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The Analysis of Instrument Automatic Monitoring and Control Systems Under Artificial Intelligence

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ABSTRACT

This integration enables the system to collect and monitor information from remote sources efficiently. During the course of this research, a novel predictive PID approach was developed, splitting the control architecture into two tiers. The upper tier utilizes the extreme learning machine (ELM) as an intelligent predictive model, while the lower tier integrates an enhanced single-neuron adaptive predictive PID control algorithm, combining the strengths of ELM and PID control. The research findings suggest that the AI algorithm-based instrument automatic monitoring and control system holds significant promise. This technology has the potential to enhance production efficiency, reduce energy consumption, improve environmental monitoring, and provide superior safety and quality control.

KEYWORDS

artificial intelligence algorithm, control system, extreme learning machine, instrument automatic monitoring, PID control

INTRODUCTION

The rapid development of artificial intelligence (AI) technology has sparked revolutionary changes across various industries. In the realm of the industrial and manufacturing fields, the application of AI has achieved notable success. From optimizing production lines to enhancing quality control, AI is enabling enterprises to boost efficiency, cut costs, and deliver higher-quality products. DALL-E, an advanced AI tool by OpenAI, transforms text prompts into creative and diverse images. This guide aims to provide an in-depth understanding of DALL-E's capabilities and offers practical advice for users. One significant application in this domain is the AI algorithm-based instrument automatic monitoring and control system, which has garnered significant attention due to its intelligence, adaptability, and high reliability.

In traditional manufacturing industries, instrument monitoring and control typically require extensive manual intervention and oversight, which not only escalates costs but also introduces the potential for human error (Xin et al., 2018; Dai, 2022). With the continuous evolution of AI technology, these tasks can be automated through the use of machine learning and data analysis, thereby improving production efficiency and minimizing errors (Kanto et al., 2022).

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Furthermore, AI systems can dynamically adjust themselves based on historical data and real-time conditions to handle changes and fluctuations in the production process (Borza & Borza, 2017). Expert control fundamentally encompasses various forms of expert knowledge related to the controlled object and control laws, which AI technology employs to optimize and make the controlled object as efficient and practical as possible (Gitis & Derendyaev, 2019). Intelligent PID controllers based on neural networks leverage the self-learning capabilities of neural networks and the approximation abilities of nonlinear functions, while adhering to specific optimization criteria (Wang et al., 2022). Kinoshita et al. (2018) introduced a PID controller based on a BP neural network (BPNN), merging the self-learning and adaptability of the BP algorithm with the simplicity and robustness of PID, enabling seamless switching between them.

BPNN does not require prior learning, making it an excellent online adaptive comprehensive controller. To address the slow convergence of neural networks, Jinsong et al. (2017) employed a combination of genetic algorithms (GAs) and the BP algorithm to fine-tune PID parameters. This approach capitalizes on the global optimization capabilities of GA and the rapid error reduction abilities of the BP algorithm, effectively resolving the parameter search space problem and significantly improving convergence speed and global optimization. Huang et al. (2018) discussed a time-delay identification scheme for linear MIMO systems using neural networks, demonstrating the feasibility of this method.

The primary objective of this study is to design and develop an automatic instrument monitoring and control system based on AI algorithms, with the aim of enhancing the efficiency of instrument monitoring and control in industrial production. The system's design will leverage modern AI technologies, such as deep learning, machine learning, and data analysis, to achieve highly intelligent monitoring and control (Jones & Venable, 2022).

In this study, we combine a wireless sensor network and mobile communication network through an embedded platform to enable the collection and monitoring of remote information sources. With a focus on the instrument automatic monitoring and control system as our research subject, we introduce a novel predictive PID methodology. The control framework is divided into two tiers. The upper tier utilizes the Extreme Learning Machine (ELM) as the intelligent predictive model, while the lower tier incorporates the enhanced single-neuron adaptive predictive PID control algorithm, harnessing the strengths of both ELM and PID control. Our simulation results demonstrate that this innovative predictive PID control approach is characterized by its simplicity, precise control, robust performance, rapid learning capabilities, and impressive control effectiveness (Dayyala et al., 2022). It is particularly well-suited for real-time control within instrument automatic monitoring and control systems.

Through this research, we aim to provide a more intelligent, efficient, and reliable instrument monitoring and control solution for the manufacturing and industrial sectors. This, in turn, will advance the field of industrial automation and confer greater competitive advantages upon enterprises. Simultaneously, this study will contribute further evidence to the potential of AI in industrial applications and promote the widespread adoption of AI technology in practical production environments (Savoli & Bhatt, 2022).

RESEARCH METHOD

Overall Design Scheme

An instrument automatic monitoring and control system is a technical setup designed for monitoring, measuring, and controlling industrial processes or systems. These systems typically comprise an array of sensors, instruments, controllers, and user interfaces that are used to collect and analyze data, as well as implement control measures to ensure the stable, safe, and efficient operation of industrial processes or systems. Instrument control systems find wide applications in various industrial sectors, including the chemical industry, oil and gas, electric power, manufacturing, water treatment, and transportation systems. They play a critical role in ensuring the safety, efficiency, and controllability of industrial processes. DALL-E interprets text prompts and generates corresponding images using sophisticated algorithms. We have expanded this section to include detailed explanations of its text-to-image conversion process, highlighting the AI's understanding of various prompts and its artistic interpretation. These systems facilitate process automation, reduce human errors, enhance product quality, and lower energy consumption.

The design of a remote instrument automatic monitoring and control system, based on an embedded platform, necessitates careful consideration of several key aspects, including hardware selection, sensor integration, communication protocols, data processing, and remote control. The selection of appropriate sensors, such as temperature sensors, humidity sensors, pressure sensors, and photosensitive sensors, is essential to monitor the required parameters. These sensors are typically connected to the embedded system via analog input, digital input/output, or communication buses (Liang et al., 2021). Data processing algorithms are developed to filter noise, correct data, and perform necessary mathematical calculations. Communication protocols, such as Wi-Fi, Ethernet, LoRa, and NB- Internet of Things (IoTs), are chosen to establish communication with remote servers or control centers. A remote monitoring interface, which may take the form of a web interface or a mobile application, is developed to enable real-time viewing of monitoring data. Throughout the entire system development process, testing and verification are crucial to ensure that the system meets stability and performance requirements. Furthermore, compliance with relevant laws and standards, especially when monitoring sensitive data, is of paramount importance.

Instrument automatic monitoring and control systems are typically used for real-time monitoring and management of instruments, equipment, and parameters within industrial or laboratory environments. These systems contribute to improved production efficiency, cost reduction, enhanced security, and provide remote access and control. It is crucial to be aware of DALL-E's usage limitations, especially concerning copyright and content sensitivity. This section now includes comprehensive guidelines on what constitutes appropriate use, emphasizing the importance of respecting intellectual property and avoiding the creation of offensive or sensitive material. The design and deployment of instrument automatic monitoring systems require careful consideration of various technical and safety factors to ensure system reliability and effectiveness. The structural block diagram of such a system is depicted in Figure 1:

The Zigbee wireless sensor network is a wireless communication protocol and technical standard explicitly crafted for low power consumption, low data rates, and short-distance communication. It is a protocol tailored for IoTs applications, with the primary goal of connecting and managing a multitude of low-power devices, including sensors, switches, lamps, temperature controllers, and more (Muliadi & Kusumoputro, 2018). The physical architecture of Zigbee is illustrated in Figure 2:

The Zigbee wireless sensor network is structured using a star topology, and Zigbee utilizes its proprietary communication protocol stack, encompassing the physical layer, MAC layer, network layer, and application layer. This comprehensive protocol stack facilitates seamless communication among devices, even within intricate network topologies. The Zigbee wireless sensor network represents a wireless communication technology purposefully designed for specialized application domains, making it particularly well-suited for situations demanding attributes such as minimal power consumption, self-organizing network capabilities, low data transfer rates, and the ability to connect a multitude of devices (Santos et al., 2022).

Selecting an appropriate embedded platform for a remote instrument automatic monitoring system is a critical decision, as it directly impacts the system's performance, scalability, stability, and cost. In this setup, the embedded platform utilizes the ESP8266, the operating system is

Figure 1. System structure diagram

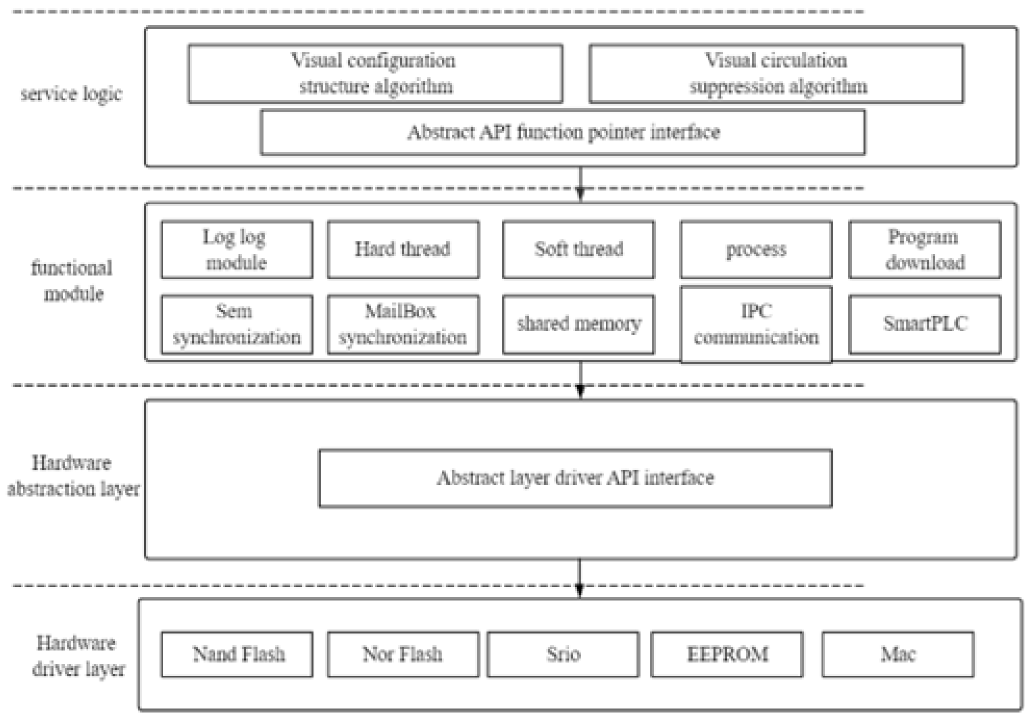
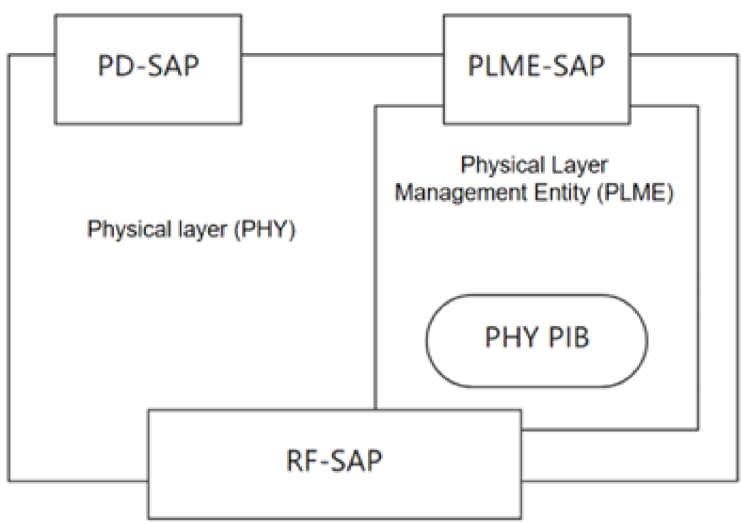


Figure 2. Zigbee physical architecture



Linux-based, and it incorporates the advanced microcontrol bus (AMBA) architecture. The main frequency of this platform is as high as 203 MHz, and it features three UART channels, with two serial ports connected to a Zigbee coordinator and a GPRS module, respectively (Song et al., 2018).

Algorithm Implementation of the System

An AI algorithm is a computer program or method created to mimic human intelligent behavior and the decision-making process. These algorithms empower computer systems to learn, understand, infer, plan, and tackle diverse complex tasks (Duan et al., 2017). Here are some common AI algorithms:

Machine learning algorithms: Machine learning represents a crucial aspect of AI and encompasses a variety of algorithms, including:

- Supervised Learning: This category includes decision trees, support vector machines, neural networks, linear regression, and more. These algorithms are utilized to learn patterns and make predictions based on labeled data.
- Reinforcement Learning: This form of learning is based on a reward mechanism and comprises algorithms like Q-learning and deep reinforcement learning, such as deep Q networks. It involves agents learning to make decisions by interacting with their environment and receiving rewards based on their actions.
- Natural Language Processing (NLP) Algorithm: This algorithm is designed to process and comprehend natural language texts, encompassing tasks like text classification, entity recognition, sentiment analysis, and machine translation, among others (Yanuarifiani et al., 2022).
- Computer Vision Algorithms: These algorithms are utilized to analyze and interpret images and videos. They cover functions such as image classification, object detection, image segmentation, and face recognition.
- Deep Learning Algorithm: Deep learning is a machine learning method centered on neural networks, incorporating deep Convolutional Neural Networks (CNNs) for image processing and deep Recurrent Neural Networks (RNNs) for sequence data processing (Tabassum et al., 2022). Various variants and architectures, such as Transformers for NLP, are also part of this category.
- GA: GA is an algorithm based on natural selection and genetic mechanisms, employed to find optimal solutions. It is applied in fields such as evolutionary computation.
- Strong AI Algorithm: This type of algorithm is used to construct intelligent agents capable of independent decision-making and task execution. It includes systems like rule-based AI, expert systems, and planning algorithms.
- Rule-Based Algorithms: These algorithms rely on predefined rules and knowledge bases for reasoning and decision-making, typically utilized in expert systems.
- Reinforcement Learning Algorithm: This algorithm is employed to develop autonomous decision-making agents that learn the best action strategy by interacting with their environment and receiving rewards based on their actions.

These algorithms are typically chosen and fine-tuned based on specific application fields and tasks to meet particular requirements. The advancement of AI algorithms has triggered a wide range of applications, including self-driving vehicles, natural language understanding, medical diagnostics, financial analysis, industrial automation, and video game development. For new users, we have added a step-by-step guide on accessing DALL-E. This includes information on registering for the service, navigating the interface, and basic steps for creating your first image. To better illustrate what DALL-E can do, we have included several examples of text prompts and the images generated by the tool. These examples showcase the range and versatility of DALL-E's image-generation capabilities (Morales & Suárez-Rocha, 2022).

PID control is a widely employed control algorithm in automatic control systems, with the aim of maintaining or adjusting the system's output to match the desired value (Chen et al., 2019). The PID controller comprises three key components, each serving distinct functions:

- Proportional (P) Part: The proportional control generates an output based on the current error, and its magnitude is directly proportional to the error's size. In other words, if the error is substantial, the proportional control output will be significant, which helps in reducing the error rapidly. However, pure proportional control can result in oscillations or overshooting, so it is usually combined with other components to achieve improved performance.
- Integral Part (I): Integral control is employed to address the issue of steady-state error in a system, which cannot be completely eliminated through proportional control alone. The integral control generates a control output based on the accumulation of historical errors, gradually reducing the steady-state errors within the system.
- Differential Part (D): Differential control is utilized to mitigate overshooting and oscillations in the system's response. It generates a control output based on the rate of change of the error, thereby slowing down the system's response and enhancing its stability.

The output of the PID controller is the weighted sum of these three components and is typically expressed as:

$$U\left(t\right) = K_p \cdot e\left(t\right) + K_i \cdot \int_0^t e\left(t\right) dt + K_d \cdot \frac{de\left(t\right)}{dt}, \tag{1}$$

where $U\left(t\right)$ is the output of the controller, $e\left(t\right)$ is the current error, and K_p, K_i, K_d is the gain parameter of the proportional, integral, and differential parts, respectively.

PID control is widely applied in various automated control applications, including temperature regulation, velocity management, and pressure control (Wu et al., 2022). Adjusting the PID controller parameters allows us to achieve objectives like rapid system response, precise tracking of desired values, and oscillation suppression. However, selecting suitable PID parameters typically requires practical experience and experimentation to ensure system stability and optimal performance.

Given that operating conditions are often limited, and the dynamic characteristics of the system change with variations in working conditions and the environment, reaching the optimal state for PID parameters can be challenging. As control tasks become increasingly complex and precision demands grow, the limitations of conventional PID controllers become more apparent. The Artificial Neural Network (ANN) offers robust capabilities in information synthesis, learning, memory retention, self-learning, self-adaptation, and the ability to approximate nonlinear functions. Addressing common queries, this new section provides quick solutions to typical issues users may encounter while using DALL-E. From troubleshooting tips to best practices for crafting prompts, this FAQ aims to enhance user experience.

Traditional neural network algorithms can be slow to converge due to the need for numerous iterations to find a solution. In contrast, ELMs can obtain network output by calculating the pseudoinverse of the output matrix in a single step, making it much faster than general neural network algorithms while retaining strong generalization ability (Lili et al., 2017). This paper introduces a novel predictive PID control approach. An ELM is chosen as the upper intelligent predictive model, while an enhanced single-neuron adaptive PID control is employed as the underlying algorithm. This approach maintains the simplicity and ease of implementation of a single-neuron controller while delivering excellent control quality and robustness.

The new predictive PID control structure based on an ELM in the instrument automatic monitoring and control system is illustrated in Figure 3.

An ELM is a machine learning algorithm designed for the rapid training of feedforward neural networks (see Figure 4). The formula for the predictive PID control algorithm based on an ELM typically encompasses nonlinear modeling and PID control.

Figure 3. Block diagram of a new predictive PID control system based on an ELM

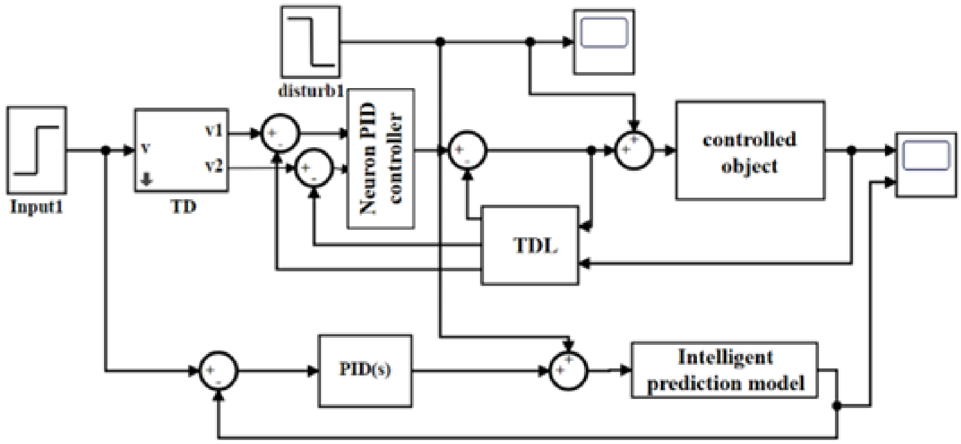
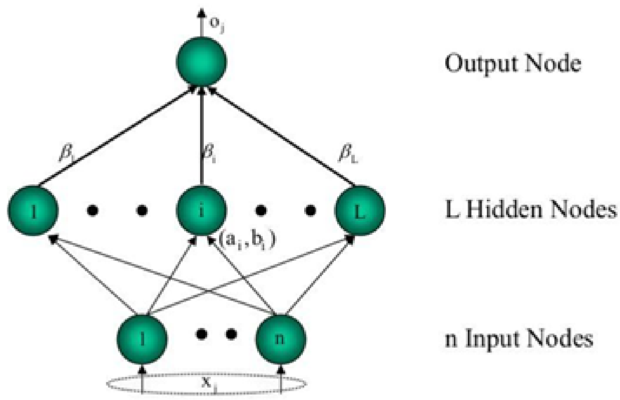


Figure 4. ELM structure



Suppose there are N training samples and M features, which can be expressed as input feature $X(n), n = 1, 2, \cdots, N$ and target output (process variable) $Y(n), n = 1, 2, \cdots, N$.

The output of an ELM can be expressed as:

$$f(t) = g\left(\sum_{i=1}^{N} w_i \cdot h_i(t)\right), \tag{2}$$

where $f(t)$ is the output, N is the number of hidden neurons, w_i is the weight between output layer neurons and hidden layer neurons, and $h_i(t)$ is the output of hidden neurons, which is usually a linear combination of activation functions (such as sigmoid or ReLU) acting on the input.

The output $O(n)$ of the prediction model can be expressed as:

$$O(n) = H(n) * V, \tag{3}$$

where V is the weight matrix from the hidden layer to output, which is also randomly initialized.

In predictive PID control, the output of the controller is usually calculated by a PID control algorithm, as shown below:

$$U\left(n\right) = K_p * \left[SP\left(n\right) - PV\left(n\right)\right] + K_i * \left[SP\left(k\right) - PV\left(k\right)\right] * K_d \left[SP(n) \text{ - } PV(n)\right] / \Delta t\,, \tag{4}$$

where $U\left(n\right)$ is the output of a PID controller, that is, the manipulated variable, $SP\left(n\right)$ is the set point (expected value), $PV\left(n\right)$ is the actual process variable, and K_p, K_i, K_d is the parameter of proportional gain, integration time, and differential time, respectively. $\sum$ represents the accumulation of errors, which is usually calculated by the accumulation of historical errors, and Δt is the sampling interval.

The output $U\left(n\right)$ of the controller is applied to the system to adjust the operating variables and realize the control of the process. The system will respond to the control output and generate a new process variable $PV\left(n+1\right)$.

It should be noted that the number of hidden nodes in the ELM model, the selection of activation function, and the parameter K_p, K_i, K_d of a PID controller need to be adjusted and optimized according to the specific application and system. The key of this method is to combine the nonlinear modeling ability of an ELM with PID feedback control to achieve better control performance.

At each time step t, the output of the predictive model and the output of the PID controller are used to control the system. Apply the output $u\left(t\right)$ of the PID controller to the system, then observe the system response and update the input of the controller to reduce the error $e\left(t\right)$.

The self-tuning PID technique represents an approach that autonomously refines PID parameters by analyzing a system's dynamic response. It draws upon principles from self-tuning control and model reference adaptive control to dynamically adapt PID parameters to match the system's frequency response. The primary goal of a self-tuning PID is to enhance critical performance metrics, including reducing steady-state error, overshooting, and response time, through automatic parameter adjustments. As a result, this approach expedites the system's ability to reach its target set point, diminishes oscillations, and augments overall stability.

RESULTS ANALYSIS AND DISCUSSION

To evaluate the neural network model's effectiveness for time-delay nonlinear systems, we conducted a simulation experiment using the MATLAB 7.11.0 environment. The selected simulation system is the Hammerstein nonlinear system, recognized for its distinctive structure that consists of a linear system followed by a nonlinear system. This configuration is often employed to model complex dynamic systems in which the input-output relationship exhibits nonlinearity.

Hammerstein-type nonlinear systems can usually be expressed in the following form:

$$y\left(t\right) = G\left[\cdot\left(u\left(t\right)\right)\right] + e\left(t\right), \tag{5}$$

where $y\left(t\right)$ is the output of the system, $u\left(t\right)$ is the input of the system, $\cdot\left(u\left(t\right)\right)$ is a nonlinear mapping function, which maps the input signal to a nonlinear function, G is a linear system, usually expressed as a transfer function or a state space equation, and $e\left(t\right)$ stands for disturbance or noise in the system.

This system structure allows a complex input-output relationship to be established between the nonlinear function $\cdot\left(u\left(t\right)\right)$ and the linear system. Nonlinear function can be used to describe the nonlinear characteristics of the system, while linear system part is usually used to describe the stability and frequency response of the system.

The input signals used for training are:

$$u\left(k\right) = 0.2\sin\left(2\pi k / 20\right). \tag{6}$$

The test signal consists of a square wave with a period of 0.2 and an amplitude of 0.5. The identification curves, depicted in Figures 5 and 6 below, display the expected value with solid lines and the network output value with dotted lines.

We initiated the simulations by applying a constant amplitude step signal as the input for the system. Subsequently, we conducted simulations involving both the predictive PID and the innovative predictive PID control methods, as illustrated in Figure 7. Furthermore, we extended our analysis to include step signals with varying amplitudes, allowing us to simulate traditional PID control, conventional single-neuron adaptive PID control, and the novel predictive PID control introduced in this study. The outcomes of these simulations are elucidated in Figure 8.

From the preceding two comparative charts, it is evident that under identical circumstances, the new predictive PID control promptly and precisely tracks the anticipated input signal without any overshooting. In contrast, the predictive PID control exhibits a slower response compared to the new predictive PID control, while traditional PID control necessitates a prolonged response period. In the case of conventional single-neuron adaptive PID control, it results in an overshoot. Therefore, the approach introduced in this paper surpasses both traditional PID control and conventional single-neuron adaptive PID control.

Figure 5. Training signal identification curve

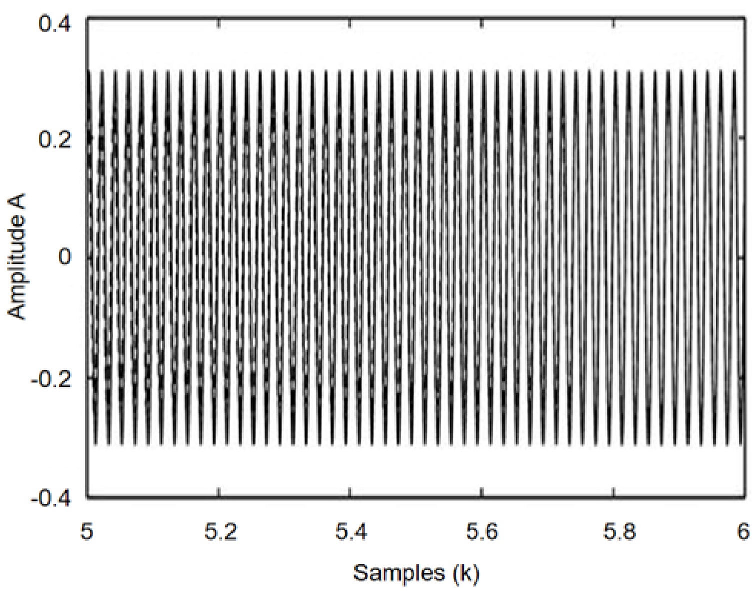


Figure 6. Test signal identification curve

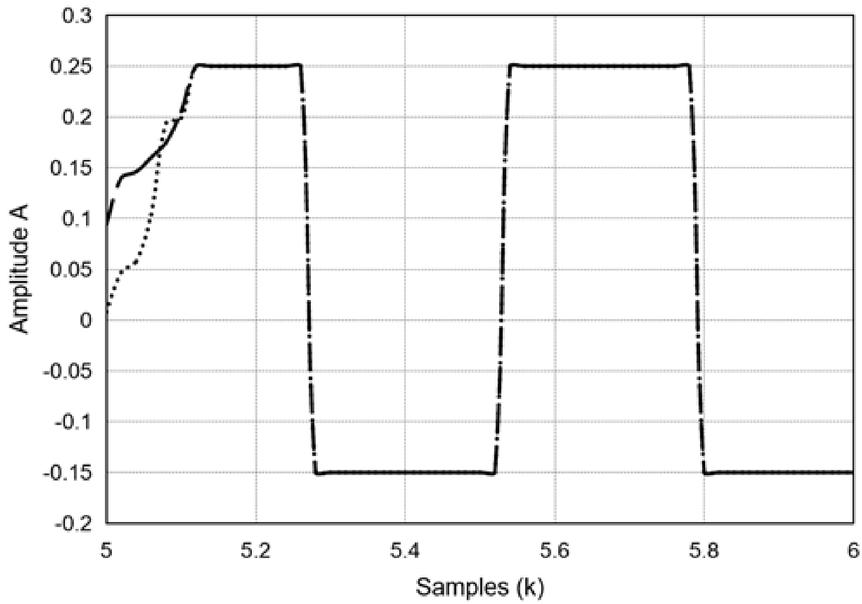
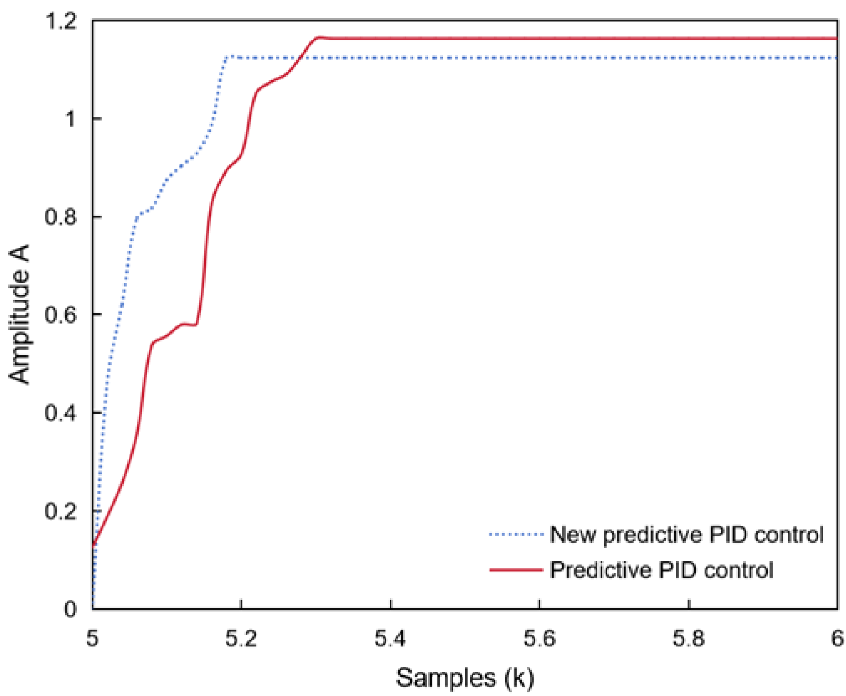
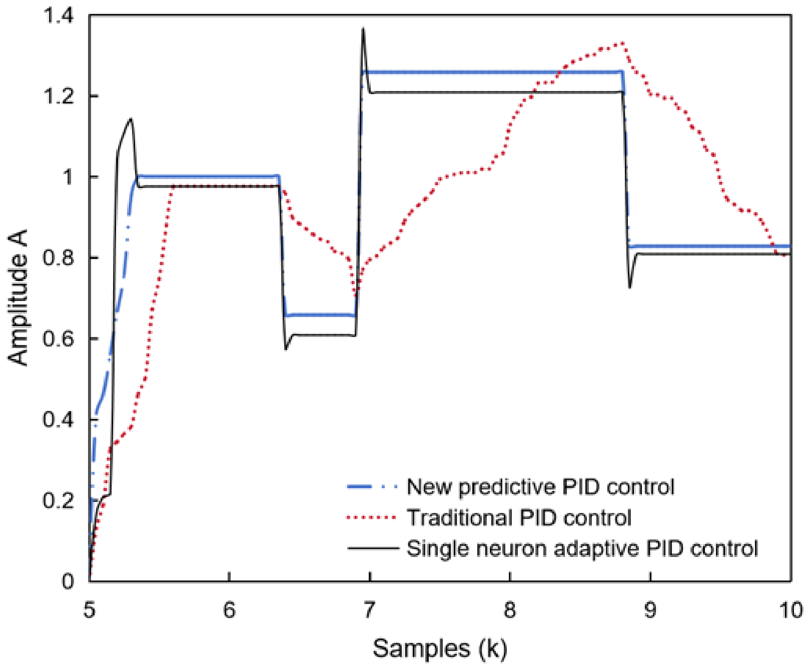


Figure 7. Comparison between new predictive PID control and predictive PID control



The predictive PID control algorithm amalgamates the strengths of ELM and PID control. The simulation findings confirm that this innovative predictive PID control technique is straightforward, offering exceptional control accuracy and robustness, swift learning capabilities, and effective

Figure 8. Comparison between new predictive PID control and other methods



control performance (Meng et al., 2022). These attributes make it well-suited for real-time management within instrument automatic monitoring and control systems. To keep our readers informed, we have added a section on the potential future updates and improvements of DALL-E. This part covers anticipated features and directions for the tool's evolution, offering insights into what users can expect in the future.

CONCLUSION

The application of the new predictive PID control algorithm based on an ELM in an instrument automatic monitoring and control system holds great promise. This algorithm has the capacity to learn from extensive data sets and adapt to changing environmental conditions, thereby enhancing the system's intelligence and decision-making capabilities. Data acquisition and sensing technology play a pivotal role in realizing automatic monitoring and control systems, with high-quality data forming the bedrock of AI algorithm-based systems. Hence, greater attention and investment should be dedicated to advancing data acquisition and sensing technologies. When compared to traditional monitoring and control systems, AI algorithm-based systems generally offer superior performance and flexibility. However, they also confront various challenges, including concerns about data quality, security, and privacy. Addressing these challenges requires continuous research and development to fully unleash the potential of AI-based systems. DALL-E presents a unique blend of art and technology, opening new possibilities in creative image generation. By understanding its functionality, limitations, and potential, users can effectively harness this tool's capabilities. We hope this guide serves as a valuable resource for both new and experienced users of DALL-E. It is our hope that future research and practical applications will consistently drive progress in this field, ultimately delivering greater benefits to both society and industry.

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