Design and Implementation of a SNA-PID controller based on RFNNI applied for the Ball and Beam System

Case Study

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Abstract *– This paper proposes an adaptive control approach for the ball and beam system using a Single Neuron Adaptive PID (SNA-PID) controller integrated with a Recurrent Fuzzy Neural Network Identifier (RFNNI). The main contribution of this study is the development of an online identification and parameter adaptation scheme, in which the RFNNI is employed to identify the nonlinear system dynamics and provide real-time Jacobian estimation, while the SNA-PID controller updates its parameters online to improve tracking accuracy and robustness against uncertainties. The combination of the single-neuron adaptive structure and the recurrent fuzzy neural network enables effective compensation for nonlinearities and dynamic variations of the system. The proposed control framework is first validated through MATLAB/Simulink simulations and subsequently implemented in real-time experiments with online parameter updating. The experimental setup is based on a DSP control platform and utilizes an infrared (IR) sensor for real-time measurement of ball position. Comparative simulation and experimental results demonstrate that the proposed SNA-PID-RFNNI scheme significantly outperforms the conventional PID controller, achieving a reduction in overshoot from 44.26% to 6.28% and a decrease in settling time from 23 s to 17 s. These results confirm the effectiveness and practical applicability of the proposed adaptive control strategy.*

Keywords: *ball and beam, nonlinear system, adaptive control, online system identification, SNA-PID-RFNNI*

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1. INTRODUCTION

The ball and beam system is one of the classic models in the research and teaching of automatic control, due to its unstable and nonlinear characteristics [1]. In terms of physical structure, the system consists of a ball rolling freely on a long beam. This beam has one fixed end, and the other end can be tilted by controlling a motor through a connecting rod attached to it. The control goal is to maintain the ball in a stable position at a desired location on the beam [2]. Due to the influence of gravity, the material of the ball and the beam, when adjusting the tilt angle of the beam (even very small), the ball will roll quickly to one side, causing the system to fall into an unbalanced state easily [3]. The unstable and nonlinear characteristics make the ball and beam system an ideal platform for testing modern control algorithms, from classical PID control to intelligent methods such as fuzzy control, neural networks and hybrid methods [4-5]. Specifically, Nguyen *et al*. in [4] focused on the design and experimental evaluation of a PID controller for stabilizing the ball and beam system. However, due to fixed control parameters, the conventional PID controller exhibits limited adaptability when the system is subject to nonlinearities and disturbances. Consequently, many studies have proposed intelligent control approaches to improve control performance. For instance, Nur Sakinah Abdul Aziz *et al*. in [6] applied a Fuzzy-PID controller to the ball and beam system and achieved improved performance compared to the classical PID controller. More

recently, C. N. Nguyen *et al*. in [3] proposed a supervisory control strategy based on a radial basis function (RBF) neural network to enhance the adaptability and robustness of the system. However, classical PID and Fuzzy-PID controllers are often designed with fixed parameters, leading to poor performance when the control object changes or when there are large noise and signal delays.

To enhance the adaptability and control accuracy of the system, an effective approach is to employ a single neuron adaptive network to optimize the PID controller, in which the control gains K_p, K_i, and K_d are adjusted online by the neural network [7]. Moreover, due to the nonlinear and time-varying characteristics of the ball and beam system, system identification plays a crucial role in providing accurate dynamic information for adaptive control. In this context, the RFNNI is a suitable tool for modeling and identifying nonlinear systems, as it is capable of capturing temporal dynamics and incorporating fuzzy inference mechanisms [8]. Based on these considerations, this paper proposes a control strategy that integrates the SNA-PID controller with the RFNNI and applies it to the ball and beam system.

2. MATHEMATICAL MODELING

The ball and beam system comprises a round ball that moves along the length of a beam. The beam's inclination angle is controlled by a motor positioned at one end, which is mechanically linked to the beam through a connecting rod attached to a rotating disk [9]. The overall architecture of the proposed system is illustrated in Fig. 1, and its key parameters are summarized in Table 1.

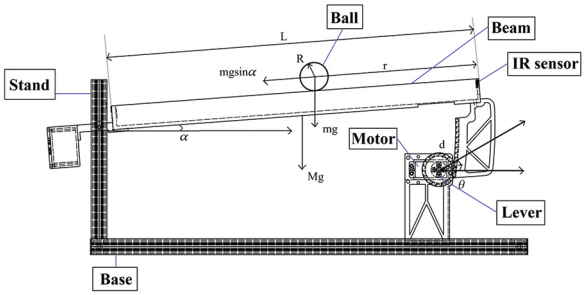


Fig. 1. Technical drawing of the ball and beam system

Table 1. Model parameters

Parameters	Unit	Value	Meaning
L	m	0.4	Length of the beam
m	kg	0.11	Mass of the ball
M	kg	0.4	Mass of the beam
g	m/s²	9.8	Gravitational acceleration
r	m	0.2	Ball position
R	m	0.015	Radius of the ball
α	rad	0	Beam angle coordinate
θ	rad	0	Servo gear angle
d	m	0.02	Lever arm offset

The motion of the ball is mainly affected by gravity and moment of inertia, making the system an unstable and nonlinear object. To build an effective controller, it is necessary to build an accurate mathematical model of the system [1].

According to the literature [9-13], we get the mathematical equation of the beam and ball system as follows:

$$\left(mr^2 + J_M\right)\ddot{\alpha} + 2mr\dot{r}\dot{\alpha} + \frac{L}{2}gM\cos\alpha + gmr\cos\alpha = \tau$$
$$\Leftrightarrow \ddot{\alpha} = \frac{\tau - 2mx_1x_2x_4 - \frac{L}{2}gM\cos x_3 - gmx_1\cos x_3}{mx_1^2 + J_M} \quad (1)$$

$$\left(m + \frac{J_m}{R^2}\right)\ddot{r} - mr\dot{\alpha}^2 + mg\sin\alpha = 0$$
$$\Leftrightarrow \ddot{r} = \frac{mx_1x_4^2 - mg\sin x_3}{m + \frac{J_m}{R^2}} \quad (2)$$

With J_M, J_m being the moments of inertia of the beam and the ball, τ is the torque generated by the motor.

The mathematical model derived from equations (1) and (2) is implemented in MATLAB/Simulink, as shown in Fig. 2.

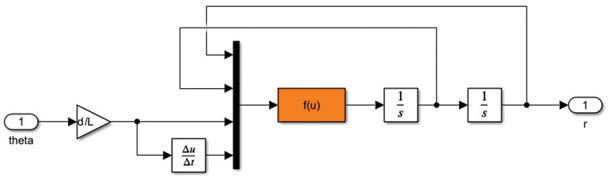


Fig. 2. Diagram of the ball and beam system in Simulink

3. DESIGN OF THE CONTROLLER

3.1. THE SNA-PID CONTROLLER

The PID controller is built by a linear neuron as shown in Fig. 3 [14].

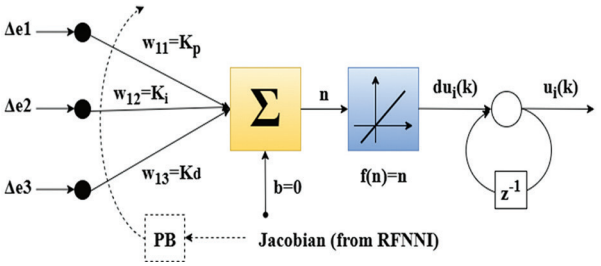


Fig. 3. Structure of the SNA-PID controller

According to the literature [14-15], the SNA-PID controller is designed based on a linear neuron architecture, in which the output neuron directly serves as the control signal of the system. The proportional, integral and derivative components are constructed from the difference between the system response and the reference signal, as expressed in (3).

$$\Delta e1 = e(k); \Delta e2 = \int_0^{\infty} e(k)dk; \Delta e3 = de(k)/dk \quad (3)$$

$$u(k) = u(k-1) + K_p \Delta e1 + K_i \Delta e2 + K_d \Delta e3 \quad (4)$$

Where, $e(k)$ with k = 1,2,3 is the difference between the reference signal and the system response.

The goal of training the single neuron PID is to adjust the network's weight set $w_{1i(i=1,2,3)}$ to minimize the cost function (5).

$$E(k) = \frac{1}{2} e^2(k) = \frac{1}{2}\left[y_{ref}(k) - y(k)\right]^2 \quad (5)$$

Where $y_{ref}(k)$ is the reference signal and $y(k)$ is the system response. To adjust the weight set $w_{1i(i=1,2,3)}$, the gradient descent method was applied [14]:

$$\begin{aligned} K_p &= w_{11}(k+1) = w_{11}(k) + \Delta w_{11}(k) \\ K_i &= w_{12}(k+1) = w_{12}(k) + \Delta w_{12}(k) \\ K_d &= w_{13}(k+1) = w_{13}(k) + \Delta w_{13}(k) \end{aligned} \quad (6)$$

Where $\Delta w_{1i}(k)_{|i=1,2,3}$ are gradients defined in references [14] and [16].

The SNA-PID controller is implemented using MATLAB S-functions, which are fully compatible with the standard Simulink library. The structure of the SNA-PID controller is illustrated in Fig. 4 [15].

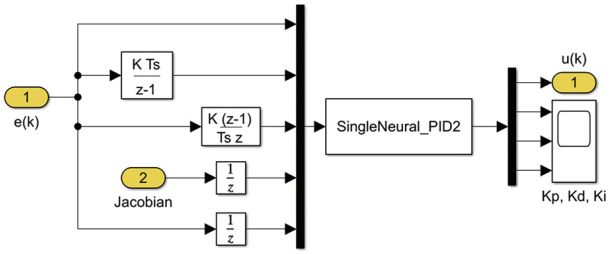


Fig. 4. The SNA-PID controller in Simulink

3.2. THE RFNN IDENTIFIER

The RFNN identifier has 4 layers, described as follows [14]:

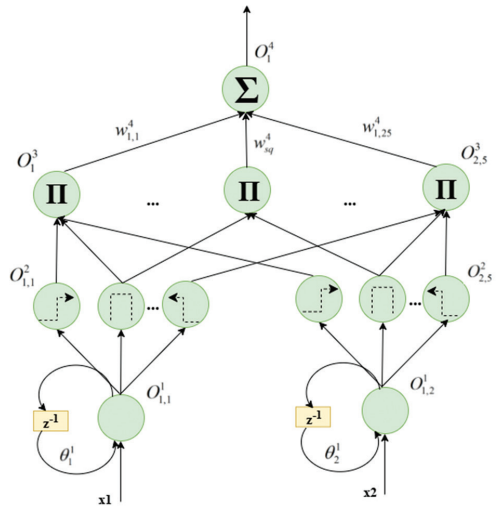


Fig. 5. The structure of the RFNN identifier

Layer 1 - Input layer is described as (7):

$$O_i^1(k) = x_i^1(k) + \theta_i^1 O_i^k(k-1), \quad i = 1,2 \quad (7)$$

With θ_i^1 is the connection weight at the current time k. The input of the corresponding RFNN identifier is the current control signal and the past output of the response:

$$\begin{aligned} x_1^1(k) &= u(k) \\ x_2^1(k) &= y(k-1) \end{aligned} \quad (8)$$

Layer 2 - Fuzzy layer: This layer consists of (2x5) nodes, each node representing a related function of the Gaussian form with a mean value m_{ij} and standard deviation, as defined in (9).

$$O_{ij}^2(k) = \exp\left\{-\frac{\left(O_i^1(k) - m_{ij}\right)^2}{\left(\sigma_{ij}\right)^2}\right\}, i = 1,2; j = 1,2,...,5 \quad (9)$$

Layer 3 - Law class: The output of the q node in this class is as follows:

$$O_q^3(k) = \prod_i O_{iq_i}^2(k), \; i = 1,2,...,5; q_i = 1,2,...,5 \quad (10)$$

Layer 4 - Output layer: This layer includes 1 linear neuron with the defined output as follows:

$$O_i^4(k) = \sum_j w_{ij}^4 O_j^3(k), \; i = 1; j = 1,2,...,25 \quad (11)$$

Where w_{ij}^4 is the connecting weights from the 3rd layer to the 4th layer. The output of this layer is also the output of the RFNN identifier:

$$\begin{aligned} O_1^4(k) &= y_m(k) = \hat{f}\left[x_1(k), x_2(k)\right] \\ &= \hat{f}\left[u(k), y(k-1)\right] \end{aligned} \quad (12)$$

The objective of the online training algorithm for the RFNNI is to adjust the network weight sets and the parameters of the fuzzy class-dependent functions to minimize the cost function defined in (13):

$$E(k) = \frac{1}{2}\left[y(k) - y_m(k)\right]^2 = \frac{1}{2}\left[y(k) - O_1^4(k)\right]^2 \quad (13)$$

The objective of RFNNI is to minimize the error between the estimated output and the actual system output by adaptively adjusting its connection weights and fuzzy parameters using an online backpropagation algorithm as reported in [14-17].

A particularly important role of the RFNNI is to compute the Jacobian information, which serves as a key element in facilitating the adaptive updating process of the SNA-PID controller. By providing accurate and timely sensitivity information, the RFNNI enables the control system to better capture the relationship between input variations and output responses, thereby enhancing system stability and reducing steady-state errors, even in the presence of noise and parameter uncertainties, as discussed in [14-15], and [16,19-20].

The RFNN identifier for the system is built in MATLAB's S-function as Fig. 6 [15].

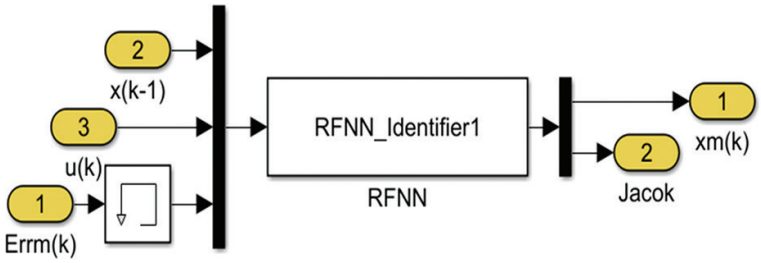


Fig. 6. The RFNN identifier in Simulink

The Jacobian information provided by the RFNNI is incorporated into the neuron weight update law, enabling the SNA-PID controller to assess the sensitivity of the system responds to control actions and to adapt the PID gains more flexibly over time [21].

4. DESIGN OF THE HARDWARE

4.1. SCHEMATIC DIAGRAM

The schematic diagram illustrates the ball and beam control system, in which an Arduino Mega 2560 serves as the central processing unit (Fig. 7). An infrared (IR) sensor is employed to measure the ball position and transmit analog signals to the Arduino via an analog input pin. The system is powered by an external adapter, and the supply voltage is regulated using an LJ245 buck converter, which steps down the input voltage from 12 V to appropriate levels (5 V) for the electronic components. Control signals generated by the Arduino are electrically isolated through a TLP281-4 optocoupler before being delivered to the motor driver. This isolation effectively protects the microcontroller from electrical noise and back electromotive force (back EMF) generated by the motor. Overall, the proposed hardware configuration ensures stable and safe operation, providing a reliable platform for implementing intelligent control algorithms.

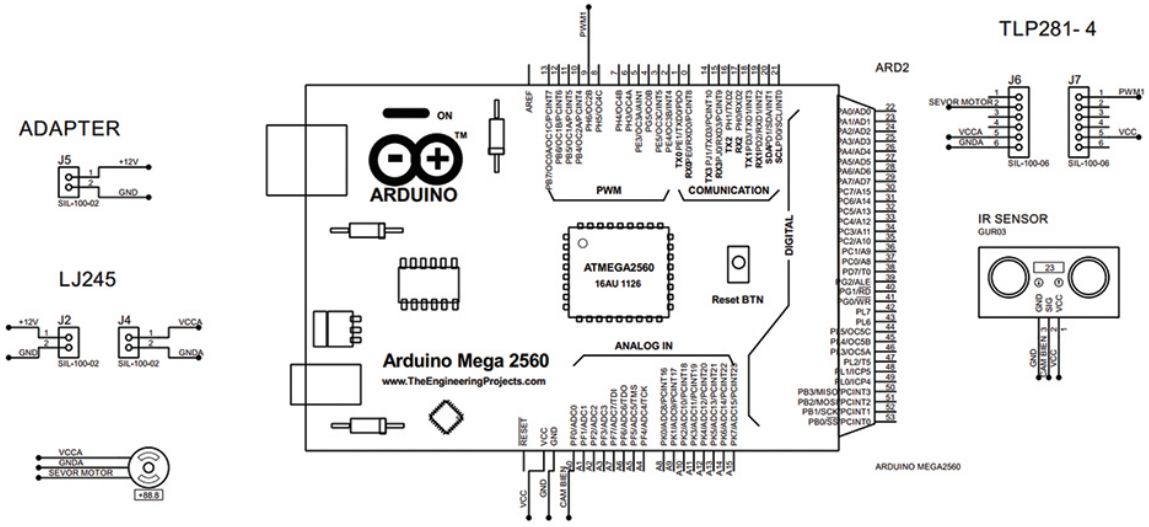


Fig. 7. Schematic diagram

4.2. EXPERIMENTAL MODEL

The system shown in Fig. 8 is an experimental ball and beam model designed to study adaptive control algorithms. The ball rolls freely along a horizontal beam equipped with a measurement scale to determine its position. The beam's tilt angle is adjusted by a motor driven through a 3D-printed gear mechanism. An Arduino Mega 2560 microcontroller serves as the central unit, collecting signals from an infrared (IR) sensor and sending control signals to the motor. Power is regulated through a buck converter to ensure system safety. Control algorithms such as PID or SNA–PID–RFNNI are executed on a computer and communicated to the Arduino via USB. When the ball deviates from the reference position, the controller adjusts the beam angle to return the ball to the desired position.

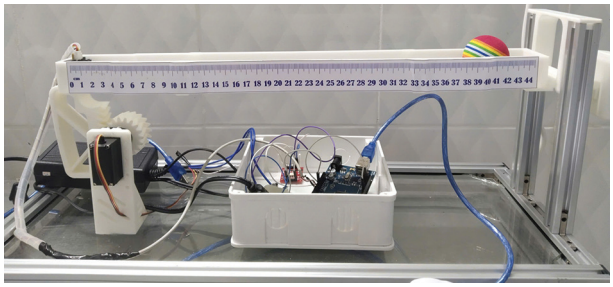


Fig. 8. Experimental model

Scan the QR code in Fig. 9 to watch the demonstration clip of the experimental setup for the ball and beam system.

Fig. 9. 3D technical drawing video

5. RESULTS AND DISCUSSION

5.1. SIMULATION

The control architecture of the proposed model is developed in MATLAB/Simulink, as illustrated in Fig. 10. The mathematical representation of the ball and beam system is derived from the differential equations described in Section 2. The parameters of the SNA-PID controller are determined using a trial-and-error approach combined with guidelines from reference [4]. The RFNNI consists of four primary layers: input, fuzzification, rule, and defuzzification. The identification network enables online adaptation through gradient backpropagation, generating both the system output signal and the Jacobian derivative, which reflects the sensitivity of the output to input variations. These outputs are utilized for the adaptive training process of the controller [22].

The ball and beam system controlled by the PID and SNA-PID-RFNNI algorithms is simulated under two operating conditions. In the first case, a fixed reference position of 21 cm, represented by a step input, is applied without output noise, and the corresponding responses are shown in Fig. 11. In the second case, a fixed reference position of 30 cm, represented by a constant input, is applied with output noise, and the resulting responses are presented in Fig. 12.

In Fig. 11, both the SNA-PID-RFNNI and PID controllers return the ball to the reference position (21 cm). However, the PID controller causes large oscillations and higher initial overshoot (27 cm), while the SNA-PID-RFNNI controller provides a smoother response, shorter recovery time, and less oscillation (23 cm).

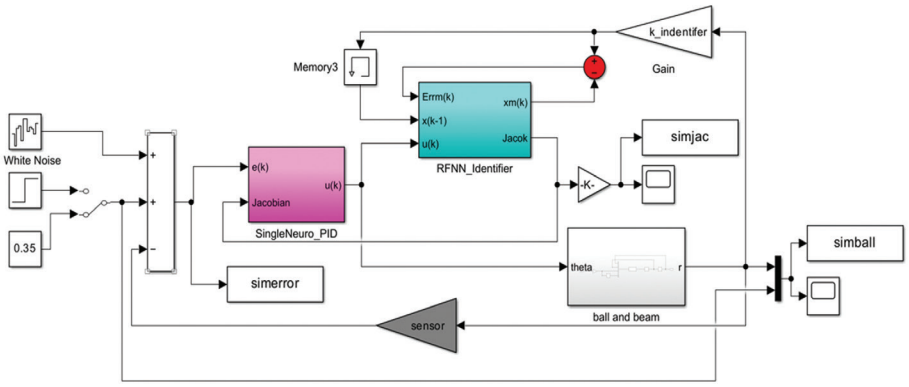


Fig. 10. The SNA-PID-RFNNI controller diagram

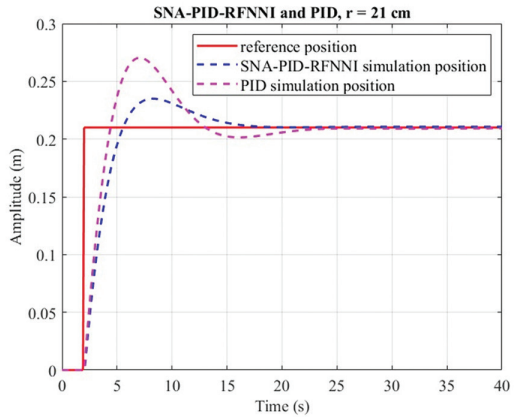


Fig. 11. Simulation results with r = 21 cm

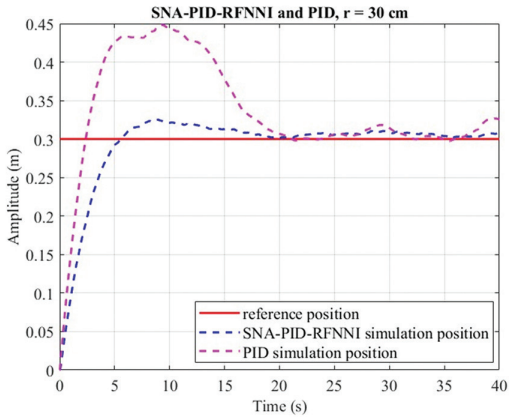


Fig. 12. Simulation results with r = 30 cm

When disturbances are present, in Fig. 12, the difference becomes more pronounced. The PID controller continues to have large overshoots (45 cm) and long settling times, while the SNA-PID-RFNN maintains a response close to the reference position (30 cm - 31 cm) with smaller oscillations.

The results in Table 2 indicate that the proposed SNA-PID-RFNNI controller provides a notable improvement over the conventional PID controller in terms of stability and steady-state performance. Specifically, the overshoot is significantly reduced from 44.26% (PID) to 6.28% with the SNA-PID-RFNNI scheme, while the set-

tling error decreases from 0.37 cm to 0.08 cm. Although the rise time (3.73 s) and settling time (17 s) of the proposed controller are longer than those achieved by the optimized Fuzzy-PID and GA-PID controllers, this behavior reflects a more conservative control action that prioritizes smooth responses and reduced oscillations.

Table 2. Compare some simulation quality indicators with four controllers

Controllers	Rise time (s)	Overshoot (%)	Settling time (s)	Settling error (cm)
PID [4]	2.35	44.26	23	0.37
Fuzzy-PID [24]	0.30	9.98	1.45	0.10
GA-PID [25]	0.225	3.68	1.08	0
SNA-PID-RFNNI	3.73	6.28	17	0.08

The ability of the SNA-PID-RFNNI controller to update its parameters online using Jacobian information provided by the RFNNI contributes to improved robustness and adaptability, particularly for nonlinear systems with uncertainties. These results demonstrate that the SNA-PID-RFNNI controller offers more accurate and stable control performance, particularly in reducing oscillations [23].

5.2. EXPERIMENT

The communication diagram between the DSP board and the IR sensor for both the SNA-PID-RFNNI controller and the conventional PID controller, implemented in the MATLAB/Simulink environment and applied to the ball and beam system, is illustrated in Fig. 13. The IR sensor signal is acquired through Arduino analog pin A0, converted from ADC values to distance, and then processed by a low-pass filter to reduce measurement noise. The filtered position signal is compared with the reference position (e.g., 20 cm) to generate the position error. This error signal is simultaneously supplied to the conventional PID controller and the proposed SNA-PID-RFNNI controller. A switching mechanism is used to select the active controller, and the selected control signal is transmitted to the actuator via Arduino digital pin 9.

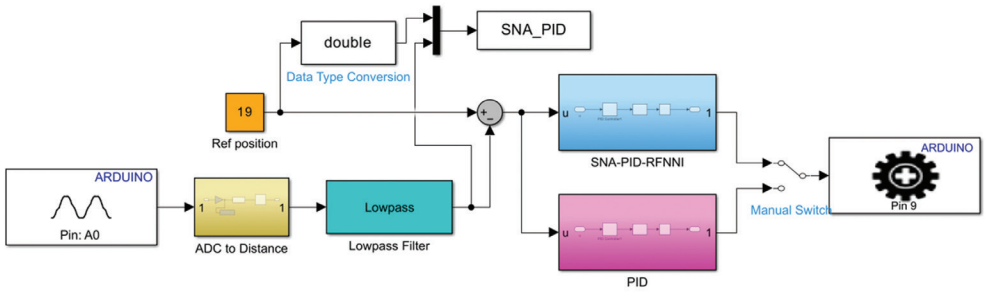


Fig. 13. The experimental diagram in Simulink for the two controllers

With the SNA–PID–RFNNI controller, the ball moves more gradually and stabilizes at the reference position (within the first 8 s in Fig. 14 and the first 10 s in Fig. 15). If a small external force displaces the ball, the controller successfully restores it to the desired position with only minor oscillations (observed from the 11th second onward in Figs. 14 and 15).

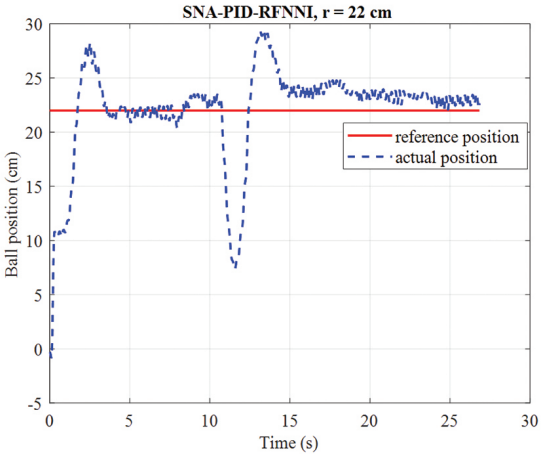


Fig. 14. Experimental result of the SNA-PID-RFNNI controller with r = 22 cm

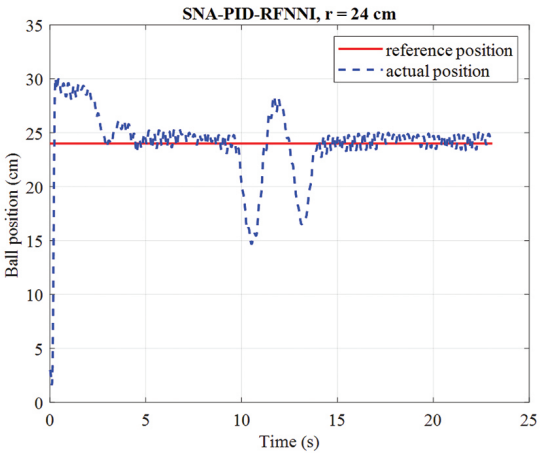


Fig. 15. Experimental result of the SNA-PID-RFNNI controller with r = 24 cm

Fig. 16 shows the experimental results of the ball position using two controllers: the traditional PID and the SNA–PID–RFNNI, with a reference position set at 20 cm.

With the conventional PID controller, the system output exhibits strong oscillations around the reference value of 20 cm. The transient response is characterized

by large oscillation amplitudes (28 cm), multiple overshoots, and a long settling time (13 s) [26]. Although the signal eventually approaches the desired position, the tracking accuracy remains limited and the stability in the initial phase is relatively poor.

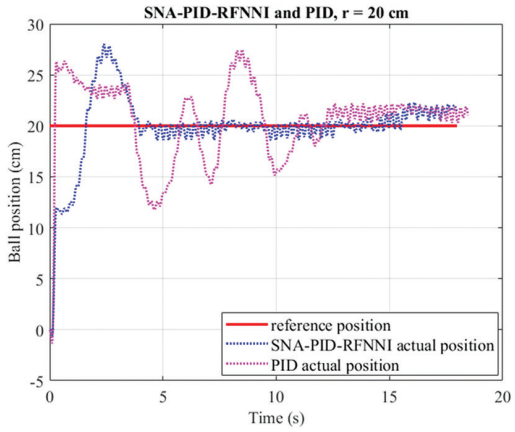


Fig. 16. Experimental results of the two controllers

In contrast, the SNA-PID-RFNNI controller enables the system output to quickly track the reference position (5 s) with minimal oscillation. The settling time is significantly shorter compared to PID, while overshoot is effectively suppressed [27, 28]. Notably, the response remains stable throughout the entire process, converging rapidly to 20 cm without sustained oscillations.

The quality indicators between the two controllers obtained from the experimental results are presented in Table 3.

Table 3. Compare some experimental quality indicators between the two controllers

Controllers	Overshoot (%)	Settling time (s)	Settling error (cm)
PID	35.26	15	2.32
SNA-PID-RFNNI	18.54	5	0.85

This demonstrates the superior adaptability and control quality of the intelligent controller compared to the conventional PID.

Scan the QR code in Fig. 17 to watch the demonstration clip of the experimental operation of the ball and beam system.

Fig. 17. Experiment video

6. CONCLUSION

This paper has presented the design, simulation, and experimental validation of an SNA-PID-RFNNI controller for the nonlinear and unstable ball and beam system. The proposed controller integrates a single neuron adaptive PID structure with a recurrent fuzzy neural network identifier, enabling online updating of the control parameters based on the system Jacobian information [29]. Simulation results demonstrate that the SNA-PID-RFNNI controller significantly improves control performance compared with the conventional PID controller, with the overshoot reduced from 44.26% to 6.28% and the steady-state error decreased from 0.37 cm to 0.08 cm, while maintaining smooth and stable responses. Although the rise time and settling time are longer than those of some offline-optimized controllers, the obtained results clearly indicate the adaptability and robustness of the proposed control scheme [30, 31].

Compared with the study by C. N. Nguyen *et al*. in [14], the proposed approach in this work has been successfully implemented on a physical experimental model. The experimental results further confirm the effectiveness of the proposed method, with the overshoot reduced from 35.26% to 18.54%, the settling time shortened from 15 s to 5 s, and the steady-state error decreased from 2.32 cm to 0.85 cm in comparison with the conventional PID controller. These results demonstrate the feasibility and practical effectiveness of the SNA-PID-RFNNI controller under real operating conditions. In future work, both simulation and experimental studies will be extended by applying other intelligent control techniques, such as the Genetic Algorithm (GA), Firefly Algorithm (FA), and Bee Algorithm (BA), to further evaluate and compare system performance.

ACKNOWLEDGMENT

The authors have no acknowledgments to declare.

DECLARATION OF THE USE OF AI TOOLS

The authors used ChatGPT for drafting descriptions of the "Schematic diagram" and "Experimental model." Google Gemini was used for improving the final conclusion. Grammarly was used for language editing and grammar correction. All AI-assisted content was reviewed and approved by the authors, who take full responsibility for its accuracy and integrity; no AI tools are listed as authors or cited as primary sources.

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