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Real-time control of ball balancer using neural integrated fuzzy controller

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Abstract
This paper presents the design, control, and validation of two degrees of freedom Ball Balancer system. The ball and plate system is a nonlinear, electromechanical, multivariable, closed-loop unstable system on which study is carried out to control the position of ball and plate angle. The model of the system is developed using MATLAB/Simulink, and neural integrated fuzzy and its hybridization with PID have been implemented. The performance of each controller is evaluated in terms of time response analysis and steady-state error. Comparative study of simulation and real-time control results show that by using the neural integrated fuzzy controller and neural integrated fuzzy with proportional-integral-derivative Controller, the peak overshoot is reduced as compared with the PID controller and lead the system prone to appropriate balancing. These control techniques provide a stable and controlled output to the system for ball balancing and plate angle control.

Keywords Ball balancer system · Neural integrated fuzzy control · Neural integrated fuzzy with PID control · Proportional-integral-derivative control

1 Introduction

Control system is a zone that trade with disciplines and approaches leading an automatic decision development to advance the performance of control benchmark problems (Murray et al. 2003). The evolution of control theory is related to analytical controller design methods, research advances in technology and their real-time implementation (Bars et al. 2006; Murray 2003). There are many control benchmark problems that carry concern about engineering systems. The most common benchmarks are Hovercraft (Aranda et al. 2006), Two tank experiment (Smith and Doyle 1988), the Twin rotor MIMO system (Chalupa et al. 2015), the Furuta Pendulum (Acosta 2010), the inverted pendulum (Boubaker 2012), the Beam-and Ball-system (Andreev et al. 2002) and the ball and plate system (Hauser et al. 1992). In

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control education, The Ball, and Plate system used to be a most significant traditional control benchmark application. In this system, a ball moving on the top of a plate and plate is mounted on the output shaft of an electrical motor. Balancing of the ball is possible about its center axis by applying an electrical control signal. Initially, conception, modeling, and development of ball on the plate balancing system have been carried out using mechatronic design (Awtar et al. 2002). Simulations and designing of mathematical modeling, kinematic constraints and dimensional analysis of the system have been carried out (Ham and Taufiq 2015). Various control designs have been demonstrated for positioning and trajectory tracking control of the ball.

In classical control, switching controller has been developed to track the trajectory of the ball based on the non-linear analysis (Tian et al. 2006) and reliant on Lyapunov stability theory. The back-stepping controller has been designed and generated specific control law to achieve the control performance (Ker et al. 2007) quickly. In another approach, a novel PID controller has been developed based on Generalized Kalman–Yanukovych–Popov lemma method and compared with standard PID in terms of steady-state response (Mochizuki and Ichihara 2013). Further, nonlinear PID controller has been designed for point to point control of the system (Sun and Li 2012). Ball and Plate model represented by Virtual Laboratory using 3D java simulation follows the predefined trajectory for the ball and achieved stability at every instant (Fabregas et al. 2015). The position of the ball is measured with a machine vision system. The image processing algorithms of the machine vision system have been pipelined and executed on a field programmable gate array (FPGA) device to meet real-time constraints (Ho et al. 2013). An innovative disturbance observer using ADRC methodology is designed to avoid harmful friction effects for balance control of the ball on the plate (Wang et al. 2014), and comparison between repetitive and resonant controller has been made based on LQR synthesis (Da Silveira Castro et al. 2014). Assessment of various control strategies has been applied on B&P with 6-DOF Stewart platform (Kassem et al. 2015). The full state feedback linearizing control law was established and could control centrifugal terms as well as coupling between the coordinate axis (Hoover and Amand 2012).

From the literature survey, it is found that time response of the ball position and plate angle using standard controllers can be improved. Hence, designing of advanced controllers on the ball and plate model can be taken up as a huge void in the research. Fuzzy (Fan et al. 2004; Lo et al. 2003; Yuan and Zhang 2010), sliding mode controller (Hammadih et al. 2016), fractional order sliding mode controller (Das and Roy 2017) with improved tracking accuracy, less chattering and excellent efficiency, etc. have been designed for balancing and trajectory tracking of the ball on a plate. It is difficult to find proper fuzzification, de-fuzzification method, and fuzzy rules. So, neuro-fuzzy identifiers are proposed to solve this problem (Lee et al. 1994). Complexed and metacognitive valued neuro-fuzzy systems are designed and studied over different control problems (Subramanian et al. 2014). Neuro-fuzzy system application has been reviewed in student modeling system, unknown nonlinear system, electrical and electronics system, traffic control, image processing and feature extraction, NFS enhancements and social sciences, technical diagnostics and measurement (Kar et al. 2014; Bosque et al. 2014; Viharos and Kis 2015; Hsu et al. 2013). Neural network with fuzzy has been proposed for nonlinear dynamic ball balancing on beam (Ng et al. 1996). A learning model has been designed based on neural-fuzzy system theory for the ball-beam system (Tzeng and Hung 2009). Modeling of the ball-beam system and designing various controllers like SMC, FLC, neuro-fuzzy hybrid controller has been done for balancing purpose (Swarnkar 2011). Neural integrated fuzzy (NiF) and neural integrated fuzzy-proportional-integral-derivative (NiF-P) controllers have not been implemented on the ball balancer system till now. In this work, authors have tested simulation and real-time implementation of above controllers on the ball balancer system successfully. Due to its inherent complexity, the ball balancer system provides complications, such as (1) balancing the ball on a plate and (2) point stabilization control, to carry the ball to a specific position and hold it there minimizing the tracking error and time. This paper contributes towards the mathematical modeling, appropriate parameter selection, and exemplary controller design for the ball balancer system to overcome the above-mentioned problems. The idea of applying the hybrid algorithms for control of the ball balancer system is relatively new.

The aim of the research is to compare control techniques implemented on the ball balancer. Work in the writing focus firstly on modeling of ball balancer setup, and secondly, the attention is on designing and implementation of controllers for ball balancer setup using Simulink and in real-time as well. Adapting hybrid algorithm for optimizing controllers proved to be a novel adaption, and its implication was depicted in the results for Ball Balancer. Lastly, the comparison is carried out based on PID, NiF, and NiF-P on ball balancer. The rest parts of the paper are organized as follows: Sect. 2 describes the ball balancer setup modeling and its working Phenomena. Section 3 is about designing PID, NiF, and NiF-P controllers for observation of the slope of the plate from the measurement of the ball position. Section 4, provides the comparative simulations and Real-Time experimental results to verify the proposed methodology. Finally, Sect. 5 presents the conclusion followed by references. As per the future aspects of work, it is possible to implement various optimization techniques on the Ball Balancer for balancing purpose.

2 Ball balancer model

The two degree of freedom Ball Balancer model consists of the square metal plate, which is movably fixed in the center through center gimble joint. For ball balance in both the directions SRV02 unit, a standard servo motor instrumented with potentiometer has been used. The control problem for the setup is to balance the ball on a plate. The block diagram of Ball Balancer system shown in Fig. 1, explains setup's working. Initially, a control signal is taken from hardware setup, i.e., the inclination of the plate and fed to the DAQ (Data Acquisition device) measure the physical movement of the ball regarding voltage. DAQ sends the signal to the controller and coordinates with the signal from the camera through signal processing block working then combined output then returned to the DAQ and forwarded to the power amplifier for signal modification and then to the hardware eventually and progress continues. The hardware requirements are HIL boards named data-acquisition card(Q2-USB), two rotary servo base unit (SRV02-ET) for x–y axis plate angle control and power amplifier (VOLTPAQ-X2). Laboratory setup of two degrees of freedom Ball Balancer is shown in Fig. 2.

When compared to the previously existing system with advancement in technology has led to making the setup reduced in complexity and easy for building it. As per the advancement from the previous setup the existing setup doesn't require any external controller kits as all the component required to carry out the control are well integrated within the setup and make it easy for optimization of controlling techniques. The system consists of an SRV02 unit which is implemented for position and balance control in current application and can be further used for vibration, gantry, self-erecting controls in various other application such as single and double inverted pendulum, solar tracker, etc. All the above make the overall system application economic.

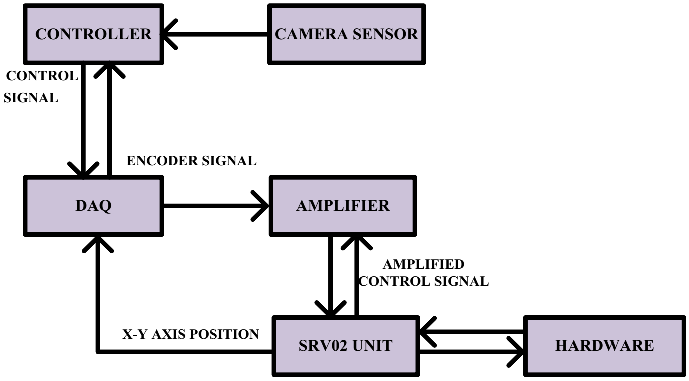


Fig. 1 Block diagram of ball balancer

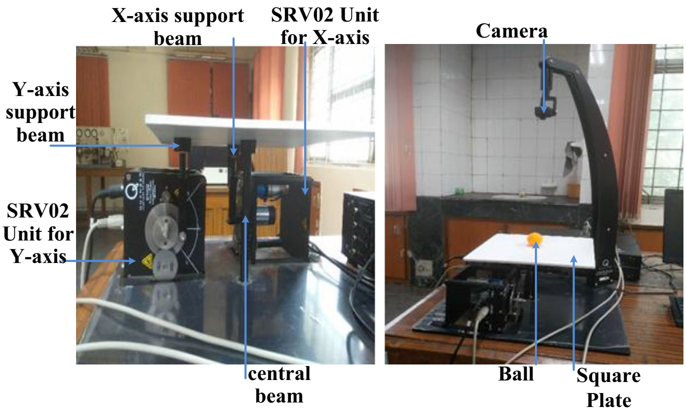


Fig. 2 Laboratory ball balancer setup

The transfer function of plant model is given in 2.1, the equation of motion representing the ball's motion along the x-axis relative to the plate angle is developed in 2.2, and the servo angle is introduced into the model in 2.3.

2.1 Transfer function of plant model

The block diagram of open loop transfer function model of Ball Balancer is shown in the Fig. 3. Dynamics between the resulting load angle and servo input voltage (SRV02) represents the transfer function $W_S(s)$. Dynamics of the position of the ball and the angle of the servo load gear is described by the $W_{SS}(s)$. As this is decoupled system, so the actuator dynamics of x-axis will not affect y-axis actuator dynamics and the SRV02 device is symmetrical for both x-axis and y-axis hence modeling is done only for one axis. Single axis (x-axis) block diagram for the 2D Ball Balancer is now denoted as a 1D Ball Balancer.

So, the complete transfer function is 1D Ball Balancer + SRV02 unit is:

$$W(s) = W_{ss}(s)W_s(s)$$

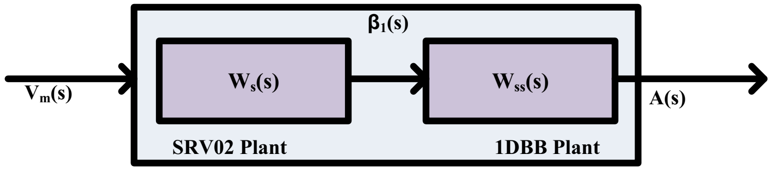


Fig. 3 Block diagram of the open loop 1D-ball balancer model

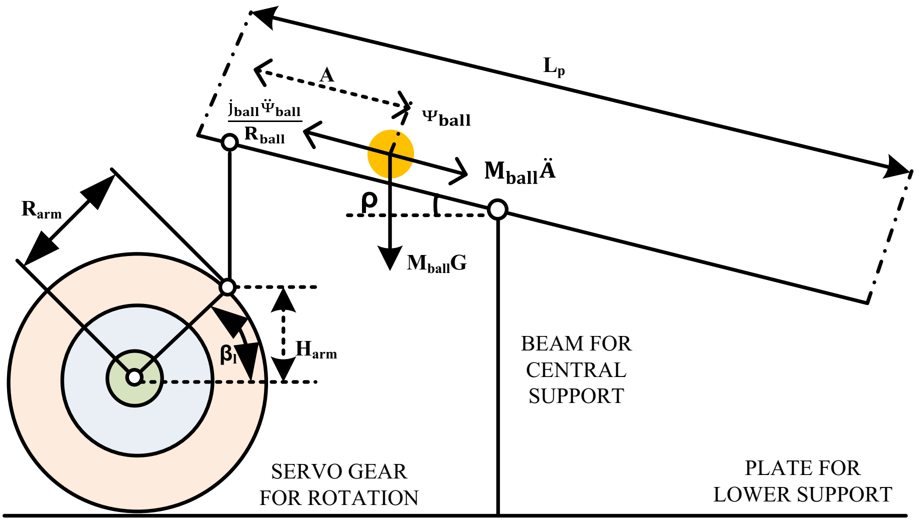


Fig. 4 Free body diagram of Ball and Plate setup

where,

$$W_{ss}(s) = \frac{A(s)}{\beta_l(s)}, W_s(s) = \frac{\beta_l(s)}{V_m(s)} \tag{1}$$

2.2 Nonlinear equation of motion from the first principle

Ball and Plate system is illustrated below by the free body diagram in Fig. 4. With the help of the equation of motion, movement of the ball to the plate angle can be found. Grounded on Newton's First Law of Motion, some forces applying on the ball along the plate equal to

$$M_{ball}\ddot{A}(t) = \sum F = F_{x,t} - F_{x,r} \tag{2}$$

where M_{ball} mass of the ball, A ball displacement, $F_{x,r}$ the force of the ball's inertia, and $F_{x,t}$ the translational force produced by gravity. Constants of viscous and friction damping are abandoned.

The force $F_{x,t}$ in the x-direction (along with the plate) that is caused by gravity can be found as:

$$F_{x,t} = M_{ball}G \ \sin\rho(t) \tag{3}$$

The force $F_{x,e}$ produced by the turning of the ball is

$$F_{x,e} = \frac{\tau_{ball}}{R_{ball}} \tag{4}$$

where R_{ball} is the ball radius and τ_{ball} ball torque. Linear acceleration gives the final equation of motion for the ball and plate system

$$\ddot{A}(t) = \frac{M_{ball} G \sin \rho(t) R_{ball}^2}{M_{ball} R_{ball}^2 + j_{ball}} \tag{5}$$

2.3 Relative to servo angle

In this section, the equation of motion representing the position of the ball corresponding to the angle of the servo load gear is derived. The obtained equation will be nonlinear. The relationship between the beam and servo angle

$$\sin \rho(t) = \frac{2R_{arm} \sin \beta_l(t)}{L_p} \tag{6}$$

where L_p is the length of the plate and R_{arm} is Distance between SRV02 output gear shaft and coupled joint.

To find the equation of motion that represents the ball's movement with respect to the servo angle θ_l, linearize the equation of motion about the servo angle $\theta_l = 0$, where j_{ball} is inertia of the ball. Now from the servo and plate angle relationship

$$\ddot{A}(t) = \frac{2M_{ball} G R_{arm} R_{ball}^2}{L_p \left(M_{ball} R_{ball}^2 + j_{ball}\right) \sin \beta_l(t)} \tag{7}$$

and the sine function can be approximated by $\sin \beta_l \approx \beta_l$ to make the equation of motion linear and so the final linear equation of the movement of the 1D Ball Balancer model

$$\ddot{A}(t) = \frac{2M_{ball} G \beta_l(t) R_{arm} R_{ball}^2}{L_p \left(M_{ball} R_{ball}^2 + j_{ball}\right)} \tag{8}$$

3 Design and structure of balancing controllers

In this section, three controlling methods have been proposed to control the stationary and dynamic location of the ball on the plate. The three controllers are a proportional-integral-derivative (PID), neural integrated fuzzy (NiF) and neural integrated fuzzy with PID (NiF-P) controller. The complete controlling model for this ball balancer is shown in Fig. 5. The control structure is divided into two loops of controlling, for ball position control and plate angle control.

3.1 Proportional-integral-derivative controller

For Ball Balancer model, the error signal is the difference between the desired position and the real one. The input is a square wave signal with amplitude 5 and running period is 20 s. The controlling for the SRV02 motor model (inner loop) is done by SRV02 position controller and provided the servo proportional gain ($K_{PG,\, servo} - 14$), which remains constant for all the cases, on the other side, PID has been implemented on outer shell in addition to pole location (£) in terms of decay in the time constant (T_p). The complete modeling for the controller is explained by the block diagram in Fig. 6.

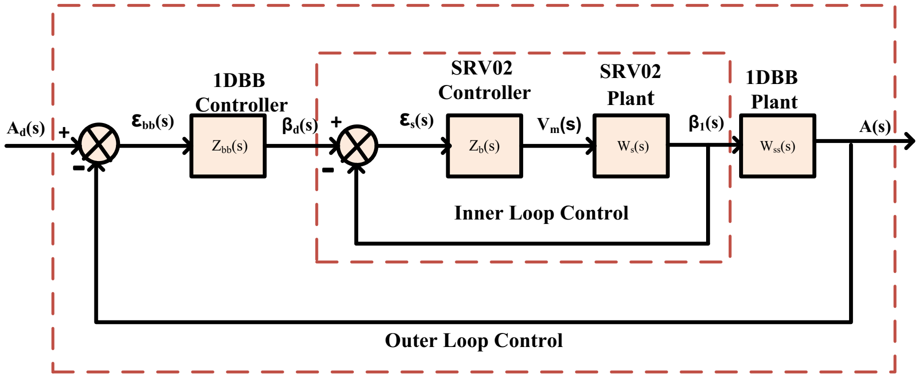


Fig. 5 Combine block diagram of ball balancer system

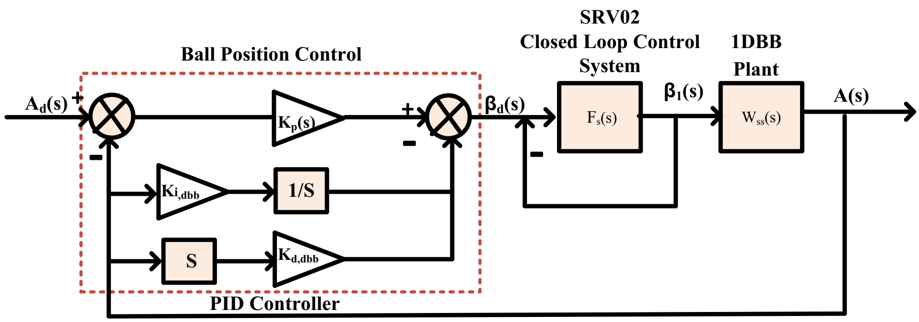


Fig. 6 Block diagram for proportional-integral-derivative controller

The equation for developing outer loop is provided as

$$\beta_d(s) = \left[K_{p,dbb} + \frac{K_{i,dbb}}{s} + K_{d,dbb}s\right](A_d(s) - A(s)) \tag{9}$$

As no servo dynamic forces, measured and desired load angle are the same for servo control, therefore, the 1D ball balancer transfer function is

$$\frac{A(s)}{A_d(s)} = \frac{K_{MG}\left(K_{p,dbb}s + K_{i,dbb} + K_{d,dbb}s^2\right)}{s^3 + K_{MG}\left(K_{p,dbb}s + K_{i,dbb} + K_{d,dbb}s^2\right)} \tag{10}$$

Controller parameters for the desired position of the ball are: $K_{p,dbb}$ proportional gain, $K_{d,dbb}$ derivative gain, $K_{i,dbb}$ integral gain and K_{MG} Model gain. Controllers gain values for the desired position of the ball specified as: $K_{p,dbb} = 5.5$, $K_{d,dbb} = 3.03$, $K_{i,dbb} = 3.45$, model gain $K_{MG} = 1.09$ with response time (t_s) and peak overshoot(M_p) limits less than 3 s and 10%. Model gain, the coefficient of servo load angle attained from model parameters and moment of inertia of the ball.

3.2 Neural-integrated-fuzzy controller (NiF)

The neuro-fuzzy controller combines the merits of both fuzzy and artificial neural network by a single structure. Thus, the neuro-fuzzy controller will have the easy to interpret control action by fuzzy logic and learning is characterized by neural optimization technique.

The fuzzy model generated after training the adaptive neural network optimization technique is called an adaptive neuro-fuzzy inference system or NiF and forms the hybrid systems. Neural networks adopt the circumstances and train data from past values. On the other hand, fuzzy provides flexibility in formulating system without the need of system model. The methods that can transfer human thoughts into a fuzzy rule base are complex and time taking. Neural learning process to adopt environment automatically adjust activation function and reduce error in the formation of fuzzy. There are five layers of NiF control. The first, linear transfer function layer and fourth, fuzzy inference layer of network architecture include those parameters that can be reformed over time. Layer 2, 3 and 5 are for fuzzification, AND logic operation and defuzzification respectively. NiF represents the T-S model and uses a hybrid learning algorithm which is the combination of gradient Descent and least square estimates method. This algorithm is used to update data from predefined fuzzy rules and the activation function of fuzzified neurons.

This combination of least square method and gradient descent is introduced with a neural fuzzy system which enhances the learning ability and optimizes its structure. However, similar to other global optimization algorithms like Genetic Algorithm and Particle Swarm Optimization, the adapted algorithm also exits in the phenomenon of premature convergence, especially in the complex multipeak searching problems. Initially, a least square method is applied on fourth, fuzzy inference layer to train the NiF and an optimized model is constructed based on training data. The gradient descent updates the system parameters based on a least square method to improve its precision and reduce the computation time while propagating back to the first layer. This hybrid algorithm has good performance and has global approximation ability as it solves the local optimization problem of back propagation algorithm.

The merit of neural and fuzzy when comes together then it makes up to for neural fuzzy controller which aids in the formation of the intelligent controller for decision making. It consists of advancement of intrinsic artificial neural network such as massive parallelism, data-rich environment and robustness into the system. In fuzzy control, qualitative knowledge and imprecise modeling and uncertainty of transmission are possible. Apart from these generic advantages, the specific merit of the neuro-fuzzy approach also provides by its easy implementation. In the system developed by Jang et al. (1997) and Ansari and Gupta (2011) notable contribution of neuro-fuzzy and soft computing is exposure.

Integrating fuzzy systems with neural networks is adapted to develop an architecture where the neural networks learning ability and interpretable representation of knowledge by fuzzy optimizes the parameters. The problem of finding appropriate member functions in fuzzy systems and the black box downside behavior in neural networks can be avoided by adopting the combined approach. A combined approach constitutes an adaptable model which is efficient at learning and can use problem-specific prior knowledge (Neuro-Fuzzy Systems 2018).

3.3 NiF architecture

If the FIS under consideration has two inputs and one output, then the fuzzy rule-based algorithm in TS form (Jang and Sun 1995) can be represented as:

Let, A and B are two inputs with $x_1, x_2 \ldots x_n$ be the linguistic terms to define membership functions of A. Likewise, $y_1, y_2 \ldots y_n$ be the linguistic term to define Y, then formed rules are:

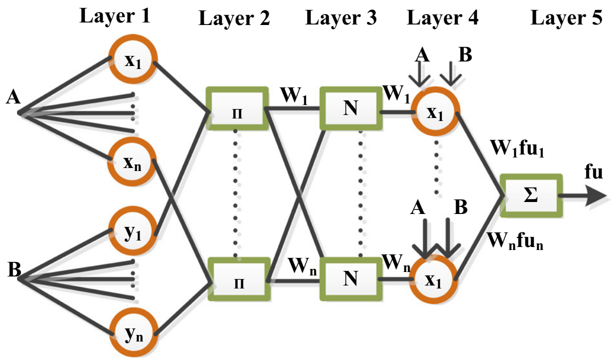


Fig. 7 Schematic diagram of neural network

$$\text{First rule: if A is } x_1 \& \text{B is } y_1, \quad \text{then } fu_1 = M_1A + N_1B + O_1$$
$$\text{Second rule: if A is } x_2 \& \text{B is } y_2, \quad \text{then } fu_2 = M_2A + N_2B + O_2$$
$$\ldots$$
$$\ldots$$
$$N^{th}\text{rule: if } A_n \text{ is } x_n \& \text{B is } y_n, \quad \text{then } fu_n = M_nA + N_nB + O_n$$

Architecture for NiF consist of five layers with these rules and is shown in Fig. 7. Where layer one represents inputs of the model, layer two represents the number of rules, layer three represents the output of normalized neurons from the previous layer, layer four represents function associated with Sugeno model where M, N, and O are adjustable parameters and finally in layer five sums of previous layer neuron output is to generate control signal. The output data for NiF model is trained by a hybrid learning algorithm presented by Jang (1993). The output fu in Fig. 7 is:

$$\begin{aligned} fu &= \frac{W_1}{W_1 + W_2} fu_1 + \frac{W_2}{W_1 + W_2} fu_2 \\ &= \overline{W_1} fu_1 + \overline{W_2} fu_2 \\ &= (\overline{W_1}A)M_1 + (\overline{W_1}B)N_1 + (\overline{W_1})O_1 + (\overline{W_2}A)M_2 + \left(\overline{W_2}B\right)N_2 + (\overline{W_2})O_2 \end{aligned} \tag{11}$$

3.4 NiF controller for ball balancer system

For the design of the NiF controller; the first step was to collect the relevant data that may be used for training. Training of the data to design NiF controller for its desired behavior, the idea was to use a fuzzy controller substituting the NiF. The second step was to choose the input–output data set for training by hybrid optimization method. The ball position error e(t) and change in position error de(t)/dt are the two inputs whose all possible combination within each range is fed to train NiF. The control signal u(t) obtained from fuzzy control is fed as a target output. The universe of discourse is chosen to be [− 0.2, 0.2] for both ball position error and change in position error and universe of discourse for the expected plate angle is [− 30, 30]. Block diagram for NiF controller is shown in Fig. 8.

NiF is trained for 200 epochs, shown in Fig. 9, using a hybrid training algorithm which is a combination of least square and back-propagation gradient descent method. Consequently, membership function parameters of single-output, Sugeno type fuzzy inference system are

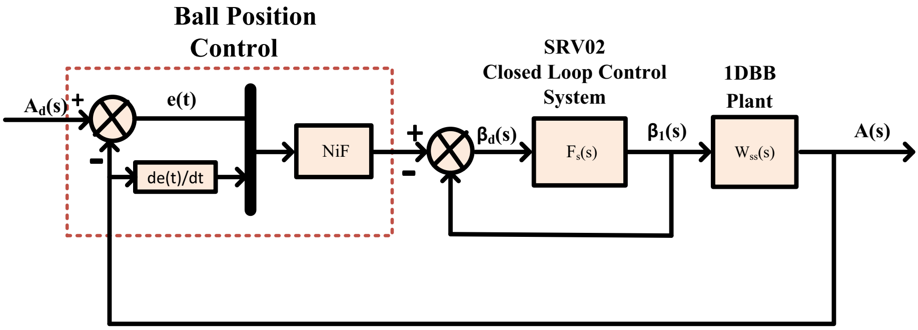


Fig. 8 Block diagram for NiF controller

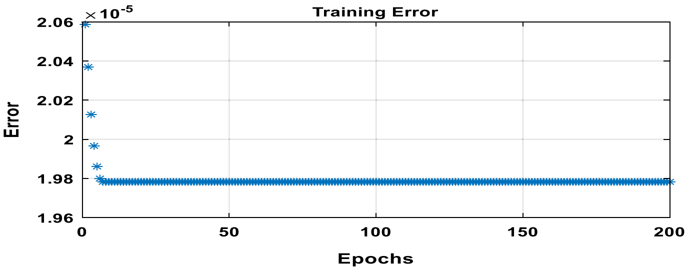


Fig. 9 Training error vs. epochs for asymmetrical NiF

obtained. Seven linguistic variables (MF1, MF2, MF3, MF4, MF5, MF6 and MF7) are associated with each input, so the input space is partitioned into 49 fuzzy subspaces, each of which is governed by fuzzy if–then rules. Thus, the first order polynomial for these functions is (MA + NB + O) where M, N and O are adjustable parameters. Scaling factor for fuzzy neural network obtained as $M_{e(t)} = n/e(t) = N_{de(t)/dt} = n/\{de(t)/dt\} = 35$ for input scaling and $O_{u(t)} = U/n = 0.07$ for output scaling. The learning coefficient for this system starts $\eta = 2.05865e{-}05$ with minimal training RMSE = 0.000020 and trained data of fuzzy output shown in Fig. 10. The membership functions for both inputs are not uniformly distributed so termed as asymmetric adaptive neuro-fuzzy inference system shown in Fig. 11a and symmetric functions before training is shown in Fig. 11b. In association with fuzzy, the neural network will have the following number of neurons in each layer: 2—layer 1; 14—layer 2; 49—layers 3, 4; 1—layer 5, the structure is shown in Fig. 12. The surface of the control signal is generated after the training of FIS data, as shown in Fig. 13.

3.5 Asymmetrical NiF-P controller

For the PID control algorithm, the key is how to tune its controlling constraints which are K_p, Ki, K_d. In this part, tuning of PID parameters is done by a Fuzzy algorithm which trained by a hybrid algorithm using the neural network, named as asymmetrical NiF-P. NiF-P is designed with respect to position error e(t) and position error rate $\dot{e}(t)$. Trained output data projects new fuzzy membership functions which fine-tunes the parameters of PID controller by changing the Proportional, Derivative and integral gains at every instant of time to attain

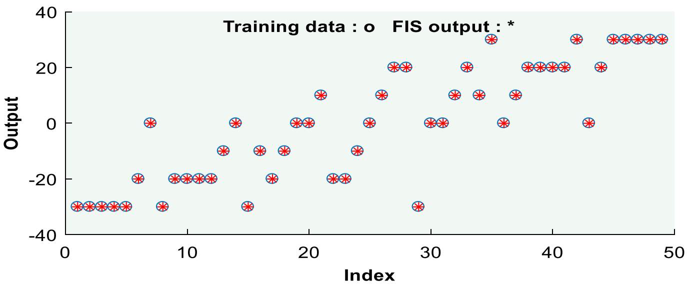


Fig. 10 Training data and FIS output

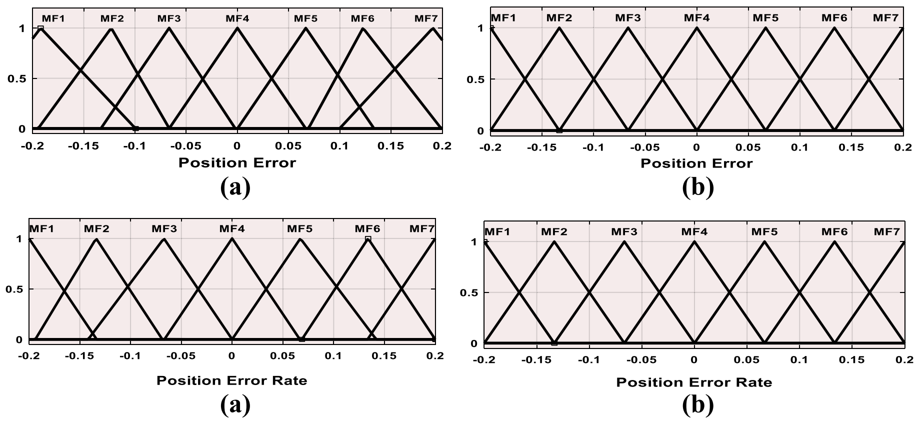


Fig. 11 **a** The asymmetrical membership function of the position error and position rate after training. **b** The symmetrical membership function of the position error and position rate before training

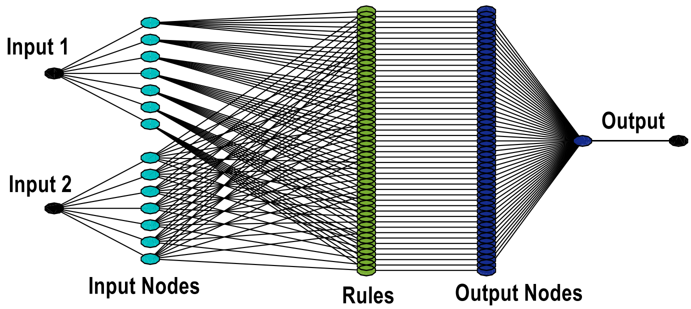


Fig. 12 The proposed structure of the NiF controller

both small overshoot and fast response. The block diagram for asymmetrical NiF-P is shown in Fig. 14.

While the controller in the outer loop computes the angle by which the plate should move to balance the ball, the inner loop controller moves the plate by that angle. At the same time, the fuzzy systems change the PID controller gains to achieve a reasonably fast response with a small overshoot.

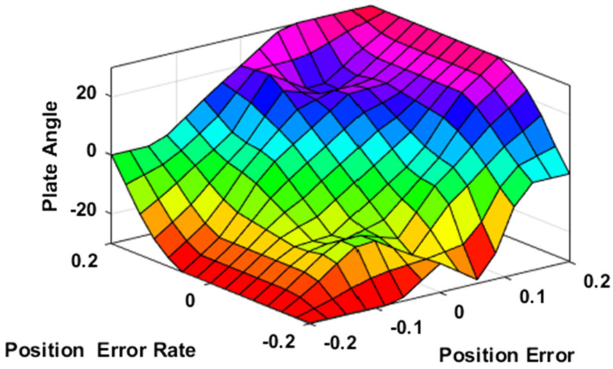


Fig. 13 The surface of control between Position error and change in b position error and output plant angle

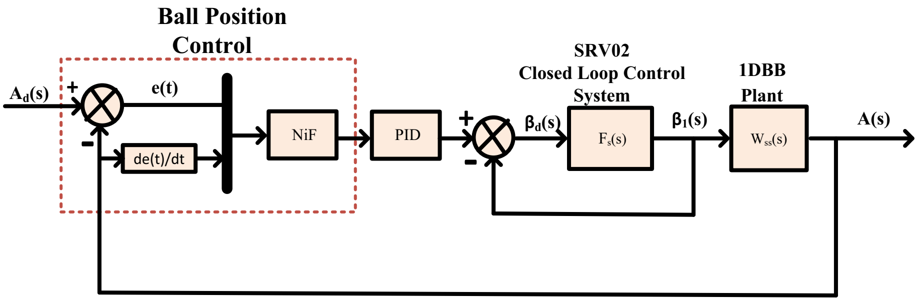


Fig. 14 Block diagram for NIF-P

4 Result and discussion

NiF, NiF-P, and PID have been designed for the study of the ball balancer model on Simulink using MATLAB and Quarc for interfacing, and the validation of results was applied on ball balancer setup shown in Fig. 2. The square input signal is of 0.08 Hz with an amplitude of 5. A comparative study of the NiF, NiF-P and PID controllers is made on both the aspect.

4.1 Simulation-based

During simulation, the involvement of integral in PID make system prone to unstable as system become delicate, these are confirmed by peak overshoot system response, but an efficient method of compensation can reduce the present oscillations. Table 1 below points out that peak time of PID, 1.35 s is less in comparison with NiF, NiF-P, so time is taken by the ball to reach its desired amplitude, is minimum, but settling time, peak overshoot and steady-state error are 2.13, 13.5% and 0.000472 cm respectively are large. For NiF settling time, peak overshoot and steady-state error are 1.48, 9.56e−06, and 8.35e−05 cm. As per the responses available in the graph it has been observing that NiF controller has an appropriate response to the lowest error with the adequate overshoot and shows the excellent balancing on the plate without any oscillations. The simulated time response, steady-state error and peak overshoot for PID, NiF and NiF-P controllers are shown in Fig. 15a–c.

Table 1 Comparative assessment of controllers on ball balancer model on simulation

Controller	Peak time (t_p) (s)	Settling time (t_s) (s)	Peak overshoot (M_p)	Steady state error (e_{ss}) (cm)
PID	1.35	2.13	13.5%	0.000472
NiF	2.89	1.48	9.56e−06	8.35e−05
NiF-P	1.36	1.36	1.14	0.000447

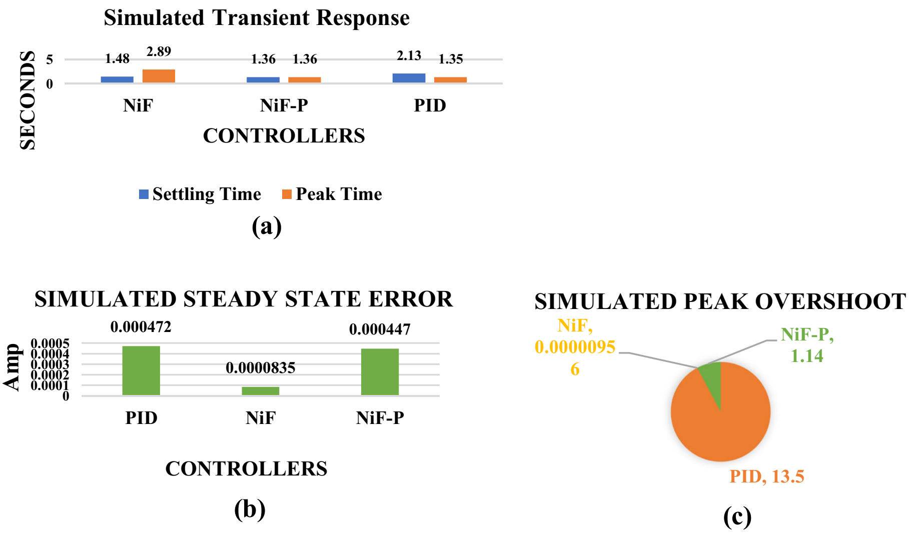


Fig. 15 Comparison of PID, NiF and NiF-P controller 'time response' to ball balancer model on simulation. **a** Peak time, settling time, **b** steady-state error, **c** peak overshoot

The comparison has been made among all controllers to find the proper regulator. The focus is on the movement of the ball on the plate with less vibration in ball movement. In this simulation of NiF, Fig. 16b, plate angle on the x-axis is 9.1 degree, which is the lowest plate angle as compared to PID and NiF-P controllers and hence the plate will not have oscillations and ball will move very slowly and steady within a short period of time. In NiF-P, PID causes to give fast response to system and training of data improves peak overshoot and steady-state-error. Hence the position of the ball from Fig. 16a shows that variation in ball position while moving on the plate surface having the lowest settling time in NiF-P. Figure 16c shows the input voltage applied to the servo motor is minimum in case of NiF. The maximum value of voltage here 2.2 volts for NiF, 2.5 volts for NiF-P, 3.8 volts for PID.

The stability of the Ball Balancer is analyzed in terms of bode for inner and outer control loops. An SRV02 position controller $Z_b(s)$ used to compensate SRV02 load position with respect to input voltage. Figure 17a. shows the bode plot of the SRV02 controller $Z_b(s)$, and SRV02 Plant $W_s(s)$ of the inner loop. Here phase and gain margin are 106°, 33.4 dB at crossover frequencies 22.5 and 0.302 rad/s respectively. On the other side, outer loop bode shown in Fig. 17b which elaborate neural integrated fuzzy with PID response in addition to the 1DBB plant. Outer loop phase and gain margin are 121°, 24.3 dB at crossover frequencies 0.181 and 9.72 rad/s respectively Thus promising stable and accurate control of the ball on a plate system can be expected using these standard control loops.

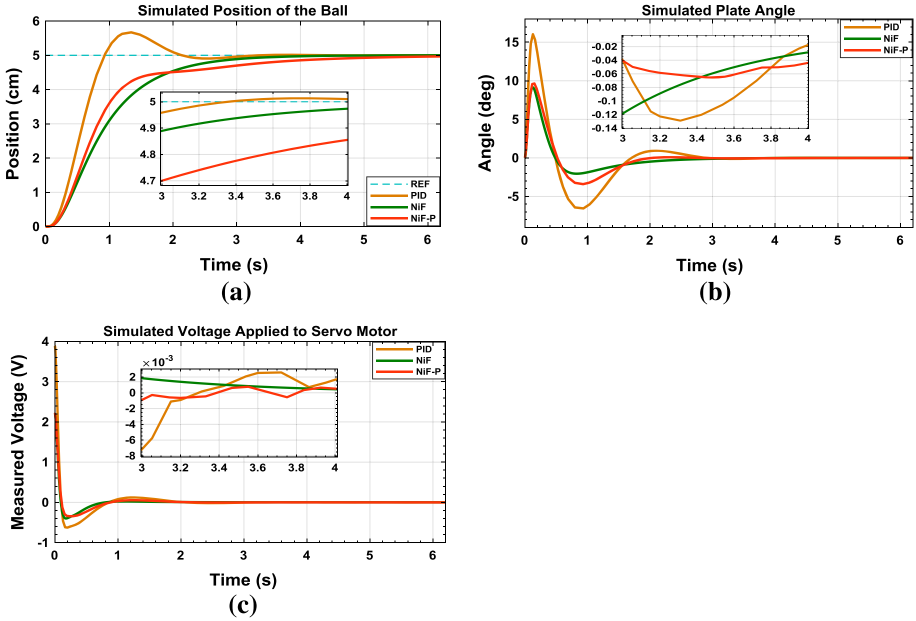


Fig. 16 PID, NiF and NiF-P response on simulation for **a** position of the ball, **b** plate angle, **c** input voltage applied to the servo motor

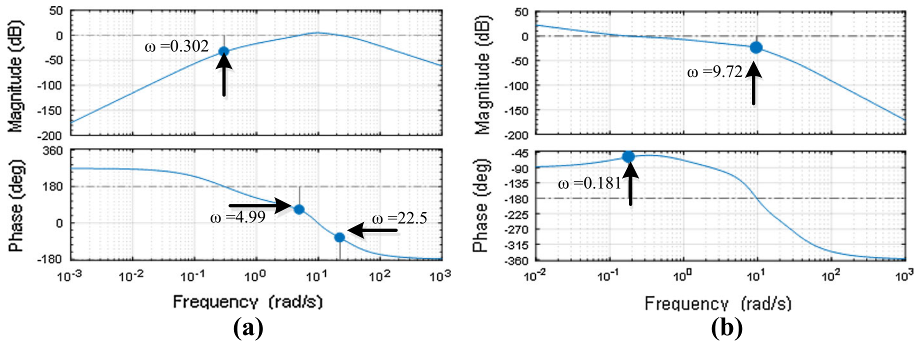


Fig. 17 **a** Inner loop bode, **b** outer loop bode

4.2 Experimental-based

Outcomes from the implementation of these controllers to the hardware and simulation are verified based on the momentary analysis. From the Table 2, the response of NiF is best based on settling time, peak overshoot and steady-state-error. Steady state error, peak overshoot and settling time are 1.08 cm, 4.16% and 1.62 s respectively for NiF, which is minimum in comparison with PID and NiF-P controller. Figures 18a–c show the position of the ball, plate angle and servo motor input voltage. Controlling the voltage signal required for the balancing the ball is in between − 5 v to + 5 v for NiF-P which is minimum as compared to another controller. Angle variation is zero to plus-minus 15 degrees, made the ball movement smooth and stable for the NiF controller. After observing simulation results, PID takes just

Table 2 Comparative assessment of controllers on ball balancer model on real-time

Controller	Peak time (t_p) (s)	Settling time (t_s) (s)	Peak overshoot (M_p) (%)	Steady state error (e_{ss}) (cm)
PID	1.26	1.76	36.8	3.86
NiF	2.48	1.62	4.16	1.08
NiF-P	1.53	1.57	35.5	1.76

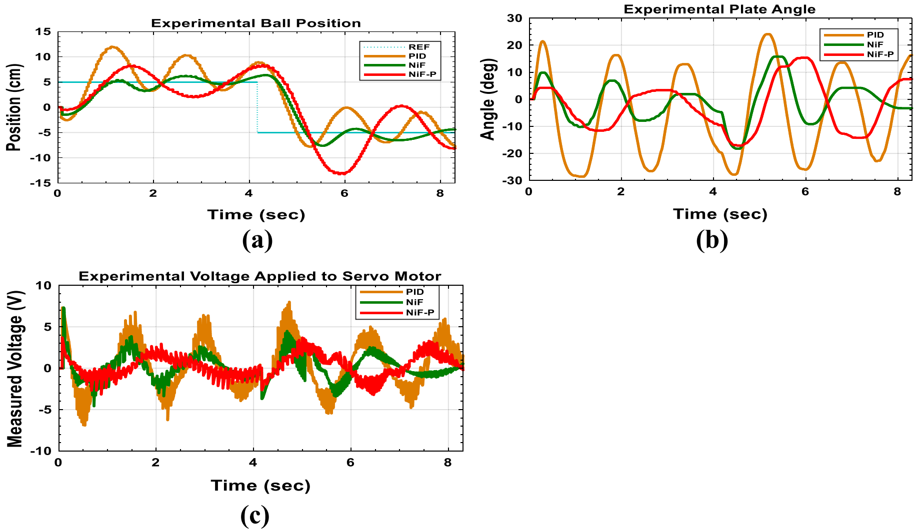
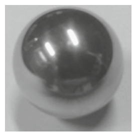


Fig. 18 PID, NiF and NiF-P response on real-time for **a** position of the ball, **b** plate angle, **c** input voltage applied to the servo motor

Table 3 Load variation

Load parameters	Ball 1	Ball 2	Ball 3
			
Radius of ball	0.0196 m	0.025 m	0.02 m
Mass of ball	0.0030 kg	0.085 kg	0.11 kg
Moment of inertia of ball	4.6217e−07 (kg m^2)	2.125e−05(kg m^2)	1.76e−05(kg m^2)

0.7 s to reach first-time reference position which is less then neuro integrated fuzzy 1.1 s but remains unstable due to high vibrations and settle for that trajectory which is away from the reference. However, NiF settled for the trajectory that almost equal to the desired one. In this case, NiF performs better as the steady-state error is less as compared to PID. The scaling factor used for error, change in error and control output in case of NiF controller were 0.5, 110 and 4 respectively.

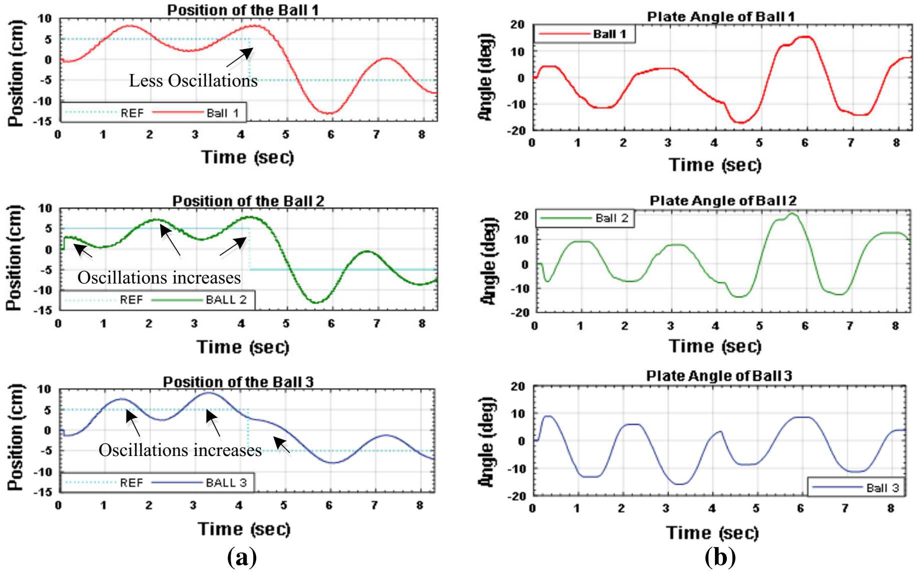


Fig. 19 **a** Position variation of ball 1, ball 2 and ball 3, **b** plate angle of ball 1, ball 2 and ball 3

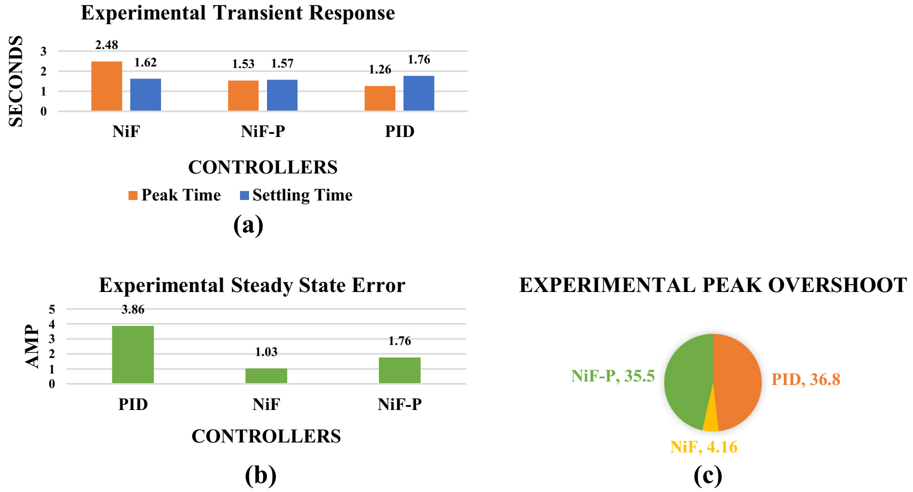


Fig. 20 Comparison of PID, NiF and NiF-P controller 'transient response of ball balancer model on real-time. **a** Peak time, settling time, **b** steady-state error, **c** peak overshoot

For ball balancing purpose ball 1 with mass, radius and moment of inertia values 0.0030 kg, 0.0196 m, 4.6217e−07 (kg m^2) respectively has been taken for implementation of neural integrated fuzzy with PID controller and achieve excellent balancing. Further controller performance is analyzed by using various balls (load variation) of different radius and mass as shown in Table 3. Variation in ball position and plate angle for the different loads are shown in Fig. 19a and b. After analyzing the results, for ball 2 and ball 3, the settling time is 1.97 s, 2.24 s respectively. From time response analysis it has been observed that as the mass of the ball increases, the settling time also increases slightly but due to the excellence of controller ball is balanced on the plate effortlessly. So, designed controller balances the ball perfectly on the plate even after the variation in load (Fig. 20).

Form the results it has been observed that hybrid algorithm-based controllers implemented on 2Dof ball balancer proved to be more efficient in terms of performance parameters such as settling time, peak time, peak overshoot and steady state error when compared with conventional controllers.

5 Conclusion

This paper depicts the modeling of the ball balancer and comparative analysis of implemented control techniques PID, NIF and NiF-P on the system. The response of the system for PID, NiF and NiF-P control strategies are validated based on simulation and hardware results. For the comparison of the PID, NiF and NiF-P controller outcomes, time response analysis has been done. The results of hardware and simulation assessment provide the values of steady-state error, and peak overshoot is the minimum for NiF, whereas rise time, peak time is less for NiF-P. The NiF controller has the adaptability, excellent control performances and strong robustness with the lowest peak overshoot and steady-state-error for ball balancer system. Simulations and practical experiments depicted that NiF and NiF-P methods achieve remarkable performance within the framework of the traditional control structure.

As per the future prospect, more advanced and hybrid control technique such as wavelet NiF, wavelet NiF-P, type 2 NiF, type 2 NiF-P with optimization like bat algorithm and python algorithm, etc. can be used for control. More analysis can be performed towards the robustness analysis and make the system more susceptible to withstand external disturbance can be studied. The SRV02 unit can be explored furthermore for performing analysis of vibration, gantry, self-erecting controls of the system.

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