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Design of a Fuzzy Intelligent Diagnostic System for Milling Machines

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Abstract

This study presents an intelligent diagnostic system for milling machines equipped with electric actuators and lubrication systems. The fuzzy system takes three input parameters: oil temperature (°C), vibration level (dB), and electric power (KW). Based on these inputs, the machine diagnoses faults and reports them online. To enhance computational efficiency, fuzzy rules were developed, categorized, and optimized, reducing the number of rules from 18 to 7. The key advantages of the proposed method are its high accuracy in fault detection and automation, leading to extended machine lifespan, prevention of severe damages, and reduced maintenance costs.

Keywords: Condition Monitoring, Microprocessor, Fuzzy, Diagnostic System

1- Introduction

The increasing complexity of modern milling machines necessitates advanced diagnostic systems to ensure operational efficiency and minimize downtime. Traditional fault detection techniques, such as vibration analysis and acoustic emission monitoring, have proven effective but often require extensive human intervention and expertise. As a result, artificial intelligence (AI)-based diagnostic methods, including fuzzy logic systems, artificial neural networks (ANNs), and hybrid models, have gained significant attention in recent years.

Fuzzy Logic in Fault Diagnosis

Fuzzy logic has been widely used in industrial diagnostics due to its ability to handle uncertainty and imprecise information. Unlike classical binary logic, fuzzy systems can model linguistic variables and human-like reasoning, making them suitable for diagnosing milling machine faults. Yang and Zhong [1] highlighted the effectiveness of machine learning and fuzzy inference systems in industrial fault detection. Their work demonstrated that fuzzy-based classifiers could enhance diagnostic accuracy by incorporating expert knowledge and empirical data. Other studies, such as those by Wang et al. [3] and Ramezanpour et al. [8], have reinforced the role of fuzzy logic in improving fault classification accuracy and real-time diagnostics.

Hybrid AI Models for Fault Diagnosis

Several studies have explored the integration of fuzzy logic with other AI techniques, such as ANNs and genetic algorithms, to improve fault detection. Li et al. [2] proposed a deep learning approach for intelligent fault diagnosis in rotating machines, emphasizing the importance of combining multiple AI techniques to enhance predictive capabilities. Similarly, Wang et al. (2021) developed a digital twin-assisted approach that leveraged AI-driven models, including fuzzy logic, for diagnosing machine faults in real-time. Additionally, Bahrami Mossayebi et al. [7] explored long short-term memory (LSTM) neural networks for fault detection in vehicle suspensions, showcasing the adaptability of AI-based models in various engineering applications.

Application of Fuzzy Systems in Milling Machines

Milling machines, with their complex cutting dynamics, pose unique challenges for fault diagnosis. Patel and Kumar [5] investigated AI-based defect prediction in milling machinery using acceleration sensors, demonstrating the advantages of machine learning techniques in detecting wear and tool defects. Zhang and Lee [6] further optimized fault detection by employing a hybrid deep learning model with a genetic algorithm, showing that AI-driven approaches could significantly improve the accuracy of fault identification in milling operations. Moreover, studies by Chen and Zhao [4] and Zhang et al. [9] highlighted the effectiveness of integrating fuzzy logic with convolutional neural networks (CNNs) for adaptive fault diagnosis.

Fuzzy Rule-Based Diagnostic Frameworks

A key advantage of fuzzy diagnostic systems is their ability to incorporate rule-based frameworks derived from expert knowledge. Chen and Zhao [4] reviewed intelligent fault diagnosis systems and emphasized the role of fuzzy rule-based models in handling small and imbalanced datasets. The study underscored that fuzzy logic could effectively classify faults even with limited training data by leveraging predefined linguistic rules. Additionally, Patel et al. [5] explored AI-driven wear prediction models, further validating the role of hybrid AI-based methods in industrial diagnostics.

In the system designed in this study, sensors continuously measure electric power, oil temperature, and vibration levels at short intervals. These data serve as inputs to the fuzzy fault detection system, which, based on predefined fuzzy functions, determines the machine's condition. The fuzzy diagnostic system then reports the motor's condition as an output.

2- Fuzzy Logic and Fuzzy Control Systems

With the advent of fuzzy logic (also known as gray logic) as an alternative to Aristotelian black-and-white logic, artificial intelligence has undergone significant advancements. This concept was first introduced in 1965 by Professor Lotfi Asgar Zadeh, an Iranian-origin scientist at the University of California, Berkeley. Initially, fuzzy logic faced opposition, particularly from Japanese scientists. However, after several years of discussions, Japan adopted the concept, and today, many mechanical and control systems use fuzzy logic in their design and manufacturing [6,7].

Although fuzzy logic faced strong opposition from many scientists, mathematicians, and engineers in its early years, its practical applications eventually gained widespread acceptance. Today, fuzzy logic is an active research field within artificial intelligence, generating hundreds of books and numerous scientific papers annually [8-10].

One of the primary applications of fuzzy logic is in industrial control systems. Similar to how the human brain makes decisions based on "if-then" conditions, this approach can be implemented in industrial control systems [11,12]. The block diagram of a fuzzy control system is illustrated in Figure 1.

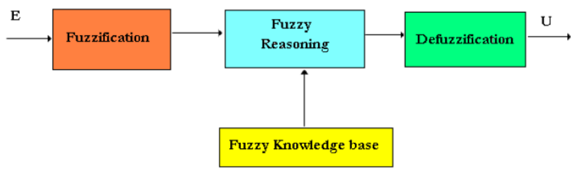

Figure 1. Schematic of the fuzzy control system

Unlike PID loops, fuzzy control loops rely on a fuzzy knowledge base rather than mathematical equations. Therefore, fuzzy logic is preferred over conventional PID control for nonlinear multivariable systems where mathematical modeling is complex.

In most industries, machinery with electric actuators and lubrication systems is commonly used. A typical milling machine, which includes an electric motor and lubrication system, is shown in Figure 2.

Figure 2. Schematic of milling machines

In rotary systems, monitoring oil temperature and vibration levels is crucial for ensuring machine functionality. Using specific sensors, these parameters are continuously measured and monitored. A fuzzy system can be designed to detect milling machine faults online.

3- Developing Fuzzy Rules for Intelligent Diagnostic System

The inputs for the intelligent diagnostic system in this study are:

- **Electric Power** (in kilowatts, KW)
- **Oil Temperature** (in degrees Celsius, °C)
- **Vibration Level** (in decibels, dB)

The output of the fuzzy system is:

- **Motor Condition**, indicating whether the machine is operating normally or has a fault.

For software implementation, the FuzzyTech software (version 5.81d) was used [9]. The general schematic of the fuzzy diagnostic system is shown in Figure 3.

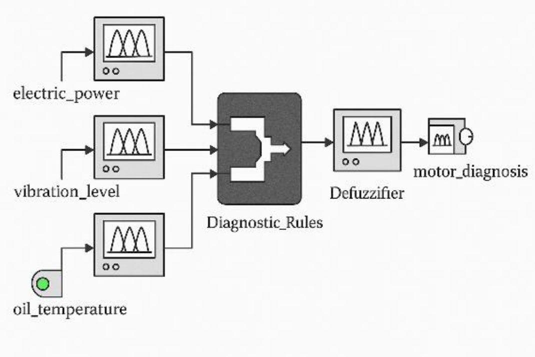

Figure 3. Schematic of milling machines

The membership functions for the input variables (oil temperature, electric power, and vibration level) are illustrated in Figures 4 and 5.

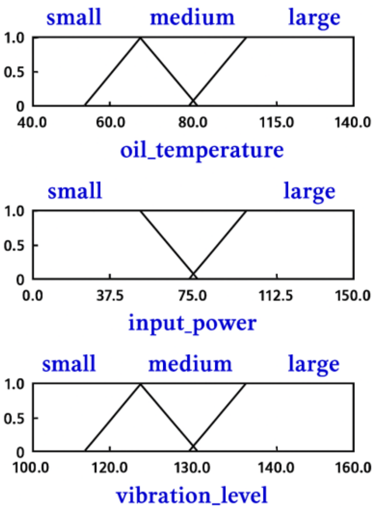

Figure 4. Membership functions of input variables oil: temperature (°C), vibration level (dB), and electric power (KW)

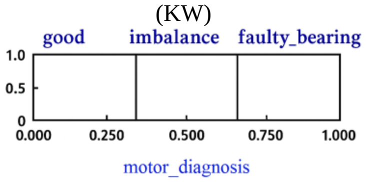

Figure 5. Output membership function: Motor Condition

Fuzzy diagnostic rules are derived based on the membership functions of input and output variables. These rules determine the machine's operational status by evaluating the fuzzy input variables (oil temperature, motor power, and vibration levels) and generating the appropriate output. The system consists of 18 fuzzy rules, which are listed in Table 1.

Table 1. Fuzzy Rules of the System

If			***Then***
Input power	**Vibration Level**	**Oil Temperature**	**MOTOR Condition**
Small	Small	Small	Good
Small	Medium	Small	Imbalance
Small	Large	Small	Imbalance
Large	Small	Small	Good
Large	Medium	Small	Good
Large	Large	Small	Imbalance
Small	Small	Medium	Good
Small	Medium	Medium	Faulty – bearing
Small	Large	Medium	Faulty – bearing
Large	Small	Medium	Good
Large	Medium	Medium	Good
Large	Large	Medium	Faulty – bearing
Small	Small	Large	Imbalance
Small	Medium	Large	Faulty – bearing
Small	Large	Large	Faulty – bearing
Large	Small	Large	Imbalance
Large	Medium	Large	Imbalance
Large	Large	Large	Faulty – bearing

After analyzing these fuzzy rules, they were categorized and optimized for efficiency. By using electric power and vibration level, the **Vibration Diagnosis** status can be determined (Table 2).

Table 2. If-Then Fuzzy Rules, Inputs: Power and Vibration Level, Output: Vibration Diagnosis

If		***Then***
Input power	**Vibration Level**	**Vibration diagnosis**
Small	Small	Acceptable
Small	Medium	Unacceptable
Small	Large	Unacceptable
Large	Small	Acceptable
Large	Medium	Acceptable
Large	Large	Unacceptable

To optimize decision-making speed, the fuzzy control rules were reviewed and simplified. After a comprehensive analysis, the number of fuzzy rules was reduced from 18 to 7 (Table 3).

Table 2. Simplified If-Then Fuzzy Rules, Inputs: Power and Vibration Level, Output: Vibration Diagnosis

If		***Then***
Input power	**Vibration Level**	**Vibration diagnosis**
Acceptable	Small	Good
Unacceptable	Small	Imbalance
Acceptable	Medium	Good
Unacceptable	Medium	Faulty – bearing
Acceptable	Large	Imbalance
Unacceptable	Large	Faulty – bearing

The fuzzy diagram of the optimized intelligent diagnostic system is shown in Figure 6.

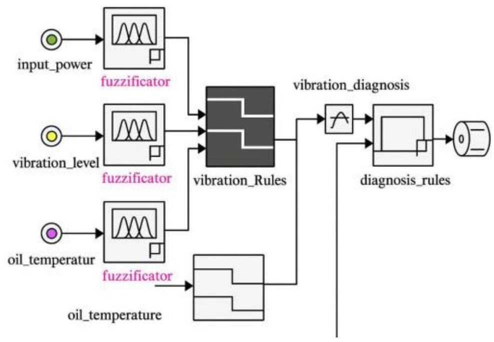

Figure 6. Fuzzy diagram of the optimized system

As illustrated, the system converts non-fuzzy inputs (temperature, power, and vibration level) into fuzzy variables and applies the designed fuzzy rules (Tables 2 and 3) to diagnose machine faults in real-time. The main advantage of this proposed method is its simplicity compared to traditional PID control systems. Additionally, by reducing the number of fuzzy rules from 18 to 7, the number of calculations is minimized, significantly improving the system's decision-making speed.

4- Conclusion

In the fuzzy diagnostic system for milling machines, three input parameters are used: oil temperature (°C), vibration level (dB), and electric power (KW). These inputs are fuzzified and processed based on predefined "if-then" fuzzy rules to diagnose machine faults. To enhance system speed, the fuzzy rules were categorized and reduced from 18 to 7, improving computational efficiency. The main advantages of this proposed method are its high accuracy in fault detection, intelligent decision-making capabilities, and automation. These benefits contribute to extending the machine's lifespan, preventing severe damages, and reducing maintenance costs.

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