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SURVEY

Machine Learning in Aircraft Design: A Comprehensive Review of Optimization, Aerodynamics, and Structural Applications

SHIMA MOHAGHEGH [1], (Member, IEEE), AND **ALI MOHAGHEGH** [2]

[1] Electrical and Electronic Engineering Department, Middle East Technical University, Northern Cyprus Campus, 99738 Mersin, Türkiye
[2] Aerospace Engineering Department, Middle East Technical University, Northern Cyprus Campus, 99738 Mersin, Türkiye

Corresponding author: Shima Mohaghegh (shima.mohaghegh@alumni.metu.edu.tr)

ABSTRACT Machine learning (ML) with approximation and numerical simulations plays an important role in aircraft design. ML techniques, such as deep learning and reinforcement learning, are increasingly being adopted to solve complex, nonlinear problems in aircraft design, offering new opportunities for optimization and innovation. This technology is used in various topics of aerodynamics, fluid dynamics, acoustics, penetration, health monitoring, automatic control, etc. This article reviews recent studies related to different areas of ML application in aircraft design. The review highlights how ML can reduce computational costs while improving the precision of simulations, ultimately accelerating the design cycle and enhancing aircraft performance. The results show that ML is able to improve in all areas of application in aircraft design and the development of techniques in future applications will have a significant impact on the design of modern aircraft.

INDEX TERMS Machine learning, aircraft design, aerodynamics, dynamics, monitoring.

I. INTRODUCTION

The new age of technology is having a huge impact on the airline industry [1]. Advancing technologies are facilitating rapid expansion across various sectors, notably the aviation industry [2]. Cutting-edge innovations such as artificial intelligence (AI), robotics, the Internet of Things (IoT), advancements in aircraft systems, and the rise of hybrid and electric aircraft are reshaping the airspace landscape [3]. The aerospace industry is widely using AI for various applications and improving aircraft with a focus on safety, human factors, environmental and ethical considerations [4]. AI's profound impact is particularly pronounced in the realm of optimizing aircraft design. Aircraft design is a complex issue that includes many functional and technical requirements; Such as size, capacity, aircraft range, aircraft load, flight control issues, aerodynamics, stability, environmental effects, etc [5]. Also, it involves a multitude of critical factors, including airfoil design, aircraft weight estimation, and performance analysis [6]. Traditional approaches to these design aspects have relied on established engineering principles and manual calculations. In recent years, machine learning (ML) techniques have been used in the field of fluid dynamics to accurately predict aerodynamic characteristics in the aerospace industry [7]. However, the integration of machine learning techniques has emerged as a powerful tool for enhancing the accuracy, efficiency, and effectiveness of these processes. AI and ML in aerospace engineering in order to optimize the efficiency and performance of systems and address various issues related to reducing the environmental impact of aircraft, including system management, data interpretation [8], new product development, Customer service or aircraft modeling, flow control, optimization problem solving, optimal sensor distributions for solid mechanics or aero elasticity applications, generation of fidelity databases with reduced cost both in economical and Central Processing Unit (CPU) [9], etc. have been used.

ML has been developed as a branch of AI with the aim of improving system performance using self-learning algorithms [10]. Both ML and AI are connected to aircraft

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aerodynamic performance by relying on Big Data [11], [12]. Research based on the combination of Big Data with ML techniques [13], [14], has resulted in the development of reduced order models (ROM) capable of accurately forecasting flow d y namics e v olution [1 5], [1 6], [1 7] or predictive models. The nose of aerodynamic forces and torques applied to the plane [18].

The estimation of key parameters, such as estimated take-off gross weight, empty weight, and mission fuel weight, is of utmost importance in aircraft design [19]. Accurate estimations of these factors guide engineers in understanding weight distributions, fuel efficiency, a n d o v erall performance characteristics. Traditionally, engineers have relied on manual calculations and established guidelines to estimate these weights [20], [21]. However, ML algorithms offer the potential to significantly improve the accuracy and efficiency of these estimations. By training ML models on historical aircraft data, flight p r ofiles, an d mi ss ion requirements, engineers can obtain more precise estimates of the take-off gross, empty, and mission fuel weights [22], [23]. This enables informed decision-making, enhances fuel efficiency, and optimizes the overall aircraft design [24].

Airbus and Boeing pay a lot of attention to ML techniques [1]. Airbus has used a combination of 1D modeling and GPU, which is able to analyze aircraft components such as wings and fuselage, weight and performance [25]. Boeing has used ML for fast and accurate aircraft design, which has led to improved aircraft performance and increased safety [26].

By using ML algorithms, it is possible to design more efficient a n d s a fer a i rcraft, a n d t h e p e rformance o f the aircraft is optimized [27]. ML has improved computational accuracy in aircraft thrust, swept wings, and composite fabrication [28]. Aircraft control systems improved using ML-based predictive algorithms [29]. ML in the field of aerodynamics has negative contribution to optimization of fuel consumption, stability and easier control of the aircraft [30]. Researchers use data from wind tunnel tests, flight tests, and ML model simulations to generate 3D models of aircraft to improve aerodynamic performance [31], [32]. In the field of aircraft manufacturing, ML is used to optimize the performance of very light and strong aircraft [33]. Researchers used ML techniques to develop maneuverable aircraft control systems and check safety records [34], [35].

In this review paper, the most advanced applications of ML in the aerospace industry have been investigated for intelligent production, development and design, aircraft production and support, acoustics, combustion, fundamental fluid dynamics, aerodynamics, flow control, flight testing and structural health monitoring. As ML has led to advances in aerodynamic design optimization in various aspects including aerodynamic modeling, shape parameterization, design optimization of airfoils, wings, airplanes, turbines, vehicles, etc. Reference [22], we will emphasize the aerodynamic shape optimization (ASO) of the design process. Focusing on the production, development, intelligent design of aircrafts, this article examines aerodynamic issues, optimization, monitoring, and other key parameters in airplane design using machine learning techniques. Route optimization and airline traffic flow forecasting is done using AI and ML to increase the efficiency and stability of flight operations [36]. Also, fleet optimization and flight operations planning have been made possible using this technology [37].

II. MACHINE LEARNING

ML can learn from data and analyze patterns using mathematical algorithms and statistical techniques [38]. Several machine learning (ML) techniques have been swiftly advanced and applied to address intricate industrial challenges such as predictive maintenance, process optimization, work scheduling, quality enhancement, supply and demand projection, defect identification, vibration signal analysis [39]. ML algorithms are typically categorized into four primary types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning.

Supervised learning involves training on a labeled dataset provided by an external supervisor, aiming to predict labels for unlabeled inputs. Unsupervised learning seeks hidden patterns within unlabeled data. In reinforcement learning (RL), an artificial agent learns optimal behavior by interacting with an environment to maximize cumulative rewards received after each action. Unlike supervised and unsupervised learning, RL doesn't rely on pre-existing datasets; instead, the agent gains knowledge through environmental interaction, refining its behavior accordingly. In RL, the agent observes the environment's current state, takes actions, and receives rewards based on its actions' effectiveness. Supervised and unsupervised learning methods are commonly employed for automatic detection [40].

III. APPLICATION IN AEROSPACE

ML has been used in aerospace design and manufacturing, digital twins, validation and aviation services [41], [42], predicting the repair time of parts, identifying fraudulent transactions, identifying objects in images and videos, assessing the risk of accidents, intelligent autopilots [43]. For example, Boeing has designed an intelligent autopilot system based on ML [44]. Also, thanks to this approach, the transportation network has been optimized and the possibility of predicting customer behavior has been provided. With ML techniques, passenger data can be analyzed, and therefore customer loyalty can be improved by optimizing operations, which in turn increases revenue [41]. ML algorithms are able to identify objects in images or videos and thus are very useful in aircraft navigation applications [45]. For example, Airbus uses an ML-based aircraft identification system on the tarmac [46].

Virtual reality (VR) relies on the real environment and engages the user in a completely actual world, and by using a virtual reality headset, he will be able to explore the factual environment[47]. Users can manipulate objects with sensors attached to the device [48]. The important application of this technology in aviation is that by using VR, experts can create 3D models of airplanes and examine performance and aerodynamics [49].

Relying on powerful ML algorithms, it is possible to design more modern, safer and more efficient aircraft, as well as to optimize aircraft performance [27]. Aircraft design with ML is associated with advantages such as data reduction, increased calculation accuracy, aerodynamic prediction and analysis algorithms, modern control systems, etc [29].

ML-based AI models are used in many research fields in data analysis and process optimization [50]. By analyzing sensor data, ML is able to identify wear and tear patterns of components and predict the time of repair or replacement, which prevents unexpected breakdowns and imposing costs and risks [51]. Real-time fault detection sensors lead to the prediction of anomalies. Outliers are identified using feature extraction and principal component analysis methods [52]. Redefining standard data formats and cross-platform data transfer is done using ML [53]. This method leads to the shortening of the manufacturing cycle of materials and data analysis of aircraft parts parameters, as well as speeding up the assembly process of parts, which ultimately simplifies future decisions. ML uses sensors and data reports to detect anomalies in the aircraft manufacturing process. ML has been used in the diagnosis of autonomous production processes [54], [55]. This approach identifies invisible defects such as cracks and warps by recognizing the patterns in the data.

The use of ML in the aircraft manufacturing process has led to cost reduction, increased safety and efficiency. Also, ML has been used in process control, independent diagnosis, material selection, trend identification, abnormal behavior detection, assembly sequence optimization [54], [56].

ML is a field of study that involves developing computer programs that can learn and improve over time from data. In ML, it is common practice to divide a dataset into two parts: the training set and the evaluation set. The purpose of this division is to train a model on a subset of the data and then evaluate its performance on a held-out portion of the data. There are two main approaches to ML: data-driven and model-driven. In data-driven learning, the algorithm focuses on learning patterns and relationships directly from data, while model-driven approaches use prior knowledge and assumptions about the system to construct mathematical models that can be used to make predictions or perform inference tasks.

Within data-driven learning, there are three main types: supervised, unsupervised, and semi-supervised learning. In supervised learning, the algorithm is trained on a labeled dataset and learns to predict outputs for new, unseen inputs. This approach is commonly used in classification and regression tasks. In unsupervised learning, the algorithm looks for patterns and structure in an unlabeled dataset, often for the purpose of clustering and anomaly detection. This approach is useful in tasks such as customer segmentation or anomaly detection. Semi-supervised learning is a combination of both supervised and unsupervised learning, in which a smaller labeled dataset is used to guide the learning process of a larger unlabeled dataset [57].

Risk assessment of aerospace accidents is done with the help of ML by analyzing traffic patterns, weather forecast data and other sources. In model-driven learning, the focus is on building mathematical models based on underlying principles and rules. The models are designed to predict the outputs based on inputs, and the data is used to validate and refine the model. This approach is often used in control and decision-making tasks. An example of model-driven learning is reinforcement learning, where the algorithm learns by interacting with the environment and receiving feedback in the form of rewards or penalties. Figure (1) shows the various applications of ML in the aviation industry and aircraft design.

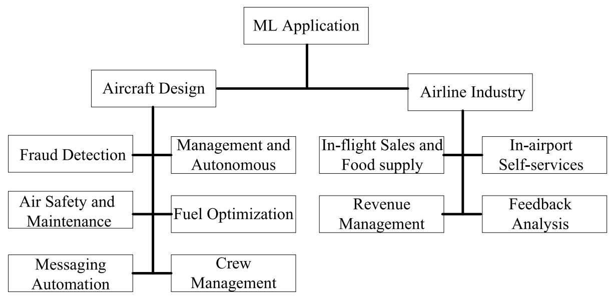

FIGURE 1. Applications of ML in aircraft design and aerospace industry.

A. DESIGN PARAMETERS

As the aviation industry grows, the demand for cost-effective and robust aircraft parts manufacturing using innovative approaches is increasing day by day [58]. Designing parts using ML provides designers with a variety of options in less time. The Boeing 777 is the first aircraft designed using 3D solids technology completely digitally [59].

ML, as a branch of artificial intelligence, aims to improve system performance based on imitating natural intelligence self-learning algorithms, capable of solving complex problems and making decisions. This approach, relying on Big Data, can manage the huge amount of aviation data. The combination of these data with ML methods leads to models with reduced dimensions (ROM) that enable things like flow dynamics control, boundary layer transfer, drag reduction, etc. These models make it possible to predict the aerodynamic forces entering the plane. The integration of Aerodynamic Shape Optimization (ASO) with Computational Fluid Dynamics (CFD) leads to reduced time and improved design performance of aircraft wings, engine nacelles and various components.

ML in the field of aerodynamic optimization leads to reduced fuel consumption, stability and better control of the aircraft. Data obtained from wind tunnel tests and flight tests can be trained in ML models and used to optimize design parameters. Design parameters are simulated in 3D environments and tested in a virtual environment [60], [61]. 3D and ML modeling systems have been used to analyze various aircraft components such as wings and fuselage and design criteria such as weight and performance [62], [63]. ML has led to new airframes with optimal performance in lighter aircraft. Trained ML models are able to create new aircraft structures based on patterns identified in aerodynamic, structural and cost datasets [64]. These structures are evaluated in a computer simulation environment. ML creates more maneuverable control systems and evaluates relationships between variables using a mathematical model [34], [35].

ML methods reduce the cost of manufacturing parts and assembly, improve the safety of tests, and lead to increased efficiency in aircraft manufacturing. Also, this approach is capable of identifying abnormal behaviors in the detection and selection of materials and process control. The use of ML makes it possible to suggest optimal assembly sequences and improve decision-making [54], [56]. GE Aviation uses AI-based analytics to optimize the performance of its jet engines and the efficiency of its production lines [65]. Lockheed Martin has used ML in aircraft design testing and evaluation [66].

B. MATERIAL SELECTION AND HEALTH MONITORING

Material selection using ML is a beneficial method due to the ability to filter suitable materials, shorten time, and determine parameter changes and best options [42]. ML models based on computer vision and thermal detection are able to simulate the weight, durability, cost and strength of materials, detect defects and identify new materials [67], [68]. Also, structural characteristics, pressure resistance, thermodynamic characteristics, temperature sensitivity are possible using ML methods [69], [70].

The use of multi-layer carbon fiber reinforced composite materials in aircraft is very common due to their superior mechanical performance and lower weight. However, these materials are susceptible to subtle damage that leads to mechanical failure in various modes such as matrix fatigue, fiber breakage, and delamination, and affects the safety of aircraft design. Therefore, early detection of damage in aircraft structure is very important. Since damage is hardly visible in the laminate composite skin, image processing techniques can be very beneficial. The structural health monitoring (SHM) system is a sensor-based system capable of detecting damage to the aircraft body [71], [72].

References [73] and [74] used a smart composite connector (SCF) based on sensor and micro transmitter. These researchers were able to identify the health status of the structure by examining the output signals in response to the strains in the joint areas of the composite body with aerodynamic loads during the flight.

ML algorithms are able to classify damage, localize and predict it [75]. Reference [76] developed an automatic in-flight damage detection approach that works using strain field pattern recognition and a self-organizing map (SOM) in a Unmanned Aerial Vehicle (UAV) composite wing. Reference [77] presented a damage detection system based on Finite Element (FE) simulations and Probabilistic Neural Network (PNN) that investigates static strain data of beam and thick plate structures. Structural damage detection using Convolutional Neural Network (CNN) has also been done through strain distribution [78]. As shown in Fig. 2, the workflow begins with sensor data acquisition (strain/vibration measurements), followed by feature extraction using principal component analysis (PCA) or wavelet transforms. These features are then classified using convolutional neural networks (CNNs) to identify damage patterns, enabling predictive maintenance alerts when thresholds are exceeded. In the following section, we will consider the application of machine learning in the field of aerodynamics, where similar techniques are used to predict and optimize the aerodynamic characteristics of fluid flow around aircraft components.

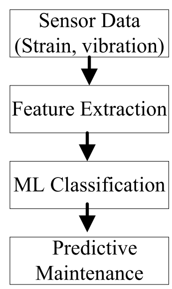

FIGURE 2. ML-based structural health monitoring workflow.

IV. AERODYNAMICS

Predicting the aerodynamic characteristics of the fluid flow around the aircraft wing or airfoil is done using ML. Also, regression models and ML classification algorithms have been used in studies to study fluid mechanics in aerospace. For example, [79] were able to predict the flow fields around airfoils based on incompressible steady state patterns using deep convolutional neural network (CNN) combined with deep multilayer perceptron (MLP) approach. In their study, these researchers extracted the geometry parameters of the airfoil using CNN and then entered this information along with the Reynolds number of the flow and the airfoil bearing angle into the MLP. The results of their study were associated with 99% prediction accuracy.

Another study to predict the pressure fields around the airfoil was done by [80] who used the CNN encoder-decoder method for Reynolds-averaged Navier-Stokes (RANS) based CFD simulation. They used a neural network model for their prediction and were able to achieve an accuracy of 88%. Reference [81] used a CNN model to predict RANS flow patterns. The input parameters of their proposed algorithm are the flow Reynolds number and airfoils carrying angles. The results of this study showed that CNN is capable of investigating the effect of airfoil shape on aerodynamic forces and solves pressure and velocity field orders faster than RANS. Reference [7] used the back-propagation neural network (BPNN) method to predict the aerodynamic coefficients of airfoils. Reference [82] used the two-layer ConvNet method to predict aerodynamic coefficients. The results indicate an increase in the prediction accuracy of drag and lift coefficients.

Reference [83] used deep neural networks (DNN) to solve RANS turbulence models. The results showed that the prediction accuracy has improved. Reference [84] used an artificial neural network (ANN) model to investigate continuous subsonic flows around an airfoil. Reference [85] used Radial Basis Function Neural Network (RBFNN) to investigate the lift coefficient of an airfoil. Reference [86] investigated unsteady aerodynamic characteristics using feed-forward and recurrent models and showed that recurrent neural network (RNN) is an effective method for modeling unsteady flows. Reference [87] used a two-input, one-output neuron-based RBFNN regression model to predict fatigue crack growth rates in aircraft aluminum alloys. Reference [88] used the RNN method to identify the unsteady aerodynamic parameters of airfoils. Reference [89] used the long- and short-term deep neural network method to investigate the aerodynamic and aero elastic responses of the pitch angle and displacement of the airfoil depression.

Turbulent atmospheric conditions are generally a problem faced by airplanes during flight, and the control of aerodynamic forces is very important in the design and safety of airplanes. Anticipating such conditions for actual control is a solution that can be proposed to deal with this challenge. Reinforcement learning (RL) and neural networks methods are proposed for effective aerodynamic control in highly turbulent environment.

A. TURBULENCE

The study of complex turbulent flows in fluid systems is done with the method of turbulence modeling based on calculations and numerical analysis. The major disadvantage of these methods is the lack of accuracy and reliability, the need for large computing resources and high simulation costs [90] and, as a result, increasing safety risks. The use of data-driven ML methods are able to solve these problems. Study [91] used the wavelet analysis method to investigate the local characteristics of chaotic signals. The methods of support vector machines (SVM) [92], Gaussian processes [93], Bayesian statistical method [94], artificial neural network method [95] and ML method [96] have been used to investigate this phenomenon. The proposed method [97] was proposed to calibrate the uncertainty in the RANS model. Other researchers [98] also improved this method in the SA model.

1) CONVOLUTIONAL NEURAL NETWORK (CNN)

CNN is a type of deep learning neural network that is used in image and video processing, and their identification and classification. This method is based on several layers of the network, which uses the extraction of features of the input data and convolution to process and classify them [99].

Turbulent flow modeling using CNN has several advantages. (1) automatic learning and feature extraction from input data, (2) processing of complex and high-dimensional data, (3) recording spatial patterns and associations of data, (4) training on large datasets, (5) pre Seeing the complex values of heat transfer and pressure fluctuations [100].

In [101] a fully convolutional neural network (FCN) was proposed to predict the flow-to-flow velocity field in turbulent open channel flows at typical wall locations and was able to accurately predict the mean flow and the profiles of the rapid flow fluctuations.

In [102] turbulence modeling was performed in a large virtual river with wall piers using CNN. This method is able to minimize the error between LES results and CNN predictions. In [103], a deep learning method was used to reduce atmospheric turbulence distortion in dynamic scenes and it produced acceptable results.

2) RECURRENT NEURAL NETWORKS (RNN)

RNN is used to process sequential data such as time series or natural language [104]. In turbulence modeling using RNN [105], [106], [107] time-dependent features of data, input sequences of variable length, and training with the time-saving Backpropagation Through Time (BPTT) algorithm are utilized.

In [108], RNN was used to predict the turbulence velocity field and resulted in increased accuracy, low mean absolute error (MAE) and high coefficient of determination (R2). In [109], RNN was used in a low-order model of near-wall turbulence. This method is able to predict the turbulence statistics and dynamic behavior of the flow using a long-term short-term memory (LSTM) network.

In [110], LSTM was used to predict wind speed and very accurate results were obtained. Perturbation control using LSTM to construct reduced order models (ROM) is proposed in [111]. The results indicate the velocity field U and high accuracy in modeling the temporal dynamics of turbulent flows.

3) RANDOM FOREST (RF)

This method includes several decision trees and is used in fluid and hydraulic modeling and is a powerful tool for turbulence modeling due to its robustness, accuracy and ability to manage complex data [112]. The study [113] used a RF-based machine learning algorithm to predict Reynolds averaged Navier-Stokes (RANS) flow fields and achieved high accuracy results. Aviation turbulence detection associated with lightning has been performed using RF [114]. RF is able to improve turbulence prediction skill [115].

4) SUPPORT VECTOR MACHINE (SVM)

SVM is used as an ML algorithm for classification and regression analysis. Various studies investigated turbulent

TABLE 1. Comparative analysis of ML techniques in aircraft design.

ML Technique	Application	Advantages	Limitations
CNN	Aerodynamic flow prediction	High accuracy in spatial data	Computationally expensive for high-resolution simulations
RNN/LSTM	Turbulence modeling	Captures temporal dependencies	Struggles with long sequences, requires large datasets
Reinforcement Learning	Flight control optimization	Adapts to dynamic environments	Requires extensive training data, high simulation costs
Random Forest	Turbulence detection	Robust to noisy data	Limited interpretability, struggles with high-dimensional data
Support Vector Machines	Step ladder flow analysis	Effective for small datasets	Poor scalability to large datasets
Physics-Informed NN	Turbulent flow simulation	Integrates physical laws	Complex implementation, sensitive to hyperparameters

flows using SVM [116], [117], [118]. LS-SVM models were used to accurately predict flow conditions and aeration efficiency of step ladders [119].

5) DEEP REINFORCEMENT LEARNING (DRL)

DRL is an ML method that allows combining deep neural networks (DNN) with reinforcement learning (RL) algorithms [120]. Turbulence modeling with DRL leads to adaptability and flexibility, automation and as a result highly accurate models. Chaos simulation has been proposed using multi-agent reinforcement learning (MARL) method [121]. Large eddy simulation (LES) with the DRL method [122] has led to more accurate results compared to the Smagorinsky model and implicit modeling strategies. Fluid dynamics control using neural ordinary differential equation (NODE) and RL led to stabilization of unstable equilibrium conditions and improved performance of turbulent Kuyt flows [123].

6) PHYSICAL INFORMATION NEURAL NETWORK (PINN)

PINN machine learning algorithm is able to combine neural networks (NN) with physical laws [124]. Studies have used PINN to solve compressible flows, turbulent convection, and free boundaries [125]. Turbulence modeling using PINN has been performed to predict the velocity and pressure fields of a two-dimensional turbulent step flow [126]. PINN has been proposed to predict wall shear stresses and transverse velocities in LES [127]. Prediction of Reynolds stress tensor and Reynolds force vector field has been done using PINN [128]. PINN is able to solve Navier-Stokes equations for natural convection in three-dimensional turbulence [129].

B. AIRPLANE WINGS

The dragonfly wing is a high-performance, lightweight structure proposed for the design of an airplane wing inspired by biological structures in recent research [130]. In this study, ML is used to study aerodynamic conditions and out-of-plane bending. Study [131] investigated the morphological aspects of the wing using Voronoi decomposition [132]. The results of [130] indicate the usefulness of ML in designing high performance wing structures for different boundary geometries.

The major environmental effects of the aviation industry have caused the United Nations to pay special attention to the aerodynamic performance of airplane wings in the 2030 agenda [133], [134], and this is done with the aim of reducing fuel consumption and the emission of environmental pollutants.

In order to develop airplane wings, the losses associated with the movement of the wing in the surrounding fluid must be reduced. It means that the force parallel to the input current is reduced and this is done by controlling the current. Different methods of flow control by reducing drag and energy have been reported in studies. Reference [135] used riblets [136], which is a passive method in reducing drag-reducing surfaces.

ML methods such as genetic programming (GP) and deep reinforcement learning (DRL) use the flow equations to investigate optimal perturbations and provide control strategies for large, complex, and nonlinear systems in fluid mechanics [137].

C. OPTIMIZATION OF AIRFOIL SHAPE

The aerodynamic design of the aircraft is highly dependent on the optimization of the airfoil shape. Airfoil shape optimization is classified into gradient-based and gradient-free optimization methods. In the traditional methods of airfoil shape optimization, there are various limitations. For example, in the prediction of airfoil shapes with the reverse design method, the problem of the non-injective nature of physical phenomena is faced due to the infinite shape of the airfoil and the problem of high dimensions [138], [139], [140]. Evaluation of airfoil performance with physical tests of wind tunnel test or numerical simulation and CFD are also limited due to the high dimensions of the design space and high computational costs. ML was developed to solve these problems and is able to reduce complexity. Since RL also provides a data-driven approach, the use of DRL in airfoil design has resulted in high-performance airfoils [141].

Optimization of airfoil shape using supervised neural network has been done in studies. Generative adversarial network (GAN) has been used to reduce the dimensions of the airfoil shape optimization problem [142]. This approach has led to a reduction in the number of assessments required. In [143] a conditional generative adversarial network (CGAN-semi-supervised learning) with lift-to-drag ratio aerodynamic characteristics is used to generate realistic airfoil shapes.

ML-based techniques have been successful in aerodynamic optimization, increasing predictive and control capabilities. DNN is suitable for solving high-dimensional nonlinear problems and, as explained earlier, performs very accurately for predicting turbulent flows.

Due to the high efficiency of the DRL approach in high dimensional and non-linear problems, it is considered as a suitable candidate for solving fluid mechanics problems [138], [139] and optimizing the shape of airfoils. In [140], DRL is used to optimize the aerodynamic shape of rocket control surfaces with the aim of finding the configuration with the highest lift-to-drag ratio. The DRL neural network method has been proposed to optimize two-dimensional airfoil shapes [139]. This method is able to produce optimal wing-like shapes in 3000 parts. In [141], the Markov Decision Process (MDP) method has been used for airfoil design, which has been able to learn in the design space with high dimensions and optimize the airfoil design in different aerodynamic conditions.

D. AIRCRAFT ENGINE FAULTS

Researchers have proposed various methods to automate the borescope inspection process using classical computer vision and advanced deep learning techniques. For example, [144] proposed a defect edge detection approach based on computer vision and Density-Based Spatial Clustering Of Applications With Noise (DBSCAN) clustering algorithm in high pressure compressor blades. Reference [145] proposed a Gaussian filter method for aircraft engine inspection image processing. Reference [146] developed an expert aircraft engine fault diagnosis system based on automatic extraction of damage feature points and measurement of internal damage cracks of engine blades. Reference [147] used Mask RCNN-based deep learning method to find borescope defects. As demonstrated in Table 1, a comparative analysis of various machine learning (ML) techniques applied in aircraft design is presented. Each ML technique has distinct applications, advantages, and limitations, offering insight into their potential use in different aspects of aircraft design.

V. AIRCRAFT MAINTENANCE

Aircraft preventive maintenance aimed at aviation safety and reliability to inspect and replace parts is usually performed in the three forms of flight hours (FHs), flight cycles (FCs), or calendar days (DYs). But due to various reasons, such as early part failure or premature replacement, this method is not cost-effective. Some maintenance cases are also performed based on error reports by the pilot, functional inspection or bird collisions, and the like, which leads to disruption in maintenance planning. The use of sensors in the condition-based maintenance (CBM) method avoids such losses. This method leads to reduction of unnecessary actions and prevention of unforeseen breakdowns. Machine learning methods and specifically reinforcement learning (RL) in aircraft maintenance scheduling problems is a new approach proposed by various studies. In [148], deep learning Q network (DQN) was used for long-term optimization of aircraft fleet. In [149], two-stage scheduling method based on Monte Carlo planning algorithm (POMCP) and deep reinforcement learning (DRL) algorithm was used in aircraft fleet forecasting tasks. This study showed that DRL produces an efficient maintenance program in a very short period of time.

VI. AUTONOMOUS DETECTION

Autonomous detection is the process of monitoring and controlling production processes using ML [3]. Supervised, unsupervised and deep learning are used in the automatic detection of manufacturing defects such as cracks and warps [150]. Fault measurement using ML reduces operation time and fault detection using sensors in real time leads to abnormality prediction [151]. Principal component analysis and feature extraction methods in automated inspections lead to the identification of outliers [52]. ML data-driven methods lead to the simplification and improvement of the quality of the aircraft testing process [152]. The multimodal signal data is improved using a complex and dynamic integration system, accelerometer, and temperature and pressure sensor data modeling [153].

VII. INTEGRATION OF BAYESIAN ESTIMATION

ML has its roots in Bayesian estimation, crucial for aerospace applications like spacecraft attitude estimation. Handling nonlinear, noisy conditions such as measurement errors and model drift is a key challenge. Robust techniques, such as the Adaptive Huber Filter Based on Multiple Strong Tracking (AHFMST), have proven effective in improving accuracy and robustness in spacecraft attitude simulations [154]. Bioinspired navigation systems, such as polarization sensors for UAVs, utilize advanced filtering techniques to address challenges like noise and magnetic interference, significantly improving performance in real-world conditions [155]. Likewise, adaptive robust cubature Kalman filters have been applied to satellite attitude estimation, offering enhanced accuracy and faster convergence by correcting model errors and optimizing estimation algorithms [156]. These Bayesian estimation techniques form the foundation of many ML algorithms, providing robust solutions to complex aerospace challenges and deepening the theoretical understanding of ML applications in aviation [157].

VIII. LIMITATIONS OF THE REVIEW AND SCOPE FOR FUTURE WORK

This paper provides an in-depth exploration of the current state of ML methodologies applied to aircraft design. However, there remain opportunities for further advancements and the development of more sophisticated techniques. As the aerospace sector continues to evolve, emerging technologies, such as hybrid learning models and adaptive algorithms, present significant potential for improving the efficiency and accuracy of design processes in complex, dynamic environments. Future research should focus on leveraging these emerging technologies to address the unique challenges of aerospace applications. Expanding beyond traditional optimization frameworks, there is room to explore innovative design paradigms that could significantly enhance performance, safety, and sustainability. In particular, the integration of ML with novel computational models and high-performance computing platforms will be essential in driving the next generation of aerospace innovation.

This work lays the foundation for future research aimed at transforming ML applications in aviation.

IX. CONCLUSION

The safe design of the aircraft is dependent on predicting and improving various flight conditions, including turbulent air flow, impacts and shocks during the flight of the aircraft, which in turn leads to a reduction in fuel consumption. Researchers use AI models to optimize aircraft design. AI algorithms are able to analyze a large amount of aerodynamic data, fuel efficiency, etc. to optimize aircraft design. ML is used as a subset of AI to simulate and analyze design changes, identify the most efficient options, accelerate the design process and optimize it. AI is capable of increasing safety in aircraft design. AI-related methods are able to predict and detect failures and take preventive measures. This capability not only increases safety but also reduces downtime and maintenance costs, in turn leading to efficiency and sustainability in the aviation industry. By integrating AI systems into aircraft, the development of autonomous aircraft has become possible, increasing the efficiency of air travel and reducing human error. Aircraft design with the help of AI leads to a significant reduction in the environmental impact of aviation. Optimizing fuel efficiency and reducing maintenance measures have led to a reduction in the carbon footprint of air travel. In order to prevent climate change, AI can be used to design airplanes that use alternative and more sustainable fuels. ML algorithms relying on aerodynamics are able to design very optimally. Since the AI electronic brain can calculate more complexity than the human brain, it is able to perform optimization in a wider space. The use of ML techniques to improve the aircraft design process is the topic discussed in this article. ML methods with available aerodynamic data and DL have been used in solving ASO problems. This paper, through an examination of recent research on machine learning (ML) applications in aircraft design, demonstrates that ML utilization has significantly contributed to advancing the aviation sector across multiple domains. These include aircraft operations, component diagnosis and resolution, streamlined component design, air traffic management, object recognition, and more. Hybrid and electric drone systems are advancing thanks to ML technology. Aircraft design with the help of different machine learning methods has various advantages. ML can analyze large amounts of data and help discover new insights. Optimization algorithms can find the best solution among a set of possible options. Modeling complex systems and creating innovative and robust solutions is possible using ML computational intelligence and optimization. These methods are able to explore the design space, manage uncertainty and non-linearity, balance conflicting goals and adapt to changing environments.

Traditional aircraft design methods rely on expert knowledge and computational simulations, but ML significantly enhances this process by enabling the analysis of vast datasets with greater precision and efficiency. ML algorithms allow for a deeper exploration of the design space, effectively managing complex non-linear systems and optimizing designs in ways not achievable through conventional techniques. This leads to more efficient design iterations, improved fuel efficiency, and enhanced safety through predictive maintenance and failure detection. Although challenges such as high computational costs and regulatory approvals remain, the trans formative potential of ML in driving data-driven optimization and innovation in aircraft design positions it as a critical tool for the future of the aviation industry. For future work, exploring federated learning could enable collaborative aircraft design by allowing multiple organizations to share data without compromising privacy. Additionally, the integration of explainable AI will be crucial for ensuring regulatory compliance, allowing stakeholders to understand and trust machine learning-based decisions. Another promising direction is the use of quantum machine learning to optimize composite materials, leveraging quantum computing's potential to enhance material properties and performance. These research avenues could revolutionize the way aircraft designs are developed, ensuring greater efficiency and innovation in the industry. Emphasizing these areas will push the boundaries of ML applications in aerospace engineering.

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SHIMA MOHAGHEGH (Member, IEEE) received the M.S. degree in electrical and electronic engineering from Middle East Technical University, Northern Cyprus Campus. Her research interests include machine learning, high-performance computing, FPGA implementations, and innovative engineering applications.

ALI MOHAGHEGH received the B.S. degree in aerospace engineering from Middle East Technical University, Northern Cyprus Campus, Türkiye. He was with Baykar Company, specializing in performance analysis. His research interests include computational fluid dynamics, data-driven modeling, and combustion modeling. He received second place in the AIAA 2021 Engine Design Competition for the best-proposed engine design in the world.