Acceleron Aerospace Journal || AAJ.11.2106-2416
Volume 2, Issue 4, pp (241-250)
Review Paper
ISSN- 2583-9942 || DOI: 10.61359/11.2106-2416

Machine Learning in Combustion: Optimization of Fuel Combustion of Rockets

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Abstract: The application of Machine Learning (ML) techniques in research has seen a drastic increase in the past few years. The primary focus in rocket propulsion is to understand the combustion process and to find various methods to optimize it. This paper provides an overview of the relationship between machine learning and combustion, with a specific focus on optimizing rocket fuel combustion. The introduction presents an overview of combustion and the various ways in which ML is associated with it. Subsequently, the paper discusses various ML algorithms, extending its discussions to supervised, unsupervised, and semi-supervised learning techniques, along with some of their types. An overview of different types of rocket engines is presented to understand the characteristics, advantages, and disadvantages of commonly used rocket engines such as solid, liquid, and hybrid propellant ones. Focusing on rocket fuel combustion, the discussion extends to various methods of optimizing the combustion process. Finally, the paper presents comprehensive results and discussions derived from the studies conducted on rocket fuel combustion optimization.

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**Received: 17-April-2024 || Revised: 29-April-2024 || Accepted: 29-April-2024 || Published Online: 30-April-2024.

1. Introduction

Combustion generally refers to the process of burning something. Combustion science involves studying various processes for deriving energy from burning and utilizing it for various purposes while considering environmental factors, the fuels used, and the impact of burned fuel on the surroundings. Combustion is an interdisciplinary study involving fluid mechanics, chemical kinetics, and chemical reactions occurring between the fuel and environmental factors. The energy obtained from combustion can power automobiles such as cars, trucks, locomotives, and even rocket propulsion. In the current scenario, environmental engineers and chemical engineers are more concerned with reducing the negative impact of the combustion process on nature. Automobile engineers and aerospace engineers involved in deriving energy from combustion focus on maximizing efficiency, i.e., obtaining more energy while minimizing fuel usage. Engineers are working to lower CO2 emissions from fossil fuel-fired power plants. Additionally, researchers in this field are searching for the best machine learning techniques for optimizing the combustion process. ML aims to uncover patterns in vast amounts of data, create data-based models for forecasting, and assist in resolving numerous challenging issues. ML can solve the complex and non-linear chemical processes of combustion. Furthermore, in this age of big data, high-performance computing facilitates managing enormous amounts of data and speeds up the simulation of physical phenomena, data mining, and AI. Initially used for rendering graphics and videos, GPU hardware is now dominant in high-performance computing due to its superior parallel computing capability [1].

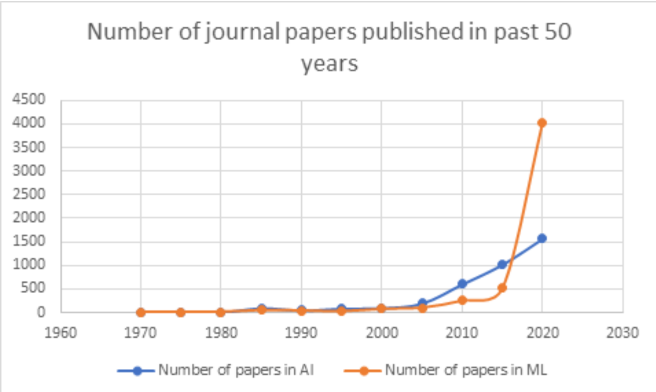


Figure-1 Number of Journal Papers Published in the Past 50 Years

The concept behind machine learning (ML) and artificial intelligence (AI) is for computers to mimic human learning and decision-making processes. AI and ML have grown in importance across a wide range of scientific and industrial fields due to advancements in computing systems. Another sector where AI and ML can be beneficial is the energy sector. We used VOSviewer software to examine the relatively recent usage of AI and ML in the energy field and suggest promising or untapped areas where these concepts can be applied to investigate the current status of these concepts in energy-related areas [2].

2. Overview of ML Algorithm

ML techniques can generally be divided into three categories: supervised, unsupervised, and reinforcement learning.

2.1. Supervised Learning

In order to make predictions or choices on unobserved data, supervised learning is a fundamental machine learning technique where a model learns patterns and correlations using labeled training data. In this type of learning, we examine the parameters of the problem, such as the type of data, the complexity of relationships, and any specific requirements, to select a suitable supervised learning algorithm. Based on our study, we choose a method that aligns with the problem's objectives and constraints, such as decision trees, support vector machines, logistic regression, neural networks, and linear regression [3]. Using the training set, we train the chosen model so that it can uncover the underlying dependencies and patterns in the data. During this training phase, the model iteratively adjusts its internal parameters to minimize a selected objective function, such as mean squared error or cross-entropy loss. Following model training, we evaluate the model's effectiveness using appropriate evaluation metrics like F1 score, recall, accuracy, precision, and area under the curve (AUC). These metrics help us assess the model's efficacy in solving the problem by providing insights into the model's predictive capabilities.

Classification Analysis: A type of supervised learning in machine learning and data mining is classification analysis, also referred to as classification modeling or a classification task. It involves grouping input data into predefined classes or categories based on their characteristics. The goal of classification analysis is to create a predictive model that can accurately classify novel, unforeseen events according to their characteristics.

For classification analysis, a set of instances or observations serves as the input data, with each instance described by a set of features or attributes. The target variable, also known as the class label or outcome variable, represents the class or category to which each instance belongs. Common class labels include "spam" or "not spam," "fraudulent" or "non-fraudulent," "cat" or "dog," etc.

The classification model is trained using a labeled dataset, where each instance has a corresponding class label. In the training set, the model discovers relationships and patterns to make predictions about the class labels of hypothetical instances. This process involves extracting relevant features, selecting a suitable algorithm, and optimizing model parameters to generate accurate predictions. Various algorithms, such as k-nearest neighbors (KNN), logistic regression, decision trees, random forests, support vector machines (SVM), naive Bayes, and neural networks, are commonly used for classification analysis **[4]**. The choice of algorithm depends on the specifics of the problem and the characteristics of the data, with each technique having its own benefits, assumptions, and trade-offs. The effectiveness of a classification model is often assessed using a variety of metrics, including accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics evaluate how accurately the model categorizes instances and how well it handles false positives and false negatives. Classification analysis finds application in various areas such as customer segmentation, sentiment analysis, fraud detection, image recognition, medical diagnosis, email spam filtering, and more. It is crucial for making informed decisions and projections based on categorical data **[5]**.

Regression Analysis: Regression analysis is a statistical technique used in supervised machine learning to model the relationship between a dependent variable and one or more independent variables. Its goal is to predict the value of the dependent variable based on the values of the independent variables. The dependent variable in regression analysis is continuous, meaning it can take any number within a specified range, while the independent variables can be categorical, continuous, or a combination of both, also known as predictor variables or features. To make predictions, one must first estimate the relationship between the independent and dependent variables. The regression model assumes a linear or non-linear relationship between the independent variables and the dependent variable. Using a training dataset, the model learns the values of the dependent variable and its corresponding independent variables. It then estimates the coefficients or parameters that represent the relationship between the variables, aiming to minimize the difference between predicted and actual values of the dependent variable.

There are several regression algorithms available, such as neural network regression, random forest regression, support vector regression, and linear regression, among others. The choice of algorithm depends on the type of data and the underlying relationship between the variables. Regression analysis finds applications across various industries, including finance, economics, social sciences, healthcare, and engineering. It can be used to solve a wide range of problems, including sales forecasting, price prediction, demand analysis, risk assessment, impact evaluation, and trend analysis. By understanding the relationships between variables and making accurate predictions, regression analysis aids in decision-making, planning, and understanding the factors influencing specific outcomes **[6]**.

2.2. Unsupervised Learning

Unsupervised learning, a branch of machine learning, aims to discover structures, relationships, or patterns in data without the aid of labels or other target variables. In unsupervised learning, the algorithm learns solely from the input data and seeks insightful patterns or data representations. A defining feature of unsupervised learning is its use of unlabeled data, meaning there are no predetermined results or established patterns to guide the learning process. Instead, the algorithm analyzes the data and identifies inherent patterns or groupings based on similarities or differences among data points.

The primary activities in unsupervised learning include:

- ***Clustering:*** Clustering algorithms attempt to group similar data points together based on their inherent characteristics. The goal is to identify natural clusters or subgroups within the data.

- ***Dimensionality Reduction:*** Dimensionality reduction methods involve reducing the number of features or variables in a dataset while retaining the most important information. This simplifies the data representation and eliminates redundant or irrelevant features.
- ***Anomaly Detection:*** Algorithms for anomaly detection identify outlier or unusual data points that deviate from expected patterns. This capability is valuable for detecting fraud, network intrusions, or any abnormal data behavior.
- ***Association Rule Learning:*** Association rule learning uncovers intriguing relationships or associations between different components or variables in a dataset. It is commonly used in market basket analyses to reveal patterns of frequently purchased combinations of goods.

Unsupervised learning greatly benefits exploratory data analysis, data pre-processing, and insight generation from unstructured or unlabeled data. It enables the discovery of subtle patterns and structures that may not be immediately apparent, facilitating the extraction of valuable information and informed decision-making.

Clustering: Clustering is a method used in unsupervised learning that aims to group data points with similar properties or characteristics. It involves dividing a dataset into clusters, where data points within a cluster are more similar to each other than to those in other clusters. Clustering helps uncover the underlying structure or patterns in data without prior knowledge of the groups or classes. It identifies potential natural groupings or clusters in the data and provides insights into data distribution and connections between data points.

To assess the similarity of data points, clustering algorithms typically define a similarity or distance metric. Common clustering algorithms include **[7]**:

- ***K-means:*** One of the most widely used clustering algorithms, K-means divides the data into a predetermined number of clusters, each represented by its centroid. Centroids are updated iteratively, and data points are assigned to the closest centroid.
- ***Hierarchical Clustering:*** This method creates a hierarchical decomposition of the data by repeatedly merging or dividing clusters based on a similarity metric. It generates a dendrogram, a tree-like structure that can be further subdivided into clusters at various levels.
- ***DBSCAN (Density-Based Spatial Clustering of Applications with Noise):*** DBSCAN identifies areas with lower densities and groups closely spaced data points together. It is useful for handling data noise and discovering clusters of any shape.
- ***Gaussian Mixture Models (GMM):*** GMM assumes that data points were generated using a combination of Gaussian distributions. By estimating the parameters of each Gaussian component, representing clusters, it fits a GMM to the data.

Clustering finds applications in anomaly detection, document clustering, customer segmentation, image segmentation, and many other areas. It helps organize and comprehend large amounts of data, discover patterns, and facilitate decision-making based on relationships and similarities between data points.

Association: The process of uncovering intriguing connections or trends among objects or variables in a large dataset is referred to as "association" in the context of data mining and machine learning. It focuses on identifying associations or co-occurrences between items based on their frequency of appearance in transactions or events. Association analysis is commonly used in market basket analysis, where it's essential to identify connections between frequently purchased items. For example, association analysis in a grocery store might reveal that customers who buy bread often also buy butter. This data has various applications, including product placement, cross-selling, and recommendation engines.

Support, which calculates the frequency or percentage of transactions containing a specific item or itemset, is the primary metric used in association analysis. Additionally, metrics like confidence and lift are crucial. Confidence measures the likelihood that, given the purchase of item A, item B will also be purchased. Lift quantifies the strength of the association between two items by comparing the observed and expected support under the independence assumption **[8]**. Frequent itemset mining is a common technique in association analysis for identifying groups of items that frequently co-occur in transactions. The Apriori algorithm generates candidate item sets and filters out those that do not meet the minimum support threshold to find frequent item sets. Association analysis finds applications in various fields, including market research, customer behavior analysis, recommendation systems, and web mining. By providing insights into connections and dependencies between different products, businesses can make data-driven decisions, optimize sales strategies, and provide customers with personalized recommendations

2.3. Semi-Supervised Learning

The semi-supervised learning process typically includes the following steps:

- ***Labelled Data***: Obtain a small set of labelled data where each instance is paired with the corresponding label.
- ***Unlabeled Data:*** Acquire a substantial collection of unlabeled data lacking corresponding labels.
- Training: Train a model using both the labelled and unlabeled data. The model makes predictions for the labelled instances using the labelled data and uncovers hidden patterns or underlying data structures using the unlabeled data.
- ***Label Propagation:*** Utilize labelled instances to propagate labels to unlabeled ones using the label propagation technique. This involves assigning labels to unlabeled instances based on their similarity or proximity to labelled instances.
- ***Model Refinement:*** Refine the model using the newly labelled data, which now includes propagated labels from the unlabeled instances.

Semi-supervised learning is particularly useful when there is abundant unlabeled data readily available but limited or no labelled data. By leveraging unlabeled data, the model can generalize better and make more accurate predictions. Semi-supervised learning has found successful applications in various fields, especially those where obtaining labelled data can be challenging, such as natural language processing, computer vision, and anomaly detection.

Reinforcement Learning: Reinforcement learning is a machine learning method that teaches an agent how to interact with its environment to maximize a reward signal, inspired by the way humans and animals learn through errors and feedback. Through reinforcement learning, an agent learns new skills by acting in a specific environment and receiving feedback in the form of rewards or punishments. The agent's goal is to learn an optimal policy, which maps states to actions, to maximize cumulative rewards over time.

The primary elements of reinforcement learning include:

- ***Agent:*** The learner or decision-maker that acts in the environment.
- ***Environment:*** The system or issue with which the agent interacts.
- ***State:*** The agent's current perception of the environment, revealing its current circumstances.
- ***Action:*** The decisions or choices the agent makes to interact with its surroundings.
- ***Reward:*** The feedback signal the agent receives after acting, indicating the desirability of its actions.

The reinforcement learning process typically involves:

- ***Exploration vs. Exploitation:*** The agent explores the environment to learn about the effects of different actions, then exploits this knowledge to maximize rewards.
- ***Policy Learning:*** Learning a policy that maps states to actions, using techniques like value-based or policy-based methods.
- ***Value Function:*** Tracking expected cumulative rewards for being in a state and taking certain actions, aiding long-term decision-making.
- ***Reward Signal:*** The agent receives rewards or penalties from the environment based on its actions, reinforcing positive behavior.
- ***Exploration Techniques:*** Using methods like epsilon-greedy or SoftMax to balance between exploring new actions and exploiting learned knowledge.

Reinforcement learning has been successfully applied in areas such as robotics, gaming (e.g., AlphaGo), autonomous vehicles, and resource management, where agents must make sequential decisions in dynamic environments to achieve long-term objectives.

Generative Approaches: In semi-supervised learning, the term "generative approaches" refers to techniques that estimate the underlying data distribution and generate new data samples using probabilistic models. These approaches leverage both labelled and unlabeled data to improve learning. A significant amount of unlabeled data can enhance the model's performance on labelled data by providing a better representation of the data distribution.

Generative approaches model the latent structure of the data or the joint distribution of input features and corresponding labels (if available). Common generative models used in semi-supervised learning include:

- ***Gaussian Mixture Models (GMM):*** GMM is based on the idea that data are generated by combining Gaussian distributions. It estimates the data distribution and assigns pseudo-labels to unlabeled data by fitting a GMM to both labelled and unlabeled data.
- ***Hidden Markov Models (HMM):*** HMMs simulate sequential data and are useful for tasks like speech recognition and natural language processing, which rely on temporal dependencies. By using unlabeled data to calculate transition and emission probabilities, HMM can be extended to semi-supervised settings.
- ***Variational Autoencoders (VAE):*** VAE trains an encoder and decoder network to learn a low-dimensional representation (latent space) of the data. It can incorporate both labelled and unlabeled data in training, reconstruct input data, and generate new samples from the latent space.
- ***Generative Adversarial Networks (GAN):*** GAN consists of a generator and a discriminator network. By including both labelled and unlabeled data, it can be adapted to semi-supervised learning. The discriminator is trained on labelled data, and the generator creates synthetic samples for unlabeled data.

Generative methods effectively utilize unlabeled data in semi-supervised learning to improve model performance and achieve better generalization. These techniques learn the underlying data distribution more thoroughly and precisely by leveraging the unlabeled data.

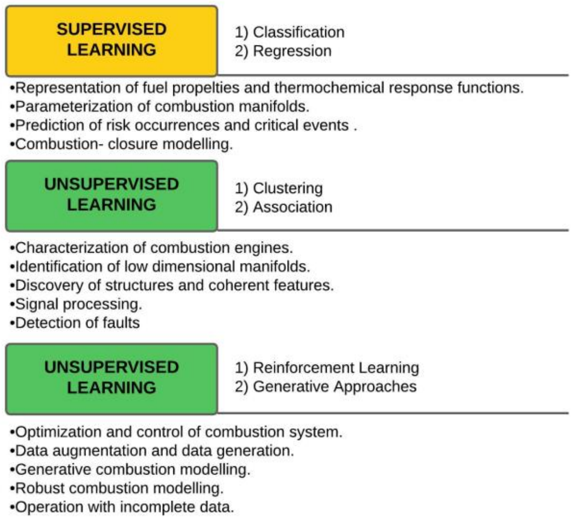


Figure-2: Machine Learning Techniques with Application in Combustion

3. Rocket Fuel Combustion

A rocket's reaction mass, or propellant, is crucial for generating thrust. Thrust is created by expelling the reaction mass from the rocket engine at high velocity. This reaction mass can either derive its energy from the propellants themselves, as in chemical rockets, or from an external source, such as with ion engines. In chemical rockets, the propellants undergo combustion, a chemical reaction that releases a significant amount of energy in the form of hot gases. These gases are expelled through a nozzle at high speeds, creating thrust that propels the rocket forward. The composition of rocket fuel varies depending on the type of rocket and its intended purpose. Typically, rocket fuel requires oxygen, initial excitation in the form of spark ignition, and sufficient time and mixing to drive the combustion reaction to completion.

For instance, methane can undergo combustion, as represented by the chemical equation:

$$CH_4 + 2O_2 + 7.52N_2 \rightarrow CO_2 + 2H_2O + 7.52N_2 + \text{Heat} \qquad \text{(Eq. 1)}$$

In this reaction, the predominant emission is CO_2. To mitigate emissions, carbon capture and storage (CCS) technology can be employed, even in existing fossil fuel power plants.

There are generally three types of rocket engines:

- ***Solid Rocket Engines:*** These engines carry fuel and oxidizer in a solid state.
- ***Liquid Rocket Engines:*** Fuel and oxidizers are carried in liquid form and fed into the combustion chamber under pressure during firing.
- ***Hybrid Engines:*** These engines utilize both liquid and solid propellants.

Each type of engine has its advantages and limitations, depending on the specific requirements and constraints of the mission or application.

Table-1 Features of Various Rocket Engines

Rocket Engine	Characteristics	Advantages	Disadvantages	Applications
Solid Rocket Engine	1. High specific impulse. 2. Predictable and reproducible burning rate and ignition characteristics. 3. High density and good ageing characteristics.	1. Easier storage of propellant as compared to liquid. 2. Simplicity and low cost. 3. Large amount of thrust can be generated.	1. Lower specific impulse. 2. Impossible to stop in case of emergency. 3. Burning control is a difficult task.	1. Booster engines. 2. Long-burning Sustainers. 3. Assisted take-off missiles
Liquid Rocket Engine	1. Propellant in the form of a liquid state is fed under pressure. 2. It consists of fuel and oxidizer in liquid form.	1. Higher specific impulse than solid rockets 2. High performance. 3. The gaseous oxidizes used are easily available.	1. Some of the oxidizers used are extremely toxic. 2. They produce some troubles with valves and pumps.	1. Supersonic research aircraft 2. Intercontinental ballistic missiles (ICBMs) 3. High-altitude research rockets
Hybrid Rocket Engine	1. Combination of both liquid and solid propellants. 2. It can be readily stopped and restarted by controlling the flow of the liquid propellant.	1. Fluid oxidizer can make it possible to throttle and restart the motor. 2. Environmentally safer than solid rocket engines. 3. It is simpler in design	1. Complicated design as compared to solid rocket engines. 2. Challenges related to refuelling.	1. Microsatellites Sub-orbital and orbital vehicles

4. Optimization of Rocket Fuel Combustion

4.1. Predictive Analysis

It plays a crucial role in optimizing fuel combustion variables for maximum efficiency and performance in rocket firing. With a vast amount of data related to rocket firing, predictive analysis utilizes this data to analyze and predict the optimal fuel combustion variables. Simulation studies, incorporating kinematics and ordinary differential equations models, reveal the impact of modulating variables on burning propagation. One method of predictive analysis is the clustering model, which divides data into distinct nested smart groups based on similar attributes. In rocket combustion, various interrelated parts are grouped based on the temperature they are exposed to and the pressure at which they act. Depending on the application of the rocket engine, the appropriate model is chosen to efficiently operate in a given situation [11].

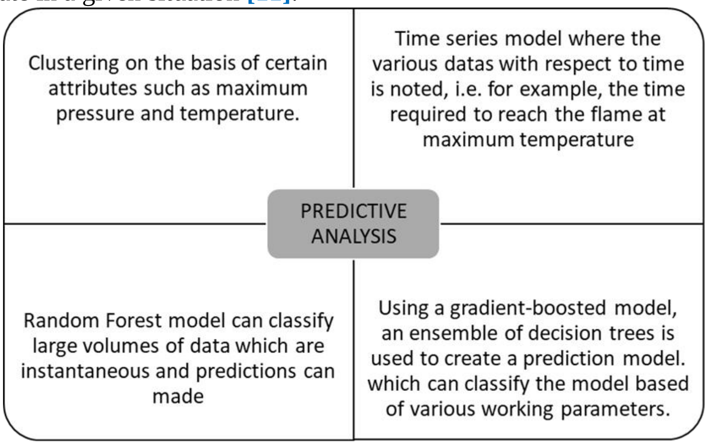
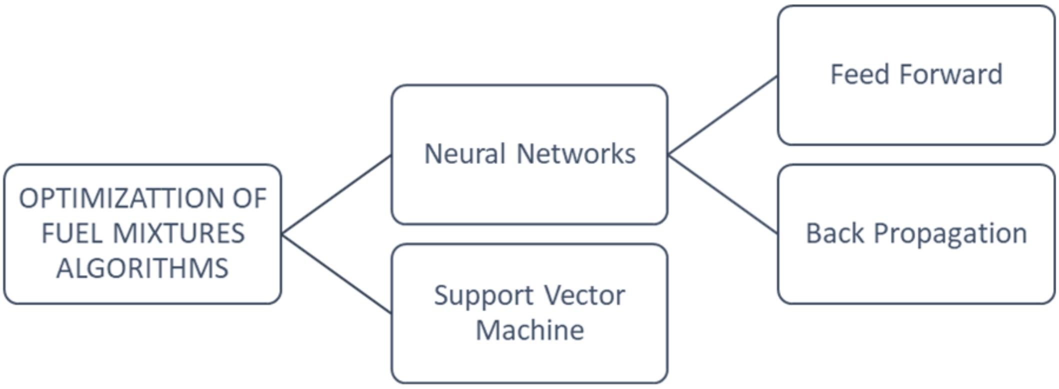


Figure-3 Some of Predictive Analysis Methods

4.2. Optimization of Fuel Mixtures

Machine learning (ML) algorithms play a crucial role in analyzing different fuel mixtures and their impact on fuel combustion performance, aiding in the determination of the optimal fuel for rocket propulsion. The direct enumeration method serves as the foundation for optimizing the composition of fuel mixtures. One significant factor contributing to combustion instability, which leads to engine shake at idle speed, is the overall perceived quality of the vehicle's construction. Properly blending the fuel can help avoid engine shake. In the realm of machine learning and artificial intelligence, various algorithms are employed for predicting idle combustion uniformity, leveraging abundant measured combustion test data. Ensembles of trees (EOT), neural networks (NN), support vector machines (SVM), and Gaussian processes (GP) are among the algorithms commonly used for this purpose. These algorithms utilize available data to forecast idle combustion uniformity, enabling the optimization of fuel mixtures for enhanced rocket propulsion performance [12-13].



Figue-4 Some of Predictive Analysis Methods

4.3. Real-time Monitoring

ML algorithms play a vital role in monitoring fuel combustion data in real-time, enabling adjustments to fuel delivery systems to maintain optimal performance. Key concerns in the design and operation of the combustion system include flame stability and pollution control. Utilizing a chemical reactor network (CRN), immeasurable combustion characteristics such as pollution formation rates, combustion efficiency, and proximity to blowout can be monitored. Additionally, CRN enhances combustion temperature measurements by incorporating modeled free radical concentrations, thus providing comprehensive monitoring capabilities [14].

4.4. Simulation Modelling

ML algorithms are instrumental in simulating rocket combustion processes before actual testing, facilitating the optimization of fuel combustion performance and prevention of failures. Various simulation tools are employed for this purpose. Three-dimensional (3D) computational fluid dynamics simulations in combustion chambers provide insights that traditional data acquisition methods cannot. These simulations guide experimental research and can be validated using experimental data. The simulation model's ability to accurately capture combustion and emission characteristics validates its efficacy in evaluating engine performance [15].

4.5. Sensitivity Analysis

ML algorithms perform sensitivity analysis to assess the impact of various fuel combustion variables on performance, identifying the most influential factors. Critical factors such as chamber pressure and exhaust temperature significantly affect combustion. Sensitivity analysis helps prioritize these factors, guiding optimization efforts to enhance combustion performance effectively [16].

Table-2 Example of Sensitivity Analysis [16]

No	Sensitivity	No	Reaction
1	1.31560E+01	9	O2+H=>OH+O
2	2.55376E+00	1	H2+O=>OH+H
3	-1.58702E+00	5	O2+H+M=>HO2+M
4	1.10723E+00	3	H2+OH=>H2O+H
5	1.09612E+00	30	H2+O2=>H+HO2

Some of the other criteria of sensitivity analysis are as follows:

- ***Parameter Tuning:*** ML algorithms play a crucial role in tuning various fuel parameters, such as chamber pressure, nozzle size, and fuel flow rate, to optimize rocket propulsion. Achieving ideal combustion conditions involves controlling the fuel split ratio and combustion air amount in a gas turbine during combustion tuning.
- ***Improved Efficiency:*** Machine learning algorithms enhance fuel efficiency by analyzing past fuel combustion data and identifying areas for improvement in fuel delivery systems. By learning from historical data, these algorithms can suggest adjustments to optimize efficiency.
- ***Reduce Emissions:*** Machine learning algorithms analyze fuel combustion data to mitigate harmful emissions and identify areas for improvement in fuel delivery systems. By optimizing combustion processes, these algorithms contribute to reducing environmental impact.
- ***Self-Optimization:*** Machine learning algorithms enable self-optimization of fuel combustion systems during rocket launches, ensuring optimal performance. By continuously analyzing real-time data, these algorithms adjust parameters to maintain efficient combustion throughout the mission.
- ***Improve Reliability:*** Machine learning algorithms analyze past failures in fuel combustion systems to predict and prevent future failures, enhancing overall rocket reliability. By identifying patterns indicative of potential failures, these algorithms facilitate proactive maintenance and troubleshooting, leading to improved system reliability.

5. Results, Discussion, and Conclusion

The application of ML techniques in optimizing rocket fuel combustion has yielded promising results, significantly advancing our understanding of rocket propulsion systems' performance. Through the integration of studies utilizing various ML techniques, including experimental data and computational simulations, several conclusions can be drawn. ML has notably enhanced the prediction accuracy of critical combustion parameters. By effectively identifying optimal operating conditions, fuel compositions, and combustion chamber geometries, ML algorithms mitigate combustion instabilities, thereby improving rocket performance and safety.

Moreover, ML algorithms play a crucial role in reducing pollutant emissions associated with rocket fuel combustion. By analyzing data obtained from the combustion process and various chamber geometries, models can be developed to minimize combustion instabilities and enhance rocket performance and safety.

In conclusion, optimization techniques applied to rocket fuel combustion demonstrate significant potential in enhancing propulsion system performance and efficiency. Predictive analysis, fuel mixture optimization, real-time monitoring, simulation modeling, sensitivity analysis, and parameter tuning collectively contribute to achieving improved efficiency and reduced emissions. These techniques facilitate self-optimization and increase reliability by continuously adapting and optimizing the combustion process. By leveraging these techniques, rocket systems can operate at peak performance levels, ensuring efficient fuel consumption, minimal emissions, and enhanced reliability, thus advancing rocket propulsion and supporting sustainable space exploration endeavors.

6. References

[1] Zhou, L., Song, Y., Ji, W., & Wei, H. (2022). Machine learning for combustion. Energy and AI, 7, 100128. **https://doi.org/10.1016/j.egyai.2021.100128**

[2] Entezari, A., Aslani, A., Zahedi, R., & Noorollahi, Y. (2023). Artificial intelligence and machine learning in energy systems: A bibliographic perspective. Energy Strategy Reviews, 45, 101017. **https://doi.org/10.1016/j.esr.2022.101017**

[3] TIWARI, S. Supervised Machine Learning: A Brief Introduction. **https://doi.org/10.58503/icvl-v17y202218**

[4] Narayanan, U., Unnikrishnan, A., Paul, V., & Joseph, S. (2017, August). A survey on various supervised classification algorithms. In 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS) (pp. 2118-2124). IEEE. **https://doi.org/10.1109/ICECDS.2017.8389824**

[5] Soofi, A. A., & Awan, A. (2017). Classification techniques in machine learning: applications and issues. J. Basic Appl. Sci, 13(1), 459-465. **https://doi.org/1814-8085 / E-ISSN: 1927-5129/17**

[6] Rong, S., & Bao-Wen, Z. (2018). The research of regression model in machine learning field. In MATEC Web of Conferences (Vol. 176, p. 01033). EDP Sciences. **https://doi.org/10.1051/matecconf/201817601033**

[7] Hloch, M., Kubek, M., & Unger, H. Graph-based Clustering Algorithms–A Review on Novel Approaches. **https://doi.org/10.25046/aj060403**

[8] Schmarje, L., Santarossa, M., Schröder, S. M., & Koch, R. (2021). A survey on semi-, self-and unsupervised learning for image classification. IEEE Access, 9, 82146-82168. **https://doi.org/10.1109/ACCESS.2021.3084358**

[9] Ihme, M., Chung, W. T., & Mishra, A. A. (2022). Combustion machine learning: Principles, progress and prospects. Progress in Energy and Combustion Science, 91, 101010. **https://doi.org/10.1016/j.pecs.2022.101010**

[10] Shalaby, A., Elkamel, A., Douglas, P. L., Zhu, Q., & Zheng, Q. P. (2021). A machine learning approach for modeling and optimization of a CO2 post-combustion capture unit. Energy, 215, 119113. **https://doi.org/10.1016/j.energy.2020.119113**

[11] Osheku, C. A., Babayomi, O. O., & Olawole, O. T. (2019). Analytical Prediction for Grain Burn Time and Burning Area Kinematics in a Solid Rocket Combustion Chamber. In Ballistics. IntechOpen.

[12] Varganova, A. V., & Lygin, M. M. (2019, October). Optimization of the Composition of the Fuel Mixture of Industrial Thermal Power Plants. In 2019 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon) (pp. 1-4). IEEE. **https://doi.org/10.1109/FarEastCon.2019.8934249**

[13] Li, X., & Zouani, A. (2019). Machine learning algorithm for the prediction of idle combustion uniformity. SAE International Journal of Advances and Current Practices in Mobility, 1(2019-01-1551), 1803-1807. **https://doi.org/10.4271/2019-01-1551**

[14] DePape, P., & Novosselov, I. (2018). Model-based approach for combustion monitoring using real-time chemical reactor network. Journal of Combustion, 2018. **https://doi.org/10.1155/2018/8704792**

[15] Liu, Z., Zhang, Y., Fu, J., & Liu, J. (2022). Multidimensional computational fluid dynamics combustion process modeling of a 6V150 diesel engine. Journal of Thermal Science and Engineering Applications, 14(10), 101009. **https://doi.org/10.1115/1.4054164**

[16] Turányi, T. (1997). Applications of sensitivity analysis to combustion chemistry. Reliability engineering & system safety, 57(1), 41-48. **https://doi.org/10.1016/S0951-8320**

7. Team Biography

With backgrounds in mechanical engineering, Nobendu Sen, Janaradhan Kamath S, and Gautam M Nair are currently pursuing postgraduate studies in aerospace engineering at Karunya Institute of Technology and Sciences, Coimbatore, India. Their collective commitment to optimizing rocket fuel combustion through machine learning techniques is fueled by their shared passion for rocket science. Leading our team is Dr. A. Immanuel Selvakumar, an experienced mentor and expert in machine learning. With his invaluable guidance and support, our team overcomes complex challenges and achieves our objectives. Dr. Immanuel Selvakumar's expertise and mentorship are instrumental in shaping our projects and fostering our professional growth.

8. Acknowledgement

. We extend our sincere gratitude to **Dr. A. Immanuel Selvakumar**, our esteemed guide, whose unwavering guidance, expertise, and encouragement have been invaluable throughout the duration of this project. His mentorship has been instrumental in shaping our project, and his insightful feedback has helped us navigate challenges and achieve our goals. We are deeply grateful for his dedication and support.

9. Conflict of Interest

The authors declare no competing conflict of interest.

10. Funding

No funding was received to support this study.