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Research Article

Design and Simulation of a PID Neural Network Controller for PMDC Motor Speed and Position Control

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Abstract

Direct current (DC) motors have many difficulties when controlling angular velocity in a variety of applications. The perfect controller cannot be carried out by traditional control alone due to the nonlinear properties of DC motors, design constraints, and mechanical variations caused by the operation conditions. This study proposes a design for an artificial neural network based PID controller (ANNPID) to control the speed of a permanent magnet DC motor (PMDC) in two methods. A detailed analysis is performed based on the simulation results of both methods. The proposed controllers are numerically simulated for various test conditions including; set-point changes, step changes in the load torque, and parameter variations, then the suggested techniques were compared in a comparative study with a traditional PID controller based on the transient response specifications and the performance indices to validate the performance of the controllers. The simulation results demonstrated that the controllers have improved dynamics, static performance, and less overshoot. The methods described here achieve control more effectively than the conventional control approaches under both nominal and disturbed test conditions over different operating ranges.

Keywords: PMDC motor, PID, Artificial neural network (ANN), ANNPID, transient response.

SMDA Motorun Hız ve Konum Kontrolü için PID Sinir Ağı Denetleyicinin Tasarım ve Benzetimi

Öz

Doğru akım (DA) motorları, çeşitli uygulamalarda açısal hız kontrol edilirken birçok zorluk içerir. DA motorların doğrusal olmayan özellikleri, tasarım kısıtlamaları ve çalışma koşullarından kaynaklanan mekanik varyasyon nedeniyle mükemmel kontrol tek başına geleneksel kontrol yöntemleri ile gerçekleştirilemez. Bu çalışma, sabit mıknatıslı bir DA (SMDA) motorun hızını iki yöntemle kontrol etmek için yapay sinir ağı tabanlı bir PID denetleyici tasarımı önermektedir. Her iki yöntemin benzetim sonuçlarına dayalı olarak detaylı bir analiz yapılmıştır. Önerilen denetleyiciler, ayar noktası değişiklikleri, yük torkundaki adım değişiklikleri ve parametre varyasyonları dahil olmak üzere çeşitli test koşulları için sayısal olarak simüle edilmiştir; ardından önerilen teknikler, denetleyicilerin başarımını doğrulamak için geçici tepki özelliklerine ve başarım endekslerine dayalı olarak geleneksel bir PID denetleyici ile karşılaştırılmıştır. Benzetim sonuçları, denetleyicilerin iyileştirilmiş dinamiklere, iyileştirilmiş statik performansa ve daha az en büyük aşmaya sahip olduğunu göstermiştir. Burada açıklanan yöntemler, farklı çalışma aralıklarında hem nominal hem de bozulmuş test koşulları altında geleneksel kontrol yaklaşımlarından daha etkili bir şekilde kontrol sağlamıştır.

Anahtar Kelimeler: SMDA motor, PID Denetleyici, Yapay sinir ağları (YSA), YSA-PID, Geçici tepki.

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1. Introduction

DC drives have historically been the backbone of applications that demand precise speed and position control, including robot manipulators and home appliances, because of their low complexity, excellent reliability, adaptability, and attractive cost (Bansal, 2013). The motor should be accurately controlled to provide the desired result, thus the speed controller must carry out a variety of functions under a wide range of load conditions. Efficient motor drive development is crucial for many applications in industry. Control's main goal is to improve the model's performance and enable reliable operation. Although direct, easy, and reliable control is possible using a conventional control algorithm (PID), it is, however, have some drawbacks. A major problem in applying PID to speed controllers is the nonlinearity effects of DC motors. DC motors' nonlinear properties, such as friction and saturation, can affect the conventional controllers' performance. In some control systems, it can be hard to adjust the three PID controller $\boldsymbol{K_P}$, $\boldsymbol{K_I}$ and $\boldsymbol{K_D}$ parameters. The traditional PID controller, which is applied in nonlinear, time-varying, uncertainties, or large inertia systems, will not be very effective. It can produce a high starting current that might be harmful to the motor's control electronics, etc., so the need for intelligent control arises.

The last decade has witnessed a rapid acceleration in control and automation and the emergence of intelligent controller which is a type of control system that employs different computing techniques with artificial intelligence such as self-tuning regulators, artificial neural networks (ANN), variable structure control (VSC), sliding mode control (SMC), and model reference adaptive control (MRAC). There is currently a strong interest in control science and practice for integrating classical automated control methods with artificial intelligence methods to control complex and weakly formalized objects and processes(Vassilyev et al, 2017), such as artificial neural networks (ANN) with conventional methods that are capable of eliminating system nonlinearity, the impacts of parameter variations, unanticipated changes in load, and system disturbance. The distributed and inherent parallel design of an ANN can be effectively exploited in order to control electric motors. Without being knowledgeable of any predefined model, the use of ANN can give a nonlinear mapping between an electric drive system's inputs and outputs. As a result, the application of an ANN to superior performance motor drives will make the system more reliable, effective, and resistant to undesirable conditions of operation. Although the Artificial neural network's historical development dates go back to 1943, the utilization of the neural network for control systems is relatively recent. Antonio E. B. Ruano (1992) presented the artificial neural networks' usefulness for control systems and their ability to implement nonlinear mappings. On the other hand, there was a lot of research on controlling the speed of DC motors with different algorithms. A PI (Proportional integral) controller and FL (fuzzy logic) controller are used for controlling the speed of the PMDC motor (Tuna, 2015). A Fuzzy controller compared to the PI had an improved variable speed load control performance. Gucin et al (2015) presented a comparison of several tuning approaches for cascade Proportional Integral (Derivative) parameters of the controller for the (PMDC) motor drives. Cozma et al (2008) presented a control system depending on ANN and PID controllers for permanent magnet DC motor drives. Through a variety of auto-tuning techniques, the system offers an automatic assessment of the PID controller's variables. The employed neural controller is learned offline with data acquired from the system's experiments. The main challenge was to create a structure that could give the highest sample rate and the lowest time of response. Muthusamy et al (2012) presented a PMDC drive in a closed loop control by an inner controller of current and an outside PID with an ANN-based speed controller. A NABSC (neuro adaptive backstepping control) technique using Chebyshev polynomial with a single-layer based neural network is presented for the tracking of angular velocity for a permanent magnet dc motor which is feeding with a buck converter (Nizami et al, 2017). A novel adaptive backstepping control technique that integrates a single functional layer Legendre neural network into the DC-DC step down converter for a permanent magnet DC motor system is also presented (Gangula et al, 2022). The standard method for modeling a DC motor is to ignore the effects of nonlinearity and create a representation of the linear transfer function for the relationship between the input output characteristics of the direct current motor and the load it powers. This assumption is adequate and valid for classical control problems. However, if the DC motor slowly operates and rotates in both directions, or if the operating range is wide and the application requires high precision control, assuming the effects of nonlinearity on the system are negligible leads to intolerable, increasing modeling errors and degraded control performance, therefore, there are many studies involving nonlinearity in DC motor modeling(Liu et al, 2013; Ahmad, 2011). An intelligent control system composed of two different neural network controllers for PMDC motor that can deal with the system's nonlinearities and load changes to reach high efficiency of the overall system and improve its performance is presented. The analysis, design, and simulation of the proposed controllers are described. Good and robust control performance is achieved. This work is divided into four sections. Section 1 presents an introduction and related investigations. The Material and method was exhibited in Section 2. Section 3 describes the results and discussion. Finally, the conclusions based on this research are shown in part 4.

2. Material and Method

2.1. PMDC motor modeling

The DC motor used for this study is PMDC, which controls the speed by armature voltage control method. We aim in building the mathematical model for the PMDC motor to model and simulate it and to link the voltage provided to the armature to the motor's velocity, we use the system's mechanical and electrical dynamics as in (1-2),

$$\frac{di_a}{dt} = \frac{v}{L} - \frac{R_a}{L} i_a - \frac{K_v}{L} w_m \tag{1}$$

$$\frac{dw_m}{dt} = \frac{T_L}{j} + \frac{K_t}{j} i_a - \frac{B}{j} w_m \tag{2}$$

Where v is the voltage source, R_a is the armature resistance, i_a is the armature current, w_m is the angular speed, L is the inductance of armature, B is the damping coefficient, K_v is the velocity constant, K_t is the torque constant, j is the inertia of the rotor, and T_L is the torque of the mechanical load. The following equations (3-4) describe the transfer functions of the motor,

$$I_a(s) = \frac{-K_V w_m(s) + v(s)}{L_a s + R_a} \tag{3}$$

$$w_m(s) = \frac{-K_t I_a(s) - T_l(s)}{js + B} . \tag{4}$$

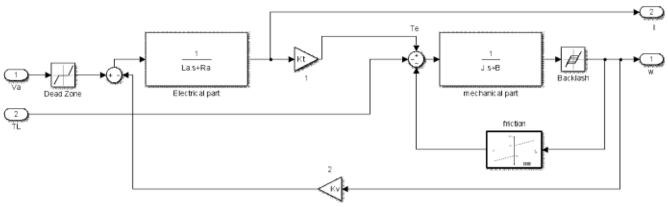

Figure 1. Nonlinear simulation model of PMDC motor.

The parameters of the PMDC motor are in the Appendix. The assumption that the nonlinear effects on the system are negligible may result in poor control performance, so we design the control system by taking into consideration all the nonlinearities as a backlash, dead-zone, and friction(Gómez et al, 2020). The simulation model of the system with nonlinearities is presented in Figure 1.

The following Figure represents the response of the system in an open loop.

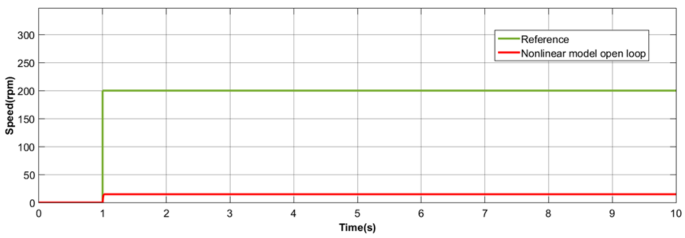

Figure 2. Open loop response of nonlinear model of PMDC motor.

We notice here there is a big overshoot in the curve that is undesirable, so, it is crucial to design a speed controller of the DC motor at different desired speeds.

2.2. Design of PID controller

Proportional Integral Derivative (PID) control is one of the earliest control strategies used in all fields where closed-loop control is applied. It produces a control depending on an error signal.

$$u(t) = K_P e(t) + K_I \int e(t) + K_D \frac{de}{dt} \qquad (5)$$

The weighted total of all these gains is used to change the process via controlling. We can tune the three constants of the PID controller algorithm to meet our specific operational needs. By tuning of PID Controller by Zeigler Nichols and after some other tunings we will fix the values of the PID parameters as K_p = 35, K_I = 260, K_D = 0.05.

2.3. Design and structure of ANN- PID controller

The study of neural networks in control systems to enhance the degree of automated processes and the economy's effectiveness of industry is of great importance. The error between the system output and predicted values can be minimized by using neural network PID controllers in place of conventional PID controllers. We have designed the controller in two different ways depending on the inputs, outputs, and structure of the neural network.

2.3.1. First controller

The first controller tested in the study is made up of a classic PID controller plus a neural controller, which we denote as ANNPID1 in short. It incorporates the advantages of neural and PID controllers. Traditional PID directly regulates the controlled object using a closed loop, while neural networks adjust their control gainsK_D, K_I and K_p based on the system's operational condition to achieve performance optimization. The model of the ANNPID1 controller with PMDC motor is shown in the Fig 3.

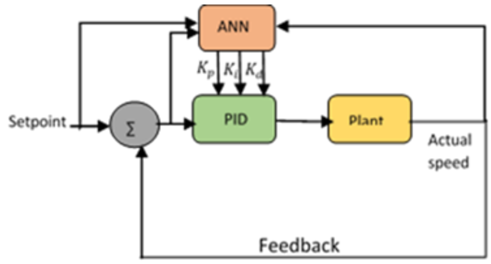

Figure 3. ANNPID1 control system block diagram.

The inputs of the controller are the reference speed, the error signal, and the output signal. Where the outputs of the controller are: Derivative gain K_D, Integral gain K_I, and proportional gain K_p. The function fitting is performed using a feedforward network with two-layer, whereas the transfer functions that we used are a linear transfer function, and a tan sigmoid transfer function for the output layer, and the hidden layer. The structure of this network is 3-10-3. The data are gathered from the traditional PID controller's closed loop response and were used to constitute a database to train the NN. We use a repeating sequence signal as a reference signal which has the sequence values of [0 300 300 300 -300 -300].

2.3.2. Second controller

The second controller which is denoted as ANNPID2 mimics a PID controller. It is designed to generate a control signal that is utilized to control the velocity of the PMDC motor. Three inputs are fed into the controller to generate a single output. The structure of ANNPID2 is depicted in Figure 4.

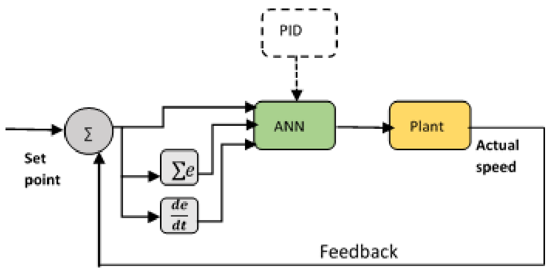

Figure 4. ANNPID2 controller model.

The inputs of the controller are the error signal between reference speed and actual value, the integration of the error signal, and the derivative of the error signal. Where the controller output is the control signal of the PMDC. The function fitting is also here performed using a feedforward network with two-layer, whereas the transfer functions that we used are a linear transfer function, and a tan sigmoid transfer function for the output layer, and the hidden layer. The structure of this network is 3-15-1.

3. Results and Discussion

In this work, the performance of a PMDC motor with different control strategies, two artificial neural networks, and conventional PID is evaluated on the basis of rise time t_r, settling time t_s, and maximum overshoot M_P. Three testing scenarios are carried out, which are set-point changes, disturbance rejection, and uncertainty rejection. Three different objective functions which are, Integral Square Error (ISE), Integral Absolute Error (IAE), and Integral of Time Weighted Absolute Error (ITAE) performance indices are calculated for each case in order to analyze the performance of each controller.

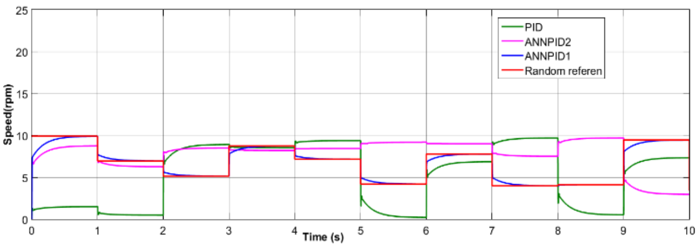

Figure 5. The response speed of the ANNPID1 (blue), ANNPID2 (purple), PID (green) with random reference speed input (red)

Table 1. Performance indices of PID, ANNPID1, ANNPID2 with random reference speed inputs

	PID	ANNPID1	ANNPID2
ISE	2.953	1.7	1.219
IAE	2.423	1.839	1.293
ITAE	14.02	7.312	5.483

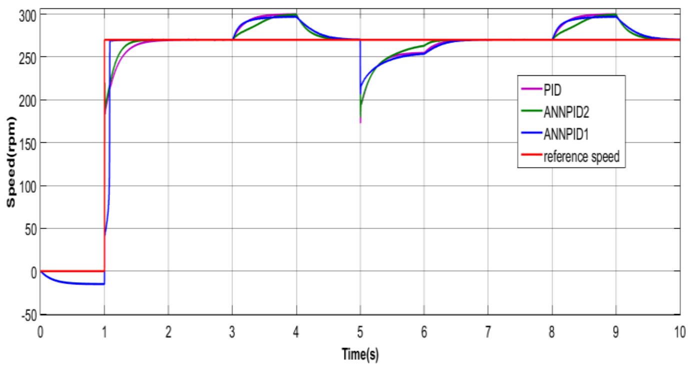

Figure 6. The response speed of the second controller PID (purple), ANNPID1 (blue), ANNPID2 (green) with 270 rpm reference speed inputs (red) and [0 300 300 300 -300 -300] input load.

Table 2. Transient Response Specification of PID, ANNPID1, ANNPID2 with disturbance

	PID	ANNPID1	ANNPID2
Rise time	0.2203	0.0808	0.1671
Settling time	9.3056	9.4040	9.3043
Overshoot	11.0627	10.0554	10.9446

Table 3. Performance indices of PID, ANNPID1, ANNPID2 with disturbance

	PID	ANNPID1	ANNPID2
ISE	3497	5730	2806
IAE	119	118.9	100.4
ITAE	560.6	560.8	472

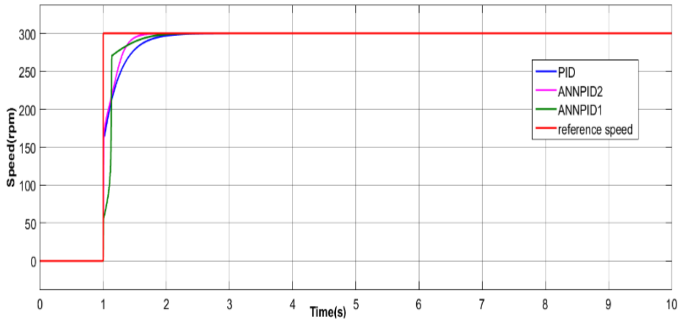

Figure 7. The response speed of PID (blue), ANNPID1 (green), ANNPID2 (purple) with 300 rpm reference speed inputs (red) and change of parameters B=1.5, J=0.01

Table 4. Transient Response Specification of PID, ANNPID1, ANNPID2 with unit step reference input and change of parameter

	PID	ANNPID1	ANNPID2
Rise time	0.4078	0.1341	0.2908
Settling time	1.8243	1.6579	1.4866
Overshoot	3.7650e-04	3.3307e-13	3.3307e-13

Table 5. Performance indices of PID, ANNPID1 and ANNPID2 with unit step reference input and change of parameters

	PID	ANNPID1	ANNPID2
ISE	2907	6119	2333
IAE	38.12	37.41	27.04
ITAE	47.92	43.02	31.11

To test the robustness properties of PID, and ANN controllers to set point variations, we used a random reference signal. The output responses of PID, ANNPID1, and ANNPID2 with random reference are shown in Figure 5. The transient response specifications and performance indices of random reference input are represented in Table 1. The proposed ANNPID2 has the smallest values of all performance indices. While the ANNPID1 comes after it. PID controller has the worst values for performance indices.

In order to test the robustness of the designed controllers to disturbance inputs, a random load torque signal is used with a 270 reference speed. The output responses of PID, ANNPID1, and ANNPID2 with a step signal and a random load torque signal are given in Figure 6. The transient response specifications and performance indices with a random load torque t are represented in Table 2, Table 3. The proposed ANNPID2 has the smallest values of all performance indices. Where the ANNPID1 has the smallest value of rise time and overshoot.

To test the performance of presented controllers against the uncertainty rejection we have changed the value of B from 0.002 to 1.5 and the value of j from 0.00471 to 0.01. The output responses of PID, ANNPID1, and ANNPID2 with a change of parameters are given in Figure 7. The transient response specifications and performance indices with a random load torque t are represented in Table 4, Table 5. The two proposed controllers show improved performance for disturbance rejection. PID controller has smaller values for ISE than the ANNPID1.

4. Conclusions and Recommendations

This paper investigates the effectiveness of enhancing a controller design for a PMDC motor. The speed of the permanent magnet DC motor is controlled using the proposed ANN-based PID controller in two methods. The simulation model of the control system has been established based on an analysis of the mathematical model for the PMDC motor based on the electrical and mechanical equations for the PMDC. A nonlinear model of the PMDC motor is used. First, a PID controller is designed and the PID parameters are tuned using the Zeigler-Nichols method. Next, an ANN-based PID speed controller is designed. The performance of the proposed controllers is validated by subjecting the PMDC motor system to angular velocity tracking set points, load torque changes, and parameter variation tests, then several characteristics are studied, including the rise time, overshoot, settling time, and many performance indices that are all crucial for the development of the DC motor performance.

The results show that the speed control of the DC motor by an ANN-based PID has better performance, high resilience, and good accuracy without oscillation. In comparison to conventional approaches, the controller also demonstrates good efficiency when tracking the motor speed, successful rejection of load torque uncertainties, and parameter variations.

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Appendix

Parameter	Symbol	Value
Armature Resistance	R_a	0.5 Ω
Armature Inductance	L_a	0.012 H
Inertia of the Rotor	j	0.00471kg m^2
Torque Constant	K_t	0.5 Nm/A
Velocity constant	K_V	0.5 Vs/rad
Damping Coefficient	B	0.002 Nms/rad