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Review

Deep Learning in Air Traffic Management (ATM): A Survey on Applications, Opportunities, and Open Challenges

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Abstract: Currently, the increasing number of daily flights emphasizes the importance of air transportation. Furthermore, Air Traffic Management (ATM) enables air carriers to operate safely and efficiently through the multiple services provided. Advanced analytic solutions have demonstrated the potential to solve complex problems in several domains, and Deep Learning (DL) has attracted attention due to its impressive results and disruptive capabilities. The adoption of DL models in ATM solutions enables new cognitive services that have never been considered before. The main goal of this research is to present a comprehensive review of state-of-the-art Deep Learning (DL) solutions for Air Traffic Management (ATM). This review focuses on describing applications, identifying opportunities, and highlighting open challenges to foster the evolution of ATM systems. To accomplish this, we discuss the fundamental topics of DL and ATM and categorize the contributions based on different approaches. First, works are grouped based on the DL approach adopted. Then, future directions are identified based on the ATM solution area. Finally, open challenges are listed for both DL applications and ATM solutions. This article aims to support the community by identifying research problems to be faced in the future.

Keywords: deep learning; air traffic management; survey; convolutional neural networks (CNN); generative adversarial networks (GAN); recurrent neural network (RNN); autoenconder

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1. Introduction

Currently, the increasing number of daily flights emphasizes the importance of the air transportation system. Furthermore, Air Traffic Management (ATM) enables air carriers to operate safely and efficiently through the multiple services provided, e.g., Air Traffic Flow Management (ATFM), Airspace Management (ASM), and Flight Information Services (FIS) [1,2]. Air Traffic Control (ATC) technologies have been improved over the decades, and new technologies are needed to further enhance existing procedures and support future demands.

Moreover, advanced analytic solutions have demonstrated their potential to solve complex problems in several domains [3]. In this context, Deep Learning (DL) has attracted attention due to its impressive results and disruptive capabilities [4]. The evolution of computational power has enabled DL to be used in several contexts, and the current massive amount of data produced by existing systems empowers new applications. New DL-based solutions are currently under development in various domains, and efforts have been made toward developing DL-based ATM solutions.

Although several ATM solutions rely on deterministic methods, adopting DL models enables new cognitive services never considered before. Solutions vary from aircraft performance (e.g., flight state, parameters, and trajectory optimization) to human factors (e.g., fatigue assessment). In all these cases, DL can be used and further improve current operations in terms of airspace safety and efficiency. Conversely, several challenges must be overcome to integrate DL solutions in airspace operations. Furthermore, it is not simple to clearly define the challenges faced by state-of-the-art strategies and open challenges. Finally, it is also complex to relate different Deep Learning (DL) architectures with ATM problems to simplify identifying research gaps.

The main goal of this research is to present a comprehensive review of state-of-the-art Deep Learning (DL) solutions for Air Traffic Management (ATM). This review focuses on describing applications, identifying opportunities, and highlighting open challenges to foster the evolution of ATM systems. To accomplish this, we discuss the fundamental topics of DL and ATM and categorize the contributions based on different approaches. First, works are grouped based on the DL approach adopted. Then, future directions are identified based on the ATM solution area. Finally, open challenges are listed for both DL applications and ATM solutions. This article aims to support the community by identifying research problems to be faced in the future.

Therefore, the main contributions of this research are:

- A comprehensive review of state-of-the-art Deep Learning (DL) solutions for Air Traffic Management (ATM);
- Future directions based on insights of single contributions and ATM solutions groups;
- An extensive list of open challenges in the context of Deep Learning (DL) applications in ATM;
- An extensive list of open challenges from the ATM solutions standpoint.

The paper is organized as follows: Section 2 discusses aspects of Deep Learning (DL) and Air Traffic Management (ATM). Secondly, Section 3 reviews DL application in ATM solutions. Then, Section 3.6 presents several insights on the review and future directions for contributions belonging to different categories. Finally, Sections 4 and 5 present several open challenges and the conclusions of this research, respectively.

2. Background

The works reviewed in this research involve several concepts related to Air Traffic Management (ATM) and Deep Learning (DL). This Section describes fundamental aspects to a better understanding of the contributions reviewed.

2.1. Deep Learning (DL)

Currently, the complexity of systems and applications in several domains is increasing. Applications need to embed some advanced reasoning to accomplish the tasks they have been designed to. Conversely, this is complex for several reasons. In the past few years, Deep Learning (DL) [5,6] applications have been exceptionally successful in multiple challenging tasks, and more attention is attracted once the intelligent decision emerges from patterns hidden in large multi-dimensional datasets.

Deep Learning (DL) can be represented by a neural network with a large number of layers and parameters using a cascade of multiple layers of nonlinear processing units for feature extraction and transformation [7,8]. Several domains have benefited from DL applications, e.g., healthcare [9,10], transportation [11,12], and manufacturing [13].

Moreover, several architectures have been proposed with different goals. More architectures are under development to solve specific problems. This research considers five of the most popular architectures: Deep Neural Networks (DNN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GANs), and Autoencoders (AE).

- **Feed-Forward Networks:** Feed-Forward Neural networks (also referred to as Deep Neural Networks—DNN—in this article) consists of neurons ordered into layers. The first layer, called the input layer, the last layer, called the output layer, and the hidden layers [14]. Neurons can be considered processing units connected to synaptic weights. These neurons produce an output using an activation function, which is sent to the following layer [15]. These networks are usually trained using the back-propagation algorithm (used to compute gradients) and the Stochastic Gradient

Descent (SGD) algorithm to optimize the weights (using the gradient computed previously). Figure 1 illustrates a simple DNN and highlights the input, hidden, and output layers. The number of nodes and hidden layers can change depending on the problem faced, similar to the input vector. This architecture has been widely used and has presented tremendous success in several initiatives.

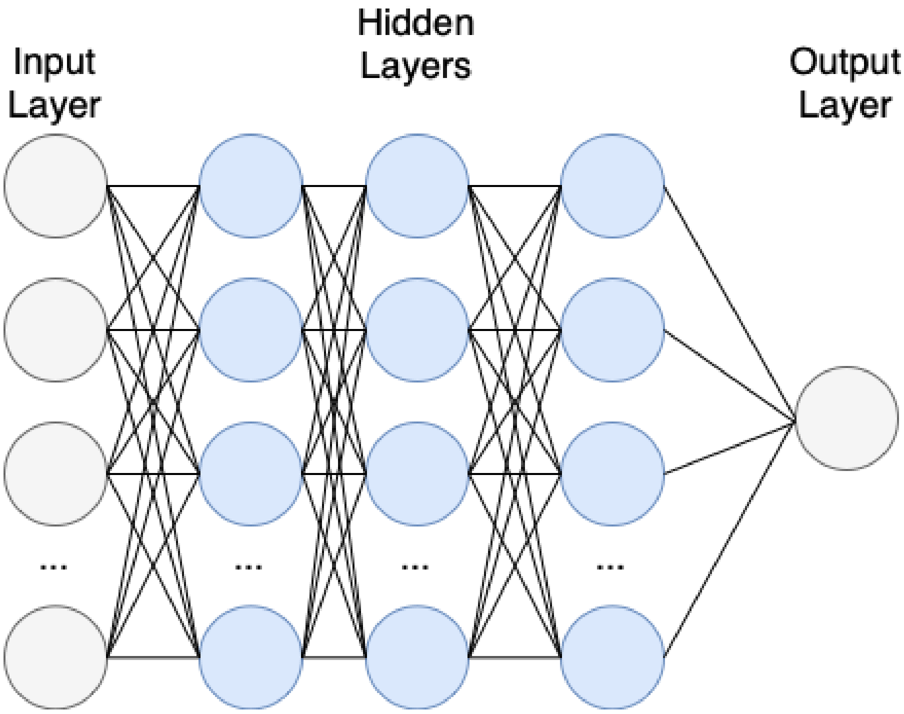

Figure 1. Example of Deep Neural Network (DNN) [14,15].

- **Convolutional Neural Networks (CNNs):** Convolutional Neural Networks (CNNs) are a category of Deep Learning (DL) models designed to process data in a grid-like topology (e.g., time-series and image data). CNNs are usually composed of three types of layers: convolutional, pooling, and fully connected layers [16,17]. The convolutional layers are responsible for extracting important features. The pooling layers reduce the resolution of features, making them robust against noise and distortion. Finally, the fully-connected layers produce class scores from the activations [18]. Figure 2 illustrates a simple CNN model.

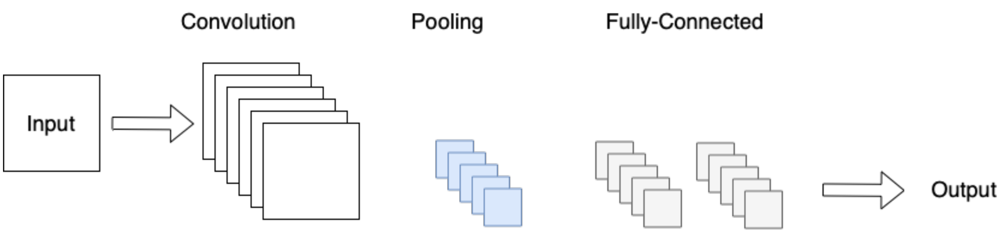

Figure 2. Example of Convolutional Neural Networks (CNNs) [16,18].

- **Recurrent Neural Networks (RNN):** Recurrent Neural Networks (RNNs) represent a neural network architecture used to detect patterns in sequences (e.g., images, text, or numerical time series) [19]. Important RNN features are the feedback connection and memory, which enable activations to flow in a loop and temporal processing [20]. Figure 3 illustrates a simple example of an RNN.

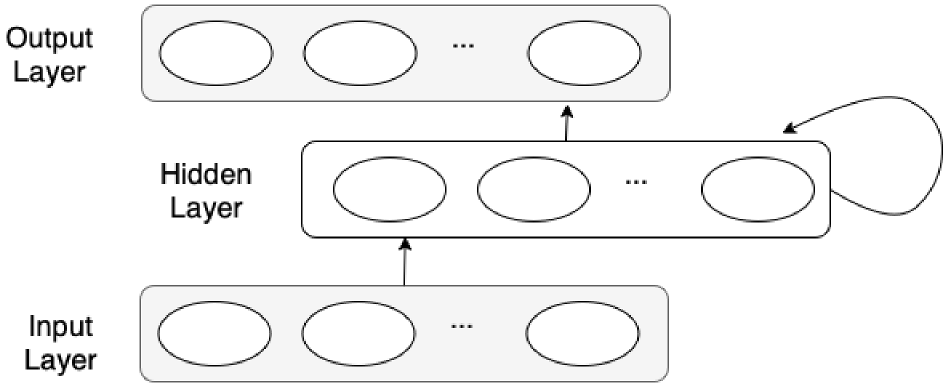

Figure 3. Example of Recurrent Neural Network (RNN) [19,20].

- **Generative Adversarial Networks (GANs):** This architecture is based on the competition between a generation and a discriminator. In this sense, the generator uses random noise to produce fake data while the discriminator tries to distinguish real data from fake data. When the generator can produce data that cannot be appropriately classified as fake by the discriminator, the model can produce realistic data [21,22]. Figure 4 illustrates a simple GAN architecture.

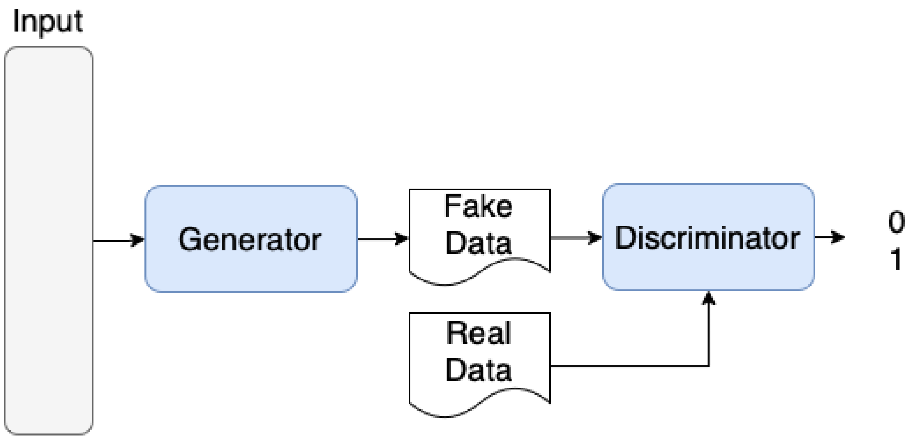

Figure 4. Example of Generative Adversarial Network (GAN) [21,22].

- **Autoencoders (AE):** This specific type of neural network was developed to encode inputs into a compressed and meaningful representation. After this reduced version of the provided features is produced, the model decodes it back, aiming to produce an output as close as possible to the input [23,24]. Figure 5 illustrates a simple AE architecture.

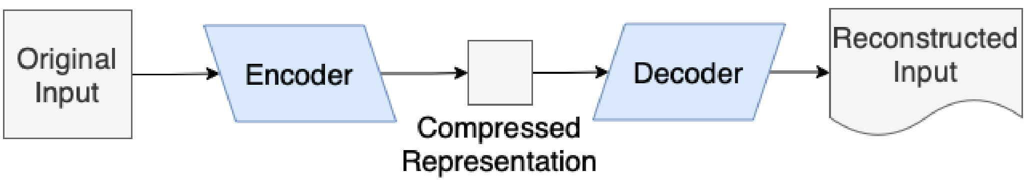

Figure 5. Example of Autoenconder (AE) [23,24].

2.2. *Air Traffic Management (ATM)*

Currently, the air transportation system connects countries and plays a major role in society. Daily operations are safe and efficient due to the many advances in technology and regulations. In fact, new technologies are required to further improve the National Airspace System (NAS) operation.

Air Traffic Management (ATM) can be defined as "the dynamic, integrated management of air traffic and airspace including air traffic services, airspace management and air traffic flow management [...] in collaboration with all parties and involving airborne and ground-based functions” [25]. To maintain safety and efficiency levels, the Air Traffic Control (ATC) guarantees smooth airspace flow through ATC services. The airspace is divided into regions [1] and served by Air Traffic Controllers (ATCos) via Air Traffic Flow Management (ATFM), Airspace Management (ASM), and Air Traffic Services (ATS), as illustrated in Figure 6. These services comprise flight information service, alerting service, air traffic advisory service, area control service, approach control service, and aerodrome control service [1,2].

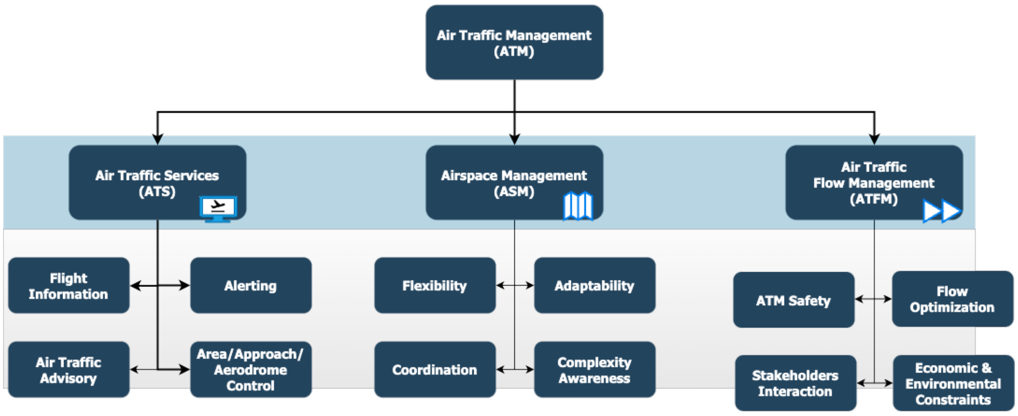

Figure 6. Overview of ATM components [1,26–28].

However, ATC faces several challenges. For example, communication [29], efficiency [30], safety [31], excessive ATCo workload [32], and congestion [33]. Several stakeholders have been working on new technologies to modernize and include new ATC capabilities in the National Airspace System (NAS). Conversely, the increasing number of flights demonstrates that further technological development is required.

These technologies vary from application and the service targeted. Furthermore, four critical ATM application-oriented research areas highlighted by SESAR [34] are:

- **ATM Operations, Architecture, Performance, and Validation (OAPV):** focuses on solutions to enhance and enable trajectory-based operations, considering technologies related to aircraft trajectory. It may include trajectory planning [35,36], prediction [37,38], generation [39,40], optimization [41,42], and clustering [43,44];
- **Enabling Aviation Infrastructure (EAI):** includes technologies to enable more flexible architectures. Involves ground and airborne systems that can be useful for ATM. For example, aircraft health prediction [45], optimization [46], and management [47];
- **High-Performing Airport Operations (HPAO):** targets emerging technologies to improve situational awareness for tower controllers. For example, it may include temporal aspects that affect the airspace operations, such are departure delay prediction [48,49] and arrival delay prediction [50];
- **Advanced Air Traffic Services (AATS):** involves tools to improve departure and arrival processes, separation management, air and ground safety, and systems to support flight planning. This area refers to solutions considering the interaction between humans and computers and may include augmentation solutions [51,52] and behavioral technologies [53]. Moreover, it also considers airspace complexity solutions [54], e.g., initiatives related to complexity estimation [55] and reduction [56,57] are examples of solutions in this portfolio.

Therefore, this research focuses on reviewing DL efforts in these five ATM solutions categories. Moreover, we also present an in-depth discussion on future efforts and open challenges for each group.

In the past few years, several ATM solutions have been proposed in the literature. These proposals are based on several methods and techniques, e.g., deterministic optimization [58], stochastic solvers [59], and data-driven strategies [60]. Furthermore, Artificial Intelligence (AI) and

Deep Learning (DL) present state-of-the-art performance in challenging tasks (e.g., image classification [61]) while solving scientific problems in multiple areas. Therefore, there has been an effort towards leveraging AI and DL capabilities to foster the development of next-gen ATM systems. Figure 7 shows the evolution of results count provided by Google Scholar using "ATM + Artificial Intelligence" and "ATM + Deep Learning" as search strings. This shows an increase in the interest of AI and DL in ATM solutions.

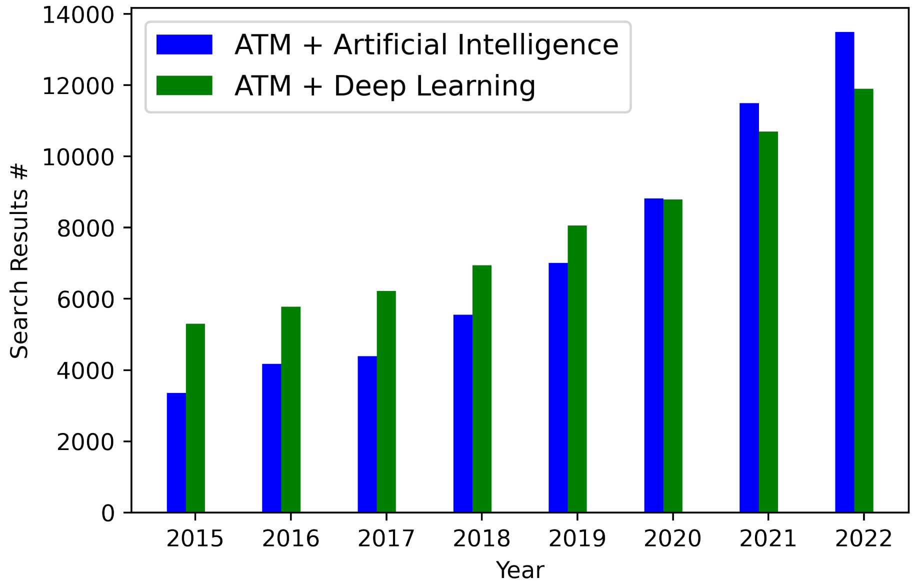

Figure 7. Evolution of AI and DL search results in ATM in the past few years.

In this sense, the development of new solutions relies on the understanding of the existing body of knowledge and research gaps. In this research, we focus on reviewing multiple DL-based initiatives in ATM to support the development of future solutions. Conversely, we focus on the identification of research opportunities while highlighting how DL methods are used. The statistical evaluation of the performance of such methods compared to baseline solutions is in the scope of future works.

3. Literature Review

This section presents all works reviewed categorized into five classes, matching the architectures previously discussed: Deep Neural Networks (DNN), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNN), Generative Adversarial Networks (GANs), and Autoencoders (AE). Once the review of all works is presented, we compare the contributions in Table 1.

Each work is classified regarding the following attributes:

- **Year:** Describes the year in which the article was published;
- **ATM Area:** Categorizes the article into one of the four ATM solutions areas previously described, i.e., OAPV, EAI, HPAO, and AATS;
- **ATM System:** Indicates if the solution focuses on Air Traffic Services (ATS), Airspace Management (ASM), or Air Traffic Flow Management (ATFM);
- **Flight solution:** Indicates if the solution is directly applicable to one (S) or multiple (M) aircraft;
- **Deep Learning (DL) Application:** Refers to the aspects of the Deep Learning (DL) application, indicating if the authors presented details on the architecture (Arc), validation (Val), and deployment (Dp);
- **Airspace Key Performance Indicator (KPI):** Indicates the main target of the proposed method regarding airspace operations. Works contributions are classified into safety

(Sft), efficiency (Ef), and sustainability (Sus). Although some initiatives overlap multiple KPIs, we intend to identify the primary focus;
- **Air Traffic Controller (ATCo):** Indicates if the proposed solution is intended to support the operation of ATC professionals. This attribute identifies if the solution proposed considers human factors (HF—e.g., mental workload and fatigue identification) and augmentation capabilities (Aug—e.g., indicates if the solution indents to help professionals in the task).

3.1. Applications of Deep Neural Networks (DNN) Networks in ATM

The authors in [62] propose an Air Traffic Control (ATC) model to guide an arbitrary number of aircraft across three-dimensional, unstructured airspace safely. This challenging problem relies on the complex set of tasks performed by ATC due to the increasing number of aircraft. Therefore, the authors emphasize that autonomous ATC functionalities are necessary to support future operations. To accomplish this, graph-based deep learning approaches are used to handle the input ordering of aircraft and the varying number of aircraft. In the 24 h simulation experiment, the proposed method managed the airspace by avoiding 100% of potential collisions and preventing 89.8% of potential conflicts. In addition to this effort, the authors in [63] focus on defining which variables determine airspace complexity based on machine learning models. In this sense, DL interpretability can play an important role in future works [64,65].

Wang et al. [66] apply cutting-edge DL techniques to predict flight departure demand in a strategic time horizon. This effort is intended to support MITRE's Pacer program to improve operators' situation awareness of the potential for departure delays during busy periods. To accomplish this, the authors leverage better data sources (i.e., Aviation System Performance Metrics (ASPM) and System Wide Information Management (SWIM)) and robust forecasting algorithms. The authors trained forecasting models with DL techniques of sequence to sequence (seq2seq) and seq2seq with attention and showed through field demonstrations that the Mean Squared Error (mse) can be reduced using the proposed strategy.

The authors in [67] investigate the effectiveness of the Hybrid Deep Learning (HDL) in the departure delay severity prediction for ten major airports in the U.S. that experience high ground and air congestion. In fact, the effectiveness of airports and airlines greatly relies on punctuality, and HDL models have demonstrated promising results in many complex problems. This motivated the authors to propose a strategy to analyze structured air traffic data as a combination of a Feed-Forward Artificial Neural Network model, and a gradient boosted tree model (XGBoost). The proposed strategy achieves a rise of 22.95% in accuracy when compared to a pure neural network model.

In [68], the authors investigate the feasibility of machine learning methods for cost reduction and service quality improvement in low-cost airlines (LCAs) based on the use of predictive modeling approaches and real airline datasets. Two major problems are faced, i.e., fuel consumption prediction and flight delay prediction. To accomplish this, the authors use different methods, such as Random Forest, XGBoost, and Deep Neural Network. The experiments conducted showed that the proposed approach predicts fuel consumption and delays with high accuracy. Finally, the authors conclude that these models are effective for the investigated airports using the information available one day before the flight.

Bala et al. [69] evaluate the performances of Deep Feed-Forward Neural Network, Neural Network, and Support Vector Machine models on a binary classification problem using flight on-time data records from the United State Bureau of Transportation Statistics. As previously discussed, flight delays impact airport and airline operations, resulting in significant economic losses. This motivates the accurate prediction of such factors to enable informed decision-making in the aviation industry. Conversely, it depends on several aspects, e.g., the air transportation system complexity and airport infrastructure. The experiments showed that the proposed strategy can be used to tackle the problem highlighted. The authors emphasized the contribution of this initiative to the aviation industry and the air transportation unit concerning improving passengers' experience through better flight delay decision support systems.

In [70], the authors develop a flight delay prediction system based on domestic flights inside the United States of America. The impact of delays on the airline business is significant. Although there is an interest in increasing the predictability of such events, this remains a major challenge currently. In order to tackle this problem, the authors use machine learning and Deep Learning methods. The case studies demonstrated that the models learn the cause of flight delays and cancellations and associate them with the link between departure and arrival delays. Similarly, the authors in [71] propose a predictive solution for fight delays based on Deep Learning (DL) and on the Levenberg--Marquardt (LM) algorithm. The results obtained from the experiments showed that the proposed model efficiently predicts delays.

Mas-Pujol et al. [72] propose two Deep Learning models to mimic the current procedure's behavior to help specialized ATCos detect the imbalances that will require regulation. The flight allocation in the current ATC system is required to be time-efficient, cost-efficient, and safe through the Demand–Capacity Balancing process. This process entails analyzing corrective actions in the form of regulations in areas with high demand to avoid overload. However, this procedure is complex, time-consuming, and based on ATCo's experience. To tackle this problem, the authors use a CNN and an RNN to demonstrate that regulation can be predicted with over 80% accuracy for the context considered.

Chakrabarty [73] focuses on the flight arrival delay prediction for flights operated by American Airlines, predicting possible arrival delays of the flight using machine learning approaches. In fact, flight delays result in airline companies operating commercial flights incurring losses, and new methods to avoid them are needed. The experiments conducted showed that the Gradient Boosting Classifier model achieves maximum accuracy of 85.73%. Finally, the author indicates that using Machine Learning-Deep Learning Hybrid Models tuned with Grid Search to achieve better model performance is in the scope of future works.

The authors in [74] examine requirements to be deployed different techniques operationally in an ATM system, exploring aspects of such as verification, regulatory certification, and end-user acceptance. The success of AI solutions motivates their application in aviation systems. In this research, the authors consider a novel cognitive Human–Machine Interface (HMI) configured through machine learning. The authors highlight that the increasing levels of automation and autonomy are expected to include certification requirements, and a discussion is conducted regarding how ATM systems can be accommodated into the existing certification framework for aviation systems. This research brings important insights into the application of how ML and DL can be part of ATM systems and presents future directions that converge with DL research topics (e.g., explainability).

In [75], the authors propose a DL method to construct an aircraft network and utilize the complexity indices to characterize it. As the basic unit of the airspace system is the Air Traffic Control Sector (ATCS) is the basic unit of the airspace system, identifying congestion in such areas enables decision support for strategic planning and daily operations. The existing approaches focus on the static structure and the dynamic operational features, which has motivated the authors to develop a more flexible strategy. In this sense, congestion identification becomes the complexity of the aircraft network and is detected by a Deep Active Learning (DAL) model. The experiments showed that this approach outperforms existing mainstream methods in the four objective evaluation indices.

Facing air transportation delays as an outcome of local airport dynamics and the global propagation process, the authors propose a method to assess airport identifiability in [76]. The focus of this research is to demonstrate how DL models can recognize airports with high precision and that delays are more dependent on each airport's characteristics than the global air transportation system's effects. As a natural result, identifiability is higher for large and highly connected airports. Finally, the authors highlight that the proposed approach is superior to the mainstream approaches in multiple aspects.

Boggavarapu et al. [77] present a delay estimation DL model trained using the air traffic and weather data obtained from the U.S. Bureau of Transportation Statistics and NOAA—National Oceanic and atmospheric administration. Facing flight delays as a major challenge in the air transportation system, the authors acknowledge that delays are influenced by several factors. In fact, this complexity hardens the accurate prediction of delays in different scenarios. To tackle this problem, a Gated Recurrent Unit (GRU) network is adopted due to the recurrent and time-series nature of the dataset. The experiments performed showed that the proposed approach is effective in estimating departure delays based on a case study focusing on the Chicago airport.

In [78], the authors address to provide an overview of the state of the art for applying DL to the aircraft design, dynamics, and control field. Several DL solutions have been proposed in this context, focusing on an information-rich, data-driven approach. Two main groups are considered: own-ship aircraft modeling, including proposals that have been/can be implemented online for the aircraft design/dynamics/control, and other airplane research works, DL-based solutions for offline monitoring of the aircraft operation. The authors describe several efforts throughout the paper and point out several open challenges to be addressed in future works.

The authors in [79] present a DL-based approach to augment the job of both ground controllers and pilots. The current challenges faced in the aviation industry (e.g., professional shortage) represent a concern for aeronautic enterprises and regulators, given the increasing number of annual flights. In this context, the Single Pilot Operations concept relies on automation in several layers of the air transportation system. The authors use Meteorological Terminal Air Reports to create a model based capable of determining the approach trajectory of an aircraft thirty minutes before the landing time. The experiments performed were conducted on aircraft trajectories from Toulouse to Seville, demonstrating that the proposed strategy achieves over 90% accuracy in the prediction task.

In [80], the authors' Machine Learning (ML) and Artificial Intelligence (AI) methods are proposed to control and predict the state of air traffic. ATC plays a pivotal role in society and acts in safety-critical scenarios. Therefore, there is a mental workload experienced by Air Traffic Controllers (ATCos) that needs to be maintained at low levels. The proposed strategy, based on different statistical methods (e.g., neural network), presents high accuracy prediction compared to other statistical algorithms with over 95% accuracy. In fact, this contribution emphasizes that DL techniques can be used to build up multiple prediction services to support the ATC operation.

The authors in [81] present a survey and a DL-based model of real-time aircraft tracking systems. This problem is a current challenging issue in the literature for several reasons, e.g., the need for an accurate and complete data transfer from aviation to ground systems. Conversely, aircraft tracking becomes difficult due to data loss caused by telemetry or data acquisition. In this context, the authors present a survey of aircraft tracking systems, categorizing works into three classes (i.e., mathematical, machine learning-based, and Deep Learning-based). After that, a real-time Deep Learning-based Aircraft Tracking (DeepAT) system that enables real-time tracking of an aircraft is introduced. DeepAT offers promising results in the experiments performed to prevent data loss in different applications.

3.2. Applications of Convolutional Neural Networks (CNN) in ATM

In [82], the authors propose an advanced Bayesian Deep Learning method for aircraft trajectory prediction considering weather impacts. Trajectory prediction is a challenge, but a required aspect of the next-generation National Air Transportation System (NATS), and reliable prediction models must consider uncertainties from various sources. Then, the authors introduce a deterministic trajectory prediction model with classical deep learning methods to handle both spatial and temporal information. Moreover, multiple layers are used, e.g., CNN, RNN, and fully connected layers. The experiments showed a significant reduction in prediction variance compared to existing methods.

The authors in [83] propose a Hybrid Deep Neural Network (HDNN) for active hazard identification of Auxiliary Power Units (APU) in civil aircraft. This method is based on a multi-time window Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN-BiLSTM) neural network, and integrates three models with different time window sizes in parallel. Hence, this combination can automatically extract features to represent the system state and learn the time-based patterns in the time series data. The authors also state that this strategy has the most stable identification performance for data with imbalanced samples in comparison to others present in the literature.

In [84], the authors introduce an automatic image-based aircraft defect detection using a pre-trained Convolutional Neural Network (CNN) for feature extraction and the Support Vector Machine (SVM) method with a linear kernel in the classification step. Throughout the paper, the author highlights that this initiative intends to support regular maintenance using visual and nondestructive Inspection (NDI) and a detailed description of the images used and how the classification process works. The experiments showed that the proposed method is accurate (96%) and presents high performance even in simple hardware.

The authors in [85] present a generalizable efficient tree-based matching algorithm to build feature maps from meteorological datasets (i.e., wind, temperature, and convective weather). This effort is focused on aviation efficiency and targets reliable 4D aircraft trajectory prediction. In this sense, the authors propose an end-to-end convolutional recurrent neural network that consists of a Long Short-Term Memory (LSTM) encoder network and a mixture density LSTM decoder network. Then, to enable high-dimension weather representation learning, the authors include convolutional layers into the pipeline. The case studies showed that the learned filters successfully locate convective weather and generalize the weather-related features using real operational data (flights from IAH to BOS).

Xie et al. [86] propose an end-to-end Sector Operation Complexity (SOC) learning framework based on deep CNN. This study is motivated by the lack of approaches that do not rely on hand-crafted factors. Indeed, these factors require specialized background and might limit the evaluation performance of the model. Then, the authors propose a Multichannel Traffic Scenario Image (MTSI) to represent the overall air traffic scenario by splitting the airspace into a two-dimension grid map, extracting high-level features, and learning the SOC pattern with the support of CNN. The experiments showed that the proposed strategy can effectively extract traffic complexity information from MTSIs.

The authors in [87] introduce two flight delay prediction models based on CNN employing fusion of meteorological data to predict flight delays. The first model is the Dual-channel Convolutional Neural Network (DCNN) based on the ResNet, whereas the second refers to the Squeeze and Excitation-Densely Connected Convolutional Network (SE-DenseNet), which is a combination of SENet and DenseNet. The main idea is to rely on flight and meteorological data fusion with efficient feature recalibration procedures. The experiments demonstrated that the accuracy of the model can be enhanced by the proposed strategy, and the two networks introduced in this paper can improve the prediction process, reaching 92.1% and 93.19%.

The authors in [88] focus on generating individual-sensitive resolution advisories for air traffic conflicts. The authors' goal is to increase the acceptance of workload-alleviating automation in air traffic control by adapting advisories to different controller strategies. In fact, this personalization is reached using a CNN model trained on individual controller data. A human-in-the-loop experiment was performed to generate datasets of conflict geometries and controller resolutions, and the results demonstrated that this strategy can predict command type, direction, and magnitude. An unfolding contribution is presented in [89], focusing on performing an exploratory investigation into conformal and individual-sensitive automation for Air Traffic Control (ATC) based on CNNs. There have been several challenges regarding ATC augmentation and automation related to a lack of trust and acceptance. The authors investigate automation from the personalization standpoint to individual controllers. This approach relies on combining visual features and a tailored CNN trained on individual controller data collection from human-in-the-loop simulations.

The results achieved showed that the proposed approach can predict command type, direction, and magnitude.

In [90], the authors present a hybrid RNN-CNN cascade architecture to predict C-ATC capacity regulations for en-route traffic. The authors investigate three different Air Traffic Management (ATM) frameworks to improve the cost-efficiency for flow and network Management considering facing the detection of regulations. To accomplish this, two Deep Learning models are combined, creating a different hybrid model. This combination comprises a Recurrent Neural Network (RNN) and a Convolutional Neural Network (CNN) to extract the overall airspace characteristics and process artificial images of the airspace configuration. The experiments used historical data from two of the most regulated European regions and showed that a cascade architecture presents average accuracy of 88.45%.

The authors in [91] propose a neural network structure combining CNN and LSTM to classify hypersonic aircraft flight trajectories. In the past few years, there has been an increase in interest in supersonic and hypersonic due to their high speed and complex maneuvering mode. Thus, the classification process compensates for their shortcomings of insensitivity to temporal and spatial characteristics and can effectively classify two kinds of hypersonic glide vehicles. The classification experiments demonstrated that the proposed model has good performance under the condition of introducing observation noise.

A CNN-based multi-feature predictive model (MF-CNN) is proposed in [92] to predict network-scale traffic flow with multiple spatiotemporal features and external factors. In today's air traffic system, traffic flow prediction is paramount for many applications, e.g., traffic control and route guidance. Conversely, it is not simple to identify important features using traditional data-driven traffic flow prediction models (e.g., periodicity and weather). Therefore, the authors classify traffic features into temporal continuity as short-term features and daily periodicity, and weekly periodicity as long-term features. After that, they are mapped into three 2D spaces. In this process, CNNs learn high-level spatiotemporal features and provide them to the logistic regression layer for final prediction. The experiments showed that the MF-CNN model improves the predictive performance compared to the five baseline models.

In [93], the authors expand previous work on thunderstorm forecasting [94] by applying CNNs to exploit the spatial characteristics embedded in weather data. In fact, thunderstorms can disrupt Air Traffic Management (ATM) procedures, causing a complex state of operation within the airspace system. Currently, it is still a challenge to have precise forecasts, hardening strategic planning. Then, the authors focus on deep learning as it has provided promising results in different scenarios. The learning task is formulated as a binary-classification problem based on satellite data. The experiments compared different Deep Learning (DL) architectures, e.g., a fully Convolutional Neural Network (FCN), a CNN-based encoder–decoder, a UNet, a pyramid-scene parsing network (PSPNet), and Multi-Layer Perceptron (MLP). The results indicate that CNN-based architectures improve the performance of point-prediction models and can be used to increase the prediction lead time of thunderstorms.

In [95], the authors present a novel processing paradigm to integrate multilingual speech recognition for robust speech recognition in Air Traffic Control (ATC). This refers to a single framework using an Acoustic Model (AM), a Pronunciation Model (PM), and a Language Model (LM). The process works as follows: the AM converts ATC speech into phoneme-based text sequences, the PM translates these sequences into a word-based sequence, and the LM corrects both phonemes- and word-based errors in the decoding results. The AM includes a CNN and an RNN considering the spatial and temporal dependences of the speech features. The authors used large amounts of real Chinese and English ATC recordings and achieved a 3.95% label error rate.

Rahman et al. [96] converted trajectory data into images, which size does not depend on the number of planes, and developed a multi-label conflict resolution model called ACRnet. This model uses a CNN to classify the obtained images. To solve aircraft conflicts, Air Traffic Controllers (ATCos) interact with flight crews observing several parameters (e.g., positioning, speed, direction, and weather), hardening the task with the currently congested airspace. In this sense, supportive systems can help ATCos in their tasks. The experiments conducted demonstrated that ACRnet achieves high accuracy for two aircraft and three aircraft.

Liu et al. [97] introduce a recurrent 3D CNN (R-3DCNN) to consider the spatial and temporal air traffic transitions comprehensively for Air Traffic Flow (ATF) prediction. The authors employ a new data representation called Traffic Situation Graphics (TSG)—generated by splitting the 3D earth space with fixed grid maps and flight levels—to illustrate traffic flow situations in a single instant. Then, the 3D CNN and LSTM extract high-level features (spatial and temporal) from a TSG sequence, assuming that inputs are determined by combining the traffic situations on different flight levels with areas affected by other real-time factors. The evaluation demonstrated that the proposed strategy can obtain accurate and stable prediction results of ATF prediction with distribution on different flight levels.

The authors in [98] present an effort to identify flight states based on CNN. To this end, a novel one-dimension CNN is introduced to automatically extract useful features from the structural vibration of a recently fabricated self-sensing wing through wind-tunnel experiments. In fact, it is challenging to identify the flight state from the complex vibration signals with high accuracy. To accomplish this, the authors decomposed the obtained signals into various sub-signals with different frequency bands and formed the best possible combination for multichannel inputs of the CNN. The two case studies showed that the proposed approach can achieve high identification accuracy and robustness, providing new perspectives on self-awareness toward the next generation of intelligent air vehicles.

3.3. Applications of Recurrent Neural Networks (RNN) in ATM

The authors in [99] propose a short-term wind speed prediction framework for bridge traffic control under strong winds. The goal is to improve the estimation accuracy for the timeframe of traffic control during a typhoon. The authors use a hybrid modeling of wind speed at the bridge and a Time-Shifted Data Correction (TSDC) method. The hybrid modeling considers two available data types (i.e., structural health monitoring and regional specialized meteorological center—RSMC) using training features based on the maximum sustained winds of a typhoon. Throughout the paper, a graphical and in-depth description of all steps is presented and, as a numerical example, typhoons from 2020 were used as test data to demonstrate the improvement in prediction performance via the use of hybrid modeling and the TSDC method. This initiative describes an approach that can be used in several aspects of Air Traffic Management (ATM) in future works.

The authors in [100] introduce a four-dimensional flight trajectory prediction model based on a Long Short-Term Memory (LSTM) network to maintain the long-term features and manage to predict accurate trajectories. Several factors contribute to stable and safe air traffic, especially during the climbing and descending phases. In this sense, technologies and equipment must present precise information in each flight phase to ensure fluidity and safety. Conversely, strong external interference or blind zones present potential risks to these operations. Throughout the paper, several aspects are described in detail, and the authors adopt a clear and graphical approach to introduce their contributions. Finally, the experiments conducted showed that the proposed system is able to provide timely decision support.

Ref. [101] proposes a combination of convolutional layers into Long Short-Time Memory (LSTM) cells to predict the aircraft trajectory based on the weather condition and flight plan. Convective weather avoidance is vital in safe operations, and it is also a primary objective of the next-generation air traffic management system. Therefore, the authors use history flight track data, the last on-file flight plan, and the time-dependent convective weather map over the period from 1 November 2018 to 5 February 2019. The flights investigated had JFK-LAX as the city pair. The experiments conducted showed that the proposed approach can reduce the deviation compared to the last on-file flight plan in 47.0% of the predicted flight tracks. Similarly, the authors in [102] propose a strategy to predict Air Traffic Flow and Capacity Management (ATFCM) weather regulations using a time-distributed Recurrent Neural Network.

In [103], the authors propose a trajectory prediction model based on a dual-self-attentive (DSA)-temporal convolutional network (TCN)-bidirectional gated recurrent unit (BiGRU) neural network. The main idea is that TCN provides highly stable training, high parallelism, and a flexible perceptual domain, whereas the self-attentive mechanism can focus on features that contribute the most to the output. Then, the BiGRU network discovers connections between features and outputs of the trajectory sequence, optimized by a Bayesian algorithm. Experiments demonstrated that the DSA-TCN-BiGRU model based on Bayesian hyperparameter optimization outperforms other models present in the literature. Similarly, Shi et al. [104] propose a flight trajectory prediction model based on a Long Short-Term Memory (LSTM) network. This approach can accurately predict flight trajectories in both 3D and 4D spaces. The authors also point out that multi-modal data (e.g., audio and video) can be included in the process in future works.

The authors propose a 4D trajectory prediction hybrid architecture based on a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) in [105]. Considering a 4D trajectory as a multi-dimensional time series with plentiful spatial-temporal features with a high degree of complexity and uncertainty, providing accurate solutions is complex. In the training process, the authors use real Automatic Dependent Surveillance-Broadcast (ADS-B) historical trajectory data and compare the proposed method with a single LSTM model and Feed-Forward (FF) model on the same data set. Experiments showed that the trajectory prediction accuracy of the proposed strategy is superior to a single model.

In [106], the authors use an improved GRU network to study the time series of traffic flows. The LSTM short-term traffic flow prediction based on the flow series is investigated as a more complex version of the GRU model in this case. In this sense, an improved GRU with bidirectional positive and negative feedback (called the Bi-GRU) is used to complete the short-term traffic flow prediction leveraged by the Rectified Adaptive (RAdam) model in the optimization process. Finally, the experiment conducted demonstrated the effectiveness of the proposed method regarding short-term traffic flow prediction. This contribution can be further extended and applied to air transportation in different flight phases and regions.

The authors in [107] propose a model based on the Social Long Short-Term Memory (S-LSTM) network to predict multi-aircraft trajectory. Facing trajectory prediction as a paramount feature in future operations, several efforts have been made to enhance such estimations. Therefore, the authors focus on building a model for each aircraft and use a pooling layer to integrate the hidden states of the associated aircraft. The experiments considered aircraft trajectories in the Northern California terminal area as the experimental data and showed that the proposed S-LSTM model presents fewer prediction errors compared with the mainstream trajectory prediction models. Moreover, the authors also emphasize the importance of considering aircraft interaction as a factor in predicting trajectories accurately.

In [108], the authors introduce the Airport Traffic Flow Prediction Network (ATFPNet), a DL-based framework to capture spatial-temporal dependencies of the historical airport traffic flow in multiple-step situational arrival flow prediction. To accomplish this, the authors rely on a special semantic graph built on the flight schedule to represent the airport network. Moreover, the graph convolution operator and the GRU are combined to extract transition patterns of airport traffic flow. The experiments used a real-world airport traffic flow dataset and showed that the ATFPNet outperforms other baselines on different prediction horizons, achieving up to a 17% MAE improvement.

Zhao et al. [109] introduce a Deep Long Short-Term Memory (D-LSTM) model for aircraft trajectory prediction tailored to complex flight environments. In Trajectory-Based Operations (TBO), several predictive capabilities are necessary for safe and efficient operations. Conversely, trajectory prediction is a major challenge and airspace complexity can compromise estimation accuracy. In fact, the current state-of-the-art forecasting methods are difficult to be applied in actual operation and management. Therefore, the authors use multi-dimensional features of aircraft trajectory, testing the proposed strategy with real flight data (ADS-B). The experiments showed that this strategy presents prediction accuracy more than existing methods in different flight phases. In addition to this contribution, the authors in [110] use Recurrent Neural Networks (RNN) to predict air traffic density in ATC sectors, while the authors in [111] propose a strategy to predict air traffic congested areas using LSTM networks.

Ref. [112] studies the problem of estimating aircraft onboard parameters using ground surveillance available parameters. The authors adopt an LSTM model and Flight Data Records to estimate target parameters upon three aspects: fuel flow rate, flap configuration, and landing gear position. In fact, this effort fosters ATM awareness regarding aircraft behaviors, enabling the evaluation of system performance in terms of safety and efficiency. Future works are also pointed out by the authors, e.g., enhanced flap and landing gear setting prediction with airspeed information. The insights of this paper highlights that predictive capabilities related to aircraft performance can support informed decisions by ATC.

3.4. Applications of Generative Adversarial Networks (GANs) in ATM

Wu et al. [113] propose a long-term 4D trajectory prediction model based on Generative Adversarial Network (GAN). The authors use three deep generative models based on one-dimensional convolution neural network (Conv1D-GAN), a two-dimensional convolution neural network (Conv2D-GAN), and long short-term memory neural network (LSTM-GAN). Although 4D trajectory prediction is a capability required for future ATM systems, it represents a complex problem due to several factors. Using this model combination, this paper trains and tests a predictive solution using historical 4D trajectory data from Beijing to Chengdu, China. The experiments conducted showed that the proposed strategy presents promising results and that the Conv1D-GAN is the most suitable generative adversarial network for long-term aircraft trajectory prediction.

In [114], a Conditional Generative Adversarial Network (CGAN) approach is proposed for weather-related aircraft trajectory prediction problems. Furthermore, the generator network focuses on weather feature extraction and includes two convolutional layers. Then, the features are provided to a single-layer long short-term network to output the generated trajectory. The discriminator network tries to discriminate the inputs from the ground truth dataset and the generated trajectory. The experiments were conducted based on the data obtained from Sherlock Data Warehouse (SDW), and the results suggest that the proposed strategy outperforms other proposals present in the literature.

Aksoy et al. [115] present a hybrid methodology to generalize the flight trajectories and decide whether they are abnormal or not. The first approach relies on considering the time-based features of the trajectories. This is composed of LSTM autoencoders to rapidly predict the class of the flight, inherently considering the time-based features of a flight trajectory. The second approach on a more pattern strategy through a Generative Adversarial Network (GAN), which generates realistic samples. Flight trajectories are different even when following patterns that are flown previously and optimized for different conditions. These patterns can be influenced by several factors (e.g., airspace utilization, controllers' cognitive complexity, weather, and NOTAMs). The obtained results showed that this approach can classify anomalies in trajectories.

The authors in [116] consider multiple operational aircraft taxi-speed factors (e.g., surrounding traffic on the ground and target take-off time) and adopt the Generative Adversarial Imitation Learning (GAIL) algorithm for modeling. The main goal is to enable the model to learn and reproduce the ground movement patterns in a real-world dataset under different circumstances. The contributions of this research are very valuable to the ATM community since it is difficult to predict the spatio-temporal component of aircraft-taxi trajectory. Furthermore, this initiative supports the ATM decision-making process. The proposed strategy outperforms all the baseline models by a significant margin. For example, it achieves up to 97.1% for arrivals and 88.3% for departures concerning Spatial Completion (SC).

In [117], the authors develop a method for using Generative Adversarial Networks (GANs) to generate condition monitoring data of aircraft engines. To accomplish this, an algorithm for generating monitoring data to extend a sample of aircraft engine condition monitoring data is proposed. Monitoring costs and difficulties represent an obstacle in today's operations since little condition monitoring data exists. This hardens data-driven approaches to aircraft engine maintenance. The experiments conducted showed that, based on the condition monitoring parameters recorded for a CF6-80C2A5 engine, the proposed strategy was able to generate data within a reasonable range. A complementary approach regarding data generation is presented in [118], in which the authors evaluated the performance of synthetically generated snow radar images based on modified cycle-consistent adversarial networks. In fact, this approach can be used in different ATM applications.

Hu et al. [119] propose a short-term aircraft Trajectory Prediction (TP) framework called TPGAN. The primary goal of this effort is to predict multi-horizon trajectories in a single step using the Conditional Generative Adversarial Network (CGAN). Regarding the trajectory prediction capabilities, existing works usually perform the multi-horizon TP task iteratively, suffering from error accumulation problems. The authors employ the generator to output the predictions, whereas the discriminator learns the discriminative features between ground truth and predictions and applies the generative adversarial training strategy to optimize the proposed framework. The experiments used a dataset collected from real-world ATC systems and demonstrated that the proposed strategy achieves significant performance improvements compared to an LSTM-based baseline.

Guo et al. [120] present a novel anomaly detection model based on Improved Generative Adversarial Networks and long short-term memory networks (IGAN-LSTM) to detect anomalies in ADS-B Systems. To accomplish this, IGAN enhances the generator architecture by upgrading the commonly used encoder architecture to encoder-decoder-encoder architecture. Then, encoding losses are used to determine whether a data sample is anomalous or not, and LSTM networks are used to model ADS-B data with temporal dependence. The experiments performed showed that the proposed approach outperforms other baseline methods from the literature.

Huang et al. [121] propose a novel method called Improved Wasserstein Skip-Connection GAN (IWGAN). The main goal is to integrate the Wasserstein-GAN (WGAN) and SkipGANomaly models to distinguish normal and abnormal images, which is called the Improved Wasserstein Skip-Connection GAN (IWGAN). The challenge of not having relatively sufficient datasets in the airport field hardens the training of DL models in different ATM applications. Since GANs can learn the latent vector space of all images, the authors adopt a GAN variant with autoencoders to create a hybrid model for detecting anomalies and hazards in the airport environment. The experiments showed that the proposed model is efficient in solving the problem faced in this research. In addition to this initiative, Zhang et al. [122] propose an image-based aircraft type recognition approach based on Conditional Generative Adversarial Networks (GANs).

The authors in [123] focus on evaluating aircraft trajectory generation methods and propose a common baseline to compare literature and new methods to generate air traffic trajectories. In fact, state-of-the-art methods to generate individual trajectories can lack realism concerning common situations implemented by ATCos. Conversely, data-driven approaches excel at imitating operational practice but may not be simple to implement due to aircraft performance limitations. Therefore, the authors present an extensive set of metrics to evaluate the quality of generated trajectories and point out as future directions the use of this framework to objectively assess trajectory generation performance (e.g., using GANs). An effort correlated with this approach is presented in [124], in which the authors explore the use of generative data models to learn real approach flight path probability distributions through the use of GANs.

Lang et al. [125] propose a fault prediction of aircraft engine based on data augmentation technology. Predicting the Remaining Useful Life (RUL) of the equipment by constructing models using historical data is challenging since the data is difficult to obtain. One possible way to solve this problem is to develop models based on data augmentation. To accomplish this, the authors use a GAN to study the distribution of the original dataset and to generate a new training set. The original and the new datasets are combined to train a Convolutional Neural Network and Long Short-Term Memory Network (CNN-LSTM) prediction model. The case studies demonstrate that the proposed GAN-CNN-LSTM model can effectively predict the RUL compared with the existing methods.

3.5. Applications of Autoencoders in ATM

In [126], the authors propose Deep Learning (DL) techniques to model Air Traffic Controllers' (ATCos) reactions in resolving conflicts. The authors focus on the Air Traffic Controllers' (ATCos) reaction prediction problem for Conflict Detection and Resolution (CD&R). DL methods that can model ATCOs' timely reactions are presented and evaluated in real-world data sets. Throughout the paper, the authors describe all contributions in a graphical and in-depth manner. The experiments conducted showed that the proposed approach presents very high accuracy in such a detection problem. Finally, multiple future directions are pointed out in this research. In fact, the authors in [127] present a correlated contribution but propose a method to analyze flight trajectories, detect unusual flight behaviors, and infer ATC actions. The authors in [128] focus on evaluating pilots' fatigue status using the Deep Contractive Autoencoder Network. The authors propose a fatigue evaluation index to compute the power spectrum of relative rhythms from electroencephalogram (EEG) signals.

A novel multivariate anomaly detection model called Contextual Auto-Encoder (CAE) is proposed in [129]. The main goal is to use the baseline of a regular LSTM-based autoencoder combined with several decoders to gather data on a specific flight phase (e.g., climbing, cruising, or descending) in training. Although ADS-B supports the tracking of the high number of aircraft in the air, it also introduces cybersecurity concerns that must be mitigated. To tackle this problem, a dataset was created using real-life anomalies and realistically crafted trajectory modifications, with which the CAE, alongside three anomaly detection models from the literature, were evaluated. Experimental results showed that CAE achieves better results in both accuracy and speed of detection. In addition to this contribution, the authors in [130] focus on focus on detecting anomalies in real-time for flight testing. To this end, the authors propose an approach based on fine-tuned autoencoder to extract generic underlying features, followed by a stacked LSTM.

Ref. [131] proposes a novel engine fault detection method based on original Aircraft Communications Addressing and Reporting System (ACARS) data is proposed. The authors divide all variables into separated groups according to their correlations and use an improved convolutional denoising autoencoder to extract the features of each group. All extracted features are then fused to form feature vectors to enable fault sample identification. The evaluation process showed that this method is efficient in fault detection and robustness while maintaining low computational and time costs. Furthermore, Fernandez et al. [132] performed descriptive and predictive analyses to detect anomalies, i.e., Flight Data Monitoring (FDM) unknown hazards, during the approach phase.

Corrado et al. [133] introduce a novel framework based on DL methods using autoencoders to identify anomalies in terminal airspace operations. The primary goal is to leverage historical aircraft trajectory data combined with weather and traffic metrics to build an anomaly detection capability. To accomplish this, data from multiple sources (e.g., aircraft trajectory, weather, traffic/congestion) is used to train the models and demonstrated on six months of arriving flight data collected for San Francisco International Airport that the proposed strategy has the potential to aid air traffic controllers.

In [134], a new deep stacked autoencoders networks method is proposed to predict flight delay based on the relationship of time and space. In fact, the stacked autoencoder approach derives the characteristics of flight delay information from massive data and optimizes all the networks' parameters with the backpropagation method. Throughout the article, the authors describe the contributions and the results achieved in detail (e.g., for different periods in the future). Results demonstrate that the prediction accuracy with deep stacked autoencoders is above 90%. Finally, several future works can be identified from this initiative based on the use of autoencoders to improve prediction performance.

Wu et al. [135] design a feature association algorithm to solve the ATM systems security situation awareness via a Deep-Related Sparse Autoencoder (DRSAE) model. In safe and efficient operations, it is pivotal that security situational awareness information is provided to the air traffic management (ATM) system with an integrated air-ground structure. However, there are problems that can impact the process of situation awareness feature extraction. In this sense, the authors design and compare the DRSAE model with other feature extraction models (e.g., Principal Component Analysis—PCA, Autoencoder—AE, and Sparse Autoencoder—SAE). The results obtained showed that the DRSAE model is robust in feature extraction of the ATM system, presenting strong expression ability.

The authors in [136] propose a Convolutional Variational Auto-Encoder (CVAE) for anomaly detection in high-dimensional time-series flight data. Currently, the current approach for identifying vulnerabilities in NAS operations leverages domain expertise, which works well when the system has a well-defined operating condition. Conversely, highly complex scenarios can be faced in the airspace, and state-of-the-art machine learning models usually rely on supervised learning. In many cases, labeling data requires specialized expertise that is time-consuming and, therefore, largely impractical. Motivated by these challenges, the authors validate the proposed approach on Yahoo's benchmark data and on a case study of identifying anomalies in commercial flights' take-offs. The results showed that CVAE outperforms both classic and deep learning-based approaches in detecting anomalies.

Zeng et al. [137] and Olive et al. [138] focus on the use of autoencoders to cluster trajectories. The former work proposes a trajectory clustering method based on Deep Autoencoder (DAE) and Gaussian mixture model (GMM) to identify the prevailing traffic flow patterns in the terminal airspace, whereas the latter explores the application of deep trajectory clustering based on autoencoders to the problem of flow identification. Both efforts face a challenging problem for ATM systems since trajectories might change substantially if unexpected events happen (e.g., weather-related events). In addition to this effort, the authors in [139] propose a framework for predicting air traffic situations as a sequence of images using an autoencoder with convolutional Long Short-Term Memory (ConvLSTM).

Table 1. Comparison of works that use Deep Learning (DL) in ATM solutions.

Model	Paper	Year	ATM Area	ATC System			Flight Solution		DL Application			Airspace KPI			ATCo	
				ATS	ASM	ATFM	S	M	Arc	Val	Dp	Sft	Ef	Sus	HF	Aug
CNN	Malekzadeh et al. [84]	2017	EAI	✓			✓		✓	✓	✓	✓				
	Liu et al. [85]	2018	OAPV			✓	✓		✓	✓			✓			
	Yang et al. [92]	2019	AATS			✓		✓	✓	✓			✓			
	Liu et al. [97]	2019	AATS			✓		✓	✓	✓			✓			
	Chen et al. [98]	2019	EAI			✓	✓		✓	✓		✓				
	Van et al. [88]	2019	AATS	✓	✓	✓		✓	✓	✓			✓		✓	✓
	Qu et al. [87]	2020	HPAO	✓				✓	✓	✓			✓			
	Van et al. [89]	2020	AATS	✓	✓	✓		✓	✓	✓		✓			✓	✓
	Lin et al. [95]	2020	AATS	✓	✓	✓		✓	✓	✓		✓				✓
	Pang et al. [82]	2021	OAPV			✓	✓		✓	✓			✓			
	Zeng et al. [91]	2021	OAPV			✓	✓		✓	✓			✓			
	Xie et al. [86]	2021	AATS			✓		✓	✓	✓		✓				✓
	Di et al. [83]	2022	EAI			✓	✓		✓	✓		✓				
	Mas et al. [90]	2022	AATS			✓		✓	✓	✓			✓			
	Jardines et al. [93]	2022	AATS			✓		✓	✓	✓		✓				
	Rahman et al. [96]	2022	AATS			✓		✓	✓	✓		✓				✓

Table 1. *Cont.*

Model	Paper	Year	ATM Area	ATC System			Flight Solution		DL Application			Airspace KPI			ATCo	
				ATS	ASM	ATFM	S	M	Arc	Val	Dp	Sft	Ef	Sus	HF	Aug
DNN	Horiguchi et al. [68]	2017	HPAO	✓			✓		✓	✓			✓	✓		
	Kistan et al. [74]	2018	AATS	✓	✓	✓		✓	✓	✓	✓	✓			✓	✓
	Boggavarapu et al. [77]	2019	HPAO	✓			✓		✓	✓			✓			
	Chakrabarty et al. [73]	2019	HPAO	✓			✓			✓			✓			
	Mollinga et al. [62]	2020	AATS			✓		✓	✓	✓		✓				✓
	Wang et al. [66]	2020	AATS	✓				✓	✓	✓	✓		✓			
	Mas et al. [72]	2020	AATS	✓	✓	✓		✓	✓	✓		✓				✓
	Yazdi et al. [71]	2020	HPAO	✓			✓		✓	✓			✓			
	Jimenez et al. [79]	2020	OAPV		✓		✓		✓	✓			✓			
	Cheevachaipimol et al. [67]	2021	HPAO	✓			✓		✓	✓			✓			
	Bala et al. [69]	2021	HPAO	✓			✓		✓	✓			✓			
	Dong et al. [78]	2021	EAI	✓	✓	✓	✓	✓	✓				✓			
	Gholami et al. [70]	2022	HPAO	✓			✓		✓	✓			✓			
	Tan et al. [75]	2022	AATS			✓		✓	✓	✓		✓				
	Ivanoska et al. [76]	2022	HPAO	✓			✓		✓	✓			✓			
	Sangeetha et al. [80]	2022	AATS	✓	✓	✓	✓		✓	✓			✓			
	Çakıcı et al. [81]	2022	OAPV		✓		✓		✓	✓		✓				
	Perez et al. [63]	2022	AATS	✓	✓	✓		✓				✓				
RNN	Shi et al. [104]	2018	OAPV			✓	✓		✓	✓			✓			
	Pang et al. [101]	2019	OAPV			✓	✓		✓	✓			✓			
	Zhao et al. [109]	2019	OAPV			✓	✓		✓	✓			✓			
	Shi et al. [100]	2020	OAPV		✓			✓	✓	✓		✓				✓
	Ma et al. [105]	2020	OAPV			✓	✓		✓	✓			✓			
	Jarry et al. [112]	2020	EAI		✓		✓		✓	✓		✓				
	Shi et al. [111]	2021	AATS			✓		✓	✓	✓		✓				
	Shu et al. [106]	2021	AATS						✓	✓	✓		✓			
	Xu et al. [107]	2021	OAPV			✓		✓	✓	✓			✓			
	Yan et al. [108]	2021	AATS	✓			✓		✓	✓			✓			
	Mas et al. [102]	2021	AATS			✓		✓	✓	✓			✓			
	Lim et al. [99]	2022	AATS			✓		✓	✓	✓	✓	✓				
	Huang et al. [103]	2022	OAPV			✓	✓		✓	✓			✓			
	Asirvadam et al. [110]	2022	AATS			✓		✓	✓	✓		✓				
GAN	Guo et al. [120]	2021	OAPV			✓		✓	✓	✓			✓			
	Olive et al. [123]	2021	OAPV			✓	✓		✓				✓			
	Lang et al. [125]	2021	EAI				✓		✓	✓		✓				
	Jarry et al. [124]	2021	OAPV		✓			✓	✓	✓		✓				
	Wu et al. [113]	2022	OAPV			✓	✓		✓	✓			✓			
	Hu et al. [119]	2022	OAPV			✓	✓		✓	✓			✓			
	Huang et al. [121]	2023	AATS	✓				✓	✓	✓		✓				

Table 1. *Cont.*

Model	Paper	Year	ATM Area	ATC System			Flight Solution		DL Application			Airspace KPI			ATCo	
				ATS	ASM	ATFM	S	M	Arc	Val	Dp	Sft	Ef	Sus	HF	Aug
AE	Olive et al. [127]	2018	AATS	✓	✓	✓		✓	✓	✓		✓			✓	✓
	Chen et al. [134]	2018	HPAO	✓			✓		✓	✓			✓			
	Xuyun et al. [131]	2019	EAI				✓		✓	✓	✓	✓				
	Fernandez et al. [132]	2019	EAI		✓		✓		✓	✓	✓	✓				
	Que et al. [130]	2019	EAI			✓	✓		✓	✓		✓				
	Wu et al. [128]	2019	AATS		✓		✓		✓	✓	✓	✓			✓	
	Memarzadeh et al. [136]	2020	Aircraft			✓	✓		✓	✓		✓				
	Olive et al. [138]	2020	OAPV			✓		✓	✓	✓			✓			
	Corrado et al. [133]	2021	AATS		✓			✓	✓	✓		✓				✓
	Zeng et al. [137]	2021	OAPV		✓			✓	✓	✓			✓			
	Kim et al. [139]	2021	AATS			✓		✓	✓	✓		✓				
	Bastas et al. [126]	2022	AATS	✓	✓	✓		✓	✓	✓		✓			✓	✓
	Chevrot et al. [129]	2022	OAPV			✓		✓	✓	✓		✓				
	Wu et al. [135]	2022	AATS	✓					✓	✓		✓				

3.6. Further Insights: Opportunities

This section presents an analysis of the works reviewed. First, a discussion on the publications and their respective keywords is conducted. Then, a granular analysis of the future direction of different ATM solutions is presented.

3.7. Paper Count and Keywords

In the past few years, several papers have been published in the context of DL and ATM. This research focuses on presenting state-of-the-art solutions published in the past few years. Figures 8 and 9 illustrate the paper count by year and by ATM area. Most of the papers analyzed have been published in the past few years in high-impact venues. In fact, the trend in the data highlights that we can expect new solutions in the next few years. Moreover, AATS and OAPV solutions are the topics of most of the papers published. However, EAI and HPAO solutions are also present.

Although there are clear categories for these solutions, they focus on different problems. Thus, Figure 10 illustrates the word cloud produced by the combination of keywords of all papers analyzed. Terms such as "Deep Learning", "prediction", and "trajectory" are clearly present in several papers. Some other words such as "speech" and "DCNN" are only present in a few articles.

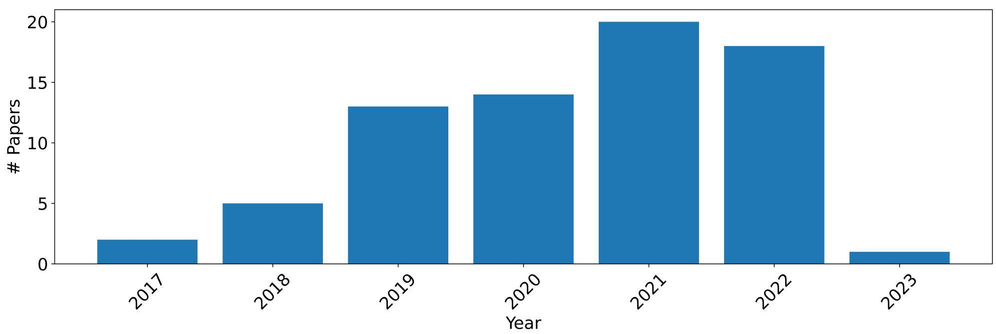

Figure 8. Paper count by year.

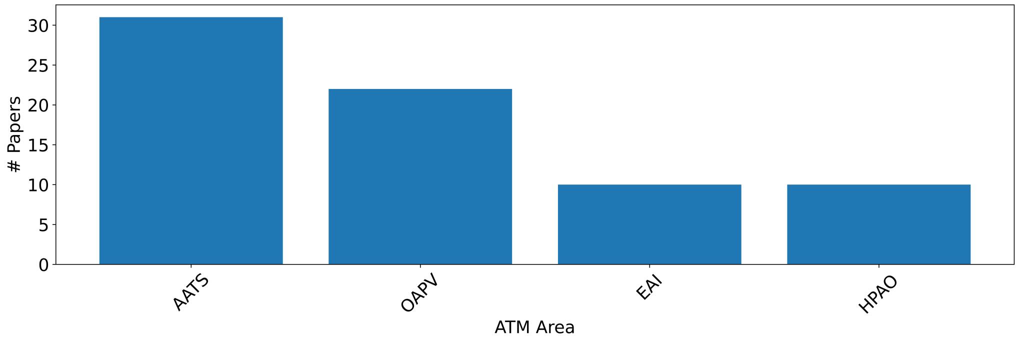

Figure 9. Paper count by ATM solution areas.

Figure 10. Word cloud of keywords.

3.8. ATM Solutions

The papers reviewed have been categorized according to their main contribution. Here, we group works by ATM areas and present their future direction, either highlighted by the authors or gathered from the text. These insights are listed in Table 2.

Several future directions are identified for OAPV, including the optimization of models, including more features, temporal dependencies, and applications in different domains. These are the direct unfolding of the works analyzed, and these directions highlight that robust and accurate trajectory-based solutions can benefit from these initiatives.

Regarding AATS, several future directions are identified. Conversely, some aspects are pointed out by different authors, e.g., the consideration of the airspace state (e.g., sector density) to optimize model performance and the use of realistic scenarios to simplify future deployments. The efforts made toward fatigue and workload detection and estimation are applicable to several ATM systems. Data diversity is also highlighted as a primary goal for future works. Finally, disruptive events are also suggested for future endeavors.

Moreover, important insights are presented in the reviewed HPAO papers, and the use of more data and further optimization of models are described in most of them as future directions. Some mention their applications in different domains (e.g., aircraft maintenance), and there is a clear demand for contributions in rare and disruptive conditions (e.g., weather).

Finally, EAI works emphasize the need for more data, cross-domain applications, and further development of the proposed models. The consideration of complexity factors (e.g., sector density) is also a concern.

Table 2. Future directions for different ATM areas.

ATM Area	Paper	Year	Model	Future Directions
AATS	Yang et al. [92]	2019	CNN	Flow prediction in severe and rare weather conditions
	Liu et al. [97]	2019	CNN	Application of proposal in a real scenario
	Van et al. [88]	2019	CNN	Automatic generation of training data consisting of solution space diagram (SSD) images and conflict resolutions
	Xie et al. [86]	2021	CNN	Application of visual-based techniques in other ATM solutions
	Jardines et al. [93]	2022	CNN	Investigate temporal relationships in weather data
	Rahman et al. [96]	2022	CNN	Inclusion of airspace information to improve conflict resolution
	Wang et al. [66]	2020	DNN	Application of different DL methods to improve performance
	Tan et al. [75]	2022	DNN	Use of Deep Active Learning in other ATM solutions
	Perez et al. [63]	2022	DNN	Application of proposal in different sector types
	Shi et al. [111]	2021	RNN	Quantification of the uncertainty in the predictions
	Shu et al. [106]	2021	RNN	Consideration of special events (e.g., weather and large activities)
	Yan et al. [108]	2021	RNN	Use of other factors to improve prediction accuracy (e.g., weather information, ATC information, the influence of international flights, and dynamic traffic movements on the network.
	Mas et al. [102]	2021	RNN	Implementation of visual framework to apply theoretical regulations and create feedback to re-train the existing model.
	Lim et al. [99]	2022	RNN	Analysis of severe weather impacts on airports
	Asirvadam et al. [110]	2022	RNN	Airspace optimization considering workload, weather and unplanned traffic
	Zhang et al. [122]	2018	GAN	Unsupervised classification method to remove the need for data labeled with type information
	Rahnemoonfar et al. [118]	2020	GAN	Simulation of other ATM systems (e.g., audio)
	Huang et al. [121]	2023	GAN	Use of attention model mechanisms
	Corrado et al. [133]	2021	AE	Hyperparameter Optimization
	Kim et al. [139]	2021	AE	Inclusion of altitude in the proposed method
	Wu et al. [135]	2022	AE	Use of more advanced classifiers
	Van et al. [89]	2020	CNN	Model Optimization
	Lin et al. [95]	2020	CNN	Increase data diversity
	Mas et al. [90]	2022	CNN	Inclusion of additional input features to improve performance
	Mollinga et al. [62]	2020	DNN	Inclusion of stochastic variables like weather, addition of waypoints, and change the simulation approach
	Mas et al. [72]	2020	DNN	Use of an hybrid DL model
	Sangeetha et al. [80]	2022	DNN	Consideration of rare events (e.g., weather-based events)
	Pham et al. [116]	2021	GAN	Implementation of a multi-agent environment
	Olive et al. [127]	2018	AE	Consideration of more evolved structures of networks
	Wu et al. [128]	2019	AE	Application of similar strategies considering ATC professionals
	Bastas et al. [126]	2022	AE	Improvements of predictions regarding low-level ATCOs' conflict resolution actions
OAPV	Liu et al. [85]	2018	CNN	Extension of proposed algorithm to more features (e.g., ATM initiatives)
	Pang et al. [82]	2021	CNN	Consideration of rare events (e.g., weather-based events)
	Zeng et al. [91]	2021	CNN	Approaches to handle loss of information from data normalization.
	Jimenez et al. [79]	2020	DNN	Use of a more extensive dataset
	Çakıcı et al. [81]	2022	DNN	Data sharing approaches considering aircraft and ATC
	Shi et al. [104]	2018	RNN	Use of multi-modal data, including images, audios and videos
	Pang et al. [101]	2019	RNN	Consideration of rare events (e.g., weather-based events)

Table 2. *Cont.*

ATM Area	Paper	Year	Model	Future Directions
OAPV	Zhao et al. [109]	2019	RNN	Application of D-LSTM to trajectory information prediction in high density airspace
	Shi et al. [100]	2020	RNN	Inclusion of of multi-modal data
	Ma et al. [105]	2020	RNN	Models for long-term 4D trajectory prediction
OAPV	Xu et al. [107]	2021	RNN	Integration of meteorological conditions to achieve more accurate and stable trajectory prediction
	Huang et al. [103]	2022	RNN	Models that use the combination of weather, control, and other uncertainties.
	Pang et al. [114]	2020	GAN	Development of models to improve the prediction performance
	Aksoy et al. [115]	2021	GAN	Consideration of rare events (e.g., weather-based events)
	Guo et al. [120]	2021	GAN	Inclusion of new features to to further improve the performance of the proposed model
	Olive et al. [123]	2021	GAN	Application of the proposed method to compare data-driven trajectory generation models
	Jarry et al. [124]	2021	GAN	Analysis of tailored network architectures and learning
	Wu et al. [113]	2022	GAN	Application of the propose method for short-term trajectory prediction and air traffic state estimation.
	Hu et al. [119]	2022	GAN	To adopt this approach in other ATM solutions
	Olive et al. [138]	2020	AE	Impact assess of clustering losses on the performance of reconstruction-based anomaly detection methods.
	Zeng et al. [137]	2021	AE	Use of the proposed model to assist trajectory prediction solutions
	Chevrot et al. [129]	2022	AE	To adopt this approach in other domains
EAI	Malekzadeh et al. [84]	2017	CNN	Use of other DNN architecture for this application
	Chen et al. [98]	2019	CNN	Consideration of rare events (e.g., weather-based events)
	Di et al. [83]	2022	CNN	Consideration of rare events (e.g., weather-based events)
	Dong et al. [78]	2021	DNN	Data Collection, Labeling, and transfer Learning
	Jarry et al. [112]	2020	RNN	Enhancing flap and landing gear setting prediction with airspeed information
	Fu et al. [117]	2019	GAN	To adopt this approach in other ATM solutions
	Lang et al. [125]	2021	GAN	To adopt this approach in other ATM solutions
	Xuyun et al. [131]	2019	AE	Use of more com prehensive fault cases to locate the fault source
	Fernandez et al. [132]	2019	AE	Consideration of other airspace aspects (e.g., sector desity)
	Que et al. [130]	2019	AE	Automate rapid development of efficient anomaly detection on FPGAs for various applications
HPAO	Qu et al. [87]	2020	CNN	Use of new models to improve results
	Horiguchi et al. [68]	2017	DNN	Inclusion of reservation data in the analysis
	Boggavarapu et al. [77]	2019	DNN	Use of more airport data
	Chakrabarty et al. [73]	2019	DNN	Use of advanced preprocessing and sampling techniques
	Yazdi et al. [71]	2020	DNN	Consideration of rare events (e.g., weather-based events)
	Cheevachaipimol et al. [67]	2021	DNN	Use of other methods to handle imbalanced data
	Bala et al. [69]	2021	DNN	Use of DNN in aircraft maintenance
	Gholami et al. [70]	2022	DNN	Consideration of rare events (e.g., weather-based events)
	Ivanoska et al. [76]	2022	DNN	Consideration of other aspects in flights (e.g., aircraft usage)
	Chen et al. [134]	2018	AE	Consideration of rare events (e.g., weather-based events)

4. Open Challenges

This Section discusses several possible directions for future works based on the insights of this review. These open challenges are presented from two perspectives: Deep Learning (DL) applications and ATM solutions.

4.1. Deep Learning (DL) Applications

- **Interpretability:** Understanding the decision made by the DL models is paramount for safe and efficient operations. Hence, the proposal of strategies to explain the

decision made in the full ATM system spectrum is a challenging but necessary step for future operations;
- **Sustainability:** From all works analyzed in this research, none of them are focused on sustainability services for future ATM systems. The use of DL techniques to foster the development of a new strategy is critical for future operations;
- **Cybersecurity:** Data are shared throughout the airspace systems in today's operations, and future applications will require even more data. In this sense, it is critical that new solutions use advanced techniques (e.g., DL) to detect and mitigate cybersecurity threats;
- **Urban Air Mobility (UAM):** Several of the points discussed in this research are also applicable to new transportation paradigms, e.g., UAM. For example, DL can enable the development of trajectory-based solutions tailored to the UAM environment. In fact, lessons learned in the National Airspace System (NAS) can provide insightful directions for UAM applications [140,141];
- **Deployment:** Few of the works reviewed in this research focus on the deployment of such solutions. Besides the complexity that developing a DL application involves, deployment is also challenging and requires coordination with several stakeholders. Indeed, solutions to simplify the deployment of such methods are part of the open challenges.

4.2. ATM Solutions

Figure 11 illustrates the open challenges in ATM solutions and directions to apply advanced methods to enhance the airspace operation. All challenges identified are discussed in detail based on their respective classification.

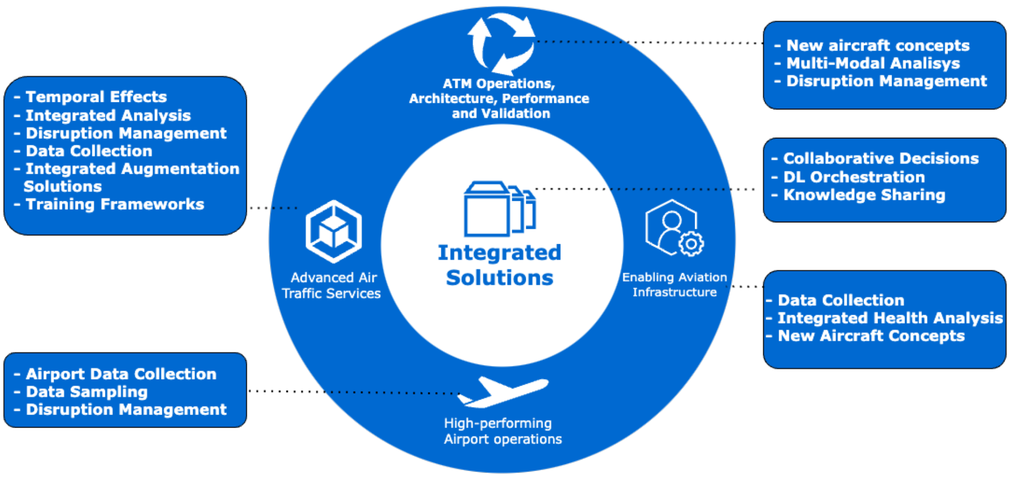

Figure 11. Open challenges: ATM solutions.

4.2.1. Advanced Air Traffic Services (AATS)

- **Temporal effects:** Throughout the daily operations, the airspace state changes several times. However, there is an intrinsic temporal dependence in the evolution of the airspace state. In this sense, initiatives can focus on identifying temporal connections to improve the complexity prediction capabilities;
- **Integrated Analysis:** The complex airspace ecosystem entails various systems operating simultaneously. In this sense, an open challenge refers to using global resources and information to understand how complexity is impacted and, ultimately, develop more accurate complexity-based solutions;
- **Disruption Management:** The consideration of rare but disruptive events is vital in the assessment and development of new complexity-based solutions. Therefore, new capabilities for predicting rare events are part of the future ATM solutions portfolio.
- **Data Collection:** Building up datasets for training models is a complex challenge due to several factors. The development of new techniques to easily collect data without compromising the operation will produce valuable resources for new applications;

- **Integrated Augmentation:** Although some initiatives focus on supporting professionals in the ATM system, they are commonly separated and not part of the same portfolio. The development of a scalable and integrated approach to be used as a baseline across the ATM system is an open challenge;
- **Training Frameworks:** The inclusion of new technologies into the National Airspace System (NAS) requires several phases of testing and certification. In this sense, proposing new training approaches to simplify the use of these new technologies is necessary.

4.2.2. High-Performing Airport Operations (HPAO)

- **Airport Data Collection:** Although following the same rules, airports operate differently due to several factors (e.g., size, number of gates, and number of flights). Collecting internal data to improve the airport performance is a pillar for future solutions, and the development of a new data collection strategy is essential;
- **Data Sampling:** The current difficulty faced in collecting the data demands methods to generate realistic samples. In this case, there is a need for new sampling methods that cover the characteristics of the airport operation;
- **Disruption Management:** The impacts of disruption in delays is difficult to predict due to the minimal number of occurrences in history. Future solutions are required to handle this imbalanced environment and accurately predict such events.

4.2.3. ATM Operations, Architecture, Performance, and Validation (OAPV)

- **New Aircraft Concepts:** There are some companies working on the production of supersonic aircraft that will be integrated into the NAS in the near future. Then, new trajectory prediction services are required to attend to the new flight configurations and capabilities (both in terms of performance and regulations);
- **Multi-Modal Analysis:** Trajectory-based solutions are integrated into a complex ecosystem composed of several subsystems. In this sense, using data from different sources and configurations (e.g., audio and video) represents another open challenge;
- **Disruption Management:** Rare events are difficult to predict accurately. The development of new methods capable of estimating when disruptive events happen and how they affect the aircraft trajectory needs investigation.

4.2.4. Enabling Aviation Infrastructure (EAI)

- **Data Collection:** For several reasons, collecting data from aircraft (e.g., engines) is a complex task. Therefore, the development of new software and hardware technologies for data collection will improve the results obtained by the existing and future ATM solutions;
- **Integrated Health Analysis:** The complex ecosystem composed of several subsystems that surround the aircraft can provide information for in-flight decision-making. In this sense, integrating the in-flight solutions with the ecosystem can yield valuable resources and is in the scope of future works;
- **New Aircraft Concepts:** As new aircraft operate in the NAS (e.g., supersonic aircraft), flight parameters are expected to differ. Then, adjusting the existing solutions for such an environment is pivotal for efficient operations.

4.2.5. Integrated Solutions (IS)

- **Collaborative Decision:** Considering that local actions can change the global airspace mesh, solutions to enable safe, rapid, and efficient collaborative decision-making represent a significant advancement in today's technologies. However, reaching this flawless collaboration is not simple, as it represents a research field in ATM systems.
- **DL Orchestration:** The use of DL solutions in several areas of ATC can improve efficiency. However, enabling these separated entities to communicate and share resources (e.g., parameters and outputs) can provide a smooth integration experience. However, the orchestration of such systems is complex and represents an open challenge.

- **Knowledge sharing:** Data belonging to different organizations is not always shared due to several reasons (e.g., privacy). Then, new privacy-preserving techniques (e.g., privacy-preserving transfer learning) can overcome this obstacle and enable DL applications to be more accurate without compromising privacy.

5. Conclusions

Currently, the increasing number of daily flights offers new travel connections and simplifies global transportation. In this context, Air Traffic Management (ATM) enables air carriers to operate safely and efficiently through the multiple services provided. The timely success of advanced analytic solutions has demonstrated their potential to solve complex problems in several domains, including Air Traffic Management (ATM). Although there are several contributions in the literature, it is not simple to define the challenges faced by state-of-the-art strategies and open challenges due to a lack of comprehensive and extensive analysis of such contributions.

Therefore, this research presented a comprehensive review of state-of-the-art Deep Learning (DL) solutions for Air Traffic Management (ATM). Several topics were discussed, focusing on applications, opportunities, and open challenges to foster the evolution of ATM systems. Several areas of ATM applications were considered, and the state-of-the-art solutions were classified, analyzed, and compared from different perspectives. Finally, an extensive discussion on the open challenges was conducted to highlight the current DL-based solutions demanded in current and future ATM contexts. This article provided the reader with a clear picture of the current DL-ATM landscape and the main directions for future works. Finally, there are several aspects to be considered in future directions, e.g., an analysis of solutions based on other Artificial Intelligence (AI) methods (e.g., optimization) and solutions for specific flight missions (e.g., Search and Rescue—SAR).

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