EXPERIMENTAL ANFIS-FUZZY CONTROLLER FOR BALL AND BEAM SYSTEM

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ABSTRACT: This paper presents the development of an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller for a mid-pivot Ball and Beam system. The nonlinear dynamic model is derived using Euler–Lagrange formulation, followed by DC motor modeling to construct the full state-space system. An ANFIS controller is trained from PID-generated data to enhance adaptability under nonlinear conditions. Simulation and hardware experiments validate the controller's performance. Results show that the proposed controller can stabilize the system with reasonable accuracy, although overshoot and oscillation remain. Directions for improving intelligent control and hardware design are discussed.

KEY WORDS: Ball and Beam, ANFIS, Fuzzy Control, Nonlinear Control, Experimental Validation.

1. INTRODUCTION

The Ball and Beam (BnB) system is a widely recognized benchmark problem in nonlinear control engineering due to its inherent open-loop instability and the strong dynamic coupling between the translational motion of the ball and the rotational dynamics of the beam [1], [2]. To accurately capture these characteristics, nonlinear modeling approaches based on Newtonian or Lagrangian mechanics have been widely adopted, as they provide a more precise representation of system dynamics compared to linear approximations and are therefore more suitable for advanced controller design [3]–[5].

A wide range of control strategies has been explored for this system, including traditional PID controllers, Linear Quadratic Regulators (LQR), fuzzy logic, and other intelligent control methods [1], [4], [6]. Among these, fuzzy-based approaches have received considerable attention due to their robustness in handling nonlinearities and uncertainties [7]–[9]. Fuzzy logic control (FLC) offers advantages over traditional methods like PID by employing a rule-based inference mechanism that is robust against nonlinearities and model uncertainties [9]. For instance, studies have demonstrated that fuzzy controllers can outperform classical linear controllers in BnB applications [8], and their effectiveness has been confirmed in specific configurations [7]. Comparative analyses indicate that both Mamdani and Sugeno fuzzy controllers provide smoother responses and improved tracking performance relative to conventional PID control [10]. To further enhance adaptability, hybrid approaches such as fuzzy-PID have been introduced, showing improved performance under varying operating conditions [11]–[15]. Fuzzy PID controllers simplify tuning problems, particularly in systems with complex dynamics [15].

More recently, neuro-fuzzy techniques, including Adaptive Neuro-Fuzzy Inference Systems (ANFIS) and NEFCON, have demonstrated superior tracking accuracy and smoother control actions by combining the learning capability of neural networks with the reasoning structure of fuzzy logic [16]. ANFIS, for example, has been shown to stabilize highly nonlinear systems like the triple inverted pendulum with better performance compared to PID controllers [17]. The design of an adaptive neuro-fuzzy inference system has been explored for uncertain ball and beam apparatus, highlighting its capability to handle systems with complex dynamics without requiring in-depth knowledge of the system [16].

Despite these advancements, several limitations remain. Many existing studies rely on simplified or partially linearized models that neglect important factors such as friction, sensor noise, and nonlinear coupling effects, thereby limiting their applicability in real-world implementations [18]. Additionally, conventional fuzzy controllers typically depend on manually defined membership functions and rule bases, which can restrict their adaptability and scalability [19]. These issues become more pronounced in mid-pivot Ball and Beam configurations, where symmetric geometry introduces additional nonlinearities that are less frequently addressed in the literature.

Based on these identified gaps, a promising research direction involves developing an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller for a mid-pivot Ball and Beam system. This approach typically begins with deriving a complete nonlinear model using methods like the Euler–Lagrange equation, integrating it with a DC motor model to accurately represent the system dynamics [20]. The ANFIS controller can then be trained using datasets generated from a well-tuned PID controller, which enables automatic learning of nonlinear control behavior without the need for manual rule tuning [21]. This training process leverages the ANFIS's ability to approximate complex functions, making it a powerful tool for controlling nonlinear dynamic systems [22]. Finally, the proposed control scheme's performance is evaluated through rigorous MATLAB/Simulink simulations and hardware experiments to assess its tracking performance and robustness under nonlinear operating conditions [10]. Such an approach aims to combine the strengths of fuzzy logic in handling imprecision with the adaptive learning capabilities of neural networks to address the challenges posed by nonlinear and uncertain systems.

2. SYSTEM MODEL

The mathematical model of the mid-pivot Ball and Beam system describes the nonlinear interaction between the rolling motion of the ball and the rotational dynamics of the beam. Two generalized coordinates are defined, namely the ball position p along the beam and the beam rotation angle θ about its midpoint.

To derive the system dynamics, the Euler–Lagrange formulation is employed, as expressed in (1), where the system behavior is obtained from the difference between kinetic and potential energies. The total kinetic energy of the system is formulated in (2), incorporating both the translational motion of the ball and the rotational inertia of the beam. Meanwhile, the potential energy, given in (3), represents the gravitational effect acting on the ball position along the inclined beam.

$$L = K - U \tag{1}$$

$$K = \frac{1}{2}m\dot{p}^2 + \frac{1}{2}J_b\dot{\theta}^2 + m\dot{p}\dot{\theta}r\cos(\theta) \quad (2)$$

$$U = mgrsin(\theta) \quad (3)$$

By applying the Euler–Lagrange equation for each generalized coordinate, as shown in (4), the governing dynamics of the system are obtained. This process results in a set of coupled nonlinear equations of motion, presented in (5) and (6), which describe the interaction between the ball position and beam angle. In these equations, the input torque applied to the beam is generated by the actuator system.

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = Q_i \quad (4)$$

$$m\ddot{p} + mr\ddot{\theta}\cos(\theta) - mr\dot{\theta}^2\sin(\theta) = 0 \quad (5)$$

$$J_b\ddot{\theta} + mr^2\ddot{\theta} + mgrcos(\theta) = T_m \quad (6)$$

To accurately represent the actuation mechanism, the DC motor dynamics are incorporated into the model. The electrical behavior of the motor is described by (7), while the mechanical dynamics are given in (8). These equations include motor parameters such as inductance and resistance, as well as back electromotive force and torque constants. The relationship between angular velocity and damping effects is further defined in (9). The motor torque is transmitted to the beam through a gear mechanism, which introduces an additional scaling factor in the system.

$$V = L\frac{di}{dt} + Ri + K_b\omega \quad (7)$$

$$T_m = K_t i - D_m\omega \quad (8)$$

$$\omega = \dot{\theta} \quad (9)$$

By combining the mechanical dynamics of the Ball and Beam system with the electrical dynamics of the DC motor, a complete nonlinear model is established. The system is then expressed in state-space form by defining the state variables as given in (10)–(13). Based on these definitions, the overall nonlinear state equations are formulated in (14)–(16), where the input to the system is the motor voltage and the system constants depend on the physical parameters.

$$x_1 = p \quad (10)$$

$$x_2 = \dot{p} \quad (11)$$

$$x_3 = \theta \quad (12)$$

$$x_4 = \dot{\theta} \quad (13)$$

$$\dot{x}_1 = x_2 \quad (14)$$

$$\dot{x}_2 = -\frac{g}{r}\sin(x_3) - c_1x_2 + c_2u \quad (15)$$

$$\dot{x}_4 = c_3x_2 + c_4u \quad (16)$$

For controller design purposes, the nonlinear model is linearized around an equilibrium operating point, as defined in (17). The resulting linear state-space representation is obtained using Jacobian matrices, which provide a local approximation of the nonlinear dynamics. This linearized model is subsequently used as the foundation for initial PID controller design and for generating training data in the ANFIS learning process.

$$(p = 0, \theta = 0): \dot{x} = Ax + Bu \quad (17)$$

3. SYSTEM MODEL

This section presents the overall control methodology developed to regulate the mid-pivot Ball and Beam system. The primary control objective is to maintain the ball at a desired reference position by adjusting the beam angle through a DC motor actuation mechanism. Due to the inherent nonlinear dynamics of the system, as described in (5)–(6), and the limitations of conventional linear controllers derived from the linearized model in (17), an Adaptive Neuro-Fuzzy Inference System (ANFIS) is adopted as the main control strategy.

The proposed control framework begins with the development of a nonlinear mathematical model based on Euler–Lagrange mechanics combined with the DC motor dynamics, as formulated in (1)–(9). This model is then transformed into a nonlinear state-space representation, as given in (14)–(16), which serves as the basis for system analysis and controller design. For initial stabilization and data generation purposes, the model is linearized around its equilibrium point using (17), and a PID controller is designed based on this linear approximation.

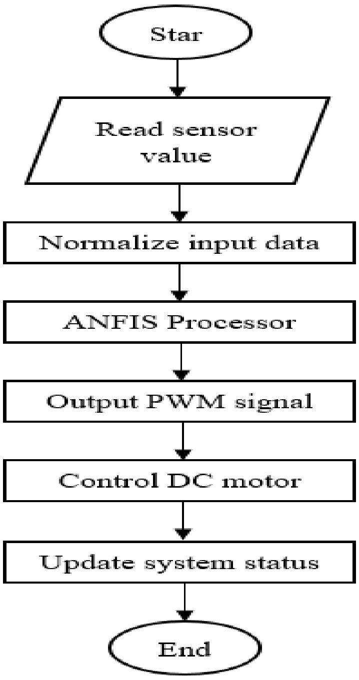


Fig. 1. Algorithm flowchart for ball and beam system

The PID controller plays a dual role in this study. First, it ensures baseline closed-loop stability of the system. Second, it is used to generate high-quality input–output datasets required for training the ANFIS controller. These datasets are obtained under various excitation conditions, including step, ramp, and sinusoidal inputs, capturing the system states—namely ball position, velocity, beam angle, and angular velocity—as defined in (10)–(13), along with the corresponding control signals produced by the PID controller.

The ANFIS controller is then constructed to learn the nonlinear mapping between the system states and the control input. The structure of the ANFIS consists of four inputs $(p, \dot{p}, \theta, \dot{\theta})$, each represented by three membership functions, resulting in a total of 81 fuzzy rules within a Sugeno-type inference system. Its five-layer architecture enables automatic tuning of membership function parameters and rule consequents through a hybrid learning algorithm that combines gradient descent and least squares estimation. Through this training process, the ANFIS controller is capable of approximating the nonlinear control law inherent in the system dynamics.

After the training phase, the ANFIS controller is implemented within a real-time closed-loop control system. During operation, sensor measurements—primarily the ball position obtained from an ultrasonic sensor and the beam angle estimated from motor feedback—are processed and normalized before being fed into the ANFIS network. The controller output is then converted into a pulse-width modulation (PWM) signal, which drives the DC motor via the L298N driver. This process is executed continuously, forming a closed feedback loop that regulates the system in real time.

The overall control workflow, including data generation, training, and real-time implementation, is illustrated in Fig. 1, which summarizes the interaction between the modeling, PID-based learning phase, and ANFIS-based control execution.

4. RESULTS

4.1. Real System Implementation

The experimental setup of the mid-pivot Ball and Beam system is shown in Fig. 2, which illustrates the main hardware components, including the ultrasonic sensor, rolling ball, beam, central pivot support, and DC servo motor. The Arduino Uno functions as a low-level real-time controller responsible for acquiring sensor measurements, generating PWM signals for motor actuation, and enabling bidirectional communication with MATLAB/Simulink.

This configuration establishes a hardware-in-the-loop (HIL) control framework, where high-level control algorithms such as PID and ANFIS are executed on a PC, while the Arduino handles real-time sampling, signal conditioning, and actuator interfacing. This separation ensures both computational flexibility and real-time responsiveness.

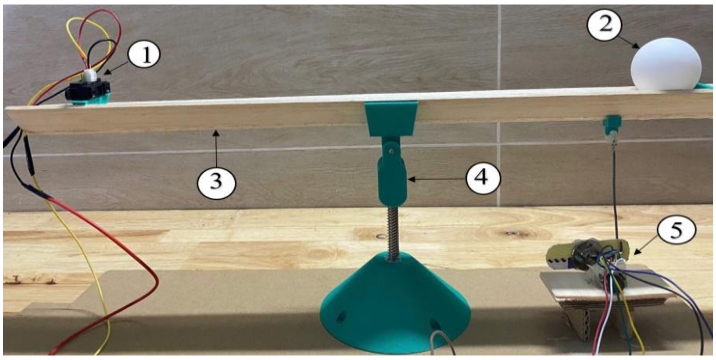


Fig. 2. Real model of ball and beam system: (1) Ultrasonic sensor, (2) Rolling ball, (3) Beam, (4) Central pivot support, (5) DC servo motor

4.2. Simulation Model in MATLAB/Simulink

Prior to experimental implementation, a MATLAB/Simulink model is developed, as shown in Fig. 3, to validate the proposed control strategy under controlled conditions. The model consists of four main functional blocks representing sensing, processing, and actuation mechanisms.

The Distance Measurement Block simulates the ultrasonic sensor by converting ADC signals into distance measurements using a nonlinear calibration function, thereby incorporating realistic noise characteristics. The Position-to-Angle Conversion Block generates the desired beam angle using a nonlinear PD-like structure, where the proportional gain decreases as the ball approaches the setpoint to reduce overshoot.

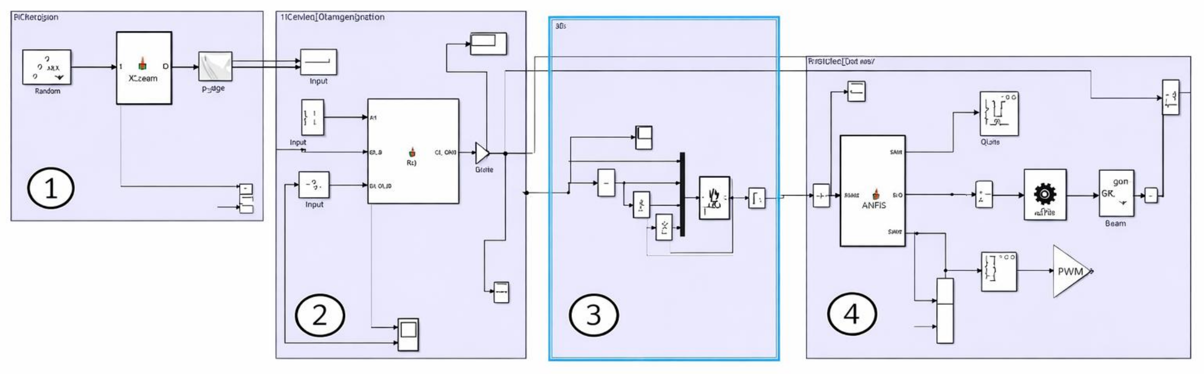
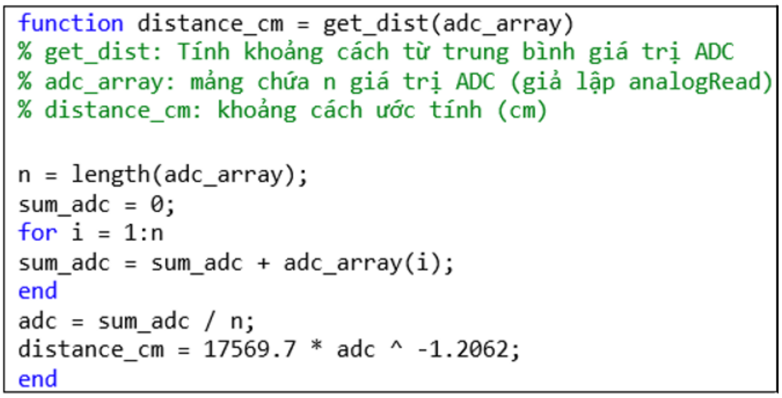


Fig. 3. Ball and beam system on Matlab Simulink

Furthermore, the Motor Control Block models the DC motor and driver dynamics by translating controller outputs into PWM and directional signals while considering practical constraints such as minimum torque and saturation limits. The ANFIS Controller Block processes system states to generate control signals based on the trained neuro-fuzzy inference system, enabling real-time nonlinear control behavior.

The embedded implementation code used for real-time execution is presented in Fig. 4, which ensures consistency between simulation and hardware operation.



```
function distance_cm = get_dist(adc_array)
% get_dist: Tính khoảng cách từ trung bình giá trị ADC
% adc_array: mảng chứa n giá trị ADC (giả lập analogRead)
% distance_cm: khoảng cách ước tính (cm)

n = length(adc_array);
sum_adc = 0;
for i = 1:n
sum_adc = sum_adc + adc_array(i);
end
adc = sum_adc / n;
distance_cm = 17569.7 * adc ^ -1.2062;
end
```

Fig. 4. Code to run the actual model

4.3. Control Performance Evaluation

The performance of the proposed ANFIS controller is evaluated through both simulation and real-time experiments using step reference inputs. The system response comparison between PID and ANFIS controllers is illustrated in Fig. 5.

During the transient phase, both controllers successfully stabilize the system; however, the PID controller exhibits higher overshoot and longer settling time. In contrast, the ANFIS controller produces a smoother response with reduced oscillations, indicating its superior capability in handling nonlinear dynamics.

The ANFIS controller reduces overshoot from 18.5% (PID) to 10.2%, decreases settling time from 4.2 s to 3.1 s, and improves steady-state accuracy by reducing the error from 0.85 cm to 0.42 cm. These results confirm that ANFIS provides enhanced transient performance and improved tracking precision.

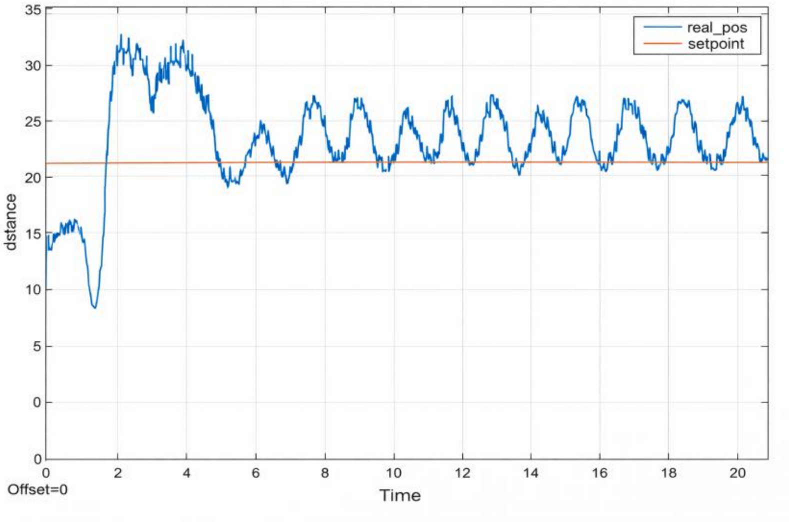


Fig. 5. Beam angle output response to set value

4.4. Dynamic Response Analysis

Further insight into system behavior is obtained from the beam angle response shown in Fig. 5. The response demonstrates a typical nonlinear transient-to-steady-state transition. In the initial phase (0–2 s), the system exhibits a rapid rise with noticeable overshoot due to aggressive control action and system inertia.

Between 2 s and 4 s, the response gradually converges toward the reference as the controller compensates for nonlinear effects. Beyond 5 s, the system reaches a quasi-steady-state condition with small oscillations around the setpoint. These residual oscillations are mainly attributed to sensor noise, mechanical backlash, and unmodeled friction.

4.5. Discussion

The combined simulation and experimental results demonstrate that the ANFIS controller effectively captures the nonlinear characteristics of the Ball and Beam system. Under various reference inputs, including step and sinusoidal signals, the ANFIS controller maintains stable tracking while improving transient performance compared to the conventional PID controller.

Although minor steady-state oscillations persist, the overall control performance is significantly improved due to the adaptive learning capability of ANFIS. These findings indicate that ANFIS is a robust and effective control strategy for nonlinear electromechanical systems. Future improvements may focus on enhancing sensor accuracy, reducing mechanical imperfections, and refining the training dataset to further improve system robustness and performance.

5. CONCLUSION

This study developed and validated an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller for a mid-pivot Ball and Beam system characterized by nonlinear dynamics, open-loop instability, and coupling between ball motion and beam rotation. A complete nonlinear model was first established using the Euler–Lagrange method and integrated with DC motor dynamics to provide a more realistic representation of the system. Based on the linearized model, a PID controller was designed to ensure initial closed-loop stability and to generate training data for the ANFIS learning process.

The results from MATLAB/Simulink simulation and hardware-in-the-loop experiments demonstrate that the proposed ANFIS controller outperforms the conventional PID controller in terms of transient and steady-state performance. Specifically, ANFIS reduced overshoot from 18.5% to 10.2%, shortened the settling time from 4.2 s to 3.1 s, and decreased the steady-state error from 0.85 cm to 0.42 cm. In addition, the controller produced a smoother response with lower oscillation amplitude, indicating better capability in handling nonlinear effects and uncertainty.

The proposed ANFIS-based approach provides a robust and effective solution for controlling the mid-pivot Ball and Beam system. These findings confirm that data-driven neuro-fuzzy control can serve as a practical alternative to conventional controllers for nonlinear electromechanical systems. Future work should focus on improving sensor accuracy, reducing mechanical backlash and friction effects, and enriching the training dataset to further enhance robustness and control precision.

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APPENDIX

Operation of operation of system is shown in link:

https://www.youtube.com/watch?v=0FeNsiqkZdk

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