimos anos, o uso da inteligência artificial (IA) cresceu significativamente, impulsionado em grande parte pela expansão da Indústria 4.0 e pela crescente geração de dados em diversos setores. A indústria aeronáutica não foi exceção a esse avanço tecnológico, e inúmeros estudos exploraram as aplicações da IA nesse campo. Este estudo tem como objetivo oferecer uma análise abrangente e atualizada sobre o uso da IA nas operações aéreas, com um foco especial no planejamento de voos, na previsão de trajetórias e na otimização de recursos. Através desta análise, buscamos aprofundar nos avanços mais recentes e nas metodologias utilizadas no setor, identificando os principais algoritmos e técnicas empregados. Além disso, o estudo oferece uma visão integrada das aplicações de IA na aviação, destacando seu potencial para melhorar a eficiência operacional, a segurança e a tomada de decisões. Finalmente, esperamos identificar as áreas de pesquisa e desenvolvimento mais promissoras para contribuir com o progresso e a inovação neste campo em constante evolução.

Palavras-chave: Aviação; inteligência artificial; aprendizado de máquina; trajetórias

Introduction

Air transportation is currently experiencing significant growth, resulting in increased fuel consumption, environmental pollution, service times, maintenance, consumables, and crew requirements, leading to higher operational costs (Calvo-Fernández, 2017; Gössling & Humpe, 2020). Furthermore, this continuous growth has necessitated the improvement of air traffic control systems to prevent delays and enhance safety (Medeiros *et al.*, 2012).

Proposed solutions include the application of Area Navigation (RNAV) techniques, a navigation method that allows aircraft to operate on any desired flight route within the coverage of navigation aids or within the limits of autonomous aids, or a combination of both. This method has been enhanced with the introduction of Required Navigation Performance (RNP), which focuses on onboard aircraft performance monitoring and alerting (Medeiros *et al.*, 2012). These methodologies have enabled the operation of more aircraft in the same airspace and improved safety, although they are not specifically focused on optimization, which is of interest to operators.

An efficient flight plan is one of the most critical factors in air operations, as it ensures safe operations, boosts crew confidence, and significantly saves fuel. However, fuel calculation is not a linear process and depends on various factors, making it challenging to predict accurately (Spencer, 2011).

Air operators employ software to plan flights, taking into account various operational aspects. However, the outcomes of this planning are not always optimal due to unexpected airspace congestion or meteorological conditions, as dispatchers rely on updated publications from the aviation authority.

The current surge in data generation enables the utilization of algorithms that transform this data into valuable information. Research efforts have allowed airlines to leverage artificial intelligence systems to develop machine learning algorithms that collect and analyze data for predicting delays, weather conditions, performance, flight plans, and fuel consumption. Some companies employ software developed by Airspace Intelligence, FlightAware, among others.

Artificial intelligence is often evaluated in relation to human intelligence through various tests, and its definition can shift based on perspective, framed either in terms of mental processes or observable behaviors. In the book *Artificial Intelligence: A Modern Approach* (Russell & Norving, 2009), is described from four distinct perspectives, as illustrated in Table 1. These perspectives are split between the goals of thinking or acting like humans and those of thinking or acting rationally. The former aims to replicate human cognition and behavior, while the latter focuses on logic and optimization without mirroring humans. This latter approach is frequently more suitable for practical tasks requiring efficiency and precision.

Table 1.
Some definitions of artificial intelligence

Systems that think like humans	"The new and exciting endeavor for making computers think... machines with minds, in the broadest sense of the word." (Haugeland, 1985) "[The automation of] activities that we associate with human thought processes, activities such as decision-making, problem-solving, learning..." (Bellman, 1978)
Systems that think rationally	"The art of developing machines with the capability to perform functions that, when performed by humans, require intelligence." (Kurzweil, 1990) "The study of how to make computers perform tasks that, at the moment, humans do better." (Rich & Knight, 1991)
Systems that act like humans	"The study of mental faculties by the use of computational models. (Charniak & McDermott, 1985) "The study of the computations that male it possible to perceive, reason, and act." (Winston, 1992)
Systems that act rationally	"Computational Intelligence is the study of designing intelligent agents." (Poole et al., 1998) "AI... is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Source: Russell & Norving (2009).

Artificial intelligence has been developed since the 1940s by Donald Hebb, and its growth and application have been evident since the 1990s. Researchers have focused their interest on the development of more general intelligences, resulting in subfields of artificial intelligence such as speech and image recognition, neural networks, robotics, machine learning, among others (McCorduck & Cfe, 2004). Currently, artificial intelligence has taken on an important role due to the high volume of data generated in different industries. Algorithms are becoming more sophisticated, faster, and capable of handling increasingly extensive and heterogeneous databases (Robert, 2014). Furthermore, with the improvement in computational power, the era of big data has emerged. This era is characterized by the 3 V's: volume, velocity, and variety. A large volume of data is stored, which comes in a wide variety of formats (numbers, images, texts, and others), and it is analyzed at a high speed (Bleu-Laine, 2021). The tools used for big data analysis are machine learning and deep learning.

Machine learning consists of a set of methods used to automatically find patterns in data (Murphy, 2013). The patterns that are found can be used to make predictions on unseen data and forecast future behavior. These forecasts can help identify subsequent actions without fully understanding the data behavior (Bzdok *et al.*, 2018). Thus, machine learning has proven to be an effective tool in applications such as decision-making, fraud detection, cancer diagnosis, recommendation systems, voice assistants, among others (Bleu-Laine, 2021).

The existing algorithms are displayed in Figure 1, illustrating two primary learning strategies: supervised and unsupervised. This figure outlines the structure of machine learning divided into these two major approaches. In supervised learning, we see classification and regression techniques. Classification includes methods such as decision trees, support vector machines, and artificial neural networks, while regression utilizes approaches like linear regression, Bayesian networks, and neural networks, among others. On the other hand, unsupervised learning encompasses clustering and dimensionality reduction. Clustering employs algorithms like K-means and hierarchical clustering, while dimensionality reduction includes techniques such as principal component analysis and neural networks. Each technique serves a specific purpose and has unique applications in data analysis and organization (Taherdoost, 2023).

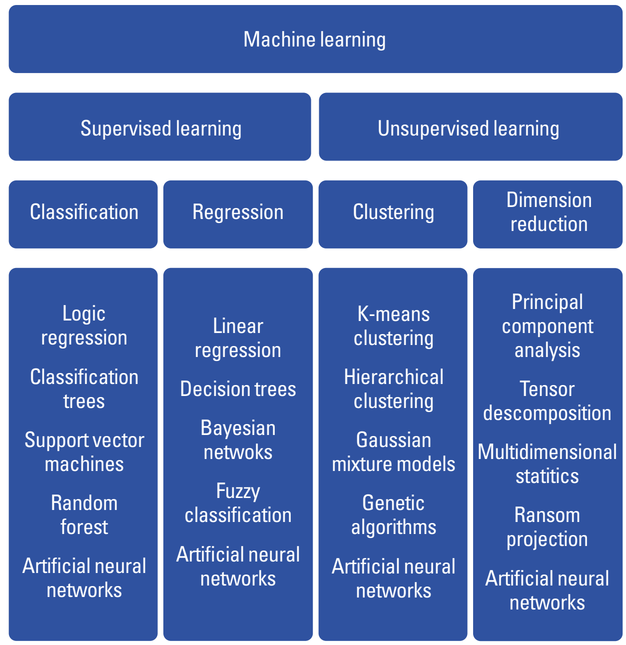

Figure 1. Machine learning algorithms
Source: Louridas & Ebert (2016).

Supervised learning allows a machine learning model to learn the mapping from an input x to an output y, using a training dataset consisting of input-output pairs (Murphy, 2013). In other words, supervised learning is used when the training set comprises the data and the authentic output of the process that uses this data (Vandehzad, 2020).

Classification Algorithms

Classification algorithms are used when the response is based on a finite set of outcomes, *i.e.*, a discrete label.

Regression Algorithms

Regression algorithms estimate and understand relationships between variables. These analyses focus on an independent variable and a series of other variables that vary, making them useful for prediction and forecasting.

Table 2 presents supervised learning algorithms for classification and regression tasks. In classification, key algorithms include logistic regression, decision trees, SVM, KNN, Naive Bayes, random forests, and boosting, all useful for categorizing data. For regression, the list includes linear regression, regression trees, and SVR, which are focused on predicting continuous values.

Table 2.
Supervised algorithms

Task	Algorithm
Classification	Logistic Regression Decision Trees Support Vector Machine (SVM) k-Nearest Neighbor (KNN) Naive Bayes Random Forest Boosting
Regression	Regresión linear Arboles de regresión Support Vector Regressor

Source: Own elaboration.

The objective of unsupervised learning is to discover knowledge from a dataset (Murphy, 2013). In this case, the data is unlabeled, and machine learning algorithms rely on the structure of the input *x* to create clusters of similar data points, determine the data distribution within the input space, or reduce higher-dimensional data to 2 or 3 dimensions for visualization purposes (Bishop, 2006). In other words, unsupervised learning is used when the training set consists of data but lacks solutions, requiring the computer to solve the problem on its own (Vandehzad, 2020). In practice, these algorithms are widely used as they do not require labeled datasets, resulting in more available data (Bleu-Laine, 2021).

Clustering Algorithms

Involves grouping together similar data points and separating dissimilar data points. The measure of similarity between data points and the representation of a cluster are key differences among various clustering algorithms (Arts, 2021).

Dimensionality reduction

Dimensionality reduction algorithms aim to reduce the number of variables considered to extract the required information. Table 3 presents unsupervised learning algorithms categorized into clustering and dimensionality reduction tasks. In clustering, algorithms like K-means, DBSCAN, hierarchical clustering, Gaussian mixture models, and hidden Markov models are used to group unlabeled data. For dimensionality reduction, key techniques include principal component analysis (PCA), tensor decomposition, multidimensional statistics, and random projection, all of which simplify data representation by reducing complexity while preserving essential information.

Table 3.
Unsupervised algorithms

Task	Algorithm
Clustering	K-means DBSCAN Hierarchical clustering Gaussian Mixture Models Hidden Markov Models
Dimensionality Reduction	Principal Component Analysis Tensor Decomposition Multidimensional Statistics Random Projection Source: Authors.

Source: Own elaboration.

The purpose of this review is to search and analyze the available information in databases related to artificial intelligence used in air operations, focusing on flight planning processes, trajectory prediction, and resource optimization.

Methodology

Conducting a systematic review requires establishing a work methodology that clarifies and simplifies the search for research and the synthesis process. For this reason, three phases are proposed: planning, execution, and reporting.

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Planning

The planning phase involves defining the research problem, formulating the search equation based on keywords, and establishing exclusion criteria. For this research, the selected search equation is:

(TITLE-ABS-KEY (artificial AND intelligence OR machine AND learning) AND TITLE-ABS-KEY (aircraft) AND TITLE-ABS-KEY (trajectory OR prediction OR delay OR flight OR fuel))

The Scopus database was chosen as the database, and the exclusion criteria included all documents that were not research articles.

Execution

The execution process involves applying the search equation across selected databases. Once the information is gathered, various filters are applied, and exclusion criteria are implemented. The exclusion criteria are as follows: the sources must be scientific articles, and they must specifically address topics related to air operations.

Reporting

The reporting phase involves presenting the most relevant information gathered and its impact. This includes an analysis of the types of documents found, the year of publication, and the interaction among studies, with the goal of examining the research objectives, algorithms used, and databases referenced.

Discussions

Analysis of Publication Trends and Keyword Relationships in Machine Learning for Aviation

By conducting the search in Scopus, a total of 423 results were found, as shown in Figure 2. It can be observed that the majority of publications are conference papers, followed by articles.

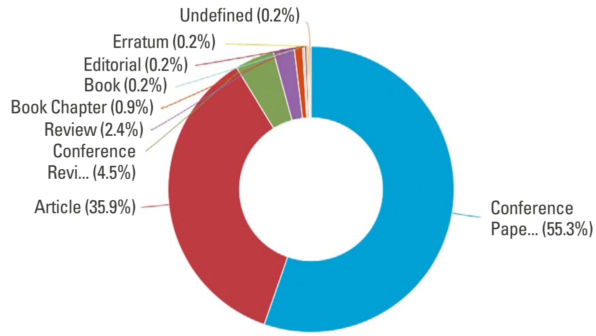

Figure 2. Document types without refinement
Source: Own elaboration.

Applying the exclusion criteria, the number of results was reduced to 162 published articles. Figure 3 displays the distribution of publications by year, revealing that artificial intelligence has had a significant impact on research since 2018.

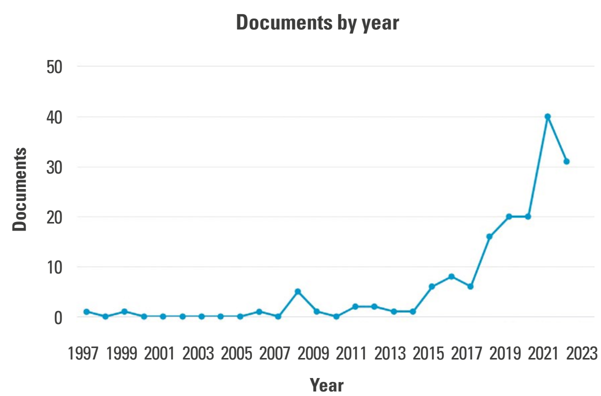

Figure 3. Publications by year
Source: Own elaboration.

Using the collected information, a relationship map was constructed using the vosViewer© program. Figure 4 illustrates the co-occurrence of keywords and the selected search equation. The figure is a relationship map in the field of machine learning as applied to aviation and related systems. The nodes and connections represent interconnected concepts such as neural networks, learning systems, aircraft, and detection technologies. Certain groups of terms are highlighted by color to indicate related topics: red emphasizes areas like deep learning and aircraft detection; blue is linked to aircraft engineering and structural monitoring; and green clusters focus on learning systems and air transport. This map illustrates how various areas of machine learning interact within the aviation context, from fault prediction and detection to aircraft control and training.

Based on this map, it can be observed that the majority of research revolves around trajectory prediction algorithms and air traffic management, as shown in Figure 5. This indicates a strong focus on these areas within the field of aviation operations.

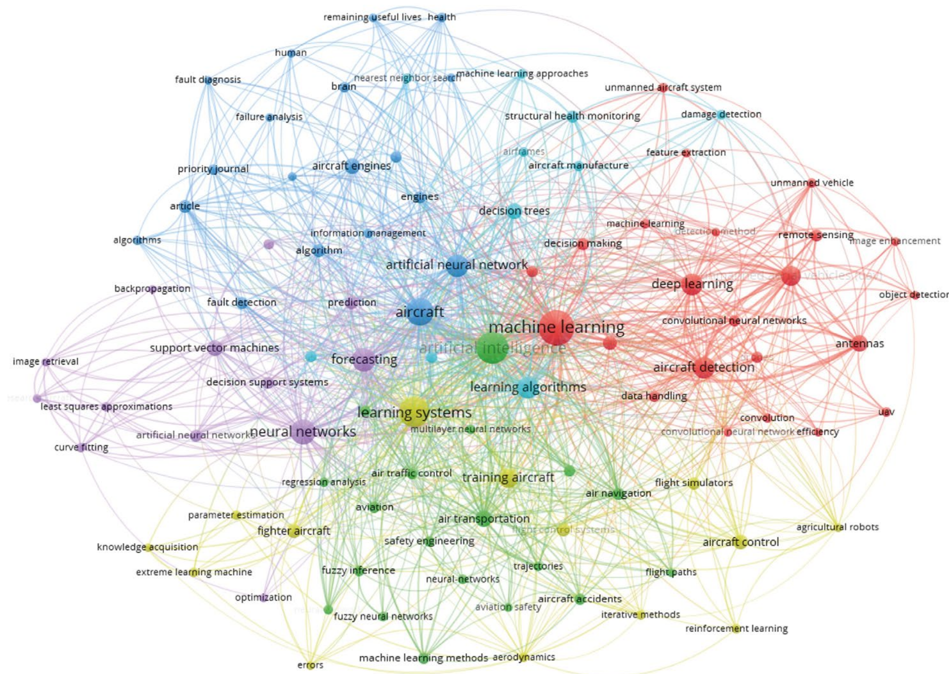

Figure 4. Co-occurrence of keywords

Source: Own elaboration.

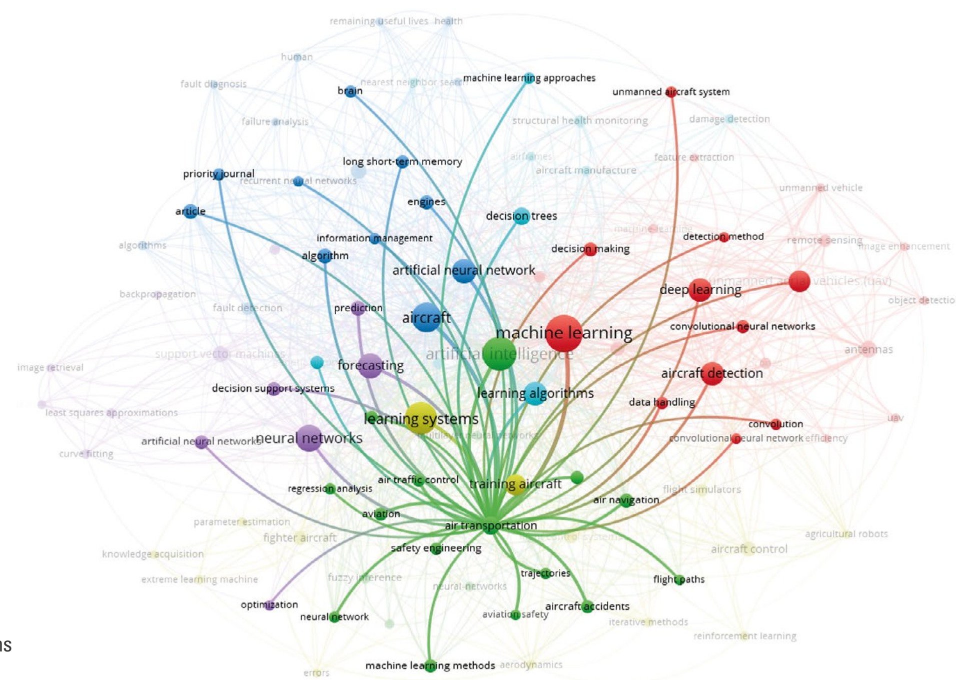

Figure 5. Co-occurrence in air operations

Source: Own elaboration.

Artificial Intelligence in Aircraft Operations

Air traffic management systems focused on trajectory-based operations (TBO) were proposed in the United States and Europe, named Next Generation Air Transportation System (NextGen) (Federal Aviation Administration [FAA], 2015) and Single European Sky ATM Research (SESAR, 2021), respectively. Nowadays, there are different technologies and equipment that allow accurate aircraft position acquisition and reporting. Integration between Automatic Dependent Surveillance-Broadcast (ADS-B) and ATM enhances flight efficiency and safety (Besada *et al*., 2000; Jeon *et al*., 2015; Yong *et al*., 22-27 May 2012). Machine learning plays a crucial role in trajectory exploitation and characterization, with clustering, neural networks, and genetic algorithms being commonly employed for trajectory planning and optimization (De Oliveira, 2019).

Most current trajectory prediction research falls under the category of "trajectory-based" methods, which rely on grid-based navigation aid planning. Regarding algorithm structure and parameters, ground-based 4-D trajectory prediction can be primarily divided into aircraft performance-based models and trajectory-based models (Shi, 2020).

Trajectory prediction is an attractive but complex research area as it requires interaction between aircraft operational models, flight planning, and environmental conditions (Courchelle *et al*., 2019; Cheung, 2018; Roskam, 1998; Takeichi, 2018). Furthermore, the increasing availability of data has facilitated more research in ATM systems. This increase is attributed to detection equipment, ground stations, satellites, and other facilities that provide an ample amount of data for air traffic management systems. An important resource in this context is the Base of Aircraft Data (BADA), which provides theoretical model specifications and related datasets for accurately simulating the behavior of any aircraft (EUROCONTROL, 2004). Additionally, historical flight trajectory data can be collected through ADS-B ground stations, which have been used for trajectory prediction (Harada *et al*., 7-11 January 2019). Although meteorological data is not easily accessible, it has a significant impact on trajectory prediction (Choi *et al*., 25-29 September 2016).

Performance-Based Models

Various research has been conducted on trajectory prediction based on models such as Point-Mass, kinematic, kinetic, and others (Musialek *et al*., 2010). State estimation models establish the motion equation based on aircraft velocity, position, acceleration, and other attributes. While this model is relatively simple, it can lead to errors due to uncertainty caused by the inability to accurately capture aircraft maneuvers. Therefore, it is effective only for short periods of time (Zeng *et al*., 2022). Kinetic models analyze aircraft forces based on ideal assumptions, often with limited consideration of real constraints and human behavior (Lymperopoulos *et al*., 21-24 August 2006; Porretta *et al*., 2008; Schuster *et al*., 2012; Schuster & Porretta, 3-7 October 2010). These kinetic models require aircraft performance data, aircraft state, environmental conditions, aircraft intentions, and other parameters, some of which are commercially sensitive and difficult to obtain. They also rely on pre-defined configurations or estimations in existing databases. The uncertainty associated with these input data induces uncertainty in trajectory prediction. For this reason, SESAR research aims to improve this situation (Zeng *et al*., 2022).

The state estimation models used include Kalman Filter (KF), Particle Filter algorithm, and Hidden Markov Model (HMM) as a single-model estimation. For multi-model estimation, multi-model KF, Interacting Multiple Model (IMM), and improved IMM have been used (Zeng *et al*., 2022). Additionally, some artificial intelligence algorithms have been employed for fuel estimation (Trani *et al*., 20-22 September 2004), thrust prediction (Dalkiran & Toraman, 2021), wind effects-based speed estimation (Porretta *et al*., 2008), aircraft conflict detection using the Residual-Based Interacting Multiple Model (RMIMM) (Hwang *et al*., 11-14 August 2003), and recent research has developed models for trajectory and performance prediction (Hrastovec & Solina, 2016; Tang *et al*., 2015).

Trajectory-Based Models

Machine learning models utilize algorithms and data mining techniques to learn from historical flight trajectories and meteorological data in order to predict future trajectories. These models are built upon weak or no assumptions and do not require explicit modeling of aircraft performance, procedures, or airspace. Instead, they learn patterns from the input data. These algorithms are also considered a type of data engineering, as their effectiveness improves with larger datasets. Due to the vast amount of trajectory data available, it is possible to extract patterns from complex trajectories and identify important features, providing a preliminary basis for trajectory prediction (Zeng *et al*., 2022).

Generally, flights follow the same planned route and sequence of waypoints, indicating regularity in historical trajectories. This makes machine learning highly viable (Lin *et al*., 2019). This methodology extracts the underlying law governing changes in aircraft trajectories over time from a large amount of data and uses this law to predict position trajectories. It typically employs two approaches: the first approach primarily relies on underlying laws of aircraft operations to excavate representative trajectory patterns, while the second approach is based on input-output space reconstruction (Lin *et al*., 2019). Different algorithms such as regression algorithms, neural networks, clustering, and other models have been used. Table 4 shows some of the algorithms employed.

Databases

There are several databases that have been used in research related to flight trajectory prediction, including aircraft performance data, aircraft surveillance data, and meteorological data.

Aircraft Performance Data

Performance data includes operational envelopes of the aircraft (speeds, weights, fuel consumption, etc.), aerodynamics, and other parameters. Currently, these data can be found in the BADA, Aircraft Noise and Performance (ANP), among others (Fukuda *et al*., 2010; Zeng *et al*., 2022).

Table 4.
Overview of models used for flight prediction

Model	Description	Reference
Regression Model	Linear regression	(Hamed *et al.*, June 2013; Hong & Lee, 2015; Kanneganti *et al.*, 23-26 July 2018)
	Stepwise regression	(De Leege *et al.*, 19-22 August 2013)
	Non-linear regression	(Hamed *et al.*, June 2013; Tastambekov *et al.*, 2014)
Neural Network Model	Feedforward neural networks	(Le Fablec & Alliot, May 1999; Verdonk-Gallego *et al.*, 2018, 2019; Wu *et al.*, 2020)
	Elman neural network	(Min *et al.*, 2020)
	LSTM	(Shi *et al.*, 8-13 July 2018, 2021; Xu *et al.*, 2021; Yang *et al.*, 27-30 July 2019; Zeng *et al.*, 2020; Zhao *et al.*, 6-8 July 2019)
	DNN + LSTM	(Zhang & Mahadevan, 2020)
	CNN + LSTM	(Ma & Tian, 2020)
	GRU	(Zhang *et al.*, 2020)
	Bayesian neural network	(Zhang & Mahadevan, 2020)
	Generative Adversarial Network	(Pang & Liu, 6-10 January 2020)
Clustering Model	Gaussian mixture model with clustering Random forest with clustering Neural networks with clustering	(Barratt *et al.*, 2019; Tran *et al.*, 2020; Wang *et al.*, 2017)
Other models	Non-parametric interval prediction Genetic programming	(Hamed, 2014; C. Zhang *et al.*, 8-10 July 2016)

Source: As shown in the table.

BADA is an aircraft performance model developed by EUROCONTROL in cooperation with aircraft manufacturers and airlines. It is based on the kinetic method for aircraft performance modeling, including the theoretical basis for calculating aircraft performance parameters and specific coefficients for calculating their trajectories. Currently, BADA has two widely used series, Series 3, which contains data for 100% of aircraft operating in Europe, and Series 4, which has improved performance calculations and covers approximately 70% of aircraft operating in Europe (EUROCONTROL, 2004).

ANP is jointly developed by the United States Department of Transportation, the European Control Center, and the European Aviation Safety Agency. This database provides noise and performance characteristics for over 150 types of civil aviation aircraft and is used for noise calculation around airports. Aircraft manufacturers provide data for each type of engine, which is published within the framework of Regulation (EU)598/2014 (Tang *et al*., 2015; Zeng *et al*., 2022).

Aircraft Surveillance Data

Monitoring data includes various aspects of current positioning and velocity and is provided in real-time. This data is used for trajectory monitoring, as done by the Automatic Dependent Surveillance-Broadcast (ADS-B) system and secondary surveillance radar. ADS-B is a surveillance system that uses satellite navigation to locate the aircraft's position and broadcast it to other aircraft or ground antennas. This technique makes aircraft visible and provides situational awareness. The data provided by ADS-B includes (Pham, 2019):

- Flight ID: a unique serial number representing each flight
- Time: date (month/day/year) and UTC time
- Position: latitude (decimal degrees), longitude (decimal degrees), and altitude (ft)
- Ground speed: relative horizontal speed with respect to the ground (knots)
- Rate of climb: change in altitude (feet per minute)
- Heading: orientation of the aircraft with respect to the north (decimal degrees)

FlightRadar24 is a global aircraft flight tracking service that allows real-time visualization of air traffic flow. It combines data from multiple sources, including ADS-B, multilateration, and radar data. FlightRadar24 operates worldwide (including Colombia) and has more than 20,000 ADS-B receivers (FlightRadar24, 2020).

There are other platforms such as FlightAware, OpenSky Network, ADS-B Exchange, and VariFlight, which also receive data from the ADS-B system, manage and visualize it. The drawback with these platforms is that they do not have an extensive network of receivers in Colombia (ADS-B Exchange, 2022; FlightAware, 2020; OpenSky Network, n. d.; VariFlight, 2022).

The Flight Plan Database (https://flightplandatabase.com/) has a large collection of flight plans primarily intended for flight simulation. For this reason, most plans do not have any flight identification or time information. However, they can be used as a guide for route planning (Kiesiläinen, 2020).

Meteorological Data

Meteorological data provides information related to environmental conditions, such as temperature, wind direction and speed, air pressure, and changes in gravity and magnetic forces. The most commonly used databases include EUROCONTROL with European Centre for Medium-Range Weather Forecasts (ECMWF), North American Mesoscale Forecast System (NAM), among others (Zeng *et al*., 2022).

The China Meteorological Data Network (CMDC, 2022) is a collector and manager of weather files and information. They collect, process, store, retrieve, and provide meteorological data worldwide. ECMWF (2022) is an organization that reanalyzes weather data, provides weather forecasts, and develops numerical models and data assimilation systems. They provide the Copernicus atmospheric monitoring and climate change services of the European community.

The National Center for Environmental Information (NCEI, 2019) provides global climate, forecasts, alerts, and analysis for external partners and user communities. It is one of the world's largest environmental data archives in terms of data quantity and forecasting models.

Aircraft Meteorological Data Relay (AMDAR) is a system composed of the World Meteorological Organization. It mainly utilizes sensors, computers, and communication systems on existing aircraft to collect, process, format, and transmit meteorological data to the ground station via satellite or radio links. The collected data can be used in various meteorological applications, including weather forecasts for the public, weather monitoring and prediction, weather disaster alert systems, and, most importantly, weather monitoring and prediction to support the aviation industry (World Meteorological Organization [WMO], 2022).

WorldClim corresponds to a high-resolution global climate database, which includes 19 types of bioclimatic databases and monthly basic climate databases (WordClim, 2022). Meteoblue calculates high-quality meteorological data worldwide, provides visualization, forecasting, storage, mobile applications, and other capabilities dedicated to various industries (Meteoblue, 2022). The open data from the Finnish Meteorological Institute contains datasets available to the public for free in a digital format (Finnish Meteorological Institute, 2013).

Conclusion

In conclusion, this study has shown that a structured methodology can refine the gathered information on artificial intelligence applications in aviation operations, especially in trajectory prediction, meteorology, fuel efficiency, aircraft performance, and air traffic management. Over the past four years, there has been a notable increase in research in this field.

The use of machine learning methodologies has led to significant improvements across various aspects of aviation. In trajectory prediction, models like linear regression, neural networks, and clustering systems have enhanced route and arrival time accuracy. In meteorology, machine learning has improved real-time weather forecasting, which is crucial for flight safety. Fuel consumption has been optimized by models that consider factors such as altitude and speed, resulting in cost savings and reduced emissions. In air traffic management, machine learning has increased system capacity, helping to manage congestion more effectively.

In summary, machine learning applications in aviation operations offer valuable benefits in efficiency, safety, and sustainability. The rising interest and research in this area reflect a strong commitment to leveraging artificial intelligence to advance the aviation industry.

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