Proceedings of the Fourth International Conference on Smart Systems and Inventive Technology (ICSSIT-2022)
IEEE Xplore Part Number: CFP22P17-ART; ISBN: 978-1-6654-0118-0

Enhanced Speed Control of Separately Excited DC Motor Using Fuzzy-Neural Networks Controller

Ricsa Alhassane Soumana
Electrical Engineering Department
Pan African University Institute for Basic Sciences, Technology, and Innovation
Nairobi, Kenya
alhassane.soumana1@students.jkuat.ac.ke

Michael Juma Saulo
Department of Electrical and Electronics Engineering, Technical University of Mombasa line
Mombasa, Kenya
michaelsaulo@tum.ac.ke

Christopher Maina Muriithi
Department of Electrical and Electronics Engineering
Murangá University of Technology
Murang'a, Kenya
cmmuriithi@mut.ac.ke

Abstract— **The dynamic behavior of a PID-type fuzzy logic control depends on the appropriate choice of its scaling factors. Fixed scaling factors cannot provide adequate control performance under a wide range of operating conditions. This paper proposes a control strategy for separately excited dc motor (SEDCM) speed control based on fuzzy logic and neural networks. The function of the neural networks is to adapt the scaling factors at the inputs and output of the fuzzy logic controller. Using MATLAB/Simulink, the performance of the proposed controller is highlighted in comparison with anti-windup proportional-integral (PI) and sliding mode controllers under variable speed reference, disturbances, and armature resistance variation.**

Keywords—Separately Excited DC Motor, Speed Control, Fuzzy Logic Control, Artificial Neural Networks, Scaling Factors.

I. INTRODUCTION

DC motors are widely utilized in various applications, including electrical mills, electric trains, robotic systems, electric cranes, elevator systems, household appliances, and, more recently, electric automobiles, due to their high reliabilities, flexibility, and low prices. [1], [2], [3]. In most of these applications, DC motors require speed control to perform their task. [4], [5]. Separately excited DC motors (SEDCMs) are probably the most studied types of motors in the field of automation and control. Because of theirs precise speed control, adjustable torque, and simplicity, SEDCMs have long been the most suitable configurations for variable speed applications. [4]. The inherent decoupling between the torque equation and the speed equation of SEDCMs makes them an excellent choice for applications requiring a broad range of speed variations.

For DC motor speed control systems, traditional control methods such as proportional-integral-derivative (PID) are extensively employed in the industry [6]. According to reports, PID controllers account for more than 90% of controllers used in industrial process control applications since no other controller compares to the PID controller's simplicity, unambiguous functionality, adaptability, and ease of use [4], [7]. However, conventional controllers such as PI, as well as PID, perform poorly under all conditions, including load changes, parameters variation, and disturbances [6], [8], [9]. Furthermore, determining and optimizing the PID parameters remains a difficult issue, and considerable work is required to achieve a satisfactory system response utilizing the commonly used tuning methods of hand-tuning and the Ziegler-Nichols frequency response approach [1], [8]. The electrical parameters of a DC motor are affected by temperature, current and voltage oscillations, and a time-varying loading condition [10]. As a result of these changes, the DC motor now exhibits its nonlinear characteristics. Therefore, nonlinear control is necessary [10].

Many advanced control techniques have been proposed in the literature to ensure robust speed control of DC motor under conditions of disturbances, parameters variation, and variable speed reference. These advanced control include sliding mode control (SMC) [10], [11], fuzzy logic control (FLC) [12], [13], neural networks controllers [3], [14], neuro-fuzzy controllers [8], [15], adaptive backstepping controllers [16], and model reference adaptive controllers [17], [18]. To furthermore increase the robustness of these advanced control techniques, some researchers have proposed hybrid technique control such as neuro-fuzzy based dual PID controllers [19], fuzzy self-tuned PID controllers [4], [20], [21], sliding mode with FLC [22], PI-neural network control [23], fuzzy model reference adaptive control [24], adaptive backstepping SMC approach [25],etc.... In most of the above-cited works, the robustness against parameter variation, disturbance rejection, and variable input reference of the proposed controllers was not highlighted.

FLC has recently caught the interest of many researchers and engineers from various sectors due to its superior capacity to deal with the nonlinearities and uncertainties of any system, its simplicity of design, and the possibility of incorporating human skills in the control process. For DC motor speed control, various FLC topologies are developed and thoroughly investigated in the literature. FLC outperforms traditional controllers [26], as demonstrated by the work of [20], [27], [28], where fuzzy self-tuned PID performance is compared to that of PID controllers. The PID-type FLC is another FLC structure for the speed of SEDCMs that are commonly encountered in the literature. This structure uses scaling factors at the fuzzy controller's inputs and output and does not employ an additional controller. The PID-type FLC has the features of a traditional PID controller [29]. The main disadvantage of the PID-type FLC structure is the difficulty in determining their scaling factors, and the controller's dynamic behavior is determined by the appropriate choice of these scaling factors [26], [29], [30]. In [1], [5], [31], and [32], a PID-type FLC is proposed to control the dc motor speed. Furthermore, the proposed fuzzy controllers' performance was highlighted compared to a PID controller. However, fixed scaling factors cannot offer suitable control performance under various operating conditions. In [33] and [29], a particle swarm optimization

(PSO) algorithm was employed to find the optimal scaling factors of a PID-type FLC for a SEDCM. The PSO technique used in [33] does not make the scaling factors adaptive because their values are fixed in the control scheme following a system's step response. As a result, the control system suffers from the same disadvantage as when the scaling factor is fixed. Moreover, the proposed controller presented a longer settling time. In [29], the scaling factor tuning problem is formulated as a constrained optimization problem, with the cost function selected as the minimization of the maximum overshoot and the integral of absolute error. Finding a cost function to optimize based on scaling factors may be difficult. Furthermore, PSO has two major flaws: early convergence and being stuck in local minima [34]. In the same perspective of optimal choice of fuzzy controller scaling factors, both [30] and [35] have employed genetic algorithm (GA) . The authors in [36] have utilized a GA to find the optimal fuzzy rules, memberships function, and scaling factors. Genetic algorithm is computationally intensive and may require more time to provide good results. In [26], cuckoo search algorithm, ant bee colony algorithm, and firefly algorithm were used to tune the scaling factors of a PID-type FLC for SEDCM speed control. Furthermore, the performance of the fuzzy logic controller, with its gain optimized by the three heuristic algorithms mentioned above, was compared to that of a firefly optimized PID controller. The heuristically optimized fuzzy controller had a longer settling and rising time, and it outperformed the firefly optimized PID controller only in terms of disturbance rejection. Although heuristic algorithms have the advantage of being easy to understand and implement in complex optimization problems, they cannot provide an optimal solution in most cases, and they are dependent on initial conditions and randomness. In [34], a new hybrid PSO search strategy called PSOSCALF, combining Sine Cosine Algorithm and Levy Flight distribution, was proposed for a PID-type FLC to optimize not only the scaling factor but also the membership function and the rule base. The proposed search technique is too complex and requires fast processing unit.

The optimization of PID-type FLC in terms of scaling factors is recently being explored [26], [34], [37], [38]. As far as the authors of this study are aware, the scaling factors of PID-type FLC have not yet been optimized using an artificial neural network (ANN). Hence, this paper proposes a PID-type FLC scheme for a SEDCM speed where feedforward neural networks optimize the scaling factors. Each scaling factor consists of a fixed gain and another adaptive. A neural network with two inputs (reference and actual speed) and one output makes each scaling factor adaptive. Trial-and-error procedures were used to obtain training data for neural networks. Furthermore, the performance of the fuzzy-ANN controller was compared to that of anti-windup PI control and SMC. The proposed fuzzy-ANN control scheme exhibits dynamic and static performance and less sensitivity against disturbances and armature resistance variation.

The remainder of the paper is organized as follows: the motor model is presented in Section II. Section III describes the fuzzy-ANN controller. The development of the anti-windup PI control and SMC are given in section IV. Section V presents and discusses the simulation results. Finally, in section VI, concluding remarks are provided.

II. SEPARATELY EXCITED DC MOTOR MODEL

SEDCM has mainly two independent sections: the field and armature sections. In such a motor, the speed control is commonly achieved by the armature voltage (V_a). The latter causes a current to flow in the armature circuit, which creates an electro-mechanical force, which is directly proportional to the rotational speed [20]. The electrical circuit of the motor is shown in fig. 1.

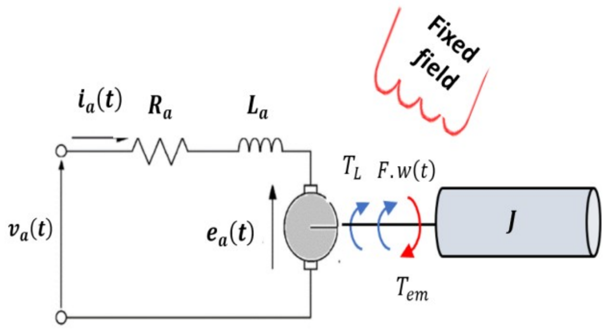


Fig. 1. Schematic illustration of a separately excited DC motor

The mathematical equations which describe the DC motor are given by the following:

$$v_a(t) = e_a(t) + R_a i_a(t) + L_a \frac{di_a(t)}{dt} \quad (1)$$

$$e_a(t) = Kw(t) \quad (2)$$

$$J\frac{dw(t)}{dt} = T_{em} - T_L - Fw(t) \quad (3)$$

$$T_{em} = Ki_a(t) \quad (4)$$

Where R_a and L_a represent armature resistance [Ω] and inductance [H], respectively. T_{em} stands for the electro-mechanic torque developed [N.m], and T_L is the load torque [N.m]. F is friction coefficient [N.m.s], j is the momentum of inertia [K_g/m^2], and $w(t)$ is the angular velocity [rad/s]. K represent both back electro-mechanical force constant [$V.s/rad$] and motor torque constant [$N.m/A$]. $e_a(t)$ is the back electro-mechanical force.

A Simulink model representing the DC motor can be obtained by conducting some mathematical manipulation and applying Laplace transforms to the preceding equations.

$$I_a(S) = \frac{V_a(S) - E_a(S)}{R_a + L_a.S} \quad (5)$$

$$W(S) = \frac{T_{em}(S) - T_L(S)}{JS + F} \quad (6)$$

Where S is the Laplace transform operator. The transfer function of the DC motor can be written as follows:

$$\frac{W(S)}{V_a(S)} = \frac{K/L_a J}{S^2 + \left[\frac{R_a}{L_a} + \frac{F}{J}\right]S + \frac{R_a F + K^2}{L_a J}} \quad (7)$$

The motor model in MATLAB Simulink is shown in fig. 2

978-1-6654-0118-0/22/$31.00 ©2022 IEEE

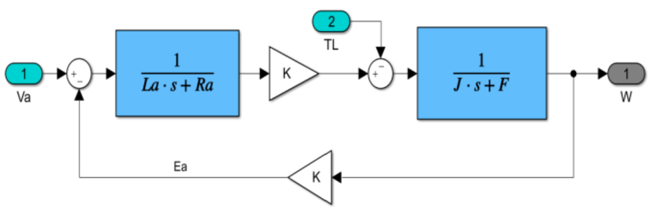


Fig. 2. Simulink model of a separately excited DC motor

III. FUZZY LOGIC CONTROL AND SCALING FACTORS ADAPTION TECHNIQUE BASED ON NEURAL NETWORKS

A. *Fuzzy logic controller Developpement*

FLC is a control method based on a linguistic control approach that attempts to account for human understanding of how to govern a system without the need for a mathematical model. The fuzzy set theory introduced by L.A. Zadeh in 1965 is one of the emerging intelligent techniques that have been developed and extensively used to control issues of nonlinear, insecure, or poorly defined systems [26]. A fuzzy logic controller is made up of four main components which are fuzzification (the process through which sensed crisp inputs are converted into linguistic variables), knowledge base (A set of expert control rules required to achieve the control objective), Inference mechanism (It performs fuzzy logic operations, resulting in control action based on the control rules and fuzzy inputs), and defuzzification (conversion of the control actions into crisp values).

In this paper, the error (e) and the change in error (ce) of speed are the inputs of the fuzzy controller. Z-shaped membership function (zmf), triangular membership function (trimf), Pi-shaped curve membership function (pimf), and Two-sided Gaussian membership function (gauss2mf) are used to represent both linguistic variable e and ce. Trapezoidal and triangular membership functions are employed for the output linguistic variable. The FLC membership functions are acquired by a trial-and-error process. The linguistic variables are denoted as NB, NS, ZE, PS, and PB, where NB stands for negative big, NS stands for negative small, ZE stands for zero, PS stands for positive small, and PB stands for positive big. The membership functions of the Fuzzy controller are depicted in Fig. 3, and Table I shows the 25 fuzzy rules. These rules are generated from the general PID fuzzy rule base [34]. The control rules presented in table I work as follows: for the first rule, if the error *e* (difference between the reference and actual speed) is negative big (NB) and the variation of the error *ce* is NB, the fuzzy controller's output will be NB. For the tenth rule, if *e* is PB (the reference speed is greater than the actual speed) and *ce* is NS (the speed declines at a slow rate.), then the output is PS (which means a small increase in the armature voltage to reach the reference speed without overshoot). For the last rule, if *e* is PB and *ce* is also PB, then the fuzzy controller's output is PB (which means a significant increase in the armature voltage to attain the reference speed quickly). The other rules work in the same way as the ones described above.

The properties of the Mamdani fuzzy inference system used are summarized below:

AndMethod: "min"

OrMethod: "max"

ImplicationMethod: "min"

AggregationMethod:

DefuzzificationMethod: "centroid"

Inputs: [1×2 fisvar]

Outputs: [1×1 fisvar]

Rules: [1×25 fisrule]

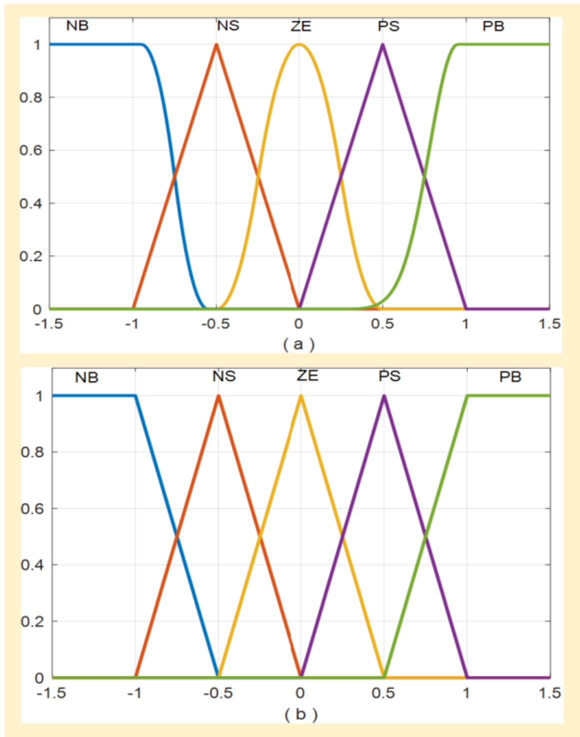


Fig. 3. (a) Normalized input membership functions for *error* and *change in error*. (b) output membership function

TABLE I. FUZZY RULES

ce \ e	NB	NS	ZE	PS	PB
NB	NB	NB	NS	NS	ZE
NS	NB	NS	NS	EZ	PS
ZE	NS	NS	EZ	PS	PS
PS	NS	EZ	PS	PS	PB
PB	EZ	PS	PS	PB	PB

B. *development of the Artificial Neural Networks*

Artificial neural networks (ANNs) are new technologies that work with learning patterns based on training data to provide successful results [2]. Feed-forward neural networks are among the most basic ANN architectures and have a high predictive capability [39]. In this study, each scaling factor is made up of a fixed gain and an adaptive gain. The adaptive gains are optimized by ANNs. The trial-and-error method is used to find the value of the fixed gains, which provide the optimum compromise over a wide range of operations. Each ANN has two inputs (reference and actual speed) and one output that adds to the fixed gains to achieve better speed control performance.

Furthermore, a MATLAB code is created to find the optimum number of neurons in the hidden layer for each neural network. The number of neurons in the hidden layer is chosen based on the root mean square (rms) training and validation error. The ANN for the error (NN1) and the change in error (NN2) have 7 and 11 neurons in the hidden layer. The ANN responsible for the output adaptation scaling factor (NN3) has four neurons in the hidden layer. The training data are obtained based on trial-error methods. The architecture of the ANNs is presented in fig. 4. Fig. 5 shows how well the ANNs learned the training data and how well they generalize. All the ANNs were trained using the Levenberg-Marquardt algorithm

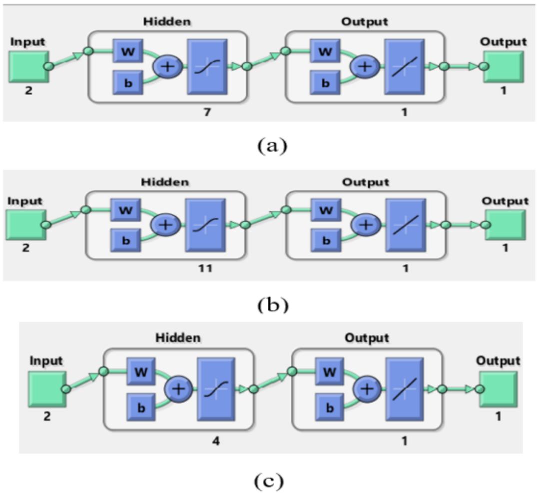


Fig. 4. Architecture of the ANNs : (a) NN1, (b) NN2, (c) NN3

The adaptive gains associated with the NN1 and NN2 have a range of [0.001 0.003] and [0.075 0.1], respectively. The range of the adaptive output gain is [100 200]. The fuzzy-ANN controller scheme is shown in fig. 6.

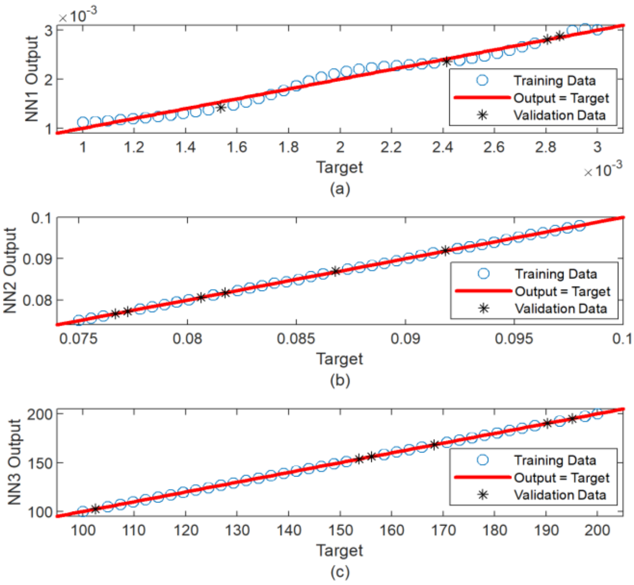


Fig.5. Demonstration of trained neural networks performance

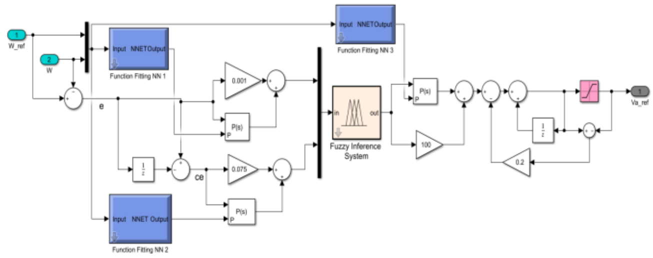


Fig. 6. Simulink model of the fuzzy-artificial neural network controller

IV. DESIGN OF THE ANTI-WINDUP PI AND SLIDING MODE CONTROLLERS

The PI and SMC controllers are described as follows:

A. Design of anti-windup PI Controller

Although a PI controller may eliminate errors or disturbances in a system, it is vulnerable to fluctuating response, significant overshoot, and a long settling time [40]. Anti-windup was a typical control system technique for resolving system performance and stability issues, particularly in linear systems [40]. The transfer function of a PI controller can be written as:

$$G_{PI}(S) = \frac{K_p}{s}\left(S + \frac{K_I}{K_p}\right) \tag{8}$$

Where K_p and K_I are the proportional and integral gain of the PI controllers respectively. The denominator of equation (7) can be written as:

$$S^2 + \left[\left(\frac{R_a}{L_a} + \frac{F}{J}\right)\right] S + \frac{R_aF + K^2}{L_aJ} = (S + P_1)(S + P_2)$$

(9)

Where P_1 and P_2 are the poles of the dc motor transfer function. If the pole P_1 is compensated by the zero of the PI transfer function, then one can write:

$$P_1 = \frac{K_I}{K_p}$$

(10)

The whole transfer function (motor + PI controller) becomes:

$$G_{system}(S) = \frac{K_p K/L_aJ}{s^2 + P_2 S}$$

(11)

By identification of equation 11 with a general second-order transfer function, the expression of W_n (Natural frequency) and K_p can be obtained.

$$W_n = \frac{P_2}{2\zeta}$$

(12)

$$K_p = \frac{W_n^2 L_a J}{K}$$

(13)

Where ζ is the damping factor of the system and its value is set to $\frac{1}{\sqrt{2}}$ to ensure a good compromise between response time and overshoot. The value of the K_I is given by:

$$K_I = K_p P_1 \tag{14}$$

The Simulink model of the anti-windup PI control is shown in fig. 7.

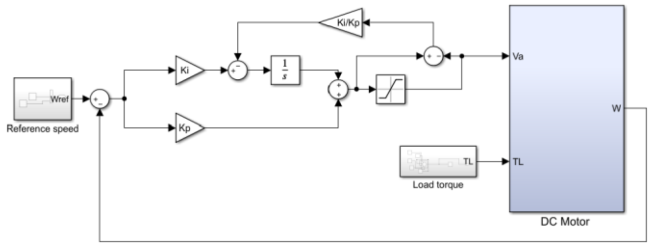


Fig. 7. Simulink model of the anti-windup PI controller

B. *Design of Sliding Mode Controller*

The SMC Method is a nonlinear control method that makes the system insensitive to modelling errors, external disruptive effects, and system parameter changes [41].

The SMC is carried out by the use of two control signals, namely the switching control ($u_{sw}(t)$) and the equivalent control ($u_{eq}(t)$) [41]. The switching control is in charge of bringing the system's state to a sliding surface, whereas the equivalent control is in charge of maintaining the system's state stable on the sliding surface. The SMC signal is given by:

$$u_{SMC}(t) = u_{sw}(t) + u_{eq}(t) \tag{15}$$

The sliding surface and its derivative are given as follows [10]:

$$s = K_{stab}\left(w_{ref} - w\right) + \dot{w}_{ref} - \dot{w} \tag{16}$$

$$\dot{s} = K_{stab}\left(\dot{w}_{ref} - \dot{w}\right) + \ddot{w}_{ref} - \ddot{w} \tag{17}$$

Where K_{stab} (a positive number) is a parameter that ensures the system's stability.
Equation 7 can be written in time Domaine as [10], [41].

$$\ddot{w}(t) + \left(\frac{R_a}{L_a} + \frac{F}{J}\right)\dot{w}(t) + \left(\frac{R_a F + K^2}{L_a J}\right) w(t) = V_a(t)\,\frac{K}{J L_a} \tag{18}$$

On sliding surface, s and $\dot{s}$ should be zero [41]. By replacing (18) in (17), with s = 0, and taking into consideration the fact that the derivatives of the reference of setpoint signal are zero, the $u_{eq}(t)$ is expressed as follows:

$$u_{eq}(t) = \frac{J L_a}{K}\left[\left(\frac{R_a}{L_a} + \frac{F}{J} - K_{stab}\right)\dot{w}(t) + \left(\frac{R_a F + K^2}{L_a J}\right) w(t)\right] \tag{19}$$

The Simulink model of the SMC is given in fig. 8. The switching control in (20) is employed to eliminate the chattering effect [10], [41].

$$u_{sw}(t) = K_{sw}\,\frac{s}{|s| + \delta} \quad , \quad 0 < \delta < 1 \tag{20}$$

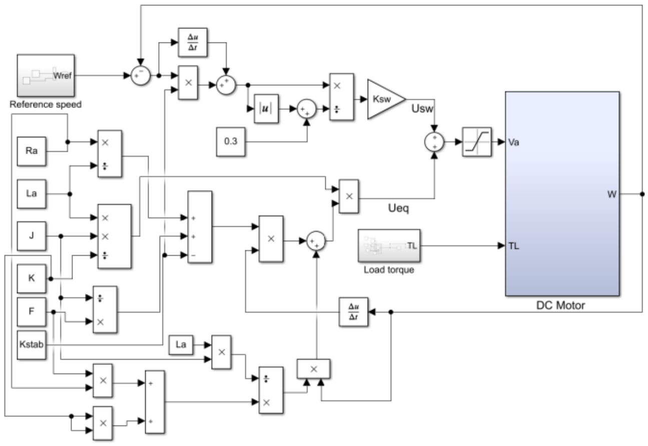


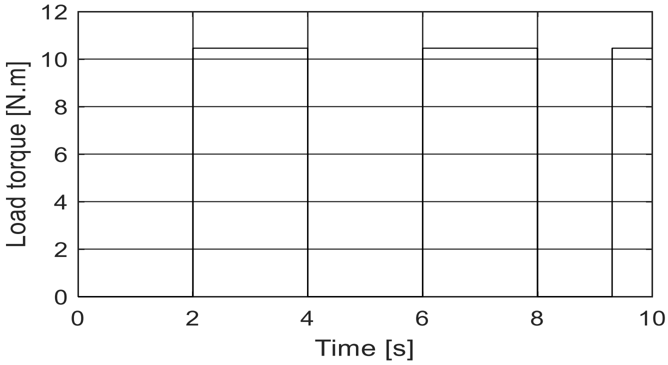
Fig. 8. Simulink model of the SMC

V. SIMULATION RESULTS AND COMPARISONS

To show the performance of the proposed fuzzy-ANN control approach, the anti-windup PI and SMC controllers, previously developed, were implemented in MatLab/Simulink. The simulation parameters are given in Table II. The performances of the three controllers were compared under disturbances, variable speed reference, and armature resistance variation.

TABLE II. SIMULATION PARAMETERS

Parameters	Values
R_a	4 [Ω]
L_a	0.072 [H]
J	0.0607 [N.m.s]
F	0.0087 [K_g/m^2]
K	1.26 [$V.s/rad$] and [$N.m/A$]
K_p	3.9889
K_I	30.8753
K_{stab}	20
K_{sw}	100



(a)

A. Simulation Results with Normal Value of Armature Resistance.

A variable speed reference is applied to show and compare the performances of the three controllers. The dc motor operates in the no-load and loaded condition in each speed reference level. The load torque profile and the speed are shown in fig. 9.

Fig. 9. (a) load torque. (b) DC motor speed for the three controllers

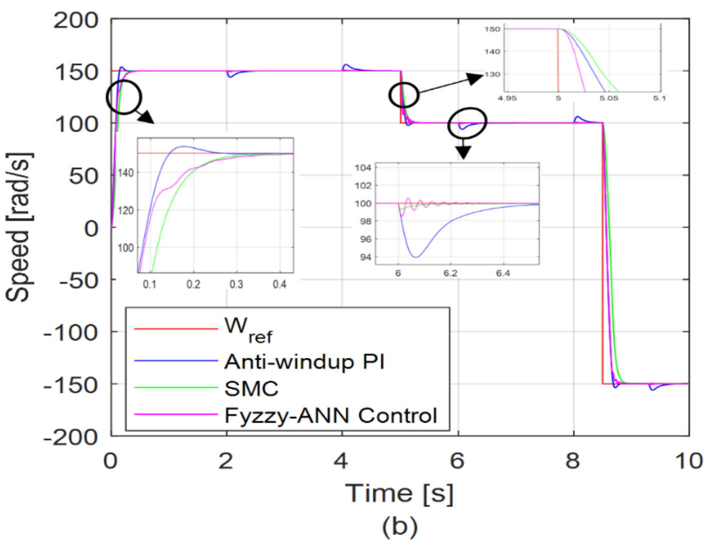
All three controllers have zero steady-state errors. The anti-windup PI controller has the lowest rise time; however, it is also the only one that exhibits an overshoot. Both anti-windup PI and the fuzzy-ANN controller have almost the same settling time; however, the fuzzy-ANN has a somewhat shorter settling time in terms of speed return to reference under loading. Both SMC and fuzzy-ANN control have better insensitivity of disturbances than the anti-windup PI controller. The performances of the three controllers are summarized in Table III.

TABLE III. PERFORMANCE COMPARISON

Types of controllers	Rise Time [s]		Settling time [s]		Maximum overshoot
	$W_{ref}[rad/s]$		$W_{ref}[rad/s$		
	150	100	150	100	
Anti-windup PI	0.0939	0.0618	0.161	0.1747	6.1%
SMC	0.1399	0.1138	0.2566	0.2141	0%
Fuzzy-ANN	0.1371	0.0754	0.276	0.1448	0%

B. Robustness Analysis Against Variation of Armature Resistance

In this section, the simulation results with the normal value of the armature resistance and when it is augmented by 100% of each controller are compared. The same profile of load torque as in fig. 9. (a) is applied. Fig. 10 shows the simulation results, and the robustness performances against armature resistance variation for a reference speed of 150 rad/s are given in table IV. The fuzzy-ANN controller is the most robust against armature resistance variation because its speed curves (for Ra and Ra augmented by 100%) are the closest to each other.



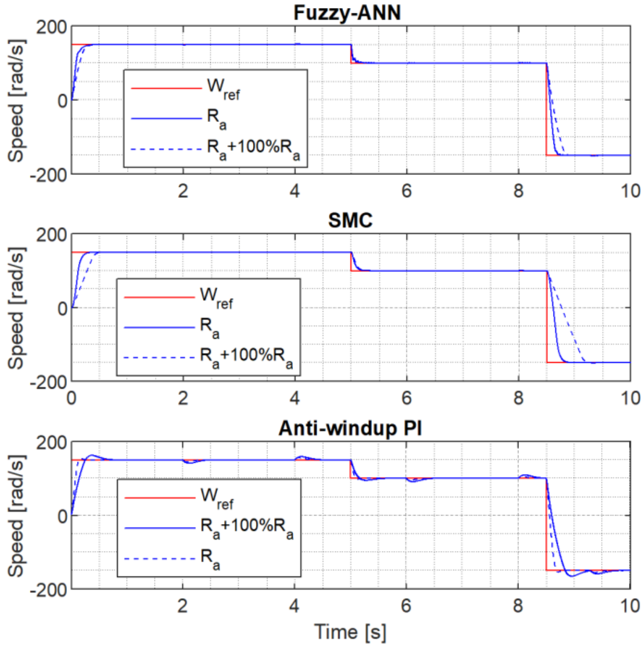


Fig.10. Robustness analysis against armature resistance variation

TABLE IV. ROBUSTNESS PERFORMANCES AGAINST ARMATURE RESISTANCE CHANGE

Types of controllers	Difference in rising time [s]	Difference in settling time [s]
Anti-windup PI	0.095	0.0456
SMC	0.1826	0.1993
Fuzzy-ANN	0.0597	0.0578

VI. CONCLUSION

The response of each controller is satisfactory in both loaded and unloaded conditions. The entire analysis reveals that the proposed fuzzy-ANN controller is the controller with the shortest response time, no overshoot, and is less sensitive to variations in armature resistance. The SMC is superior to the anti-windup PI control in the sense that it has no overshoot and is less susceptible to disturbances; nonetheless, it has a longer settling and rising time. Furthermore, the anti-windup PI and SMC controllers are more sensitive to armature resistance fluctuation than the fuzzy-ANN controller because their control law directly depends on the armature resistance value. This proposed approach has two main limitations. The first limitation is that it cannot be applied to other sorts of systems directly. A training process of the neural networks is required for each new system. The second barrier is the time-consuming trial-and-error technique utilized to build fuzzy-membership functions and training data. The real-time implementation of the proposed control scheme is recommended for further research. Also, metaheuristic algorithms such as PSO are recommended to obtain the training data for the neural networks.

ACKNOWLEDGMENT

The authors gratefully acknowledge the contributions of the African Union Commission for their support in this study.

REFERENCES

[1] W. Gubara, M. Elnaim, and S. F. Babiker, "Comparative Study on the Speed of DC Motor using PID and FLC," in *2016 Conference of Basic Sciences and Engineering Studies (SGCAC)*, 2016, pp. 24–29, doi: https://doi.org/10.1109/SGCAC.2016.7458001.

[2] M. A. H. Azman, J. M. Aris, Z. Hussain, A. A. A. Samat, and A. M. Nazelan, "A Comparative Study of Fuzzy Logic Controller and Artificial Neural Network in Speed Control of Separately Excited DC Motor," in *2017 7th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, 2017, no. November, pp. 336–341, doi: https://doi.org/10.1109/ICCSCE.2017.8284430.

[3] Z. S. Mahmood, A. N. Nasret, and T. Mahmood, "Separately excited DC motor speed using ANN neural network Separately Excited DC Motor Speed using ANN Neural Network," vol. 080012, no. October, 2021.

[4] M. S. Mohiuddin, "Comparative study of PID and Fuzzy tuned PID controller for speed control of DC motor," *Int. J. Innov. Eng. Technol.*, vol. 2, no. 4, pp. 291–301, 2013.

[5] K. Venkateswarlu and C. Chengaiah, "Comparative Study on DC Motor Speed Control using VariousControllers," *Glob. J. Res. Eng. Electr. Electron. Eng.*, vol. 13, no. 17, pp. 6–11, 2013, [Online]. Available: https://engineeringresearch.org/index.php/GJRE/article/view/933.

[6] T. S. Tamir, G. Xiong, S. Member, Z. Shen, X. Gong, and S. Liu, "Comparative Study of Four Speed Controllers of Brushless DC Motors for Industrial Applications," *IFAC-PapersOnLine*, vol. 53, no. 5, pp. 59–64, 2021, doi: 10.13140/RG.2.2.29092.40325.

[7] E. Flores-mor and Y. Wendy, "Particle Swarm Optimization and Genetic Algorithm PID for DC motor position controllers," in *2020 IEEE ANDESCON, 2020*, 2020, pp. 1–6, doi: https://doi.org/10.1109/ANDESCON50619.2020.9272127.

[8] H. Chaudhary, "ANFIS Based Speed Control of DC Motor," in *2016 Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH*, 2016, pp. 63–67, doi: https://doi.org/10.1109/CIPECH.2016.7918738.

[9] A. K. Naik, "SPEED CONTROL OF DC MOTOR USING LINEAR AND NON-LINEAR CONTROLLERS," in *2021 1st Odisha International Conference on Electrical Power Engineering, Communication and Computing Technology(ODICON*, 2021, pp. 1–5.

[10] H. Maghfiroh *et al.*, "Basic Tutorial on Sliding Mode Control in Speed Control of DC-motor," *J. Electr. Electron. Information, Commun. Technol. (JEEICT*, vol. 2, no. 1, pp. 1–4, 2020.

[11] U. Ch, "Sliding mode speed control of a dc motor," no. 1, pp. 1–5, 2011, doi: 10.1109/CSNT.2011.86.

[12] P. Gautam, P. Mahapatra, R. Sripradha, M. Sujith, and R. Mahalakshmi, "A Comparative Study of Distinct Speed Controllers for a Separately Excited DC Motor (SEDM)," pp. 1–7, 2020.

[13] J. Chakravorty and R. Sharma, "Fuzzy Logic Based Method of Speed Control of DC Motor," *Int. J. Emerg. Technol. Adv. Eng.*, vol. 3, no. 4, 2013.

[14] M. Alhanjouri, "Speed Control of DC Motor Using Artificial Neural Network," *Int. J. Sci. Res.*, vol. 6, no. 2, pp. 2140–2148, 2017, doi: 10.21275/ART20172035.

[15] P. Tripura, S. Kishore, and B. Yadlapati, "Intelligent speed control of DC motor using ANFIS," *J. Intell. Fuzzy Syst.*, vol. 26, no. 1, pp. 223–227, 2016, doi: 10.3233/IFS-120729.

[16] A. Harrouz, H. Becheri, I. Colak, and K. Kayisli, "Backstepping control of a separately excited DC motor," *Electr. Eng.*, pp. 1393–1403, 2017, doi: 10.1007/s00202-017-0592-5.

[17] G. Shahgholian, M. Maghsoodi, M. Mahdavian, and M. Janghorbani, "Analysis of Speed Control in DC Motor Drive by Using Fuzzy Control Based on Model Reference Adaptive Control," pp. 3–8, 2016.

[18] S. Id, "Model Reference Adaptive Control for DC Motor Based on Simulink," in *2016 6th International Annual Engineering Seminar (InAES)*, 2019, pp. 101–106, doi: https://doi.org/10.1109/INAES.2016.7821915.

[19] Y. Guo, M. Elhaj, and A. Mohamed, "Speed Control of Direct Current Motor Using ANFIS Based Hybrid P-I-D Configuration Controller," *IEEE Access*, vol. 8, pp. 125638–125647, 2020, doi: 10.1109/ACCESS.2020.3007615.

[20] M. Eduardo, F. Morán, N. Aracely, and P. Viera, "Comparative study for DC motor position controllers," in *2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM)*, 2017, pp. 1–6, doi: https://doi.org/10.1109/ETCM.2017.8247475.

[21] M. M. Nishat, F. Faisal, M. Rahman, and A. Hoque, "Modeling and Design of a Fuzzy Logic Based PID Controller for DC Motor Speed Control in Different Loading Condition for Enhanced Performance," *2019 1st Int. Conf. Adv. Sci. Eng. Robot. Technol.*, vol. 2019, no. Icasert, pp. 1–6, 2019.

[22] H. Ahmed and A. Rajoriya, "A hybrid of sliding mode control and fuzzy logic control using a fuzzy supervisory switched system for DC motor speed control," *Turkish J. Electr. Eng. Comput. Sci.*, pp. 1993–2004, 2017, doi: 10.3906/elk-1511-213.

[23] Y. Naung, S. Anatolii, and Y. H. Lin, "Speed Control of DC Motor by Using Neural Network Parameter Tuner for PI-controller," *2019 IEEE Conf. Russ. Young Res. Electr. Electron. Eng.*, no. Ci, pp. 2152–2156, 2019, doi: https://doi.org/10.1109/EIConRus.2019.8656911.

[24] D. Baidya and R. G. Roy, *Speed Control of DC Motor Using Fuzzy-Based Intelligent Model Reference Adaptive Control Scheme*. Springer Singapore, 2018.

[25] "Speed Control of a DC-DC Buck Converter Fed DC Motor Using an Adaptive Backstepping Sliding Mode Control Approach," in *2021 31st Australasian Universities Power Engineering Conference (AUPEC)*, 2021, pp. 1–6, doi: https://doi.org/10.1109/AUPEC52110.2021.9597745.

[26] P. Pal, V. Mukherjee, and S. Bhakta, "Design of an intelligent heuristic algorithm-based optimised fuzzy controller for speed control of a separately excited DC motor," *Aust. J. Electr. Electron. Eng.*, 2020, doi: 10.1080/1448837X.2020.1804678.

[27] A.F. SHEET, "Optimization of DC motor speed control based," *Anal. data Process. Syst.*, vol. 83, no. 3, pp. 143–153, 2021, doi: 10.17212/2782-2001-2021-3-143-153.

[28] I. Ahmed, T. El, and A. Ahmed, "Enhancement of the Dynamic Performance of a DC Motor using Fuzzy Logic Algorithm," *nternational J. Eng. Res. Technol.*, vol. 8, no. 10, pp. 324–330, 2019.

[29] J. Hagg, M. Ayadi, M. Benrejeb, and S. Bouall, "PID-type fuzzy logic controller tuning based on particle swarm optimization," *Eng. Appl. Artif. Intell.*, vol. 25, pp. 484–493, 2012, doi: 10.1016/j.engappai.2011.09.018.

[30] B. Ghoulemallah, B. Sebti, C. Abdesselem, and B. Said, "Genetic algorithm and particle swarm optimization tuned fuzzy PID controller on direct torque control of dual star induction motor," *J. Cent. South Univ.*, vol. 26, pp. 1886−1896, 2019, doi: https://doi.org/10.1007/s11771-019-4142-3.

[31] E. J. Akpana, "Simulink Design of a DC Motor Control for Water Pump using Fuzzy Logic," in *2nd International Conference on Electrical Power Engineering*, 2021, pp. 16–19.

[32] Y. A. Almatheel and A. Abdelrahman, "Speed Control of DC Motor Using Fuzzy Logic Controller," 2017, doi: https://doi.org/10.1109/ICCCCEE.2017.7867673.

[33] N. Basil, "Improve DC Motor System using Fuzzy Logic Control by Particle Swarm Optimization in Use Scale Factors," *Int. J. Comput. Sci. Mob. Comput.*, vol. 8, no. 3, pp. 152–160, 2019.

[34] E. Yazdani, A. Bagheri, B. Yazdani, S. Buyamin, and S. Nezamivand, "A new adjusting technique for PID type fuzzy logic controller using PSOSCALF optimization algorithm," *Appl. Soft Comput. J.*, vol. 85, p. 105822, 2019, doi: 10.1016/j.asoc.2019.105822.

[35] "Performance evaluation of a hybrid fuzzy logic controller based on genetic algorithm for three phase induction motor drive," *Int. J. Power Electron. Drive Syst.*, vol. 10, pp. 117–127, 2019, doi: 10.11591/ijpeds.v10.i1.pp117-127.

[36] B. Allaoua, A. Laoufi, B. Gasbaoui, and A. Nasri, "Intelligent Controller Design for DC Motor Speed Control based on Fuzzy Logic-Genetic Algorithms Optimization," *Leonardo J. Sci.*, no. 13, pp. 90–102, 2008.

[37] A. Taieb, A. Ferdjouni, and A. Taieb, "A new design of fuzzy logic controller optimized by PSO-SCSO applied to SFO-DTC induction motor drive," *nternational J. Electr. Comput. Eng.*, vol. 10, no. 6, pp. 5813–5823, 2020, doi: 10.11591/ijece.v10i6.pp5813-5823.

[38] C. K. Nguyen, D. T., Ho, J. R., Tung, P. C., & Lin, "A Hybrid PSO–GWO Fuzzy Logic Controller with a New Fuzzy Tuner," *Int. J. Fuzzy Syst.*, pp. 1–19, 2021, doi: https://doi.org/10.1007/s40815-021-01215-6.

[39] "Tackling environmental challenges in pollution controls using

artificial intelligence: A review, Science of The Total Environment," *Sci. Total Environ.*, vol. 699, 2020, doi: https://doi.org/10.1016/j.scitotenv.2019.134279.

[40] T. L. Chiah, C. L. I. H. Hoo, E. Chin, and Y. A. U. Chung, "HARDWARE SIMULATION OF A NEW ANTI-WINDUP PI CONTROL FOR MOTOR SPEED APPLICATION," *J. Eng. Sci. Technol.*, no. 5, pp. 43–57, 2017.

[41] E. H. Dursun and A. Durdu, "Speed Control of a DC Motor with Variable Load Using Sliding Mode Control," *Int. J. Comput. Electr. Eng.*, vol. 8, no. 3, pp. 219–226, 2016, doi: 10.17706/ijcee.2016.8.3.219-226.