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Machine Learning Applications in the Aeronautical Field: A Review

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Author: **Marco Antonio John Funaro**

Student ID: 945114
Advisor: Prof. Stefano Cacciola
Co-advisors: Name Surname, Name Surname
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Abstract

Thanks to the huge availability of data in the aeronautical sector, combined with the increasing computational capabilities of modern computers, Machine Learning (ML) has become a transformative tool for aerospace engineering applications. This thesis presents a structured review of Machine Learning methodologies and their applications within the aeronautical field, in particular in the fields of Aerodynamic Modeling, Safety Analysis, Uncertainty Analysis, Air Traffic Controland Management, Unmanned Aerial Vehicles (UAVs) and other. After a brief introduction on the fundaments of ML, the methods used, the work examines key computational models that are used in the reviewed articles. Their theoretical foundations are discussed to provide the necessary framework for understanding aeronautical applications. In Aerodynamic Modeling, ML models significantly reduce the computational burden associated with CFD simulations while maintaining acceptable accuracy. In Safety and Health and Usage Monitoring Systems (HUMS), data-driven anomaly detection methods demonstrate superior capability in identifying latent faults and operational risks compared to traditional threshold-based systems. ML approaches to Uncertainty Analysis improve computational efficiency in nonlinear structural and aerodynamic problems while preserving reliability. Applications in Maneuvering, Flight Phase Recognition, and Air Traffic Control show an enhance trajectory prediction, fuel optimization, and Estimated Time of Arrival (ETA) forecasting. Furthermore, UAV-related applications highlight the role of ML in autonomous navigation, swarm coordination,and energy management. Finally, various applications are reported, including some military oriented methods. Overall, this work demonstrates that Machine Learning techniques offer computational efficiency, adaptability, and improved decision-support capabilities.

Keywords: Machine Learning, Aeronautical Engineering, Neural Networks, Deep Learning, Aerodynamics, Safety Monitoring, Air Traffic Management, UAV, Uncertainty

Abstract in lingua italiana

Grazie alla grande disponibilità di dati, combinata con l'aumento delle capacità di elaborazione dei computer moderni, l'utilizzo del Machine Learning (ML) è sempre più diffuso ed efficace nel settore dell'ingengeria aeronautica. Questa tesi presenta un'analisi strutturata delle metodologie di Machine Learning e delle loro applicazioni, in particolare nei campi dell'aerodinamica, dell'analisi della sicurezza, dell'analisi dell'incertezza, del controllo e della gestione del traffico aereo, degli Aeromobile a Pilotaggio Remoto (APR) e altri. Dopo una breve introduzione sulle nozioni base del ML, esaminiamo alcuni dei modelli computazionali che vengono utilizzati negli articoli esaminati. Viene spiegato il principio di funzionamento base per fornire il necessario quadro concettuale utile a comprendere le applicazioni aeronautiche presenti nei capitoli seguenti. Per quanto riguarda l'aerodinamica, i modelli ML riducono significativamente il costo computazionale associato alle simulazioni CFD, mantenendo un livello di accuratezza accettabile. In ambito di Safety and Health and Usage Monitoring Systems (HUMS), i metodi di rilevazione delle anomalie data-driven hanno dimostrato di riuscire ad identificare i guasti latenti e i rischi operativi rispetto meglio dei sistemi tradizionali basati sul superamento delle soglie. Le tecniche di Machine Learning per l'analisi dellle incertezze migliorano l'efficienza computazionale nei problemi strutturali e aerodinamici in cui sono presenti nonlinearità, mantenendo però l'affidabilità. Le applicazioni nell'ambito delle manovre, della fase di volo e del controllo del traffico aereo mostrano il miglioramento della previsione delle traiettorie, l'ottimizzazione del consumo di carburante e la previsione del Estimated Time of Arrival (ETA). Inoltre, le applicazioni relative agli APR mettono in risalto il ruolo del ML nella navigazione autonoma, nella coordinzione dello stormo, e nella gestione dell'energia. Infine, vengono riportate varie applicazioni, incluse alcune in ambito militare. In conclusione, questo lavoro dimostra che le tecniche di ML offrono milioramenti in efficienza computazionale, adattabilità e capacità di supporto decisionale.

Parole chiave: Machine Learning, Ingegneria Aeronautica, Reti Neurali, Deep Learning, Aerodinamica, Safety Monitoring, Gestione del Traffico Aereo, APR, Incertezze

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Introduction

The term "Artificial Intelligence" (AI) is nowadays widely recognised, also associated with the futuristic visions of autonomous robots, vehicles or aircraft, and human-like machines; yet the concept extends beyond mere familiarity. It is evident in many tangible applications that have become integral to our daily lives in devices such as smartphones and computers. Although we are still far from the AI portrayed in science fiction books or films, in the past century, significant progresses have been made to create a sentient machine, and this topic remains of interest. Generally, if we think about AI, we think about robots or software capable of mimicking human behaviour with precision, and engaging in arbitrary conversations at a level comparable to that of humans.
Despite the existence of high-level AIs available for everyone, these systems still seem far from resembling human interactions, and our expectations of them being flawless when providing information are disappointed. These issues have the potential to produce widespread scepticism with regard to the application of Artificial Intelligence in specific and safety-critical situations.
The European Commission's definition of Artificial Intelligence is as follows:
Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals.
AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications).[10]
Among the various branches of AI, Machine Learning (ML) has become widely used thanks to its adaptability to a wide variety of problems and its learning directly from the supplied data, without the need for external intervention, such as additional coding. In the engineering field, ML has demonstrated considerable potential with numerous applications of its models; therefore, it is beneficial to delve into it and its various methods before approaching some of the applications that have been studied for the aeronautical field.

1 | Machine Learning

Before diving into the Aeronautical Engineering-specific applications, it is useful to explain the different methods that are mainly used. So in this chapter, I'll introduce some concepts about Machine Learning that will be useful for the following chapters.
The methods used in ML are applied in different areas of knowledge: computer vision, speech recognition and natural language processing, automation, financial analysis, model prediction, predictive maintencance and so on. The baseline for ML is to learn from a huge amount of acquired data and extrapolate a model to use to adapt to or predict future situations. These algorithms are based on the mathematical concept of optimisation applied in different ways. Modern aircraft produce a huge amount of data in a very short period of time and from different sources, thus allowing ML algorithms to gain popularity in the aeronautical field to improve the performance of different systems and also their use. The sources of these data are, among others, Flight Data Monitoring (FDM) systems, Aircraft Health Monitoring Systems (AHMS), Automatic Dependent Surveillance - Broadcast (ADS-B), simulation outputs and the huge amount of sensors spread all over the aircraft.
To simulate the dynamic behaviour of aircrafts it is required to solve complex, nonlinear and high-dimensional problems. Even though the computational power of modern computers keeps increasing, maintaining a simpler hardware setup is cost-saving. Another advantage of ML approaches is their ability to reduce the computational effort for the solution of such problems.
Applications are different: aerodynamic modelling, structural health monitoring, predictive maintenance, flight control optimisation, air traffic management, fault detection, and autonomous navigation systems. ML techniques, therefore, can be used to enhance performance and efficiency, increase the safety in the use of an aircraft and reach the goal of sustainability in aviation systems.

1.1. Methods

In this section I'll briefly explain how ML can be classified based on different training methods. Then, in *chapter 1.2* NEURAL NETWORKS I'll explain some of the computational models that are used and that I'll cite later in the thesis.
The methods used in Machine Learning are several; we'll focus only on some that are mentioned in the following chapters. These methods are divided into different categories based on the learning model they use[42]:

- Supervised Learning
- Unsupervised Learning
- Semi-Supervised Learning
- Reinforcement Learning
- Meta Learning

1.1.1. Supervised Learning

The Supervised Learning method starts by teaching the machine (algorithm) using a given set of data points and the correct answers to the questions they correspond to. If we can teach the learning algorithm with a sufficiently large set of data points with the corresponding answers, then the algorithm will be able to learn the main characteristics for each data point; this means that the next time a new data point is provided, the machine should be able to give the correct answer.
A practical example that we can experiment on our smartphones is related to the possibility of identifying objects inside pictures: the algorithms used by the applications are given thousands of pictures, with the right answer for each picture (e.g. the image is of a dog, cat, car, airplane, etc.), hence giving a label to the picture. In this way, the machine learns the characteristics within these pictures and will be able to identify the content of each picture.

1.1.2. Unsupervised Learning

Similar to the Supervised method, in the Unsupervised Learning method, the machine is provided with a set of data, but it is not provided with any right answer. The algorithm will identify the main characteristics of the data points without knowing what those points mean. If we want to use the previous example, the algorithm might be able to tell a car from a plane, but wouldn't be able to identify them respectively as "car" or "plane".

1.1.3. Semi-Supervised Learning

The Semi-supervised Learning method has both the characteristics of the Supervised and the Unsupervised methods. Like in the Supervised, we give labelled data points to the machine, but this time the dataset also contains some data points that are not labelled. The algorithm will use Unsupervised Learning techniques to identify groups within the given dataset; the labelled data points will be used to provide labels to the other data points that have the same key characteristics but are not initially provided with a label. This technique allows to reduce the time spent classifying all the data points because we could create a template dataset that could be used by the algorithm to identify future data points.

1.1.4. Reinforcement Learning

The Reinforcement Learning method is the one that takes into account the variation of the external conditions as well as those scenarios with huge possible situations, for example, the algorithm of the chess game. Just like humans, the machine requires a longer learning time to understand the long-term impact of its decisions and benefits.

1.1.5. Meta Learning

The Meta Learning method is focuses on improving the learning process itself rather than solving a single fixed task. Instead of creating a model for one specific dataset, this method is used to create model that can adapt to new and different tasks using limited and unlabled data. The knowledge is extracted from multiple related tasks during the learning phase, allowing to create a model for the learning phase itself. A Meta Learning algorithm can also select hyperparameters or learning optimisation strategies. (See *chapter 1.2.1* TRAINING)

1.2. Neural Networks

We have seen the different methods that are usually applied to differentiate the Machine Learnings algorithms, but it is also useful to understand how these algorithms are made and how they act. For this reason, in this chapter I'm going to talk about the Artificial Neural Networks (ANNs), also called Multilayer Perceptrons, which are the structures that may be used in these algorithms. The Neural Networks are networks of interconnected artificial neurons, inspired by an old idea of how those in the human brain work, arrange in layers and that are generally used to create Supervised Learning models but sometimes are also used in Unsupervised Learning for dimensionality reduction [42]. The layers are divided in: input layer, one or more hiddel layers and an output layer. To understand better how this work it's better to compare the functionalities of a real neuron to a node of the Neural Network:

• Neurons input may come from other neurons or from the external world, they are connected to each other via synapses, which allow them to transfer the signal amplified by the strength of the synapses that carry it, which may vary over time if the brain is learning new experiences.

• In the Neural Networks the output of the neurons, which are nodes that perform non-linear operations, is weighted before being sent to the next nodes, and both the external input and output are a fixed set, both being real numbers. The way a Neural Network works might be by adjusting the weights of the interconnections based on the behaviour of several input/output examples.

1.2.1. Training

The characteristics of a Neural Network, such as the number of layers in which the nodes are situated, the function that connects the nodes..., are chosen at the beginning of the training and are called hyperparameters. The training then consists in a loop that automatically fixes the weights to meet a desired value of the cost function. This is similar to Gradient Descent algorithm but the solution for the weights in closed form is not known.

1.2.2. Deep Learning

Depending on the number of hidden layers and the architectural design, Neural Networks may range from shallow models with limited representational capacity to deep neural networks capable of hierarchical feature extraction. Thanks to the increased computational power, Deep learning is widely used nowadays for speech recognition, image processing, language translation, and many others, thanks to its capability of extracting hidden feature in the submitted data.

Convolutional Neural Network

Convolutional Neural Network (CNN) methods rely on the convolution technique, which is a mathematical technique used to extract significant features needed to identify the target classes. This method is used for different applications such as image recognition, handwriting reading or reading the street signs. This technique is design to process data with a grid-like structure and applies filters to local regions to detect if the data analized is similar to the ground truth or not.

Recurrent Neural Network

Recurrent Neural Networks (RNNs) models are best suited for processing a sequence of data that has repetitive properties. Examples of sequence data are the base pairs in the human chromosomes or a word pertinent with the meaning of the sentence it is included into. Continuing the example of words, in Natural Language Processing (NLP), a simple NN would make mistakes because it has no "memory" of the other word in the sentence, instead, a RNN model would remember the context of the other words and recognize correctly the meaning of an ambiguous one based on the context.

Long Short-Term Memory

Long short-term memory (LSTM) networks tackle the problem of long-term dependency modeling in RNNs while elaborating time-dependent data and mitigating the vanishing and exploding gradient problems. These result is obtained controlling the influence of past data on the present retaining or ignoring information after a certain amount of time. This means that this method can be used both for long and short term dependencies on the provided data, making it particularly useful for NLP problems, speech recognition, sentence forecasting and suggestion.

Physics-Informed Neural Networks

Physics-Informed Neural Networks (PINNs) are a class of neural network models that incorporate prior physical knowledge directly into the learning process. This model is provided with governing equations to ensure that some physical laws are satisfied in the output model, usually expressed as partial differential equations into the loss function. If during the training the model deviates from the imposed physical constraints, the loss function penalizes this behaviour It is clear that the granted physical consistency intrinsic in this model makes it suitable for engineering applications.

1.3. Support Vector Machines

Support Vector Machines (SVMs) are supervised machine learning algorithms used also before the advent of the Deep Learning techniques. These algorithms are used for classification and regression tasks. The underlying idea is to maximise the margin between distinct classes in the feature space until a predetermined threshold is reached. The support vectors are a subset of training samples, thanks to them this method ensures robustness and computational efficiency.

1.4. Heuristic Search

Even though Heuristic Search cannot be considered Machine Learning, it is still an Artificial Intelligence method and I decided to include it in this work. The aim of this method is to explore large solution spaces by using informed strategies to guide the search process. To reduce computational effort, only the most promissing paths are explored with Heuristic Search, still implementing cost functions. These methods are widely applied in planning, scheduling, pathfinding, and optimization problems, and can also be integrated with machine learning techniques to enhance adaptability and performance in complex decision-making environments.

2 | Aerodynamic Model

The accurate prediction of aerodynamic characteristics has always represented a central challenge in aeronautical engineering. From airfoil analysis to full aircraft modelling across the entire flight envelope, the computation of lift, drag, pressure distributions, and stability derivatives plays a fundamental role in design, optimisation, and control. Traditionally, these quantities are obtained through wind tunnel experiments or high-fidelity Computational Fluid Dynamics (CFD) simulations. While highly reliable, such approaches are often computationally expensive, time-consuming, and difficult to integrate into iterative design or real-time applications.

In recent years, machine learning techniques—particularly artificial neural networks—have emerged as powerful surrogate modelling tools capable of approximating complex aerodynamic relationships with significantly reduced computational cost. By learning from real-world and simulations collected data, neural networks can provide fast predictions while maintaining acceptable levels of accuracy. This capability is especially relevant in optimisation loops, flight control design, and real-time simulation environments, where repeated evaluations of aerodynamic models are required.

The majority of recent research efforts have focused on airfoil and wing modelling, addressing objectives such as drag reduction, lift enhancement, pressure distribution reconstruction, and performance prediction across varying Reynolds numbers and Mach regimes. Furthermore, hybrid approaches combining experimental and computational data, Bayesian hyperparameter optimisation strategies, physics-based architectures, and adaptive sampling techniques have been proposed to improve accuracy and generalisation. This chapter reviews selected contributions in this area, highlighting different methodological approaches, performance outcomes, and the evolving role of neural networks as surrogate models for aerodynamic analysis and aircraft performance prediction.

2.1. Aerodynamic Model

A significant portion of the literature focuses on airfoil modelling, where the objective is typically the prediction of lift and drag coefficients or surface pressure distributions.
In the field of aircraft modelling, there exists a range of objectives that must be considered. One of these objectives, relevant to the domain of transport aviation, is the reduction of the overall drag coefficient in order to enhance fuel efficiency. Another objective, pertinent to the domain of manoeuvrability, is the improvement of the lift coefficient. The utilisation of conventional CFD models to compute the outcomes is a rather time-consuming process that demands a high computational effort. Consequently, the employment of a neural network may facilitate the identification of a more optimal solution for the aerodynamic coefficients of the wings, thereby enabling the reduction of both the time required to reach the solution and the computational effort demanded by the computer.
To address the computational effort of the CFD computations, Jianbo Zhou [62] proposes a novel Multilayer Perceptron (MLP), which, as said in *Chapter 1.2*, is an ANN. Using a feed-forward Neural Network, this model eliminates the preprocessing steps both in training and prediction, with the aim of enhancing prediction accuracy. This model takes airfoil coordinates and flow field conditions as input and gives the lift coefficients as outputs. Clearly, the gain of complexity reduction due to dimensionality reduction of the airfoil coordinates needs to be balanced with the loss of information and predictive capabilities. Compared to previous CNN models the training time is reduced by only 2% but the prediction time is reduced by a significant 54%. Furthermore, performance is enhanced by introducing regularisation terms into the loss function, paying attention not to excessively increase the regularisation strength, which may induce model underfitting.
The use of wind tunnels plays an important role in modelling an aircraft, but it's quite expensive; an alternative could be the use of CFD, with the issues that I just addressed. Kai Li proposes a combined method in his article [28], which merges experimental (high-fidelity) and computational (low-fidelity) aerodynamic data. He used a Deep Neural Network to compute the aerodynamic pressure distribution on the surface of a transonic wing, using both numerical and experimental data in the loss function with proper weighting factors. Results predicted high-fidelity accurately at varying Mach numbers and angles of attack across different wing sections. Although his model still needs to rely on a few wing tunnel data in the training, it can accurately predict the pressure distribution in a transonic wing, and he reported the results with respect to other Deep Neural Networks that rely only on a single fidelity training, showing a higher accuracy.
The use of Reynolds–averaged Navier–Stokes (RANS) equations for numerical load analysis or optimisation of aerodynamic components is nowadays common, but reliable solu-

tions are computationally demanding. Christian Sabater [43] proposes another method to reduce the computational time to compute the pressure distribution on an aircraft. He proposes a Deep Learning method that employs Bayesian optimisation techniques to determine optimal hyperparameters. Specifically, three data-driven methods are investigated: Gaussian processes, proper orthogonal decomposition combined with an interpolation technique, and Deep Learning. The Gaussian process regression is the method with fewer modelling assumptions, suitable for airfoil prediction, but not ideal for 3D modelling. The proper orthogonal decomposition, combined with an interpolation technique, can accurately predict pressure distributions when there aren't any strong local nonlinearities, such as shock of flow separations. The Deep Neural Network-based model obtains good predictions even in the presence of strong local effects, at the cost of a higher computational effort in the training phase, related to hyperparameter optimisation. Results show how the DNN outperforms other data-driven methods both in subsonic conditions and when the nonlinearities show up in the transonic flow. In the transonic case, it is capable of capturing the shock wave location and strength accurately. An interesting aspect of all the models is the possibility to evaluate them in near-real time, allowing to obtain highly accurate aerodynamic data in time-critical tasks.

Aiming to reduce the time required by the CFD simulations, in 2017 Emre Yilmaz [58] proposed a Supervised Learning method that predicted airfoil performance given its geometry. Thanks to the automatic feature detection capability of Deep Networks, unstructured data is analysed, allowing the avoidance of the limitations of particular geometric parameterisations. Subsequently, the Supervised Learning problem is formulated to predict the airfoil performance. Results show that the CNN reaches more than 80% validation accuracy for the predictive capability of this method.

Xiaosong Du [14] shows another way to reduce the design time with respect to a conventional CFD-based optimisation method, realising it in a matter of seconds. In this paper, a combination of multilayer perceptron, recurrent neural networks, and a mixture of experts for surrogate modelling is used to predict both the scalar value of lift and drag coefficients as well as the vectorial pressure distribution over a range of velocities and Reynolds numbers. Unrealistic airfoils are filtered out by a B-spline-based generative adversarial network model for shape parameterisation. Multilayer Perceptron (MLP) surrogate models are used to predict drag and lift coefficients, while Long Short-Term Memory (LSTM) models are used to predict the pressure coefficient distribution for richer design information. The strength of this method is that it allows to obtain an optimal design close to the one with CFD models in subsonic and transonic conditions, only requiring a few seconds to compute all the forces and coefficients. Finally, the proposed method is integrated into a web-based interactive aerodynamic design framework, allowing users to

obtain optimal airfoil shapes for a range of flow conditions in seconds.
In a similar way, Kensley Balla in his work [5] shows a NN for the prediction of aerodynamic coefficients in two dimensions and for wings in three dimensions, using inviscid compressible data from a vertex-centred CFD solver. The output of his NN is the pressure in some selected points on the aerodynamic shape and the accuracy is shown to be higher with respct to the case of aerodynamic coefficients prediction. In addition, the method is compared with a traditional proper orthogonal decomposition method to show the increased performances, specially when the flows presents a shock. Also the influence of the accuracy of the CFD data used for the prediction is studied and the increase of the shock due to a finer mesh creates a bigger challenge for the NN. Furthermore, the 3D swept wing case is compared with the 2D case, and the results highlight how the accuracy of the 3D is higher due to a lower shock, due to the delayed appearance in the swept wing configuration. Overall, the NN enables a faster aerodynamic forces prediction and can be used to speed up the design process of aircrafts.
The work from Ney Rafael Secco [45] develops an ANN that predicts the aerodynamics coefficients of the assembly wing-fuselage with high accuracy, taking also into account the flight condition as an input parameter. The NN is trained with a database of full potential computations. He also tried to change the configuration of the network to minimise the regression error, obtaining a sensible reduction in the time required to find the solution. He then modifies the method to let it minimise both the regression error and the drag coefficient, reaching an optimal solution close to the one obtained with the full potential code
When it is required to model the aircraft across the entire flight envelope, it is usual to interpolate between two single points in the envelope obtained using a first-order Taylor series to approximate forces and moments. Terrin Stachiw, in his article [50], proposes a novel physics-based nonlinear autoregressive exogenous neural network model architecture that allows the use of the second-order Taylor series terms, thus capturing a more complex and nonlinear behaviour across the whole flight envelope. What is possibly more important is that his model creates a continuous simulation model.

Even back in 1993 Dennis J. Linse [29] created a novel method to implement a NN that could compute the aerodynamic coefficients used in an on-line non-linear aircraft control strategy. But today the computers have advanced quite a lot in the 3D environment and in the computational speed, this allowed to create flight simulators that today manufacturers rely on these simulators to design efficient flight control systems. However, for general aviation planes it is not easy to create a simulator that well represents the real behaviour.

In his article [51], Giorgio Valmorbida proposes the use of a NN method to simplify the realization of a flight simulation software without the need of detailed aerodynamics and thrust models.
In a bit different scenario, specifically a water landing, it is possible to study the interaction of the water with the belly of a wing-in-ground plane using a Neural Network. Cenwei Ma [32] presents a method that uses an adaptive neural network combined with Monte Carlo simulation, the aim of this method is to study the structural integrity of the belly of the plane reducing the number of required samples. The Neural Network is employed with a U learning function to perform adaptive sampling in regions with high predictive variances and near the failure boundary.

3 | Safety Analysis/Health and Usage Monitoring

The safety and reliability of an aircraft along its operational life depend mainly on the continuous monitoring of both structural and electronic components. Modern aircraft are equipped with a vast network of sensors that measure mechanical strains, vibration levels, loads, control surface deflections, system states, and pilot inputs. The resulting data streams are high-dimensional, heterogeneous, and often generated at high frequency, creating both an opportunity and a challenge for effective analysis trough Machine Learning algorithms. Traditionally, aircraft monitoring systems have relied on threshold-based exceedance detection methods and expert-defined safety margins. While such approaches have proven effective for identifying known failure modes, they are inherently limited in their ability to detect novel, complex, or multi-component anomalies. As aircraft systems become increasingly integrated and data-rich, conventional monitoring strategies may struggle to capture subtle deviations, latent faults, or emerging risk patterns. In recent years, machine learning techniques have emerged as powerful tools for enhancing aircraft safety analysis and health monitoring. By leveraging supervised, unsupervised, and semi-supervised learning algorithms, these methods can identify hidden patterns in large-scale flight data, detect anomalies in real time, and support predictive maintenance strategies. Applications range from automated anomaly detection in flight data records to load monitoring, digital twin development, pilot behavior analysis, and operational risk identification. This chapter reviews selected research contributions in the fields of anomaly detection, Health and Usage Monitoring Systems (HUMS), and safety analysis, highlighting how machine learning methodologies can complement and extend traditional aerospace monitoring frameworks.

3.1. Safety Analysis/Health and Usage Monitoring

3.1.1. Anomaly detection

On an aircraft, there is an enormous amount of components, both physical and electronic, and keeping track of all the issues that may happen might not be trivial. The NASA Ames developed an algorithm (MKAD) that can perform automated anomaly detection on large heterogeneous data sets that contain both discrete symbols and continuous data streams, but it is possible to do better than that. Vijay Manikandan Janakiraman proposes [22] an anomaly detection algorithm that uses Extreme Learning Machines (ELM). This method aims to reduce the computational complexity of the MKAD, which is time-consuming over a very large data set. Adapting unsupervised ELM algorithms and applying it on a real aviation safety benchmark problem, this method shows a result comparable with that of the MKAD algorithm but with a training time faster by two orders of magnitude. Also Anvardh Nanduri used MKAD as a reference in his work [38]. His idea is that industry standar rely on threshold Exceedance Detection algorithms, but Machine Learning algorithms can detect unknown unusual patterns in the data, both with Unsupervised and Semi-supervised Learning. He identified the limits of the MKAD algorithm as the need of dimensionality reduction, poor sensitivity to short term anomalies, and the inability to detect anomalies in latent features. He created a method based on the adjoint work of Recurrent Neural Networks with Long Term Short Term Memory (LTSM) and Gated Recurrent Units (GRU) to improve the limits of the MKAD. On a test dataset, his method detected 9 anomalies out of 11, with respect to 6 that were detected by the MKAD. He also stated that his method is suited for real-time anomaly detection. If we consider an offline application, Julian Oehling [40] created a method to analyse existing data that airlines routinely monitor. The airlines monitoring is based on the exceedances of expert-defined thresholds, but as we have just seen Machine Learning algorithms might detect trends better than a simple threshold method: if the exceedance method was not instructed with a filter, it will not create an anomaly for novel occurrences, therefore an Unsupervised Learning method called “Local Outlier Probability” can help to find novel occurence types which were undetected by a contemporary flight data monitoring system. The capacity to detect a multi-component coupling fault might be aided by ML methods, since it might be difficult in complex airborne machines. Liu Liu [30] shows a method to implement a meta model algorithm that can achieve a high accuracy and an improvement with respect to traditional methods under small sample condition.

3.1.2. Health and Usage Monitoring

Thanks to the history of maintenance, engineers in the aeronautical field began scheduling maintenance, repairs, or replacements before damage appeared on mechanical components. To do this, it is required to monitor the forces and the frequencies that acts on the components, monitor them with machine learning methods might help in certain situations. Michael Candon, in his article [7], proposed a Multi-Input Single-Output (MISO) loads monitoring problem and used a range of machine learning models to predict bending and torsional load spectra in the dynamic case (buffet) and quasi-static during transonic buffeting manoeuvres. He found that in different cases, the MISO coherence ranges from high to very weak depending on the load case. A possible and new application in this field is the digital twin: since the uncertainty in the transmission network might be due to an increase in time intervals, the use of the digital twin allows the monitoring of diverse parameters minimizing uncertainty, as Shitharth Selvarajan shows in his work [46]. He suggests a system model enhanced by Deep Learning methods, and testing it in different situations, concludes that his method is able to significantly enhance the maintenance period while minimising data errors.

3.1.3. Safety Analysis

The anomaly detection operates after the event has happened and is mainly focused on the malfunction of physical objects, but if we want to prevent the events, we need to study the past and try to consider the human interaction with the aircraft as well. The work of S. Budalakoti [6] addresses the problem and uses randomized clustering-based approach to cluster the data collected and then proceedes to the anomaly detection based on the deviation from the clusters. The data that he aims to collect and analyse is composed of the actions of the pilots in the cabin, which includes the sequence of buttons and switches actuated by the humans: he shows how his method discovers actionable and operationally significant safety events. He then compares it with standard hidden Markov models to show the superiority of the result.

If we talk about the safety issues during flight operations, we need to address the method used to prevent events. Milad Memarzadeh [34] states that the National Airspace System operations vulnerabilities identification still relies on domain expertise knowledge and known safety margins. This works only if the operations are well defined, which is not always true due to the large ammount of operations in the NAS, however ML models can be applied for event detection in aerospace data, but not a supervised model since it would still require the aid of an expert to label the data. Instead he proposed a Convoluitional Variational Auto-Encoder, an unsupervised deep generative model, that is used to detect anomalies in a the data. His method has been able to outperform classic and Deep Learning based approaches when detecting anomalies.

Lucas Coelho e Silva [9] proposes a ML integrated method to detect anomalies in flight operations that can be applied online and offline. He demonstrated the results of his work in two scenarios: the first being of routine flight operations monitoring, applying the framework to aircraft performance data with an unsupervised learning method, comparing it with an exceedance-based method. And in the second scenario, he used a supervised learning method on flight tracking data supported by an anomaly explanatory model that provides novel insights about contributing factors to the anomalies identified. His work shows that ML methods can still help experts in this field better than the classic threshold methods, allowing to link different causes for an issue.

The pilot workload in stressful situations may be considered a safety issue, therefore there are studies about pilots' physiological reactions in emergency situations. Jiajun Yuan, with his work [59], shows that ML methods may also be implemented in this field to help with a better understanding of the situation. Using four different ML models to monitor the heart rate of the pilots in the event of a Power-off stall training session, he noted that the increase of workload may be the cause for an operational error, and also found which of the four methods was the best suited for this situation. This kind of work may lead to modifying the checklists during these kinds of occurrences to try to reduce the pilot workload.

4 | Uncertainty Analysis

Uncertainty plays a fundamental role in the design, analysis, and certification of aircraft systems. Throughout the operational lifespan of an aircraft, structural components are subjected to variable aerodynamic loads, environmental conditions, manufacturing tolerances, and operational variability. Accurately estimating these uncertainties is essential to ensure structural integrity, safety, and performance while avoiding excessive conservatism that may lead to unnecessary weight penalties. Traditional Uncertainty Quantification (UQ) methods rely on deterministic simulations, interval analysis, probabilistic approaches, or Monte Carlo techniques to propagate input variability through complex physical models. While these methods provide reliable bounds, they can become computationally expensive when applied to highly nonlinear systems or high-dimensional parameter spaces, which are common in aeronautical structural and aerodynamic problems. Moreover, repeated evaluations of high-fidelity models significantly increase design time and computational cost. In recent years, Machine Learning techniques have emerged as promising tools for uncertainty modeling and propagation. Neural Networks can approximate nonlinear mappings between uncertain inputs and structural or aerodynamic responses, reducing computational effort while maintaining acceptable accuracy. Furthermore, hybrid approaches such as Physics-Informed Neural Networks (PINNs) enable the integration of physical laws with data-driven uncertainty quantification, enhancing robustness and interpretability. This chapter reviews selected research contributions addressing uncertainty analysis in aeronautical applications.

4.1. Uncertainty Analysis

In the aeronautical field, the structural problem is relevant because a mistake in the uncertainty range of the forces may lead to an excess in the mass of the structural components, directly impacting fuel efficiency and overall aircraft performance. To identify uncertainties in the structural model's output, the models used are both time- and cost-consuming, and when dealing with strong nonlinear systems, it might be helpful to use Machine Learning methods. In his work, Yan Shi shows a Deep Learning approach [47] to deal with the limits posed by the Interval Uncertainty Propagation, which is a method used to identify the output range given an input with a lower and upper bound interval, in the aeronautical structural field. The capacity of this method is tested in various applications and shows the accuracy and efficiency of the Machine Learning approach with respect to the standard method.

The presence of aerodynamics uncertainty may pose some challenges for extreme flight conditions due to the high nonlinearity of the problem. A Physics-Informed Neural Network may be exploited in this scenario, Nathaniel E. Michek [35] incorporated uncertainty quantification methods in a PINN that has aerodynamic coefficients and flight trajectories, both with a calibrated confidence interval. He then uses a case study to train many PINN models to propagate the uncertainty in the flight trajectories in a simulation environment.

Kyung-Mi Na shows another aeronautical application of PINN: in his work [37], he shows how his method can identify four different structured uncertainties that usually affect a missile flight performance. The results have estimation errors within 1% of the mean value for each of them, despite noise corruption in the data.

5 | Maneuvering

The different phases of a flight, from climb and cruise to descent and maneuvering, are characterized by highly dynamic conditions that influence aircraft performance, fuel consumption, navigation accuracy, and operational safety. Traditionally, the analysis and control of these phases rely on precise onboard sensors, deterministic flight dynamics models, and rule-based algorithms. While such approaches provide reliable results, they may involve high equipment costs, complex calibration procedures, and limited adaptability to variable operational environments. Machine Learning techniques offer an alternative approach for identifying and estimating key flight parameters during maneuvering and operational phases. By exploiting large volumes of flight data, these methods can infer latent variables, classify flight conditions, and predict performance indicators. This chapter examines selected applications of machine learning in Maneuvering analysis and Flight Phase Recognition.

5.1. Maneuvering

The implementation of Machine Learning algorithms might help to analyse the data and improve fuel consumption as well as flight route planning, but may also be used by some aircrafts that don't have a gyroscope.

In his work [13], Raul de Celis applies a Machine Learning method to one of the basic problems in navigation: the attitude determination. Due to the high cost of high precision in high-demand manoeuvres, for accurate navigation and control, he uses gravity and velocity in body and inertial frames to obtain the attitude instead of the classical instruments. To determine the velocity vector in the two different frames, he uses a GNSS sensor and accelerometer measurements, while for the gravity one, he uses a Machine Learning approach that determines the aerodynamic forces trough the flight dynamics equations. He then proceeds to compare the result with a simulation that employs nonlinear flight dynamics models and shows that his model is quite accurate.

The climb phase is the most demanding in terms of fuel consumptions and it depends on different factors such as atmospheric condition and flight parameters. Using a ML model, Ahmed Salem Ahmed Al-Khanbashi proposes a novel approach [1] to predict the fuel flow rate during the climb. The high accuracy and the versatility of his model offer a real-time fuel optimisation instrument that may help to reduce the fuel consumption and therefore the cost of the flight.

5.2. Flight Phase Recognition

Airports perform different studies on the flights, and some of these studies require identifying the flight phase the plane was in to be carried out, for example, operation counts, fuel burn modeling and estimation, but also safety analysis. Some extreme values of bank angle, fuel burn rate or low altitude are acceptable during certain phases, but are not during others; this information is crucial during fault detection. The issue comes when we try to identify the flight phase during post-flight processing, and it is even harder in General Aviation (GA). As Nicoletta Fala says in her works [15, 19], in GA maneuvers are a bit more chaotic, and it is not always trivial to understand where a flight phase ends, and another one begins, so she used two ML methods for a precise clustering with respect to flight phase recognition, and the results suggest that both are adequate for the role.
Pilots know the flight phase, but this information is not accessible publicly, so E. Arts's idea [3] is to carry out a real-time Machine Learning method that uses the ADS-B trajectory data to classify the flight phase. Using a flight simulator, he created a training dataset that was used for supervised learning. Combining K-means clustering with Long Short-Term Memory (LSTM) network, his method has identified a larger variety of phases with respect to other methods, even though his algorithm is suited for flights shorter than 6 hours.
Seokhwan Lee's study [25], instead, is concentrated on clustering the different cruise phases during a flight: since there are a lot of vertical manoeuvres and rule-based algorithms tend to be inaccurate, a Machine Learning approach is proposed and is shown to be able to extract the cruise phase in almost all of the flights it was tested on, 36712 flights over total of 38051.

6 | Air Traffic Control

Airports represent one of the most complex operational environments within the aeronautical field. Unlike en-route flight operations, airport and Terminal Maneuvering Area (TMA) activities are characterized by high traffic density, constrained airspace, tight scheduling constraints, environmental considerations, and strong safety requirements. In this context, even small improvements in prediction accuracy, sequencing efficiency, or resource allocation can translate into significant operational, economic, and environmental benefits. Machine Learning applications in airport environments extend beyond traditional control functions. The increasing availability of surveillance data—particularly ADS-B streams, together with meteorological datasets and flight plan repositories, has enabled the development of predictive and classification models capable of learning complex spatiotemporal patterns in air traffic flows. These approaches can support trajectory prediction in congested TMAs, optimize landing sequences, enhance aircraft categorization, detect unstable approaches, and improve statistical monitoring of traffic behavior. In parallel, the accurate estimation of the Estimated Time of Arrival (ETA) has become a strategic objective for airport operations. Machine Learning techniques offer a data-driven alternative capable of integrating heterogeneous inputs and capturing nonlinear dependencies in trajectory evolution and delay propagation. This chapter therefore investigates Machine Learning applications in two closely related domains: Air Traffic Management within the TMA and Estimated Time of Arrival prediction.

6.1. Air Traffic Management

Airports need to control all traffic in the Terminal Maneuvering Area (TMA), mainly for safety reasons but also to ensure a high-quality service. Today, all commercial flights are equipped with ADS-B systems, but in the vicinity of airports, the situation can quickly become confusing and dangerous. Therefore, the possibility of having real-time evolution of all the aircraft trajectories would help the ATM to ensure the safety of all the people involved. The intrinsic time dependency of all the points that belong to a flight trajectory makes the LSTM method perfect for this application. In his work [49], Jorge

Silvestre shows us an application of this method to a real case scenario: using trajectories from OpenSky for a chosen airport, he trained the algorithm with a consistent amount of trajectories (72.5%), validated it with the 12.75% and then tested the results with the remaining 15%. Even if under certain restrictions, his work shows a lower Mean Absolute Error (MAE) with respect to state-of-the-art methods and paves the way for improvement in foreseeing the trajectory of the air traffic with a very low error.

Changqi Yang has implemented another application of the LSTM method combined with an Attention Mechanism (AM) for aircraft trajectory prediction [55]. The AM method works like a human mind, selectively deciding which features require more attention and which less. Using selective weighting, this model can focus on the precision of the trajectory prediction, and comparing his AM-LSTM model with a simple LSTM shows a lower mean square error in the longitude prediction and a similar one, still lower, for the latitude prediction. Another feature was added to this method: the influence of the aircraft dimensions is taken into account for different aspects: aerodynamic characteristics, inertia, manoeuvring performance and flight environment. With this added feature, the computational effort increases, and the accuracy is significantly improved.

Always considering the final approach in the TMA, Dabin Xue [54] considered the ADS-B data to create a Heuristic Search Method that continuously updates the landing time to minimize the total flight time, with the possibility to assign a higher landing priority due to operational failures. A peculiarity of his model is that it runs whenever a new flight enters the TMA, allowing for an automatic and continuous rework of the scheduled landing sequence.

Néstor Jiménez-Campfens' work [23] adds to the list of the different approaches used to predict the trajectory of incoming air traffic in the TMA: using an ANN he integrated the flight data gathered from FlightRadar24 and the weather reports of the arrival airport to predict the final 30 minutes of the approach trajectory.

Deepudev Sahadevan [44] used a Bi-directional Long-Short-Term-Memory (Bi-LSTM) method to predict an aircraft trajectory trained and tested on ADS-B and weather data. A Bi-LSTM is a bidirectional RNN that can capture forward and backward dependencies in historical trajectory data, improving the model accuracy. He compared the performance of his model with a classical LSTM approach and other combined LSTM methods on a chosen trajectory between two airports, and showed how it outperforms them considerably.

As I said, airports need to control the TMA, so Air Traffic Control (ATC) needs to monitor the air traffic and classify the aircraft based on trajectory, type and flight phase. Due to the large number of flights that need to be controlled, it's ideal to have an identification method that requires a low computational effort and is versatile for different applications.

Thanks to the availability of many different datasets, e.g., ADS-B from OpenSky Network, Nicolas Vincent-Boulay proposed an Unsupervised Machine Learning approach to aircraft categorisation [52], specifically a k-means model. Aircraft are divided based on their sharing similar patterns across large volumes of real-life air traffic data and over a period of time. In the K=4 case, the behaviours clustered were: taking off, landing, or cruising based on the altitude variation; general heading or direction and if aircraft are operating locally near an airport or are performing longer flights across two airports located far from each other. For K=5 his model was able to separate the group of descending aircraft based on differen initial altitudes. For K=6 the climbing routes are separated based on heading. For K=7, the model identifies two groups of aircraft operating at low altitude in three groups based on heading. Obviously, adding more and more groups would not help the categorisation, but for K=30 this model was able to cluster the flights in groups similar to Airworthiness and Performance-Based categories. This shows that this model can be used in different applications and situations, as well as on a scalable traffic dataset.
In the final flight phase, namely the landing, a big part of the incidents involves the incorrect amount of energy that the plane has when approaching. Using the Specific Total Energy (STE), Dhanuj M. Gandikota [17] created an Unsupervised Machine Learning approach, with 4 methods, to identify aircrafts that have an energy profile that may lead to an Unstable Approach and may cause incidents. The STE is the sum of the kinetic and potential energy of the aircraft in a specific moment and is obtained with non-proprietary surveillance data. Generally, STE is identified as high or low to classify a potentially unsafe approach, but the STE varies sensibly during the approach and landing with different patterns depending on the aircraft type and configuration. For better results, data are normalised according to the mean and standard deviation for the aircraft fleet statistics. Thanks to the high frequency at which surveillance data are collected, this method offers a fast approach to landing accident risk detection.
Zhiheng Guo's work [20] is another use of ADS-B data for emitter identification using a Soft-Decision Weighted CNN model. The output of his model is a combination of the soft-decision information and the output of the CNN k-means algorithm. Results show how the addition of the soft-decision significantly increased the accuracy of the model from 60% to more than 90%, thus proposing an efficient method for statistical analysis for ATM.

6.2. Estimated Time of Arrival

Another key factor considered by airports is the Estimated Time of Arrival (ETA) predictions for incoming flights: a more precise allocation of resources allows lower service cost

and reduced safety risk. In 2018 [4], Samet Ayhan, anticipating unprecedented growth in commercial air traffic worldwide in the next 10 years, decided to create a novel ETA Prediction System for commercial flights to compete with the European air traffic control project controlled by EUROCONTROL, Single European Sky ATM Research (SESAR), and the American one Next Generation Air Transportation System (NextGen). These systems were based on a deterministic approach to airspace capacity and efficiency, without accounting for external factors such as environmental conditions and air traffic. Instead, Samet Ayhan's system collects data relative to the position and the potential flight trajectory, including air traffic and weather parameters, then feeds them into regression models and a RNN. Comparing the resulting ETAs prediction with the ones calculated by EUROCONTROL, he shows how they are more accurate.
In a very similar way, and in the same year, Andrés Muñoz proposed [36] a method that uses ADS-B data from the European company FlightRadar24 and estimates ETA whenever a new flight appears in the system via a new surveillance message. He compared the results with the ETAs calculated by EUROCONTROL and by FlightRadar24, obtaining a better result with respect to both and a quicker response than FlightRadar24.
Even Jorge Silvestre, in 2024 [48], addressed the ETA estimation using an LSTM method to include both the 4D trajectory of the flight taken from OpenSky surveilance ADS-B data, EUROCONTROL data for the flight plan, and the meteorological data of the Airport of arrival. He compares his model with others, also with the one from Samet Ayhan, reporting a better accuracy in the prediction. Applying this method to a chosen airport, he then reports that the MAE and the root-mean-squared error RMSE are lower than the leading models in this field.
To avoid the aforementioned issues for airports and air transportation efficiency, Wenxing Liu implemented a Multi-View clustering approach [31] to predict flight delays. Multi-View clustering is an Unsupervised Machine Learning method that uses different heterogeneous sets of features to create clusters in the data, allowing for multiple points of view of the input data. A soft decision tree is then applied to the clustered data to verify the beneficial effect on the prediction task. This method's performance is compared with the single-view one and the respective versions without the soft decision tree; the results show that there is a significant improvement in the accuracy.

7 | UAVs

This chapter explores the role of machine learning in Unmanned Aerial Vehicles (UAVs) platforms. The UAVs sector is one of the most dynamic and rapidly evolving of modern aerospace engineering. Their operational flexibility, reduced onboard human intervention, and expanding mission profiles—from civil inspection and logistics to military surveillance and combat—make them a particularly suitable domain for the integration of machine learning techniques. Machine Learning applications in UAV systems span multiple layers of operation. At the system level, fault detection and anomaly identification are critical due to the absence of direct human supervision and the potentially severe consequences of delayed responses. At the mission level, autonomous decision-making and trajectory planning—both for single vehicles and cooperative swarms—require adaptive strategies capable of handling uncertain and partially observable environments. Furthermore, lightweight onboard implementations demonstrate the feasibility of deploying learning-based methods even on resource-constrained hardware platforms. The integration of Machine Learning techniques has enabled UAVs to optimize energy consumption, adapt to dynamic operational scenarios, coordinate multi-agent behaviors, and enhance survivability in adversarial environments.

7.1. UAVs

Even for UAVs, the fault detection plays an important role, and it may also be important how quickly anomalies are detected since the UAV automatic control may take decisions before a human sees any issue, and this may lead to serious damages of the vehicle and to the sorrounding. Zaifei Fu [16] used a One-Class Support Vector Machine, which is a special Support Vector Machine ideal to identify outliers or anomalies, in the case of a complex flight control system output coupling and demonstrates how this method significantly redced the fault detection time with still a very high detection rate.
In his work [56], Lei Yang addresses other issues in identifying anomalies in a UAV system: PINN models are way too challenging in this situation, data-driven methods are less tunable and rely on labelling anomalous data, and the random noise present on the flight

data may lead to incorrect anomaly detection. This method uses a long- and short-term memory and autoencoder (STC-LSTM-AE) neural network for anomaly detection in an unsupervised manner.

The use of UAVs may not require the presence of a pilot's input, which means that decisions on the flight path and manoeuvres may be delegated to the autopilot. In a single UAV scenario or in a swarm one, the mission requirements are different, and this leads to the definition of different Machine Learning methods.

The Swarm scenario addressed by Jiaxi Chen [8] is a post-disaster rescue situation in an urban environment. His algorithm is based on a Deep Learning method that uses the initial inspection points as training to complete the remaining inspection points faster and more efficiently with respect to traditional multi-agent algorithms. His algorithm is capable of reducing the number of UAVs required to inspect all the points and also to reduce the distance covered in total, taking into account the UAV capacity consumed in the travel and in the inspection and also the remaining capacity.

Yanfan Zhang instead, shows us [60] a single UAV scenario, where a reward function related to his energy is used to help the vehicle in the mission planning trough Deep Reinforcement Learning. He confronted the normal scenario to one in which the drone has the possibility to recharge the energy and created a decision making algorithm based on the energy needed for maneuvers and the energy left for the drone. Results show that the method is capable of smoothing the energy and with the possibility to recharge it's able to complete more missions.

During validation, it is crucial to relate the data collected to the flight phase if we need to carry out some analysis later. Paulo H. A. Andrade shows an application of TinyML [2], which is a Machine Learning network suited for small hardware, capable of classifying the flight phases with an accuracy exceeding 80% and a very low power consumption. This result open the road to future applications that may require a rapid flight phase recognition for flight test data. A similar work was carried out by Jakub Leško [27], with the use of a low number of neurons, the NN was capable of classifying basic flight phases with a high accuracy and a limited set of input parameters.

If we think about UAVs we may think about simple and slower quadcopter that may help in post-disaster rescues as in the previous work, but also the possibility to have military scenarios. Fei Wang addresses this topic in his article [53], in an enemy intrusion scenario, where the enemy has a maneuvrability superiority, multiple UAVs ma be used to intercept the enemy. Using a modified MADDPG algorithm, which is a method that can be applied to mixed cooperative-competitive environments where all the training is shared but the decision is taken by each single agent, he added ab Experience Screening Mechanism to help the defending UAVs take a decision. Since the superiority of the enemy would lead to avoiding action, his method tries to weight the first impression memeories differently and the results show that his algorithm performs better compared with the base MADDPG.

8 | Other Objectives

As data availability increases across the aviation ecosystem, from flight operations and maintenance logs to cybersecurity systems and cockpit manufacturing processes, new opportunities arise for Machine Learning model to be exploited. Some applications do not fit withing the previous chapters, yet they show promising results for the application of data-driven methodologies across the industry. Overall, this chapter aims to illustrate the versatility of machine learning across heterogeneous aerospace domains.

8.1. Other Objectives

Traditionally, flight routes are planned before departure, after weather data is gathered, minimising the flight time while trying to avoid weather hazards. Since the weather conditions may vary during the flight, pilots may be required to change the route manually, even though there are tools that automatically generate a new path, e.g. the NASA TrafficAware Planner (TAP), and reduce the pilot's workload. Routes generated by TAP are limited to 90 minutes prediction. In his article [24], Junghyun Kim proposes an ML implementation that continuously generates new flight routes based on the latest weather information available. This model combines Supervised and Unsupervised ML for weather forecasting and generates routes that are not constrained by Federal Aviation Administration(FAA) waypoints, and that minimise flight time. The results show that the time saved was up to 2% in most cases analysed, which over a large amount of flights becomes a big fuel, money and time saving. This method can become a bigger advantage for private or smaller companies that lack experienced or dedicated personnel.
Since the Advisory Council for Aeronautics Research in Europe (ACARE) has set very demanding goals to reach by 2050, the technologies needed to satisfy these goals require modelling from scratch, with better implementation and collaboration between different actors in the industry. Ana Garcia Garriga [18] proposed an ML application that helps model a novel aircraft system architecture in early stages, integrating different technologies and considering the effects on all the different systems in the aircraft. Due to the assessments on all the systems, evaluating all the feasible architectures is computationally

demanding, so the number of those that are evaluated needs to be limited. The proposed framework consists of two modules, one that filters the unfeasible architectures and the other that can capture the effect of the changes in the system; the results are then clustered for similarities in architecture and the optimal one of the cluster is extracted. The framework is tested on the modelling of two systems on a short-range aircraft, towards more electrification. With the addition of specific libraries, the model can be extended to other KPIs, depending on the design requirements.

In the aeronautical field, accidents and incidents are studied to prevent them from happening again. Luckily, incidents are the most frequent between the two, and to study them, it's important to correlate the event timeline with the large, multidimensional, heterogeneous dataset collected from an aircraft. Vijay Manikandan Janakiraman's work [21] proposes a precursor mining algorithm to analyse the collected data, which correlates prior events with a safety incident. His model combines Multiple-Instance Learning (MIL) and Deep Recurrent Neural Networks (DRNN) to go from human, manual explanations to an automated flight data analysis and explanation. The MIL is modified, adding a Deep Temporal module that allows to correctly analyse time series data and the application of flight-level labels on them. This framework is confronted with similar baseline models, and the results show a higher accuracy in predicting the adverse event.

In the aviation maintenance field, Dan Zhao [61] proposes a storage sorting model for maintenance data based on three Machine Learning models: the BERT model, which is a Natural Language Processing (NLP) method used to learn contextual information; the LSTM model, which I've already mentioned and is used to learn text features; and the Conditional Random Field (CRF) model, which is Supervised Machine Learning technique used to predict structured objects, rather than discrete or real values. The result of these three models is a knowledge graph obtained from information recorded by maintenance personnel using natural language. A storage model is created that helps with intelligent decision-making in aviation maintenance. The proposed method is significantly faster than traditional methods and can also withstand a larger query number.

Machine Learning can also be used in cybersecurity, as proposed by Jarul Mehta in his paper [33]. The Controller Area Network (CAN) protocol, used for inter-device communications, leaves some space for security breaches and thus to control system sabotage. Standard security measures are computationally expensive for a real-time cyber defence. ML-based approaches have some disadvantages, such as additional hardware and the fact that all anomalies are assumed to be attacks. The proposed method in a CAN network operating ARINC-825, using three tree-based ensembles, a Supervised Learning method, outperforms anomaly-based techniques while facing attacks that increase the bus utilisation. The proposed model, called (DT-DS), is used for intrusion detection, analysing the

time interval and frequency of CAN messages. It is important to note that this method cannot detect all kinds of attacks, since it is limited to those that affect the interarrival timing of the messages on the bus, and was tested only on detecting an active, predictive attacker. They compared three tree-based ensembles methods for the detection capacity (DT-DS) and found promising results, which can also be increased to nearly perfect detection if the observation window is increased, at the expense of a bigger latency in the detection of the attacks. These methods also outperform other time-based Intrusion Detection System strategies, which accuracy degrades with smaller time windows.
Based on the fact that the human factor in the batch manufacturing process plays a significant role, Jiaqing Yao proposes Machine Vision model for automatic identification of aircraft cockpit indicators [57]. During the testing phase of the cockpit display, it's essential to correctly identify the indicators and the information on the display. Using a Machine Vision aid may avoid errors in this process. The proposed system automatically corrects and segments images taken in the cockpit, then different algorithms are applied on different regions based on the content, wether it's a symbol, words or numbers: YOLOv5 for unconventional indicators; an improved version of EasyOCR (Optical Character Recognition (OCR)) for character recognition based on Convolution Recurrent Neural Network; and other general indicators recognitions methods. The results show a considerably low average error rate in the identification, that is 1.96% and the time required is 4.8 faster with respect to the manual method. The automation of this process allows to exclude errors due to misjudgment,heavy workload or distraction in the batch production process of civil aircraft.

8.1.1. Military Applications

One of the purposes of the military divisions is to quickly and efficiently respond to threats to the safety of civilians, as shown in different papers Machine Learning applications in the aeronautical field significantly reduce response time in several situations. Some works in this direction are conducted all around the world, and I'll report on some of them.
A Machine Learning application for image recognition is described in the paper from Seunghan Lee [26]. An optical-flow-based Markov Decision Processes (MDP) application is analysed for a proactive surveillance system design for motion detection and analysis, and decision making. This implementation can be installed on UAVs facing quickly changing environments for homeland security, and it aims to anticipate and mitigate potential security challenges in urban surroundings with an improved situational awareness that allows for responding to imminent threats. The author tested his algorithm on a real setup, designing the hardware to incorporate physical controls that aid in simulations:

e.g. simulated bombing attacks, across various environmental conditions and camera configurations.
Machine Learning can also be used to aid in guidance problems. In his paper, Weilin Ni [39] proposes a model for the active defence guidance problem for the hypersonic vehicle in a target-interceptor-defender scenario based on a Convolutional Deep Q-Network (CDQN) algorithm. In the active defence scenario the hypersonic attacker (target) is aided by a defender that engages the interceptor, Target-Interceptor-Defencer (TID) scenario. In this scenario the interaction between the target and the defender is crucial, and the target cannot obtain complete motion information of the interceptor, which will be filled with with the aid of the CDQN. For this reason the TID is the partially observable Markov decision process. This method is proved more effective and robust with respect to traditional Reinforcement Learning based methods for this scenarios.
Computers can potentially take decisions faster than humans so, it is possible to use some Machine Learning approaches for decision making in autonomous air combat to achieve better performances. Existing methods focus on the decision making, but lack in the timing and rely on a finite library, which is an issue when facing an opponent with a more updated tactic library. With this premises Hai Yin Piao [41] proposes a novel Deep Reinforcement Learning (DRL) method for autonomous air combat tactics discovering algorithm called ENACTIVE, composed of two parts: ENHANCE and FACTIVE, appointed for choosing the maneuvers. The ENHANCE module, inspired by neuroscience, adjusts the decision making interval to increase the opportunities in combat, and it's proved to wing against state-of-the-art algorithms with a 62% rate. The FACTIVE module instead adopts adopting DRL with added prior knowledge to factorise original maneuvers into two groups: one for offensive and defensive maneuvers, and the other to accomplish energetic maneuvers, namely climb or descent. These two groups are then combined by the DRL to combine them and obtain a variety of air combat tactics consistent with human experts' knowledge.
Conghui Huang's work [11] set the requirements for a DRL Simulink implementation for a credible and realistic infrared air combat simulation platform and the realisation of the simulator. Results show that the simulation system developed can be used to train and test other Reinforcement Learning algorithms for infrared scenarios, saving cost and time.
If pilots do not have vision of the opponents, they rely on instruments such as radar, this is called Beyond Visual Range (BVR) air combat. The correct moment for firing is decisive for the combat outcome, and Joao P. A. Dantas' work [12] addresses this problem, comparing Supervised Machine Learning methods to estimate the most effective moment for launching missiles in a BVR scenario. The firing moment estimation is based on different parameters related to the target and the missile, and is designed as a probabilistic

function of them. The method is trained on data obtained through constructive simulations, and results show that these techniques increase recall and f1-score with a slight decline in accuracy and precision, increasing the effectivenes in offensive mission for both unmanned and manned vehicles.

9 | Conclusions and future developments

This thesis has examined the role of Machine Learning within the aeronautical field, highlighting how data-driven techniques are progressively reshaping traditional aerospace methodologies. Across Aerodynamic modeling, Safety and Uncertainty Analysis, Maneuvering optimization, Air Traffic Control and Management, and UAV systems, ML has proven capable of addressing problems characterized by high dimensionality, nonlinear behavior, and computational intensity. A significant contributions of Machine Learning lies in surrogate modeling for aerodynamic analysis. Neural networks and hybrid physics-informed models allow near-real-time prediction of aerodynamic coefficients and pressure distributions, substantially reducing reliance on computationally expensive CFD simulations. Similarly, in structural and Uncertainty Analysis, ML techniques enable efficient propagation of uncertainties while maintaining robustness and physical consistency. In safety-critical applications, including Anomaly Detection and Health and Usage Monitoring Systems, ML demonstrates superior performance compared to traditional threshold-based methods by detecting complex, multi-component, and previously unknown fault patterns. In Air Traffic Management and ETA prediction, learning models such as LSTM and attention-based networks enhance trajectory forecasting accuracy and operational efficiency within increasingly congested airspaces. The UAV domain further illustrates the strategic importance of Machine Learning, particularly in autonomous mission planning, swarm coordination, fault detection, and energy-aware decision-making. Lightweight implementations also show the feasibility of deploying learning-based algorithms on embedded systems with limited computational resources. Despite these promising developments, several challenges remain. The interpretability of complex models, certification in safety-critical environments, data quality and availability, and robustness against adversarial or unexpected scenarios represent open research areas. Moreover, ensuring compliance with strict aerospace regulatory frameworks requires transparent validation and verification methodologies for ML-based systems.

Future research should therefore focus on:

- Strengthening hybrid approaches that integrate physical laws with data-driven models.
- Improving explainability and certification pathways for safety-critical ML systems.
- Expanding real-time onboard implementations with constrained hardware.
- Promoting standardized datasets and benchmarking procedures within aerospace applications for wide access.

In conclusion, Machine Learning is not merely an auxiliary computational tool but an enabling technology that supports the evolution of aeronautical engineering toward greater efficiency, safety, sustainability, and autonomy.

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