



Reframe The Field Of Aerospace Engineering Via Machine Learning: Application And Comparison

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Abstract— Since the early 1990s, when the term "Big Data" first appeared, machine learning (ML) has demonstrated its remarkable efficiency and computational capability while managing a variety of co

Complicated issues in numerous fields. Spacecraft design and manufacturing present a variety of multi-objective and restricted optimization challenges that can be effectively resolved with big data analysis and machine learning (ML). These technologies have the potential to be advantageous to the aerospace sector. A thorough analysis of machine learning's application in aircraft engineering is presented in this research article. While the primary focus of rockets is on thermoacoustic instability detection and lunar landing, the artificial satellite portion falls under the categories of satellite communication and default diagnostics. Since each piece of data gathered helps create a better-trained system for attitude control, navigation, and default diagnosis, the widespread application of machine learning in aerospace engineering undoubtedly contributes to the growth of the contemporary aerospace industry by raising the success rate of upcoming space exploration missions.

Keywords—Anomaly Detection, Collision Avoidance, Attitude control, Thermoacoustic, Instabilities, Detection, Rocket landing.

1. Introduction

An important advancement in space exploration was made with the first successful lunar landing of the previous century. And behind-the-scenes sophisticated aerospace engineering methods are credited with the victory. Aerospace engineering is a formal area that includes robotic technologies that help humans explore the wide universe and the design, production, and operation of spacecraft that travel beyond Earth's atmosphere [1]. The area of aeronautical engineering covers a wide range of topics, including as acoustics, thermodynamics, flight mechanics, structural technologies, fluid dynamics,

guidance, and attitude control systems. The origins of aeronautical engineering can be found in the fusion of aerodynamics and mechanical engineering, with a particular emphasis on aircraft operating inside Earth's atmosphere. The first artificial satellite launch, which also signaled the beginning of Space Time, did not occur until the middle of the 20th century, during the Cold War. Three main aerospace industry products are manned spacecraft, artificial satellites, and rockets. Liquid fuel for engine chunk and landing prediction under different conditions are the primary study areas for rockets. Artificial satellite research concentrates on communication networks and fault diagnosis to monitor satellite power systems, even though both manned spacecraft and artificial satellites depend on specific types of rockets for launch and landing.

The widespread use of machine learning (ML) in aerospace engineering in recent decades has accelerated the development of the contemporary aerospace sector. Formally speaking, machine learning (ML) is the study of how different machines can learn without having to be specially programmed beforehand. The goal of machine learning is to extract the information required from prior datasets so that the machine that has been trained can predict future conditions [2]. Machine learning (ML) techniques have emerged as important instruments for resolving huge data-related problems and have had a profound impact on many facets of society, including computer science, pathology, neurology, nutrition, and communication security as well as natural language comprehension [3].

The architecture of this research study is mentioned below and it offers a comprehensive examination of machine learning applications in aerospace engineering. A brief overview of the DL and RL techniques is given in section 2. The uses of machine learning (ML) in aerospace engineering for three major products—spacecraft, artificial satellites, and rockets—are covered and finished in the sections that follow. (i) The spacecraft has attitude control, collision avoidance techniques, and anomaly

detection (section 3). (ii) Default diagnostic and satellite communication are included in the artificial satellite (section 4). (iii) The rocket's identification of thermoacoustic instabilities and lunar landing are included in section 5. Section 6 lists and discusses the benefits and drawbacks of the related machine learning models that are described in the article, as well as some hopes for the future in the field of aerospace engineering.

Big data analysis and ML that are effective at resolving various multi-objective as well as limited optimization issues that emerge in spacecraft design and manufacture, are positioned to benefit the aerospace industry. This research paper demonstrate a radical analysis of the use of ML in aerospace engineering and its architecture is listed as follows.

In recent decades, the vast application of machine learning(ML), in aerospace engineering boosts the growth of the modern aerospace industry. ML is formally defined as field of study that allows different machines to learn without being specifically programmed in advance and the purpose of machine learning is to extract needed information from previous dataset so that the trained machine learning could makes predictions on future conditions [2], ML technique have become major tools.

rewards the activities that result in the best possible outcome. An agent in reinforcement learning (RL) is a machine or the learner. By definition, an environment is a setting for interaction that bestows rewards and states based on the behaviours the agent learns.

(MDP) is the most common mathematical-based framework to describe an environment in RL where its structure can be observed in the Figure 1 below [7].

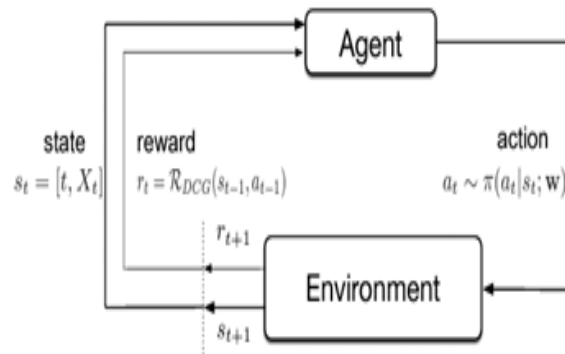


Figure 1. Agent-environment interaction in MDP [7].

2 Overview of the approaches

2.1. Deep Learning

DL is a subclass of ML and is described as a neural network (NN) that uses numerous layers to gradually extract higher-level information from the original input data. It may be further divided into two types: semi-supervised learning and supervised/unsupervised learning [4]. These layers allow the NN to mimic the functions of the human brain, facilitating the processing, categorization, and learning of vast amounts of data. Even if a single layer is capable of making erroneous predictions, several hidden layers can help with optimization and refining to increase prediction accuracy[5].

The suggested design has significantly improved performance and adaptability to changes following ongoing training and data depth increases, enabling it to function well on a variety of problems [5]. However, there are also potentially deadly drawbacks of DL that can outweigh the benefits. DL typically calls for high-end gear with fast processing capabilities and costly resources. Furthermore, unless the entire algorithm is changed—a tedious and opaque process—it is unlikely that a detected flaw will be fixed. Based on its features, deep learning (DL) demonstrates its effectiveness over other methods in the field of aerospace engineering, particularly in satellite communication and rocket landing prediction, where a lot of fresh data in the form of images needs to be analysed.

2.2. Reinforcement Learning (RL)

ML is a subclass that also includes autonomous systems like RL. RL's formal definition places its focus on learning a behavioural policy with the intention of maximizing rewards [6]. More precisely, during reinforcement learning (RL), a computer learns by trying different things and then, depending on feedback,

It should be noted that Deep Reinforcement Learning (DRL) is regarded as a fusion of deep learning and reinforcement learning. In order to handle the judgments that are too complicated for RL, DRL uses a NN to help forecast the states in the interaction. Compared to other learning approaches, the RL/DRL exhibits significantly higher efficiency in spaceship collision avoidance and attitude control related problems because of its capacity to learn from an environment with goal-oriented objectives.

3 Machine Learning in Spacecraft

3.1. Anomaly Detection

Finding anomalies After decades of launching expertise, spacecrafts are well-designed taking various considerations into consideration. But even a minor unforeseen circumstance could cause the entire trip to fail. In spacecraft flight, anomaly detection plays a critical role in identifying unusual occurrences or suspicious observations, tracking the spacecraft's status, and forecasting potential malfunctions.

The present anomaly detection system aboard spacecraft is mostly based on two complementing approaches: Perform Out-Of-Limits (OOL) verification on critical parameters for each new telemetry reception. (2) Daily observation of the parameters' statistical properties.

OOL techniques are still thought to be the most widely applied techniques for achieving anomaly detection to this day. Fuertes et al., however, highlight the shortcomings of OOL based on two real-world anomalies that happened on a CNES spacecraft,

arguing that the approach fails to recognize aberrant behaviours and respond quickly enough [8]. This study presents an enhanced approach, the One-Class Support Vector Machine (OC-SVM), for unsupervised detection. It has been demonstrated to yield remarkable outcomes in detecting anomalies that OOL was unable to detect [8]. The comparison of the Local Outlier Factor (LOF)-based K-nearest neighbours (k-NN) classification algorithm and the OC-SVM shows that the latter performs worse, particularly for symbolic data.

To find anomalies based on normal datasets, two unsupervised deep learning algorithms—Variational Autoencoder (VAE) and DANomaly—are utilized. In conclusion, the GANomaly model outperforms the VAE model in terms of performance. Additionally, a different article outlines ADTM, a data-driven method for ISHM that monitors the health of spacecraft and space habitats. It is a semi-supervised machine learning technique designed to quickly identify anomalies [10]. Additionally, we created a typically pre-trained model for particular unique telemetry channels called Channel-particular Long Short-Term Memory (LSTMs) based on transfer learning principles [11]. This can decrease the overall number of unique models required as well as the training time required for each model.

For the datasets from the Mars Science Laboratory rover (MSL) and Soil Moisture Active Passive satellite (SMAP), the average normalized absolute error of the suggested model is as low as 5.9%. Ultimately, as illustrated in Figure 2, we created OmniAnomaly, a stochastic Recurrent Neural Network (RNN) for multivariate time series anomaly detection [13].

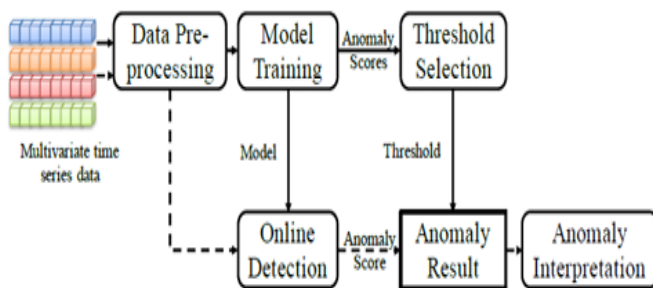


Figure 2. Structure of OmniAnomaly [13].

In contrast to the previously discussed machine learning method, OmniAnomaly's overall structure is split into two sections: offline training and online detection, which are shown in the figure as separate solid and dashed lines, respectively. The suggested approach shows its ability to interpret observed entity abnormalities with an accuracy of 85.35% for SMAP dataset and 90.14% for MSL dataset when compared to other candidate models. All of the previously listed studies are included in Table 1 under the anomaly detection category.

Table 1. Summarizes all mentioned papers above under the category as anomaly detection.

Articles	Features/Data	Approaches	Models/Algorithms	Results
[8]	Time-series data from CNES's spacecraft	Unsupervised learning	k-NN/OC-SVM algorithm	OC-SVM show significant improvement in symbolic data
[9]	Time-series data by attitude control simulator LUNASIM	Unsupervised DL	VAE/GANomaly	GANomaly performs better than VAE
[10]	LabSat test cases	Semi-supervised learning	Topological-feature Map (ADTM)	ADTM identified all known faults in LabSat
[11]	Time-series data from Mars Reconnaissance Orbiter (MRO)	Transfer learning	Channel-Specific LSTMs	Significantly less training time but a bit lower precision compared to existing models
[12]	Time-series data from SMAP/MSL	Unsupervised learning	LSTMs-based model	Average normalized absolute error: 5.9%
[13]	Time-series data from SMAP/MSL	Supervised DL	OmniAnomaly (RNN based)	85.35% Accuracy for SMAP 90.14% Accuracy for MSL

3.2. Preventing Collisions

Even with the most advanced technologies and meticulous design, spacecraft can be completely destroyed in the event of a minor collision with satellites or meteorites. The increasing number of spacecraft and satellites being launched into Low Earth Orbit (LEO) makes it imperative to identify the most effective machine learning algorithms that aid in preventing collisions. Four studies on collision avoidance are reviewed in this subsection. First of all, it should be noted that all machine learning methods used in collision avoidance are predicated on the dataset of conjunction data messages (CDMs), which are generated when two objects approach one another [14–16].

Additionally, a method for numerically propagating State Transition Matrices (STMs) that incorporates drag and solar radiation pressure is provided. Additionally, we introduce the Kessler Python module, which applies machine learning to collision avoidance. Kessler has features built in that enable CDM to be imported and exported in the common format and to forecast conjunction event progression using Bayesian RNNs that have been trained. By creating the first unique probabilistic generative model based on physics, another article [16] presents an alternative methodology. The model may derive posterior.

Table 2. Summarizes all mentioned papers above under the category of collision avoidance.

Articles	Features/Data	Approaches	Models/Algorithms	Results
[14]	CDMs	Semi-supervised learning	low-thrust CAM model	Faster and more accurate than the previous semi-analytical solution
[15]	CDMs	Supervised learning	Bayesian LSTMs	Kessler performs Bayesian inference and make reliable predictions
[16]	CDMs	Probabilistic programming approach	physics-based probabilistic stochastic generative model	Proposed model is reliable in predicting and preventing collision
[17]	Two canonical spacecraft docking scenarios	RL	PPO	Spacecraft can avoid collision events within centimeters
[18]	Two target spacecraft.	RL	DDPG	The energy consumption is decreased by 16.44%

distributions by Bayesian inference and the probabilistic programming method to conjunction assessment, which enable the model to make more accurate predictions and identify the critical factors and orbital properties that improve the likelihood of a collision.

They provide an autonomous navigation system that can manage unpredictable circumstances while keeping an efficient computing load, according to the process. [17]. More specifically, a control policy is created using Proximal Policy Optimization (PPO), and its effectiveness is assessed in a simulated Three-Degree-of-Freedom (3-DoF) dynamics setting. However, in order to achieve the autonomous spacecraft rendezvous (ASR), Qu et al. suggest a deep deterministic policy gradient (DDPG) approach [18].

As a result, the proposed control strategy's efficiency and accuracy are verified numerically. Table 2 shows all mentioned papers above under the category of collision avoidance.

3.3. Attitude Control

For the spacecraft to travel safely and avoid being exhausted by the atmosphere, the shell must be resistant to extreme temperatures and wear. In this instance, spacecraft often have enormous masses, which result in significant inertia and make the spacecraft difficult to manually operate. Additionally, the combined inertia of a spacecraft docking with an object of unknown mass would be difficult to calculate and might easily lead to the spacecraft's annihilation. As a result, using machine learning for attitude control is crucial for spacecraft operations.

Our team has developed a framework for generating an adaptive attitude controller for spacecrafts that can effectively perform large-angle slew maneuvers and overcome various unforeseen disturbance torques while training [19]. Additionally, the Partially Observable Markov Decision Process, or MDPs, decision-making model quantifies RL (POMDP). Conversely, we Favor the predetermined ideal paths of straightforward Ordinary Differential Equations (ODEs) in order to compel the attitude controller to function as a nonlinear feedback controller [20]. The spaceship attitude control system has demonstrated the efficacy of the algorithm. A new framework for online learning is introduced in another article [21]. As illustrated in Figure 3, the proposed framework can produce attitude controllers that can self-tune to the local dynamics of the system and achieve optimal pointing precision in scenarios where the physical characteristics of the system may be unknown or untested.

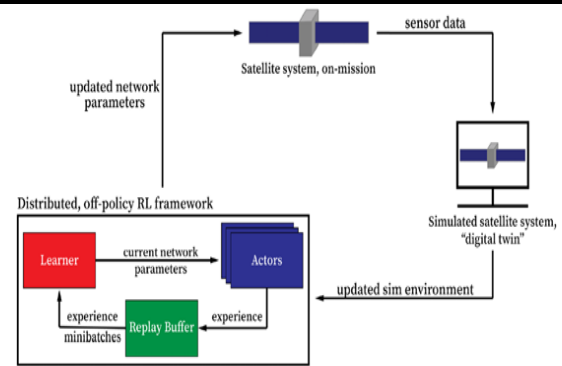


Figure 3. Structure of proposed online learning framework [21].

Ultimately, our group created the RL-based sliding mode observer (RLSMO) in order to diminish the periodic disturbance and explore nondeterminacy, including angular velocity and the unknown inertia matrix [22]. The stability of RLSOMO has been demonstrated, and in hypothetical scenarios, the suggested controller doesn't need to modify any parameters. All of the previously listed publications are included in Table 3 under the attitude control category.

Table 3. Summarizes all mentioned papers above under the category of attitude control.

Articles	Features/Data	Approach	Models/Algorithms	Results
[19]	Lockheed Martin Corporation LM50 spacecraft system	DRL	MDPs/POMDP	Accomplish industry-standard accuracy.
[20]	N/A	RL	ODEs with attractive behaviors (first/higher order)	Accuracy is tested in different simulation
[21]	Lockheed Martin Corporation LM50 spacecraft system	RL (Online learning)	TD3/PPO	TD3 predicts more accurate than PPO
[22]	2 target spaceships	RL	RLSMO	Able to counter unknown inertia matrix or a change in the target spacecraft

4. Machine Learning in Satellite

On October 4, 1957, the Russian space probe Sputnik, which was about the size of a beach ball, was launched into orbit, making the artificial satellite a reality. These days, the three primary purposes of artificial satellites are observation, navigation, and communication. And those are only achievable with machine learning's help.

4.1 Satellite Communication

The fifth-generation mobile networks, or 5G, have hinted in recent years that the forthcoming 6G may not be confined to the earth. There would be ubiquitous communication across satellite, aerial, and ground networks if networks were expanded to the sea or perhaps space [23]. The need for ML algorithms and models in satellite communications is even more critical given the industry's continued reliance on human processes. Four studies on artificial satellite communication are examined in this subsection.

Generalized polarized enhanced spatial modulation (GPESM) is a novel multiple-input multiple-output (MIMO) transmission technique that was presented in one study [23] for dual-polarized land mobile satellite (LMS) communication. Figure 4 illustrates this scheme.

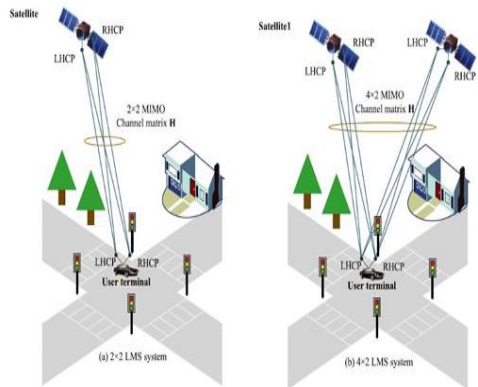


Figure 4. MIMO system [23].

According to the figure, for 2×2 MIMO systems, the GPMoD system is used, and for 4×2 MIMO systems, the GPESM System Model. According to the testing findings below, GPESM outperformed the traditional generalized polarized modulation (GPMoD) scheme in terms of bit error rate (BER). Furthermore, the BER performance of both the AMMD-based and the Deep Learning Network (DNN)-based PA techniques for GPESM improves, with the AMMD-based PA method having a comparatively higher BER performance and greater complexity cost than the DNN-based PA approach. Additionally, Qian et al. propose that the most ideal model is GPESM with DNN-based PA approach by weighing the advantages and disadvantages of each model [23]. Ferreira et al. take a different tack and use multiobjective RL to concentrate on satellite communications [24].

The effectiveness of the RL algorithm is evaluated using various simulated communication mission goals, particularly in the GEO satellite channel, where the results show a significant improvement of 3:59 times in the 25th percentile and 6:8 times under rainy conditions when compared to the same weather conditions without the proposed algorithms.

A different study suggests a unique radio resource allocation technique that makes use of multi-objective reinforcement learning and Artificial Neural Network (ANN) ensembles to handle competing mission-based goals and available resources [25]. More precisely, the NN-based RL (RLNN) algorithm is applied to the case of nonchanging AWGN channels utilized for the downlink to a stationary ground station from geostationary (GEO) satellites.

The trained RLNN system can forecast the multi-objective fitness ratings of any activity. The simulation restricts the parameter value range to make sure that system simulations adhere to the DVB-S2 standard's changeable parameters.

The simulation results demonstrate the algorithm's exceptional performance, particularly in the Power Saving mission where the error is as low as 1.77%.

The cognitive engine is implemented using the MORL-based architecture, whose structure is depicted below in Figure 5 [26].

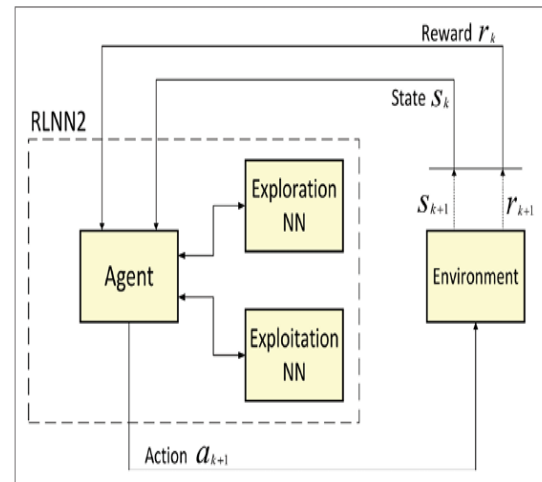


Figure 5. MORL-based framework structure [26].

4.2 Default Diagnosis

Maintenance and repair of artificial satellites are difficult and cannot be done manually because they are in the thermosphere and exosphere. Satellite components are prone to failure, particularly the power system, which is the central nervous system of the spacecraft [27]. Furthermore, an on-orbit mission failure could arise from any satellite component flaws that are not identified in a timely manner. The default diagnosis that aids in the satellite's proper operation is largely influenced by machine learning. For the data-driven methodology for defect diagnosis based on fuzzy Bayes risk (FBR) and SVM, one publication provides a heuristic filter feature selection procedure, as shown in Figure 6 [27].

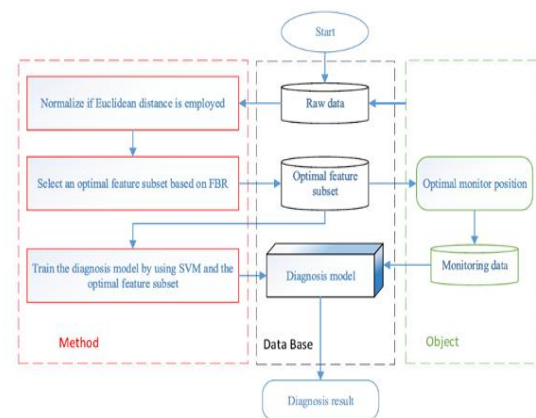


Figure 6. The strategy of Fault Diagnosis [27].

The proposed technique is divided into three primary sections, as depicted in the figure: the "Method," "Database," and "Object" sections. The computing effort and classification accuracy of the suggested feature selection are the two-importance metrics that are used to assess the classification performance. Consequently,

the comparative trials show a notable increase in classification accuracy at a longer running period than any of the preceding techniques. However, a different study noted that it is challenging to extract the rules from unlabelled data using data-driven diagnostics [28].

Instead, the authors propose a clustering technique based on neighbourhood relationships and spatial grid partitioning to address the aforementioned weakness [28]. A approach based on neighbourhood grid clustering (NGC) and information entropy is developed to address complex data-driven fault diagnosis problems. The suggested technique is capable of automatically processing and clustering data with any shape thanks to the artificial data experiment.

Consequently, when studying the failure data of the satellite power systems, NGC exhibits much stronger clustering effects for 2/3 clusters and running duration when compared to other current candidate models. Additionally, given a relatively limited set of samples, Chang et al. use a unique metalearning network to accomplish shipborne antenna function state recognition [29].

This research uses three different algorithms to compare the proposed metalearning network (MN) with the following: Convolutional Neural Network (CNN), Transfer Component Analysis (TCA), and Transfer Learning Network (DaNN). The end result shows that the suggested MN performs better than the other three methods and can classify under the need of few data. Finally, a different study creates a DL-based unique defect diagnostic methodology with two stages: (1) feature selection phase utilizing k-NN classifier and Binary Grasshopper Optimization (BGOA); (2) prediction phase employing three distinct ANN algorithms [30].

The dataset of satellite power plants and airplane engines serves as the foundation for the simulation. Consequently, the suggested methodology exhibits noteworthy efficacy and efficiency in contrast to the two extant fault detection methodologies, namely the Deep Belief Network (DBN)-based diagnosis approach and the neighbourhood decision-theoretic rough set (DNDTRS).

5. Machine Learning in Rocket

Rockets are made to propel spacecraft further beyond our solar system, even though spacecraft allow humans to travel within it. Nonetheless, the machine learning structure for collision avoidance and anomaly detection is the same for the rocket and the spacecraft. Two primary sections are introduced in these subsections to prevent material from being repeated: (1) Identification of Thermoacoustic Instabilities (2) The landing on the moon.

5.1 Thermoacoustic Instabilities Detection

The central component of a rocket is the combustion chamber, which is where fuel and oxidizer are combined and detonate. The combustion process produces hot exhaust that travels through the nozzle, accelerating flow and producing thrust [31]. Consequently, any thermoacoustic instabilities that arise could cause the rocket launch to fail completely, costing billions of

dollars. Three publications on the detection of thermoacoustic instabilities are reviewed and summarized in this subsection. First to note, the experimental thrust chamber "D" (BKD), whose structure is depicted in figure 7 below [32], is the dataset used in all three studies.

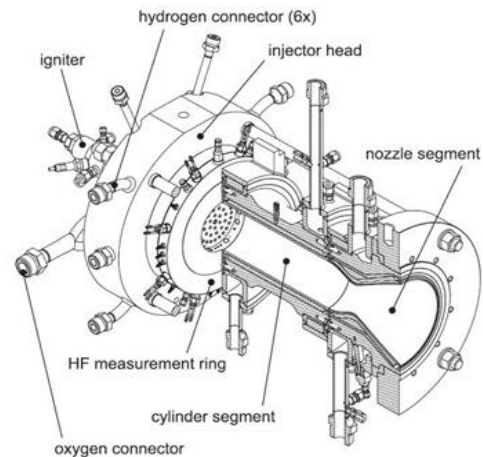


Figure 7. Inner structure of BKD [32].

In order to create a data-driven warning signal that can predict high-amplitude thermoacoustic instabilities with a very low probability of false alarms, we suggest using the recurrence quantification analysis (RQA) and SVMs models [32]. In the near future, the trained SVM may enable the active control of combustion instabilities. However, Sengupta et al. [33] employ an alternative strategy based on Bayesian Deep Learning. The authors specifically describe a model for predicting the amplitudes of dynamic pressure signals that is based on a Bayesian neural network (BNN).

Depending on the different combinations of inputs selected, the suggested autoregressive BNN exhibits varying accuracy (about 25–40%). Lastly, we compared the effectiveness of the binary classification algorithms for thermoacoustic instabilities, Decision Tree (DT), KNN, Multilayer Perceptron (MLP), and Random Forest (RF) [34]. OSCILOS is used to construct the setups and search for unstable thermoacoustic phenomena. With the RF algorithm achieving the highest accuracy of 99.6%, all four algorithms offer accuracies of higher than 98%.

5.2. Lunar landing

Despite this, rockets are frequently employed to launch spacecraft beyond Earth by producing thrust and accelerating flow. However, the rocket can generate thrust in opposition to the spacecraft's speed, which would cause it to slow down. In the realm of aerospace engineering, rockets that are specifically designed for these purposes are referred to as retrockets. Four studies are studied in total in this part, which focuses on the soft lunar landing employing retrocket. We both use the same technique, DNN under DRL approach, to target rocket fuel-optimal control concerns for lunar landing, as seen in Figure 8 [3536].

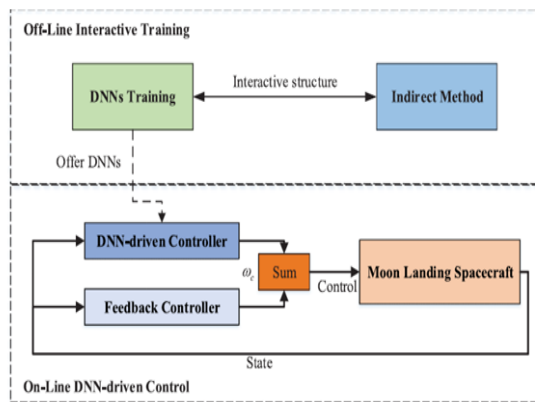


Figure 8. Proposed DNN-driven optimal controller [35].

We suggest a cooperative nonlinear control approach driven by DNNs [35]. Comparing the proposed methodology to the previous homogeneous polyhedral algorithms reveals much improved accuracy and reduced training time. However, Cheng et al. improve upon this by creating a DNN-driven approach in conjunction with Costate normalization, yielding a testing model accuracy of 97.9% [36]. Our team suggests an image-based approach to address lunar landing problems [37–38]. More precisely, a prior paper favours a reinforcement meta-learning approach for landing job handling.

The Apollo 16 landing site data is used to immediately train the suggested PPO model, which shows good precision across all testing scenarios. Lastly, our team presents a CNN-based approach model for Hazard Detection/Avoidance intended to enable precise landings on the moon [38].

The suggested model attains an average accuracy of 83% after training on Digital Elevation Maps (DEM) data from the Lunar Reconnaissance Orbiter (LRO) mission. All of the papers listed above that fall under the heading of rocket lunar landing are compiled in Table 4.

Table 4. summarizes all mentioned papers above under the category of rocket lunar landing.

Articles	Features/Data	Approaches	Models/Algorithms	Results
[35]	fuel-optimum data	DRL	DNN	The DNN-driven controller performs better than homogeneous polyhedral methods.
[36]	fuel-optimum data	DRL	DNN + Costate normalization	Model accuracy 97.9%
[37]	Apollo 16 landing site	DRL	PPO	Demonstrates good precision in all testing cases
[38]	DEM data from LRO mission	DL	CNN	83% average accuracy

6. Discussion

The adoption of ML methods, particularly DL and RL, has accelerated the development of the aerospace sector in a variety of ways. Thirty publications are examined in the body of the report, which is divided into three main sections: spacecraft, artificial satellite, and rocket. As some ML applications are similar, the subsections under each main part are thoroughly examined and created to prevent material overlap. The spacecraft anomaly detection area uses a variety of methodologies, but two RL-based approaches stand out. Both the RNN technique under supervised DL and the GANomaly model under unsupervised DL,

which result in the surveillance program NOSTRADAMUS and OmiAnomaly, respectively, exhibit great detection efficiency and accuracy.

Nevertheless, both methods lack data post-processing, which prevents the abnormalities from being correctly identified once they are discovered. In order to emphasize the patterns even more, adding Transformers and attention to time-series data is one potential approach.

This will be the primary focus going forward. Research on attitude control indicates that controllers based on off-policy algorithms generally yield a more acceptable result than other controllers; in particular, RL and DRL techniques are preferred.

That being said, neither of the approaches uses data post-processing, thus once anomalies are found, they cannot be properly identified. Adding Transformers and paying attention to time-series data is one possible way to highlight the patterns even more. Moving ahead, this will be the main area of concentration. Studies on attitude control show that off-policy algorithm-based controllers, in general, perform better than other controllers; RL and DRL approaches are especially recommended.

Future work in attitude control systems aims to reduce training time, which is seen to be the primary barrier in the field, and to make use of the ability to generate data from a constellation of satellites, building on recent successes in distributed reinforcement learning. The dual-polarized LMS MIMO system built on the DNN-based GPESM model in the artificial satellite communication section shows its superiority over other systems in terms of accuracy and running time. Future studies should integrate the suggested MIMO system with a multiple-unmanned aerial vehicle (UAV) system and enhance the current simulation process's imitations of less realistic satellite channels. The detection of thermoacoustic instabilities in rockets has advanced to a point where it is considered a fundamental subject for actual rocket launch.

Building on previous advances in distributed reinforcement learning, future work in attitude control systems aims to cut training time, which is considered the main obstacle in the field. Additionally, future work will leverage the capability to generate data from a constellation of satellites. In the artificial satellite communication portion, the dual-polarized LMS MIMO system, which is based on the DNN-based GPESM model, demonstrates its advantage over other systems in terms of accuracy and running time. Future research should improve the existing simulation process's imitations of less realistic satellite

channels and combine the proposed MIMO system with a multiple-unmanned aerial vehicle (UAV) system. Nowadays, the detection of thermoacoustic instabilities in rockets is regarded as an essential topic for actual rocket launches due to its significant advancements.

7 Conclusion

The Conversation Manager, responsible for initializing the conversation history, plays a pivotal role in overseeing the high-level management of the ongoing conversation. It handles the task of deciding when to interrupt the process and ensures seamless communication between the user, AI agents, and the system as a whole. It maintains a conversation object which includes the messages from the AI agents and the result of the actions from the Evaluation Environment.

Parser. The Parser interprets the responses generated by agents, extracting commands and arguments in a predefined format. It ensures that the instructions are correctly formatted, validating the number and accuracy of arguments (e.g., a file editing command requires the file path argument). In case of parsing failures, error messages are injected into the conversation, preventing further actions on the repository. Successfully parsed commands are further analysed, by enforcing specific agent permissions and conducting additional semantic checks. It ensures that the suggested actions comply with the fine-grained permissions specified by the user. If the command passes scrutiny, the conversation manager invokes the corresponding action in the tools library.

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