Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 53-5 (2020) 59–64

Comparative Study of Four Speed Controllers of Brushless DC Motors for Industrial Applications

Tariku Sinshaw Tamir [1, 2], Gang Xiong [1, 3], Senior Member, IEEE, Zhen Shen [4], Xiaoyan Gong [1], Sheng Liu [4], Ehtisham Lodhi [1, 2], Li Wan [5], Xisong Dong (Correspondence author) [1, 3]

[1] State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China
[2] School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing 100049, China
[3] Guangdong Engineering Research Center of 3D Printing and Intelligent Manufacturing, Cloud Computing Center, Chinese Academy of Sciences, Donggguan 523808, China
[4] Beijing Engineering Research Center of Intelligent Systems and Technology, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China
[5] Ten Dimensions (Guangdong) Technology Co., Ltd., Foshan 528225, China
tamir@ia.ac.cn, gang.xiong@ia.ac.cn, zhen.shen@ia.ac.cn, xiaoyan.gong@ia.ac.cn, sheng.liu@ia.ac.cn, lodhi2018@ia.ac.cn, li.wan@10dim.com, xisong.dong@ia.ac.cn

Abstract: Direct current (DC) motors are one of the most important kind of motors and are widely used in robotic and industrial applications. Recently, there have been significant efforts to develop direct current (DC) motors in an attempt to control speed of motors. However, conventional controlling approaches perform undesirably in terms of stability and quick response. Therefore, this paper presents a hybrid intelligent controller configuration for optimized speed control of brushless direct current (BLDC) motors in a factory supervisory control data acquisition (SCADA) system. We compare this hybrid intelligent controller with a conventional PID controller, fuzzy logic controller (FLC), and artificial neural network model reference controller (ANNMRC) in *MATLAB*, and the results show that the hybrid (neuro-fuzzy) controller performs superior in terms of stability, speed trajectory tracking capability, fast response, and simplicity for implementation.

Copyright © 2020 The Authors. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0)

Keywords: BLDC motor, fuzzy logic controller (FLC), artificial neural network model reference controller (ANNMRC), hybrid (neuro-fuzzy) control

1. INTRODUCTION

Direct current (DC) motors and their drive mechanisms are extensively used in industrial applications such as actuation, positioning, servo and variable speed operations. Very precise speed control is needed for such applications. DC motors are one of the most important kind of motors widely studied in the field of automation and control. Brushless DC (BLDC) motors are electronically commuted DC motors which require no brushes, no commutators, and no connections. Instead, they employ control circuitry and provide pulses of current to the motor windings and hence can avoid problems caused by mechanical commutators (Chaudhary et al., 2016, Saputra et al., 2019).

So far, various types of control system approaches for DC motor control have been developed. A sensorless control technique for a high-speed brushless DC motor is proposed based on line-to-line back electromotive force (back EMF) (Liu et al., 2016). In this paper, line-to-line voltages are obtained by low pass filters to obtain commutation signals. However, acceleration of the motor is limited due to wide speed range, low-pass filters, and other factors. Similarly, Sundeep and Singh presented a new mechanical sensorless control method of a permanent magnet brushless DC (PMBLDC) motor (Sundeep and Singh, 2018). The digital low-pass filters and phase compensators are used to eliminate commutation ripples from line voltages. In terms of system stability, a sensorless position control technique is proposed in Li and Zhou's paper to improve stability of low-speed BLDC motors (Li and Zhou, 2019). This paper discussed an open-loop and a closed-loop algorithm to compensate for commutation error. However, it suffers speed feedback delay at low speed.

The practical nonlinearity of systems in nature gives traditional control system approaches a limited guarantee in terms of stability, response time, and trajectory tracking capability. As a result, intelligent controllers have been getting attention in control system applications. A fuzzy logic controller (FLC) and an artificial neural network (ANN) are developed for speed control of a separately excited DC motor based on personal computer (PC) and 8-bit AVR Atmega16 microcontroller (Thanh et al., 2014, Azman et al., 2017, kushwah and Wadhwani, 2013). This paper signifies advantages of FLC and ANN over conventional PID controllers in terms of complexity and performance.

Intelligent controllers discussed so far are far from enough and would be wise to extend the existing control system designs to hybrid control algorithm formulations. Herein, we first design and evaluate the PID controller, FLC, and ANN separately, and then the FLC model could be used to generate training datasets to construct a hybrid control algorithm which is the

2405-8963 Copyright © 2020 The Authors. This is an open access article under the CC BY-NC-ND license.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2021.04.124

main contributions of the paper. Moreover, the paper gives a comparative study between conventional PID controllers and hybrid intelligent controllers applied to BLDC motors used in the factories.

The rest of the paper is organized as follows: Section 2 introduces system design and dynamics of the BLDC motor. Section 3 shows controller design and description. Section 4 outlines simulation results, followed by concluding remarks and perspectives in Section 5.

2. SYSTEM DESIGN AND DYNAMICS OF BLDC MOTOR

Generally, a factory system consists of supervisory control data acquisition (SCADA) systems and partial human intervention in the loop. The component's interconnection is shown in Fig.1.

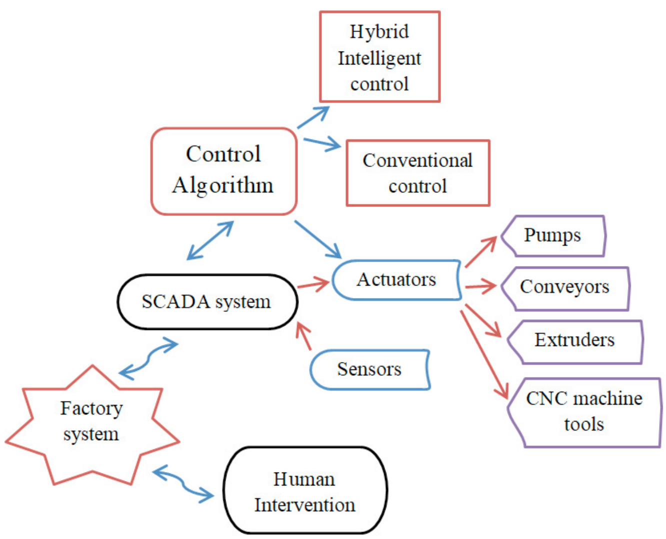


Figure 1. Factory system components

Currently, most factories are becoming flexible, smart, and fully automated with advanced SCADA systems. Nevertheless, there are some factories which still need human intervention for sensing and actuation task.

SCADA systems monitor the overall activities of the factory, make control actions, and generate actuation commands to actuators (Tamir et al., 2020). Pumps, conveyors, extruders, and computer numerical control (CNC) machine tools are factory system components where DC motors could be mostly used for actuation. PID controllers are the commonly used control systems applied so far in industry. Whereas, this paper presents and evaluates hybrid intelligent controllers for DC motor control applications.

DC motor dynamics equations can be expressed as follows (Kangbeom Cheon, December 2015, Tamir et al., 2019):

$$\frac{d\omega}{dt} = \frac{1}{J}(K_t i - b\omega) \tag{1}$$

$$\frac{di}{dt} = \frac{1}{L}(-Ri + V - K_e\omega) \tag{2}$$

Where: $\boldsymbol{\omega}$ is the angular speed of the motor, i is the armature current, J is the moment of inertia of the rotor, K_t is the motor torque constant, v is the armature voltage, b is the motor viscous friction constant, L is the electric inductance, R is the electric resistance, and K_e is the electromotive force constant.

3. CONTROLLER DESIGN AND DESCRIPTION

3.1 Conventional PID Controller Approach

The Proportion Integration Differentiation (PID) controller is a commonly used control algorithm in industrial control applications. In the PID controller design approach, model-based automatic tuning technique is used to find controller gains to achieve optimal system design. Equation (3) shows the PID control action.

$$u(t) = k_p e(t) + k_i \int e(t)dt + k_d \frac{de(t)}{dt} \tag{3}$$

where $u(t)$ is the control signal, $e(t)$ is the error between reference speed and actual speed, K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain.

The Simulink model of auto-tuned PID controller with plant (DC motor) dynamics is shown in Fig.2.

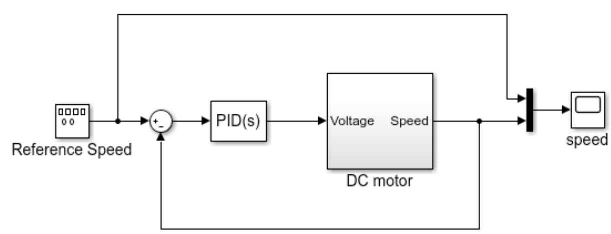


Figure 2. Simulink model of PID controller

3.2 Fuzzy Logic Controller (FLC) Approach

Nowadays, Fuzzy logic controller is one of the expert control systems applied in industrial applications. Fig. 3 shows Simulink model of fuzzy logic controller with DC motor dynamics.

Fuzzy logic controller is designed to have two inputs and one output. The input variables are error (e) and the integral of error (Ie) whereas, the output variable is the drive voltage. In the fuzzification procedure, triangular membership function is chosen to take the advantage of its simple calculation.

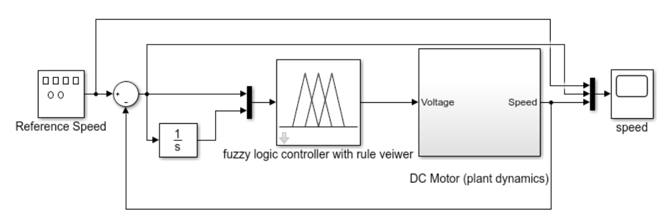


Figure 3. Simulink model of fuzzy logic controller

The range of Fuzzy membership functions is determined by trial and range procedure. The inference system operations are fixed as 'AND-Min', 'Implication-Min', 'Aggregation-Max, and 'Centroid' type of defuzzification. There are twenty-five *IF-THEN* structured fuzzy rules generated from two linguistic input variables each having five linguistic values. A single rule is highlighted from the set of rules shown in Table I.

***IF** error is Negative Large **and** Integral of error is Negative Large **THEN** voltage is Negative Large*

Table I: Fuzzy rules matrix

Ie \ e	**NL**	**NS**	**Z**	**PS**	**PL**
NL	NL	NL	NL	NS	Z
NS	NL	NL	NS	Z	PS
Z	NL	NS	Z	PS	PL
PS	PS	Z	PS	PL	PL
PL	Z	PS	PL	PL	PL

Where: e = Error, Ie = Integral of error, PL = Positive Large, PS = Positive Small, Z = Zero, NS = Negative Small, NL = Negative Large.

3.3 Artificial Neural Network Model Reference Controller (ANNMRC) Approach

A special type of neural network controller is designed, including two neural network models: a plant model network and a controller network, as shown in Fig. 4. First, plant identification is done using the plant model network. Second, the controller network will be trained and tested on time-series datasets. As a result, the plant output follows the reference model output.

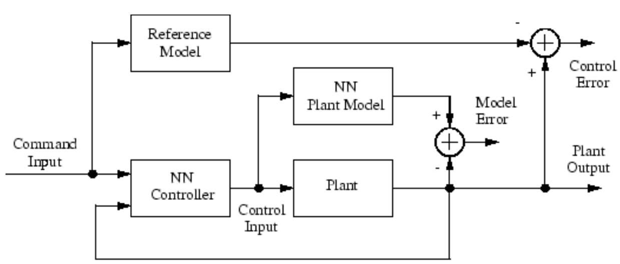


Figure 4. Neural network model reference control architecture

The Simulink model of neural network model reference controller is shown in Fig. 5. The model comprises the control algorithm along with DC motor dynamics.

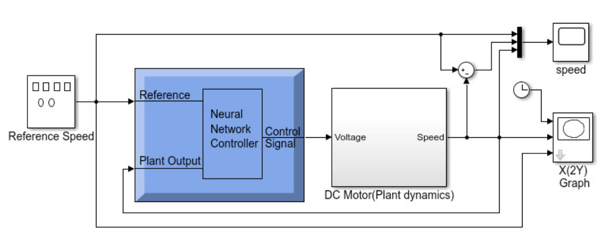


Figure 5. Simulink model of neural network model reference controller

To design the neural network plant model and the neural network controller, datasets need to be presented. Two possible approaches are considered for datasets generation.

The first approach is generating input-output datasets by applying a random input signal to the model. As a result, for *plant model network,* 10,000 time-series samples of data with voltage as plant input and speed as plant output are generated and shown in Fig. 6. Similarly, for *controller network*, 6,000 time-series samples of data with reference speed as reference model input and actual speed as reference model output are generated and shown in Fig.7.

The second approach of generating dataset could be from fuzzy logic controller (FLC) model. FLC control algorithm under run condition is used to extract four parameters: reference motor speed, FLC generated voltage, and speed error as input samples while actual motor speed as output samples. Consequently, 1,560 time-series samples of input-output data are generated to construct neural network controller.

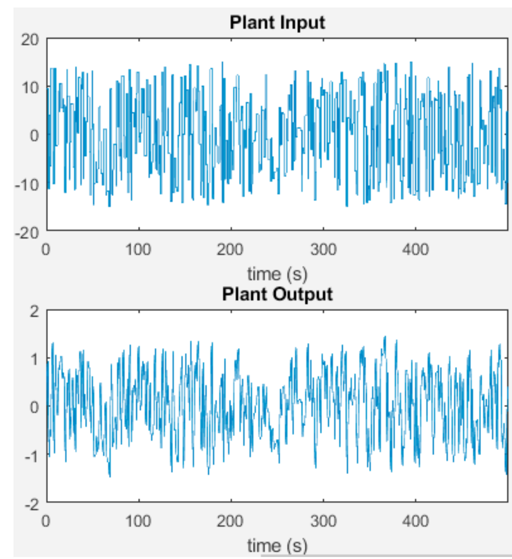


Figure 6. Input-output datasets for creating a neural network plant model

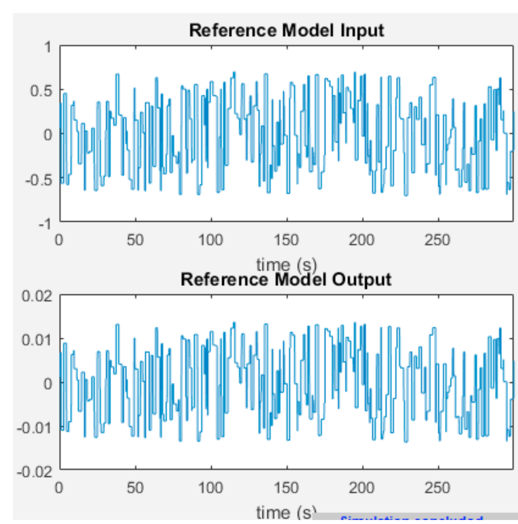


Figure 7. Input-output datasets for creating a neural network controller

3.4 Hybrid (Neuro-Fuzzy) Controller Approach

Artificial neural networks have good learning capabilities at a numerical level while Fuzzy systems are proven to have a great capability of interpretation and can integrate an expert's knowledge. A combination of the two techniques is assumed to capture the merits of both algorithms. Fuzzy-based neural network is constructed in layered structure considering the parameters, i.e., error and integral of error as input variables and voltage as output variable. In this hybrid control algorithm, Takagi Sugeno fuzzy inference file has been generated based on error and its integral as input variables, each consisting of five membership functions with a total of twenty-five possible combinations of rules. 1,560 time-series input-output data is generated from FLC algorithm to train fuzzy inference based neural network. Consequently, the Root Mean Squared Error (RMSE) of network training is found to be 0.0015 at epoch 20. The hybrid (neuro-fuzzy) model is shown in Fig.8.

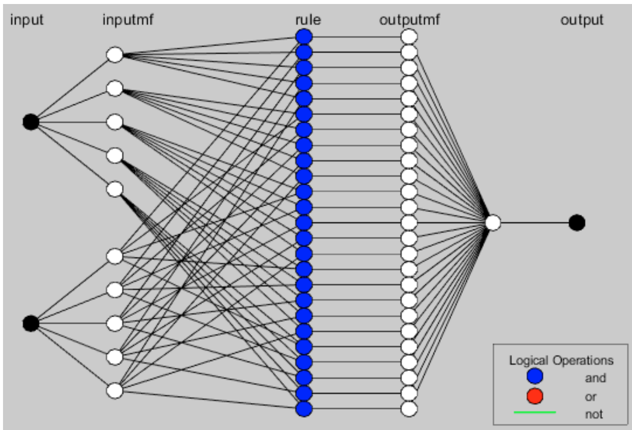


Figure 8. Hybrid (Neuro-Fuzzy) model structure

4. SIMULATION RESULTS

4.1 Artificial Neural Network Model Reference Controller (ANNMRC) design analysis

Case-1: Random generation of datasets

In this case, the first approach data sample generation technique presented in section 3.3 is used to construct *the two neural network models.*

A. Plant model network

The network is composed of 1 hidden layer with 15 neurons, single input single output (SISO) time-series data, *trainlm* as a training function, *sigmoid* types of activation function, and Mean Squared Error (MSE) as performance function. Random data division algorithm is used to get training, testing, and validating data. The errors associated with training, testing and validation results are shown in Fig. 9, Fig. 10, and Fig. 11 respectively. The performance of plant model network is evaluated by the errors generated between plant output and neural network (NN) output during the three operations. The best validation with mean squared error of 3.39e^{-10} at epoch 300 is achieved as it can be seen from the network performance plot shown in Fig. 12.

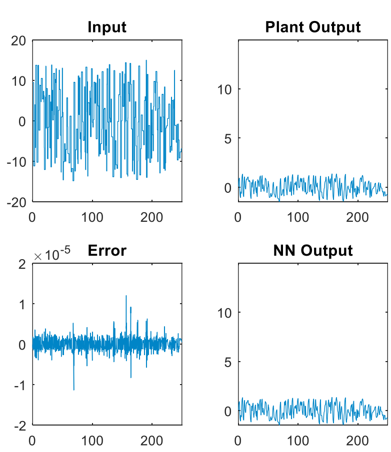


Figure 9. Training NN plant model

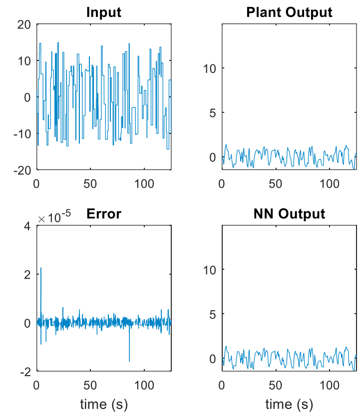


Figure 10. Testing NN plant model

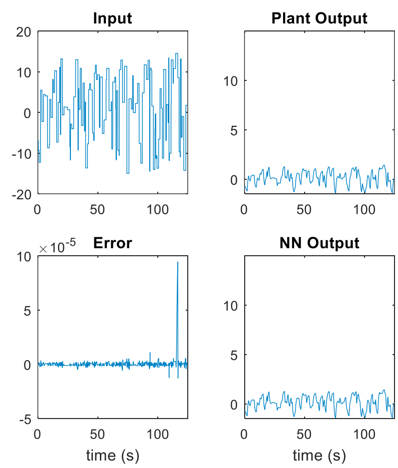


Figure 11. Validating NN plant model

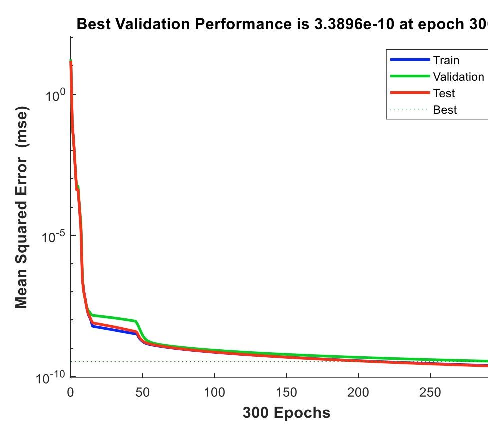


Figure 12. Network performance plot

B. Controller network

Next to plant identification, neural network controller is trained so that plant output follows reference model output. The network is composed of 1 hidden layer with 15 neurons, single input single output (SISO) time-series data, *trainlm* as a training function, and *sigmoid* type of activation function. The performance of controller network would be evaluated by the error that occurred between neural network outputs (green line) and reference model outputs (blue line) as shown in Fig. 13. The training error is summarized using an error histogram as shown in Fig.14. It is observed that the error ranges from -0.00026 to 0.000203, and in most instances, the error approaches to 9.04e$^{-0.6}$.

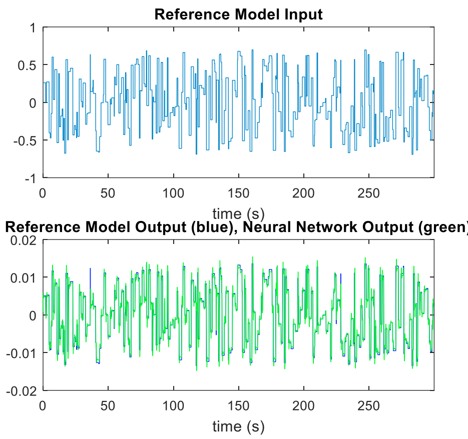


Figure 13. Training NN controller

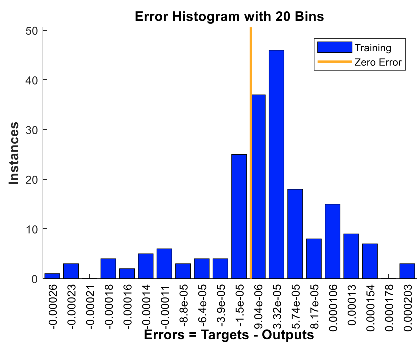


Figure 14. Error histogram

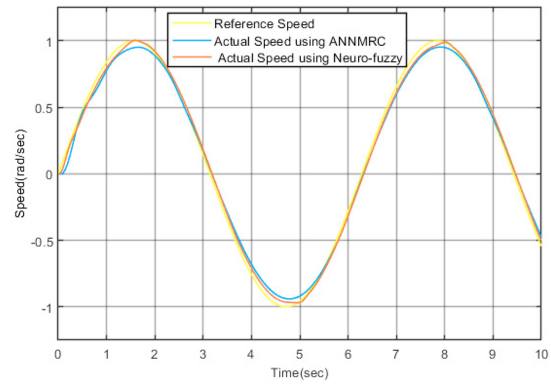
Case-2: FLC driven datasets generation

As discussed in Section 3.3, the second approach is to extract datasets from the FLC model. The neural network is designed to use 80% of datasets for training and the rest of 20% for testing. Furthermore, the network is modeled by multi-input single-output (MISO) fashion (i.e. three inputs and one output). Generally, the neural network has the following specifications: (1) it has two hidden layers with 20 and 10 neurons respectively; (2) loss function is Mean Absolute Error (MAE); (3) the optimizer is "ADAM"; (4) evaluation metrics is Mean Squared Error (MSE). The TensorFlow machine learning framework executes the multi-layer network in the Python programming environment. Best testing performance is achieved at epoch 30 with a mean squared error of 0.0018.

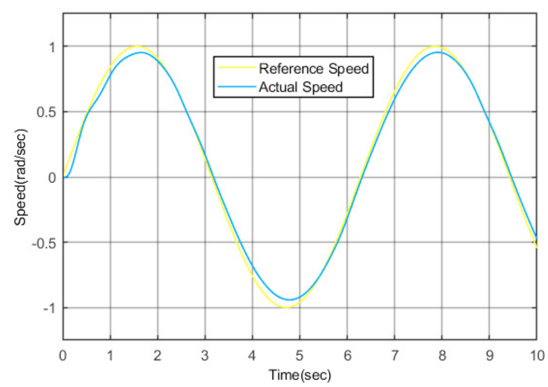
Overall, the number of datasets is an influential factor for neural network construction. The random dataset generation approach discussed under case-1 assures large datasets and would be the ideal solution to construct a neural network model and then, better model performance can be achieved. This model could be used in the next controller performance comparison section.

4.2 Speed Trajectory tracking performance analysis

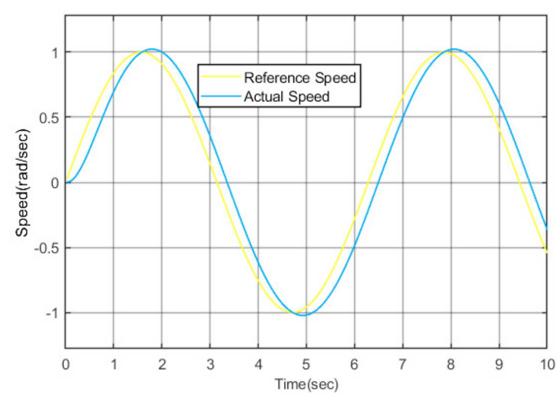
A sine wave reference speed trajectory is given to four types of control algorithms to drive BLDC motor with a possible trajectory. From Fig.15 (a), (b) and (c), trajectory tracking Mean Squared Error (MSE) of hybrid (neuro-fuzzy) control, ANNMRC, FLC, and PID controller is calculated as 0.0013, 0.0024, 0.0031 and 0.0049 respectively. Hybrid (neuro-fuzzy) control algorithm gets much better trajectory tracking performance followed by ANNMRC and FLC algorithms. Thus, we can say that intelligent controllers lead conventional PID controllers in terms of trajectory tracking performance.



(a)



(b)



(c)

Figure 15. Sine wave speed trajectory responses using (a) hybrid (neuro-fuzzy) control and artificial neural network model reference controller (ANNMRC), (b) Fuzzy logic controller, (c) conventional PID controller

Moreover, Step input response characteristics of the entire control algorithms along with DC motor dynamics are shown in Fig. 16. The figure clears that hybrid (neuro-fuzzy) control algorithm achieved fast response with less settling time, less overshoot, and zero steady-state error followed by ANNMRC and FLC approach as compared with conventional PID controllers.

To evaluate intelligent control algorithms in the worst conditions (i.e., the presence of uncertainty in model parameters, the presence of un-modeled dynamics, and different loading conditions), a unit step disturbance is applied in to DC motor dynamics. From Fig. 17, the trajectory mean squared error in hybrid (neuro-fuzzy) control, ANNMRC, and

FLC is recorded as 0.0046, 0.0051, and 0.0069 respectively. In general, intelligent controllers achieved good trajectory tracking in the presence of unit step disturbance. Finally, the entire controller trajectory tracking performance is summarized in Table II.

Table II: Trajectory tracking performance summary

Types of controller	Mean Squared Error (MSE) without external disturbance consideration	Mean Squared Error (MSE) with external disturbance consideration
Neuro-fuzzy control	0.0013	0.0046
ANNMRC	0.0024	0.0051
FLC	0.0031	0.0069
PID controller	0.0049	-

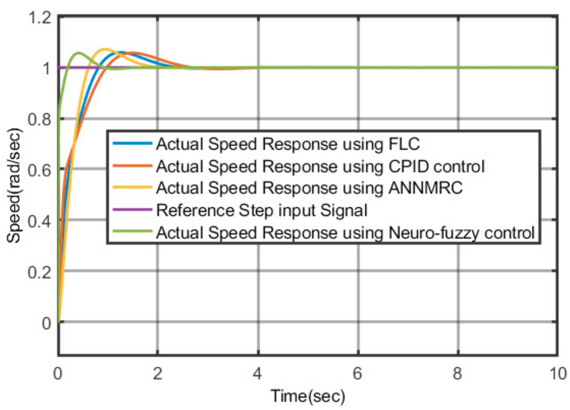


Figure 16. Step input response comparisons of conventional PID and intelligent controllers

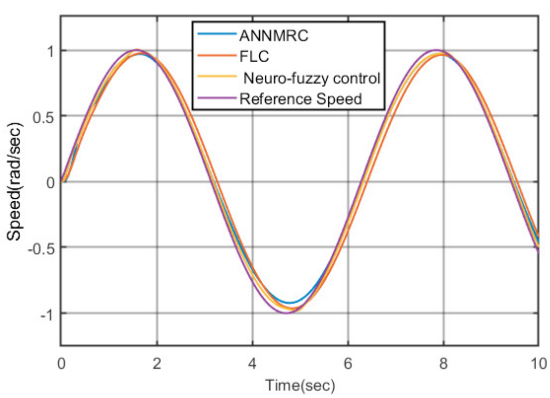


Figure 17. Speed Trajectory response in the presence of disturbance

5. CONCLUSIONS

This paper presents the comparison between intelligent controllers (i.e. hybrid (neuro-fuzzy) control, ANNMRC, and FLC) and conventional PID controllers, and in the meantime to understand the controlling capability of intelligent controllers in industrial control applications. BLDC motor dynamics along with its control mechanism is developed in *MATLAB Simulink*. Generation of datasets and constructing a hybrid intelligent control algorithm is the major contribution of the paper. Given the reference speed trajectory, it is observed that the three controllers, i.e., FLC, ANNMRC, and hybrid (neuro-fuzzy) control algorithms give superior features over conventional PID controllers in terms of trajectory tracking performance in both cases of disturbed and undisturbed systems. Moreover, with a step reference input signal, hybrid (neuro-fuzzy) control algorithm achieved fast response with less settling time, less overshoot, and zero steady-state error followed by ANNMRC and FLC respectively. The future work will be to extend the control algorithms by adding deep learning concepts in the additive manufacturing (3D printing) industry for printed object quality monitoring.

ACKNOWLEDGMENT

This work was supported in part by the National Key Research and Development Program of China (No. 2018YFB1700403), National Natural Science Foundation of China under Grants U1909204, 61773381, U1811463, 61773382 and 61872365, Dongguan's Innovation Talents Project (Gang Xiong), Foshan Science and Technology Innovation Team Project (2018IT100142), and the Scientific Instrument Developing Project of the Chinese Academy of Sciences.

REFERENCES

Azman, M. A. H., Aris, J. M., Hussain, Z., Samat, A. A. A. and Nazelan, A. M. 'A comparative study of fuzzy logic controller and artificial neural network in speed control of separately excited DC motor'. *2017 7th IEEE International Conference on Control System, Computing and Engineering (ICCSCE)*, 24-26 Nov. 2017, 336-341.

Chaudhary, H., Khatoon, S. and Singh, R. 'ANFIS based speed control of DC motor'. *2016 Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH)*, 18-19 Nov. 2016, 63-67.

Kangbeom Cheon, J. K., Moussa Hamadache, and Dongik Lee (December 2015) 'On Replacing PID Controller with Deep Learning Controller for DC Motor System', *Journal of Automation and control engineering,* 3(6), pp. 452-456.

Kushwah, R. and Wadhwani, S. (2013) 'Speed Control of Separately Excited Dc Motor Using Fuzzy Logic Controller', *International Journal of Engineering Trends and Technology (IJETT),* 4(6), pp. 2518-1523.

Li, T. and Zhou, J. (2019) 'High-Stability Position-Sensorless Control Method for Brushless DC Motors at Low Speed', *IEEE Transactions on Power Electronics,* 34(5), pp. 4895-4903.

Liu, G., Cui, C., Wang, K., Han, B. and Zheng, S. (2016) 'Sensorless Control for High-Speed Brushless DC Motor Based on the Line-to-Line Back EMF', *IEEE Transactions on Power Electronics,* 31(7), pp. 4669-4683.

Saputra, H. M., Nurhakim, A. and Firdaus, M. N. 'Servo Motor Controller Device for Stewart Platform Based on Simple Pulse Generator'. *2019 International Conference on Radar, Antenna, Microwave, Electronics, and Telecommunications (ICRAMET)*, 23-24 Oct. 2019, 104-108.

Sundeep, S. and Singh, B. (2018) 'Robust Position Sensorless Technique for a PMBLDC Motor', *IEEE Transactions on Power Electronics,* 33(8), pp. 6936-6945.

Tamir, T. S., Xiong, G., Menkir, H. M., Shang, X., Shen, Z., Dong, X. and Gong, X. 'Developing SCADA Systems to Monitor and Control Liquid and Detergent Factories'. *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)*, 20-21 Aug. 2020, 691-696.

Tamir, T. S., Xiong, G., Tian, Y. and Xiong, G. 'Passivity Based Control Of Stewart Platform For Trajectory Tracking'. *2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, 19-21 June 2019, 988-993.

Thanh, S. N., Thanh, K. N., The, C. N., Hung, P. P. and Xuan, H. H. 'Development of fuzzy logic controller for DC motor using personal computer and inexpensive microcontroller'. *2014 13th International Conference on Control Automation Robotics & Vision (ICARCV)*, 10-12 Dec. 2014, 1310-1314.