

Neural Network Based Control of a Two-Mass Drive System

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Abstract: In this paper, two-mass drive system is modelled and speed control of the two-mass system is presented. The speed control of the system offers the challenge due to handle torsional vibrations. In the control structure, Particle Swarm Optimization (PSO) based conventional Proportional-Integral-Derivative (PID) controller and single-layer, feed-forward Neural Network (NN) controller with back-propagation learning algorithm are proposed. NN controller is investigated to show the effectiveness of the control performance compared with PSO based PID controller. In order to realize a fair comparison, PSO method is used to determine the optimum gain parameters of PID controller and NN controller is designed with online learning algorithm. In the NN learning, back-propagation, which is the most preferred method, is adapted. Simulation studies are performed in different two parts to examine the performance of the proposed controller. In the first part, the controllers are tested for different step references and comparative results of the optimized PID and NN controllers are illustrated. In the second part, the effect of load torque is explored with proposed NN control method. According to the obtained simulation results, it can be seen that the designed NN controller provides better performances without and with load speeds.

Keywords: Two-mass drive system, neural network control, particle swarm optimization, robust control

1. Introduction

In most of the industrial applications, like rolling mill, wind turbines, automotive industry, servo drives or robot arms drive systems, very low mechanical resonance is occurred because of a long shaft between the motor and the load machine. The mechanical resonance results in the mechanical coupling shaft stresses, especially in the high performance speed and torque regulation. Therefore, this stress in the shaft can cause some undesirable situation on the mechanical coupling and also it can decrease the quality of the system. Also, some different modes affect the drive performance and may lead to the failure of the whole drive system in these cases. In order to handle torsional vibrations, various control methods have been proposed to control two-mass drive system such as Proportional-Integral-Derivative (PID) with feedback loop, sliding mode, robust, adaptive, predictive and intelligent control, etc. [1-6].

A conventional PID speed controller is proposed for two-inertia system by Zhang [1]. Three types of pole assignments which should be considered for different inertia ratios are applied to the control system. In [2], two types of speed controllers are designed for the two-mass Direct Current (DC) drive systems. The comparatively simulation results of the nonlinear fuzzy logic and classical PI control systems are presented and much better performance and robustness against parameter variations are ensured by the fuzzy logic control. Also, Erenturk presents a fuzzy speed controller for two-mass system with a gray estimator [5]. In the other study, an adaptive neuro-fuzzy controller is designed for one and two-mass systems. Abilities of fuzzy reasoning and neural networks learning are combined with the proposed controller [3]. These studies aimed to decrease the torsional vibrations both motor and load sides with different control methods.

Soft computing methods such Neural Networks (NNs) play an important role on the industrial applications due to their generalization capabilities to predict complex relationship between system parameters. The increasing interest of NNs have attracted the attention of researchers with the learning ability of a nonlinear function used for identification and control [7,8]. Several structures of NN systems are studied in the literature. The training of NN is basically achieved by using back-propagation algorithm developed by Rumelhart et al. [9]. The back-propagation algorithm is the most preferred method for neural networks training for resolving various problems of real life [10,11].

In the conventional control methods, PID control is still preferred to control different systems by tuning the control parameters with different optimization methods [12,13]. In the solution of optimization problems, mathematical methods have some disadvantages such as the lack of flexibility and the need to define them with mathematical functions. This leads scientists to heuristic methods inspired by events in nature. The widely used heuristic optimization methods are Genetic, Differential Evolution, Particle Swarm Optimization (PSO) algorithms and etc. [13-15]. PSO is a widely preferred method motivated by swarm behaviours. It is highly promising for tuning PID control parameters with its simplicity, low calculation cost and good performance [16].

In this paper, a two-mass drive system is modelled and it is aimed to performed to realize motor and load speed control in order to achieve a robust control with decreasing the torsional vibrations. In the control system, PSO based PID controller and NN based intelligent controller are implemented. PSO algorithm is used to tune the PID control parameters and NN controller is designed with online back-propagation learning algorithm. The NN control method is investigated with comparing the optimized PID control to validate the robust control structure. Simulation studies are also performed without and with load torque.

This paper is organized as follows: in Section 2, mathematical equation of two-mass mechanical drive system is given. The designs of control methods are presented in Section 3. Then, simulation results are illustrated in Section 4 in order to show the

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performance of the proposed neural controller. Finally, conclusions of the proposed controller for two-mass drive system are summarized in Section 5.

2. Two-Mass Drive System Dynamics

The considered mechanical two-mass drive system and block diagram are given in Fig. 1. Motor and load are coupled by a long shaft of finite stiffness K_s in the two-mass system. J_M, J_L are denote motor and load inertias and T_e, T_L, T_s are denote motor driving, load and shaft torques, respectively. Similarly, the angular motor speed is ω_M and angular load speed is ω_L .

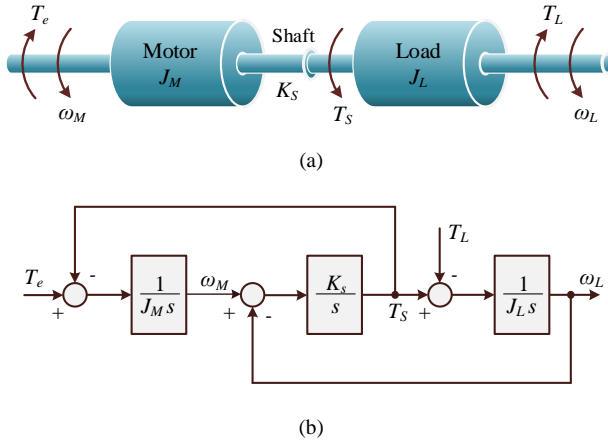


Fig. 1. System representation: (a) Mechanical model of the two-mass drive system. (b) Block diagram of the two-mass drive system.

According to the mechanical structure, considered the two-mass drive system is described by the following state equations:

$$\dot{\omega}_M = \frac{1}{J_M} (T_e - T_s), \quad (1)$$

$$\dot{\omega}_L = \frac{1}{J_L} (T_s - T_L), \quad (2)$$

$$\dot{T}_s = K_s (\omega_M - \omega_L). \quad (3)$$

The damping losses, nonlinear frictions and backlash are considered to be comparatively low and neglected in studies [17-19].

3. Control of the Two-Mass Drive System

3.1. Optimized PID Control with PSO

PSO is a population-based optimization method that provides robust control performances in nonlinear optimization problems that are motivated by swarm behaviors. It is a highly promising method for tuning parameters of PID. PSO is considering as an effective method due to its simplicity, low calculation cost and good performance [12].

Let the current position of h th particle of the swarm is denoted with P_h which is considered in the search space of S_D . The best position of the particle and the best position of the swarm can be also denoted with P_{best} and G_{best} , respectively. At step k , the h th particle velocity can be described with $V_h(k)$ as;

$$V_h(k) = V_h(k-1) + c_1 rand_1 (P_{best}(k-1) - P_h(k-1)) + c_2 rand_2 (G_{best}(k-1) - G_h(k-1)). \quad (4)$$

Where c_1 and c_2 are positive acceleration coefficients and $rand_1, rand_2$ are random values between [0-1]. The Equation (4) is used to adjust the velocity of the particles. The position of the particle is also adjusted with the following equation;

$$P_h(k) = P_h(k-1) + V_h(k). \quad (5)$$

In this study, the PID control parameters are tuned by using PSO method for two-mass drive system.

3.2. NN Control

In this part, back-propagation algorithm for NN training is presented and then the proposed control model is implemented to the two-mass drive system in order to ensure more effective performance than optimized PID control system.

NN framework has the ability to learn a nonlinear function, recall and generalize from training data. The general structure of NN is chosen as a feed-forward network with input layer, hidden layer and output layer. Fig. 2 shows a simple NN structure. The output of the NN, considering a single-layer NN structure in order to simplify the equations, can be expressed as;

$$U(I) = \varepsilon(w_2 f(w_1 I + b_1)). \quad (6)$$

Where I is the input vector augmented by the bias term, U is the network output vector, w_1 and w_2 are weights for input and output layer, respectively, and $f(\cdot), \varepsilon(\cdot)$ are the hidden layer and the output layer activation functions, respectively.

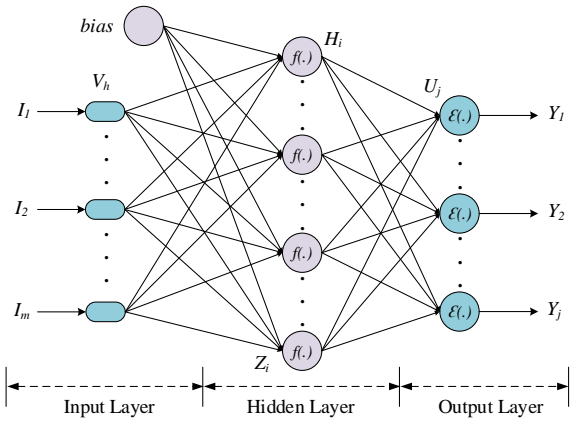


Fig. 2. The structure of a simple single-layer NN.

In order to update weights of NN, standard back-propagation algorithm is the most widely used technique [20]. It is a supervised learning method, and is a generalization of the delta rule which is a gradient descent learning rule for updating the weights of the artificial neurons in a single-layer perceptron. The update rule of the weights can be given for the output layer by;

$$w_{ji}(k+1) = w_{ji}(k) + \alpha \delta_j H_i(k). \quad (7)$$

Here w_{ji} is the weight which represents the strength of the output node j and hidden node i , α is the learning constant and H_i is the output of hidden node i . δ_i is the local gradient and can be expressed as;

$$\delta_j = e_j(k) \cdot \varepsilon'_j(U_j(k)). \quad (8)$$

Here, e_j is the output node error, $\varepsilon'_j(\cdot)$ is the derivative of output node j activation function and U_j is the linear output of the output node j .

Similarly, the update rule of the weights for the hidden layer can be given by;

$$w_{ih}(k+1) = w_{ih}(k) + \alpha \cdot \delta_i \cdot V_h(k), \quad (9)$$

where w_{ih} is the weight, which represents the strength of the hidden node i and input node h , V_h is the output of input node h . δ_j is the local gradient and can be expressed as;

$$\delta_i = f'_i(V_h(k)) \cdot \sum e_j(k) \cdot f'_i(Z_i(k)) \cdot w_{ji}(k). \quad (10)$$

Equation (7) and (9) show the update rules for the output and hidden layer, respectively. It can be seen from the equation (7) that the update rule for the output layer is obtained from the gradient of the error. However, the update rule for the hidden layer is not directly discovered from the gradient of the error due to the output values of the hidden layers are not known and it can be found by propagating back the output error to the inputs.

Weight updates of the NN learning algorithm can be defined as;

$$\Delta w_{ji}(k) = \eta \cdot |e_j(k)| \cdot H_i(k) \cdot \text{sgn}(e_j(k)), \quad (11)$$

$$\Delta w_{ih}(k) = \sigma \cdot |e_i(k)| \cdot V_h(k) \cdot \text{sgn}(e_i(k)). \quad (12)$$

In these equations, η and σ are learning constants. e_i and e_j for nodes i and j can be given by;

$$e_j(k) = (Y_{dj} - Y_j) \cdot \varepsilon'_j(U_j(k)), \quad (13)$$

$$e_i(k) = f'_i(Z_i(k)) \cdot \sum_{j=1}^p e_j(k) w_{ji}(k). \quad (14)$$

Similarly, optimum NN model biases can be obtained with the same propagation method. Finally, back-propagation learning algorithm is used for the proposed NN control structure of two-mass drive system in this study.

4. Results

In order to validate the accuracy of the proposed controller, the simulation studies are realized in Matlab/Simulink environment. As shown in Fig. 3, the closed loop system is simulated for the PID control of two-mass drive system.

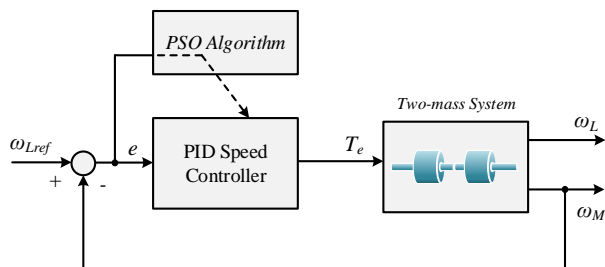


Fig. 3. Block diagram of the closed loop PSO based PID control system.

In order to enhance performance of PID control model, PSO algorithm is adapted to optimize control parameters for the system. The specifications of the mechanical properties of the considered drive system is given in Table 1 and Table 2 shows the proposed PSO algorithm parameters.

Table 1. Mechanical system parameters.

Parameter	Value
J_M	0.1 kgm ²
J_L	0.001 kgm ²
K_s	20 Nm/rad

Table 2. PSO parameters.

Number of particles	21
Acceleration coefficients (c_1, c_2)	2
Number of maximum iteration	35

The closed loop system for NN control model is also shown in Fig. 4. For learning of the NN controller, one needs the virtual error e_u and it can be expressed for discrete time as;

$$e_u(k) = \frac{w_m(k) - w_m(k-1)}{u(k) - u(k-1)} e(k). \quad (15)$$

However, due to the system dynamics and sampling, equation (15) is not real. Therefore, the sign of the numerical derivative is taken into account, which is known as reflection of the error through the system.

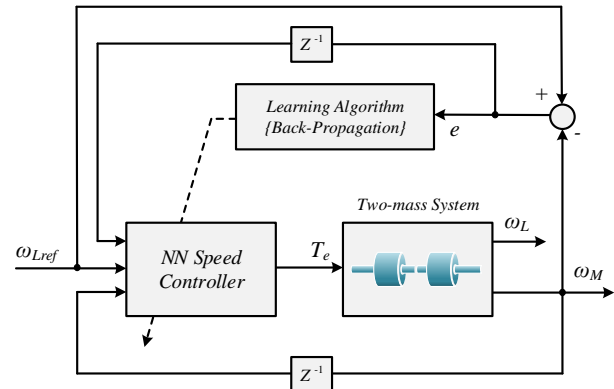


Fig. 4. Block diagram of the closed loop NN control system with learning algorithm.

The model parameters of NN controller is also given in Table 3.

Table 3. NN parameters.

Learning rate	0.001
Number of hidden layer	20
Number of inputs	3
Number of outputs	1
Hidden Layer Activation Function	Tangent Sigmoid
Output Activation Function	Linear
Learning Algorithm	Back-Propagation

Learning rate is set to 0.001 which is very low value for the NN controller to be applicable in experimental studies. It is noted that online NN controller is designed as a single-hidden-layer, feed-forward framework. The performance of the proposed controller is investigated in different two parts. In the first part of the simulation studies, controllers are tested in different speed regions in order to see the system behaviors with the NN controller which is based on

standard back-propagation algorithm, and PID controller based on PSO algorithm. In the other part of the study, the effect of load torque is explored with proposed NN controller in order to see how the controller is robust against load torque. It is noted that the performance of both controllers are evaluated in terms of settling time and overshoot criteria.

4.1. The Performance of Controllers in Different Speed Regions

In this part of the simulation studies, the designed controllers are tested in different speed regions. In Fig. 5 and Fig. 6, angular motor and load speeds in the various step references are illustrated at 130s for both control algorithms, respectively. In these figures, two different regions are also presented by zooming in order to show the variations in detail.

As shown in Region 1 and 2 of Fig. 5 that the settling time of PSO based PID control system is more than NN control. Settling time of the PID and NN controllers are 7.5s and 1.8s, respectively. Also, PID control response have nearly %1 overshoot while NN control response does not have any overshoot.

Region 1 and 2 of Fig. 6 show the angular load speed response

details. PID control response has angular load speed fluctuations in the transient state and this fluctuation is nearly %1 while NN control does not cause any fluctuations. The settling time of PID and NN control systems are the same and equal to 0.95s. It can be clearly seen that NN control performance is better than PSO based PID control for both speeds.

The angular motor and load speed errors are given in Fig. 7 and 8 for above reference responses, respectively. In these figures, different regions are also presented in order to show the error variations in detail.

It can be seen from Region 1 and 2 of Fig. 7 that NN controller has more oscillation errors occurring in the reference transition values, but settling time of the NN is faster. Therefore, error of the NN control response reaches to zero, rapidly. The zoomed region of Fig. 8 shows the detailed angular load speed error. PID controller causes the bigger oscillation error due to angular load speed fluctuations in the transient state.

In Fig. 9, motor torques generated with PID and NN controllers are given. As seen from Fig. 9, NN controller generates much smaller torques than PID controller.

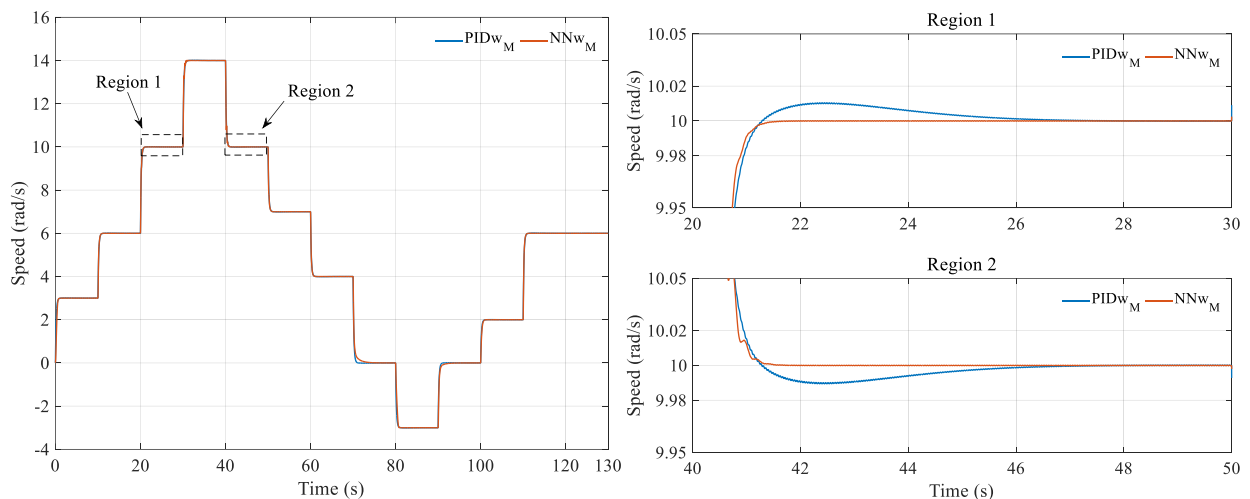


Fig. 5. Angular motor speed response.

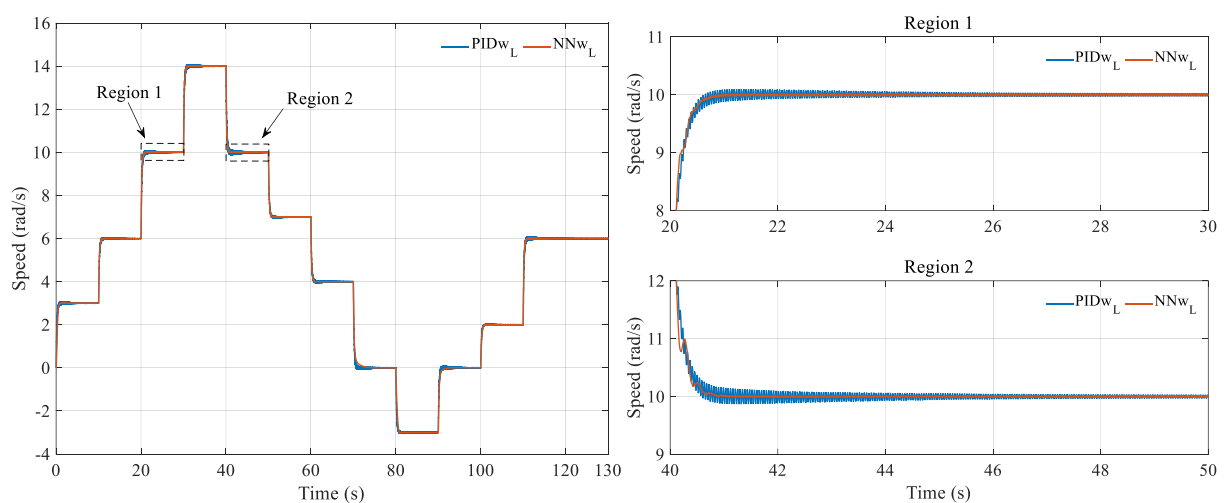


Fig. 6. Angular load speed response.

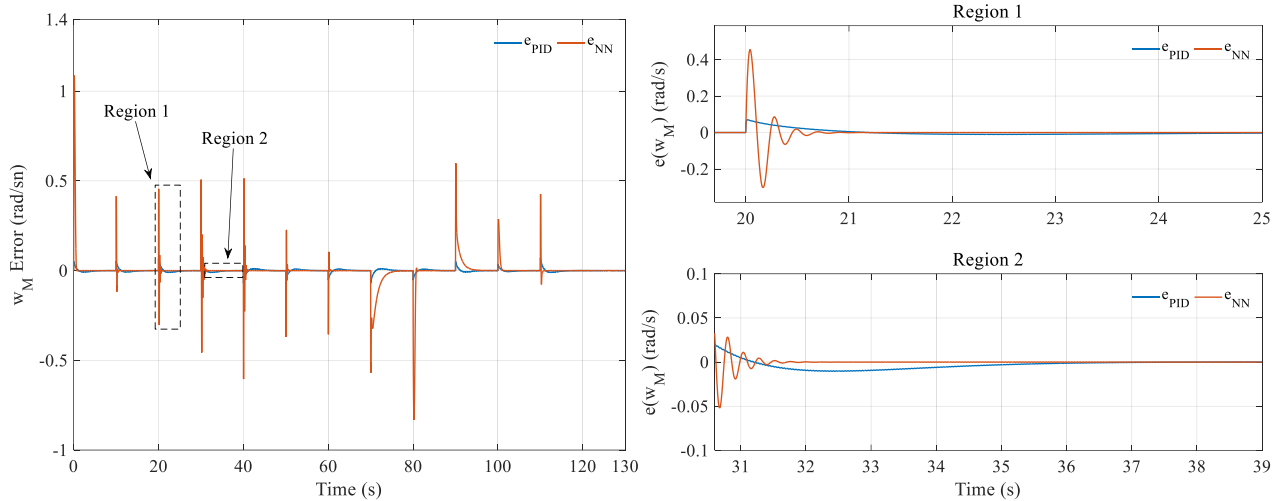


Fig. 7. Angular motor speed error.

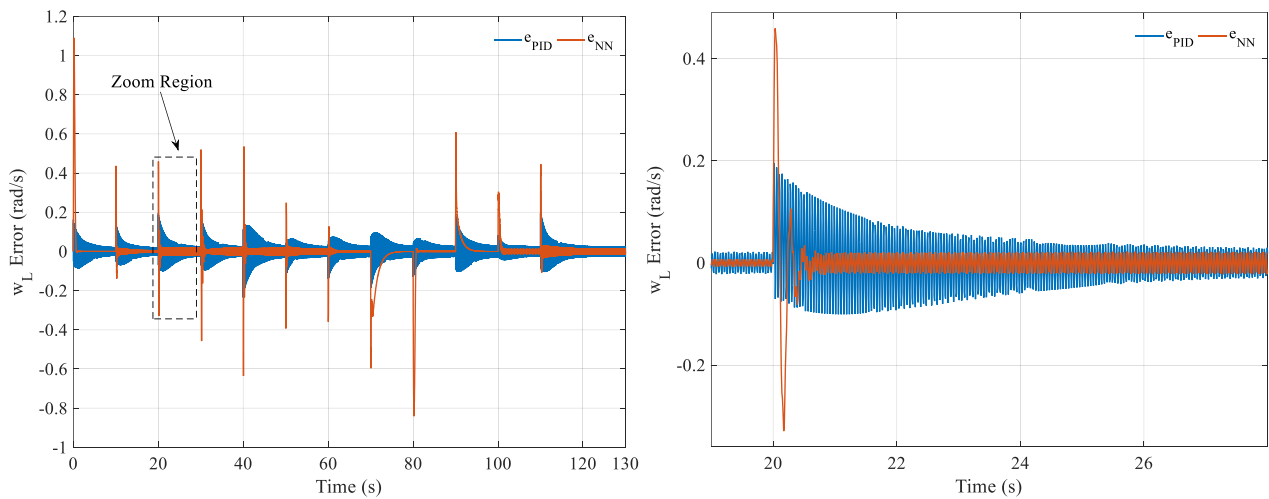


Fig. 8. Angular load speed error.

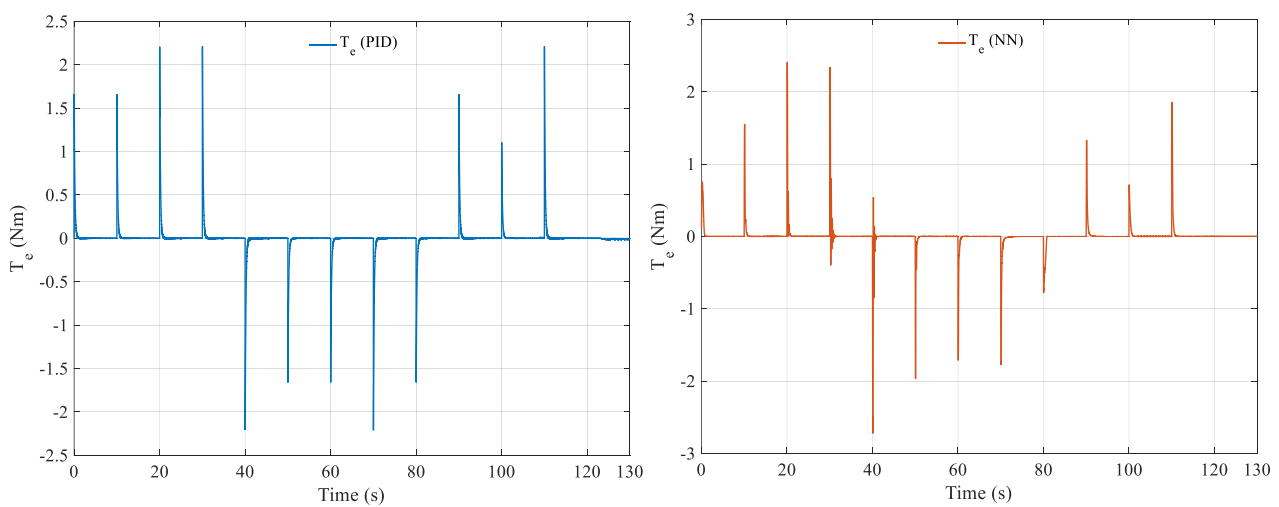


Fig. 9. Motor torques generated with both controllers.

Fig. 10 shows the PID parameter tuning process based on PSO algorithm. In this algorithm, 21 particles are randomly distributed and maximum iteration is determined as 35. After the tuning process, optimum proportional gain (K_p), integral gain (K_i) and derivative gain (K_d) are obtained in 20 iterations as follows: $K_p=8.6587$, $K_i=4.8171$, $K_d=4.8780$.

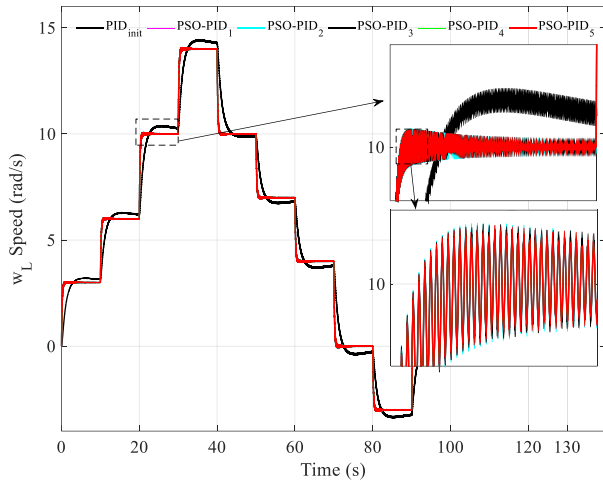


Fig. 10. PID parameter tuning process with PSO algorithm.

According to the online learning process of the proposed NN controller, Fig. 11 and 12 indicates the changing of input layer and output layer weights. NN controller has a number of 3 input and 20 neurons in the hidden layer and these conditions occurs the input layer weight matrix as 3×20 . During the learning process, input and output weights changes and adapt in order to control the two-mass system.

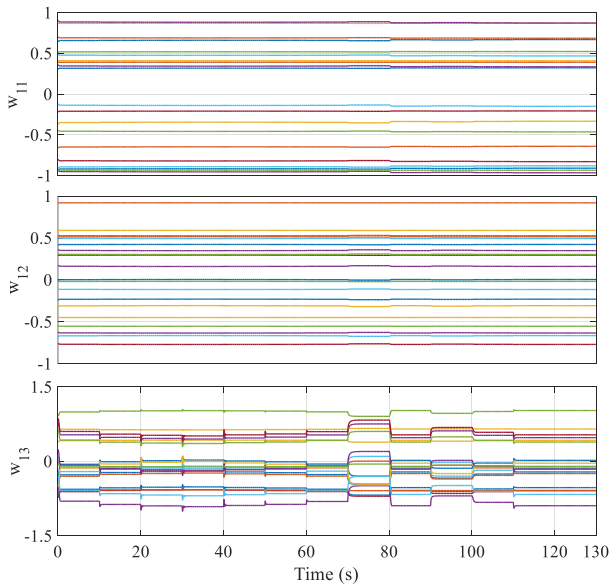


Fig. 11. Input layer weights during reference speed variations.

In the same way, learning process of the input layer and output layer biases are given in Fig. 13 and 14, respectively. According to the designed NN controller, input layer bias matrix is equal to 1×20 and output layer bias is 1×1 . During the network learning, input and output biases also changes and adapt in order to control the two-mass system. It can be clearly seen from the weight and bias changes, the learning process in the different reference inputs are fairly rapid and these parameter changes are quite smooth. Consequently, success of the NN learning algorithm is validated

with given results.

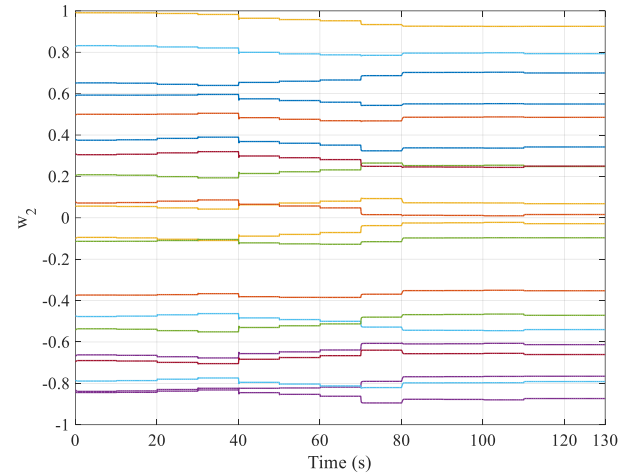


Fig. 12. Output layer weights during reference speed variations.

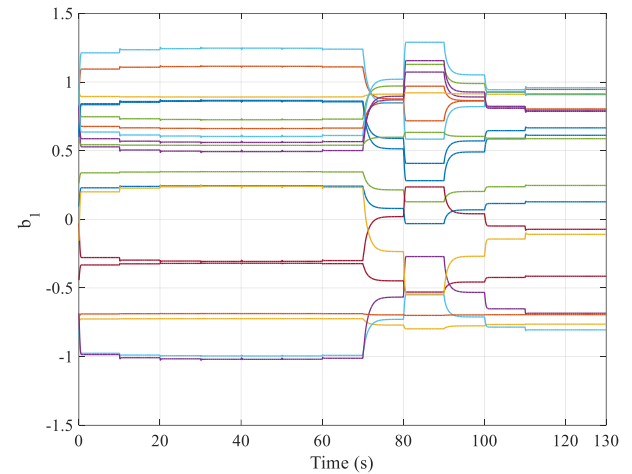


Fig. 13. Input layer biases during reference speed variations.

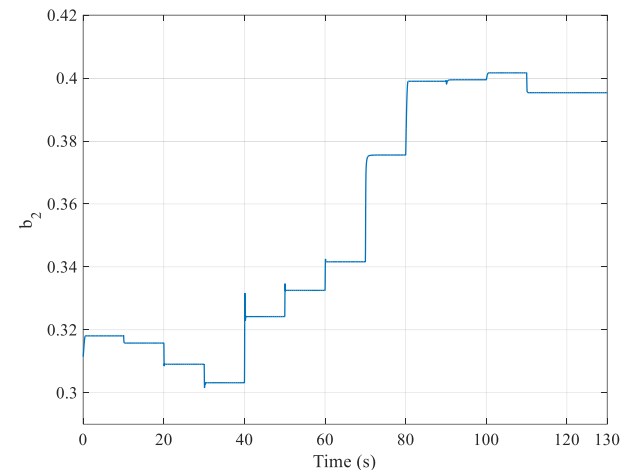


Fig. 14. Output bias during reference speed variations.

4.2. The Performance of the Controller Against Load Torque

The second part of the simulation studies includes the investigation of the robustness of the proposed NN controller against load torque. As shown in Fig. 15, load torque is applied to the two-mass drive system at 5s. The step reference of the angular load speed is set to 20rad/s.

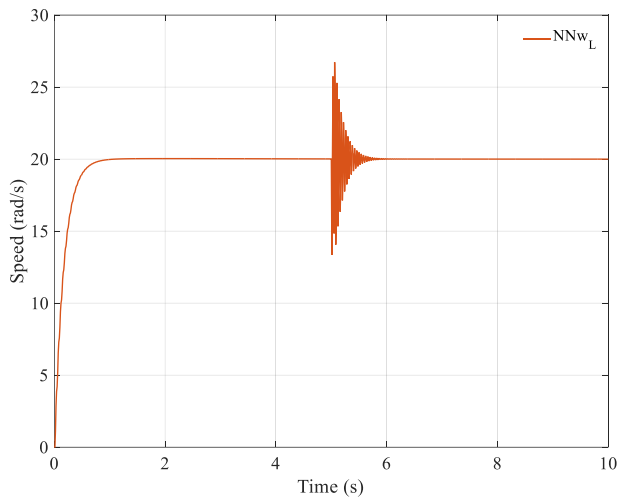


Fig. 15. Load speed response against load torque.

Two-mass drive system is unloaded in the initial state and 1rad/s step load torque is applied during 0.1s. In this case, load speed exhibits decreasing amplitude oscillations from 26.73rad/s to 13.35rad/s and load speed of the system follows the reference after 1.32s. This result also validates the success of the NN control response against the disturbances in the two-mass drive system.

5. Conclusion

The speed control of two-mass drive system offers the challenge due to handle torsional vibrations. NN with back-propagation learning algorithm is an effective nonlinear control method for two-mass drive system control. In this paper, NN control is investigated for two-mass drive system to show effectiveness of the method compared with conventional PID control. In order to have a fair comparison, control parameters of PID are obtained by updating with an effective PSO method.

Simulation studies are carried out in different two parts to investigate the performance of the proposed controller. In the first part of the simulation studies, the controllers are tested for different speed regions. Comparatively results of the back-propagation learning algorithm of NN controller and PSO tuning based PID controller are illustrated. The proposed NN control method is also analyzed for the case of applying load torque in the second part of the simulations. Simulations confirm that the proposed NN control algorithm not only provides better performance in different speed regions but it is also more robust against applying load torque.

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