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Optimized Adaptive Neuro Fuzzy based Controller for lifetime maximization in power electronics stage for brushless DC drives

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ABSTRACT

In recent days, the lifetime of the power electronics stages in electric drives is considerably degraded through the command signal from the speed controller owing to the fact that the characteristics of the power electronics stage are not considered in the design of the controller. The minimization of the power electronics lifetime creates early faults in the functioning of electric drives that majorly directly affect the industrial process where the power electronic stages are utilized. Therefore, power electronics stage for the controller is often over-designed, which decreases the performance and increment the cost, weight, and size. In electric drives, the power electronics elements operate on high-switching frequency in driving high electric power to accomplish the anticipated mechanical reference in electric brushless DC motors. With this motivation, this paper presents a new Barnacles Mating Optimizer with Adaptive Neuro Fuzzy based Controller (BMO-ANFC) for lifetime maximization in power electronics stage for brushless DC drive. The proposed BMO-ANFC technique is used to optimize the network design of the ANFC model. Besides, the BMO-ANFC technique derives an objective function involving required speed and reference temperature. In fact, the speed response of the motor and the temperature of the semiconductor are treated in the objective function to tune the fuzzy logic controller for increasing the lifetime of power electronics devices. For ensuring the enhanced outcome of the BMO-ANFC technique, a series of experiments were performed. The experimental outcomes highlighted the enhanced performance of the BMO-ANFC technique over the recent state of art controllers.

1. Introduction

Currently, electric brushless drives have been utilized in many applications like electric vehicles, robotics, and manufacturing process. But, when these electric drives are implemented, the power electronic stage isn't implemented often for increasing and improving its lifetime by the position and speed controller due to the difficulty of the controller increases [1]. Brushless DC motors (BLDCM), are extensively utilized in the industry as they give beneficial properties like noise robustness, large lifetime, smaller size, higher efficiency, and good enough torque velocity ratio when compared to inductions motors, and rotor losses in BLDCM are minor than induction machines.

The BLDC motor cover a wider range of applications in many areas like aerospace industry, medical industry, robotic systems, electronic device, and automotive industry [2,3]. Their control structure is incorporated with sensors, BLDC motor, and power drive stages. The power drive is incorporated with semiconductor as IGBT and MOSFET, this semiconductor often works in higher thermal stress for reaching the mechanical references of speed, and sometimes, afterward a specific period of process, it is damaged because of the generation of command signal using the speed controller [4-6]. Various approaches for predicting and evaluating the lifetime of power electronic device, the manufacture develops this study as an evaluation of specific condition and operation feature, however, in few applications, this condition isn't often similar

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and modify on the basis of control objective, that affect the power electronics lifetime consumed. Because of this, it can be significant that the controller design assumes the mechanical references like velocity and position in the event of BLDCM and the lifetime of semiconductors [7]. Henceforth, lot of efforts for improving and predicting the semiconductor's lifetime have been pushed for developing a novel control method that assists to enhance the conditions in the semiconductor [8].

Discrete power semiconductors are employed on distinct regions based on operation frequency and power requirements [9]. Particularly, GTOs & SCRs are utilized on higher power applications whereas MOSFET and IGBTs are utilized on higher frequency applications. Later, consider the applications and control needs, different power semiconductors are presented to be used, [10]. Nonlinear and Linear controllers have been implemented for ensuring the control objectives in spite of uncertainties and disturbances requesting a higher efficiency for power electronics ensuring robustness, accuracy, and precision, in return for a short lifetime of power electronics [8]. In recent times, FL controls for regulating the BLDCM speed, considered thermos stress for estimating lifetime of power electronics (h-bridge), are proposed. Major benefits of Fuzzy controllers are: proficiency for controlling nonlinear system without scientific models; work as adoptive control, generally Fuzzy methods are integrated by a traditional PID and nonlinear controller methods for adapting controller attainments; potential to work as multi input controllers, and the most significant is the ability for encapsulating the data from operators including human experience and knowledge in the controller efficiency [11].

This paper presents a new Barnacles Mating Optimizer with Adaptive Neuro Fuzzy based Controller (BMO-ANFC) for lifetime maximization in power electronics stage for brushless DC drives. The proposed BMO-ANFC technique is used to optimize the network design of the ANFC model using an objective function involving required speed and reference temperature. In fact, the speed response of the motor and the temperature of the semiconductor are treated in the objective function to tune the fuzzy logic controller for increasing the lifetime of power electronic devices. For tuning the learning rate of the ANFC technique, the BMO algorithm is applied with an objective function. To ensure the improved outcomes of the BMO-ANFC technique, a set of simulations were carried out the obtained values pointed out the supremacy of the BMO-ANFC technique over the recent state of art controllers.

2. Related works

López et al. [12] presented power electronic lifetime optimization and a fast speed response in a brushless dc motor drive utilize a Fuzzy-PSO controller that is an FLC adapted with PSO. Furthermore, an objective function involves reference temperature and the desired speed is projected. Kumar and Singh [13], presented a solar water pumping scheme that employs brushless DC motor drive. The overall load demand is allocated using photovoltaic array and grid. It leads to continual water pumping. The full consumption of motor pump is attained by increasing trustworthiness. Akin and Bhardwaj [14] presented a resolution for controlling Brushless DC motors by TMS320F2803x microcontroller. TMS320F280x devices are portion of the C2000 microcontroller family that enables cost-efficient design of smart controllers for 3 phase motors by decreasing the scheme modules and improving performance. With these devices, it can realize accurate control methods.

In Ponce et al. [1], a brushless DC motor drive is aimed at the basis of fuzzy controller altered by PSO method, in which the speed set points and temperature oscillations are deliberated for increasing the lifetime of IGBT model. The authentication of the projected fuzzy PSO controller is executed using the co-simulation amongst Multisim™ and LabVIEW™. García-López et al. [9] estimate the lifetime cycle in the power electronic stages after a fuzzy logic speed controller is executed in BLDC. The analyses are depending upon co-simulations amongst Multisim & LabVIEW for calculating the response, stabilized using FL controller, of temperature due to power loss switching or conduction of the semiconductor (IGBTs), speed control, and power electronic stages. In Agrawal et al. [15], the performance of BLDC motor has been estimated with & without traditional controllers PID & PI. The outcomes have been related to the fuzzy based controller. Compared to traditional controllers, fuzzy controller provides efficient speed response however traditional controller provides greater response by altering loads. In this study, a new BMO-ANFC technique is presented based on the inspiration from [12].

3. The proposed BMO-ANFC technique

Fig. 1 demonstrates the overall working process of the proposed BMO-ANFC model. In this study, a BMO-ANFC based controller is derived with an objective function of considering the temperature of the power electronics stage for lifetime maximization as track the reference speed of the motor. Generally, the speed of the motor and temperature of the semiconductor is treated in the presented objective function of the BMO algorithm to tune the BANFC technique for boosting the lifespan of the power electronics devices.

3.1. Structure of ANFC technique

Generally, a fuzzy system with learning capability can be designed and trained straightaway from the input and output data. As the NFLC is a characteristics of learning, the membership function and fuzzy rule of the controller is optimally modified using the learning technique [16].

In this study, the ANFC technique is employed to resolve the limitations of the neuro-fuzzy logic control system (NFLC) related to the performance error signal. The ANFC technique makes use of the neuro-emulator (NE) to imitate the plant dynamics and back propagate, the errors amongst the original and preferable outcomes via the NE. Fig. 2 illustrates the process involved in FL controllers. The ANFC includes a 2 input–single output NFLC and the NE, where k_1, k_2 and k_3 denotes the scaling gains for x_1, x_2 and u correspondingly. At every individual time step, the parameters of the NE get adjusted prior to the controller update [17]. To accomplish this, the EBP training scheme is employed for the minimization of the performance error e_p as given below:

$$e_p(t) = \frac{1}{2}\left\{(y_r(t) - y_E(t))^2\right\} \tag{1}$$

From equation (4), the $\bar{y}_j$ can be trained using the following as:

$$\bar{y}_j(t) = \bar{y}_j(t-1) + \Delta\bar{y}_j(t) \tag{2}$$

$$\Delta\bar{y}_j(t) = -\eta\frac{\partial e_p(t)}{\partial c_{ij}(t)} + \alpha\Delta\bar{y}_j(t-1) \tag{3}$$

where η and α denote learning rate and constant momentum term respectively. By the use of chain rule,

$$\frac{\partial e_p(t)}{\partial\bar{y}_j(t)} = e_p(t)\frac{\mu_j}{\sum_j^N \mu_j}\sum_{i=1}^{n_2} w_{ij}^c w_{jk}^c g'(net_i) \tag{4}$$

Therefore, the training process of $\bar{y}_j$ can be represented by

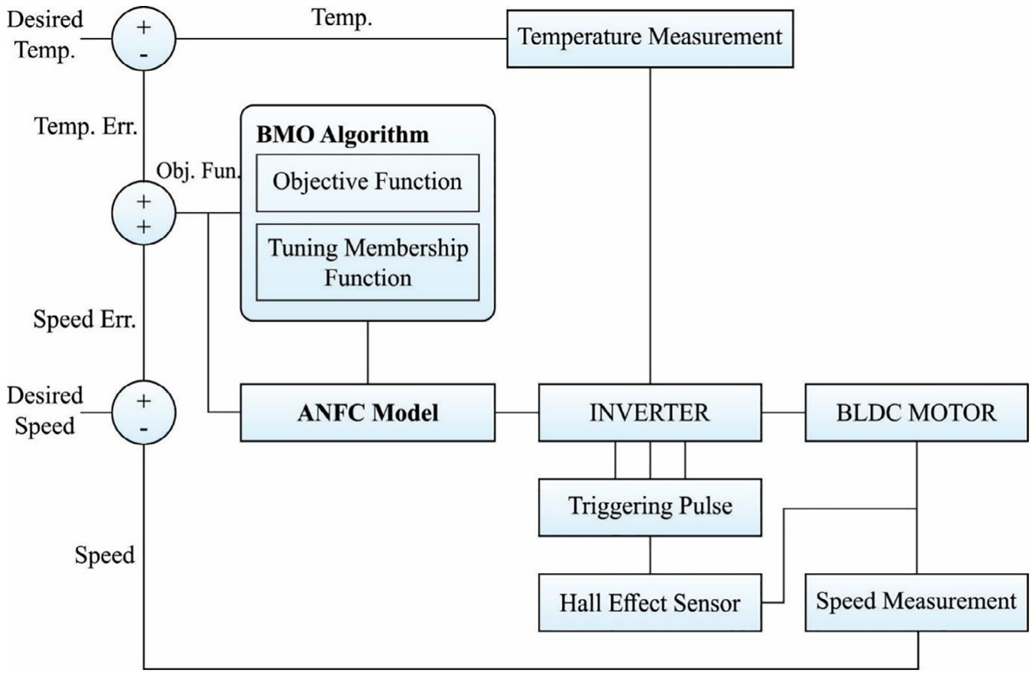

Fig. 1. Overall architecture of Proposed Model.

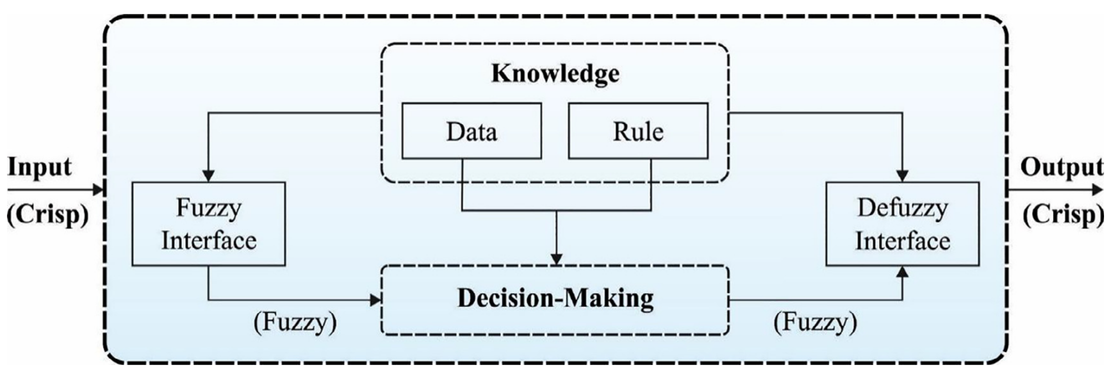

Fig. 2. General Process involved in Fuzzy logic controllers.

$$\bar{y}_j(t) = \bar{y}_j(t-1) - \eta\left[e_p(t)\frac{\mu_j}{\sum_j^N \mu_j}\sum\nolimits_{i=1}^{n_2} w_{ij}^c w_{jk}^c g'(net_i)\right] + \alpha\Delta\bar{y}_j(t-1) \quad (5)$$

The c_{ij} can be trained using Eqs. (6)-(7) as given below.

$$c_{ij}(t) = c_{ij}(t-1) + \mathrm{D}c_{ij}(t) \quad (6)$$

$$c_{ij}(t) = c_{ij}(t-1) + \mathrm{D}c_{ij}(t)$$

$$\mathrm{D}c_{ij}(t) = -\eta\frac{\partial e_p(t)}{\partial c_{ij}(t)} + \alpha \mathrm{D}c_{ij}(t-1) \quad (7)$$

Besides, the chain rule can be denoted as follows.

$$\frac{\partial e_p(t)}{\partial c_{ij}(t)} = e_p(t)\sum\nolimits_{i=1}^{n_2} w_{ij}^c w_{jk}^c g'(net_i)\left(\frac{\bar{y}_j(t)-u(t)}{\sum_{j=1}^N \mu_j}\right)\left(\frac{x_i(t)-c_{ij}(t)}{(\sigma_{ij})^2}\right) \quad (8)$$

and the training algorithm for c_{ij} can be provided by

$$c_{ij}(t) = c_{ij}(t-1) - \eta\left[e_p(t)\sum\nolimits_{i=1}^{n_2} w_{ij}^c w_{jk}^c g'(net_i)\left(\frac{\bar{y}_j(t)-u(t)}{\sum_{j=1}^N \mu_j}\right)\left(\frac{x_i(t)-c_{ij}(t)}{(\sigma_{ij})^2}\right)\right] + \alpha\Delta c_{ij}(t-1) \quad (9)$$

By the use of similar approaches, σ_{ij} can be trained by:

$$\sigma_{ij}(t) = \sigma_{ij}(t-1) + \Delta\sigma_{ij}(t) \quad (10)$$

Therefore, the training approach for σ_{ij} can be given as follows:

$$\sigma_{ij}(t) = \sigma_{ij}(t-1) - \eta[e_p(t)\sum\nolimits_{i=1}^{n_2} w_{ij}^c w_{jk}^c g'(net_i)$$

$$\left(\frac{\bar{y}_j(t)-u(t)}{\sum_{j=1}^N \mu_j}\right)\left(\frac{(x_i(t)-c_{ij}(t))^2}{(\sigma_{ij})^3}\right)] + \alpha\Delta\sigma_{ij}(t-1) \quad (11)$$

3.2. Overview of BMO algorithm

BMO algorithm is stimulated from the characteristics of barnacles mating process, which are micro-organisms. The process included in the BMO method is deliberated in [18].

Initialization

Now, it considers that the candidate of the outcome is a barnacle whereas the vector of the population is described by:

$$X = \begin{bmatrix} x_1^1 & \cdots & x_1^N \\ \vdots & \ddots & \vdots \\ x_n^1 & \cdots & x_n^N \end{bmatrix} \tag{12}$$

Whereas N denotes the amount of controlling variables and n indicates the population amount. The control parameter in Eq. (12) is focus to upper and lower bounds of the problem that should be resolved as follows:

$$llb = [llb_1, \cdots, llb_i] \tag{13}$$

$$lb = [lb_1, \cdots, lb_i] \tag{14}$$

Whereas ub & lb denote the upper and lower bounds of i th parameter. Estimation of vector X is comprehensive at first, and the arranging process has been executed to place an optimum solution controlling the vector X.

3.2.1. Selection process

A proposed BMO method was employed by the technique for selecting that is interrelated to EA modules, for example, the election of 2 barnacles is dependent upon the penises length pl. The selection procedure reflects the nature of barnacles that is dependent upon the given deliberations:

i. The election procedure is executed in an arbitrary method; but, it can be constrained to the penis length of a barnacle pl .
ii. The selection procedure selects a related barnacle which represents that self-mating is executed. Self-mating is arbitrary and barnacle male and female reproduction, henceforth, self-mating is considered, and new offspring was created.
iii. Once an election is depending upon certain iteration that is greater compared to pl, the sperm casting is executed.

The offspring production is calculated using the sperm cast procedure which is determined as follows. This method is executed regarding the virtual distance. The provided simple election was employed and it is given by:

$$barnacle\_d = randperm(n) \tag{15}$$

$$barnacle\_m = randperm(n) \tag{16}$$

Whereas $barnacle\_d$ & $barnacle\_m$ denotes parent that should be mated and n indicates the amount of the population. Eqs. (15) & (16) demonstrates the selected is established randomly and fulfills the deliberation value 1 in the present section. Fig. 3 depicted the flowchart of BMO technique [22].

3.2.2. Reproduction

This process is existing in BMO is interrelated to EAs. As there are no certain formulas to derive the reproduction of barnacles, the BMO is illustrated on inheritance genotype frequency of barnacle's parent in creating the offspring depends on Hardy Weinberg approach. To represent the easiness of this presented BMO, the succeeding functions are existing to develop new parameters of offspring from barnacle's parent:

$$x_i^{N\_new} = px_{barnacle\_d}^N + qx_{barnacle\_m}^N \tag{17}$$

Whereas p represents the scattered generally using pseudo arbitrary values from zero and one $,q = (1-p), x_{barnacle\_d}^N$ and $x_{barnaclem}^N$ denotes the parameters of Dad and Mum of barnacles respectively. It can be determined in Eqs. (15) and (16). It can be essential for pointing a measure of pl that acts as a substantial one in computing the exploitation and exploration processes. Once the selected barnacles are mated in a particular range of penis length of Dad's barnacle, the exploitation operation has been carried out (Eq. (17)). Sperm cast is executed when the selected barnacles are processed and pl is distributed at first.

$$x_i^{n\_new} = rand() \times x_{barnacle\_m}^n \tag{18}$$

Whereas $rand$ () denotes the arbitrary amount between zero and one. It is stated in Eq. (18) shows a sophisticated technique of barnacles offspring. The new offspring is generated from Mum's barnacle for explorations. It can be due to the novel offspring is generated by Mum's barnacle since it attains the sperm from water that is discharged by the alternative barnacles.

3.3. Algorithmic design of BMO-ANFC technique

In order to tune the learning rate of the ANFC technique, the BMO algorithm is applied with an objective function. The design of the BMO-ANFC based controller involves two goals namely reaching required motor speed and enhance lifespan of the semiconductor. Therefore, the speed control of the BLDCM depends upon the BMO-ANFC based controller. The BMO algorithm is applied for tuning the learning rate of the ANFC technique. The objective function of the BMO-ANFC based controller follows a weighted sum technique in which a weight wl is allocated to the objective functions as given below.

$$\text{Min } F(x) = w_1 f_1(x) + w_2 f_2(x) + \cdots + w_l f_l(x)$$

Such that

$$\sum w_l = 1 \tag{19}$$

Also, major characteristics of the objective function f_c is the consideration of the temperature error e_t and speed error e_c as given below.

$$f_c = w_1 e_c + w_2 e_t \tag{20}$$

where, e_t denotes the variance among the required temperature and operating semiconductor temperature as $e_t(t) = t_d(t) - t(t)$, and e_c denotes the variance among the desired and sensed speed respectively. The BMO-ANFC based controller restricts the extreme junction temperature which is influenced through different factors such as switching frequency, rise, and peaks of current. The BLDCM drive is highly related to the semiconductor lifetime and speed control of the BLDCM. During the operational process, the BLDCM drive functions under rising and peak temperatures. Here, w_1 and w_2 are assumed as $w_1 = w_2 = 0.5$ for satisfying both objectives and investigate the advantages of the proposed BMO-ANFC based controller over other ones. The learning rate of the ANFC technique is optimally adjusted by the BMO algorithm in such a way that the rise and peak of current can be minimized. The major goal of the BMO algorithm is to maintain the power electronics element at lower temperatures at the time of operation for increasing the lifetime.

4. Performance validation

The performance of the BMO-ANFC technique is examined using an extensive set of experiments carried out on LabVIEW™

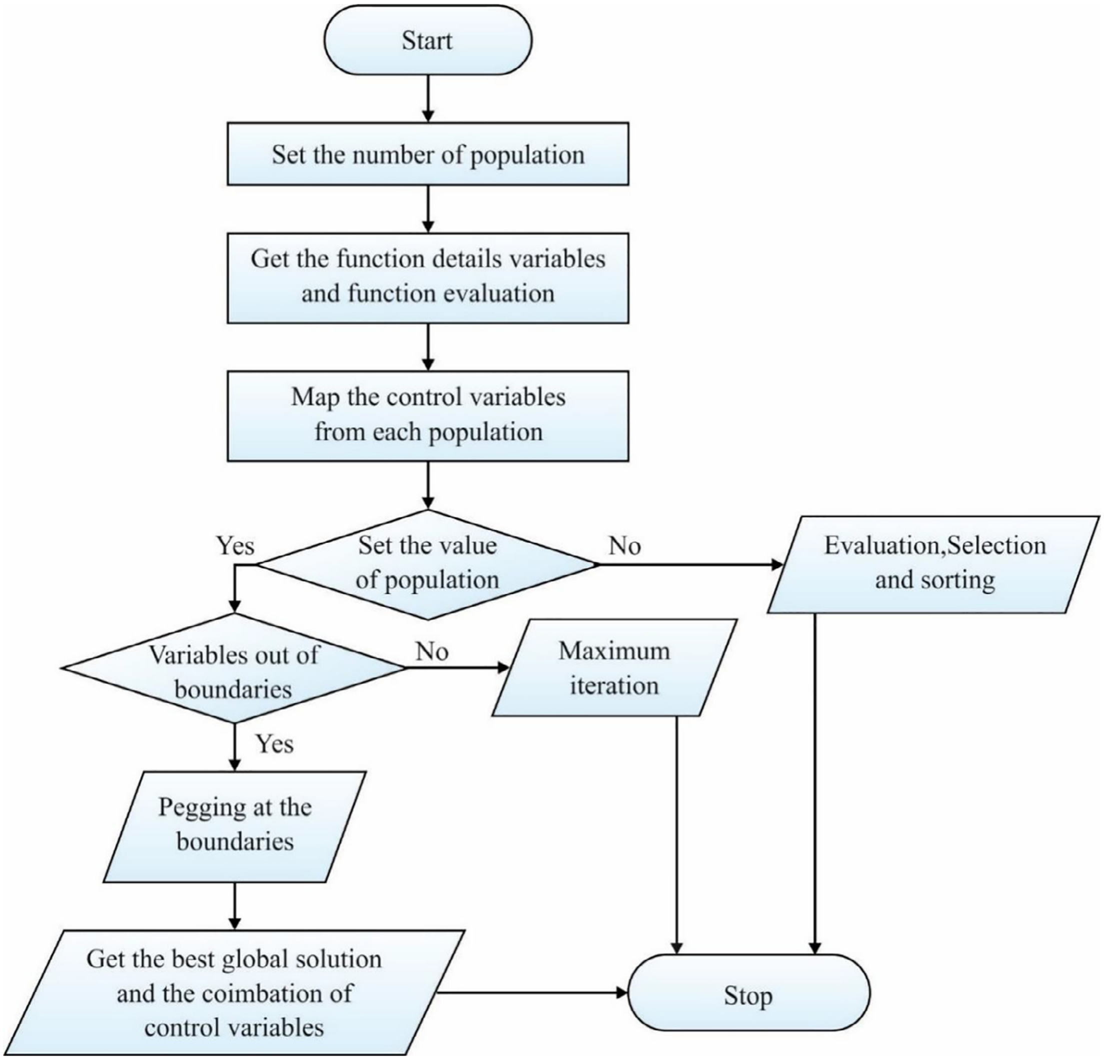

Fig. 3. Flowchart of BMO algorithm.

and Multisim^{TM} tools. The experimental results of the BMO-ANFC technique are assed using a thermal acceleration test. The BMO-ANFC with other controllers is tested under varying temperature levels (20^0, 40^0, 60^0, and 80^0) in Tables 1-2 and Fig. 4. Once the temperature gets decreased, the time taken to attain the required speed gets increased.

The outcome of the temperature variances needed to reach the particular set point is examined. On comparing other controllers, the BMO-ANFC controller offers optimal responses with respect to the attainment of the control objectives due to the fact that it minimizes the overshoot of the current if the reference temperature gets reached. The optimal response is accomplished by the BMO-ANFC technique under all the temperatures. The required speed is obtained smoothly with minimal current overshoot and offers higher time to get the required speed compared to other techniques.

Table 3 offers a brief MSE analysis of the BMO-ANFC technique with other controllers under different temperature levels. From the table, it is obvious that the BMO-ANFC technique has resulted in a least MSE under all temperature levels. For instance, with 20 °C temperature, the BMO-ANFC technique has offered minimal MSE of 34.20 whereas the PID, Fuzzy, and Fuzzy-PSO controllers have attained a maximum MSE of 61.80, 44.40, and 39.60 respectively. Eventually, with 40 °C temperature, the BMO-ANFC manner has offered minimum MSE of 39.60 whereas the PID, Fuzzy, and Fuzzy-PSO controllers have gained a superior MSE of 60.80, 33.20, and 42.40 correspondingly.

Meanwhile, with 60 °C temperature, the BMO-ANFC method has offered minimal MSE of 49.90 whereas the PID, Fuzzy, and Fuzzy-PSO controllers have achieved an increased MSE of 60.80, 39.00, and 52.50 correspondingly. Lastly, with 80 °C temperature, the BMO-ANFC technique has offered lower MSE of 41.40 whereas the PID, Fuzzy, and Fuzzy-PSO controllers have obtained a maximal MSE of 60.80, 43.70, and 44.00 correspondingly.

A brief comparison study of the BMO-ANFC technique takes place interms of time before failure (TBF) in Table 4. The value of the TBF needs to be high for improved performance and lengthier lifespan. The experimental results showcased that the proposed BMO-ANFC technique has gained maximum TBF under varying temperatures. For instance, under 25 °C temperature, the BMO-ANFC technique has attained a higher TBF of 2.516yrs whereas the PID, fuzzy, and fuzzy PSO controllers have achieved a lower TBF of 0.004, 0.001, and 2.141 yrs respectively. Followed by, under 30 °C temperature, the BMO-ANFC approach has gained a superior TBF of 9.241yrs whereas the PID, fuzzy, and fuzzy PSO controllers have attained a minimal TBF of 0.005, 0.001, and 8.731 yrs correspondingly.

Table 1
Comparison Study of BMO-ANFC Controller under different temperatures (20° and 40°).

Temperature at 20°				
Time (s)	PID	Fuzzy	Fuzzy-PSO	BMO-ANFC
0.00	26.033	26.033	26.033	26.033
0.05	120.404	60.653	49.777	37.548
0.10	57.648	45.304	36.662	31.313
0.15	53.533	44.069	36.662	30.902
0.20	58.883	44.069	35.017	30.079
0.25	55.591	44.481	35.839	30.490
0.30	53.533	42.423	36.251	30.490
0.35	65.055	51.064	39.131	32.136
0.40	58.471	47.361	37.074	32.136
0.45	56.002	46.127	36.662	30.079
0.50	61.351	44.069	35.017	29.256
0.55	58.471	44.481	35.428	31.313
0.60	55.591	43.246	39.543	30.902
Temperature at 40°				
Time (s)	PID	Fuzzy	Fuzzy-PSO	BMO-ANFC
0.00	26.033	26.033	26.033	26.033
0.05	124.807	66.022	57.225	44.028
0.10	61.224	47.627	39.629	34.430
0.15	54.425	41.629	39.629	34.830
0.20	59.224	42.828	41.629	35.230
0.25	54.825	43.228	42.828	35.630
0.30	54.425	44.828	42.428	36.830
0.35	92.416	70.021	65.623	51.626
0.40	58.824	45.228	45.228	38.829
0.45	56.425	45.228	46.028	39.229
0.50	60.824	44.428	49.627	41.629
0.55	58.424	44.028	49.227	40.829
0.60	54.825	44.428	50.426	40.029

Table 2
Comparison Study of BMO-ANFC Controller under different temperatures (60° and 80°).

Temperature at 60°				
Time (s)	PID	Fuzzy	Fuzzy-PSO	BMO-ANFC
0.00	26.033	26.033	26.033	26.033
0.05	124.815	61.023	41.886	31.121
0.10	60.226	45.474	33.912	27.134
0.15	53.847	42.683	32.716	25.140
0.20	57.435	42.683	30.324	24.742
0.25	54.245	41.886	30.722	24.742
0.30	55.043	45.075	34.311	27.134
0.35	70.193	54.644	31.918	25.539
0.40	60.226	46.670	30.722	25.539
0.45	54.644	44.278	30.722	23.944
0.50	60.226	44.278	27.931	23.546
0.55	57.834	43.879	30.722	23.944
0.60	56.239	45.474	30.722	23.944
Temperature at 80°				
Time (s)	PID	Fuzzy	Fuzzy-PSO	BMO-ANFC
0.00	26.033	26.033	26.033	26.033
0.05	125.707	64.214	45.846	40.255
0.10	65.811	46.644	39.057	33.866
0.15	55.429	43.050	36.262	33.866
0.20	58.623	42.252	39.457	33.866
0.25	56.228	42.252	37.460	33.068
0.30	54.630	42.651	39.057	31.071
0.35	65.412	48.641	38.658	29.474
0.40	59.023	46.644	34.266	27.078
0.45	55.828	45.047	34.665	23.085
0.50	62.217	44.648	34.665	23.484
0.55	57.825	45.047	36.262	25.880
0.60	55.828	45.047	35.464	26.679

Next to that, under 35 °C temperature, the BMO-ANFC manner has achieved a superior TBF of 3.810yrs whereas the PID, fuzzy, and fuzzy PSO controllers have achieved a lesser TBF of 0.005, 0.001, and 2.141 yrs correspondingly. In line with, under 40 °C temperature, the BMO-ANFC technique has reached an improved TBF of 0.461yrs whereas the PID, fuzzy, and fuzzy PSO controllers have obtained a reduced TBF of 0.005, 0.074, and 0.382 yrs respectively. Moreover, under 60 °C temperature,

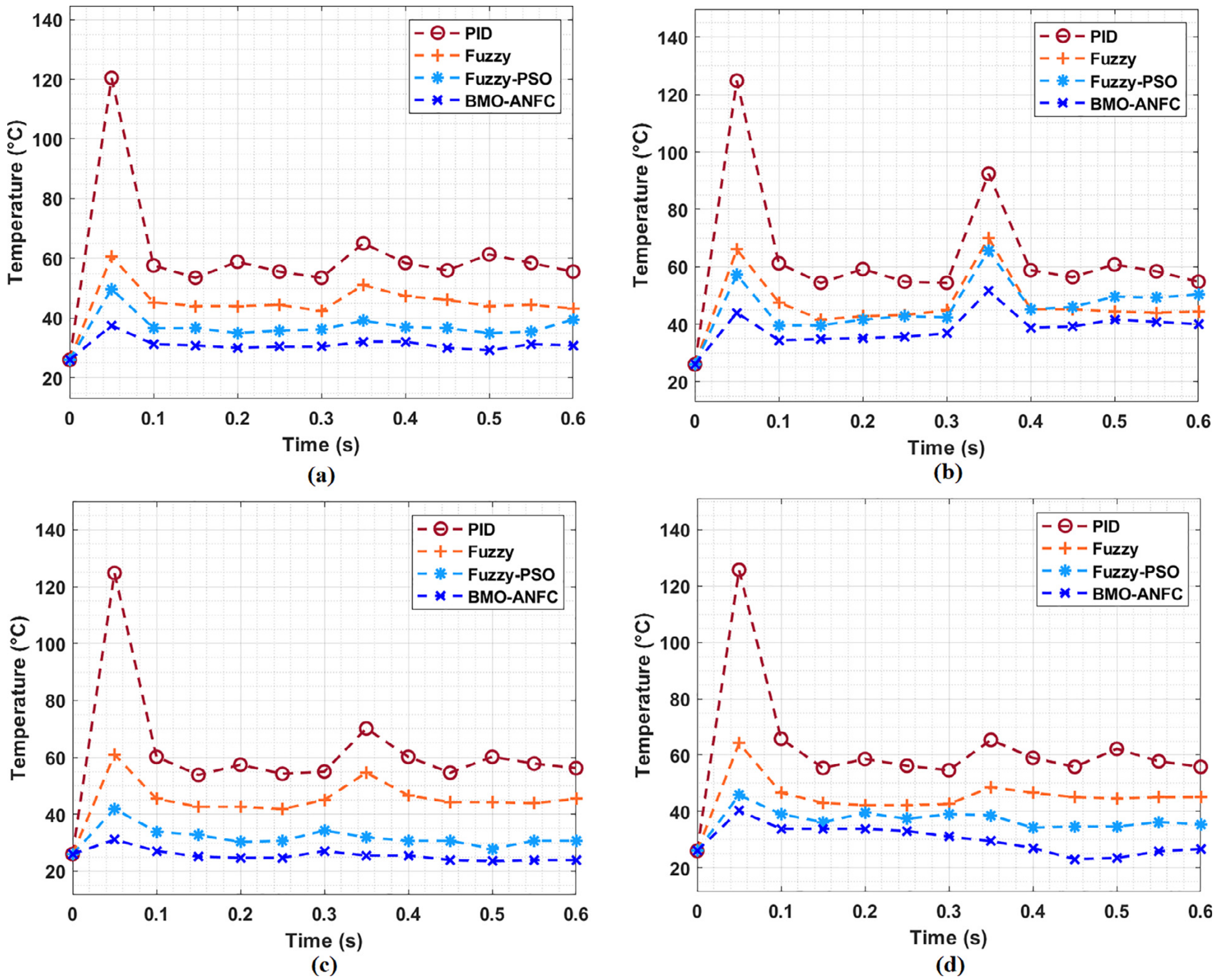

Fig. 4. Result analysis of BMO-ANFC model under different temperatures.

Table 3
MSE analysis of BMO-ANFC with other controllers.

Temp.	20°	40°	60°	80°
PID	61.80	60.80	60.80	60.80
Fuzzy	44.40	33.20	39.00	43.70
Fuzzy-PSO	39.60	42.40	52.50	44.00
BMO-ANFC	34.20	39.60	49.90	41.40

Table 4
TBF analysis of BMO-ANFC with other controllers.

Temperature (°C)	TBF [in years]			
	PID	Fuzzy	Fuzzy PSO	BMO-ANFC
25	0.004	0.001	2.141	2.516
30	0.005	0.001	8.731	9.241
35	0.005	0.001	2.141	3.810
40	0.005	0.074	0.382	0.461
60	0.005	0.003	6.714	7.350
80	0.005	0.001	0.842	0.983

the BMO-ANFC algorithm has reached an increased TBF of 7.350yrs whereas the PID, fuzzy, and fuzzy PSO controllers have achieved a lower TBF of 0.005, 0.003, and 6.741 yrs respectively. Lastly, under 80 °C temperature, the BMO-ANFC methodology has obtained a maximum TBF of 0.983yrs whereas the PID, fuzzy, and fuzzy PSO controllers have gained a minimum TBF of 0.005, 0.001, and 0.842 yrs correspondingly. From the above mentioned results and discussion, it is evident that the BMO-ANFC technique has effectively maximized the lifetime of the power electronics drives.

5. Conclusion

This paper has presented an effective BMO-ANFC technique to improve the lifetime of the power electronics in brushless DC drives. The proposed BMO-ANFC technique is used to optimize the network design of the ANFC model using an objective function involving required speed and reference temperature. In order to tune the learning rate of the ANFC technique, the BMO algorithm is applied which is stimulated from the characteristics of barnacles mating process. To ensure the improved outcomes of the BMO-ANFC technique, a set of simulations were carried out the obtained values pointed out the supremacy of the BMO-ANFC technique over the recent state of art controllers. The proposed BMO-ANFC technique improves the lifetime of the power electronics and reduces the overshoot of the current at the transition time. In future, an improved version of the BMO algorithm can be designed by the incorporation of other metaheuristics concepts.

CRediT authorship contribution statement

N. Priya: Investigation, Writing – original draft. **N.B. Rajesh:** Conceptualization, Writing – review & editing, Supervision. **D. Sivanandakumar:** Formal analysis, Data curation. **N.B. Prakash:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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