Enhancing PID Control with Neural Network Integration: Analysis of RBF, BP, and Fuzzy Neural Network Models

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Abstract. Traditional PID controllers, despite their widespread use due to simplicity and robustness, often falter in handling nonlinearities and time-varying systems without frequent retuning. Since scholars are not satisfied with conventional control theory, an integration of neural network and PID controlled have been explored and new control theory is constructed. The advent of neural networks offers a dynamic enhancement to PID controllers by introducing adaptive capabilities, self-learning, and fault tolerance. With the assistance of neural network, PID controllers have gained new method to automatically control the target. This paper aims to presents a comprehensive review of the integration of neural network technologies with Proportional-Integral-Derivative (PID) controllers, emphasizing their application in complex and nonlinear control systems. The design, operation, and application domains of a number of neural network models, including Radial Basis Function (RBF), Backpropagation (BP), and Fuzzy Neural Network PID controllers, are examined. These neural network-based PID controllers have shown considerable success in diverse sectors including robotics, process control, and environmental systems, reflecting improved performance over traditional methods. This paper not only outlines the operational principles and advancements in neural network PID controllers but also discusses the challenges and future prospects for further enhancement of feedback control mechanisms.

Keywords: Neural Network, PID Control, Integration

1 Introduction

PID control is a fairly widely used control algorithm. It can not only adjust the temperature of small electrical elements, but also control the speed or the movement of large vehicles. PID control has been around for 102 years now. It was first theoretical developed in 1922 by Minorsky [1]. PID controllers are now among the top algorithms in many different fields due to their straightforward algorithm, superior stability, resilience, quick response, and dependable operation [2]. In many control fields, PID control have been proved to be one of the most dominant control systems. In the industrialfield, PID control algorithms can achieve precise control of

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machinery, such as industrial heat treatment, motor speed control, position control, etc. PID control algorithms can also be applied to the control system in the field of meteorology, environmental protection, medical care, etc. Nowadays, PID control is also commonly used to automate robots, drones, or vehicles. Nevertheless, PID control retains considerable shortcomings. PID controllers require parameter adjustment according to the specific control system, which requires a certain degree of expertise and experience. And it may be difficult to have proper parameters every time, which may lead to bad performance of the control system [3]. Meanwhile, PID controllers are suitable for linear systems. And for non-linear or time-varying systems, PID controllers show poor adaptability when dealing with these objects [3]. Besides, PID controllers are sensitive to noise. Even small noises that may cause the control system to oscillate or become unstable. On the other hand, the continuous development of control system and technologies have led to complexity and abstraction of controlled target [4]. Conventional PID controllers cannot handle these objects very well, especially when controllers are dealing with time-varying and nonlinear system [2].

In order to handle these intricate systems, PID controllers are being updated in several ways, and new PID controllers are being created. PID controllers with neural networks, fuzzy logic, adaptive logic, etc. Different types of PID controllers are invented to tackle complex, dynamic, and nonlinear systems effectively. Neural Network PID controllers, among these cutting-edge PID controllers, are frequently very flexible and appropriate for certain complicated nonlinear control systems due to their self-learning, adaptive, and nonlinear capabilities as well as their great robustness and good fault tolerance [5]. These enhanced controllers are increasingly common in sectors like robotics, where precision and adaptability are crucial, or in process industries where conditions frequently change and downtime due to controller re-tuning needs to be minimized. Principles of PID Controllers

With a focus on their use in intricate and nonlinear control systems, this paper attempts to provide a thorough analysis of the integration of neural network technologies with PID controllers. The first part of this paper introduces the basic law of PID control. Structure and mathematical theory are provided in this part. The second part focuses on the introduction of three different neural network PID controller: Radial Basis Function (RBF) neural networks PID control, BP neural network PID control, and Fuzzy neural network PID control. Detailed information is provided in this part. The third part is the discussion of these three neural network PID control. Comparison, limitation, strength, and suggestion are claimed. In the fourth part, conclusion of this paper is made.

2 Related Works

2.1 Three Basic Components

In industrial control applications, a sort of feedback control system called proportional-integral- derivative control, or PID control, is used to maintain a controlled variable at a desired set point. Fig. 1 shows basic structure of PID controller:

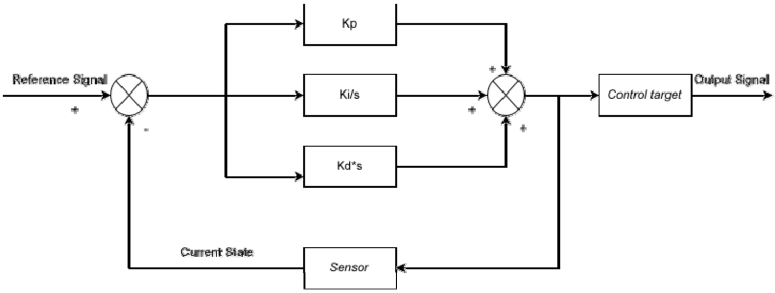

Fig. 1. Structure of PID controller (Photo credited: Original)

It combines three types of controllers:

Proportional(P) Controller. In response to the present error—that is, the discrepancy between the intended set point and the actual value—a proportional (P) controller operates. The proportional response can be adjusted by changing the proportional gain. A higher proportional gain results in a larger output response, which can help the system respond more quickly to errors, but can also lead to overshoot where the process variable exceeds the set point. Fig. 2 shows the basic structure of proportional controller:

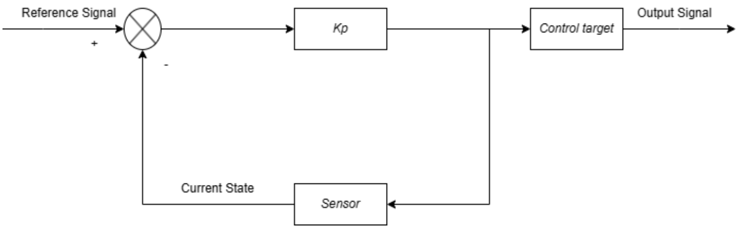

Fig. 2. Structure of P controller (Photo credited: Original)

Integral(I) Controller. Integral controller addresses the cumulative error over time, helping to eliminate the residual steady-state error that can occur with a proportional controller alone. By integrating the error over time, the integral action seeks to eliminate the offset by increasing or decreasing the controller output depending on the duration and magnitude of the error. Fig. 3 presents the basic structure:

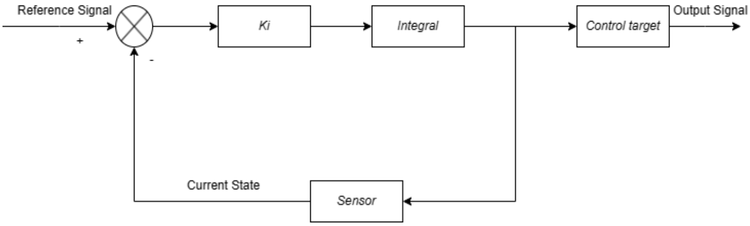

Fig. 3. Structure of I controller (Photo credited: Original)

Derivative(D) Controller. With the use of a derivative controller, which projects future mistakes depending on the error's rate of change, overshoot and oscillation brought on by the proportional and integral components can be lessened. It essentially adds a corrective action that is proportional to the rate at which the error is changing. Basic structure of proportional controller is shown in Fig. 4:

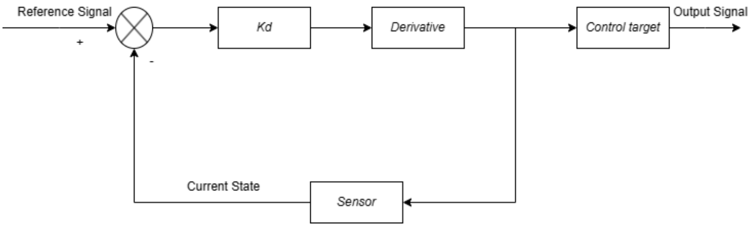

Fig. 4. Structure of D controller (Photo credited: Original)

2.2 Basic Control Law

The mathematical representation of a PID controller can be expressed as follows:

$$u(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{de(t)}{dt} \tag{1}$$

where u(t) is the system's control input, which it uses to gradually drive the error to zero in order to preserve stability and fast response time without experiencing steady-state error. And the tuning parameters that are essential to achieving excellent performance are Kp, Ki, and Kd. In addition to e(t), there is the error resulting from the measurement at time t and the set point.The transfer function can be presented as follows:

$$G(s) = K_p + \frac{K_i}{s} + K_d s \tag{2}$$

3 Classification of Neural Network PID Control

3.1 RBF Neural Network PID Control

Artificial neural networks that employ radial basis functions as activation functions are known as radial basis function (RBF) neural networks. They are typically employed in many different contexts, such as time series prediction, function approximation, and classification. RBF neural networks have one hidden layer and are feedforward networks with three layers. There is no weight sharing between the input layer and the concealed layer. The output of an RBF neural network can be generated by first moving the vector input to the hidden layer, and then summing the values of the output linearly and weightedly [6]. RBF neural network has showed strong function approximation ability and can deal with any continuous function [7]. RBF neural networks also own some key advantages: simple structure, fast training, robustness to input noise, good generalization, etc. And RBF neural networks have caught tremendous scholars' attention. In the study of Tang [8], reactor temperature is predicted using an RBF neural network. Additionally, forecast accuracy has significantly increased. Based on an RBF neural network, Ying's study developed a GDP economic forecasting model that outperforms other models in terms of accuracy [9].

Due to the fast pace of development of science and technology, more complex and abstract control objects have emerged frequently. Conventional PID controller cannot meet the needs of dealing with these complicated systems. As a result, neural networks were combined with PID controllers. Among them, RBF neural network PID controller draw great attention because of its excellent quality: good generalization, noise tolerance, adaptive control, etc. RBF neural network can be designed to adaptively tune the PID parameters in real-time. The network inputs could include the error, the change in error, and any other relevant system states, while the outputs would be the optimal PID parameters. Jie's [9] study used an RBF neural network to automatically adjust the PID controller's parameters. Furthermore, the RBF neural network PID controller responds well to unpredictable nonlinearities. A PID controller based on an RBF neural network was used to regulate an inverted pendulum system in Hong's study [10]. The outcome demonstrated a decrease in overshoot and an improvement in response speed. And Cao solved the constant-tension control problem using an RBF neural network PID controller [11]. Additionally, RBF neural networks can be used to model and anticipate the behavior of the controlled system itself in certain situations. This model can then be used to design a model-based PID controller that anticipates system responses to control inputs.

3.2 BP Neural Network PID Control

In the 1980s, researchers under the direction of Rumelhart and McClelland proposed the BP neural network method [12]. The three layers of the BP neural network are the input layer, hidden layer, and output layer. Every layer contains a specific quantity of neurons. Every neuron possesses a threshold value, and weights connect every level [13]. Furthermore, every neuron generates its output through the application of an activation function to its input. Tangh, Rectified Linear Unit, and sigmoid are examples of common activation functions. The network's ability to represent intricate patterns, including non-linearities, is influenced by the activation function selection. After passing through multiple hidden layers and the input layer, neurons use their activation functions to produce output. Every layer's output up to the output layer is used as the subsequent layer's input to create the final output. A comparison between the output and the goal value is made when the output is moved to the output layer. The network measures the discrepancy between the actual target values and its anticipated outputs using a loss function. Following the comparison, the network uses the chain rule to calculate the gradient of the loss function with respect to each weight in the network. Starting at the output layer, errors spread backward through the network layers. Weights are then changed to achieve more control if the gradient method lowers the error.

BP Neural Network PID controller includes all the self-learning ability. Like the BP neural network, the most important progress is still forward propagation and back propagation. Fig. 5 presents the basic components:

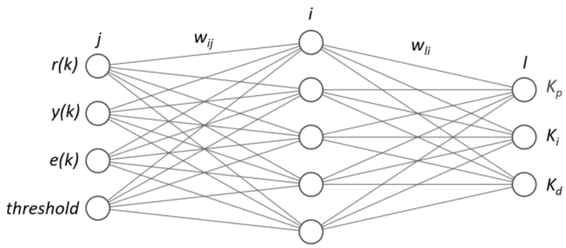

Fig. 5 Structure of BP neural network PID controller (Photo credited: Original)

Intuitively the output of the output layer is replaced with the parameters of the PID controller. The input of neurons in input layer is:

$$O_j = x(j) \quad (j = 1,2, \dots, M) \tag{3}$$

These variables are modifiable based on the particular status of the controlled object [14]. The input and output of the hidden layer are:

$$net_i = \sum_{j=0}^{M} w_{ij} O_j \tag{4}$$

$$O_{i(k)} = f\big(net_i(k)\big) \; (i = 1,2, \dots, Q) \tag{5}$$

And the transformation is shown as:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{6}$$

The input and output of output layer are:

$$net_l(k) = \sum_{i=0}^{Q} w_{li} O_i(k) \tag{7}$$

$$O_l(k) = g(net_l(k)) \tag{8}$$

The performance indicator function can be used to determine the error mean square value, which is used in back propagation to determine the system's performance and modify the weight:

$$E(k) = \frac{1}{2}(r(k) - y(k))^2 \tag{9}$$

Connection weights between layers can be calculated as:

$$\begin{cases} w_{li}(k+1) = -\mu_1 \frac{\partial E(k)}{\partial w_{li}} + \alpha_1 \Delta w_{li}(k-1) + \Delta w_{li}(k) \\ w_{ij}(k+1) = -\mu_2 \frac{\partial E(k)}{\partial w_{ij}} + \alpha_2 \Delta w_{ij}(k-1) + \Delta w_{ij}(k) \end{cases} \quad (10)$$

In conclusion, decisions must be made regarding the network's structure, the t network's parameters, and the PID controller's starting values while building a BP neural network PID controller. Next, load the controlled target into the system and run the BP neural network's learning phase. Adaptively, the PID controller's parameters are obtained [15]. Because of the BP neural network PID controller's remarkable adaptive self-learning ability and decreased requirement for manual tuning, it has been widely utilized. Researchers have used BP neural network PID controllers in a variety of fields, including process control and manufacturing. Wu created a PSO-BP-PID control for the autonomous greenhouse system that provides the best possible temperature and humidity management as well as sensor error correction [16]. And the result shows that after reaching steady state, there is a 0.5°C discrepancy between the average temperature and the target value, and a 1% RH discrepancy between the average humidity and the target value. And in Ren's study [17], BP-PID controller is applied to wind turbines. The proposed controller shows excellent dynamic performance and strong robustness. Nevertheless, there are still challenges to overcome. It's crucial to ensure the BP neural network can work and operate in real-time for practical applications.

3.3 Fuzzy Neural Network PID Control

Fuzzy systems can handle nonlinearity, uncertainty, and other complicated problems because they are effective at expressing structural and ambiguous knowledge [18]. Fuzzy controllers are particularly useful in scenarios where the processes are not well-understood mathematically and can't be modeled accurately with conventional control techniques. Generally fuzzy controllers are organized with four steps: fuzzification, rule evaluation, inference system, defuzzification. In fuzzification, real input values have to be converted into scales ranging from 0 and 1, which is known as fuzzy sets. And each set is defined by membership function. Then a set of fuzzy logic rules have to be defined to operate the fuzzy controller. And the inference system processes all applicable rules to generate the fuzzy output distribution. In the final step, fuzzy output distribution is converted back into real and actionable control output. Fuzzy controllers are widely used in various areas, such as automative systems, industrial control, etc. In Hou's study [19], a modified adaptive fuzzy control is applied to get power quality improvement. And the outcomes confirm that the suggested control strategies exhibit better performance in various scenarios. Chiu uses fuzzy controller to control an omnidirectional inverted pendulum [20]. The excellent efficiency of the proposed controller is illustrated by the result.

Neural network control excels in its strong self-learning capabilities and adaptability in complex environments with numerous inputs and outputs, while fuzzy control simply depends on empirical data and is inappropriate for scenarios needing multivariable control [18]. To lessen the negative effects of changing fuzzy rules or models, the fuzzy neural network PID algorithm leverages both the neural network's learning capabilities and the stability of fuzzy logic control [21]. Fig. 6 gives a basic structure:

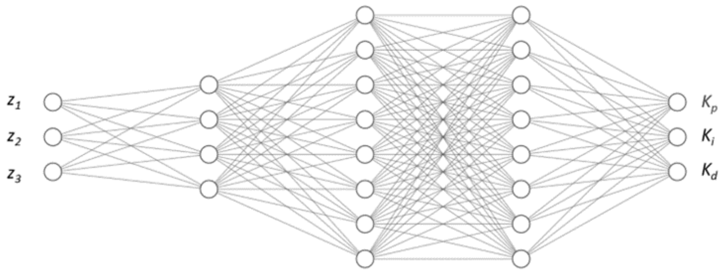

Fig. 6. Structure of Fuzzy Neural Network PID Controller (Photo credited: Original)

In the input layer, real control value is imported. The input and output of the input layer can be expressed as follows:

$$O_{ij} = x_i \qquad (i = 1,2,\dots,M) \tag{11}$$

In fuzzification layer, each input neuron corresponds to seven linguistic variable value which means there will be 21 neurons in fuzzification layer if there are 3 neurons in input layers [18]. The input and output are expressed as follows:

$$\begin{cases} I_{ji} = O_{ij} \\ L_{ij}(x_i) = \exp\left(-\left(\frac{x_i - c_{ij}}{b_{ij}}\right)^2\right) \\ O_{jk} = L_{ij}(x_i) \end{cases} \tag{12}$$

where Lij(xi) is the jth linguistic variable value corresponding to the ith neurons in the input layer, and cij is the affiliation function's center. Bij is the affiliation function's width. The input and output of the rule layer can be expressed as follows:

$$\begin{cases} I_{kj} = O_{jk} \\ O_{kl} = L(x_1)L(x_2) \end{cases} \tag{13}$$

Additionally, the normalization of the fuzzy inference layer's output is computed in the normalization layer and is displayed as follows:

$$\begin{cases} I_{lk} = O_{kl} \\ O_{lm} = \frac{O_{kl}}{\sum O_{kl}} \end{cases} \tag{14}$$

In the output layer, the fuzzified value is converted back into real value. In Fuzzy Neural Network PID Controller, three outputs are declared: K_p,Ki,K_d. The output of the output layer can be shown as follow:

$$\begin{cases} I_{ml} = O_{lm} \\ O_{final} = \sum w_{ij} O_{lm} \end{cases} \tag{15}$$

Besides, our error function could be calculated as follow:

$$E(k) = \frac{1}{2}[r(k) - y(k)]^2 \tag{16}$$

Neural networks have outstanding capacities for self-learning and adaptation, whereas fuzzy logic systems are adept at handling ambiguity. Fuzzy Neural Network PID Controller allows researchers to efficiently handle a variety of uncertain and nonlinear systems. A control scheme based on fuzzy neural network PID is used to a constant deceleration compensation device in Li's study [22]. And with the help with this device, the risk of hazardous hoist decelerations will reduce and the dependability and safety of mining hoists will significantly increase. Yang applies Fuzzy Neural Network PID Controller to the active vibration control technology of helicopters [23]. His results show that the proposed control law can be theoretically be applied to reduce helicopter vibration loads. But challenges still remain. In fuzzy neural network, the real-time operation could be computationally intensive. And the combination of fuzzy logic system and neural network will increase the complexity of the controller design. Besides, it still requires large amount of training data to reach better performance.

4 Discussion

The ability to handle nonlinearity and uncertainty is significantly improved by the combination of PID control and neural networks. Numerous academics appreciate all of the newly released neural network PID controllers. These neural network PID controllers have a wide range of applications. Nevertheless, in order to give a clearer review of neural network PID controllers, limitation and strength of each neural network PID controller are stated in this part.

RBF neural network PID controllers excel in function approximation and can effectively handle continuous functions. They are characterized by their simplicity, quick training times, and robustness to input noise, making them well-suited for real-time applications where rapid and reliable performance is critical. But RBF neural network PID controllers may struggle with very complex nonlinear systems or systems with abrupt changes, as their approximation capabilities have limits depending on the diversity and range of the training data.

BP neural network PID controllers demonstrate superior adaptive learning capabilities, significantly reducing the need for manual tuning. This feature is crucial in environments like manufacturing where conditions can vary and precise control is required continuously. However, are heavily dependent on the quality and quantity of training data. They also require significant computational resources for training, which can be a drawback in resource-constrained settings.

Fuzzy neural network PID controllers integrate the qualitative aspects of fuzzy logic with the quantitative techniques of neural networks, offering a powerful tool for dealing with uncertain and nonlinear systems. They excel in scenarios where the process dynamics are not well-defined mathematically, providing a more intuitive control mechanism. But it's also clear what their limitations are. PID controllers for fuzzy neural networks can become computationally demanding, particularly when the system's complexity and number of rules rise. Furthermore, these controllers might have complicated designs that need for a high level of skill and meticulous membership function and rule set tuning.

There're still tremendous challenges to overcome to develop neural network PID controllers. The learning algorithm of neural network should be enhanced in order to improve the adaptability and efficiency which is crucial to the control system. And more extensive testing and validation in real-world applications are necessary to understand the practical limitations and to tune these controllers for optimal performance. Besides, it still requires research into simplifying the training and implementation processes. This could make neural network PID controllers more accessible to industries that currently rely on traditional methods due to their simplicity and low cost.

5 Conclusion

PID controllers have been widely used as feedback control loop mechanism in various control systems. The basic idea of PID controller is to keep controlled value consistent with reference signal. The system continuously monitors the error value and applies proportional controller, integral controller, and derivative controller to it. Typical PID controllers contain proportional, integral, derivative controller, while it's still practicable to apply only one or two of these controllers. The dominant place of PID controllers have been guaranteed by its superiority. Its simple structure, robustness, fast response and other unparallel advantages have proved its versatility. Nevertheless, with the development of control systems, more complex control targets emerge and traditional PID controllers perform bad when dealing with these targets. As neural network develops quite fast, scholars have discovered ways to optimize PID controllers with the help of neural network algorithms. Different PID neural network controllers were developed: BP Neural Network PID controller, RBF Neural Network PID controller, Fuzzy Neural Network PID controller, etc. They have been proved to be efficient when dealing with complexity and uncertainty. However, tremendous challenges still should be overcome in order to develop feedback control mechanism further. Sufficient training data should be provided in order to reach the best performance of neural network. And great number of computations is needed. Besides, requirements of expertise in both automatic control and machine learning is also demanding. It's necessary to further study neural network PID controllers.

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