Application of Intelligent Sensors in the Collection of Electrical Engineering Automation Equipment

Lei Wang
School of Electrical and Information Engineering, Heilongjiang University of Technology, JiXi, Heilongjiang, 158100, China
E-mail: leiwang65@163.com

Keywords: intelligent sensors, electrical engineering automation, fuzzy PID algorithm, neural network

Received: December 2, 2023

This research presents a fuzzy PID controller enhanced by an RBF neural network, utilizing MATLAB for simulation and testing to explore the integration of intelligent sensors in electrical engineering automation systems. The study initially focuses on the specific characteristics and accuracy requirements of electrical engineering and automation control, using a permanent magnet brushless DC motor as a case study for intelligent technology applications. The fuzzy neural network PID algorithm is applied to analyze the control performance of the motor circuit breaker's closing speed. Simulation results indicate that the fuzzy neural network PID algorithm reduces the motor's closing tracking speed error rate by 0.33 m/s compared to traditional PID algorithms, demonstrating its superior control effect. Subsequently, an experimental platform was established with a permanent magnet brushless DC motor, and the fuzzy neural network PID control algorithm was implemented. Experimental results show that the algorithm maintains the closing tracking speed error rate at a low level of 0.22 m/s. These outcomes highlight the potential of integrating fuzzy neural network-based controllers in enhancing the efficiency and precision of automation systems. The findings confirm that intelligent fuzzy neural network control algorithms significantly improve the accuracy and reliability of automation control in electrical engineering, paving the way for more advanced applications.

Povzetek: Članek obravnava uporabo inteligentnih senzorjev in naprednih algoritmov, kot sta PID mehke množice in RBF nevronske mreže, za izboljšanje avtomatizacije in učinkovitosti električnih inženirskih sistemov.

1 Introduction

Electrical engineering automation control plays an important role in the operation of the entire power system. The automation construction of electrical engineering plays a decisive role in the quality of the entire power system operation. To promote the comprehensive and rapid development of electrical engineering and improve the technical level of electrical engineering automation control, it is necessary to integrate more advanced scientific and technological achievements into electrical engineering automation control. Intelligent technology is a relatively advanced technology that has been widely applied in electrical engineering automation control and has provided a promoting role for the development of electrical engineering automation control. With the rapid development of the national economy and the continuous progress at scientific and technological levels, people's requirements for quality of life are becoming higher and higher. It is urgent to hope that all work, daily life, and other things can be achieved through computers or artificial intelligence. Of course, it is indeed a bit difficult to fully achieve automation at present, but for various monitoring systems, it is easy to achieve automated monitoring, especially in the electrical equipment department environment for the power system [1].

Automated monitoring systems play a very important role in the safe operation of electrical equipment in the power system and play an indelible role in fully realizing computer automation and artificial intelligence monitoring. The safe operation of the power system plays a crucial role in the stability and unity of a country, the stability and harmony of a society, and the rapid development of an enterprise. In the power system, electrical equipment is a very important and indispensable component of the entire system. To ensure the safe and stable operation of the power system, a monitoring system for the safe and stable operation of electrical equipment is essential. In the entire safety and stability monitoring system, intelligent sensors are the key components, which can not only convert various abnormal signals into electrical signals for transmission but also complete corresponding data processing, display, and other functions. Monitoring the safe and stable operation of electrical equipment in the power system is very important. Therefore, the application research of intelligent sensors in electrical equipment monitoring is of great practical significance for learning the safe and stable operation of electrical equipment in the power system, as well as for subsequent maintenance and repair. With the continuous promotion of the automation industry, achieving integrated and collaborative control with artificial intelligence as the benchmark and terminal control devices as the carrier plays an important role in promoting social development and people's lives at this stage.

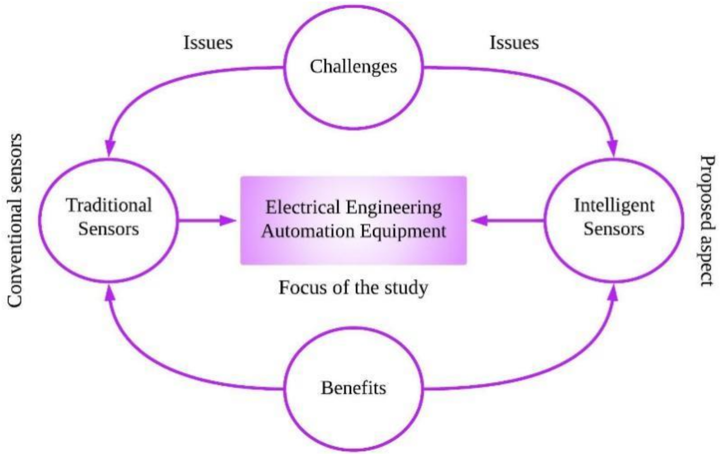


Figure 1: Intelligent sensors for automation equipment in electrical engineering

For electrical equipment, the development and application of automated monitoring systems can supervise the entire process of the equipment system, relying on intelligent sensor technology and its equipment to act in various control links of electrical institutions, and combining information sensing technology, intelligent control technology, etc. to achieve integrated and collaborative management of equipment in the entire power system, once a potential malfunction occurs, the warning function of the main system can be triggered promptly, allowing staff to clearly understand the current location of the malfunction and the various operating conditions of electrical equipment, providing decision-making suggestions for the later operation and maintenance work. Figure 1 depicts the intelligent sensors for automation equipment in electrical engineering, which gives a summary of the key concept of the research and shows how intelligent sensors work with automation equipment in electrical engineering. From the perspective of device operation mode, comprehensive and three-dimensional monitoring is carried out through intelligent sensors. The process of converting signal information into electrical signals for digital processing can achieve full processing and 24/7 detection, ensuring the reliability of power equipment and its system operation [2].

Automation in electrical engineering has transformed numerous industries by improving accuracy, productivity, and dependability in intricate operations. With the increasing demand for advanced and self-sufficient systems, the integration of cutting-edge technologies has become essential. The objective of this study is to investigate and create new control strategies using intelligent sensors, with a particular emphasis on enhancing control systems by incorporating a fuzzy PID algorithm and RBF neural networks. The main goals are to create, enhance, and verify these intelligent control strategies to enhance system performance, even when faced with uncertainties and nonlinearities. Automation in electrical engineering plays a vital role in streamlining processes, minimizing human involvement, and enhancing safety and efficiency in industrial settings. Historically, control systems predominantly utilized conventional PID controllers because of their simplicity and reliability. However, these controllers encounter difficulties when handling intricate, nonlinear, and time-dependent systems. As a result, there has been a rise in advanced control techniques that can adjust to varying circumstances and enhance the overall efficiency of the system. Intelligent technology encompasses systems that employ sophisticated computational methods, including machine learning, fuzzy logic, and neural networks, to analyze data, make informed choices, and enhance operational efficiency without human intervention. In the realm of electrical engineering automation, intelligent technology empowers the creation of adaptive and self-tuning control systems capable of managing uncertainties, nonlinearities, and dynamic environments. Some examples of smart technology in this field include fuzzy logic controllers, neural network-based control systems, and sensors that can analyze data in real time and make decisions accordingly.

An area of growing interest in electrical engineering automation equipment is the integration of intelligent sensors. Nonetheless, a dearth of thorough studies addressing the particular difficulties and possibilities in this situation exists. The widespread reliance of existing systems on conventional sensors may limit the effectiveness and flexibility of automation processes. The goal of this study is to investigate how intelligent sensors might improve the efficiency and dependability of automation equipment used in electrical engineering. Our goals are to maximize energy efficiency, enhance fault detection, and strengthen the overall robustness of the automation system by utilizing the capabilities of these sensors. This might have a big impact on sectors like manufacturing and energy production that depend on reliable and efficient automation systems. By offering a comprehensive analysis of the use of intelligent sensors, this research aims to advance the field of electrical engineering. The study will provide information on the development and application of intelligent sensors for automation equipment, emphasizing the effects of these sensors on fault tolerance, adaptability, and energy efficiency. The results of this study can help design more intelligent and effective electrical engineering automation systems, which will ultimately help a variety of sectors and advance environmentally friendly automation techniques.

2 Literature review

With the rapid development of the electrical industry, safety accidents have also increased. In the electrical engineering industry, safety issues have always been an important issue affecting the sustainable development of the industry. Therefore, reducing or preventing the occurrence of safety accidents has become a major challenge in the electrical engineering industry. The main functions of the electrical control system include monitoring and measurement, protection, and automatic control. The electrical control system consists of three main parts: sensors, buttons, switches, and other input parts; logic components such as relays and electric shock; electromagnetic coils, indicator lights, and other executive parts. Due to the complex structure of electrical engineering, it is relatively difficult to regulate between system modules, which can lead to a series of problems in stable operation. This is also an important issue in traditional electrical engineering automation control. By applying intelligent technology and integrating it into electrical engineering automation control systems, the system's operational efficiency can be better improved, thereby creating favorable conditions for the progress of electrical engineering automation control. Lee *et al.* presented a fuzzy PID control algorithm based on a neural network model is proposed. Because neural network models can learn a lot, electrical engineers can accurately change the dynamic control of variables. This lowers the error rate in changing variables and raises the accuracy of automatic control in electrical equipment [3].

Song *et al.* operated with a permanent magnet motor where fuzzy neural network PID control algorithm is used to control the permanent. The control experiment of the closing time of the magneto vacuum switch proves that, compared to other control algorithms, the fuzzy neural network PID algorithm can be more flexible in controlling the closing time [4].

Currently, intelligent technology has been continuously promoted and applied in various industries, gradually forming a complete system and greatly improving its comprehensive performance. Therefore, there is a stronger demand for intelligent technology in many fields. To better achieve system intelligence, research in this field should also be strengthened in future development so that intelligence can better liberate human labor, especially in some high-risk industries. The application of intelligence can better avoid casualties caused by production activities and reduce losses. The application of intelligent technology in electrical engineering automation control mainly focuses on three research directions: how to achieve intelligent control, establishing a complete neural network, and implementing fuzzy logic. Intelligent technology, as a branch of computer technology, is an extension of human thinking. By imitating human thinking, it can promote the better development of intelligent technology [5]. The application of intelligent technology mainly involves collecting information and then converting and processing it to achieve final feedback. Against the backdrop of rapid technological development, the application of intelligent technology has become ubiquitous in people's living environments and has also been applied in automation technology. In the future, continuous in-depth research on intelligent technology can better enhance its operability in automation applications, thereby achieving effective control of machines, intelligent production, and effectively improving work efficiency [6]. Table 1 presents an overview of research articles on the use of intelligent sensors in automation equipment for electrical engineering.

Table 1: An overview of intelligent sensors in automation equipment for electrical engineering

References	Contribution	Technology Used	Benefits	Drawbacks	Solutions
[7]	Improved fault detection	IoT, Machine Learning	Enhanced reliability	High initial costs	Cost-effective sensor networks
[8]	Energy efficiency	Wireless Communication	Reduced energy waste	Limited sensor lifespan	Sensor energy harvesting
[9]	Real-time monitoring	Edge Computing, Sensors	Minimized downtime	Data security concerns	Enhanced encryption
[10]	Adaptive automation	AI, PLC systems	Increased flexibility	Complex integration	Advanced system integration
[11]	Sustainable automation	Nanosensors, MEMS	Green Automation	Limited precision	Improved calibration
[12]	Predictive maintenance	Big Data, Data Analytics	Cost savings	Data overload	Efficient data processing
[13]	Human-machine collaboration	Robotics, IoT	Improved safety	Potential cyber threats	Robust cybersecurity
[14]	Industrial IoT	5G, Cloud Computing	Enhanced connectivity	Network latency	Low-latency networking

[15]	Condition monitoring	Wireless Sensor Networks	Early fault detection	Limited network coverage	Distributed sensor nodes
[16]	Automation adaptability	Machine Vision, AI	Improved adaptability	Data privacy concerns	Secure data handling

This literature focuses on the incorporation of intelligent sensors in electrical engineering automation equipment and is summarized in this table. Together, the publications advance several areas in this discipline, including real-time monitoring, energy efficiency, and defect identification. IoT, machine learning, and wireless communication are some of the technologies used, which have advantages including lower downtime, more energy efficiency, and enhanced dependability. Researchers suggest low-cost sensor networks, energy harvesting, improved encryption, and stronger system integration as ways to solve these problems. From the above research, it can be seen that the application of intelligent technology in electrical engineering and automation control mainly focuses on improving control accuracy. Therefore, based on the characteristics of intelligent technology in electrical engineering and automation control, this study focuses on permanent magnet brushless DC motors and uses a fuzzy neural network PID algorithm to study the control effect of the closing speed of motor circuit breakers [17].

The integration of intelligent sensors into electrical engineering automation has gained considerable attention in recent years. Various studies have investigated the use of advanced control strategies to solve problems that present nonlinearities, uncertainties, and dynamic environments in control systems. Recent research has investigated a wide range of intelligent control methods beyond fuzzy PID algorithms and neural networks. For instance, studies have examined the application of genetic algorithms, model predictive control (MPC), and adaptive neuro-fuzzy inference systems (ANFIS) in enhancing the performance of control systems in various industrial applications. Chowdhury *et al.* (2024) explored the use of MPC in energy management systems, demonstrating improved efficiency and stability in power grids [18]. Similarly, Nassef *et al.* (2023) highlighted the effectiveness of ANFIS in optimizing control strategies in robotics [19]. These approaches illustrate the diversity of methodologies being explored to address complex control challenges. While many studies have shown the potential of intelligent control strategies, there are still gaps and inconsistencies in the literature. For example, despite the widespread use of fuzzy PID controllers, some research has pointed out their limitations in handling highly nonlinear systems without significant tuning efforts [20]. Additionally, while neural networks have been praised for their adaptability, they often require extensive training data and computational resources, which may limit their applicability in real-time control scenarios [21]. These challenges highlight the need for further research to develop more robust and efficient control algorithms that can be applied in diverse industrial contexts. In control systems, various algorithms like traditional PID controllers, Model Predictive Control (MPC), Sliding Mode Control (SMC), and adaptive control are used. Traditional PID controllers are simple but struggle with nonlinearities and require manual tuning. MPC handles multi-variable systems but is computationally heavy, limiting real-time use. SMC is robust but can cause high-frequency oscillations, known as chattering. Adaptive control adjusts in real-time but can be complex and unstable. The proposed fuzzy neural network PID control algorithm outperforms these methods by combining the adaptability of neural networks with the robustness of fuzzy logic, offering better control accuracy and handling of nonlinearities without extensive manual tuning.

3 Fuzzy PID algorithm

The Fuzzy Proportional-Integral-Derivative (PID) algorithm is a widely used control strategy that combines the traditional PID controller with fuzzy logic to handle nonlinearities and uncertainties in control systems. This hybrid approach allows for more adaptive and robust control, particularly in complex industrial environments. In the design of the Fuzzy PID algorithm, specific choices, such as the selection of membership functions and fuzzy rules, play a crucial role in determining the controller's performance. The triangular membership function was selected due to its simplicity and effectiveness in capturing the gradual transitions between different control states. Additionally, the fuzzy rules were designed based on expert knowledge and system requirements, aiming to optimize the control response by adjusting the PID parameters dynamically. If the error is large and positive, the fuzzy rules might increase the proportional gain to speed up the response, while simultaneously adjusting the integral and derivative gains to avoid overshooting. Figure 2 shows the fuzzy PID algorithm control process. It includes fuzzification, fuzzy reasoning, speed PID adjustment, and deblurring modules. By setting membership functions and fuzzy rules, fuzzy PID figures out the error e and error rate ec between the given speed and the motor's output speed. It then gets the changes in control parameters and finally gets the control variables by blurring.

Figure 2: Fuzzy PID control process

i. ***Fuzzification:*** Perform fuzzy processing on the error e and error rate ec between the given input speed and actual output speed of the system. The specific fuzzy processing formula is shown in Equation 1.

$$\begin{Bmatrix} e(k) = r - y(k) \\ ec(k) = \dfrac{e(k) - e(k-1)}{T} \end{Bmatrix} \tag{1}$$

In the formula, k represents the output quantity; T represents time; r represents the given value; Y (h) represents the output value

ii. ***Resolve ambiguity:*** The ultimate goal of deblurring is to obtain clear variable values, and the specific deblurring formula is shown in Equation 2.

$$\mathrm{u} = \sum x_i \bullet \mu(x_i) / \sum \mu(x_i) \tag{2}$$

In the formula, Xi represents the ith fuzzy output quantity, and (X) represents the membership degree of the ith fuzzy output quantity.

3.1 RBF neural network

RBF neural networks have the advantages of simple structure and strong learning ability, so they are widely used in the field of control. Considering the negative correlation between the number of network layers and computational complexity, to balance the control and computational capabilities of the algorithm, a three-layer neural network structure was selected as the control subject, which includes an input layer, an output layer, and a hidden layer.

3.2 Design of fuzzy neural network PID controller

Fuzzy PID can adjust parameters without a precise mathematical model to achieve precise control objectives. At the same time, RBF neural networks have strong learning abilities and use membership functions to determine the weight at a certain time, thereby controlling variables. Therefore, combining the two algorithms can more effectively achieve precision control. In the combination of fuzzy PID and RBF neural networks, commonly used methods include using a certain algorithm as the main method or a comprehensive combination of the two. It is tried using both RBF neural networks as the main control method and fuzzy PID control as an extra method. This is because RBF neural networks can learn on their own. During the control process, the neural network improves the performance of the speed control system through adaptive learning, adjusting network parameters, and real-time processing of the speed and current information of the driving motor [22].

According to Figure 1, the control process of the RBF neural network structure is as follows: The fuzzy PID algorithm's output is first linearized by the input layer. The processing results are then sent to the hidden layer to be discretized using Gaussian functions. Finally, the results are sent to the output layer to be added up linearly to get the final parameter variables. The specific calculation formula is as follows:

i. In the hidden layer, the Gaussian function expression is shown in equation (3).

$$h_i = \exp(-\frac{x - c_j}{2b_j^2})\ j = 1,2,\ldots,m \tag{3}$$

ii. In the output layer, the linear summation formula is shown in equation (4), where ω represents the network weight.

$$y_m = \omega_1 h_1 + \omega_2 h_2 + \cdots \omega_m h_m \tag{4}$$

The Radial Basis Function (RBF) Neural Network is a type of artificial neural network that is particularly well-suited for function approximation, pattern recognition, and control system applications. The RBF network is valued for its ability to model complex nonlinear relationships with a relatively simple structure, which includes an input layer, a hidden layer with radial basis functions, and an output layer. The core concept of an RBF Neural Network lies in the transformation of input data into a higher-dimensional space, where it becomes easier to separate or approximate the desired output. In this network, the hidden layer consists of neurons that employ radial basis functions (typically Gaussian functions) as activation functions.

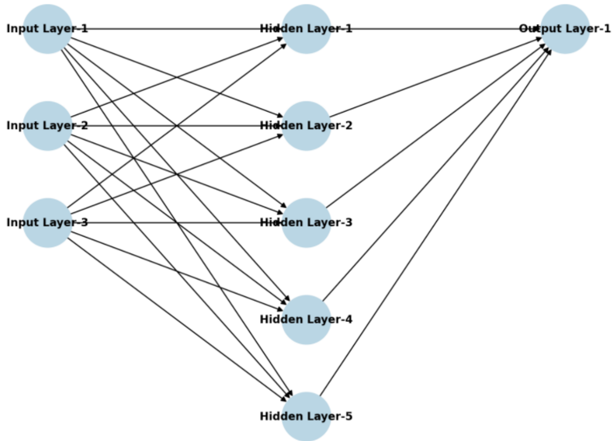


Figure 3: Structure of RBF neural network

Each neuron in the hidden layer calculates the distance between the input vector and a center point (a prototype vector), and then applies the radial basis function to produce an output. This output, which represents the activation level of the neuron, is then weighted and summed in the output layer to produce the final result. The RBF Neural Network offers several advantages in the context of control systems. One of the primary benefits is its ability to approximate nonlinear functions with high accuracy due to the localized nature of the radial basis functions. This makes the RBF network particularly effective in scenarios where the system dynamics are complex and highly nonlinear. Additionally, the training process for RBF networks is often faster than that of traditional multilayer perceptrons (MLPs), as it typically involves solving a linear problem once the centers are fixed.

The structure of the RBF Neural Network is depicted in Figure 3. The input layer receives the raw input data, which is then passed on to the hidden layer. Each input corresponds to one neuron in this layer, meaning the number of neurons in the input layer equals the dimensionality of the input data. The second layer is hidden layer which is the core of the RBF network. Each neuron in this layer computes the distance between the input vector and a predefined center, applies a radial basis function (such as a Gaussian function) to this distance, and outputs a value representing the neuron's activation level. The number of neurons in the hidden layer determines the network's capacity to model complex functions. Each hidden neuron has an associated width (spread) parameter, which controls the radius of influence of the radial basis function. The final layer is the output Layer that computes the weighted sum of the activation levels from the hidden layer to produce the final output. In a control system application, the output might represent control signals or predicted system behavior. The weights connecting the hidden and output layers are typically adjusted during the training process to minimize the error between the predicted and actual outputs.

4 Experimental verification

The experiments were conducted in a MATLAB/Simulink environment. The system being controlled was modeled as a nonlinear dynamic system, with parameters chosen to reflect realistic conditions. The fuzzy PID controller and RBF Neural Network were implemented using custom MATLAB functions and Simulink blocks. The design involved selecting appropriate membership functions for the input and output variables. The fuzzy rules were created based on expert knowledge of the system dynamics. The network was trained using a dataset generated from the system's response under various control conditions. The number of neurons in the hidden layer and the spread parameters were optimized using cross-validation.

4.1 Simulation experiment verification

Build the motor and its control system using Matlab software; analyze and compare the control effects of the fuzzy neural network PID controller and the traditional PID controller [23]. To verify the driving effect of the simulation motor system, the following no-load simulation driving experiments are conducted on the simulation model, and the simulation motor parameters are set as: The stator winding inductance of the motor is 3.3 mL, the resistance is 0.335, the motor has 2 pairs of pole pairs, the rotational inertia is 0.36 kg/m2, the voltage is 210 V, and the simulation time is 72 ms [24].

4.2 Simulation of fuzzy neural network PID algorithm

4.2.1 Load and parameter settings

The experiment in simulation is done with no load on the motor. In real life, the motor control system will create load from the driving motor's angular displacement, which is mostly seen in the circuit breaker opening and closing. The opening and closing processes of circuit breakers are opposite but have analogies. The author takes circuit breaker closing as an example, starting from the perspectives of constant load and variable load and combining the simulation model of the motor control system. The simulation experiments are conducted on the algorithm control in Chapter 2, comparing the control effect of the traditional PID algorithm and the fuzzy neural network PID algorithm on the motor speed during the circuit breaker closing process. The simulation experiment parameters are set as shown in Table 2.

4.2.2 Control algorithm simulation

The simulation is carried out for constant and variable load simulation and each of these analyses is explained below.

i. Constant load simulation:

Keep the load power of the driving motor constant, and set the maximum speed change node at the gate close position with a size of 2.20 m/s and a simulation time of 65 ms. The resulting curves obtained from the two control algorithms are shown in Figure 4 (a), (b), (c), and (d). According to the results, the maximum error of traditional PID control is 0.04 m/s within 0–25 ms before just closing. Within the first 25 ms to 65 ms after the fusion, the maximum tracking speed error is 0.20 m/s, while the maximum error of traditional PID control is 0.20 m/s. Under the control of a fuzzy neural network, the maximum error is 0.03 m/s within 0 ms to 25 ms before the initial closure; within the first 25 ms to 65 ms after the collision, the maximum tracking speed error is 0. At 7 m/s, the maximum error of fuzzy neural network control is 0.07 m/s. The comparison results demonstrate that fuzzy neural network control reduces traditional PID control's error in the pre-closure stage by 0.02 m/s and that in the post-closure stage, fuzzy neural network control's maximum error is 0.05 m/s less than that of traditional PID control. The experimental results show that under constant load conditions, the fuzzy neural network control algorithm has smaller errors, smaller curve fluctuations, and more accurate control results compared to traditional PID control algorithms [25, 26].

ii. Variable load simulation:

At the same time, adjust the constant power of the driving motor to the same magnitude and change the speed. The preset maximum speed is still set at the gate close position, with a value of 2.26 m/s and a simulation time of 66 ms. The control algorithm's control effect on the variable and the simulation experimental results are shown in Figure 5 (a), (b), (c), and (d).

According to the results, the maximum speed error in the pre-closing stage (0 ms~26 ms) under traditional PID control is 0.08 m/s. In the post-closing stage (26 ms~66 ms), the maximum speed following the difference is 0.49 m/s. Therefore, the maximum PID control error is 0.49 m/s. The maximum error of fuzzy neural network control is 0.08 m/s in the pre-closure stage (0 ms~26 ms) and 0.16 m/s in the post-closure stage (26 ms~66 ms). Therefore, the maximum error of fuzzy neural network control is 0.16 m/s. The comparison of experimental results shows that in the pre-closure stage, the maximum error of fuzzy neural network control is 0.03 m/s lower than that of traditional PID control. In the post-closure stage, the maximum error of fuzzy neural network control is 0.33 m/s lower than that of traditional PID control. In the experimental process, the error value of fuzzy neural network control is smaller than that of PID control, and the control effect is better [27, 28]. According to the comparison results of (a) and (c) in Figure 4, both control algorithms experience speed fluctuations when the motor changes load. Among them, the maximum error between the actual speed of the motor and the preset speed under PID control is 0.47 m/s, with a fluctuation duration of 24 ms, a large fluctuation amplitude, and a long time, indicating that PID control cannot quickly and effectively suppress fluctuations caused by variable loads. In comparison, the maximum error between the actual speed of the motor and the preset speed under fuzzy neural network control is 0.14 m/s, with a fluctuation duration of 12 ms, a small fluctuation amplitude, and a short time. Under the same load change, the fuzzy neural network reduces the speed error of PID control by 0.14 m/s. The comparison of experimental results shows that under variable load conditions, the fuzzy neural network control algorithm has better control performance than traditional PID control [29, 30].

4.3 Intelligent control test of motor operating mechanism

To fully validate the effectiveness of the fuzzy neural network control algorithm in electrical automation control, control experiments will be conducted on the closing process of circuit breakers in permanent magnet brushless DC motors, tracking and testing the control performance of the PID algorithm and fuzzy PID algorithm in practical applications.

Set the motor testing parameters with a capacitance of 0.27F, a voltage of 210 V, and a tracking sampling frequency of 0.3S/time. The PID parameters are kp = 55.3, ki = 20.9, and kd = 4.3, with a preset maximum speed of 2.26 m/s and a duration of 65.7 ms.

Table 2: Circuit breaker closing simulation experimental parameters

Parameter Name	Output k_p	Output k_p	Output k_p	Working voltage	Model learning rate
Parameter value	0.3	0.4	0.6	210v	0.9

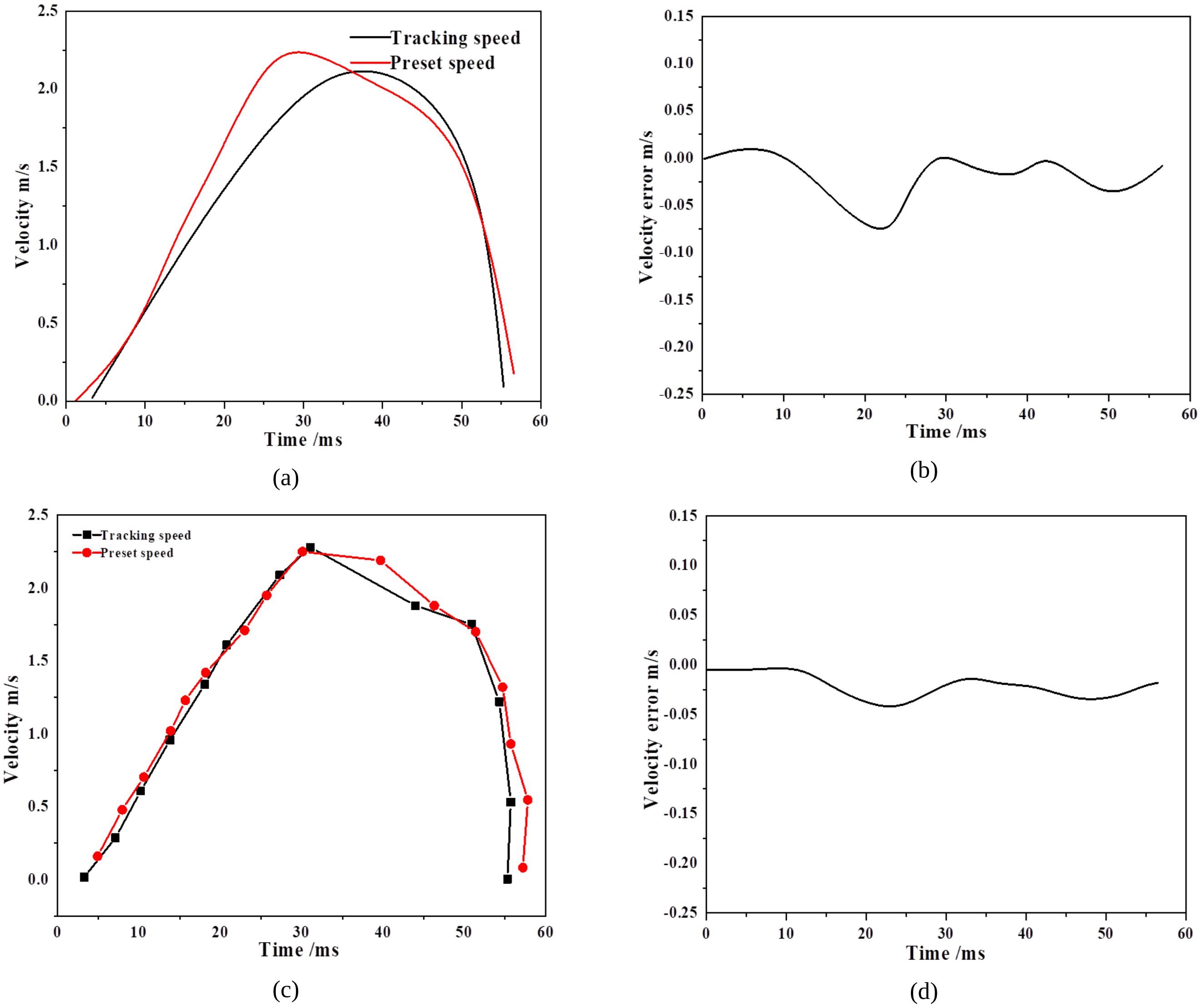
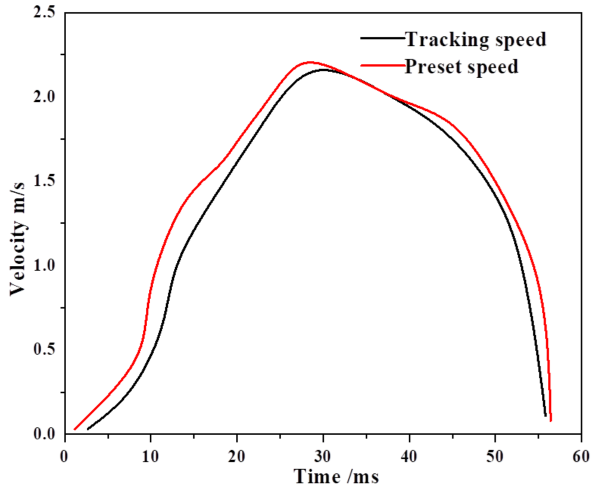


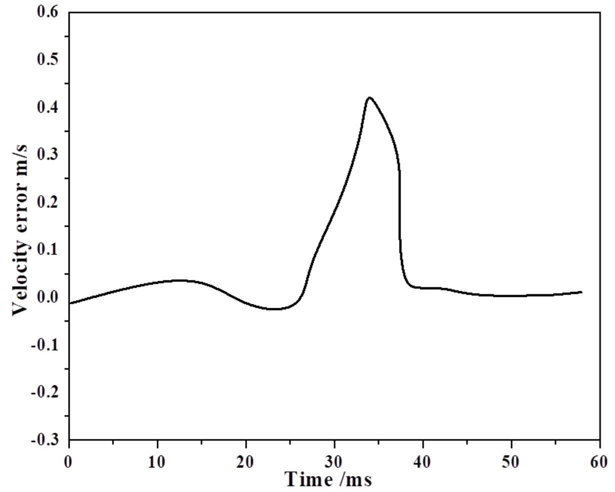
Figure 4: Constant load simulation results of different control algorithms. (a) Traditional PID controller speed change; (b) Traditional PID control speed error; (c) Fuzzy Neural PID Control for Speed Change; (d) Fuzzy Neural PID Control for Speed Error

The control results of the circuit breaker closing speed based on PID control are shown in Figure 6. According to Figure 5, the higher the motor driving speed, the greater the speed tracking error under PID control. Before the circuit breaker is closed, the maximum tracking speed error is 0.23 m/s, which is relatively small. When the motor speed suddenly increases when it reaches the just-reach position (33 ms), the speed error reaches its maximum at 0.45 m/s, and the curve fluctuates greatly, lasting for 12 ms. The experimental results indicate that traditional PID control lacks the ability to adjust parameters when driving motor speed changes, resulting in significant errors in speed tracking and the inability to effectively control the system beyond a certain speed [31]. The results are shown in Figure 7.

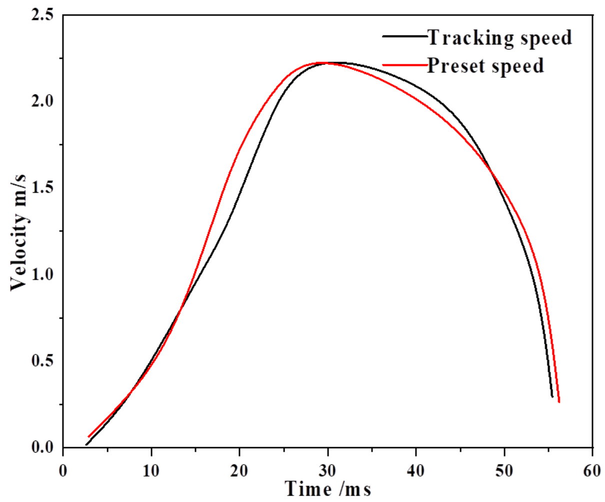
From the experimental results in Figure 6, it can be seen that fuzzy neural network control can achieve ideal control effects in the motor driving process. Before the circuit breaker is closed, the maximum tracking speed error is 0.02 m/s, which is very close to a constant load and has a good control effect. The entire control process experienced a brief fluctuation at the rigid junction, with a maximum tracking speed error of 0.22 m/s, which belongs to a lower level. The control effect of nearly constant load was restored within the following 6 ms, and the control effect was good. The above experimental results indicate that motor operation based on a fuzzy neural network control algorithm has the best control effect [32].



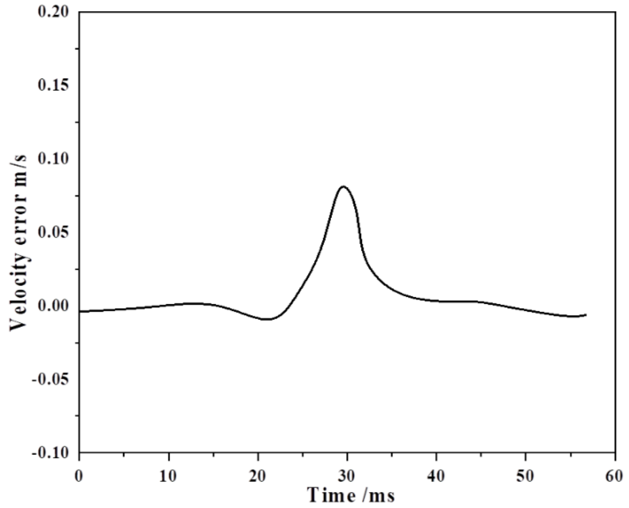
(a)



(b)



(c)



(d)

Figure 5: Curve chart of variable load simulation experiment results. (a) Traditional PID speed change; (b) Traditional PID speed change error; (c) (C) Fuzzy Neural PID Control for Speed Change; (d) Fuzzy neural PID control for speed variation error

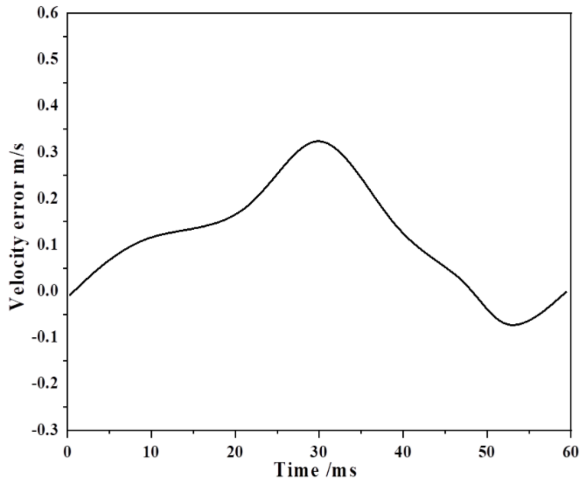


Figure 6: Experimental results of motor operation PID control

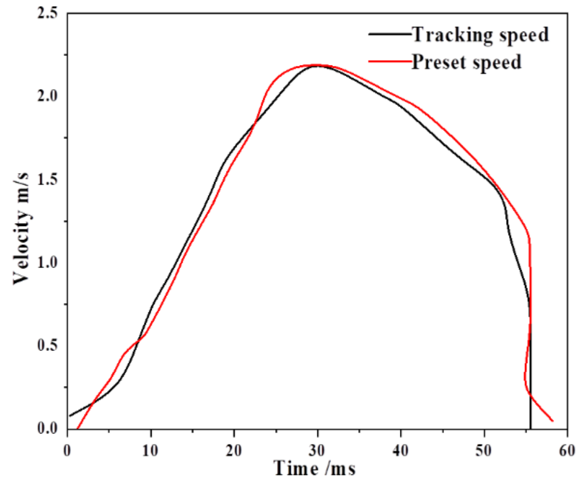


Figure 7: Fuzzy neural PID control speed change

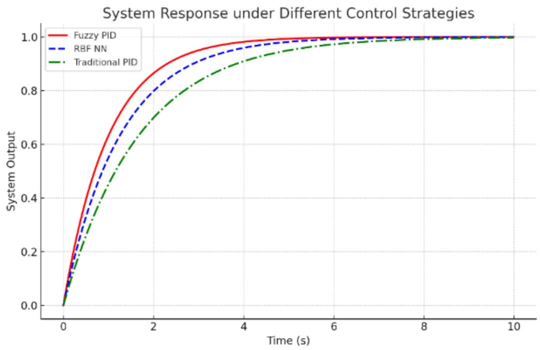


Figure 8: Performance evaluation in terms of system response under several control strategies

Before closing, the tracking speed error of the fuzzy neural network PID control algorithm was reduced by 0.22 m/s compared to the traditional PID algorithm. After the initial closure, the fuzzy neural network control algorithm reduced the speed error by 0.21 m/s, significantly improving the control accuracy.

Figure 8 presents the graph that compares the system responses under different control strategies: Fuzzy PID, RBF Neural Network (NN), and Traditional PID [18, 19]. The graph illustrates how each method performs over time, showing the system output as it stabilizes. The experiments have shown that fuzzy neural network control algorithms can achieve ideal control effects in complex electrical engineering automation control. The computational complexity of the Fuzzy PID algorithm is a critical consideration, especially when applied in real-time control systems. The algorithm's complexity arises from the fuzzification process, the evaluation of fuzzy rules, and the defuzzification process. The number of fuzzy rules exponentially increases with the number of input variables and membership functions, potentially leading to higher computational demands. However, optimizations, such as reducing the number of fuzzy sets or employing efficient rule evaluation techniques, can mitigate this issue. In practical applications, it's essential to balance the algorithm's complexity with the system's real-time requirements, ensuring that the controller can operate efficiently without causing delays or instability. The Fuzzy PID algorithm is particularly effective in addressing challenges such as nonlinearities and uncertainties in the control process. Nonlinearities, which often arise in complex systems, can lead to significant performance degradation in traditional PID controllers. The fuzzy logic component of the Fuzzy PID algorithm allows for more flexible and adaptive control by adjusting the PID gains based on the system's current state, thus accommodating nonlinear behaviors more effectively. Furthermore, the algorithm can handle uncertainties by incorporating expert knowledge into the fuzzy rules, which helps in predicting and compensating for unexpected changes in the system's dynamics.

5 Conclusion

The study thoroughly examined the control method, simulation tests, and system adaptive control tests of a permanent magnet brushless motor operating system, leading to four key conclusions. First, a fuzzy neural network PID control algorithm was successfully developed, integrating an RBF neural network as the core with a fuzzy PID algorithm, demonstrating a synergistic approach for enhanced control. Second, a MATLAB-based simulation model of the drive motor control system was created, enabling the testing of the fuzzy neural network PID control method. The simulation results revealed a reduction in tracking speed error by 0.01 m/s under constant load conditions and 0.33 m/s under nonlinear load conditions, highlighting the algorithm's robust learning and adaptation capabilities. Third, an experimental setup for the control of high-voltage circuit breakers using a permanent magnet brushless motor was established, with results indicating that the conventional PID control method exhibited a speed error rate of up to 0.45 m/s during rapid load changes, while the fuzzy neural network control method maintained a significantly lower error rate of 0.22 m/s, confirming its superior accuracy in motor operation control. Finally, the overall experimental findings underscored the potential of intelligent technology to correct errors and enhance intelligent control in electrical engineering automation, paving the way for more precise and reliable automation systems. Future work will explore optimizing the fuzzy neural network PID algorithm for more complex and dynamic systems, aiming to enhance control accuracy and computational efficiency in broader electrical engineering applications.

References

[1] Yang, S. (2023). Application of intelligent voice technology and sensor network in production and operation management vr intelligent teaching system. *International journal of reliability, quality and safety engineering*, *30*(01), 2250025.https://doi.org/10.1142/S0218539322500255

[2] Liu, J., Zhao, Z., Ji, J., & Hu, M. (2020). Research and application of wireless sensor network technology in power transmission and distribution system. *Intelligent and Converged Networks*, *1*(2), 199-220.https://doi.org/10.23919/ICN.2020.0016

[3] Lee, M., Seung, H., Kwon, J. I., Choi, M. K., Kim, D. H., & Choi, C. (2023). Nanomaterial-based synaptic optoelectronic devices for in-sensor preprocessing of image data. *ACS omega*, *8*(6), 5209-5224.https://doi.org/10.1021/acsomega.3c00440

[4] Song, Z., Huang, X., Ji, C., & Zhang, Y. (2023). Intelligent identification method of hydrophobic grade of composite insulator based on efficient ga-yolo former network. *IEEJ Transactions on*

Electrical and Electronic Engineering, *18*(7), 1160-1175.https://doi.org/10.1002/tee.23822

[5] Ma, L., & Li, J. (2023). Design of a wearable multi-point temperature monitoring system–practical application in waist temperature monitoring. *International Journal of Clothing Science and Technology*, *35*(4), 545-556.https://doi.org/10.1108/IJCST-03-2022-0047

[6] Pu, H. (2021). Application electrical engineering training and intelligent technology of electrical and electronic technology under artificial intelligence technology. In *E3S Web of Conferences* (Vol. 253, p. 01070). EDP Sciences.https://doi.org/10.1051/e3sconf/202125301070

[7] Javaid, M., Haleem, A., Singh, R. P., Rab, S., & Suman, R. (2021). Significance of sensors for industry 4.0: Roles, capabilities, and applications. *Sensors International*, *2*, 100110.https://doi.org/10.1016/j.sintl.2021.100110

[8] Navulur, S., & Prasad, M. G. (2017). Agricultural management through wireless sensors and internet of things. *International Journal of Electrical and Computer Engineering*, *7*(6), 3492.https://doi.org/10.11591/ijece.v7i6.pp3492-3499

[9] Channi, H. K., & Kumar, R. (2021). The role of smart sensors in smart city. In *Smart Sensor Networks: Analytics, Sharing and Control* (pp. 27-48). Cham: Springer International Publishing.https://doi.org/10.1007/978-3-030-77214-7_2

[10] Vlasov, A. I., Grigoriev, P. V., Krivoshein, A. I., Shakhnov, V. A., Filin, S. S., & Migalin, V. S. (2018). Smart management of technologies: predictive maintenance of industrial equipment using wireless sensor networks. *Entrepreneurship and Sustainability Issues*, *6*(2), 489-502.https://doi.org/10.9770/jesi.2018.6.2(2)

[11] Pech, M., Vrchota, J., & Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factory. *Sensors*, *21*(4), 1470.https://doi.org/10.3390/S21041470

[12] Di Graziano, A., Marchetta, V., & Cafiso, S. (2020). Structural health monitoring of asphalt pavements using smart sensor networks: A comprehensive review. *Journal of Traffic and Transportation Engineering (English Edition)*, *7*(5), 639-651.https://doi.org/10.1016/j.jtte.2020.08.001

[13] Zhang, Z., Wen, F., Sun, Z., Guo, X., He, T., & Lee, C. (2022). Artificial intelligence-enabled sensing technologies in the 5G/internet of things era: from virtual reality/augmented reality to the digital twin. *Advanced Intelligent Systems*, *4*(7), 2100228.https://doi.org/10.1002/aisy.202100228

[14] Paul, K., Chatterjee, S. S., Pai, P., Varshney, A., Juikar, S., Prasad, V., & Dasgupta, S. (2022). Viable smart sensors and their application in data driven agriculture. *Computers and Electronics in Agriculture*, *198*, 107096.https://doi.org/10.1016/j.compag.2022.107096

[15] Sony, S., Laventure, S., & Sadhu, A. (2019). A literature review of next-generation smart sensing technology in structural health monitoring. *Structural Control and Health Monitoring*, *26*(3), e2321.https://doi.org/10.1002/stc.2321

[16] Alsalemi, A., Himeur, Y., Bensaali, F., & Amira, A. (2021). Smart sensing and end-users' behavioral change in residential buildings: An edge-based internet of energy perspective. *IEEE sensors journal*, *21*(24), 27623-27631.https://doi.org/10.1109/JSEN.2021.3114333

[17] Qiao, D., & Wang, Y. (2021, March). A review of the application of discrete event simulation in manufacturing. In *Journal of Physics: Conference Series* (Vol. 1802, No. 2, p. 022066). IOP Publishing.https://doi.org/10.1088/1742-6596/1802/2/022066

[18] Chowdhury, I. J., Yusoff, S. H., Gunawan, T. S., Zabidi, S. A., Hanifah, M. S. B. A., Sapihie, S. N. M., & Pranggono, B. (2024). Analysis of Model Predictive Control-Based Energy Management System Performance to Enhance Energy Transmission. *Energies*, *17*(11), 2595.https://doi.org/10.3390/en17112595

[19] Nassef, A. M., Abdelkareem, M. A., Maghrabie, H. M., & Baroutaji, A. (2023). Metaheuristic-based algorithms for optimizing fractional-order controllers—a recent, systematic, and comprehensive review. *Fractal and Fractional*, *7*(7), 553.https://doi.org/10.3390/fractalfract7070553

[20] Tang, S., He, Z., Zhao, Y., Fang, A., Li, K., Mei, L., & Tao, Y. (2021). Design and Application of Intelligent Diagnosis System for three Pumping Stations of Stamping Automation. *Journal of Electronic Research and Application*, *5*(1). https://doi.org/10.26689/jera.v5i1.1890

[21] Zhu, M. (2021, February). Application of intelligent information technology in intelligent home decoration design. In *Journal of Physics: Conference Series* (Vol. 1744, No. 2, p. 022012). IOP Publishing.https://doi.org/10.1088/1742-6596/1744/2/022012

[22] Su, H., Yan, X., Zhao, Q., Liao, C., Tian, L., Wang, Z., ... & Wang, X. (2023). Layered design of a highly repeatable electroactive biofilm for a standardized biochemical oxygen demand sensor. *ACS sensors*, *8*(6), 2383-2390.https://doi.org/10.1021/acssensors.3c00583

[23] Li, J., & Wang, T. (2021, August). Research on the application of artificial intelligence technology in intelligent operation and maintenance of industrial equipment and system. In *Journal of Physics:*

Conference Series (Vol. 1992, No. 3, p. 032090). IOP Publishing.https://doi.org/10.1088/1742-6596/1992/3/032090

[24] Yu, H. (2021, November). Application and design of intelligent building automation control system. In *Journal of Physics: Conference Series* (Vol. 2074, No. 1, p. 012077). IOP Publishing.https://doi.org/10.1088/1742-6596/2074/1/012077

[25] Tanuma, T. (2022). Introduction to steam turbines for power plants. In *Advances in Steam Turbines for Modern Power Plants* (pp. 3-10). Woodhead Publishing.https://doi.org/10.1016/B978-0-08-100314-5.00001-4

[26] Dahl, M., Bengtsson, K., & Falkman, P. (2021). Application of the sequence planner control framework to an intelligent automation system with a focus on error handling. *Machines*, *9*(3), 59.https://doi.org/10.3390/machines9030059

[27] Zou, Y., Wang, J., Tian, X., Li, N., & Gong, G. (2023). Intelligent generation of combat simulation scenarios based on UML diagram recognition. *International Journal of Modeling, Simulation, and Scientific Computing*, *14*(03), 2350043.https://doi.org/10.1142/S1793962323500435

[28] Chakraborty, R., Anoop, A. G., Thakur, A., Mohanta, G. C., & Kumar, P. (2023). Strategies to modify the Surface and Bulk properties of 3D-Printed solid scaffolds for tissue Engineering Applications. *ACS omega*, *8*(6), 5139-5156.https://doi.org/10.1021/acsomega.2c05984

[29] Mellah, H., Hemsas, K. E., & Taleb, R. (2019). Intelligent sensor-based Bayesian neural network for combined parameters and states estimation of a brushed dc motor. *arXiv preprint arXiv:1901.08661.https://doi.org/10.14569/IJACSA.2016.070731*

[30] Saetchnikov, A. V., Tcherniavskaia, E. A., Saetchnikov, V. A., & Ostendorf, A. (2021). Intelligent optical microresonator imaging sensor for early-stage classification of dynamical variations. *Advanced Photonics Research*, *2*(12), 2100242.https://doi.org/10.1002/adpr.202170040

[31] Li, T., Su, Y., Chen, F., Zheng, H., Meng, W., Liu, Z., & Zhou, Z. (2022). Bioinspired stretchable fiber-based sensor toward intelligent human–machine interactions. *ACS Applied Materials & Interfaces*, *14*(19), 22666-22677.https://doi.org/10.1021/acsami.2c05823

[32] Zhao, C., Li, M., Wang, T., & Yang, H. (2021). A novel offloading strategy for high-speed mobile and data intensive intelligent sensor. *International Journal of Sensor Networks*, *35*(4), 230-242.https://doi.org/10.1504/ijsnet.2021.114744