



## OVERVIEW OF INTELLIGENT FAULT DIAGNOSIS TECHNOLOGIES FOR SOLID FUEL ROCKETS

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### ABSTRACT

Solid-fuel rockets, crucial for space missions, face various potential failures due to internal and external environmental factors. The engine, being central to the rocket's propulsion system, directly impacts mission success. Historical research from various countries since the last century has yielded numerous results in fault detection systems and methods. This paper discusses fault types in solid-fuel rockets, their impacts on missions, and outlines the intelligent fault diagnosis concept. It also establishes a universal framework and mathematical model for intelligent fault diagnosis of solid rocket engines, exploring the application methods of intelligent fault diagnosis technologies in solid-fuel rockets. The findings may offer valuable insights for future advancements in rocket fault diagnosis.

Keywords: Solid-fuel rocket, Fault diagnosis, Intelligence

### 1 INTRODUCTION

Rocket carriers are transportation tools used to send payloads from the Earth's surface into space. Due to the complexity of their systems and operational environments, various types of faults may occur during their operation. To ensure the stability of rocket flight and improve the success rate of individual missions, it is necessary to perform fault detection and isolation (FDI), or fault diagnosis, when anomalies appear in the rocket. Traditional fault diagnosis techniques [1] are mainly divided into two categories: model-based and model-less diagnostic techniques. In recent years, with the development of information technology, intelligent theories and methods have gradually been applied to rocket fault diagnosis, greatly enhancing the efficiency and accuracy of fault diagnostics. With the introduction of intelligent algorithms, the system can quickly analyze massive amounts of data, identify fault patterns, thereby achieving accurate fault localization, identification, and prediction in a short time [2], reducing rocket maintenance costs [3], and enhancing the rocket's fault tolerance. This article systematically analyzes rocket intelligent fault diagnosis from three aspects: types of rocket, system faults, and their impact on missions, the concept and content of intelligent fault diagnosis, and the application methods of

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intelligent fault diagnosis technology in solid-fuel rockets. Finally, it discusses some of the issues, challenges, and future prospects of intelligent fault diagnosis technology in the field of solid-fuel rockets, proposing new ideas for the difficulties faced by intelligent control of rockets.

## 2 TYPES OF ROCKET SYSTEM FAILURES AND THEIR IMPACT ON MISSIONS

Rocket failures are complex and varied, encompassing multiple levels from material defects to system design and operational errors. By reviewing existing solid launch rocket failure cases, the author proposes different classifications of typical failures in solid launch rockets from three perspectives: the working periods of the rocket, the subsystem to which the failure belongs, and the energy attributes of the failure, as shown in Table 1.

**Table 1: Fault Types and Their Impact on Missions**

Classification	Subcategory	Description of Fault Phenomenon
Work Phase	Guidance-Ignition	Includes ignition failures, pressure fluctuations, and hardware/software malfunctions.
	Ignition-Separation	Involves structural design changes, booster ruptures, and ignition transient complexity.
	Separation-Mission Completion	Includes payload deployment issues, orbital maneuver failures, and communication problems.
System	Propulsion System	Includes ignition failures, nozzle erosion, etc.
	Control System	Covers software errors, hardware failures, and sensor/actuator malfunctions.
	Structural System	Includes structural integrity degradation, debonding issues, and O-ring seal failures, etc.
Energy Attribute	Micro Energy Faults	Involves guidance control system information disarray and loss, not affecting precise orbit insertion.
	Small Energy Faults	Includes slight thrust decrease and booster not separating as expected, potentially causing orbit insertion accuracy deviations.
	Medium Energy Faults	Involves significant thrust decrease and actuator jamming, requiring deorbit planning, affecting subsequent missions.
	Large Energy Faults	Includes rocket explosion, thrust loss, and control instability, leading to mission failure.

## 2.1 Classification of Rocket Failure Types by Working Periods

The working periods of a rocket can generally be divided into three stages: from the commencement of the guidance system operation to ignition, from ignition to the separation of the spacecraft and the rocket, and from the separation of the spacecraft and the rocket to the completion of extended missions.

In the stage from the commencement of the guidance system operation to ignition, the ignition system of a solid rocket motor may experience ignition delay, incomplete ignition, or erroneous ignition. These failures may stem from design defects in the ignition device, malfunctions in the electronic control system, or issues with the propellant. Additionally, the ignition stage may produce significant pressure fluctuations, leading to propellant rupture, structural damage, or performance degradation[4]. The guidance system may encounter software failures, hardware failures, or sensor misalignment, and communication system failures could prevent the rocket from receiving or executing launch commands. In the stage from ignition to the separation of the spacecraft and the rocket, failures may involve structural design changes, booster ruptures, the complexity of ignition transients, and pressure peaks[5]. In the stage from the separation of the spacecraft and the rocket to the completion of extended missions, failures may involve payload deployment and mission execution, including spacecraft mechanical failures, electronic failures, propulsion system failures, guidance system failures, communication, and data transmission issues[6].

## 2.2 Classification of Rocket Failure Types by Subsystems

Rocket subsystem failures can generally be classified into three types: propulsion system failures, control system failures, and structural system failures. The failure types in the propulsion system typically occur in the ignition system and manifest as ignition battery activation failure, improper component function, inability to ignite or abnormal ignition, and delayed ignition or explosion of the energy release subsystem. In the control system, software errors, hardware failures, and sensor and actuator malfunctions can lead to the rocket deviating from its trajectory or becoming uncontrollable[7][8]. Structural system failure types include compromised rocket strength, debonding at propellant/liner/insulation interfaces, sealing component failures, and connector joint failures[9].

## 2.3 Classification of Rocket Failure Types by Energy Attributes

Rocket failures can be divided into micro, small, medium, and large energy failures based on energy attributes. After the launch of a space launch vehicle, the total energy is fixed, and during the flight, the vehicle continuously converts its carried energy into orbital energy (dv). A significant failure of the launch vehicle essentially results in the loss of the remaining stored energy onboard. The goal and approach for handling launch vehicle failures online are to convert as much of the remaining usable energy onboard into orbital energy to approximate the originally intended orbit as closely as possible.

(1) Micro Energy Failures: Non-(micro) energy failures include partial data corruption or loss in the guidance control system. These can be adjusted through communication or adaptive measures without affecting accurate orbit insertion.

(2) Small Energy Failures: Small energy failures include a slight decrease in thrust of a certain stage beyond the expected threshold or partial boosters not separating at the expected time. Under controllable flight conditions, the guidance system can use a

predetermined guidance scheme or replan to send the payload into the designated orbit, though there may be some deviation in orbit insertion accuracy, which does not affect or minimally affects subsequent mission execution.

(3) Medium Energy Failures: Medium energy failures include a significant unexpected decrease in thrust of a certain stage or partial actuator jamming. Under controllable flight conditions, the guidance system will implement a deorbit plan and send the payload into a biased orbit, which can impact subsequent mission execution to some extent.

(4) Large Energy Failures: Large energy failures include rocket explosion, complete loss of thrust of a certain stage, complete actuator jamming, or stage separation failure, leading to uncontrolled flight, explosion, or other unexpected flight events. These failures prevent the payload from operating normally, ultimately resulting in mission failure.

Finally, based on the status of the rocket mission completion and the energy level of the failure, the mission command forms the conclusion of the rocket mission as complete success, success, or failure[10].

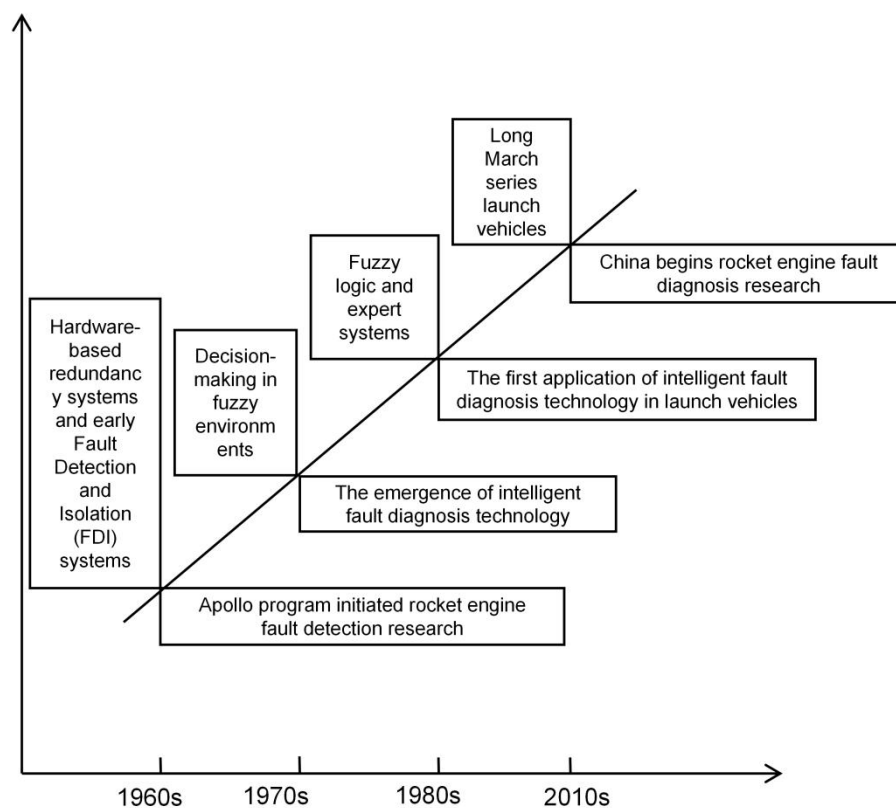
### 3 CONCEPT AND CONNOTATION OF INTELLIGENT FAULT DIAGNOSIS

#### 3.1 Development History of Fault Diagnosis Technology Centered Around Engine Failures

Among all the failures in solid launch rockets, rocket engine failures often play a decisive role in the success or failure of space missions[11]. On June 28, 2015, SpaceX's Falcon 9-1.1 rocket failed and exploded 139 seconds after launch while performing its seventh International Space Station cargo resupply mission (SpaceX CRS-7). In November of the same year, the SpaceX investigation team pinpointed the failure to a manufacturing material issue with the helium bottle support bracket in the second stage liquid oxygen tank[12]. On July 2, 2017, the Long March 5 (CZ-5) Y2 rocket was launched from the Wenchang Space Launch Site in Hainan. When the rocket reached 346 seconds into its flight, an anomaly in the partial structure of the turbine exhaust device of the first-stage YF-77 engine caused a sudden drop in engine thrust, leading to mission failure[13]. The failures of these launch missions had profound impacts on aerospace research and development worldwide. With the rapid development of related sensor detection technologies, engine reliability monitoring has gradually become a focal point of launch vehicle fault diagnosis research.

Rocket engine fault detection can be traced back to the 1967 Apollo program in the United States[14]. Since then, with the enhancement of space transportation technology and transport requirements, scholars have conducted extensive research to improve the safety and reliability of rocket engines, resulting in numerous research achievements. Since the 1970s, the United States has developed various rocket engine fault detection and diagnosis systems, which have been widely used in the Space Shuttle Main Engine (SSME)[15]. China began researching rocket engine fault diagnosis in the early 1990s, focusing mainly on the Long March series of launch vehicles. Domestic research institutions have undertaken work on rocket engine fault mode recognition, engine fault simulation system design, and related fault detection and diagnosis algorithms, including research on ground engine test fault detection systems[16] and real-time fault detection and alarm systems[17] (LRE-rtfdas). In practical applications, besides the CZ-6A launch vehicle engine health diagnosis system, China's only manned launch vehicle, the Long March 2F (CZ-2F), is also equipped with an

automatic fault detection and handling system[18]. This system can detect rocket faults and autonomously decide whether to initiate emergency astronaut escape based on the situation. The emergence of intelligent fault diagnosis technology can be traced back to the 1970 publication of "Decision-Making in a Fuzzy Environment"[19]. This document introduced fuzzy set theory and demonstrated its potential in handling uncertainty and fuzzy information. This theory laid the foundation for the development of intelligent fault diagnosis technology, as fault diagnosis often involves processing fuzzy and uncertain information. The earliest traceable application of this technology in launch vehicle fault diagnosis is the 1983 research report[20], which detailed the application of fuzzy logic and expert systems in launch vehicle fault diagnosis.

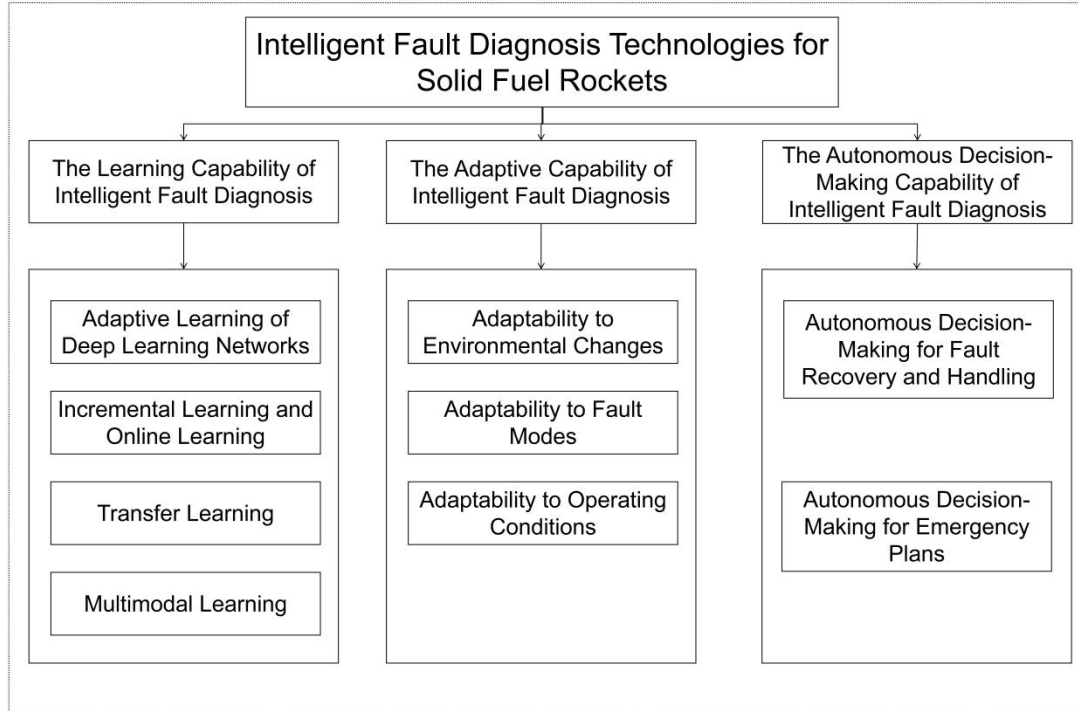


**Figure 1: Development History of Intelligent Diagnostic Technology for Solid Launch Vehicle Engine Faults**

### 3.2 Concept and Connotation of Fault Diagnosis for Solid Launch Rockets Under Machine Intelligence

Traditional fault diagnosis techniques or singular fault diagnosis methods can no longer meet the practical needs of large, complex systems such as launch rockets. With technological advancements and the increase in onboard computational power, intelligent fault diagnosis has become a crucial part of the intelligentization of launch vehicles. Combining the rich experimental data and fault handling knowledge accumulated in the aerospace field, we believe that a fault diagnosis system for solid launch rockets under machine intelligence

should possess three key capabilities: self-learning, self-adaptation, and self-decision-making, as illustrated in Figure 2.



**Figure 2: Characteristics of Intelligent Fault Diagnosis for Solid Launch Vehicles**

### (1) Self-Learning Capability

One of the core characteristics of machine intelligence is the ability to learn models, driven by data, to identify and discover fault patterns and regularities in launch rockets through the analysis and understanding of large datasets. Currently, widely used algorithms are mainly focused on supervised learning and unsupervised learning. In intelligent fault diagnosis systems for solid launch rockets, self-learning algorithms capture, identify, and analyze sensor data to adjust and optimize models, making them applicable to different faults and various models of solid launch rockets. Despite facing challenges such as the "black box" problem, ongoing research is improving model interpretability, making the decision-making process more transparent.

### (2) Self-Adaptive Capability

The self-adaptive capability of machine intelligence encompasses the ability of machines to automatically adjust their behavior and strategies based on new data, environmental changes, and mission requirements. This primarily includes environmental perception and model evolution capabilities. The characteristics of self-adaptation include flexibility, continuous learning, robustness, personalized adaptation, and efficiency optimization, enabling machine intelligence systems to handle diverse tasks and environments, continuously absorb new information, and optimize workflows. Intelligent fault diagnosis systems for solid launch rockets can train environment-specific fault diagnosis models, making them better suited to various fault scenarios and environmental changes. As

technology advances, adaptive machine intelligence is expected to bring revolutionary changes across various industries, enhancing system stability, reliability, and the level of personalized service.

### (3) Self-Decision-Making Capability

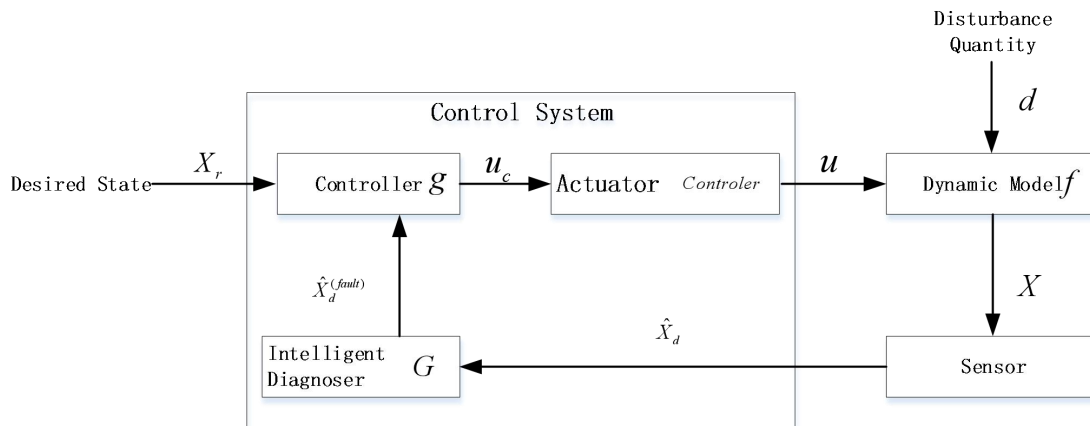
The self-decision-making capability of machine intelligence refers to the ability of machines to analyze, interpret, and make decisions based on their algorithms without direct human intervention. This ability covers everything from the automatic execution of simple tasks to the selection and execution of strategies in complex situations. Self-decision-making is characterized by environmental perception and dynamic adaptation, learning and evolution, self-optimization, independence, and interactive collaboration. In the face of disturbances and faults, intelligent fault diagnosis systems for solid launch rockets can achieve tasks such as online trajectory re-planning through self-decision-making.

## 4 METHODS FOR APPLYING INTELLIGENT FAULT DIAGNOSIS TECHNOLOGY IN SOLID LAUNCH ROCKETS

### 4.1 Control Model for Intelligent Fault Diagnosis of Solid Launch Rockets

#### 4.1.1 Control Logic

Based on modern control theory, intelligent fault diagnosis for solid launch rockets is abstracted as a typical nonlinear closed-loop control system. The control logic is illustrated in Figure 3.



**Figure 3: Control Logic for Intelligent Fault Diagnosis of Solid Launch Vehicles**

Given the desired state of the rocket (including expected position, velocity, attitude, etc.), when the rocket experiences propulsion system failures due to internal and external environmental factors, these failures can be abstracted as a set of disturbances  $d$ . The intelligent fault diagnosis system achieves fault diagnosis and control through the interaction between the controller ( $\mathcal{G}$ ), actuator (controller), dynamic model ( $f$ ), and intelligent diagnoser ( $G$ ).

The control system is the core part of the entire process, mainly comprising three components: the controller ( $\mathcal{G}$ ), the actuator (controller), and the intelligent diagnoser ( $G$ ).

The controller (g) generates control commands based on the rocket's desired state. The actuator (controller) receives the control commands from the controller and applies control inputs to the dynamic model to achieve rocket control under fault conditions. The intelligent diagnoser (G) performs fault detection and diagnosis by comparing the actual state measured by sensors with the estimated fault state  $\hat{x}_d$  from the dynamic model. The diagnosis result  $\hat{x}_d^{(fault)}$  is fed back to the controller to adjust the control strategy, ensuring that the system can still operate stably under fault conditions.

#### 4.1.2 Mathematical Model

Let  $X_r = [X, V, P, W]$  represent the desired state of the rocket, where:  $X$  is the position vector of the rocket,  $V = [v_x, v_y, v_z]^T$  is the velocity vector of the rocket,  $P$  denotes the attitude angles (pitch, yaw, roll) of the rocket,  $W = [\omega_x, \omega_y, \omega_z]^T$  denotes the angular velocities (pitch, yaw, roll) of the rocket. We establish the dynamic model of the rocket under disturbed conditions, as shown in Equation (1).

$$\dot{X} = f(X, d, u, t) \quad (1)$$

In the equations, the disturbance  $d = (d_1, d_2, \dots, d_n)$  represents a set of  $n$  faults affecting the carrier rocket, The function  $f$  describes the rocket's state  $X$  at time  $t$  under disturbances  $d$  and control input  $u$ .

The intelligent diagnostic unit  $G$  utilizes the estimated state  $\hat{X}_d$  Using intelligent diagnostic algorithms  $G$ , Generate rocket fault diagnosis state  $\hat{X}_d^{(fault)}$ , as shown in Equation (2).

$$\hat{X}_d^{(fault)} = G(\hat{X}_d, t) \quad (2)$$

The controller  $g$  According to the fault diagnosis state  $\hat{X}_d^{(fault)}$ , Generate the control command  $u_c$  at time  $t$ .

$$u_c = g(\hat{X}_d^{(fault)}, t) \quad (3)$$

Equations (1) to (3) constitute the general mathematical model for intelligent fault diagnosis and control of solid propellant rockets. In this model, the synergistic interaction between the controller and the intelligent diagnostic unit enables the system to promptly adjust control strategies under fault conditions, ensuring the rocket operates normally. The intelligent diagnostic unit can be categorized into self-learner, self-adaptive, and self-decision-making units based on the chosen intelligent methods.

#### 4.2 Implementation Methods of Self-Learners

Self-learners continuously collect system states and control inputs, analyze data samples, and extract patterns and trends. With increasing data volume, self-learning algorithms iteratively train to enhance the accuracy and efficiency of diagnostic models. Research focuses on machine learning and deep learning models, including deep learning networks, incremental and online learning, transfer learning, and multimodal learning.

#### (1)Deep Learning Networks

Deep learning networks analyze complex sensor data to autonomously learn features of the rocket system's health, such as abnormal engine vibration frequencies, fluctuations in propellant pressure, or anomalous temperature distributions. These networks continuously analyze new data and can issue alerts upon detecting data matching known fault patterns. For instance, literature [21] proposes a deep CNN architecture for quantifying crack dimensions and layer defects, using sufficient annotated data from the crack and layer domains for effective training.

#### (2)Incremental and Online Learning

Rockets operate in various environments (e.g., microgravity, solar radiation), where online learning algorithms adjust performance based on real-time feedback. Through incremental learning, new fault patterns are continuously added to the fault library, enabling updates to the fault diagnostic model even after launch and enhancing predictive capabilities.

#### (3)Transfer Learning

New rocket models may differ in design and functionality from older models, yet share common components and systems (e.g., propulsion systems, power systems). Transfer learning leverages these similarities to rapidly apply fault diagnosis experience from older rocket models to new ones, reducing data collection and training time. Literature [22] presents a deep transfer learning method, pre-training basic deep learning models with relevant training data, and enhancing model discriminative power using generative adversarial networks (GANs) for anomaly detection tasks.

#### (4)Multimodal Learning

Comprehensive system analysis integrates data from multiple sensors such as optical camera images, infrared thermal images, and various physical sensors. By fusing and analyzing data from different sources, the system can provide comprehensive and accurate fault diagnosis. During launch or flight, if cameras capture abnormal visual signals (e.g., smoke, flames, structural deformations) corroborated by anomalous sensor data (e.g., sudden temperature rise), multimodal learning algorithms can quickly pinpoint fault location and nature. Literature [23] supplements physical data from ground static tests of solid rocket engines and enhances performance measurements on a limited number of digital flight instruments. The multimodal learning method focuses on developing solutions for anomaly detection, impact detection, and sensor reconstruction through virtual sensing and image processing algorithms, for predictive performance analysis of solid boosters.

### 4.3 Implementation Methods of Self-Adapters

Self-adapters dynamically adjust control strategies based on real-time monitoring of rocket system states and internal/external disturbances, using adaptive control theory, fuzzy logic, or neural networks. This approach ensures rapid and efficient fault diagnosis in complex and variable environments, aiming to restore the rocket system to the desired state. Specific adaptive issues addressed include environmental adaptation, fault mode adaptation, and operational condition adaptation. Advanced sensors and data analytics technologies enable real-time monitoring of environmental variables (e.g., temperature, humidity, radiation

levels), with dynamic adjustments to fault detection algorithms. For example, in high-temperature environments, the system enhances temperature sensor sensitivity. By collecting data under different environmental conditions, the system can train environment-specific fault diagnosis models. Additionally, employing deep learning and machine learning algorithms enables recognition and learning of complex fault patterns, automatically categorizing new faults and updating databases without human intervention. Depending on different flight stages of the rocket, the system can automatically switch monitoring modes and diagnostic strategies, analyze feedback information in real-time, optimize diagnostic processes, and enhance efficiency.

#### 4.4 Implementation Methods of Self-Decision-Makers

Self-decision-makers generate execution decisions autonomously based on diagnostic results, current rocket states, and estimated states. These diagnostic systems typically integrate expert systems, reinforcement learning, and intelligent decision-making algorithms, enabling automatic fault handling and system optimization with minimal human intervention. By validating execution effectiveness through sensor feedback results and making necessary adjustments, these systems implement closed-loop control logic. Moreover, autonomous decision-makers can transmit real-time fault data, risk assessment results, and suggested action plans to ground control centers, providing comprehensive data support for human decisions, ensuring rapid and accurate decision-making.

Fault detection methods often combine with swarm intelligence optimization algorithms to enhance effectiveness and convergence speed of these methods. Particle swarm optimization (PSO) and genetic algorithms (GA) are common swarm intelligence optimization algorithms. PSO algorithm mimics bird flock foraging behaviors, conducting random searches through collective cooperation. Literature [24] utilizes an improved PSO algorithm to optimize weights of wavelet neural networks (WNNs), establishing LRE fault detection models with WNN's local convergence capabilities. Literature [25] employs PSO-optimized least squares support vector machines (LSSVMs) for fault detection methods, comparing predicted model-derived changes with standard thresholds to determine engine faults.

Genetic algorithms (GA) simulate natural evolutionary processes to solve optimization and search problems. Literature [26] integrates genetic algorithms with neural networks and fuzzy C-means (FCM) for fault diagnosis of a certain type of liquid rocket engine. Combining dynamic cloud models and uncertainty theories can synthesize stochastic and fuzzy uncertainties. Literature [27] combines cloud models with BP neural networks, proposing a dynamic cloud BP network-based LRE fault diagnosis method.

## 5 ISSUES, CHALLENGES, AND PROSPECTS

In the aerospace sector, launch vehicles play a crucial role in deploying satellites or other payloads into space, emphasizing the criticality of their performance reliability and safety. With continuous advancements in sensor technology, big data processing capabilities, and machine learning algorithms, intelligent fault diagnosis technologies for launch vehicles are rapidly evolving, promising new heights in safety, reliability, and efficiency for future rocket launch missions.

## 5.1 Challenges Faced by Intelligent Fault Diagnosis of Launch Vehicles

The development of intelligent fault diagnosis technologies for launch vehicles encounters several challenges. During rocket launch and flight, a vast array of diverse data is generated that requires efficient and accurate processing and analysis. The variety of fault modes, encompassing issues like engine problems, structural damages, and navigation failures, some of which are unprecedented, increases the diagnostic complexity. Real-time diagnosis is crucial, as any delay could result in irreparable consequences. Environmental factors such as extreme temperature variations, severe vibrations, and high-speed airflow may interfere with sensor operations, affecting diagnostic accuracy. Furthermore, the reliability and safety of diagnostic systems are crucial; any errors could lead to serious accidents. Developing precise diagnostic algorithms and models requires domain knowledge and advanced technologies, and effective human-machine interaction design is also essential. Research in intelligent fault diagnosis necessitates interdisciplinary collaboration to enhance system performance and ensure the safety and reliability of rocket launches and flights.

## 5.2 Future Directions for Intelligent Fault Diagnosis Algorithms

There are promising future prospects for the application of deep learning and neural networks in fault diagnosis. Convolutional neural networks (CNNs) can identify minor cracks and anomalies on rocket surfaces, while recurrent neural networks (RNNs) and its variants like long short-term memory networks (LSTMs) are suitable for predicting abnormal engine performance parameters. Furthermore, integrating multisource data and optimizing sensor network layouts to enhance data collection accuracy and efficiency through advanced data fusion algorithms is critical for improving diagnostic accuracy. Quantum computing holds tremendous potential for handling complex systems and large-scale optimization problems, providing robust computational support for real-time diagnosis within extremely short time frames. Additionally, drawing insights from advanced algorithms and technologies in domains such as finance, healthcare, and manufacturing can offer new perspectives and methods for fault diagnosis, promoting algorithmic innovation and improving the generality and adaptability of diagnostic systems. Lastly, enhancing the interpretability and transparency of algorithms by developing interpretable machine learning models and technologies such as explainable deep learning and causal reasoning models will enhance trust and acceptance of diagnostic results, supporting effective expert intervention and decision-making, making the fault diagnosis process more transparent and reliable.

## 6 CONCLUSION

Currently, traditional fault diagnosis methods for launch vehicles still face challenges such as slow response speed, low accuracy, and poor decision-making capabilities. With the development of computer and information technologies alongside big data models, the demand for self-learning, self-adaptive, and self-decision-making capabilities in solid propellant rocket onboard systems for practical engineering applications has gradually increased. These capabilities help ensure the precision and safety of mission execution through real-time monitoring and simulated operational processes, minimizing the risks of mission failure. In the future, further development of diagnostic systems and model technologies will enhance the reliability of intelligent fault diagnosis processes. This article comprehensively reviews and summarizes the characteristics, key technologies, future challenges, and development prospects of intelligent fault diagnosis for solid propellant

rockets, focusing on fault types and their mission impacts, the concept and connotation of intelligent fault diagnosis, and its applications in solid propellant rockets. The successful application of intelligent fault diagnosis systems in the future is certain.

## 7 REFERENCES

- [1] Niu, Q., Liu, Y., Li, Q., & Ren, Z. 2019. Fault diagnosis of carrier rocket actuator based on multiple-model method, Proceedings of the 34th Youth Academic Annual Conference of Chinese Association of Automation (YAC), IEEE, pp. 589-596.
- [2] Cao, H. 2021. Big Data Technology Application in Mechanical Intelligent Fault Diagnosis, Journal of Physics: Conference Series, Vol. 2066, No. 1, p. 012064, IOP Publishing.
- [3] Wang, S., Li, P., & Niu, W. 2022. Application and challenges of deep neural network in fault diagnosis of aviation equipment, Proceedings of the International Conference on Neural Networks, Information, and Communication Engineering (NNICE 2022), SPIE, Vol. 12258, pp. 111-115.
- [4] Wirzberger, H., & Yaniv, S. 2007. Solid Rocket Motor Ignition Transient Phenomenon and Pressure Buildup CFD Simulation, In 43rd AIAA/ASME/SAE/ASEE Joint Propulsion Conference & Exhibit, p. 5795.
- [5] Kierski, J., Pazik, A., & Cieśliński, D. 2023. Solid Rocket Boosters Separation System Development for the ILR-33 Amber 2K Rocket, Transactions on Aerospace Research, 2023(3), pp. 16-27.
- [6] Di Giacinto, M., Cavallini, E., Favini, B., & Steelant, J. 2015. Parametric study on solid rocket motor ignition transient and pressure oscillations onset, Journal of Propulsion and Power, 31(4), pp. 1117-1126.
- [7] Cha, J., & de Oliveira, É. J. 2022. Performance comparison of control strategies for a variable-thrust solid-propellant rocket motor, Aerospace, 9(6), p. 325.
- [8] Cui, Z., Zheng, M., Wang, J., & Liu, J. 2023. Reliability Analysis of a Three-Engine Simultaneous Pouring Control System Based on Bayesian Networks Combined with FMEA and FTA, Applied Sciences, 13(20), p. 11546.
- [9] Li, S., Liu, X., Ye, S., & Lin, Z. 2022. Research Progress on Guidance and Control Technology under the Failure of Launch Vehicle Propulsion Systems, Aerospace Shanghai (Bilingual), (04), pp. 76-93.
- [10] Wang, T., Ding, L., & Yu, H. 2022. Research and development of fault diagnosis methods for liquid rocket engines, Aerospace, 9(9), p. 481.
- [11] Chen, H., Gardner, B. M., Grogan, P. T., & Ho, K. 2021. Flexibility management for space logistics via decision rules, Journal of Spacecraft and Rockets, 58(5), pp. 1314-1324.
- [12] Gordon, K. E. 2018. Analysis of Chinese Cryogenic Long March Launch Vehicles and YF-100 Liquid Rocket Engine, Master's thesis, The Ohio State University.
- [13] Lozano-Tovar, P. C. 1998. Dynamic models for liquid rocket engines with health monitoring application, Doctoral dissertation, Massachusetts Institute of Technology.

- [14] **Duyar, A., Eldem, V., Merrill, W., & Guo, T. H.** 1994. Fault detection and diagnosis in propulsion systems-A fault parameter estimation approach, *Journal of Guidance, Control, and Dynamics*, 17(1), pp. 104-108.
- [15] **Figueroa, F., Schmalzel, J., Walker, M., Venkatesh, M., Kapadia, R., Morris, J., ... & Smith, H.** 2009. Integrated system health management: Foundational concepts, approach, and implementation, In *AIAA Infotech@Aerospace Conference and AIAA Unmanned... Unlimited Conference*, p. 1915.
- [16] **Xue, W., Zhang, Q., & Wu, X.** 2019. Research on real-time fault diagnosis method for liquid rocket engines based on ARMA model, *Computer Measurement & Control*, (09), pp. 4-7+22.
- [17] **Liu, H., Wei, P., Xie, T., Huang, Q., & Wu, J.** 2007. Research on real-time fault detection methods during ground testing of liquid rocket engines, *Journal of Astronautics*, (06), pp. 1660-1663+1688.
- [18] **Xu, Y., Peng, Y., Wang, H. T., Wang, Z. Y., & Ren, Y. H.** 2020. Design and Realization of Highly Reliable Logic Control Software for Pre-Launch Escape Command and Control System, *Procedia Computer Science*, 166, pp. 269-273.
- [19] **Bellman, R. E., & Zadeh, L. A.** 1970. Decision-making in a fuzzy environment, *Management science*, 17(4), B-141.
- [20] **Fagan, J. R., & Bratton, R. R.** 1983. Application of Expert Systems and Fuzzy Logic to Rocket Engine Fault Diagnosis, *NASA Technical Memorandum*, NASA-TM-85634.
- [21] **Liu, D., Sun, L., & Miller, T. C.** 2021. Defect diagnosis in solid rocket motors using sensors and deep learning networks, *AIAA Journal*, 59(1), pp. 276-281.
- [22] **Kong, J. W., Xu, Y., & Yu, H.** 2019. Deep Transfer Learning For Abnormality Detection, In *Proceedings of the 4th International Conference on Crowd Science and Engineering*, pp. 233-237.
- [23] **Williams, A., Himschoot, A., Saafir, M., Gatlin, M., Pendleton, D., & Alvord, D. A.** 2020. A machine learning approach for solid rocket motor data analysis and virtual sensor development, In *AIAA Propulsion and Energy 2020 Forum*, p. 3935.
- [24] **Xu, L., Ma, S., Xue, W., & Li, N.** 2021. Fault detection of liquid rocket engines using WNN optimized by improved PSO, *Aerospace Control*, (04), pp. 74-80.
- [25] **Mohd Ghazali, M. H., & Rahiman, W.** 2021. Vibration analysis for machine monitoring and diagnosis: a systematic review, *Shock and Vibration*, 2021, pp. 1-25.
- [26] **Zhang, W., Tian, G., Xu, Z., & Yang, Z.** 2016. Failure characteristics analysis and fault diagnosis for liquid rocket engines, *Cham, Switzerland: Springer*, Vol. 233, No. 12, pp. 3321-332.
- [27] **Nie, Y., Cheng, Y., & Wu, J.** 2018. Dynamic cloud back-propagation networks and its application in fault diagnostic for liquid-propellant rocket engines, *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, 232(3), pp. 583-594.