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Copyright Statement

ARTIMATION

TRANSPARENT ARTIFICIAL INTELLIGENCE AND AUTOMATION TO AIR TRAFFIC MANAGEMENT SYSTEMS’

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Abstract

This report presents a state –of-the-art on Artificial Intelligence (AI) in Air Traffic Management (ATM) domain. Here, the main objective is to review and identify AI techniques, methods and algorithms that have been applied in different ATM domain’s related tasks. Also, it discusses transparency and explainability in AI algorithms based on a systematic literature review of the most relevant topics i.e., Take-off Time Prediction, Delay Propagation and Conflict Avoidance in the ATM domain. Besides, the report includes state-of-art techniques and approaches for data visualisation, and lifelong machine learning with human-centered AI. Finally, challenges in ATM with respect to AI are also reported here.

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1 Introduction

Artificial Intelligence' term was first used in 1956 for the first "Dartmouth Summer Research Project on Artificial Intelligence". Since then, the discipline has gone through several 'summers' implying important interests and developments, and 'winters' referring to disinterest from the field, associated with scepticism[1]. EXplainability of Artificial Intelligence (XAI), is strongly linked to the systems it explains, went through the same phases, and is actually in its third generation now [1]. AI in ATM roughly followed the same pattern with some delay. During the last decade, AI in ATM roughly evolved, from AI systems used to optimize the traffic to AI systems used to predict various objects i.e., predicting 4D trajectories.

Under normal conditions, Europe has to deal with very complex and busy airspace. In this regard, it is expected that automation and AI solutions would not obviously replace humans, but on the contrary, they should ensure that air traffic controllers have the necessary support tools to make the best decisions and manage traffic efficiently. In many ways, it's about making AI part of the team.

In recent years, ATM services have successively built air traffic control systems, airport surface monitoring systems, electronic flight data systems, digital clearance systems, collaborative decision-making systems, traffic management systems, etc. These systems have accumulated a large amount of air traffic control data that has potential value. Analyzing the data of air traffic control by using machine learning (ML) algorithms can provide a guarantee for safe production and enable the air traffic control system to provide services more safely and efficiently [2]. There are also some limitations of using machine learning algorithms in the ATM domain such as explainability and transparency which are discussed more elaborately in chapter 3.

Therefore, the establishment of aviation *big data storage and analysis platform* has become an important task of air traffic management. A big data platform is designed using Hadoop Storage Module (HSM) which stores the data output by each system used by the ATM system and the platform provides decision making including flight delay analysis, operational efficiency, and experience routes using Mahout machine learning library [3].

Machine Learning algorithm is deployed to *forecast the workload of the air traffic controllers* using the routinely-recorded flight data [4]. For instance, in [5], an AI system is developed as a digital assistant to support air traffic controllers in resolving potential conflicts. The proposed system consists of two core components: an intelligent interactive conflict solver (ICS) to acquire air traffic controller's preferences, and an AI agent based on reinforcement learning to suggest conflict resolutions capturing those preferences. While such a system shows interesting advances in Human/AI collaboration, it fails to propose transparent and explainable reasoning for the proposed solution. Such a lack of transparency is not suitable for live critical systems.

[1] https://www.bbc.com/news/technology-51064369

2 Background and related work

With the rise in the airline industry[2] and the construction of new airports and runways such as Istanbul New Airport, Beijing Daxing International Airport, Western Sydney Airport etc.[3], air traffic has increased dramatically in the past few years. The reason behind this increment of air traffic is economic and demographic growth: the growing middle-class is stimulating airline activity. Another development factor is the emergence of low-cost airlines offering competitive prices on popular destinations[4]. Consequently, the growing air traffic has put additional pressure on air traffic control system that handles thousands of flights per day. To avoid delays and collisions, ATM must work efficiently. Today, airspace control has the challenge of merging information from independent and heterogeneous systems to minimize air safety risks and facilitate the decision-making process. Some notable information those are vital for the ATM are:

Communication: Communication between air traffic controllers and pilots remains a vital part of air traffic control operations, and communication problems can result in hazardous situations [6]. Air traffic controllers constantly need to intensely listen to every single word said by pilots and other controllers. They need to be aware of what is going on in their space as well as other sectors around them. If a problem arises, they need to act on it at the very moment. It puts a lot of pressure on air traffic controllers.

Weather: Another biggest issue for a controller is the weather [8]. It adversely affects the work and function of air traffic control staffs. The more it is complex; the more workload is laden on them. A bad weather means a bad day for them.

Frequency congestion: Frequency congestion is another common cause of communication breakdown in ATM system[5]. It's important to remember that a single radio frequency is capable of handling only a limited number of radio messages within any specified time. The limitations are determined by multiple factors including length of each transmission, number of aircraft, frequency re-transmission and associated workload. Ideally, a pilot should be able to transmit a message at any time of his/her choosing and receive an immediate reply. As radio traffic increases above the ideal, the frequency becomes congested. The pilot must wait for a break in transmissions to pass a message and may have to wait for a response from the ATCO, who must judge different priorities.

Air Traffic Management (ATM): "ATM is the dynamic, integrated management of air traffic and airspace including air traffic services, airspace management and air traffic flow management safely, economically and efficiently through the provision of facilities and seamless services in collaboration with all parties and involving airborne and ground-based functions"[6]. For safe and efficient movement of aircraft during all phases of operations both airborne and ground-based functions (i.e., air traffic services, airspace management and air traffic flow management) are required. Air traffic management comprises three main services: air traffic services (ATS), air traffic flow management (ATFM) and airspace management (ASM).

[2] https://www.statista.com/statistics/193533/growth-of-global-air-traffic-passenger-demand/
[3] https://edition.cnn.com/travel/article/new-airports-and-terminals/index.html
[4] https://coflight-cloud-services.com/growth-by-2035/
[5] https://www.flightsafetyaustralia.com/2020/07/frequency-congestion/

Air traffic services (ATS): Main functions of ATS are to prevent collisions by applying appropriate separation standards and issue timely clearances and instructions that create an orderly flow of air traffic (e.g., accommodate crew requests for desired levels and flight paths, ensure continuous climb and descent operations, reduce holding times in the air and on the ground). Their tasks include:

a) Air traffic control (ATC): Area Control service, Approach control service, Aerodrome control service.
b) Advisory Service
c) Flight information service (FIS)
d) Alerting service

ATS with the general purposes of ensuring safe and orderly traffic flow (facilitated by the air traffic control (ATC) service) as well as providing the necessary information to flight crews (flight information service, FIS) and, in case of an emergency, to the appropriate bodies (alerting service). ATS is mostly performed by air traffic controllers. ATS relies on tactical interventions by the controllers and direct communication with the flight crews usually during the entire flight.

Air traffic flow management (ATFM): The primary objective is to regulate the flow of aircraft as efficiently as possible to avoid the congestion of certain control sectors. The ways and means used are increasingly directed towards ensuring the best possible match between supply and demand by staggering the demand over time and space and by ensuring better planning of the control capacities to be deployed to meet the demand. Supply and demand can be managed by imposing various restrictions on certain traffic flows (e.g., assigning CTOTs or requiring flights matching certain criteria to use specific routes). Also, supply can be increased by appropriate sector management (e.g., increasing the number of controllers working at the same time). AFTM measures can be seen as pre-tactical, as they do not affect the current situation but rather the near future.

Airspace management (ASM): The purpose of ASM is to manage airspace as efficiently as possible to satisfy its many users, both civil and military. This service concerns both the way airspace is allocated to its various users (by means of routes, zones, flight levels, etc.) and the way in which it is structured to provide air traffic services.

The overview of the ATM structure is presented in Figure **1** below.

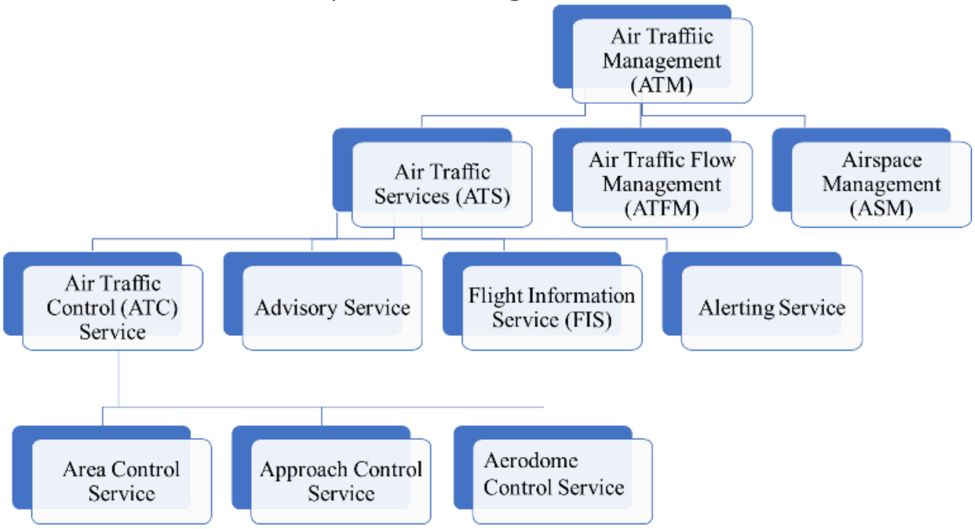


Figure 1. Overview of ATM structure

Other than the above-mentioned structure and roles of them in ATM, there are other ground tasks such as Take-off Time Prediction, Delay Propagation and Conflict Avoidance which are of importance that must be addressed. These tasks are described briefly below:

Take-off Time Prediction

The direct or indirect costs induced by delay in ATM have driven research to predict and minimize air traffic delays. The take-off time being one of the roots (indicator) of the delay of an airplane, it impairs all transportation network, and predicting it is a key to better predict and enhance air traffic. As a result, it is the not such a surprise that it has been widely studied in the last decade, surely catalyzed by the growing availability of aircraft trajectory data like ADS-B data, radar data lately, and the availability of user-friendly machine learning frameworks.

Research investigating departure delay can be classified based on

i) The spatial granularity of the delay being predicted, from aggregated delay e.g., predicting the aggregated delay of the network [7]–[9] of a particular route, or an airport to the delay of a simple aircraft trained on a particular Origin- Destination route[10], [11], or more general training [9]
ii) The temporal granularity of the prediction, from a simple classification e.g., delayed or not delayed [12] to general classes of delay e.g., less than 10 minutes, more than 15 minutes [10], or even to precise delay and eventually with probabilities[12]–[14]
iii) The look-ahead time of the prediction e.g., strategic, pre-tactical [11], tactical
iv) The model used to predict the delay
v) The features used to predict the delay e.g., leg delay [13], weather [10].

Delay Propagation

Like Take-off time prediction, delay propagation has gained an interest with the increasing congestion of the traffic and the need to predict better the demand, to better balance it with the capacity, and is surely catalysed by data and ML framework availability. In delay propagation, the main objective is to understand how the delays originating at one location propagates downstream into all or parts of the network, that is from aircraft to airports and airlines.

Delay propagation can be studied from the point of view of one aircraft, and how the delay propagates on the trajectory, or any subsequent trajectory for the aircraft or the airline [15], [16], and how robust are airlines to such delay, and how they can recover from it [17], [18].

Nonetheless, from ATM point of view, it is more interesting to focus on the system as all [19]–[21], must it be:

i) From a microscopic point of view i.e., representation of the different aircraft, mostly using multi-agent systems [22], [23] [24]
ii) From a macroscopic point of view i.e., density, flows, statistics, using statistical models and heuristics [25], [26]

iii) From any intermediate mesoscopic point of view, using queuing models [20], network theory approaches [18], [21] and machine learning [9], [11], [27] [28].

Indeed, any delay can induce delay on other aircrafts, generating problem not centralised on one aircraft or company. Problems can even propagate again to aircraft or the company by increasing the number of flights during a certain period, thus creating an imbalance with the capacity.

Conflict Avoidance

Conflict avoidance in ATM is one of the important and searched subjects in the ATM domain. Being one of the primary task of ATCos from the beginning of ATM, the domain naturally contains a lot of work, from the beginning of ATM [29] to now with lot of various approaches.

In the following, we use Latombe's formalization [30] which is widely used in the general motion planning problem is based on the notion of configuration space as defined in Lozano-Perez and Udapa's work [31], [32].

The conflict avoidance problem is combinatorial: the huge number of heterogeneous airplanes, the size of the airspace and the four dimensions (space + time) make the configuration space (C) tremendous. The size of the configuration space has led most research to either i) sample non iteratively the configuration space C by mostly using so-called 'operational' manoeuvres, which mimic orders that controllers would give to avoid separation losses, or ii) use heuristics to navigate iteratively in C.

Non-Iterative Sampling

Most algorithms, with a non-iterative sampling of the configuration space C, generate a graph of possible manoeuvres for each airplane, and explore this graph. Some algorithms use exact methods that will explore extensively this graph, using methods such as Mixed-Integer Linear Programming (MILP) [33], [34], constraint programming [35],or an hybridization between branch and bound algorithm and evolutionary algorithm [36], the later to reduce the exploration of the first. Other algorithms use approximate methods, exploring this graph by using meta-heuristics such as genetic algorithms [37], benchmarked in [38] or ant algorithms [39]. Other algorithms that samples non iteratively C will sample differently, parameterizing B-splines with genetic algorithms [40] or modifying way-points with simulated annealing [41], [42].

Iterative Sampling

Iterative Navigation Algorithms, navigating iteratively in the configuration space C, may be centralized or decentralized. Centralized algorithms use wave propagation analogies [43], [44], Mixed-Integer Linear Programming at discrete times to find the minimal modification to avoid separation losses [45], bi-harmonic field—extended potential field—[46], centralized harmonic navigation functions [47], or geometric methods—methods using speed vector to determine speed vector modifications [48], [49]. In Decentralized algorithms, airplanes decide their trajectories according to their local behaviour, using algorithms such as modified voltage potential [50] which is a modification of potential fields , bi-polar navigation functions[51], [52], or multi-agent systems [53]–[56].

2.1 Related projects in ATM domain

Resurgent interest in AI techniques focused research attention on their application in aviation systems including ATM. Recent developments and considerations for certification of ATM task through different AI/ML techniques (specially different neural networks) are presented in [7]. Considering the tasks in the projects, most of the work is centered around prediction and forecasting. A list of ATM related projects, its timeline and AI/ML models are presented in Table 1.

Table 1. List of ATM projects and AI/ML models

No.	Project Name/Task	Year	AI/ML Models	Project Link
1	Sector Capacity Prediction	2018	Feed Forward Neural Network (FFNN)	[6]
2	Take-off time prediction	2019	Gradient Boosted Decision Trees (GBDT)	[7]
3	Runway configuration prediction	2019	Recurrent Neural Network Encoded Decoder with Attention Mechanism	[8]
4	Pre-Tactical Traffic Forecast	2020-present	Random Forest	[9]
5	Air Traffic Control (ATC) with Multi Agent Reinforcement Learning	2020	Message Passing Neural Networks (MPNN)	[10]
6	Air traffic flow management (ATFM) with multi-agent reinforcement learning	2020-present	Graph Neural Networks (GNN)	[11]
7	Carfew infringement prediction	2020-present	Recurrent Neural Network (RNN)	[12]
8	AICHAIN A platform for privacy preserving federated machine learning using blockchain	2020-present	Federated machine learning and blockchain	[13]
9	Novel tools to evaluate ATM systems coupling under future deployment scenarios - Domino	2018-2019	Agent-based model, Trip Centrality	[14]
10	Capacity optimization in trajectory-based operations – COTTON	2018-2019	Bayesian Networks	[15]

[6] https://www.sesarju.eu/sesar-solutions/management-dynamic-airspace-configurations
[7] https://www.sesarju.eu/sites/default/files/documents/sid/2019/papers/SIDs_2019_paper_36.pdf
[8] https://www.sesarju.eu/sites/default/files/documents/sid/2019/papers/SIDs_2019_paper_37.pdf
[9] https://www.sciencedirect.com/science/article/abs/pii/S0191261518310464
[10] https://www.sesarju.eu/sites/default/files/documents/sid/2020/papers/SIDs_2020_paper_26red.pdf
[11] https://www.sciencedirect.com/science/article/abs/pii/S0191261518310464
[12] https://www.researchgate.net/publication/348717571_Toward_ATM_resiliency_A_Deep_CNN_to_predict_number_of_delayed_flights_and_ATFM_delay
[13] https://www.sesarju.eu/projects/aichain
[14] https://cordis.europa.eu/project/id/783206
[15] https://cordis.europa.eu/project/id/783222/reporting

11	GNSS navigation threats management - GATEMAN	2018-2019	Support Vector Machine (SVM) and Convolutional Neural Network (CNN)	[16]
12	Advanced prediction models for flexible trajectory-based operations - ADAPT	2018-2019	ad-hoc visualisation tool for the strategic flight planning	[17]
13	Airspace User supporting Demonstrations of Integrated Airport Operations- AUDIO	2019-2021	Human Machine Interface (HMI), Augmented Tower Vision (ATV)	[18]
14	Enhanced situational awareness through video integration with ADS-B surveillance infrastructure on airports ENVISION	2018-2019	Convolutional Neural Network (CNN)	[19]
15	Modern ATM via Human/Automation Learning Optimisation (MAHALO)	2020-2022	explainability (transparency) methods, potential model is CNN	[20]
16	From Prediction to Decision Support - Strengthening Safe and Scalable ATM Services through Automated Risk Analytics based on Operational Data from Aviation Stakeholders (SafeOPS)	2021-2022	Not found (Project has just started)	[21]
17	AI Situational Awareness Foundation for Advancing Automation (AISA)	2020-2022	Random Forest, Decision Tree	[22]
18	Airspace User supporting Demonstrations of Integrated Airport Operations	2019-2021	Other Method	[23]
19	Participatory Architectural Change Management in ATM Systems	2016-2018	Other Method	[24]

[16] https://cordis.europa.eu/project/id/783183
[17] https://cordis.europa.eu/project/id/783264
[18] https://cordis.europa.eu/project/id/783161
[19] https://cordis.europa.eu/project/id/783270
[20] https://cordis.europa.eu/project/id/892970
[21] https://cordis.europa.eu/project/id/892919
[22] https://cordis.europa.eu/project/id/892618
[23] https://cordis.europa.eu/project/id/783161
[24] https://cordis.europa.eu/project/id/699306

20	COMPetition for AIR traffic management	2016-2018	Other Method	[25]
21	Resilient Synthetic Vision for Advanced Control Tower Air Navigation Service Provision	2016-2018	Other Method	[26]
22	Expecting the unexpected and know how to respond	2015-2018	Other Method	[27]
23	Advanced User-centric efficiency metRics for air traffic perfORmance Analytics	2016-2018	Other Method	[28]
24	Machine Learning of Speech Recognition Models for Controller Assistance	2016-2018	Rule based model/ Assistant Based Speech Recognition (ABSR) model	[29]
25	Probabilistic Nowcasting of Winter Weather for Airports	2016-2018	Other Method	[30]

[25] https://cordis.europa.eu/project/id/699249
[26] https://cordis.europa.eu/project/id/699370
[27] https://cordis.europa.eu/project/id/653289
[28] https://cordis.europa.eu/project/id/699340
[29] https://cordis.europa.eu/project/id/698824
[30] https://cordis.europa.eu/project/id/699221

3 Transparency in AI algorithms in ATM

AI is “blackbox” by nature in most of the applications. When it comes to ATM, it lacks transparency and explanation for an operator while taking a decision. An operator facing a problem in the ATM domain will find no guide or explanation on how to resolve problems.

The goal of the following review is manyfold, and should provide an asset, both for operational, and different actors of this ARTIMATION project: 1) Provide a Design Space of the problem faced in ATM domain, and the solution provided—if any—by AI domain, 2) Assess the possibility to add explainability to the AI systems used in ATM, 3) Assess the need for explainability in those systems.

The following three research questions (RQs) motivated this work, and directed the keywords of our methodology:

RQ1: What are the AI/ML algorithms used in ATM domain?
RQ2: What are the potential explainability methods in AI and ML?
RQ3: How visualization techniques can be used for XAI in ATM domain?

3.1 SotA on AI/ML algorithms in ATM

This section seeks to answer the first research question (RQ1). It describes the methodology used to perform this review as well as the meta results, followed by explaining the categorization of the reviewed works, with the general results, and finally explaining the detailed results.

The following review was performed by reviewing several papers from different conferences and journals mostly from the ICRAT conference[31], ATM seminar event[32] and the Transportation part C journal[33].

[31] http://www.icrat.org/icrat/
[32] http://www.atmseminar.org/
[33] https://www.journals.elsevier.com/transportation-research-part-c-emerging-technologies

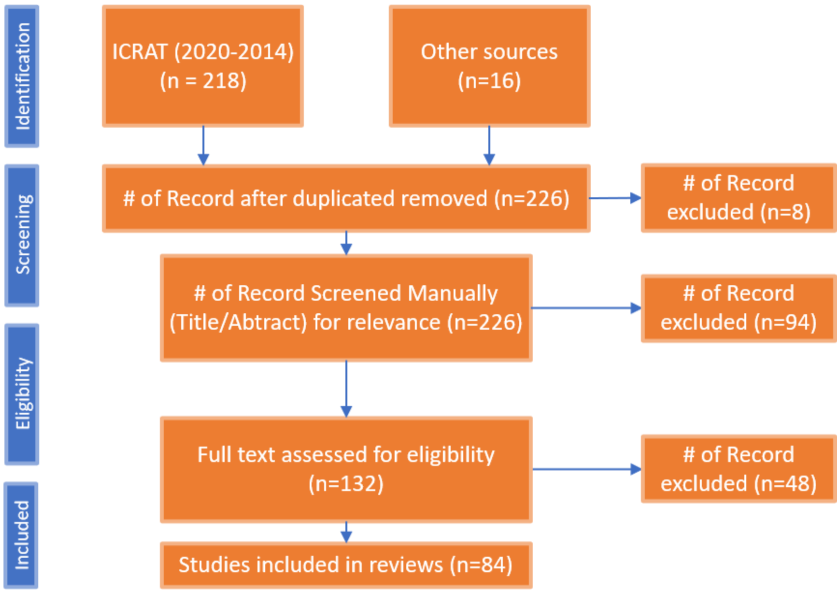


Figure 2 . PRISMA Flow of the AI in ATM review

We followed a PRISMA Flow ( ) to perform this review, with a formal primary selection based on the title and abstract of the papers using primary keywords—listed below. Selected papers where then filtered based on the full text with a superficial reading based on an empirical keyword list containing mostly primary keywords and methods employed. Afterwards, filtered papers were fully reviewed.

Based on the RQ 1, and the fact that this review was mostly performed on ATM conferences, our primary keywords were the following—i.e., the list does not have to include any keywords to restrain to the ATM domain:

- Predict*
- Estimat*
- Optimi*
- Cluster*
- Analys*
- Visu*
- Explain*

Because our review was primarily focused on ATM conferences, the papers selected in the Identification stage (n=226) were already consistent with the ATM field and needed to be consistent with the AI field. Hence exclusion was mostly because they did not use AI techniques. When it was detected at the screening phase (n=94) which was roughly 40 percent, they were excluded. Because techniques employed as clearly defined in the title/abstract, were not from the AI field. When it was detected at the eligibility phase (n=48), it became around 36 percent. As a result, the exclusion, compared to a systematic review, was low which was around 37 percent.

The following section describes the result of this review, from most general to the most specific assessments.

From our review as presented in Figure 3, AI in ATM can globally be divided in 4 sub-groups, strongly connected with AI in general, that globally defines the purpose of the application:

- **Prediction**, e.g., prediction of the traffic, prediction of the runway occupancy time.
- **Optimization/Automation**, e.g., sequencing arrival airplane, avoiding conflict, optimizing a trajectory.
- **Analysis**, e.g., assessing the workload of an Air Traffic Controller (ATCo) in a sector, evaluating the important factor influencing the arrival of an airplane.
- **Modelling/ Simulation**, e.g., simulating the air traffic of an airspace, modelling the arrival of airplane.

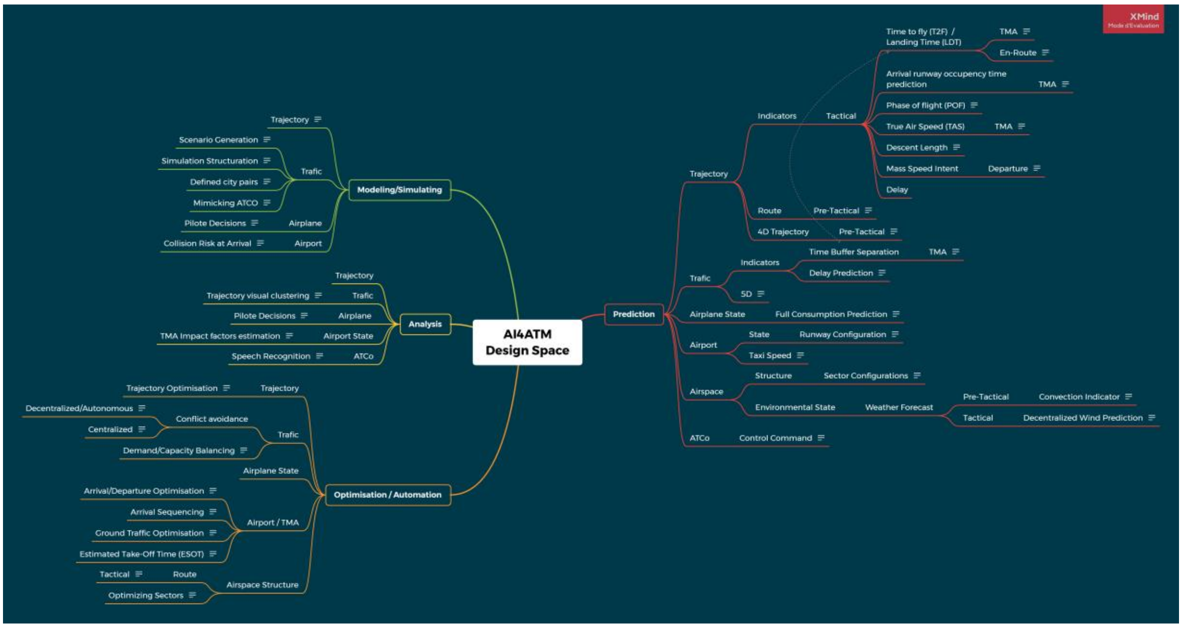


Figure 3. AI for ATM design space

Note that, this categorization is not to be confused with any time frame of ATM, like the simplified pre-tactical, tactical and post analysis time frame. Since, for example, one may predict the arrival time of airplane before the airplane departure, or after, and likewise, assessing the workload of a controller in each sector, one can be useful before, during, and after the trajectories have been flown. The categorization rather emphasizes the goal required by the operator e.g., predict the trajectory and how it can be achieved. Additionally, those groups are not strongly separated, since the output of one group can be used as an input by another group, and some are ambivalent. As an example, the output features of an AI algorithm used to cluster air traffic flows can be used to predict the arrival time by another algorithm. Similarly, an AI algorithm, that can predict 4D trajectories, can also be used as an input to another algorithm, or to model the traffic. In a sense, the more the AI model embrace the innate complexity of the ATM domain, the more it can perform. This categorization is used in the following to present this review of AI in ATM as presented in Figure 4.

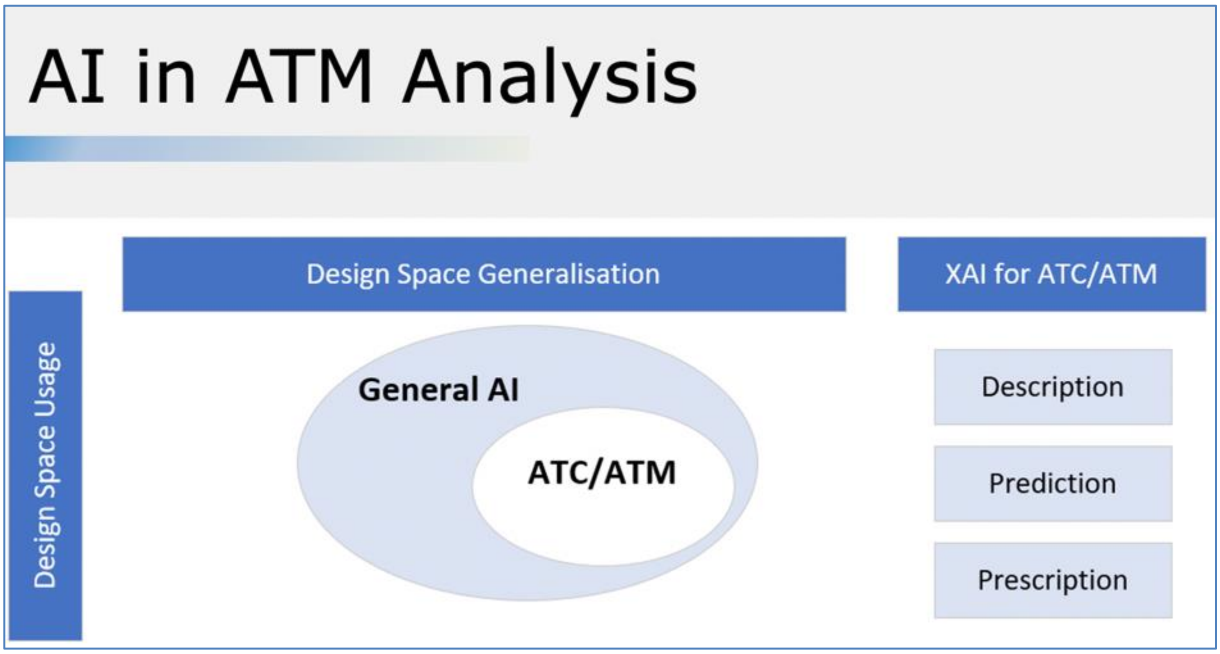


Figure 4. AI in ATM analysis

General insights

Despite the narrow scope of our review, some insights about the evolution of publications of AI in ATM can already be drawn. From a global point of view, AI in ATM is a growing domain: the number of publications of AI in ATM as shown in Figure 3 has doubled in the last four years. This maturity of AI technologies applied to ATM, also emphasize the need of explainability of those systems to be accepted and used by the end users i.e., ATM operators, and the purpose of the ARTIMATION project.

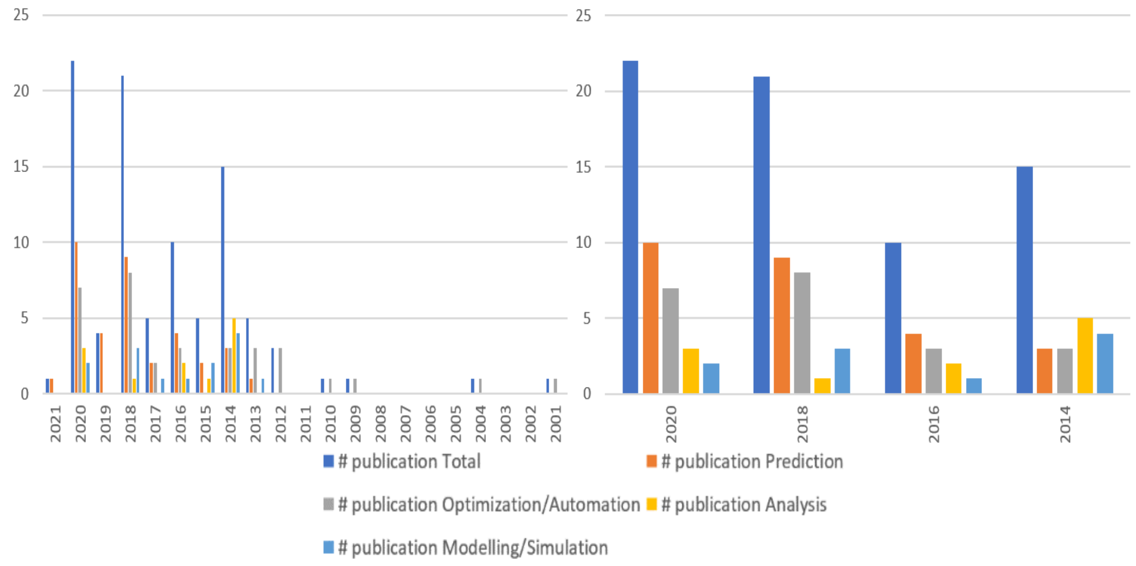


Figure 5: Evolution of the number of publications of AI for ATM from our review; left graph shows the evolution of the categories with years, right shows the most relevant years due to our review being primary made on ICRAT—that occurs every two years—between 2020-2014

Through the lens of our categorization, the growth of the last four years publications seems to originate from the growing work in prediction and optimization—publications about prediction tripled between

2014 and 2020. From the number of publications, it seems that AI in ATM highly benefit from the AI community work, researcher work or developer community of the last decade, that democratize and made AI model generation far more accessible, e.g., scikit, TensorFlow, keras. In some area, its more effective like particularly in prediction and optimization. The time window of the review is too short to assess any previous trend in AI for ATM. However, previous work and other reviews [57] suggest that publications of AI in ATM have grown in the last decade but had a strong core base for many years, in particular in optimization, collision avoidance and traffic flows being arguably one of the most consistent subjects of AI in ATM.

AI model used in ATM can vastly be categorized in function i) the primary goal of the model, i.e., is it to predict, analyse, model, or optimize, and ii) the object associated with this primary goal, e.g., to predict a *trajectory*, to predict the *departure time*, to model *arrivals*. The following describe the different categories and object associated.

Categorization insights

The primary goal of the model already categorize well enough the different AI models used in ATM. The different models used in the different categories is presented in Table 2, using selected references.

AI *prediction* in ATM is performed using a vast range of AI model, most used ones are i) Multi-Agent Systems (MAS), ii) Neural Network (NN), iii) Random Forest (RF), iv) Gradient Boosting Machine (GBM), v) Support Vector Machine (SVM), and vi) Linear Regression. The five later models—NN, RF, GBM, SVM and linear regression are mostly used to predict i) an indicator of the trajectory of an aircraft, e.g., mass estimation [58], descent length [59], phase of flight [60], ii) a state indicator of an airport, e.g., the estimated take-off time [14], or taxi speed [61]. Authors using these models are mostly capitalizing on framework availability of the past years and often uses them jointly to compare them, using often linear regression as a baseline. Nonetheless, ii)-v) AI models have also been used for other type of predictions such as route choice [62], sector configuration [63], controller action prediction [64], or short-term 4D trajectory prediction [65]. Multi-Agent Systems on their side has been used to model and predict more complex tasks, such as delay propagation on networks [24], or 4D trajectory and to a certain extend traffic prediction [66]. Predicting the traffic and its delays is one key element to enhance the general traffic, its congestion, and better balance the demand and the resources. In this sense, fully understanding the underlining reasons of congestion, trajectory routes, and delay is more than required to better enhance latter traffic. Giving the fact that the different used algorithms have been a focus of the XAI community as mentioned in section 3.2, this category both can have explainability and requires it.

AI *optimization* and *automation* works use mostly a more restricted range of AI model, i) Multi-Agent Systems (MAS), ii) Evolutionary Algorithm (EA), mostly genetic algorithms, and iii) Simulated Annealing (SA). Majority of these works focus on optimizing the traffic and/or avoiding collisions, from the point of view of the trajectories. Traffic optimization works focus in general on one flight phase, such as optimizing *En-Route* traffic using centralized, i.e., SA [42] or EA [37], or decentralized, i.e., MAS [67], [68], arrival [69], departure [70], ground optimization, or the whole airport traffic [71]. Notable other focus of AI model for optimization are optimizing airspace structure, such as route network [72], sectors [73], and optimizing a trajectory [74]. Optimizing the general traffic and avoiding collision is the most important thing to enhance the general traffic and its safety. Due to the utmost importance of the safety in ATM, fully understanding the underlying reasons of conflict avoidance procedures, sequencing, or any other optimization result, is required to be accepted and used by human operators such as ATCo. The different algorithms used have been a bit neglected by the XAI community as seen in section 3.2. Hence, adding explainability could require more time and efforts, but it is of the utmost importance to add it to this category.

Analysis of ATM activities using AI model is mostly composed of i) techniques that clusterize e.g., DBSCAN, BIRCH, or auto-encoder NN—trajectories in order to analyse the different factor influencing such as route choice [75], arrival [76], or delays [77] in order to understand the different influencing factors and/or as a first analysis to latter predict, or ii) more precise analysis, such as trajectory analysis to detect ATCos actions [78], or speech recognition and analysis or utterance of ATCos [79]. Adding explainability could be interesting, and direct with certain methods like auto-encoder NN in particular, but explainability seems less required in this category.

AI *modelling* in ATM is mostly performed using multi-agent systems, which is unsurprising, considering their importance in simulation in many domains, such as the simulation of car traffic. Nonetheless, AI modelling is not that prevalent in ATM compared to other domains since in ATM, modelling and simulation are mostly made using records, and mathematical models [80] e.g., BADA [81], ASTOR. Multi-Agent modelling is quite broad, stretching from modelling aircraft arrival to assess risks in TMA [82], simulate network delay [24], simulation of air traffic [83], or simulate the all ATM environment [84]. Other AI models found focused on more simple tasks, such as modelling go-around pilot decision [85], with neural network (NN). Latest work on graph neural network [86] could possibly become important in modelling in the future, such has modelling an ATCOs [87]. In a sense, AI modelling most of the time start from the underlying reasons motivating actions of the different actors taking part in the simulated world. This is particularly true with MAS systems that are dominant in this category, where MAS designers try to represent the different entities in the system, their actions and reasoning, and they let emerge global state for the agent interactions. Explainability could be added to explain some emerging behaviours i.e., delay propagation, and have a valuable impact to the global understanding. Nonetheless, in general, explainability is less required in this category and is already provided to a certain extend.

Table 2. Different AI algorithms/models used in the different categories in ATM

Category		Prediction	Optimization / Automation	Analysis	Modelization / Simulation
Multi-Agent System (MAS)		[88] [89] [66] [83] [90] [91] [92]	[72] [68] [80] [93] [94] [95] [96] [97]	[98]	[66] [80] [82] [99] [100] [101] [66] [83] [90] [89] [91] [92] [84]
Metaheuristics	Evolutionary Algorithm (EA)	[102]	[103] [104] [105] [106] [107] [108] [73] [109] [110]		
	Simulated Annealing (SA)		[111] [112] [113] [74] [69] [71] [70] [110]		
	Ant Colony Optimization algorithm(ACO)		[114]		

Neural Network	Neural Network (NN)	[115] [58] [59] [116] [63] [117] [118] [60] [119] [85] [120]	[121] [87]	[85] [78] [76] [79]	[85] [87]
	Deep Deterministic Policy Gradient (DDPG)		[122]		
	Deep Q-Network (DQN)		[123]		
Tree-based	Random Forest (RF)	[61] [124] [125] [126] [127] [65] [62] [128] [129] [64] [130]			
	Quantile Regression Forest	[125] [126]			
	Gradient Boosting Machine (GBM)	[59] [116] [124] [127] [62] [131] [128] [129]			
	Decision Trees	[124] [129]			
Support Vector Machine (SVM)		[102] [60] [62] [128]	[121]		
Fuzzy Logic		[132]			
Regression	Linear Regression	[59] [117] [60] [62] [75] [133]	[121]	[134] [75] [135] [136] [137]	[133]
	Binary logistic regression models			[138]	
Bayesian	Bayesian Network	[139]			
	Recursive Bayesian Estimation	[140]	[141]		
	Dynamic Bayesian Belief Network	[142]			[142]
Clustering	BIRCH			[132]	
	DBSCAN			[132]	
	OPTIC			[77]	

	Gaussian Mixture Model	[143]			
Non Negative Matrix Factorization (NMF)				[144]	
A*			[105]		
Not referenced			[145]		

Below different categories of AI/ML algorithms are listed with a generic overview, motivation, and connection with the sub-four tasks i.e., Prediction, Optimization/Automation, Analysis and Modelization/Simulation:

Multi-Agent System (MAS): There are many definitions of the term agent as well as many paradigms using it. A commonly accepted definition of an agent is that it is "an autonomous physical or virtual entity able to act (or communicate) in a given environment given local perceptions and partial knowledge. An agent acts in order to reach a local objective given its local competence" [146]. In a nutshell, a MAS is a system composed of various agents interacting between themselves and their environment.

The paradigm being inherently decentralized, and focused on the different entities composing a system, for example the airplanes, it is highly appreciated in the simulation community in many domains—car traffic for example—, and can be found in air traffic simulation as well, even if it is in the minority among all the simulation works in this domain, for air traffic simulation [66] [80] [90] [83] [66] [100] [101], delay propagation simulation [89] [91] [92], arrivals [82] [99] ,or the whole ATM environment [84].

Interestingly, even if the MAS are first created to simulate objects—e.g., airplanes composing the air traffic—, the more accurate the behaviours of the different actors of the simulation is, the more the MAS simulated traffic can be used to predict the future state of the simulated objects—e.g., the air

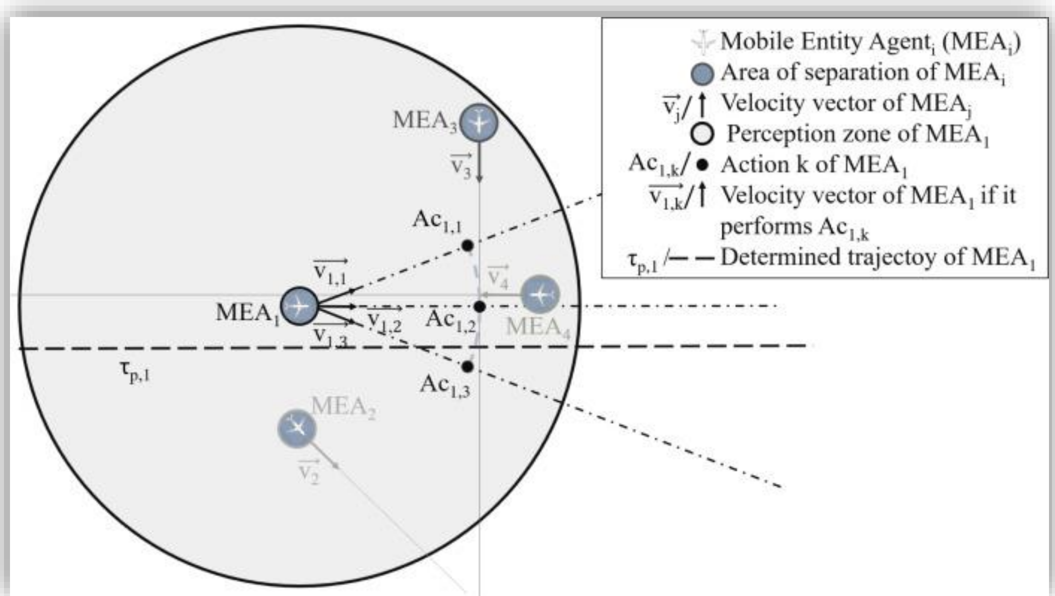


Figure 6. A MAS optimizing the traffic by letting airplanes agents (MEAi) decide of the trajectory of the airplane i, by choosing, according to the perceived environment—mostly neighbours airplane—, an action it can perform [97].

traffic—if inputted with real data like traffic prediction [66], delay prediction [89], or meteorological indicators [88].

On another note, MAS can also be used to solve complex problem in a decentralized way, in ATM it has particularly been to optimize *En-Route* air traffic [97] [68] [94] [95] [96], the capacity/demand balance [93], or the route network [72].

The strengths of MAS lie in the natural decomposition of the problem that comes with its use—e.g., optimizing the traffic is the result of the interactions of airplane optimizing their trajectories—and a more understandable global result—e.g, the trajectories in previous example—, since it results of understandable entities and their understandable behaviour that can be traced and understood easily.

Metaheuristics: Metaheuristics can be defined as "high level concepts for exploring search spaces by using different strategies. These strategies should be chosen in such a way that a dynamic balance is given between the exploitation of the accumulated search experience (which is commonly called intensification) and the exploration of the search space (which is commonly called diversification)" [147]. Metaheuristics is a category of algorithm containing lots of different type of algorithm, presented in figure 7. In this state of the art, three categories have been found:

- Genetic Algorithms (GA)
- Simulated Annealing (SA)
- Ant Colony Optimization algorithm (ACO)

Most of the applications of these categories are made to optimize the traffic and/or avoid conflicts, most of the time only in one flight phase, such as optimizing *En-Route* trajectories with SA [42] or EA [37], but also optimizing arrivals [69], departure [70], ground optimization, or the whole airport traffic [71]. Those algorithm can also be used to optimize the airspace structure, like sectors [73], or optimize a trajectory [74].

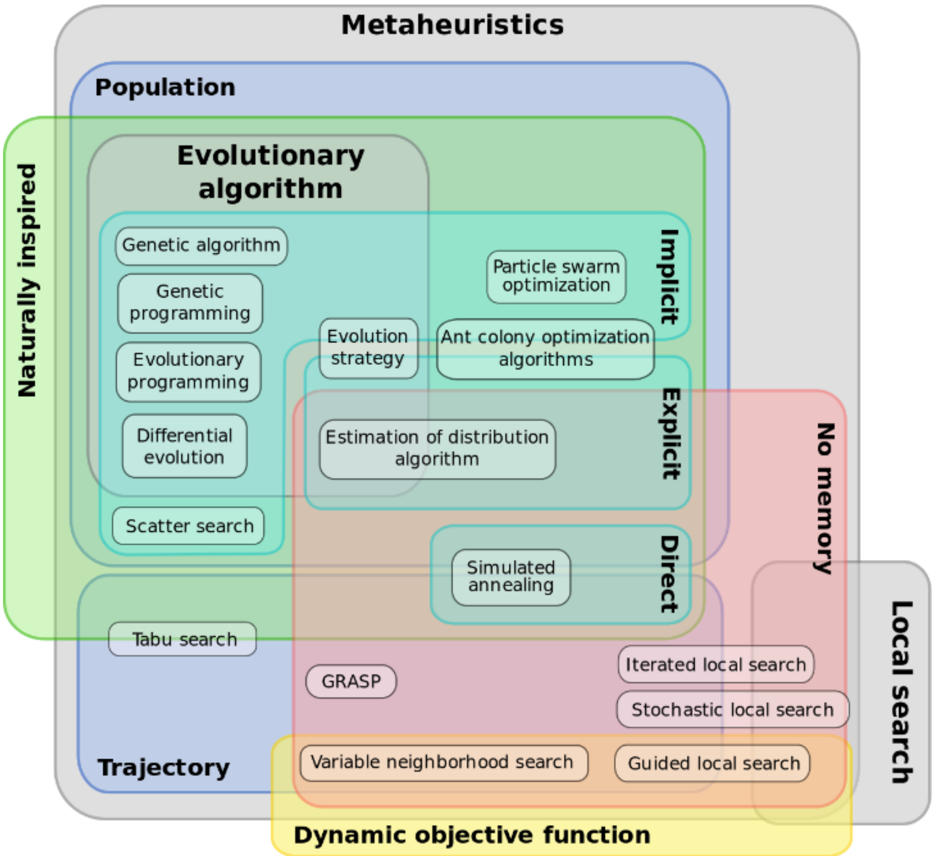


Figure 7. Euler diagram of the different classifications of metaheuristics, Johann Dréo via Wikimedia Commons

Neural Network: A neural network (NN) is a system designed to act like a human brain. It's simple but prevalent in our day-to-day lives. A complex definition would be that a NN is a computational model that has a network architecture. This architecture is made up of artificial neurons. This structure has specific parameters through which one can modify it for performing certain tasks. They have extensive approximation properties. This means they can approximate a function to any level of accuracy irrespective of its dimension. NN find extensive applications in areas where traditional computers don't fare too well. From Siri to Google Maps, neural networks are present in every place where Artificial Intelligence is used. They are a vital part of artificial intelligence operations. NN take inspiration from the human brain and so their structure is like one as well. A NN has many layers. Each layer performs a specific function, and the complex the network is, the more the layers are. That's why a neural network is also called a multi-layer perceptron. The simple form of a neural network has three layers: input layer, hidden layer, and output layer. As the names suggest, each of these layers has a specific purpose. These layers are made up of nodes. There can be multiple hidden layers in a neural network according to the requirements. The input layer picks up the input signals and transfers them to the next layer. It gathers the data from the outside world. The hidden layer performs all the back-end tasks of calculation. A network can even have zero hidden layers. However, a NN has at least one hidden layer. The output layer transmits the result of the hidden layer's calculation. Like other machine learning applications, you will have to train a neural network with some training data as well before you provide it with a particular problem. NN consisting of many hidden layers called Deep learning. There are several Deep-learning architectures such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks, and convolutional neural networks.

Considering ATM domain, literature show that NN has been deployed in many tasks such as prediction, optimization, analysis and simulation. Several ATM tasks related to prediction such as runway configuration prediction [115], aircraft climb prediction [58], predicting aircraft descent length [59], aircraft phase of flight prediction [60], take -off time prediction [116] and [117], predicting sector configuration transitions [63], airport capacity prediction [119], predictive modelling for decision making [85], prediction of the propagation of trajectory uncertainty [120] have been conducted using NN. Again, other ATM task such as optimization tasks for aircraft landing [121] and free air-space [87], analysis tasks such as pilot decision making [85], controller action [78], trajectory clustering [76], context-aware speech recognition and understanding system for air traffic control [79] and simulation tasks [87] have been performed where NN has been deployed. Deep learning NN such as Deep Deterministic Policy Gradient (DDPG) model [122] for conflict detection, and Deep Q-Network (DQN) [123] for aircraft sequencing and separation have been developed.

Tree-based Models: Mostly Random Forest (RF) is witnessed to be used in various task related to ATM. RF is one of the ensemble methods for supervised learning, which is developed with several binary decision trees, thus it is called forest. Here, the target value is predicted based on the results from several distinct trees. During the classification or regression, the decision is made at each level of the trees depending on the values of different features. For the two different tasks, i.e., classification and prediction, the outcome of the model is determined through voting or averaging the individual outcome of the trees respectively. Generally, randomized bootstrapping process is followed while training a RF classifier/regressor. Here, the training set is sampled several times depending on the predefined number of trees in the forest. All the samples contain same number of instances and chosen randomly. Since, the process is performed by replacing the samples time and again, the effect of duplicate and missing records persists. After generating the sample sets, decision trees are built for each of the samples. A tree is grown by an iterative splitting of the data sample into two parts based on a decision criterion that gives the reduction in variance to determine the quality of a split [125]. The Quantile Regression Forest (QRF) trains in a similar way of training a RF except the handling of values at the leaves of the distinct trees. In a classical RF regression model, the average of all the values from the leaves are stored. On the contrary, in QRF, all the observations are preserved. During the prediction phase, individual weights are utilised to generate quantile function that generates the final prediction.

Gradient Boosting Machine (GBM): GBM is a boosting algorithm that ensembles new predictors with a view to correct its predecessor models. Generally, GBM tries to fit in new predictors built on the residual errors from the previously built predictors. The ultimate concept behind this model is to build a strong model from an ensemble of several weak models. There main advantages of GBM is increased performance accuracy reducing bias and variance with less number of trees than other tree-based models like RF. On the contrary, GBM is prone to overfitting and cannot run in parallel like RF or QRF which can be considered as the limitations of GBM [148]. From the literature, it was observed that, the tree-based models are mostly used in prediction tasks from the ATM domain as described in Table 2.

Support Vector Machine (SVM): SVM is a supervised machine learning algorithm commonly used in pattern recognition, which can be used for solving both classification and regression problems. The goal of the SVM algorithm is to find a hyperplane in an N-dimensional feature space that minimizes the empirical classification error and maximizes the geometric margin in the classification. The data points that maximize the margin are called support vectors. Support vectors lie closer to the hyperplane, influence the orientation and position of the hyperplane. The advantage of using SVM is that it can map the original data points from the input space to a high dimensional feature space so that the classification problem becomes simple in this feature space. Besides, SVM is effective for training a model with high dimensional features and memory-efficient since a subset of training points, i.e., support vectors, are used in decision making. Also, SVM can be versatile as it can use different kernel (similarity) functions for the decision function.

In the ATM domain, SVM primarily used in prediction tasks such as trajectory prediction [60] [62] [128] and fuel consumption prediction [102]. Although SVM has been proven to be a good algorithm in pattern recognition, however, based on the results of [60] [62] [128], SVM has not been found as the best performing algorithm in trajectory prediction. On the other hand, support vector regressors could quickly and accurately estimate the cheapest-sequence cost for fuel consumption prediction [102].

Fuzzy Logic: Fuzzy logic is basically used to handle uncertainty based on the fuzzy set's theory. This is used to illustrate a real-world concepts where no precise definition of criteria for membership exist [132]. The membership functions are applied to define the degree of truth of features. And the logic operators e.g., AND, OR, NOT are applied as minimum, maximum, and complement operation. The basic steps in fuzzy inference system are a) crisp value as input, b) crisp values are converted into fuzzy membership functions, c) fuzzy rules-rules evaluation-aggregation, d) defuzzification. The authors in [132], applied fuzzy logic beside other machine learning algorithms to identify flight phase in aircraft performance models. Here, other machine learning models such as clustering methods are used to create sub-clusters, but they cannot handle the certain level of consistency and failed to cluster when there is a flight behavior variance. To solve the issue three input membership are considered i.e., altitude (low, ground, high), rate of climb (zero, positive, negative) and ground speed (high, medium, low) and one output membership function to determine phase (ground, climb, descend, cruise). They have considered four fuzzy rules as [132]:

1. If **Altitude** is *ground* and **Speed** is *low*, then **Phase** is *ground*
2. If **Altitude** is *low* and **Speed** is *medium*, and **Rate-of-climb** is *positive* then **Phase** is *climb*
3. If **Altitude** is *high* and **Speed** is *high*, and **Rate-of-climb** is *zero* then **Phase** is *cruise*
4. If **Altitude** is *low* and **Speed** is *medium*, and **Rate-of-climb** is *negative* then **Phase** is *descended*

Regression: Regression analysis is a fundamental concept in the field of machine learning. It falls under supervised learning wherein the algorithm is trained with both input features and output labels. It helps in establishing a relationship among the variables by estimating how one variable affects the other. Regression in machine learning consists of mathematical methods that allow data scientists to predict a continuous outcome (y) based on the value of one or more predictor variables (x). There is different regression model such as linear regression, logistic regression etc. Linear regression is probably the most popular form of regression analysis because of its ease-of-use in predicting and forecasting.

Linear regression finds the linear relationship between the dependent variable and one or more independent variables using a best-fit straight line. Generally, a linear model makes a prediction by simply computing a weighted sum of the input features, plus a constant called the bias term (also called the intercept term). In this technique, the dependent variable is continuous, the independent variable(s) can be continuous or discrete, and the nature of the regression line is linear. Logistic regression on the other hand, is named for the function used at the core of the method, the logistic function. The logistic function, also called the sigmoid function was developed by statisticians to describe properties of population growth in ecology, rising quickly and maxing out at the carrying capacity of the environment. It's an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits.

linear regression is used mostly for prediction and analysis related ATM tasks. A number of prediction tasks such as predicting aircraft descent length [59], predicting the time to fly and aircraft speed profile on final approach [117], aircraft phase of flight prediction [60], predicting aircraft trajectory choice [62], route choice prediction [75], prediction model for for aircraft performances [133] etc. have been conducted using linear regression model. Also analysis tasks such as identification of significant impact factors on arrival flight efficiency [134], capacity estimation and robustness analysis [135], maximum flow estimation [136] etc. have been exploited using linear regression model. Again logistic regression model such as binary logistic regression model has been deployed for analysis of airspace infringements [138].

Bayesian: Our observations and understanding of the world are limited, and we often need to consider the uncertainty to deal with our imperfect knowledge of the world. Probabilistic models play a vital role in machine learning, which explicitly consider the uncertainty of the real world and can act as a kind of expert system. In machine learning, probabilistic models are generated by Bayesian reasoning that includes Bayesian estimation and Bayesian Belief Networks. Bayes estimator is a decision rule that minimizes the posterior expected value of a loss function. The general design of Bayesian inference using Bayesian estimation works as follows: initial a prior probability is guess based on the observable data. Then successively Bayes rule is applied to update the initial guess and measurement of the observable. The updated distribution obtained this way is known as the posterior [139] [140]. Bayesian Networks (BN) or Bayesian Belief Networks (BBN) are generative models. BN or BBN is a probabilistic graphical model representing the conditional dependencies of a set of random variables using a Directed Acyclic Graph (DAG). For a set of inputs X, and output Y, BN's learns the joint distribution $P(X,Y)$, whereas other machine learning algorithms such as SVM models the conditional distribution $P(Y|X)$. In the ATM domain, Bayesian Networks and Bayesian estimation mainly applied for predict e.g., predicting future location in [139] and ATM Network Delays [142]. It is hard to design the Bayesian Networks and difficult to learn the joint distribution, however, BN's is effective when we have a lot of missing data. Since it is a graphical representation, BNs are visually transparent and can help to capture the cause-effect relationship.

Clustering Algorithms: Several clustering algorithms are prominent in the literature which were deployed in different tasks in ATM domain. Mostly, in analysis-based tasks clustering algorithms, e.g., BIRCH [132], DBSCAN [132] and OPTIC [77] were used. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a clustering method that distinguishes data into clusters based on area of high and low density. It uses two fundamental parameters, namely, *Eps* and *MinPts*. Here, the maximum distance between two data points in the same neighbourhood is expressed with *Eps* and the number of data points in the neighbourhood of a core point is presented with *MinPts*. The prime advantage of DBSCAN is that it can eliminate noise by considering the data points from low density area and performs well with large datasets containing higher number of clusters. Another clustering algorithm BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) incrementally constructs a Characteristic Feature (CF) tree from the dataset. In the construction of the CF, BIRCH utilises two user-defined constraints - the threshold (T) and the branching factor (B). Finally, the leave nodes of the CF are clustered with an arbitrary clustering algorithm. Both clustering algorithms are proved to be superior in terms of handling outliers and large diverse datasets than other simpler clustering algorithms like K-means [132].

Non-negative Matrix Factorization (NMF): Non-negative Matrix Factorization (NMF), can be defined as methods or algorithms in multivariate analysis and linear algebra where a matrix is factorized into (usually) two matrices, with the property that all three matrices have no negative elements [149]. NMF can be used for dimensionality reduction and data analysis. NMF is particularly relevant when nonnegativity is inherent to the data being considered, such as audio spectrograms, such as analysing speech utterance of controllers [144].

A*: A* is a graph traversal and path search algorithm [150] that can easily be used to find shortest path on a route network that is used in ATM, and is used in particular by different simulators to find a first the shortest path for a city pairs before further optimizing it [105].

3.2 Overview on Explainability in AI/ML

This section is dedicated to the second research question (RQ2). Prior to the overview of AI/ML and explainability, it is expedient to form a general understanding of the term explainability in the context of AI/ML. The prime hindrance towards developing the ground knowledge of explainability concerning AI, is the interchangeable use of several terms in the literature, such as, interpretability, transparency, explainability etc. Before proceeding to the literature review, the commonly used terms are presented briefly according to the definitions compiled by Barredo Arrieta et al. [151].

Understandability, often termed as *Intelligibility* also, is the characteristics of a model that makes a user realise its functions. In other words, how the model works without any requirement of further explanation for the model's internal operations on the data. Another similar term that has been used to define the ability of an ML model to represent its learned knowledge to humans in an understandable way is ***Comprehensibility***. Clearly the prior terms differ on representing the internal operations on the data and the knowledge acquired from the data. In addition, the terms ***Interpretability*** and ***Transparency*** are mostly used in describing similar concepts to *Explainability*. In fact, interpretability refers to a model's ability to provide meaning or explain in an understandable way to human beings. Nonetheless, transparency of a model indicate the ability to be understandable to humans, and there are three types of transparent models [152] -

- *Simulatable Models* have the capacity to make humans understand their structure and functioning entirely.
- *Decomposable Models* can be decomposed into individual components, i.e., input, parameters and output, and their respective intuitions.
- *Algorithmically Transparent Models* behave "sensibly" in general with some degree of confidence.

Above all, the term *Explainability* affiliates the interface between humans and decisionmakers, which is concurrently comprehensible to humans and accurate representation of the decision-maker [153]. In XAI, explainability is the interface between the models and the end-users through which an end-user gets clarification on the decisions he/she gets from an AI/ML model.

3.2.1 Stages, Scopes and Forms of Explainability

The AI/ML models learn the underlying characteristics of the available data and subsequently try to classify, predict or cluster new data. The stage of explainability refers to the period in the process mentioned above when a model generates the explanation for the decision it provides. The stages are found to be ante-hoc and post-hoc [154]. Brief descriptions of the categorised methods based on these stages are :

- Ante-hoc methods generally consider generating the explanation for the decision from the very beginning of the training on the data while aiming to achieve the optimal performance.

Mostly, explanations are generated using these methods for transparent models, such as, Fuzzy models, Tree-based models etc.

- Post-hoc methods comprise an external or surrogate model and the base model. The base models remain unchanged, and the external model mimics the base model's behaviour to generate an explanation for the users. Generally, these methods are associated with the models of which the inference mechanism remains unknown to users, e.g. Support Vector Machines, Neural Networks etc. Moreover, the post-hoc methods are again divided into two categories - model-agnostic and model-specific. The model-agnostic methods are applicable to any AI/ML model, whereas the model-specific methods are confined to particular models.

Scope of Explainability

Scope of explainability defines the extent of an explanation produced by some explainable methods. Vilone and Longo deduced after scanning more than 200 scientific articles published on XAI that the scope of explainability can be either global or local [154]. The whole inferential technique of a model is made transparent or comprehensible to the user at global scope, for example, a decision tree. On the other hand, a single instance of inference is explicitly presented to the user in local scope, for decision trees, a single branch can be termed as a local explanation.

Forms of Explanations

Literature indicates that mostly four different forms of explanations are generated to explain the decisions of the AI/ML models as well as the process of deducing a decision. The forms of explanations are *numeric*, *rules*, *textual* and *visual*. The Figure 8 below illustrates the basic forms of explanations. In some of the previous researches, authors used these forms in a combined fashion to make the explanation more understandable and user friendly. All of the forms of explanation are discussed along with the references to key works with the corresponding forms in the subsequent sections.

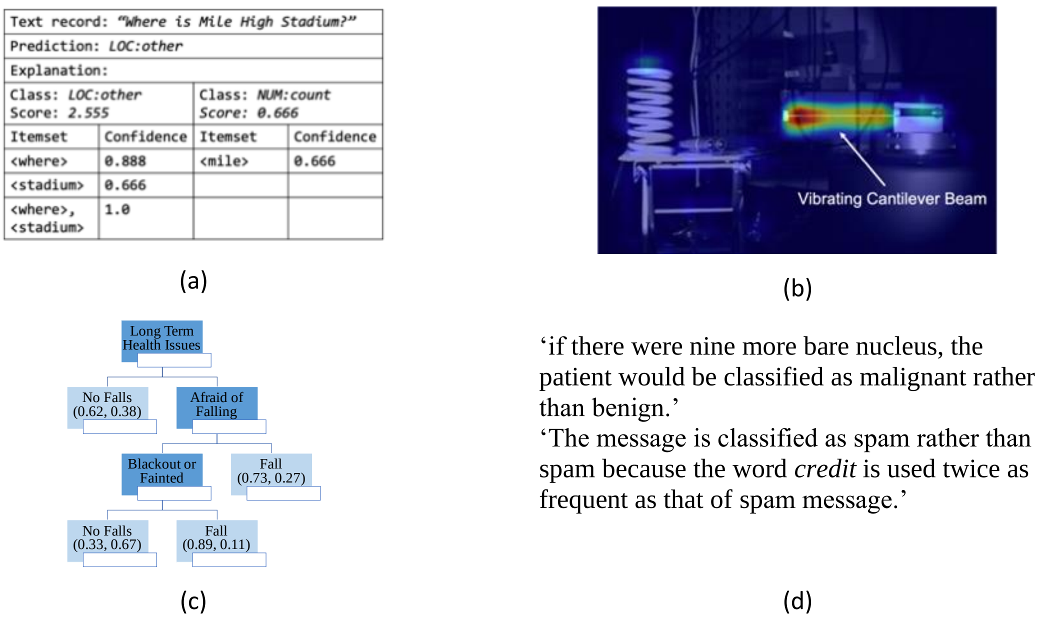


Figure 8. Different forms of explanations. (a) numeric explanation from confidence itemsets **[155]**, (b) visual explanation with class activation map (CAM) for vibrating cantilever beam by Sun et al. **[156]**, (c) example of rule-based explanati on in the form of tree **[157]** and (d) explanation text generated with GRACE, proposed by Le et al. **[158]**.

3.2.2. Methods for Explainability

The available methods for adding visual explainability to the existing and proposed AI/ML models are clustered based on two properties: i) stage of generating explanation and ii) scope of the explanation. Here visual explanations are prioritized because of its significant utilization in ATM. The summary of the clustering is represented in Table 3 where model-specific methods are cross-referred to the AI/ML model types. A good number of model-agnostic (MA) methods were also deployed to generate in the selected articles of this review, such as Anchors [159], Explain Like I'm Five (ELI5) [160], Local Interpretable Model-agnostic Explanations (LIME) [161], Model Agnostic Supervised Local Explanations (MAPLE) [162] etc. LIME was modified and proposed as SurvLIME by Kovalev et al. [163]. Afterwards, they incorporated well-known Kolmogorov-Smirnov bounds to SurvLIME and proposed SurvLIME-KS [164]. Authors also utilised feature importance to generate numeric explanations in several research works [165]–[168]. Shapley Additive Explanations (SHAP) was proposed by Lundberg and Lee [169], and later it was used by several authors to generate mixed explanations containing numbers, texts and visualisations [170], [171].

Table 3. Methods for explainability for visual explanations with stage (Ah: Ante-hoc, Ph: Post-hoc), scope (L: local, G: global) of explainability, design spaces (P: Prediction, O/A: Optimisation/Automation, A: Analysis, M/S: Modelling/Simulation) and the type of AI/ML models used for performing the primary tasks.

Method For Explainability	AI/ML Model	References	Stage		Scope		Design Space			
			Ah	Ph	L	G	P	O/A	A	M/S
Anchors	Model Agnostic (MA)	[159]		X	X	X	X			
ANFIS	Fuzzy Model (FM), Genetic Algorithm (GA), Neural Network (NN)	[172]–[175]		X	X	X		X	X	
ApparentFlow-net	NN	[176]	X		X		X		X	
Attention Maps	NN	[177], [178]		X	X		X			
BB-BC IT2FLS	FM	[179]	X		X					X
BN	Bayesian Model (BM)	[180]	X		X				X	
CAM	NN	[156], [181]		X	X		X			X
Candlestick Plot	NN	[182]		X		X			X	
CIT2FS	FM	[183]	X		X			X		
DeconvNet	NN	[184]		X	X	X	X			
DTD	NN	[185]		X	X				X	
ELI5	MA	[160]		X	X	X			X	
Encoder-Decoder	NN	[186]	X		X		X			
ExNN	NN	[187]	X		X	X	X	X		
FACE	NN	[188]		X	X				X	
Feature Importance	MA	[165]–[168]		X	X	X	X			
FINGRAM	Tree-based Model (TM)	[189]	X		X		X		X	
FormuCaseViz	Case-Based Reasoning (CBR)	[190]		X	X				X	X
GLAS	MA	[191]		X	X		X			
Grad-CAM	NN	[175], [192], [193]		X	X		X			
HFS	FM	[194]	X		X	X		X		
iNNvestigate	NN	[195]		X	X	X	X			
Interpretable Filters	NN	[196]		X	X				X	
KSL	NN	[197]	X			X	X			
LGNN	NN	[198]	X			X	X			
LIME	MA	[160], [199]–[201]		X	X	X	X		X	

Linear Interpretability Probes	NN	[202]		X	X	X	X	X		
LPS	NN	[203]		X		X			X	
LRP	NN, Support Vector Machines (SVM)	[204]		X	X					X
MAPLE	MA	[162]		X	X	X	X			
MTDT	TM	[205]	X			X	X			
MWC, MWP	NN	[206]		X		X	X			X
Nilpotent Logic Operators	NN	[207]	X		X	X			X	
NMF	Ensemble Model (EM)	[196]		X	X				X	
pGrad-CAM	CBR	[208]		X	X		X			
Prescience	MA	[209]		X	X		X	X	X	
PRVC	CBR	[210]	X		X	X		X		X
RAVA	MA	[211]	X			X		X		X
RBIA	CBR	[212], [213]		X	X	X		X		
RetainVis	NN	[214]		X	X	X			X	
RuleMatrix	MA	[215]		X		X			X	X
SHAP	MA	[160], [169]–[171]		X	X	X	X		X	
Shapelet Tweaking	EM	[216]		X	X				X	
SRM	Rule-based Model (RM)	[217]			X	X		X	X	X
SurvLIME-KS	MA	[164]		X	X	X	X		X	
Time-varying Neighbourhood	NN	[218]		X	X					X
TreeExplainer	MA	[169]		X	X	X	X			X
Tripartite Graph	RM	[219]	X		X			X		

3.3 Overview and SotA on Visualization

Lastly, this section tries to address the third research question (RQ3). Visualization technics in ATM can be divided in two big families: i) Information Visualization (InfoVis), and ii) Visual Aalytics (VA), visualization to analyse, in this context is the traffic.

The first family in the following, regroup mostly all the work in ergonomics e.g., to seize how the colours influence the operators, assess the impact on the operator of the way information is displayed and mostly evaluate new ways to display information to Air Traffic Controllers (ATCos).

The second family regroups methods that help in extracting and understanding information from data by visualizing it, either i) from a unique and static visualization perspectives e.g., with dimension reduction, new way to visualize the data and, ii) by combining the visualisation with interactions techniques.

3.3.1 Visualization in ATM

Visualization is heavily used in ATM, in ATC where it is a critical tool. As a result, lot of work will assess how any visualization or changes in the visualization might change the ATCo perception of the airspace, trajectory behaviour, or its results.

As an example, visualization works focus on i) the way airplane present and past positions are displayed, e.g. by representing past movements by means of symbols showing the last 5-8 aircraft positions called the comet [220], or the rate at which this comet is refreshed [221], [222] , ii) the way notifications are displayed and designed [223] , for example change in aircraft parameters [224], iii) a visual support for conflict detection and resolution, for speed and heading [225], or for speed, heading, and altitude [226]–[229].

Immersive environments are also used in this domain, like virtual or mixed representation of the strips used by the controllers [230], virtual reality to represent the ATCo radar view[231] or, remote tower or related concepts [232]–[234].

This family stays at the edge of our interest for the ARTIMATION project. While we will keep in mind the different available visualizations, we will not review it more than this small presentation. The following section presents visual analytics techniques applied to ATM.

3.3.2 Visual Analytics in ATM

Thomas and Cook in [235] defines visual analytics (VA) as “the science of analytical reasoning facilitated by interactive visual interfaces. People use visual analytics tools and techniques to synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data; detect the expected and discover the unexpected; provide timely, defensible, and understandable assessments; and communicate assessment effectively for action”. This definition clearly emphasize on how visual analytics as a domain seems appropriate to be applied to explain artificial intelligence, in particular machine learning that generates lot of data, from the data set used to learn, to the result given by the system, passing by how the model it works internally.

In ATM, different VA methods have been used. Most of them focused on the visualization and the analysis of the trajectories and can be separated in two sub-categories: i) methods that try to represent all the data in a unique and static visualization, mostly by aggregating trajectories, and ii) methods that combine visualization and interaction to analysis the data. Nevertheless, both categories can be used jointly to explore the dataset and completement themselves. Additionally, both categories present methods using classical visualisation or interaction tools e.g., WIMP techniques (windows, icon, mouse, pointers) and methods using newest tools e.g., immersive environment or virtual reality.

‘Static’ Visual Analytic

Naive representations of the aircraft trajectory data rapidly suffer from cluttering, and providing unique static visualization of the trajectories may help the end user e.g., ATCos to understand different aspect of the traffic, like indicators e.g., extraction and representation of wind data [236] which may provide important information to him, or more general view of traffic partly or fully.

Among the general view of the traffic, aggregation of aircraft trajectories is widely represented and provide interesting insights about the traffic and its patterns [237]–[239] , like flight corridors and their usages in function of the circumstances e.g., weather conditions and supports measure for identifying air traffic complexity [240]. In particular, density maps have been well used to analysis aircraft trajectories, to simply summarise the traffic in an areas [241], [242] , potentially with detail and overview technics [237], [239], [243], eventually combined with other metrics such as conflict probabilities [244]. As an example, in [241], authors used density maps to aggregate flight direction of airplanes, density of airplanes, and more generally analyse local air traffic impact regarding noise, and violations of air traffic regulations. Temporal bundling of the trajectories i.e., bundling evolving with time, statical with different view of different time windows, or dynamically evolving with time for the visualization of trajectories have also been widely used on different large datasets [245] [246], [247]. This aggregation technique can also successfully add additional attributes while bundling the data, like the direction of the aircraft or time—hence not separating time windows— enhancing its value for ATCOs [248]. Aggregating trajectories based on their functional decomposition-–i.e., the decomposition of the trajectory with functions—has also proven to be effective with bundling [249]. In general, bundling and aggregation have proven to be effective to give insights about the traffic and will surely be used to explain decisions of AI systems on trajectories.

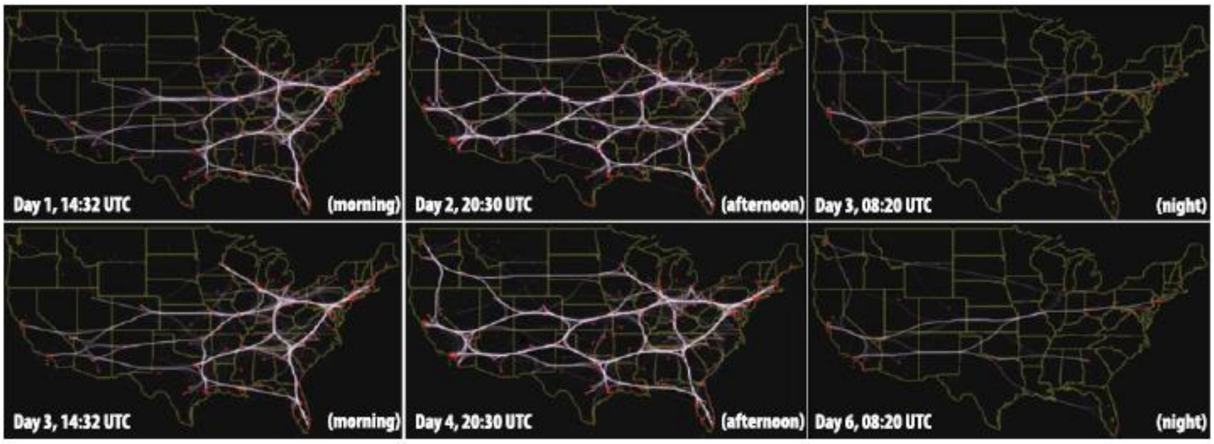
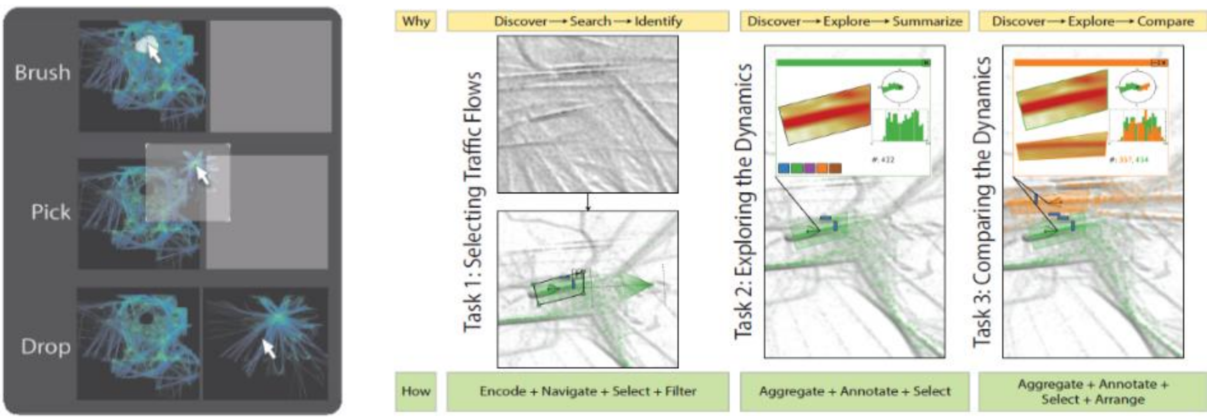


Figure 9: Trajectory Bundling with time window of a day of traffic in the USA Airspace **[245]**

Combining both aggregation and particle systems by using animations to visualize the direction of the movement provide a good trade-off between the aggregation and the representation of the complete dataset [250] [246], benefiting from the general overview, and keeping an aggregated information.

Interactive Visual Analytics

Interacting with the dataset through visualization is also a reliable way to explore and analyse data. It implies using techniques to encode e.g., labelling, colouring, select, annotate, and/or arrange the data in order to extract insights from the visualization. As an example, brushing, visual selection, and linking i.e., display the selected data in another view are effective ways to explore large number of trajectories [251]. The previous selection can be enhanced by adding new constraints to the selected data, such as direction range to better filter it, and can also be annotated to be compared with other annotated sub



(a) (b)

dataset [250]. Filtering can be performed using uniquely the trajectory data e.g., filtering trajectory by date [237], [238], [252], or associated with regulation rules [253].

Figure 10: (a) Brushing+Linking of trajectory data from **[251]**, (b) Boolean addition of different filters, annotation and comparison from **[250]**

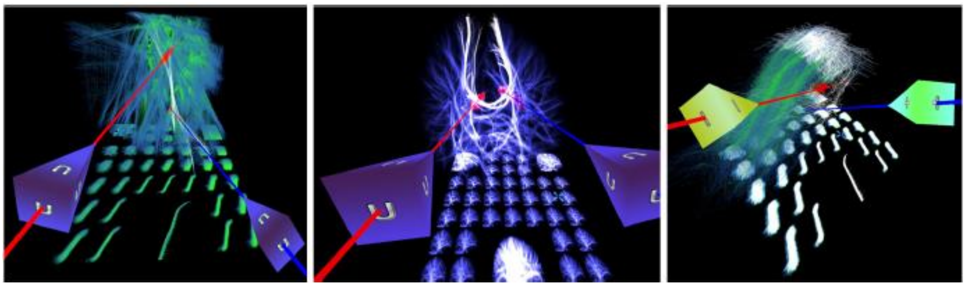
Finally, interaction and aggregation can also provide a powerful way to analyse aircraft trajectories. Density-based and graph-based techniques, as well as edge-bundling, have been combined with brushing+linking techniques [252], filtering [237], [238], and more complex interactive framework using analytical procedure for pairwise comparison of trajectories [242], [254]. Generally, aggregation allows to seize a general idea of the dataset, while interaction techniques allow to seize the nuances, and enhance the mind map one had of the dataset. Combining aggregation, filtering, brushing+linking technics have been quite effective to extract information from data and will surely be used to explain decision and process of AI systems on trajectories.

Immersive Visual Analytics

Virtual reality is also an interesting tool to visualise of aircraft trajectories, and corresponding data, such as weather information [255] e.g., wind speed, wind direction. Previously seen visualisation and interactions can benefit from Virtual Reality (VR), with the depth dimension, such as brushing and linking [256], filtering using 3D shapes [257], and combining interactions with reactive aggregation to explore statistical data of trajectories [258].

Nonetheless, Immersive analytics is not widely used in ATM, despite its promising uses in different domains [259], combining VR with touch input surfaces to support the analysis of medical images, analyse badminton trajectory data by combining VR brushing with a display of statistical data and using VR controller to support immersive filtering—using virtual stroke to select trajectories—, or hierarchical brushing+linking in augmented reality [260]. Further exploration of Immersive Visual Analytics to analysis trajectory data and explain AI decisions is very promising.

Figure 11. Immersive Visual Analytics tool: Fiber Clay **[256]**



4 Human-centered AI

Today's technologies are being developed with human centric. The purpose is to keep human in the loop. Now, humans can be integrated or kept in the loop in two ways. Lifelong Machine Learning (LML) and Human-centered AI.

4.1 Lifelong Machine Learning

The current trend of using ML is to train an ML model on a given dataset and then run that model for tasks like prediction, classification or clustering on a new dataset. If it requires updating the model with a new dataset, then the whole ML training process needs to carry out again. This paradigm is referred to as isolated learning since it does not consider any previously learned knowledge from the past model [261]. On the contrary, we human use previously learned knowledge to solve problems and to make a decision. The issue of isolated learning is that it does not retain, accumulate, and use past knowledge for future learning and decision-making as a human does. Lifelong machine learning (LML) is the learning paradigm that mimics the human learning process and capability, that is, using gained knowledge from previous tasks seamlessly in future learning and over time learning more and more to become more knowledgeable.

Definition of LML

LML is a continuous learning process. The general idea of LML is that a system has performed *n* tasks. When the system is doing (*n*+1)th task, it uses the knowledge obtained from the *n* task to complete the (*n*+1)th task. Here the system needs to accumulate the knowledge in a knowledge base and, when required, retain that knowledge from previous learning. We can define LML as follows:

Consider at a given time a learning is performed *n* sequence of learning tasks, T_1, T_2,….,T_n. These tasks are called previous tasks and each of them have corresponding datasets D_1, D_2,…, D_n. Here tasks can be same or different type and can come from same or different domains. The learner utilizes and takes the leverage of previous knowledge from the knowledge base (KB) when the learner has to solve a new or current task T_{n+1} with the new dataset D_{n+1}. The goal of LML is to optimize the performance on the new task T_{n+1}, but it can optimize on any task by treating the rest of the tasks as the previous tasks. KB maintains the knowledge learned and accumulated from learning the prior tasks. After completing learning T_{n+1}, KB is updated with the knowledge (e.g., intermediate and the final results) gained from learning T_{n+1}. The updating can involve consistency checking, reasoning, and meta mining of additional higher-level knowledge.

The key characteristics of a LML are:

- Should have continuous learning process
- Accumulation and maintenance of the knowledgebase
- Ability to use past knowledge in future learning
- Ability to discover new tasks
- Ability to learn while working on the task

Figure 12 shows a schematic architecture of a LML system that consist of six components, i.e., task manager, task-based knowledge miner, knowledge-based learner, Knowledge Base, model, and the application domain. The task manager is responsible for receiving and managing tasks in the system. Tasks can come sequential manner or can be discovered in the ATM application domain. The centre part of LML architecture is the Knowledge Base that stores previous knowledge learned by a machine learning algorithm. The learned knowledge can be the past information obtained from the learning, such as the outcome of a machine learning model, patterns identified from data etc. The knowledge base can also include meta-knowledge and meta knowledge miner that store suitable knowledge representation schemes. Here, the application is the ATM domain for which the model learns new knowledge and discover new tasks. The ATM application domain also sends feedback to the knowledge-based learner for future improvements of the LML model. Two other essential parts, i.e., task-based knowledge miner and knowledge-based learner, mine knowledge and continually update and improve the LML model utilising the knowledge base.

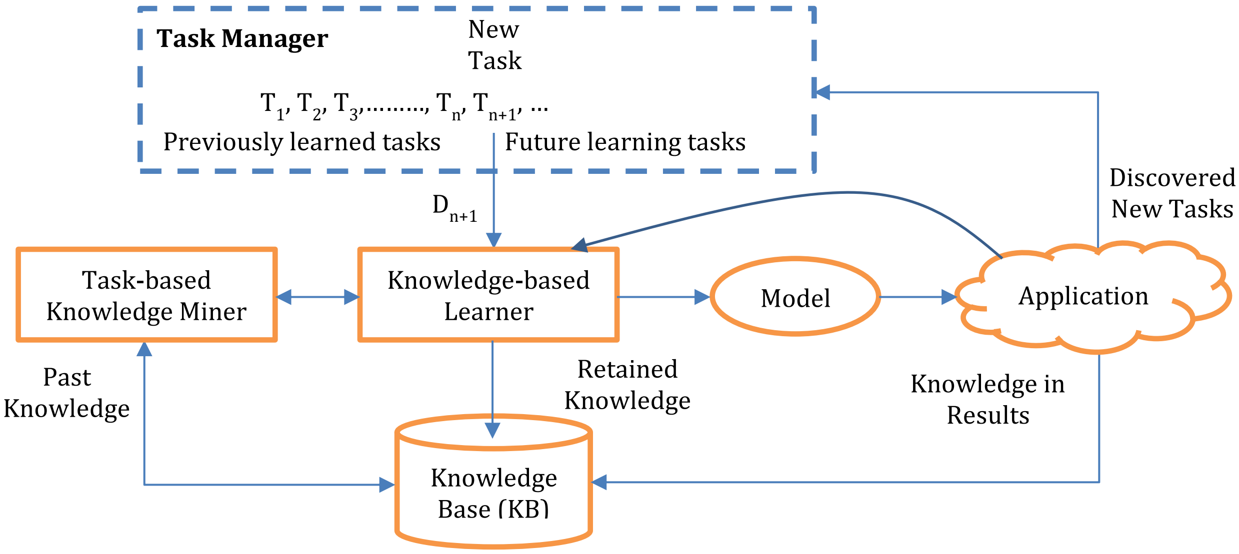


Figure 12. Lifelong Machine learning system Adapted from [261]

Approaches for LML

Traditionally in ML, a model is developed, tuned, and validated before deployment. Historical data is used and tested with some unseen data (test dataset) for generalization during the model development process. This approach is known as learning in isolation, and in the future, if it requires training the model again with a new dataset, the existing model forgets all the trained information. In LML, this problem of forgetting is known as catastrophic forgetting. New approaches to continuous learning have been proposed in recent years, but this research is still in its infancy. Some state-of-the-art models of Deep Learning and neural networks, to name a few, are Elastic Weight Consolidation (EWC), Learning without Forgetting (LwF), and progressive neural network. Many different approaches address catastrophic forgetting and try to imitate various aspects of how mammals' brains are behaving during learning. When a mammal learns a solution to a task, the synapse's plasticity between neurons is reduced [262]. That means connections between neurons are strengthened and the knowledge learned is more likely to be remembered by the brain. The human brain can also leverage the knowledge acquired for one task to improve other tasks' learning. There are solutions such as iCaRL (Incremental Classifier and Representational Learning) that instead directly try to deal with the problem, slowly adding classes over time [263]. iCaRL demonstrates a solution based partially on knowledge distillation, meaning it learns from a more extensive, already-trained network. Several approaches have been proposed for LML that are as follows:

Elastic Weight Consolidation

Inspired by how the human brain addresses continual learning, an approach named Elastic Weight Consolidation (EWC) was suggested by Kirkpatrick et al. [262]. The idea is to identify the weights and biases necessary for a specific task and constrain them not to change too much.

Learning without Forgetting

A method proposed by Li and Hoiem [264], Learning without Forgetting (LwF), uses the new tasks images during training to maintain the knowledge from the previous tasks. The network records the response for the new task's images using the old task and updates the weights in the network where it has a low impact on the old task predictions.

Progressive Neural Network

As Rusu et al. [5] suggested, a progressive neural network is an approach that leverages the previously gained knowledge, and it is immune to catastrophic forgetting. The idea is to add new columns of weights for different tasks so that the learned knowledge remains intact while the network learns another task, and the new task can draw benefit from the acquired knowledge. With the use of non-linear lateral connection adapters [265], they reduce the dimensionality from simply duplicating the network and in the case of dense layers, another option is used.

Grow-When-Required Network

Suggested by Parisi and Ji [266], the Grow-When-Required Network is a model that employs unsupervised learning and can adapt its size in term of neurons and connections depending on the need. They show results both in terms of utilizing less memory and having a more efficient network while still addressing catastrophic forgetting.

Online Lifelong and Continual Learning

Existing LMLs are mainly taking either batch learning or takes offline training and testing approach. They perform no learning after the learned model is deployed in its intended application, i.e., no learning while working on a task or the job. The problems and challenges of online LML are addressed by Liu, Bing [267]. Gautam et al. [268] has proposed continual learning for zero-shot learning (CZSL) that combines the concept of experience replay with knowledge distillation and regularization. The problem of catastrophic forgetting is overcome by utilizing knowledge distillation, where a model is trained with the sample's dark knowledge.

4.2 SotA on Human Centric AI model in ATM

AI is now increasingly entering the mainstream and supporting high consequence human decisions. However, the effectiveness of these systems will be limited by the machine's inability to explain its thoughts and actions to human users in these critical situations, and fully understand the needs and desire of the end-user.

The goal of human-centred AI is to improve the cooperation between the machine and its computing capacity, and the operator and his ability to adapt and make decisions, placing the human in the centre of the decision process, in other word, place back human-computer interactions (HCI) in XAI [269]. Creating such AI systems for the human by the human requires the end-user to be able to understand, trust, and interact with these algorithms, requiring many user-centred innovative algorithm visualizations, interfaces, and toolkits [161], [270], [271], [272], [273], making human-centric AI a cooperative [274], [275] and continuous [276] process. Enabling the human to understand the machine has been the primary focus of explainability in the last decade. Nonetheless, developed XAI systems are more directed to the developer or the debugger than the final end-user [1]. Although some are focused on explanation that might be presented to non-developer [161], [277]. Little justification is provided for choosing different explanation types or representations, and it is unclear why these explanations will be feasibly useful to actual users or simply understood [278]. Because some researchers argue against [152] it. Already existing formal psychological theories which are greatly summarized for XAI in [279], [280], [281], [282], are poorly used to guide explanations facilities, as argued in [1], [283]. The last concern is essential to move towards human-centric AI since it is essential to understand how humans think and also being able to adapt to different ways of thinking. As a second or parallel step can be to to understand what information they seek, and what are their biases that impair their reasoning, in order to [283] understand what reasoning method trigger actual XAI facilities, and how can XAI can be leveraged to mitigate decision biases.

Furthermore, explanation is both a product and a process, in particular a social process [284]. XAI systems require to fully understand the user, which means to adapt to the one that receive the explanation [283], [285]. This is crucial to determine the explanation requirements for a given problem, and understand the ‘why’ behind actions of the user [269]. Furthermore, understanding is rquired to adapt to its socio-technical environment since the AI user will interact with other humans outside of the 1-1 human-computer interaction, and thus trust should be transitive to them [286]. Lastly, the systems also needs to understand the user to be able to interact with the user, which here is beneficial in both ways, i.e., human understanding the machine and machine understanding the human. In order to adapt while the XAI systems is in use and not only during the development process to enhance the explainability, adapt to the user and possibly provide information which is not about the internal state of the AI system [287].

4.3 SotA on Cognitive Human-AI-Interaction Interfaces in ATM

Indeed in the ATC system, the controller’s work is highly cognitively demanding. Activities for managing air traffic, such as solving conflicts, maintaining separation between aircraft and coordinating air traffic, involve cognitive processes such as visual scanning, information processing, decision making, and attention. In this panorama, technologies and techniques based on the analysis of neurophysiological signals [e.g., the electroencephalogram (EEG), the galvanic skin response (GSR), etc.] have the potential of providing reliable information about operators’ internal state (namely neurometrics) [288], and understanding. For example, if the operator’s workload is exceeding his/her cognitive capacity, or if some kind of incapacitation is occurring, the neurophysiological signals can identify them. In this regard, neurometrics related to the operator’s internal states become a necessary information to realize a so called Cognitive-HMI (C-HMI, i.e. machine trust in the human). A Cognitive-HMI is one which automatically adapts the information displayed and functions available based on an assessment of operator cognitive state and environmental conditions. The system may also use this assessment to execute actions autonomously along an escalating scale of automation (i.e. adaptive automation, [289]).

The concept of adaptive automation goes beyond traditional modes of human–computer interaction. It entails that the system receives information on the operators’ physical and cognitive status, to then adapt its behavior. Examples of such application are the following:

- interface changes to reduce visual clutter (e.g., filtering nonrelevant flights), or to ease visual scanning tasks (e.g., increasing salience of alarms);

- changes to interaction modalities to support hand-free operations or to offload the visual channel (e.g., haptic or aural feedback would be typical cases);
- shifts in the processing logic for data filtering or decision support, e.g., moving to a less conservative detection logic to reduce the number of nonrelevant alerts being displayed.

In recent years, several neuroergonomic systems, which use neurophysiological measures to trigger changes in the state of automation, have been studied and their impact on operators' performance has been analyzed [290]. Pieces of evidence show that people not only think of adaptive systems as "co-workers," but also expect them to behave like humans. Despite its potential advantages, AA also holds a potential pitfall. The dynamic behavior changes of adaptive systems make it more complex and less predictable for the user. Situations in which users are surprised and confused by "*what is the system doing?*" must be minimized. In this regard, trust in automation is a long-standing issue in ATM. EUROCONTROL investigated conflict resolution assistants/advisories nearly 20 years ago [291], and they never achieved acceptance by air traffic controllers, with some early lessons discernible [292]. These and earlier studies highlight the need to consider the opinion of the end user. Some lessons can be learned from flight deck automation, most notably the introduction of first generation of glass cockpits [293]. The concept of AA may hence need to be revisited or fine-tuned, to increase the operator acceptance. It may be that an intermediate stepping stone is needed, such as adaptable automation. In this scenario, the user can trigger advanced automation at her/his discretion, avoiding confusion and retaining the sensation of being in control. Users could also regain control if things go wrong, and the automation can no longer cope with the situation. In this context, the research contribution of neurometrics could address the following two important issues:

1. Neurometrics could define the thresholds by which to activate the transitions between the automation levels (lower or higher than the previous one). Thresholds may be binary (ON–OFF), or more accurate along larger time windows, to avoid continuous transitions, and to consider cumulative effects. For instance, a medium–high workload level lasting for several minutes could trigger the same transition as a very high workload peak. Similarly, after a sustained period of work with high automation, the same level could be maintained for some time, even with low workload to ease recovery.
2. Neurometrics could provide scientific validation of the AA effectiveness, for instance by showing an actual workload decreasing after the AA intervention.

Byrne and Parasuraman [294] assessed that the advantage of applying neurometrics in triggering AA was very clear, but the "effective application of psychophysiology in the regulatory role may require years of effort and considerable maturation in technology". Nowadays, 25 years later, such "effective application" could become reality due to the progresses in Brain-Computer Interfaces (BCI) research. Briefly, a BCI is defined as "a system that measures Central Nervous System (CNS) activity and converts it into artificial output that replaces, restores, enhances or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment" [295]. Such definition summarizes the progresses of the scientific community in this field during the last decades, since at the moment the possibility of using the BCI systems outside the laboratories by developing applications in everyday life is not just a theory but a potential reality [296]. This technology has been defined as passive Brain-Computer Interface (pBCI). In particular, in pBCI technologies, the system recognizes the spontaneous brain activity of the user related to the considered mental state (e.g., emotional state, workload, attention levels), and uses such information to improve and modulate the interaction between the operator and the system itself. Thus, in the context of AA, the pBCIs (or in other words C-HMI) perfectly match the needs of the system in terms of Human-Machine Interaction [297]. Example of C-HMI has been provided by Aricò and colleagues in the framework of the project NINA [298], realizing an AA system based on a continuous and online measure of an EEG-based workload index experienced by operator. Authors demonstrated the effectiveness of the AA system in mitigating overload situation, and so to enhance ATCOs performance. In another work, within the context of the MINIMA project, Di Flumeri and colleagues demonstrated how a similar system, based instead on the online measure of EEG-based vigilance could be used to prevent out-of-the-loop phenomenon, during the ATM control of futuristic interfaces [299], [300]. Also, Borghini and colleagues, within the framework of STRESS project, demonstrated the possibility to measure even online the stress of ATCOs during operational tasks, and how to employ this measure to enhance the human performance envelop of operators [301], [302].

As a conclusion, it has to be underlined that Neurometrics, employed in the framework of Cognitive-HMI for ATM, could not only provide machine for determining whether the human is still performing within acceptable parameters, before adjusting variable autonomy (i.e. machine trust in the human), but also if he/she is accepting the machine's XAI explanation, before adapting that explanation if needed (i.e. human trust in the machine).

5 Discussion

For the ARTIMATION project, this SotA identified the potential ATM tasks where AI and XAI are needed, for example, Take-off Time Prediction, Delay Propagation, and/or Conflict Avoidance. Based on the data availability and feasibility, the project can decide an area of the ATM task to be investigated. While studying the transparency in AI algorithms in ATM this report considers: 1) SotA on AI/ML in ATM, 2) a general explainability in AI/ML, and 3) SotA on Visualization. In the SotA on AI/ML in ATM, the study found 4 sub-groups in the design space of AI/ML in ATM, and they are: predication, optimization/automation, analysis, and modeling/simulation. These are the selection criteria set for the algorithms. Basing bon them, the algorithms are selected that best suits the purposes. The study considers the last 10 years of related publications, however, most of the publications are observed between the years 2014 and 2021, where prediction and optimization/automation are the most frequent ATM tasks that implement AI/ML algorithms. The study found a list of AI/ML algorithms that have been applied in the ATM domain recently. Among them i) Multi-Agent Systems (MAS), ii) Neural Network (NN), iii) Random Forest (RF), iv) Gradient Boosting Machine (GBM), v) Support Vector Machine (SVM), and vi) Linear Regression are used frequently for prediction purpose. On the other hand, for the optimization i) Multi-Agent Systems (MAS), ii) Evolutionary Algorithm (EA), mostly genetic algorithms, and iii) Simulated Annealing (SA) are considered and a majority of these works focus on optimizing the traffic and/or avoiding collisions, from the point of view of the trajectories. Thus, the mentioned algorithms will be considered as the most potential for the ARTIMATION project. At the same time, while studying explainability in AI/ML, a list of different algorithms is observed that can be used for explainability, e.g., SHAP, LIME, Grad-CAM, ANFIS, etc. However, these algorithms haven't been used for the ATM domain or at least not found in the recent publication yet to the best of our knowledge.

For the ARTIMATION project, to make the AI/ML algorithm more transparent and explainable, the study also identified different techniques for visualization, it can be either i) from a unique and static visualization perspectives e.g., with dimension reduction, new way to visualize the data and, ii) by combining the visualisation with interactions techniques. Immersive environments are also used in this domain, like virtual or mixed representation. Visual analytics is another potential to be considered, such as 'Static' Visual Analytic, Interactive Visual Analytics, and/or Immersive Visual Analytics. Based on the data set availability, the complexity of the task, and the level of transparency ARTIMATION road map will decide what algorithm should be used.

ARTIMATION project also considers human-centered AI, that is human and AI system can learn from each other through human-computer interactions (HCI) implement in XAI system to understand, trust, and interact with these algorithms, requiring many user-centred innovative algorithm visualizations, interfaces, and toolkits. This study also investigates the potential algorithms for life-long machine learning e.g., Elastic Weight Consolidation (EWC), Learning without Forgetting (LwF), and progressive neural network. Again, Cognitive-HMI (C-HMI, i.e., machine trust in the human) is identified for the project as it automatically adapts the information displayed and functions available based on an assessment of operator cognitive state and environmental conditions. Thus, this report will help the ARTIMATION from an overall perspective, i.e., the report will work as the foundational knowledge for the direction/roadmap of the development of XAI system in ATM.

So, the state-of-the-art report will be used for the ARTIMATION project as:

- We have studied several ATM tasks as potential where AI and ML will be developed with explanation. For example, Delay Propagation and Conflict Avoidance is considered as ATM tasks in ARTIMATION.
- As per the above mentioned several AI/ML algorithms listed in the ATM domain and for ARTIMATION, Decision Tree and Random Forest is selected.
- For explanation in AI part, SHAP, LIME, and ANFIS are selected for the ARTIMATION project.
- For ARTIMATION, the level of transparency will be provided based on Visual analytics, such as 'Static' Visual Analytic, Interactive Visual Analytics, and/or Immersive Visual Analytics.
- Lifelong Machine Learning in ARTIMATION will consider Elastic Weight Consolidation (EWC), Learning without Forgetting (LwF), and progressive neural network.

Above mentioned bullet points are the potential algorithm techniques which will be inputted in Task 3.2 and Task 3.3. In this task, further workshops will be conducted where ATM experts and AI experts will be involved. Based on the results from the workshop, a roadmap will be created which will be presented through Deliverable 3.2. This roadmap will be followed till the end of the project.

6 Conclusions

One of the main goals of this WP is to define the specifications regarding AI-based solutions employment in the ATM field and related support in operational activities based on a state of the art (SotA) studies on AI solutions characteristics, together with weaknesses of the current solutions. The report presents a general background with related work in the ATM domain where several related ongoing/finished projects in the ATM domain are addresses. To identify AI transparency in ATM, first, a state of the art of AI/ML algorithms in the ATM domain is analysed. The state-of-the-art provides specific ML/AI algorithms that are analysed here. Then an overview of AI/ML and their explainability is provided. Again, a state-of-the-art study on different visualization technics and approaches in the ATM domain are given. Finally, an overview on lifelong machine learning with human-centered AI is presented where a SotA on human centric AI model development and a SotA on cognitive human-AI-interaction interfaces in the ATM domain is presented. Several other issues in ATM are identified that can be solved by AI in the future.

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