Speed control of brushless DC motors using (conventional, heuristic, and intelligent) methods-based PID controllers

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ABSTRACT

One of the most often utilized types of direct current (DC) motors in both the industrial and automotive sectors are brushless DC motors (BLDC). This research presents a comparative analysis on brushless DC motor speed management. A mathematical model of the BLDC motor is developed using MATLAB/Simulink, and its speed is tested using three alternative controller types. The first controller is a traditional proportional integral derivative (PID) controller for BLDC motor speed control. The second controller used the particle swarm optimization (PSO) approach with PID which give the best response for BLDC motor speed. The PID controller in the third method based on neural network also give best reaction on motor speed. Finally, comparison made in speed and torque profiles by using sudden changes in speed and load torque under the three proposed methods. The results show when using first controller the speed rise to 1,526 r.p.m and drop to 1,400 r.p.m at the test conditions. These oscillations will disappear when using the second and third controller.

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1. INTRODUCTION

Many high-performance applications use brushless DC motors (BLDCMs), they have special characteristics including high efficiency high, power density, great torque to inertia ratios, and continuous control at maximum rotating force (torque) [1]–[3]. Due to electronic commutation and the requirement for rotor position feedback, brushless dc (BLDC) motors have more complex control algorithms than other types of motors. Therefore, a full and accurate control scheme requires an exact model of the motor. The power ratings of the BLDC motors range widely, from very small motors used in computer hard drives to massive motors used in electric vehicles. There are single-phase, two-phase, and three-phase BLDC motors available. Motors with three phases are the most public and widely utilized. The BLDC motor is similar to the DC motor in the torque-current characteristic, and it has linear torque-speed performance characteristics. It is also similar to AC motors in that moving magnetic field causes rotor movement or rotation [4], [5].

For BLDC motors, numerous control strategies have recently been widely suggested. In 2016 Han-Chen Wu and other proposed a BLDC speed method of control employing hall effect sensors. Hall effect sensors operate the motor by detecting the position of the rotor. Trapezoidal pulse-width-modulation (PWM) wave, often known as trapezoidal control, is the driving method. The proportional-integral (PI) controller is used to regulate the rotation speed. Several tests are shown to show that the control of motor speed with PI control is more precise and stable than the control without PI control [6]. A complete control method was created in 2017 by Wen and Li [7], modeling and analysis of the motor yields the brushless DC motor's mathematical model. The simulation tests by comparing three control strategies: proportional integral derivative (PID), fuzzy, and fuzzy PID. The results of the simulation show how effectively the fuzzy PID controller controls [7]. Potnuru [8] in 2018 used the dSPACE DS1103 controller board to perform closed loop speed control utilizing rapid control prototyping for a BLDC motor drive. The execution of real-time control software, speed and position measurements, and data collection, however, all have a significant impact on the drive's real-time performance. In general, simulation results for control algorithms created for the motor drive may be advantageous in steady-state and transient situations. The actual issue with hardware implementation is choosing the right hardware and attaching it to the controller board flawlessly. Because it can translate MATLAB/Simulink blocks into integrated DSP code, high performance electric motor control is perfect for the dSPACE DS1103 controller board. The BLDC motor drive is successfully controlled in detail in this article using a real-time [8]. In 2020 Auliansyah [9] described the use of a fuzzy logic controller to regulate the speed of a BLDC motor. The output of a 3-phase inverter is controlled in this study using the PWM approach. The developed fuzzy logic controller has two inputs and one output parameter. By using the designed fuzzy logic controller, the BLDC motor's speed response may be made to spin in accordance with the specified set point value [9]. In 2021 Agrawal and other used a speed-based neural controller to develop on a soft tuning-based controller that may provide noticeably superior outcomes for that. The main goals of this study are developing a neural controller for BLDC motor control, validating the results obtained with the proposed controller with the results obtained using PI, PID, and fuzzy logic controller, and developing a MATLAB simulation model for BLDC motor integrated with soft tuned controller and inverter simultaneously. The results of the simulation indicate that the torque and current ripples are reduced, improving drive performance. A BLDC motor has no steady state error using a neural controller [10].

The PID control, which has three terms and can treat both transient and steady-state responses, provides the most straightforward yet effective solution to many control problems encountered in daily life [11]. Despite this method's durability and simple construction, optimizing gains of PID controllers has proven to be fairly challenging. One of the contemporary strategies for solving global optimization issues is particle swarm optimization (PSO). So, PSO uses a condensed social model to disentangle an optimization problematic. Application of the PSO has several advantages over other approaches, including ease of implementation, speedy discovery of numerous high-quality solutions, and characteristics of stable convergence. The PSO and neural network methods are a viable strategies for resolving the optimal PI controller parameters problem and a top-notch optimization and intelligent methodologies [12], [13].

Using the MATLAB/Simulink program, the BLDC motor is initially modeled using the main example of the motor. The motor's speed response is evaluated under both full and no-load scenarios. The motor's speed response is developed using a conventional PID controller. To compare the validity and effectiveness of the heuristic and intelligent method in speed control, so PSO and neural network is utilized to provide greater speed performance. The simulation results show that combining PSO and a simple neural network with the PID controller optimizes speed and torque response when the motor experiences a sharp variation in the load torque and reference speed. This work also investigates the energy usage of the various controller types suggested.

2. METHOD

2.1. BLDC motor modeling

The BLDC motor has a permanent magnet rotor and three stator windings. Rotor-induced currents need not be taken into account, and no damper windings need to be modeled because of the high electrical conductivity of the stainless steel retaining sleeves and the magnet [14]–[19]. The mathematical model for the three-phase BLDC motor.

$$\begin{bmatrix} V_{as} \\ V_{bs} \\ V_{cs} \end{bmatrix} = \begin{bmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} L_{aa} & L_{ab} & L_{ac} \\ L_{ba} & L_{bb} & L_{bc} \\ L_{ca} & L_{cb} & L_{cc} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \tag{1}$$

Where V_{as}, V_{bs}, and V_{cs} represent phase voltages on the stator, and R_s represents per-phase stator resistance. The stator phase currents are denoted by i_a, i_b, and i_c, respectively. The three phases' self-inductances are L_{aa}, L_{bb}, and L_{cc}. The mutual inductance between phases a, b, and c is represented by L_{ab}, L_{ac}, L_{ba}, L_{bc}, L_{ca}, and L_{cb}. The phase back electromotive forces are represented by e_a, e_b, and e_c. All winding resistances are thought to be the same, it has been presumed. Furthermore, since it has been assumed that there is no noticeable rotor and that the rotor reluctance does not change with angle:

$$L_{aa} = L_{bb} = L_{cc} = L \quad (2)$$

$$L_{ab} = L_{ac} = L_{ba} = L_{bc} = L_{ca} = L_{cb} = M \quad (3)$$

the stator phase currents are constrained to be balanced i.e.

$$i_a + i_b + i_c = 0 \rightarrow i_a + i_b = -i_c \quad (4)$$

Therefore,

$$\begin{bmatrix} V_{as} \\ V_{bs} \\ V_{cs} \end{bmatrix} = \begin{bmatrix} R_s & 0 & 0 \\ 0 & R_s & 0 \\ 0 & 0 & R_s \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} L-M & 0 & 0 \\ 0 & L-M & 0 \\ 0 & 0 & L-M \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \quad (5)$$

phase to phase voltages are:

$$V_{ab} = R_s\,(i_a - i_b) + (\,L - M\,)\frac{d}{dt}(\,i_a - i_b\,) + e_{ab} \quad (6)$$

$$V_{bc} = R_s\,(i_b - i_c) + (\,L - M\,)\frac{d}{dt}(\,i_b - i_c\,) + e_{bc} \quad (7)$$

$$V_{ca} = R_s\,(i_c - i_a) + (\,L - M\,)\frac{d}{dt}(\,i_c - i_a\,) + e_{ca} \quad (8)$$

the back EMFs are:

$$\begin{Bmatrix} e_a = \frac{k_e}{2}\omega_m F(\theta_e) \\ e_b = \frac{k_e}{2}\omega_m F(\theta_e - \frac{2\pi}{3}) \\ e_c = \frac{k_e}{2}\omega_m F(\theta_e - \frac{4\pi}{3}) \end{Bmatrix} \quad (9)$$

where: ω_m is speed of the rotor and k_e is the constant of back-emf

By multiplying the mechanical rotor angle θ_m by the number of pole pairs, one may get the electrical rotor angle θ_e:

$$\theta_e = \frac{P}{2}\theta_m \quad (10)$$

$$\omega_m = \frac{d\theta_m}{dt} \quad (11)$$

P is the number of poles in this case.

The trapezoidal waveform of the back-emf is provided by the function $F(\theta_e)$. This function's one period may be expressed as:

$$F(\theta_e) = \begin{cases} \frac{3}{\pi}\theta_e & 0 < \theta_e < \frac{\pi}{3} \\ 1 - \frac{3}{\pi}(\theta_e - \frac{2\pi}{3}) & \frac{2\pi}{3} < \theta_e < \pi \\ -\frac{3}{\pi}(\theta_e - \pi) & \pi < \theta_e < \frac{4\pi}{3} \\ -1 & \frac{4\pi}{3} < \theta_e < \frac{5\pi}{3} \\ -1 + \frac{3}{\pi}(\theta_e - \frac{5\pi}{3}) & \frac{5\pi}{3} < \theta_e < 2\pi \end{cases} \quad (12)$$

given are the electrical torque values:

$$T_e = \frac{k_t}{2}\left[F(\theta_e)i_a + F\left(\theta_e - \frac{2\pi}{3}\right)i_b + F(\theta_e - \frac{4\pi}{3})i_c\right] \quad (13)$$

and the mechanical part is given as:

$$T_e - T_L = J\frac{d\omega_m}{dt} + B\omega_m \quad (14)$$

where k_t stands for torque constant, T_e stands for electrical torque, T_L stands for load torque, J is the moment of inertia of the rotor, and B is the frictional force.

The BLDC motor Matlab simulation block to calculate the position, current, torque, and speed of the back-EMF generators is made up of three parts. Figure 1 shows the internal block construction of a BLDC motor. The designed concept for a three-phase BLDC motor drive with proposed controller is depicted in Figure 2 as an overall block diagram.

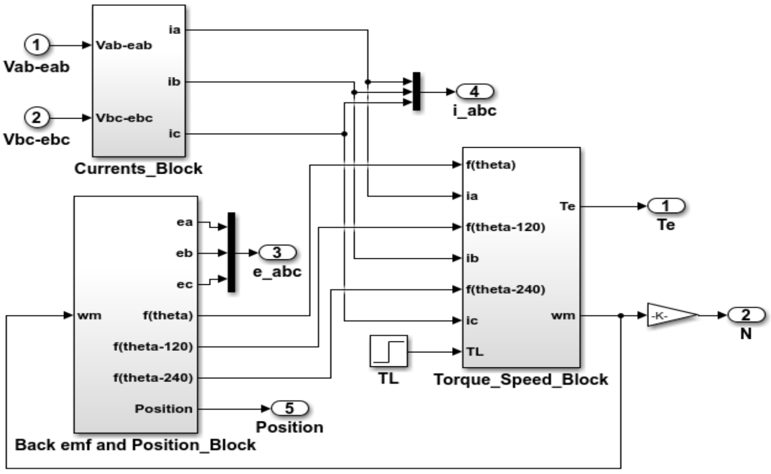

Figure 1. The BLDC motor's block diagram

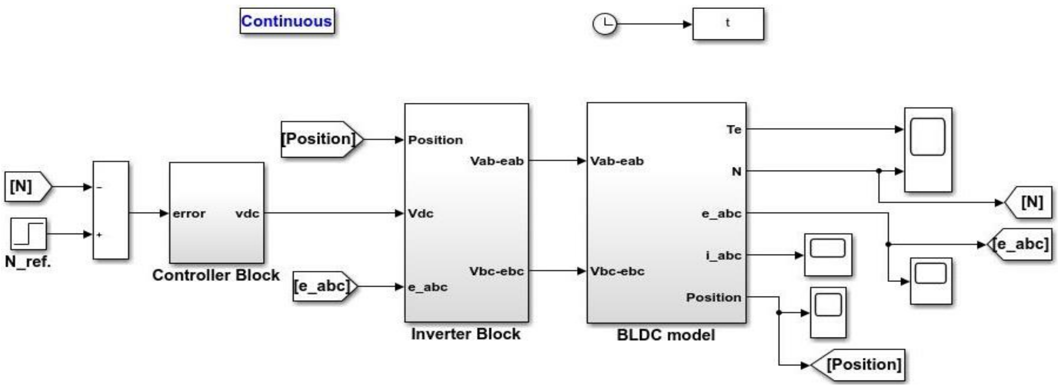

Figure 2. Block diagram for the BLDC motor's overall modeling

2.2. PID controller

The discrepancy between the anticipated fixed point and the measured process variable serves as the "error" value as determined by a PID controller. To try and cut down on error, the controller adjusts the process control inputs. Proportional, integral, and derivative values are the names given to the three different constant parameters utilized in the PID controller computation (method). One method for adjusting these values is by trial and error [10], [20], [21]. Giving the differential formula for the PID organizer:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_D \frac{d}{dt} e(t) \qquad (15)$$

where $u(t)$ represents the output signal, $e(t)$ represents the error signal, K_p indicates the proportional gain, K_i represent the integral gain, and K_D is the derivative gain.

2.3. Particle swarm optimization

An evolutionary algorithm based on swarms is called particle swarm optimization. Eberhart and Kennedy were the first to develop PSO, which is used to optimize continuous non-linear functions. The simplicity of implementation and the absence of a need for gradient information are two appealing aspects of PSO [22]–[25]. Numerous various optimization issues may be resolved using it. PSO approach conducts search utilizing a population of particles that correspond to individuals, just like evolutionary algorithms. Each particle stands for a potential answer to the current issue. In the PSO system, particles move about in a multidimensional search space to alter their places until computational limits are reached. Figure 3 illustrates the idea of a searching point being modified using PSO.

The example is used to modify the particles mathematically [12]. The equaitions that describe the algorithm are given below. Also the PSO algorithm is applied to the suggested PID controller in the flowchart presented in Figure 4:

$$V_i^{k+1} = w_t v_i^k + c_1 r_1 [P_{best}^k - X_i^k] + c_2 r_2 [G_{best}^k - X_i^k] \quad (16)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (17)$$

where V_i^k: is the velocity of the *ith* particle at iteration k, X_i^k: is the position of the *ith* particle at iteration k, P_{best}^k: is a particular particle Is personal best position, G_{best}^k: is a specific particle's personal best location that I discovered in [0 t], c_1, c_2: is cognitive and social factors respectively, r_1, r_2: is random coefficients, and w_t: is inertia weight.

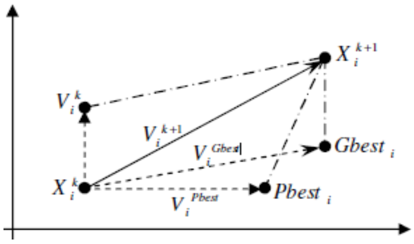

Figure 3. PSO algorithm

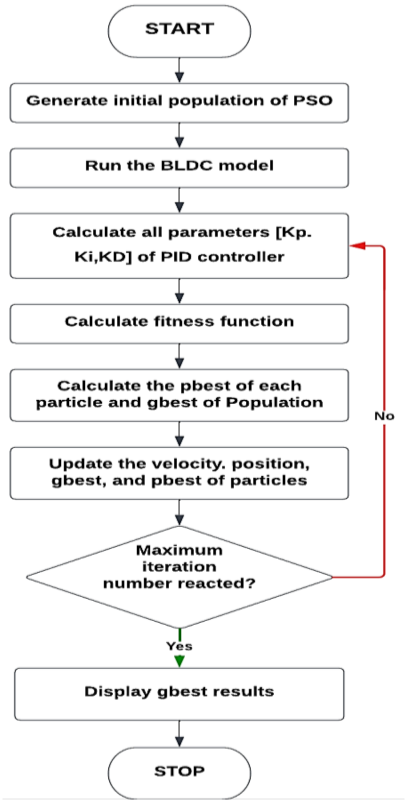

Figure 4. The PSO-based PID controller flowchart

2.4. Neural network based PID controller design

The PID controller was supplemented with a neural network to construct and improve the speed controller proposed in this study. A simulation in Matlab is used to build a neural network employing the data in Table 1. This table contains the neural input, which is speed error, and the related neural output, which is inverter DC voltage (V_{dc}), as shown below. Figure 5 shows the suggested neural network architecture.

Table 1. Data for developing neural network

Neural input speed error	Neural output V_{dc}	Neural input speed error	Neural output V_{dc}
325	35	-725	115
240	45	-830	125
100	55	-920	135
0	60	-1010	145
-45	65	-1100	155
-200	75	-1180	165
-293	85	-1260	175
-405	95	-1340	185
-580	105	-1420	195

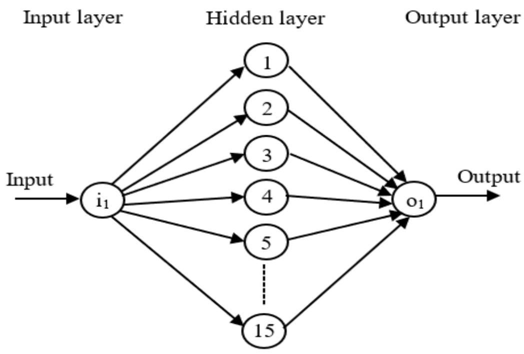

Figure 5. The proposed neural network internal architecture

3. RESULTS AND DISCUSSION

The BLDC motor is simulated with the aid of MATLAB. A list of the motor specifications is included in Table 2. The settings of the PID controller's parameters for the motor controller are calculated through a process of trial and error. Additionally, PSO is used to determine the PID controllers' optimal parameters to determine the PID's perfect speed control settings. Likewise motor speed and torque responses were improved when the neural network was added to the PID controller. The PID controller parameters when applying the three distinct methods are given in Table 3.

Table 2. Motor parameters

Motor parameters	Value
Stator resistance	0.7 Ω
Self-inductance	2.72 mH
Mutual inductance	1.5 mH
Moment of inertia	$2*10^{-4}$ Kg.m^2
Number of poles	4
Friction constant	0 N.m./rad./Sec.
Back-EMF constant	0.5218 V.Sec./rad.
Torque constant	0.049 N.m./A
DC voltage	60 V
Load torque	2 N.m.

Table 3. PID controllers parameters

Motor controller	KP	KI	KD
Traditional-PID	0.5	9.6	0,004
PSO-PID	6.545	6.77	0.06696
Neural network-PID	10	8	0.01

The speed and torque responses of the BLDC motor in response to changes in reference speed without and with loading is shown in Figures 6-7. In these figures the reference speed for the motor changes from 1,000 rpm to 1,500 rpm at instant time 0.2 seconds and at 0.6 seconds the motors are fully loaded. The results show the validity of the three controllers with superiority of PSO and neural network based PID controller over traditional PID controller, because the motor speed remains stable at the moment when speed and load suddenly increase. While in traditional PID controller the motor suffers from speed oscillation at instant of reference speed change and its speed reach to 1,526 r.p.m also at the instant of applied the full-load its speed drop to 1,400 r.p.m. Also the motor torque profile has very fast response when the same test conditions apply on the motor with the PSO and neural network based PID controller better than conventional PID controller. The motor torque profile have two high values at (t=0 sec and t=0.2 sec) because the sudden change in motor speed from (0 to 1,000) r.p.m and from (1,000 to 1,500) r.p.m. Figures 8-9 provide the position signal and back-emf voltages for the motor in the same operation conditions. The motor speed performance parameters at instant of sudden change in reference speed at (t=0.2 sec) with using the proposed controllers are given in Table 4.

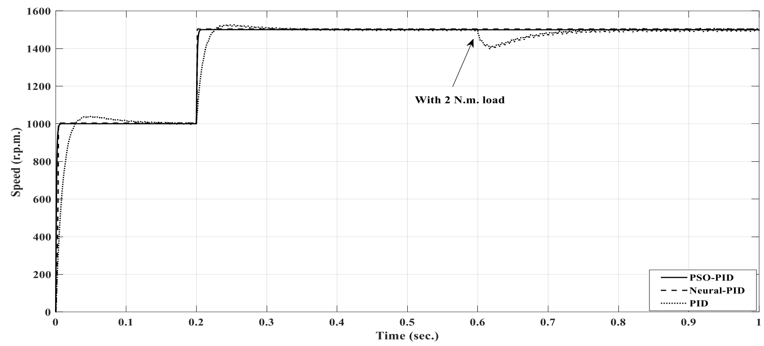

Figure 6. Response of the motor speed to a rapid change in the reference speed and the load torque

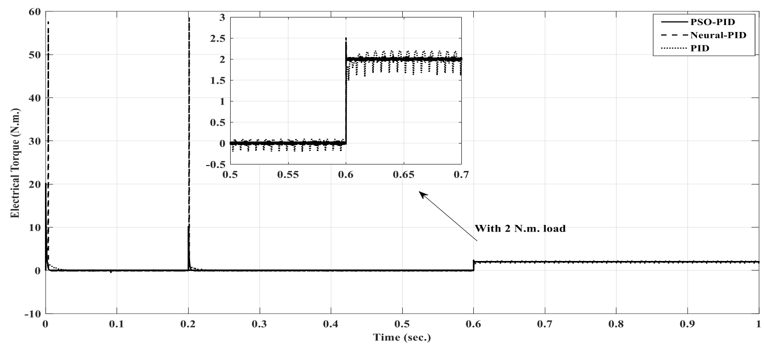

Figure 7. Response of the motor's torque to a rapid change in the load torque and reference speed

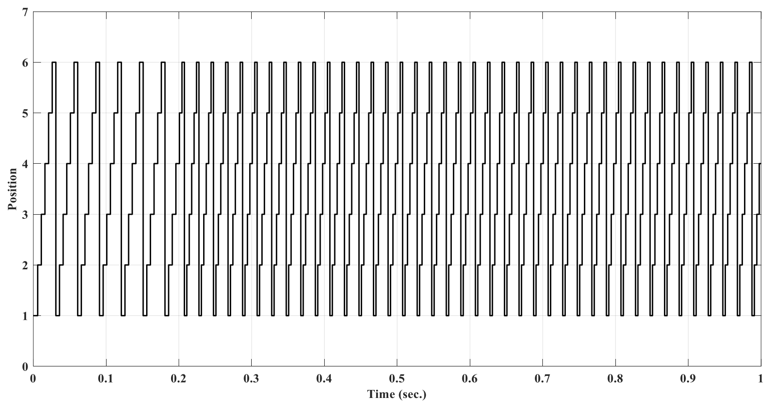

Figure 8. Motor position signal

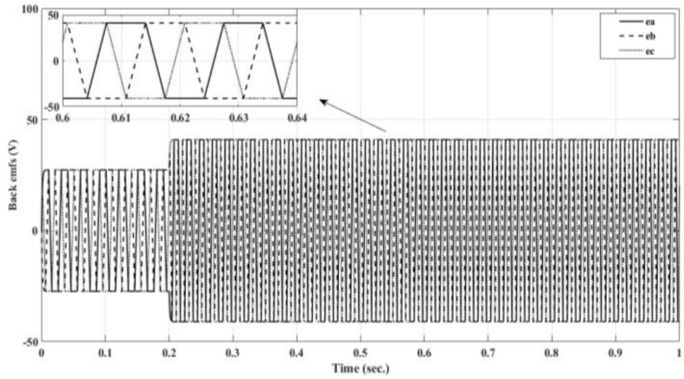

Figure 9. Motor back EMFs voltages

Table 4 demonstrates that when the traditional-PID controller is utilized, the motor speed overshoots with a maximum value (26 r.p.m). When employing a PSO and neural network based PID controller, the speed overshoot will eliminate. Additionally, the neural network-based PID controller's time responsiveness is excellent and superior to that of conventional and PSO-based PID controllers. The rise time, peak time, and settling time when using neural network-based PID controller was improve by ratio 100% comparing with traditional-PID controller. But with PSO-based PID controllers the ratio was improved by 96.94%, 95.23%, and 94.56% for rise time, peak time, and settling time respectively.

Because energy usage is a major concern today [26], [27]. The energy profile of the motor is drawn as shown in Figure 10 for the same test conditions. This figure provides small different in energy consumption for different types of controllers. Energy profile of the motor is drawn based on the simulation results of the motor.

Table 4. Motor speed performance parameters

Motor controller	Maximum overshoot M_p (r.p.m)	Rise time t_r (sec)	Peak time t_p (sec)	Settling time t_s (sec)
Traditional-PID	26	0.225923	0.253	0.2624
PSO-PID	1	0.2063	0.21	0.2115
Neural network-PID	0	0.2	0.2	0.2

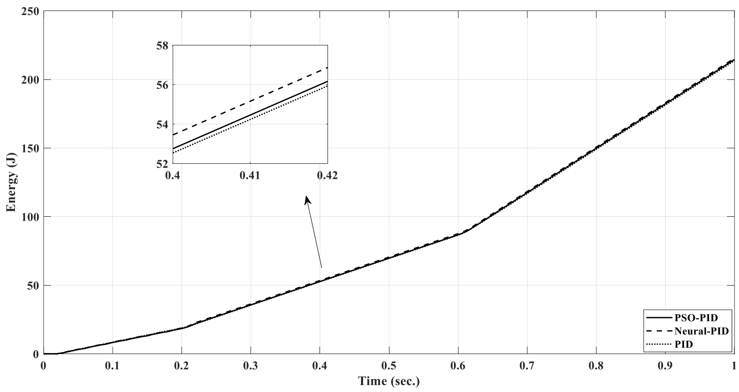

Figure 10. The motor energy profile

4. CONCLUSION

This study examines the three-phase BLDC motor simulation model for speed control. Three different controller kinds are used for speed test under two different conditions, sudden reference speed change and sudden load change. The first controller controls the speed of a BLDC motor using a conventional PID controller. Then PSO technique combined with PID in the second controller provided the optimum response for BLDC motor speed. The third option, which uses a neural network based PID controller, likewise provides the best response in terms of motor speed. The result shows the speed rise to

1,526 r.p.m at moment of when sudden reference speed change and drop to 1,400 r.p.m at the time of applied the full-load when using traditional-PID controller. For the same conditions the speed rise to 1,501 r.p.m and stile constant when using PSO based PID controller. But with neural network based PID controller the speed has no oscilation at the two conditions. Also, for rising time, peak time, and settling time, the ratio was enhanced by 96.94%, 95.23%, and 94.56% respectively using PSO-based PID controllers comparing with traditional-PID controller. PID controller performance improved 100% by employing neural network-based technology. Also, when the test conditions are applied to the motor with using the PSO and neural network based PID controller the motor torque profile has a much faster reaction than a conventional PID controller. Finally, utilizing abrupt changes in speed and load torque under the three suggested techniques, a comparison of speed and torque profiles was done.

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