Chapter 9

Fuzzy Logic and Neuro-Fuzzy Control: DC Motor Position Control

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Abstract

In this chapter, a brief explanation is given about fuzzy logic and neuro-fuzzy systems. DC motor position control is realized to explain usage of neuro-fuzzy controller. DC motor model is given in the form of mathematical equations and transfer function. First, a tuned by trial-error method PID controller is applied to DC motor system and responses are collected as a dataset to train neural networks of neuro-fuzzy system. Trained neuro-fuzzy system is used to design an adaptive neuro-fuzzy controller to control position of a DC Motor. Matlab Neuro-Fuzzy Designer Toolbox and Matlab/Simulink is used to design neuro-fuzzy and simulate the control system. As a results, neuro-fuzzy controller achieved successfully in the position control of DC motor. The results also shows that neuro-fuzzy controller can support energy consumption.

1. INTRODUCTION

The foundations of fuzzy logic were laid by Lotfi A. Zadeh in the mid-20th century. Zadeh introduced this new mathematical modeling approach in 1965 with his article "Fuzzy Set Theory" [1]. Fuzzy logic is a mathematical modeling approach used to solve problems involving uncertainty. This method does not use absolute truth values (0 or 1) as in classical logic. Instead, it recognizes the concept of a "degree of uncertainty" that expresses uncertainty. This is extremely useful in situations where the truth of a statement cannot be expressed in an exact number. Fuzzy logic has achieved great success in various application areas. Its use has become widespread, especially in fields such as control systems, artificial intelligence, engineering, finance and medicine [2].

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The use of fuzzy logic in the field of control systems is widely seen in the literature. Fuzzy logic control studies were first done by Mamdani, and these studies led to a great impact on Fuzzy control research [3]. Different control studies are encountered in many disciplines that use control systems. Uncertainties in factors such as ambient temperature and humidity levels in Heating, Ventilation and Air Conditioning (HVAC) Systems enable fuzzy logic to be used effectively in HVAC systems [4]. This is important for energy efficiency and comfort. Robotic systems can operate in environments where environmental conditions are uncertain. Fuzzy logic can control robot movements using sensor data [5]. Mechanical systems such as washing machines must respond to uncertain combinations of different types of pollutants and fabrics [6]. Fuzzy logic provides ease of control of industrial machines and industrial applications such as hydraulic systems [7]. In academic studies, the most common mechanical systems are different types of inverted pendulum systems and quarter car models, which are considered as the benchmark problems in the field of control systems [8-10]. Neuro-fuzzy systems have been created by using fuzzy logic and artificial neural networks together, and in addition to these studies, the use of fuzzy logic approach is also seen in many multidisciplinary studies [11].

In this chapter, the basics of fuzzy logic and neuro-fuzzy control systems are discussed, and an example is given on the position control of the DC motor system, which is the most common of electro-mechanical systems.

2. FUZZY LOGIC AND NEURO-FUZZY

Fuzzy logic is a mathematical modeling approach developed to handle uncertainty and imprecise data. This approach uses a degree of uncertainty that determines the truth of each statement, rather than using sharp truth values (0 or 1) as in classical logic [12]. This degree of uncertainty indicates how certain a situation or data is. Other important components built on this basic concept include membership functions and fuzzy sets used to express uncertainty. These sets indicate the degree of an element in a set and express this degree with a range containing uncertainty. Fuzzy logic enables modeling and control of complex systems in the real world using these basic principles. Therefore, understanding the basic principles of fuzzy logic provides a great advantage in solving problems involving uncertainty.

For example, a classical example how to explain fuzzy logic, in Figure 1, the expressions cold, warm and hot are represented by membership functions [13]. In this representation, a point has three “truth values”, one for each of the three functions. The truth values of the vertical green dashed line in the image are equal to zero for the red membership function, this means temperature is not hot, while other truth values can be defined as 20% warm for the orange membership function and 80% cold for the blue membership function. Therefore, this temperature has a 0.2 degree of membership in the hot membership function and a 0.8 degree of membership in the cold membership function. The membership degree assigned to each fuzzy set is the result of fuzzification. Here is an example of triangular membership functions. There are different types of membership functions depending on their shapes, such as gauss, generalized bell-shaped and trapezoid membership functions [14].

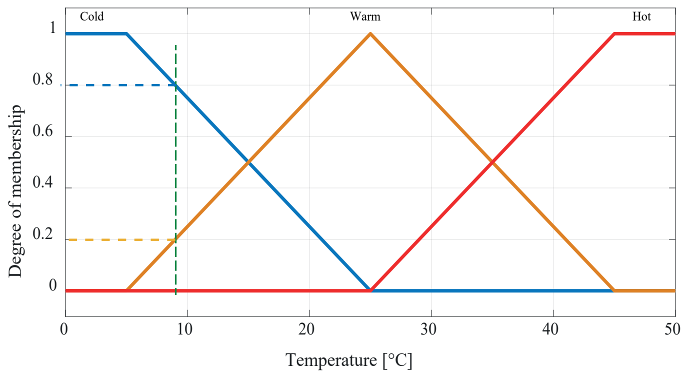

Figure 1. Membership functions and degree of membership.

Classical logic operators (and, or, not) are also used in fuzzy logic. However, here, the process is done based on degrees of uncertainty. The union of sets brings together the degrees of uncertainty of the elements of the sets. Fuzzy logic is a rules-based system. These rules specify the outcome of a particular situation. The fact that such rules accept uncertainty is crucial in modeling complex systems in the real world.

Fuzzy logic uses the if-then rule system. When there is more than one modeling parameter, if-then rules are created between inputs and outputs. For example, in a fuzzy logic model with inputs a and b and output c, rules are created as follows;

rule 1: IF a IS 1 AND b IS 2, THEN c is 3.

rule 2: IF a IS 3 AND b IS 4, THEN c is 4.

The result obtained at the output varies depending on the defuzzification method. Different methods can be used for fuzzification and defuzzification.

Another fuzzy logic method is neuro-fuzzy systems [15, 16]. Neuro-Fuzzy systems are a type of artificial intelligence model created by combining traditional fuzzy logic systems with neural networks. These systems are used to address problems involving uncertainty, increase learning capabilities, and model more complex, dynamic systems. By combining advantages from fuzzy logic and artificial neural networks, neuro-fuzzy systems offer more flexible, data-driven and faster decision-making capabilities. Control systems are one of the areas where neuro-fuzzy systems are commonly used.

While creating the Neuro-Fuzzy model, the necessary data sets for a specific application area are collected and prepared appropriately. Fuzzy logic rules and membership functions appropriate to the problem are determined, and the neural network is used to train the system using the specified input variables and output variables. It consists of basic components: input layer, hidden layer and output layer. The trained neural network makes inferences according to the determined fuzzy logic rules and membership functions and results are obtained.

The most common applications of the above mentioned in academic studies are made using Fuzzy Logic Designer and Neuro-Fuzzy Designer toolboxes. In addition, Matlab/Simulink is used for fuzzy logic control and neuro-fuzzy control studies [17, 18].

3. DC MOTOR POSITION CONTROL

In this section, neuro-fuzzy controller was used in position control is of a DC motor, which is widely used electro-mechanical system in the literature. These models are important for predicting how the motor will operate in real-world applications. Figure 2. represents the DC Motor's electrical and mechanical parts [19].

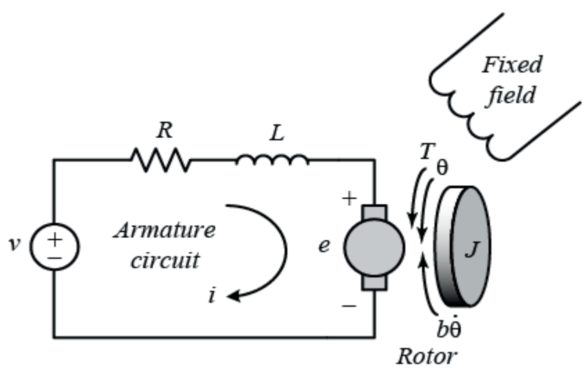

Figure 2. DC Motor.

DC motor model can be written as equations that mathematically express the electrical, mechanical and magnetic properties of the motor. DC motor models help engineers analyze, design and optimize the behavior of the motor. Equation (1) - (2) represent the motor torque that is proportional to current i and the back emf that is proportional to angular velocity of the rotor $\dot{\theta}$, respectively.

$$T = K_t i \tag{1}$$

$$e = K_b \dot{\theta} \tag{2}$$

Here, K_t and K_b are the torque constant and the force constant, respectively. In this example these constants are used equal. Therefore $K_t = K_b$, K is used to represent both constants.

Equations (3) - (4) are mathematical model equations of DC motor and Equation (5) represents the transfer function of DC motor. V represents system voltage and θ represents the position of the rotor.

$$J\ddot{\theta} + b\theta = Ki \tag{3}$$

$$L\frac{di}{dt} + Ri + K\dot{\theta} = V \tag{4}$$

$$\frac{\theta(s)}{V(s)} = \frac{K}{s((Js + B)(Ls + R) + K^2)} \tag{5}$$

DC motor parameters used in this study is a commonly used model parameters such as a benchmark problem in the literature. The model parameters are given in Table 1.

Table 1. DC Motor model characteristics [19].

J	Moment of inertia of the rotor	$3{,}2284.10^{-6}$	$kg.m^2$
b	Motor viscous friction constant	$3{,}5077.10^{-6}$	N.m.s
K_b	Electromotive force constant	0,0274	V/rad/sec
K_t	Motor torque constant	0,0274	N.m/Amp
R	Electric resistance	4	Ohm
L	Electric inductance	$2{,}75.10^{-6}$	H

First, PID controller [20], which is the most widely used in control engineering, is used in the position control of the DC motor. PID gains determined by trial and error and used to control DC motor position, these K_p, K_i and K_d gains are 1, 10 and 0.01 respectively. PID control block diagram is shown in Figure 3.

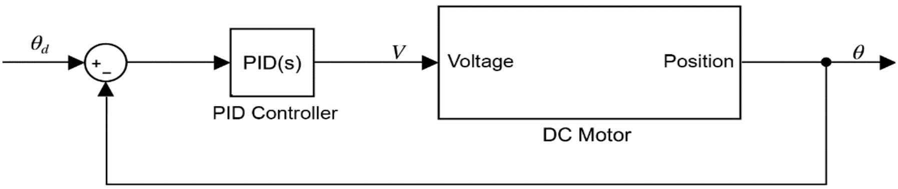

Figure 3. PID control block diagram.

The responses against different reference positions are collected as a data set. This dataset is used to train Neuro-Fuzzy controller to create adaptive neuro-fuzzy inference system. Position error and derivative of position error are used as input, control voltage is uses as output while training Neuro-Fuzzy system.

Triangle membership functions are selected to design neuro-fuzzy controller in this chapter. Five membership functions are used for inputs of position error and derivative of position error as seen Figure 4. and Figure 5.

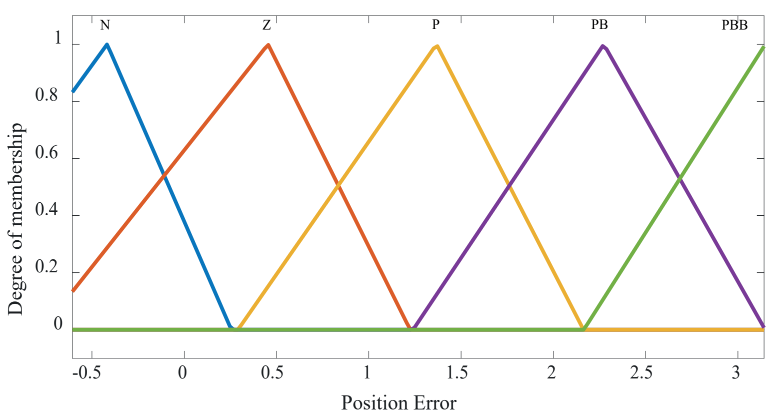

Figure 4. Position error membership functions.

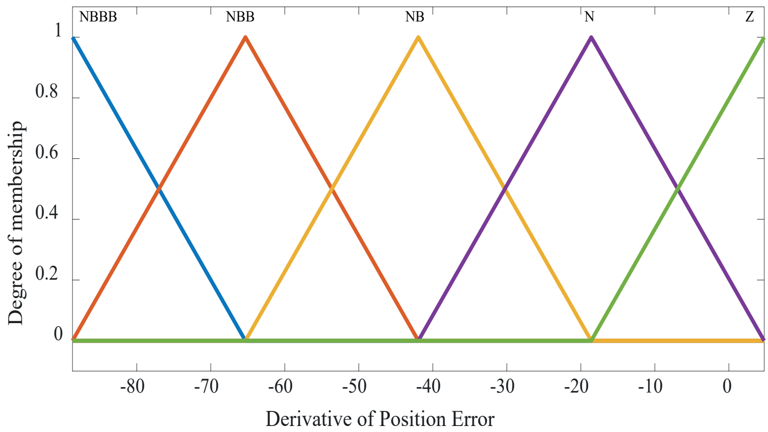

Figure 5. Derivative of position error membership functions.

Neuro-Fuzzy systems contains constant values as outputs. This means adaptive neuro-fuzzy inference system uses Sugeno type inference system [21]. Rule table of neuro-fuzzy system shown in Table 2.

Table 2. Neuro-Fuzzy system rule table.

		Position error				
		N	Z	P	PB	PBB
Derivative of position error	NBBB	0	0.6571	1.358	2.668	4.711
	NBB	-0.4057	0.5236	1.251	2.765	5.081
	NB	0.0961	0.3957	1.14	2.863	5.435
	N	-0.00354	0.2039	0	2.92	5.828
	Z	-0.1904	0.06256	0	-19.14	6.575

Designed neuro-fuzzy controller used to realize DC Motor position control. Fuzzy logic control block diagram is shown in Figure 6. As seen in this figure, neuro-fuzzy controller used instead of PID controller.

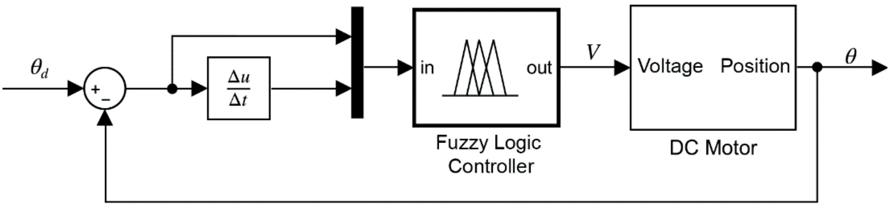

Figure 6. Fuzzy logic control block diagram.

4. RESULTS AND DISCUSSION

Desired DC motor position is selected 30° and both controllers are applied using Matlab/Simulink environment. Designed neuro-fuzzy controller is compared to classical PID controller. This PID controller is applied to create dataset used in training neuro-fuzzy controller. Comparison of position results of PID controller and Neuro-Fuzzy controller is shown in Figure 7. This figure shows that PID controller has overshot but Neuro-Fuzzy controller reached reference position successfully without overshot.

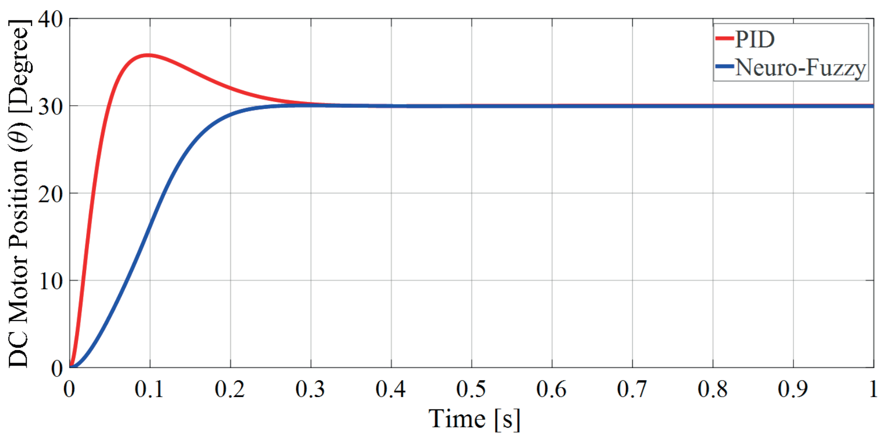

Figure 7. Comparison of position results of PID and Neuro-Fuzzy controller.

Comparison of control voltage results of PID and Neuro-Fuzzy controller is shown in Figure 8. This figure shows that Neuro-Fuzzy controller uses less voltage than PID controller. This means that neuro-fuzzy controller is effective in energy consumption.

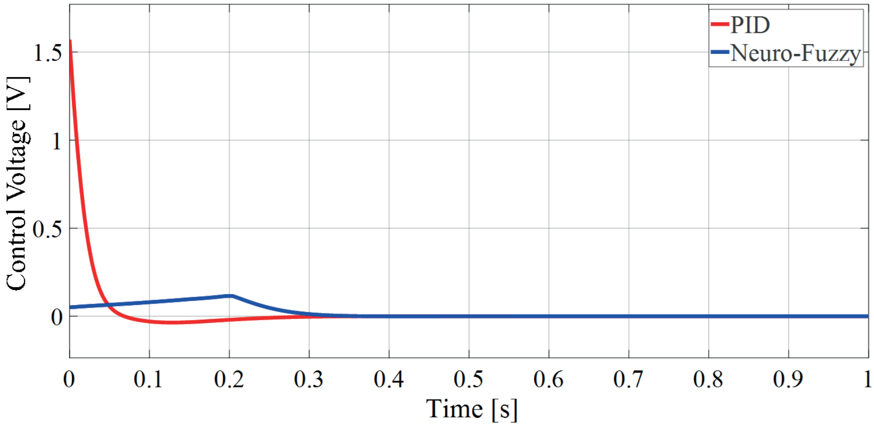

Figure 8. Comparison of control voltage results of PID and Neuro-Fuzzy controller.

5. CONCLUSION

In this chapter, an adaptive neuro-fuzzy controller is designed to control position of a DC Motor which is basic electro-mechanical system. First, a trial error PID controller is realized and control responses are collected as a dataset to train neural networks system of neuro-fuzzy. As seen in the results in the form of graphics, neuro-fuzzy controller achieved successfully in the position control of DC motor. Control voltage result shows that neuro-fuzzy controller can support energy consumption.

Neuro-fuzzy control usage for an electro-mechanical system is explained as an example in this chapter. Results can be changing according to collected dataset, membership function types and rules. While training neural networks Neuro Fuzzy Designer toolbox uses an optimization algorithm. This algorithm can be change with a novel optimization algorithm. It also can be changing the results. Different usages of Fuzzy Logic and Neuro-Fuzzy will always be encountered in the modelling and control theory for the future works in the literature.

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