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A Study on PID Control System using a Neural Network for a Small Modular Reactor

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1. Introduction

Energy consumption by growing population has been increased every year. Environmental concerns and issues such as global warming caused by exhaustion of fossil fuel and carbon dioxide emissions have been gaining its importance. Utilization of various energy sources including nuclear energy is required now in the current energy situation. Especially, power generation using environmental-friendly and semi-permanent energy source has been getting a lot of attention worldwide [1-2]. One approach to minimize these emissions involves substituting fossil fuels with Nuclear energy sources. Small Modular Reactor (SMR) power plants have been spotlighted due to significant improvement of safety and economics compared to large-scale nuclear power plants, integrating main components, such as a steam generator and a pressurizer into reactor vessel. However, achieving power generation of the SMR poses a significant challenge from a control engineering perspective, due to the non-linearity, uncertainty, time varying systems they entail. To effectively operate the SMR power plants, appropriate control systems must be developed considering operating conditions and strategies.

Proportional–integral–derivative (PID) controllers are widely used in various industrial and commercial applications, because of their simplicity and reliability. However, fine-tuning the PID controller parameters in the SMR power plants becomes intricate because of constraints, such as varying operating conditions and strategies of the SMR power plants. The conventional PID control system with fixed parameters may not deliver optimal control performances in the SMR power plants under these constraints. This has inspired the application of neural network (NN)-based control methods, offering a potential solution to these challenges. Due to its simplicity and reliability, a PID control system employing an NN has been utilized in several reported studies [4-6]. Consequently, challenges remain for developing a suitable control system to ensure effective operation of the SMR power plants under the constraints.

In this context, we considered a PID control system that uses a back-propagation neural network (BP NN), which can enhance the system's self-adjusting ability to compensate for the fixed parameters in the conventional PID control system when operating such SMR power plants.

2. Control system using a neural network

This section introduces a self-adjusting PID control system that uses a BP NN, ensuring efficient operation of the SMR power plants, and outlines the design strategy for this control system. It further considers a stability analysis based on Lyapunov stability.

2.1 Overview

An NN based-PID control system consists of two parts: PID controller and BP NN as shown in Fig.1. The BP NN learns from features of SMR power plants under varying operating conditions and strategies. Utilizing the learning process of the NN enables the update of the weight coefficients with respect to the adjustment in the fixed PID parameters. Subsequently, the PID parameters undergo changes to accommodate the constraints. Consequently, the actions of PID controller result in new outputs, creating a dynamic loop of continual parameter adjustments.

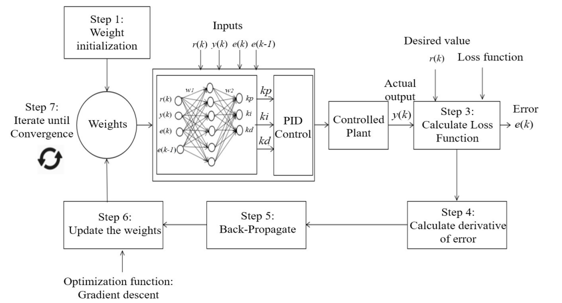

Fig. 1. Schematic of a control system using a BP NN

2.2 Structure of NN-based PID controller

The desired value, the actual plant output, the control error, $e(k)$ defined by the difference between the actual output $y(k)$ and the desired value $r(k)$, and past error $e(k–1)$ can be employed as input patterns. Firstly, the fixed PID parameters are initialized using Ziegler-Nichols' closed-loop method for the initial stability of the control system. Subsequently, the output layer produces PID parameters kp, ki and kd according to the learning process. Consequently, the PID controller gives the new control input $u(k)$ based on the difference between the desired value $r(k)$ and the actual output $y(k)$. The detailed procedure of the design strategy underlying the BP NN-based PID control approach is as follows:

Step 1: Initialization of neural network in BP NN-based PID controller.
Random, zero, constant, gaussian, uniform, XAVIER and HE initialization methods in the several reported studies can be utilized on the neural network in BP NN-based PID controller.

Step 2: Feed Forward
Feed Forward is one of the structure of NNs. Herein, we considered the widely used multilayer feed-forward network. The three layers are classified into the input, hidden, and output layers.

Step 3: Calculate loss function based on the actual output and desired value
The loss functions of the BP NN-based PID control for the control loop is denoted as follows:

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

Utilizing the loss function enables the update of the weight coefficients in the BP NN' structure with respect to the adjustments in the fixed PID parameters.

Step 4: Calculates the derivative of the error
The derivative of error is calculated based on the loss function, as follows:

$$\frac{\partial E(k)}{\partial w_{ij}}=e(k)\frac{\partial e(k)}{\partial w_{ij}}, \tag{2}$$

where w_{ij} is the weight coefficients.

Step 5: Back-propagation
Back-propagate the gradients from the output layer to the input layer in the BP NN's structure.

Step 6: Update the weights
Most common optimization function used to update the weight coefficients is calculated as follows:

$$w_{ij}(k)=w_{ij}(k-1)-\alpha e(k)\frac{\partial e(k)}{\partial w_{ij}}, \tag{3}$$

where α is the learning rate.

Step 7: Iterate until convergence
The iterative algorithm updates the weights coefficients, along with the loss function based on the actual output and desired value. Consequently, the output, $y(k)$ provides a close approximation of the desired value during the learning phase.

$$r(k)\simeq y(k). \tag{4}$$

2.3 Stability Analysis

Every control system involves a stability problem, which should be carefully studied. Lyapunov stability methods have received wide interest in several fields, such as control systems, and they are popular among researchers because of their simplicity, universality, and usefulness [6–9]. It is shown in [7–9] that a Lyapunov function of the error between the desired value and NN outputs is defined, where the weight coefficients are adjusted such that the error asymptotically converges to zero. According to this theory, if a positive definite function $V(k) = e(k)^2$ is found such that its discrete time difference along a trajectory is always negative ($\Delta V(k)<0$), then as time k increases, $V(k)$ ultimately converges to zero; therefore, the error also converges asymptotically to zero.

3. Conclusions

To effectively operate the SMR power plants, appropriate control systems taking into account varying operating conditions and strategies must be developed. For the operation of the SMR power plants, effects in such constraints can be main obstacles in designing a high performance controller and its parameters. We introduced a PID control system that incorporates a neural network, ensuring efficient operation of the SMR power plants, even under scenarios in these constraints, and presented the design strategy for this system. It further delved into a stability analysis of the NN-based PID control system based on Lyapunov stability theory.

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