

The idea of achieving mechanical self repair through sensor artificial intelligence and 3D printing

Haoyang Sun^{1, *}

¹Beijing luhe international Academy
, Beijing, China

*Corresponding author:
Sunhaoyang2008@126.com

Abstract:

With the industrialization of the world, the application of machinery in modern society is becoming increasingly widespread, with significant applications in production, scientific research, aerospace, and other fields. However, these machines are prone to malfunctions, which can impair their functionality, so it is necessary to do a good job of maintenance, which is usually done manually. However, manual maintenance has some limitations and may be difficult or inefficient in certain situations. in extreme environments such as space, machinery is difficult to maintain manually. If it needs to be repaired, there will be great risks and huge costs, and the self-repair of machinery can greatly reduce maintenance conditions in this process. Based on this, exploration was conducted on mechanical self-maintenance, and the possibility of relying on sensor AI and 3D printing technology to achieve mechanical self-maintenance was explored based on existing achievements. Proposed a concept of mechanical self-maintenance operation that combines these three elements to achieve the process of detection, diagnosis, and repair. And during this process, it was discovered that there are some difficulties that are currently difficult to solve in achieving mechanical maintenance To improve the efficiency of mechanical maintenance and reduce the difficulty of mechanical maintenance.

Keywords: Sensor; AI; 3D printing technolog; Mechanical self-maintenance.

1. Introduction

Machinery, as a crucial component and tool in modern human society for production, daily life, and scientific research, plays a vital role in most fields.

However, since mechanical systems inevitably experience failures and wear that can render them inoperable or reduce efficiency, mechanical maintenance has remained a critical issue in the field of machinery since its inception. Therefore, mechanical maintenance

nance has been a key issue of social concern long time. According to National Bureau of Statistics of China, In China, the average cumulative number of workers in the metal products, machinery, and equipment repair industry from January to June 2025 is 273000, with a cumulative increase of 3%. This can reflect that a large number of human resources are still needed in mechanical maintenance, and it can also be seen that mechanical maintenance is of great importance in mechanical engineering. Moreover, there are some issues with manual repair that can lead to a decrease in efficiency [1]. Moreover, in extreme environments such as space, machinery is difficult to maintain manually. If it needs to be repaired, there will be great risks and huge costs, and the self-repair of machinery can greatly reduce maintenance conditions in this process. There are currently many studies on the maintenance and repair of machines. For example, improving sensor efficiency to enhance the speed and accuracy of fault monitoring, researching more efficient and rapid specific maintenance methods for specific machinery, and researching new advanced or specialized maintenance tools that can improve maintenance efficiency. How to enhance personnel management for maintenance and repair personnel and improve their maintenance strategies. These research focuses on improving the speed and accuracy of fault detection, maintenance methods, maintenance tools, maintenance strategies, and personnel management, and enhancing the efficiency of manual maintenance. But it still relies on manual maintenance. However, there is still a gap in the self-maintenance of machinery. Mechanical self-maintenance has many advantages over manual maintenance. Therefore, improving the efficiency of mechanical maintenance is crucial for the development of engineering and society. While previous studies have focused on Fault detection, mechanical maintenance, and improving manual repair efficiency, the mechanism of mechanical self-maintenance remains unexplored. In order to improve mechanical maintenance efficiency and reduce mechanical maintenance conditions. Firstly, maintenance is necessary in production, and if long-term mechanical automation is required, autonomous maintenance of production machinery is also quite important. Therefore, mechanical self-maintenance will be of great help to future production automation. Then, mechanical self-maintenance can enable machines to operate for longer periods of time in extreme environments that are difficult to repair, such as deserts, space environments, and extraterrestrial environments. So mechanical self-maintenance will be of great help to future scientific research and exploration. This study aims to address this gap by employing Search and organize existing achievements on sensor AI and 3D printing technology to investigate how to enhance mechanical self-maintenance

capability [2-4]. The current problem in mechanical self-maintenance is how to build a process for mechanical self-maintenance. The goal of this study is to construct a closed-loop process for mechanical self-maintenance. So, we have studied the research results of technologies such as AI, detectors, and 3D printing that enable machines to operate autonomously through previous literature. Imagine a process for mechanical self-maintenance. mechanical faults, solve installation difficulties during the repair process, and develop sensor systems that can detect more abnormalities and faults in machinery. These advances may pave the way for fully autonomous maintenance systems in industrial environments. Based on this, exploration was conducted on mechanical self-maintenance, and the possibility of relying on sensor AI and 3D printing technology to achieve mechanical self-maintenance was explored based on existing achievements. Proposed a concept of mechanical self-maintenance operation that combines these three elements to achieve the process of detection, diagnosis, and repair.

2. Methodology

2.1 How does the model work

This article uses a literature review method to search for existing maintenance related literature on sensors, 3D printing, and artificial intelligence, and applies it to the closed-loop process of detection, diagnosis, and repair in mechanical self-maintenance, as shown in Fig. 1. Firstly, in terms of monitoring, existing research has shown that through the multi data aggregation point network structure data transmission technology of wireless sensor networks, the vibration state of machinery can be detected with relatively high accuracy and speed [2,5]. By analyzing abnormal vibration data of machinery, statistical comparison and analysis can be used to identify specific mechanical problems and achieve mechanical fault diagnosis. According to existing research, artificial intelligence (AI) can diagnose faults through information and data about faults in databases. Literature 3 suggests that fault diagnosis can be achieved through techniques such as expert systems, neural network fault diagnosis methods, and machine learning technology. And this type of technology has already been applied in some industrial fields. Therefore, AI technology can be used to diagnose mechanical faults, and the specific type of damaged parts can be determined based on the type of mechanical fault and sensor data. In the final repair process, metal 3D printing technology can be used to produce new replacement parts for damaged components. For example, electron beam selective melting (EBM) or SLA methods are used to manufacture complex and pre-

cise parts [6]. However, disassembling damaged parts and installing new ones during the repair process is still too complicated and may be difficult to implement. Therefore, it is still necessary to manually replace parts based on AI diagnostic reports.

So based on these technologies, we can build a monitoring diagnosis repair process. When a fault occurs, the sensor will detect abnormal data that is different from the data generated during normal operation due to the fault. Then

the AI will compare this data with the fault information database, determine the type of fault, report it based on the fault type, and give the next instruction. When there is a need to replace parts, AI will transmit specific types of damaged parts to the 3D printer for metal 3D printing. After that, the replacement of parts can be carried out. Complete the detection and repair of faults through this process.

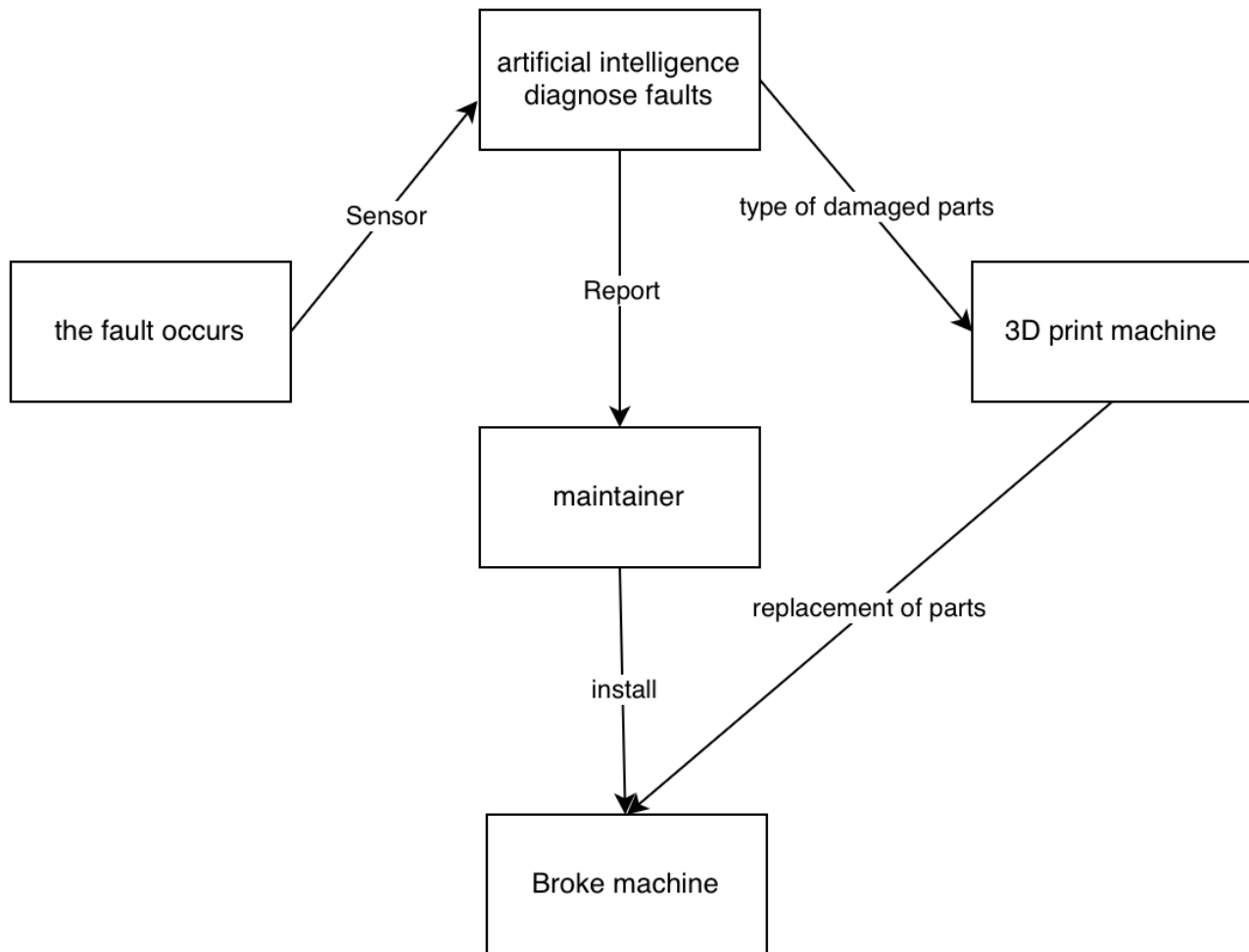


Fig. 1 The flowchart of Methodology

2.1.1 How sensor test data of mechine

The monitoring system plays a pivotal role in sensor fault detection, which has been extensively applied in thermal power plants. These plants utilize a Distributed Acoustic Sensing (DAS) system to monitor multiple operational subsystems from various aspects. This enables the collection of vast information flows. By employing the Aqirori algorithm and subsequent improved versions, continuous data mining is performed through round-the-clock sampling. Under such conditions, the data generated by tur-

bines and other mechanical components in thermal power plants can be fully controlled under sensor surveillance. Moreover, these algorithms can analyze historical data from power plants to detect common fault types, including bias faults, gain faults, and periodic interference faults. Therefore, with a comprehensive database, an adequate sensor system, and appropriate algorithms, similar sensor-based monitoring can be achieved for other industrial machinery. This ensures accurate and diverse data reception and analysis around the clock. Additionally, the

system can identify the specific data patterns generated by machinery during fault conditions.

Thermal power plants rely on advanced sensor networks to ensure operational efficiency and safety. The DAS system collects real-time data from various subsystems, including turbines, boilers, and generators. This multi-dimensional monitoring approach allows for comprehensive fault detection. Thermal power plants used Aqirori algorithm serves as a foundational tool for data analysis in fault detection. And enhanced versions of this algorithm improve accuracy in identifying anomalies in sensor data. these algorithm's Continuous sampling ensures that no critical data points are missed during operation [7-8].

In practical applications, these also enable the sensing system in thermal power plants to detect abnormal data of the following common faults. for example, Bias faults: occur when sensor readings deviate from expected values due calibration issues, gain faults: arise when sensor sensitivity changes, leading to inaccurate measurements, and periodic interference faults: caused by external disturbances. Historical data training of thermal power plants helps algorithms recognize these patterns efficiently.

So as long as there is a complete database, a suitable sensor system, and algorithms, sensors in other industrial production machinery can also receive and judge data with accuracy and diversity throughout the day. And it can determine the type of data generated by the mechanical failure.

2.1.2 How AI judgment faults

Then in the judgment section, AI is widely applied in various industries. In the decision-making stage, artificial intelligence (AI) has been widely applied in various industries Its widespread application has demonstrated its outstanding ability in data analysis tasks. The advanced fault diagnosis technology based on artificial intelligence methods has made significant progress. By utilizing machine learning and building intelligent diagnostic systems, artificial intelligence can quickly and accurately identify complex faults with sufficient information In this case, AI is less affected by the type of machinery being used, and any machine that generates specific data during a malfunction can be identified by AI in this way to determine the specific form of the malfunction and search for repair methods. However, currently there is a lack of data and AI for determining the specific damaged parts. So judging this step may encounter some difficulties.

According to existing research, artificial intelligence can diagnose faults in complex processes through various methods, each tailored to the specific characteristics of the system. The most advanced fault detection methods utilize expert systems, rule-based expert systems that simulate

human expertise by encoding domain specific knowledge into decision algorithms.

They are particularly effective for well-defined fault modes, where logical reasoning can isolate the root cause. Neural networks, deep learning models, especially recurrent neural networks (RNNs) and convolutional neural networks (CNNs), are adept at identifying subtle patterns in time series or image-based sensor data. Their ability to learn from historical fault cases enables them to detect highly nonlinear processes, anomalies in fuzzy mathematics, and systems with imprecise or fuzzy data (such as language descriptions of vibration intensity).

Fuzzy logic provides a framework for handling uncertainty, enabling more robust fault classification in noisy environments and utilizing machine learning techniques to analyze complex process faults.

Machine learning and supervised learning algorithms (such as SVM and random forest) can use labeled datasets to classify faults, while unsupervised methods (such as clustering and autoencoders) can discover hidden fault patterns without prior knowledge. Reinforcement learning further enables artificial intelligence to adaptively improve diagnostic strategies through trial and error interactions with dynamic systems. These technologies enable artificial intelligence to make precise judgments based on the nature of observed data, while continuously improving through self optimization.

2.2 How 3D print fix faults

Finally, the metal printing technology for the parts has now been perfected. Metal printing currently achieves excellent precision at the micrometer level, enabling it to completely produce replacement parts for damaged machinery. Technologies such as electron beam melting (EBM) and stereolithography (SLA) are used to manufacture complex and high-precision components. These methods allow for the replication of complex mechanical parts with extremely high precision, ensuring compatibility and functionality in industrial applications.

However, this technology does have certain drawbacks. The high cost and operating expenses of metal printing equipment make it difficult to widely adopt in most manufacturing industries. The price, maintenance, and material costs of advanced metal printers currently make it difficult to achieve widespread application. In addition, the specialized knowledge required to operate these machines further limits their usability.

Despite these challenges, there is a feasible solution that combines prefabricated parts with AI driven reporting systems. By maintaining a digital inventory of commonly used components and utilizing artificial intelligence

to predict failure modes, manufacturers can proactively prepare replacement parts before they are urgently needed. This method reduces downtime and optimizes supply chain efficiency. Artificial intelligence can analyze historical fault data, wear patterns, and environmental factors to predict when specific parts may fail, thereby producing substitutes in a timely manner through metal printing.

However, there is still a key limitation in the installation process after printing. At present, there is not enough technology to fully automate the installation of printed parts without human intervention, especially for complex components. Although robot assistance can help accomplish simpler tasks, complex mechanical systems typically require skilled technicians to ensure proper alignment, coordination, and functionality. This reliance on physical labor undermines the unmanned advantage of mechanical self maintenance. Further research is needed to develop advanced automated installation systems. The integration of quality control driven by robots, computer vision, and artificial intelligence may enable seamless assembly of printed parts.

3. Limitations & Future outlooks

However, according to current research, implementing this self-healing process for mechanical systems faces several technical challenges. The first major obstacle lies in the fault detection capability of artificial intelligence. Given the significant structural differences between different machines, the data generated during faults also exhibit different patterns. Artificial intelligence systems rely on knowledge bases to compare signals received from sensors with known fault characteristics in order to diagnose problems. This requires a large dataset containing operational data and corresponding fault diagnosis records to train AI for accurate fault recognition. For many mechanical systems, the critical database of specific fault types and damaged components that cause these faults is still incomplete, which fundamentally limits the system's learning ability.

The second major challenge involves the final installation phase of the maintenance process. Complexity arises from the diversity of mechanical failures and component damage, as well as the complexity of replacing damaged parts in some cases. In many cases, the replacement process is so complex that current technology is difficult to accomplish. Therefore, human intervention is still inevitable for these critical maintenance tasks. This makes the mechanical self-maintenance. of the system described in this article unable to generate the expected advantages of mechanical self-maintenance. in areas that are difficult for personnel to maintain, Even if the final step is not too difficult for manual installation, it may still cost a lot or pose

extremely high risks. So in these situations, technology that can complete remote installation or AI autonomous installation is needed

Looking ahead, the increasing popularity of sensor technology in mechanical fault diagnosis provides promising solutions. As more and more sensors are deployed in various mechanical systems, the amount of data available for artificial intelligence training will continue to increase. This data expansion will enhance the ability of artificial intelligence to identify subtle fault patterns and improve diagnostic accuracy. The synchronous development of robotic arms and artificial intelligence research enables mechanical systems to autonomously perform increasingly complex tasks. These technological developments indicate that through continuous innovation, solutions will emerge to address these challenges.

4. Conclusion

This article explores the concept of mechanical self-maintenance by reviewing existing research. Explored a possible way for machinery to achieve the self-maintenance that integrates technologies such as sensors, artificial intelligence, and 3D printing. Several technical challenges that currently hinder the practical implementation of this process have been identified. And looked forward to the future possibilities of mechanical maintenance methods. Specifically, it proposes a potential method to improve repair efficiency while reducing complexity. By utilizing AI driven diagnostics and additive manufacturing, the proposed framework can achieve autonomous fault detection and on-demand replacement of parts. And during this process, this study also identified some issues that need to be addressed to achieve this process, as well as some ideas for addressing these issues, such as robotic arm technology and higher intelligence AI. In addition, the study also outlined future research directions. For example, how to optimize the ability of artificial intelligence to diagnose mechanical faults, solve installation difficulties during the repair process, and develop sensor systems that can detect more abnormalities and faults in machinery. These advances may pave the way for fully autonomous maintenance systems in industrial environments.

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