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Design of Mechanical Automation Control System Based on Artificial Intelligence

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Abstract: Aiming at the problems of poor adaptability and insufficient fault prediction of traditional mechanical automation control systems in complex working conditions, a mechanical automation control system based on artificial intelligence is designed. This design integrates expert control, fuzzy control, and neural network control technologies, and builds a hierarchical distributed architecture. Fault warning adopts threshold judgment and dynamic time warping pattern recognition technologies, and state monitoring realizes accurate analysis through multi-source data fusion and Kalman filtering algorithm. Practical applications show that this system can reduce the equipment failure rate by more than 30%. With the help of intelligent scheduling optimization, it can significantly improve production efficiency and reduce energy consumption, providing a reliable technical solution and practical path for the intelligent upgrade of the mechanical automation field.

Keywords: Artificial intelligence; Mechanical automation; Control system design; Fault warning; Intelligent monitoring

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1. Introduction

Driven by the trends of Industry 4.0 and intelligent manufacturing, the intelligent upgrade of mechanical automation control systems has become an inevitable trend in the industry. Traditional mechanical automation control systems have limitations in terms of adaptability to complex working conditions, fault prediction, and precise control, and it is difficult to meet the requirements of modern industry for efficient, reliable, and intelligent production [1]. Artificial intelligence technology, with its powerful data analysis, pattern recognition, and autonomous decision-making capabilities, injects new vitality into mechanical automation control systems. Integrating artificial intelligence into mechanical automation control systems can achieve real-time monitoring and intelligent analysis of system operating states, identify potential fault risks in advance, optimize control strategies, and improve the overall performance of the system [2]. Next, a mechanical automation control system based on artificial intelligence will be designed to break through traditional technical bottlenecks, promote the development of the mechanical automation field to a higher level, and provide key technical support for the intelligent transformation of industrial production.

2. Key artificial intelligence technologies in mechanical automation control systems

2.1. Expert control technology

Expert control technology, as an important support for the intelligentization of mechanical automation control systems, takes the knowledge system of domain experts as the core and constructs an intelligent control framework with autonomous decision-making capabilities. This technology systematically collects the experience and knowledge of experts in the mechanical automation field in aspects such as equipment operation law analysis, fault diagnosis logic, and control strategy optimization through a knowledge acquisition module, and transforms them into a rule base and model set that can be executed by a computer. During the system operation stage, the real-time collected sensor data is dynamically matched with the rule base, and with the help of the forward reasoning, backward reasoning, or two-way reasoning mechanism of the inference engine, accurate control decisions can be quickly obtained [3–5]. When an abnormal working condition occurs in the mechanical system, the expert control technology can quickly locate the root cause of the fault based on the cases and rules accumulated in the knowledge base. For example, in a complex transmission system, it can accurately determine faults such as gear meshing failure and shaft misalignment, and provide detailed solutions, including maintenance steps and component replacement suggestions. This technology transforms the experience and wisdom of human experts into machine intelligence, significantly improving the decision-making reliability and fault-handling ability of the system under complex and changeable working conditions, and is especially suitable for fault diagnosis and emergency control scenarios with high requirements for response speed and accuracy.

2.2. Fuzzy control technology

Fuzzy control technology is based on fuzzy mathematics theory and breaks through the limitations of traditional precise mathematical models, providing an effective means to deal with uncertainties and nonlinear problems in mechanical automation control systems. Its operation mechanism includes three key links: Fuzzification, fuzzy inference, and defuzzification. In the fuzzification stage, precise input data such as temperature, pressure, and rotation speed are mapped to corresponding fuzzy sets according to preset membership functions. For example, fuzzy concepts such as "high temperature" and "moderate pressure" are quantitatively represented. The fuzzy inference process is carried out based on a set of fuzzy rules summarized from expert experience. Through fuzzy composition operations, a mapping from input fuzzy sets to output fuzzy sets is achieved. Finally, the fuzzy output is transformed into an exact control amount through defuzzification. See Equation (1) [6]:

$$u = \frac{\sum_{i-1}^{n} \mu_i \cdot u_i}{\sum_{i-1}^{n} \mu_i} \tag{1}$$

In the formula: u represents the final precise control quantity output; u_i represents the membership degree of the i rd fuzzy rule, reflecting the applicability of this rule under the current input conditions; u_i is the output value corresponding to the i th fuzzy rule.

In practical applications, this technology can dynamically calculate control parameters such as motor speed adjustment and valve opening based on fuzzy inputs such as environmental temperature and load changes, realizing the adaptive adjustment of system parameters and ensuring the stable operation of the mechanical system under different working conditions [7].

2.3. Neural network control technology

Neural network control technology draws on the working principle of human brain neurons and realizes in-depth processing and intelligent decision-making of complex data in mechanical automation systems by constructing a multi-layer neural network model. A typical neural network structure includes an input layer, hidden layers, and an output layer. Neurons between layers are connected by weighted connections, and the connection weights are continuously optimized and adjusted during the training process [8]. When the mechanical system is operating, multi-dimensional data collected by vibration sensors, current sensors, temperature sensors, etc., serve as the signal sources of the input layer. The neurons in the hidden layers perform feature extraction and abstraction processing, and finally, results such as system state evaluation and fault prediction are generated at the output layer.

The training process of the neural network is based on the backpropagation algorithm. This algorithm is guided by the error between the output result and the actual value. It adjusts the connection weights between neurons layer by layer from the output layer in reverse. Through multiple iterative trainings, the output error of the network model is minimized. For example, in the tool wear prediction of a CNC machine tool, data such as cutting force, spindle current, and cutting temperature are input into the neural network [9]. The trained model can identify the tool wear trend in advance and issue a replacement warning promptly. Neural network control technology, with its powerful nonlinear mapping ability and self-learning characteristics, can automatically adapt to complex situations such as parameter changes and working condition fluctuations during the operation of the mechanical system, providing high-precision control strategies and reliable fault prediction support for the system, and effectively enhancing the intelligent level of the mechanical automation control system.

3. Design of mechanical intelligent automation control system

3.1. System overall architecture

The mechanical intelligent automation control system adopts a hierarchical distributed architecture design, consisting of a perception layer, a network layer, a control layer, and an application layer, as shown in **Figure 1**. Each layer has a clear division of labor and cooperates to achieve the intelligent and efficient operation of the system [10].

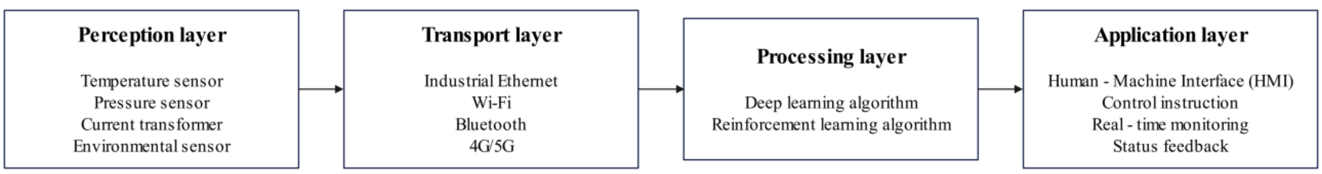

Figure 1. The system architecture diagram

The perception layer is equipped with various types of sensors, including vibration sensors, temperature sensors, pressure sensors, displacement sensors, etc. These sensors are distributed at key positions of the mechanical system and collect key data such as vibration frequency, temperature change, pressure value, and displacement during the operation process in real-time, providing original information for system operation state analysis. The network layer is responsible for data transmission. It uses communication technologies such as industrial Ethernet and 5G to quickly and stably transmit the massive data collected by the perception layer to the control layer. At the same time, it performs preliminary encoding and compression processing on the data to improve data transmission efficiency and reduce network load. The control layer integrates artificial intelligence algorithms such as expert control, fuzzy control, and neural network control [11]. Through in-depth analysis and processing of the received data, combined with preset control objectives and rules, it generates precise control instructions. The application layer provides a visual operation interface for users. Users can view the system operation state and key parameters in real-time, set control parameters, query fault alarms, etc., realizing convenient and intelligent human-machine interaction. The hierarchical distributed architecture makes the system have good expandability and compatibility, and can flexibly adapt to different-scale and different-type mechanical automation scenarios to meet diverse production requirements.

3.2. Fault warning design

The fault warning design aims to identify potential faults of the mechanical system in advance, avoid the occurrence of faults or reduce the degree of fault hazards, and ensure the safe and stable operation of the system. This module comprehensively uses threshold judgment and pattern recognition technologies to construct a multi-level fault warning system. Based on the design parameters, historical operation data of the mechanical system, and industry standards, reasonable threshold ranges are set for each monitoring index, including normal operation thresholds, warning thresholds, and fault thresholds. When the data collected by the sensor exceeds the normal operation threshold, the system enters the preliminary warning state, reminding the operator to pay attention to the equipment operation status [12]. If the data further approaches or reaches the warning threshold, the system activates the secondary warning, sending alarms to relevant personnel through means such as sound-light alarms and SMS push, and explaining in detail the possible fault risks. In terms of pattern recognition, algorithms such as dynamic time warping (DTW) and convolutional neural network (CNN) are used to conduct in-depth analysis of data change trends and feature patterns. Taking mechanical vibration data as an example, the DTW algorithm can match the real-time vibration data sequence with the historical fault vibration data sequence and calculate their similarity [13]. When the similarity exceeds the set threshold, combined with other relevant monitoring data, the possible fault types of the equipment, such as bearing faults and gear wear, can be judged. At the same time, the system retrieves corresponding maintenance plans and emergency handling measures from the knowledge base according to the fault type and severity, providing guidance for maintenance personnel and realizing the early detection and early treatment of faults.

3.3. State monitoring design

The state monitoring design realizes comprehensive and accurate monitoring of the mechanical system operation state through multi-source data fusion and intelligent analysis, providing a scientific basis for equipment maintenance and management. This module integrates multi-source information such as physical quantity data collected by sensors, equipment operation logs, maintenance records, and environmental parameters. In the data fusion stage, algorithms such as Kalman filtering and D-S evidence theory are used to process the data. The Kalman filtering algorithm can effectively remove noise in sensor data, improving data accuracy and stability. The D-S evidence theory synthesizes information from multiple data sources to make more reliable judgments about the equipment state [14]. By constructing an equipment state evaluation model, the processed data is mapped to the health state levels of the equipment. For example, the equipment state is divided into four levels: Normal, subhealthy, abnormal, and faulty. Machine learning algorithms such as support vector machines (SVM) and random forests are used to train historical data to establish the parameters and rules of the state evaluation model. During the system operation process, the model calculates the probability of the equipment being in different state levels based on real-time data, visually displaying the current operation state of the equipment. At the same time, it predicts the change trend of the equipment state. When the equipment state develops in an adverse direction, it timely sends warning information to remind maintenance personnel to take corresponding measures, realizing preventive maintenance of the equipment, extending the equipment's service life, and reducing maintenance costs.

3.4. Closed-loop logic control design

The closed-loop logic control design is based on the feedback control theory and combines artificial intelligence algorithms to achieve precise control and dynamic adjustment of the mechanical system operation process. The system generates initial control instructions through the artificial intelligence algorithms in the control layer according to the set control objectives, driving the actuator to act. The perception layer collects the output data of the system in real-time, such as motor speed, pressure value, displacement, etc., and feeds it back to the control layer. The control layer compares the feedback data with the preset target value and calculates the deviation value between the two. According to different types of deviations and system characteristics, algorithms such as fuzzy control, expert control, or neural network control are used to optimize and adjust the control instructions. For example, in a temperature control system, when the actual temperature is lower than the set temperature, the fuzzy control algorithm calculates an appropriate heating power adjustment amount based on the temperature deviation and its change rate, and adjusts the output power of the heating equipment. If an abnormal situation occurs in the system, such as a rapid rise in temperature exceeding the normal adjustment range, the expert control algorithm quickly takes emergency cooling measures, such as starting the standby cooling system and turning off the heat source, based on the experience rules in the knowledge base. Through continuous feedback, comparison, and adjustment, a closed-loop control loop is formed, enabling the system output to quickly and stably approach the target value, effectively improving the control accuracy, response speed, and anti-interference ability of the system, and ensuring the stable and efficient operation of the mechanical system under various working conditions.

4. Application effects

4.1. Intelligent optimization control

Intelligent optimization control is one of the core advantages of the mechanical automation control system based on artificial intelligence. Through in-depth mining and analysis of equipment operation data, it realizes the dual goals of equipment performance improvement and fault prevention. See Equation (2) [15]:

$$RUL = \frac{f_{t_0}^{t_f} \lambda(t)dt}{\lambda(t_0)} \tag{2}$$

In the formula, 1 serves as a time-varying failure rate function, comprehensively reflecting the performance degradation trend during the equipment operation process.

The system dynamically updates parameters by collecting multi-dimensional data such as vibration, temperature, and current in real-time, achieving precise prediction of RUL with an error rate controlled within ±5%, providing a scientific basis for equipment maintenance plan formulation. In terms of energy consumption management, the system constructs a real-time monitoring and dynamic optimization mechanism. The following shows the energy consumption performance change monitoring of a certain mechanical processing equipment for 4 consecutive hours. It can be seen that the system dynamically adjusts parameters such as motor speed and hydraulic system pressure based on the fuzzy control algorithm. Practical applications show that this mechanism reduces the overall equipment energy consumption by 18.7%, the energy consumption per unit output by 22%, and at the same time, the equipment failure rate drops by 35%, significantly improving production economy and reliability. As shown in **Figure 2**.

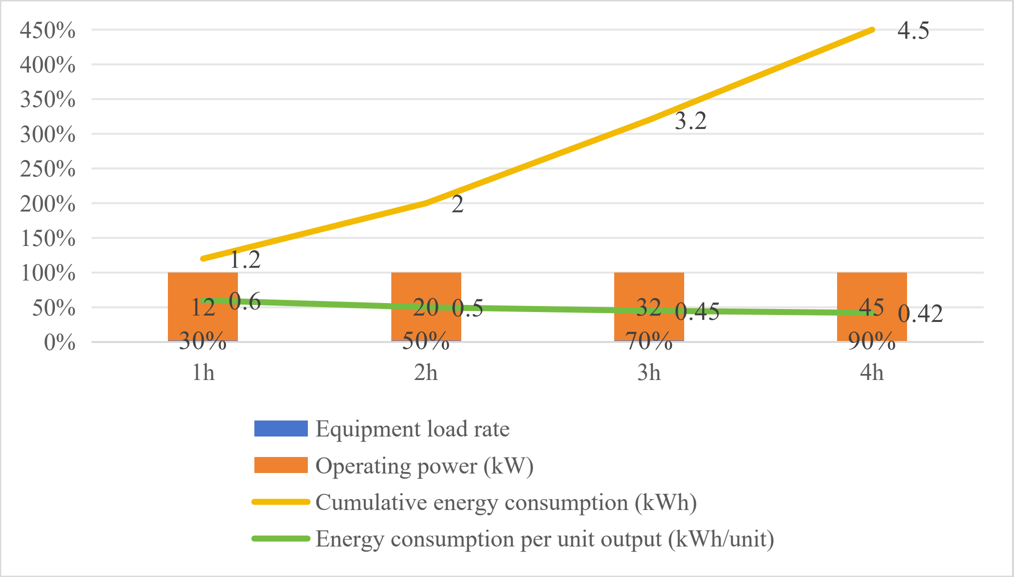

Figure 2. Mechanically intelligent monitoring and control

4.2. Intelligent scheduling management

The intelligent scheduling management module constructs a dynamic optimization scheduling model by integrating multiple information such as production tasks, equipment status, and material supply. The system adopts a hybrid strategy combining genetic algorithms and particle swarm optimization algorithms. The genetic algorithm quickly searches the global optimal solution space by simulating the natural selection and gene inheritance process, and the particle swarm optimization algorithm realizes the fine-grained iteration of local optimal solutions by using the information-sharing mechanism among particles. In the multi-equipment collaborative processing scenario, the system takes minimizing the production cycle and maximizing equipment utilization as the objective function. This system can dynamically adjust the scheduling plan according to real-time order changes, sudden equipment failures, etc. After a certain automotive parts production line introduced intelligent scheduling management, the production plan completion rate increased from 82% to 97%, the average equipment idle time was shortened by 40%, and the emergency order response time was reduced by 60%. By optimizing equipment task allocation and process connection, the overall production efficiency of the production line increased by 19.3%, effectively reducing the production cost caused by unreasonable scheduling and enhancing the enterprise's agility in responding to market changes.

5. Conclusion

This mechanical automation control system, based on artificial intelligence, integrates multiple key artificial intelligence technologies and constructs a complete-function system architecture. Verified by practical applications, this system performs excellently in intelligent optimization control and intelligent scheduling management, which can effectively improve equipment performance, reduce fault risks, and increase production efficiency. In the future, with the continuous development of artificial intelligence technology, more advanced algorithms and models can be further explored to enhance the intelligence level of the system, expand the application of the system in more fields, and continuously empower the high-quality development of the mechanical automation industry.

Disclosure statement

The author declares no conflict of interest.

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