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Optimizing Industrial Process Control with Artificial Intelligence: A Case Study of the Feedback Procon Level and Flow Process.

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Abstract

Artificial Intelligence (AI) techniques have brought about transformative changes across various industries, and the field of industrial process control is no exception. This paper presents an innovative approach centered around the development of an artificial neural network known as ANN-PID. This network emulates the decision-making process akin to that of a human operator for configuring parameters in a water Flow PID controller. At the heart of this approach lies a multi-layer perceptual neural network (MLP). The research entails training the ANN-PID model using real-time process data, aiming to optimize process parameters and elevate the efficacy of industrial process control. Through rigorous experimental tests conducted on the Feedback 38-003 Procon Level and Flow with Temperature process, the study confirms the prowess of the ANN-PID system in enhancing control performance when compared to traditional control methods. These findings represent a significant contribution to the evolution of intelligent control systems within industrial settings, ushering in novel opportunities for the automation and optimization of intricate processes.

Keywords: Artificial intelligence, Control System Performance, Process Optimization, Neural Network Training

1. Introduction

In today's fast-paced industrial landscape, optimizing process control stands as a pivotal endeavor, one with the potential to enhance efficiency, reduce operational costs, and ultimately elevate productivity. The integration of Artificial Intelligence (AI), particularly Artificial Neural Networks (ANN), into industrial process control systems has emerged as a transformative solution, offering advanced capabilities to tackle complex challenges. This article delves into the realm of AI-driven optimization, with a specific focus on utilizing ANN for enhancing control precision and efficiency. Our exploration centers around a compelling case study—the Feedback Procon Level and Flow Process. As we embark on this journey, we uncover how ANN-based AI techniques revolutionize control mechanisms, providing a promising path toward unparalleled control precision and efficiency [1]. Artificial Neural Networks (ANNs) can be effectively used in optimization tasks across various domains, including industrial processes. An Artificial Neural Network (ANN) is a computational model inspired by the human brain's neural structure. It consists of interconnected nodes, or artificial neurons, organized into layers. ANNs process complex data by simulating the learning and decision-making abilities of the brain. Key components include neurons, weighted connections, activation functions, feedforward architecture, and backpropagation for training. ANNs require labeled training data to learn patterns and relationships, with hidden layers capturing hierarchical features. They are used in diverse applications, leveraging their ability to adapt and generalize from data to solve complex problems. However, determining the optimal number of layers and neurons within an ANN poses a challenge [2]. Given its opaque nature, gaining additional insights into the system's characteristics becomes crucial for comprehending its operations [2]. While various ANN architectures exist, including feedforward, recurrent [3], self-organizing [4], Hopfield ANN [5], and feedforward radial basis function (RBF) [6], feedforward and recurrent ANNs stand out as the most prevalent and widely applied in robotics. In recurrent ANN configurations, feedforward connections are integrated, establishing links across all layers from input and hidden to the output layer. Additionally, the gradient backpropagation technique is frequently employed for training, and random weight perturbations are introduced to prevent convergence to local minima.

This paper highlights the application of Multi-Layer Perceptron (MLP) neural networks in the realm of industrial process control. MLPs are recognized for their ability to model complex non-linear relationships, making them valuable for optimizing control parameters and enhancing process performance. The approach introduced, termed ANN-PID, aims to mimic human operator decision-making for superior control, outperforming traditional Proportional-Integral-Derivative (PID) controllers. The core of the study focuses on developing and training the ANN-PID system using real-time process data. MLPs leverage this data to predict and regulate industrial processes accurately. Rigorous experimental tests on the Feedback 38-003 Procon Level and Flow with Temperature process assess the system's effectiveness, offering insights into its advancements compared to conventional control methods. This research contributes to advancing intelligent control systems in industry, providing innovative solutions for process optimization and automation, ultimately increasing efficiency and precision in industrial operations.

2. The Proposed Approach

The intelligent ANN-PID system presented here is grounded in an MLP neural network. It harnesses the gradient backpropagation algorithm to assimilate process characteristics. ANN-PID adeptly replicates the decision-making process of a human operator when configuring controller settings. To bolster this system, a dedicated database was established, translating insights into water flow PID controller parameter configuration gleaned from empirical testing. Rigorous experiments were conducted on the Feedback 38-003 Procon Level and Flow with Temperature process [17], thereby corroborating the system's efficacy. Subsequent sections of this paper delve into a comprehensive analysis of the fundamental 38-100 process, employing a SADT (Structured Analysis and Design Technique) diagram. This analysis is followed by the implementation of our ANN-PID. The SADT diagram (Figure 1) provides a functional analysis of the 38-100 industrial prototype, denoted as level A0. Within this level (A0), the primary function involves the regulation and control of water level and flow. Inputs are derived from SV1, SV2, SV3, the servo valve, along with water quantity and a fixed signal. Control data is sourced from two water and electrical supplies, overseeing manual valves MV1, MV2, MV3, MV4, and MV5. The system's outputs encompass the flow rate of the drain valve and a 4-20 mA current signal. Additionally, there exists a secondary output, namely the analog level display. It's worth noting that this system is further subdivided into four distinct levels.

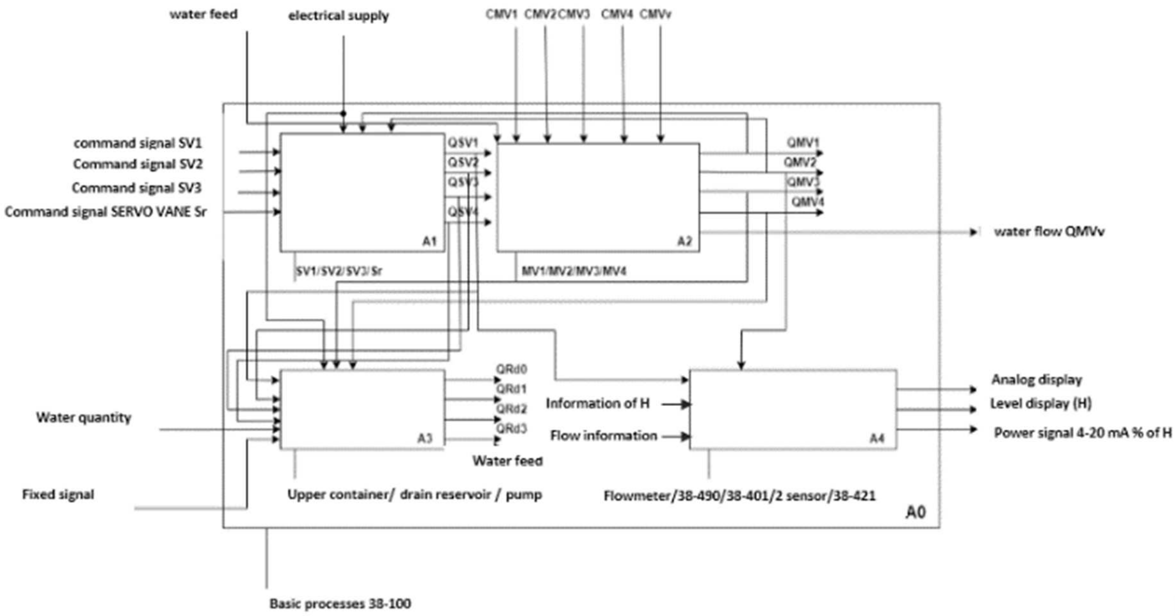

Figure 1: SADT diagram of the A0 system and its levels A1 A2 A3 A4

The following figure (Figure 2) shows the steps involved in creating our ANN PID. The control parameters are Pb(%), t i and td. They represent respectively: the proportional band, time reset and time derivate respectively. These parameters are implemented on the ABB CM30 control system.

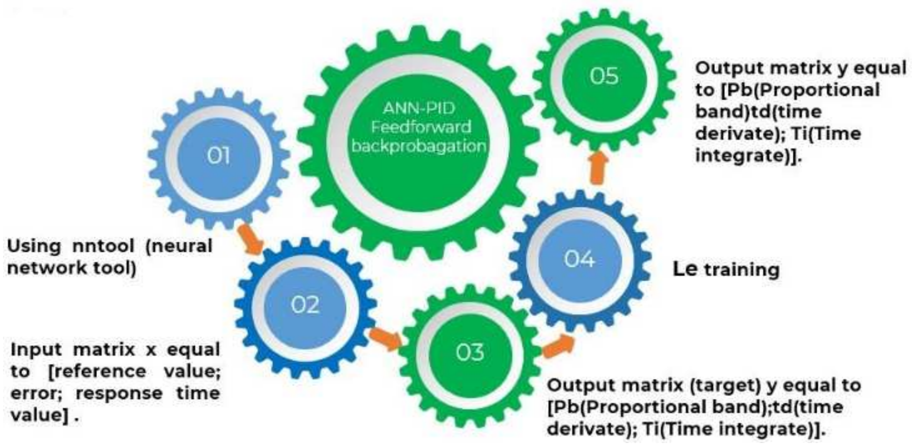

Figure 2: ANN-PID realization

Figure 3 shows its architecture. It has four inputs and three outputs. The inputs represent respectively: the reference, error, response time. The RNA-PID outputs are the values of the controller parameters: Pb(%), Ti and Td.

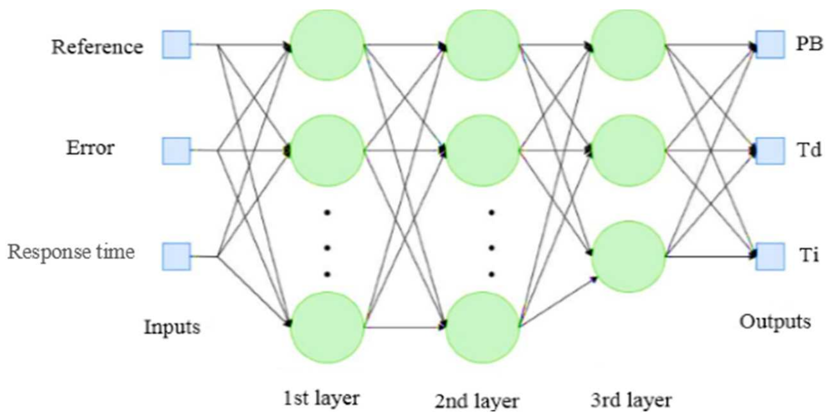

Figure 3: ANN-PID network architecture

This network imitates the pattern of an expert operator when he is adjusting the parameters of a control loop for an industrial process. Hence, this presents a challenge in pattern recognition. To solve this problem, we created a database of the flow through hundreds of experiments. The pseudo-code represents the algorithm used to learn this pattern. We chose the back-propagation training method.

Algorithm the Backpropagation training method

Execute the training process using the backpropagation method

```
Training process
Initialize all elements of wi and also rand (-0.01, 0.01);
Repeat
Begin
 For all i
         Begin
         δwi = 0;
         end;
 For all instances (x,c) in S;
           Begin
            Calculate output: Pb%, td, ti for inputs: reference, error, time reset;
             For all i
                    Begin
                     δwi = δwi +ϵ×(c −0)×xi × ˙σx.w ;
                     end ;
 end ;
For all i
    Begin
    wi = wi +δwi ;
     end;
end.
```

3. **Experiments in flow regulation**

We describe the learning procedure utilized to create a flow control database, including a series of experiments conducted. To configure the parameters of the PID controller for the flow loop, we proceeded with the following steps:

1. Begin by ensuring that the flow control is inverted - it is crucial to verify and set this correctly.
2. To configure the control action, access the control module in mode configuration from the main operating display. Navigate to the control menu page and select it.
3. Choose 'loop1 control' and press 'select,' then proceed to 'Control Action' and press 'select' to make the necessary adjustments.
4. Verify the configuration to ensure it displays the desired reverse action, then return to the main page.

Furthermore, it is essential to note that all instruments must undergo calibration before commencing the procedure [7].
To initiate the recording of experiments we followed these steps:

1. Initially, fully open MV2 and position MV3 halfway, and then activate the pump.
2. Switch to automatic mode using the auto/manual key.
3. Open the data logger and bar graph display to monitor the measured input value, setpoint value, and output value displays

Table 1
A Subset of the Database for Testing Flow Adjustments

	Reference	Pb%	Ti	Td	Response time	Error
1	15 %	02 %	01	04	0,36 sec	1,82
2	15 %	03 %	01	04	1,34 sec	1,82
3	06 %	10 %	00	00	1,91 sec	1,82
4	14 %	08 %	00	00	1,91 sec	1,82
5	20 %	02 %	01	04	0,56 sec	1,82
6	20 %	03 %	01	04	1,34 sec	1,82
7	20 %	03 %	00	02	1,91 sec	1,82

Figures 4 and 6 depict the flow index response curves, while figures 5 and 7 illustrate the error curves. These responses were obtained using parameter numbers 1 and 2 from Table 1.

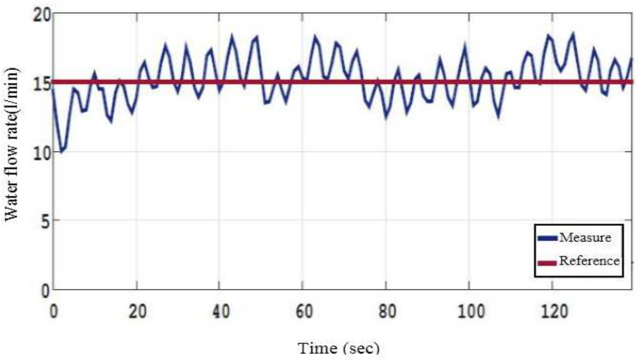

Figure 4: Index response of flow at 15 l/min

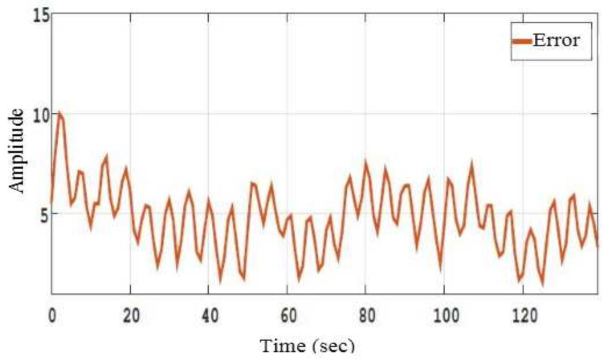

Figure 5: Flow regulation error curve at 5 l/min

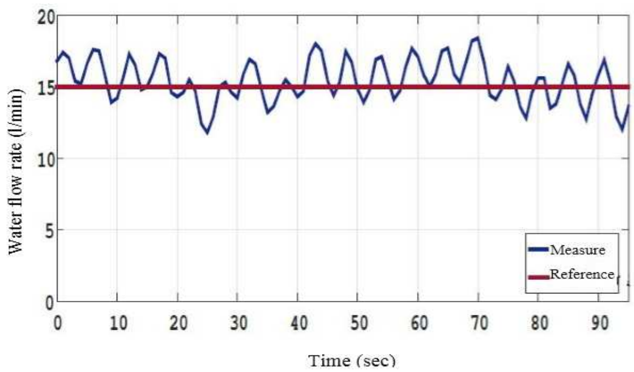

Figure 6: Index response of flow at 15 l/min

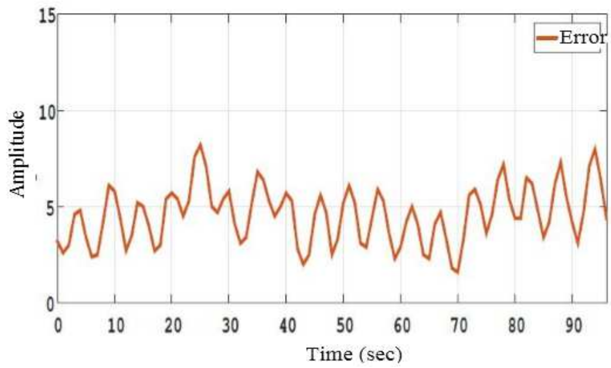

Figure 7: Flow regulation error curve at 5 l/min

Figure 6 reveals that the system exhibits oscillations around the reference point. It is worth noting that, despite numerous attempts, we encountered challenges in mitigating the oscillation rate with the parameters at hand. Additionally, it is essential to perform instrument calibration before commencing the process, as emphasized in [7].

4. Implementation And Validation Of The ANN-PID System

In this section, we have outlined the steps involved in implementing the pattern recognition approach for setting control loop parameters. We employed NNTool,whitch is a tool in Matlab for training the neural network. It is important to emphasize that the configuration chosen for the network before training plays a pivotal role in achieving the desired result (target). In this study, we conducted extensive testing with various configurations to identify the optimal targets.

For the initial configuration at the first level, we opted for a neural network consisting of three layers. The first layer comprised 70 neurons, the second had 140 neurons, and the third featured 3 neurons, We experimented with different architectures and found that this specific three-layer configuration offered the best performance in terms of accuracy and generalization on our validation data. Regarding other parameters, we selected 1000 iterations with a step size of 0.00005. The training curves obtained from these configurations are presented in Figures 8, 9, and 10.

(2)

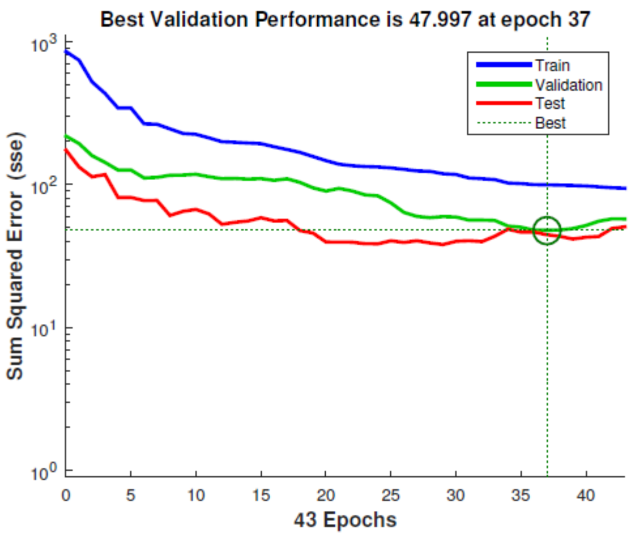

Figure 8: performance curve for network

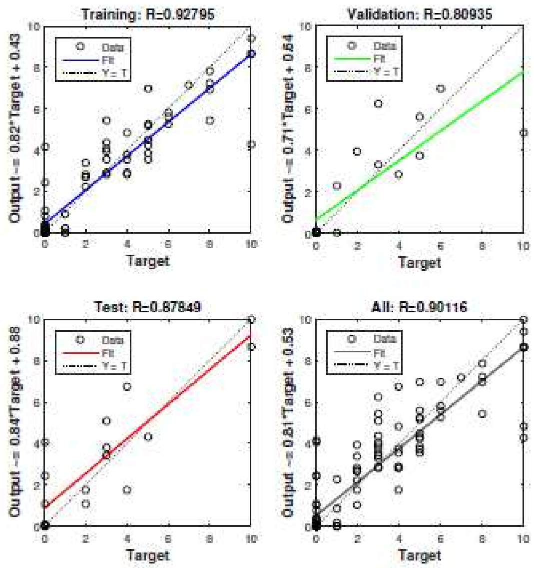

Figure 9: regression curve for network

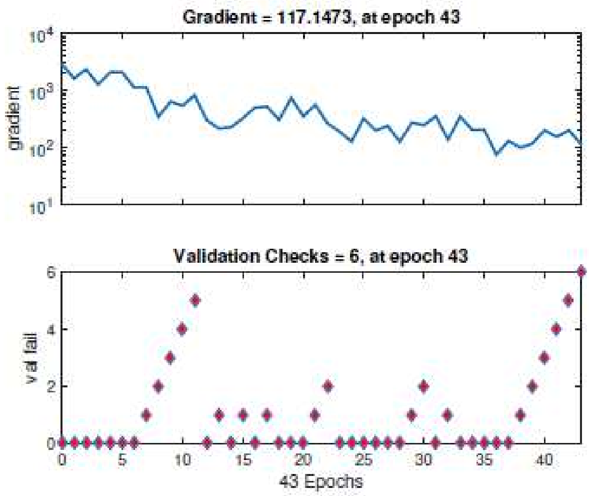

Figure 10: Training state curve for network

To validate the network, we simulated the ANN-PID using inputs x as [reference value, error, response time value], and obtained outputs y as [Pb%, td, ti].
Such as:

-For x= [18; 3; 0.5], ANN-PID gave y= [2; 0; 1]

We subsequently applied these parameters to the flow control, and Figures 11, 12, 13, and 14 illustrate the curves of the obtained result.

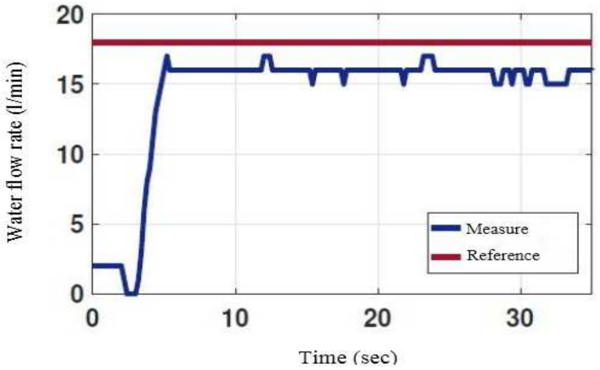

Figure 11: Index response of ANN-PID flow regulation at 16 (l/min)

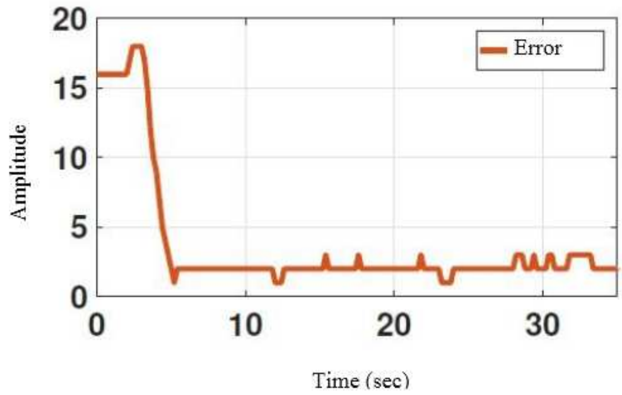

Figure 12: ANN-PID flow regulation error curve at 16 (l/min)

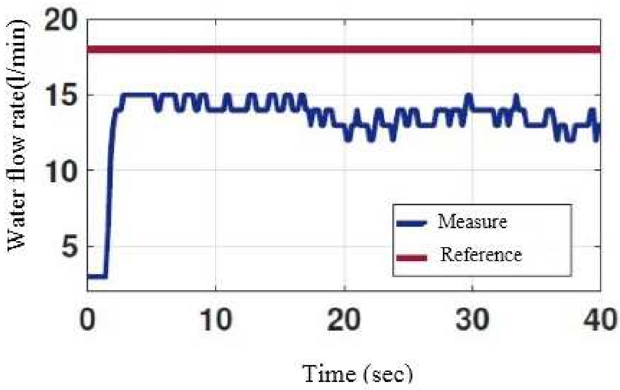

Figure 13: Index response of ANN-PID flow control at 15 (l/min)

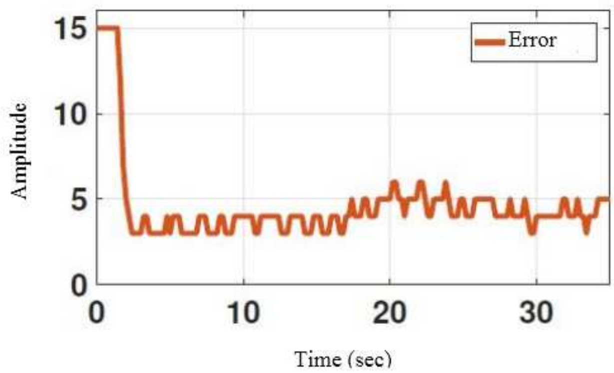

Figure 14: ANN-PID flow regulation error curve at 15 (l/min)

As observed in these curves, we achieved a lower tracking error compared to the one mentioned in ANN-PID (for input x). Additionally, the figures reveal that the measurement curve converges swiftly toward the reference, resulting in a shorter response time. Furthermore, ANN-PID effectively minimizes oscillations. Consequently, the yield obtained by ANN-PID surpasses the target.

5. Conclusion

In this study, we introduced an innovative ANN-PID system based on a multilayer perceptual neural network (MLP) to address the complex pattern recognition challenges in PID controller regulation. Extensive experiments were conducted to acquire the necessary training data for the ANN-PID model. Validation tests on the Feedback 38-003 Procon Level and Flow with Temperature process confirmed the system's remarkable effectiveness, significantly improving control performance beyond initial estimates.

Our future work will focus on implementing deep neural networks with extensive long-term data (big data). This promises to usher in advanced control systems, paving the way for further optimization and automation of complex industrial processes.

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