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# Introduction of Particle Swarm Optimization for Trapezoidal Commutation of BLDC Motor

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**ABSTRACT:** Recently, the development of close-looped water pressure control system has garnered the attention of many researchers. It offers several advantages, such as reduced operating costs and increased motor efficiency. Also, various methods of BLDC motor commutation are being investigated and developed. This is linked directly to the water pressure generated by the pump due to the motor's commutation efficiency. Among the various commutation method, Trapezoidal control offers efficient speed control, low hardware requirement, and an easy-to-understand control mechanism. However, due to the simplicity and abundant research on the trapezoidal commutation method, this project aimed to design and develop an efficient method of BLDC motor commutation, allowing the pump to generate a stable desired water pressure. Therefore, the methodology has been suggested based on the literature review, particularly the implementation of Particle Swarm Optimizer, PSO, on the PI Speed Controller for a Trapezoidal Commutation. Trapezoidal Commutation is a close-looped commutation system that obtains the stator's position from the hall sensors and feedback it to increase the commutation's efficiency. However, additional improvement is made by introducing PSO into the PI Speed controller, allowing the best proportional and integral gain constant of the PI Controller. This would reduce the error and therefore, increase the implementation efficiency of the motor's commutation method, which reduce both rising time, settling time, and percentage overshoot of the motor. The results of this study, however, serve as a preliminary investigation that demonstrates the further improvement of trapezoidal commutation on a BLDC motor required to improve the commutation error for more accurate water pressure operation.

**KEYWORDS:** Particle Swarm Optimizer, Trapezoidal Commutation, Number of Iterations, Change in Inertia, Efficiency.

## I. INTRODUCTION

The introduction of close-looped water pressure control system is widely adopted by the community, whether it is for private residences, city water systems, agricultural irrigation, or industrial applications [1]. Many favored it due to several advantages, such as reduced operating cost and increased motor efficiency [2]. Many BLDC motor control techniques, such as Field-Oriented Control, FOC, and Sinusoidal Control, are much more efficient than Trapezoidal Commutation [3]. Nonetheless, Trapezoidal Commutation is opted as the commutation method for the BLDC motor as it offers effective speed control, minimum hardware requirements, and a simple control mechanism [4]. However, Trapezoidal Commutation control would require BLDC motor with hall sensor for the feedback mechanism. With this simple commutation technique, Particle Swarm Optimizer, PSO, is introduced and integrated with Trapezoidal Commutation, to improve the commutation efficiency. By doing so, an increase in the BLDC motor efficiency would lead to a better water pressure control performance operated by the BLDC based water pump.

Trapezoidal Commutation, also known as Six step commutation, is a commutation method used to manage three-phase BLDC motor. Torque ripple happens during commutation, particularly at low speeds, even though it can be effective in controlling motor speed. Hence, it is very well-liked for low-end applications that require effective closed-loop operation [4]. PSO, in short for Particle Swarm Optimization, is a computer technique that seeks to solve a problem more effectively by repeatedly attempting to make a candidate solution better in terms of a specified quality metric [5]. In other words, it is a population-based stochastic search method that Kennedy and Eberhard first suggested in 1995 [6]. It was inspired by the behavioral imitation study of flocks of birds, where all birds in the flock would share their discoveries and aid in the greatest possible hunt, while a bird is flying and seeking randomly for food [6] [7]. PSO differs from other optimization techniques, such as genetic algorithm (GA), ant colony algorithm (ACA) & Gravitational Search algorithm, where it does not depend on the gradient or other differential forms of the objective [7].

It only requires the objective function and a few hyperparameters to make it operate. The actual global optimal solution found can never be verified, thus it is a heuristic solution [6]. Nonetheless, the global optimal solution obtained through PSO is usually quite near to the global optimal solution and is hence accepted. Therefore, this research focuses on the adaptation of PSO onto the PI Speed controller of the Trapezoidal Commutation System, in hopes that the proportional gain constant,  $K_p$ , and integral gain constant,  $K_i$ , found by the PSO, would best suit the commutation method and the BLDC motor to generate a much more efficient speed response of the motor. The adaptation of PSO onto the PI Speed controller of the Trapezoidal Commutation is shown in Fig. 1.

## II. TRAPEZOIDAL COMMUTATION

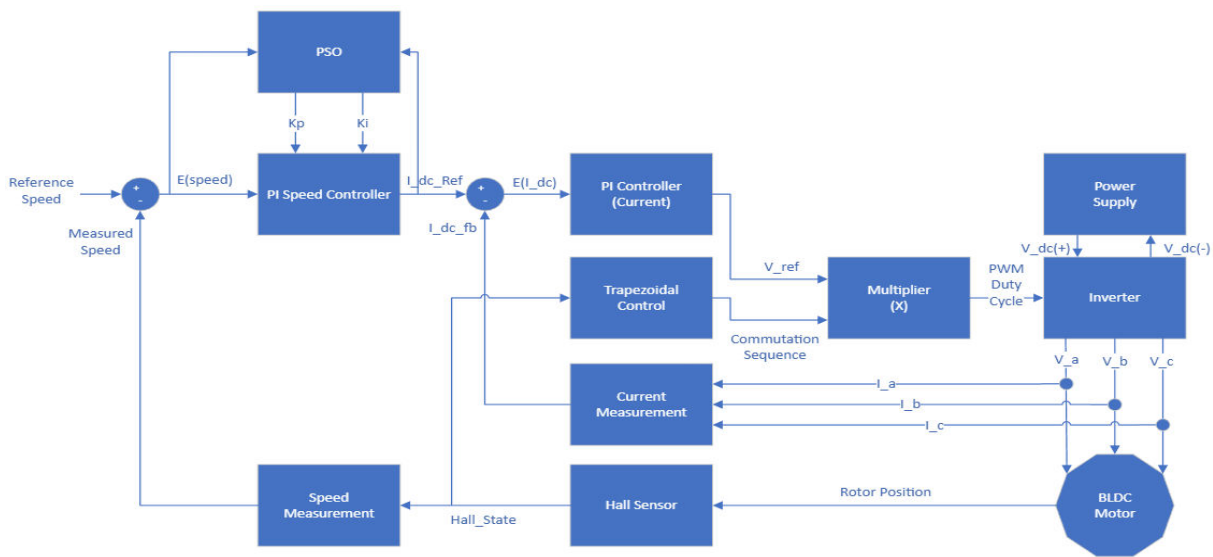


Fig. 1. Trapezoidal Commutation control with PSO adaptation mechanism for BLDC drive system

A set of back EMF and torque equations that are similar to those used in DC motors and are reasonably simple allows BLDC motors to regulate torque and speed successfully [8]. The Back EMF magnitude can be expressed as such:

$$E=2NlrB\omega \tag{1}$$

where,  $N$  is the number of windings per phase,  $l$  indicates the rotor length,  $r$  denotes the rotor's internal radius,  $B$  is the rotor magnetic flux density, and  $\omega$  indicates the motor's angular velocity.

Furthermore, the torque term,  $T$ , of the BLDC motor can also be expressed as such:

$$T = \left(0.5i^2 \frac{dL}{d\theta}\right) - \left(0.5B^2 \frac{dR}{d\theta}\right) + \left(\frac{4N}{\pi} Brlni\right) \tag{2}$$

where,  $i$  represents phase current,  $L$  indicates phase inductance,  $\theta$  is the rotor's position, and  $R$  indicates phase resistance.

The BLDC motor stator are made of three-phase windings, surrounding the rotor. Trapezoidal Commutation operates by energizing the stator windings, inducing electric field around the windings. The electric field then interacts with the magnetic field generated by the permanent magnet rotor to produce a force that rotates the rotor [9]. This is defined by Lorentz Force Law, as shown in the equation below:

$$\vec{F} = q\vec{E} + q\vec{v} \times \vec{B} \tag{3}$$

where,  $q$  indicates the charge of the particle,  $\vec{E}$  represents the electric field,  $\vec{v}$  is the particle's velocity,  $\vec{B}$  represents the magnetic field, and  $x = \sin\theta$ . Besides that, energizing the windings in a six-step rhythm, in a specified order, will cause the motor to begin spinning. Hall sensors, mounted  $120^\circ$  apart from each other, are mounted onto the stator to determine the position of the permanent magnet rotor. The hall sensors would provide feedback on the present state of the rotor and energize the stator windings accordingly as referred to TABLE. I.

TABLE. I. TRAPEZOIDAL COMMUTATION CONTROL TABLE

Mode	Hall Sensor			Stator Phase Winding		
	A	B	C	A	B	C
I	1	0	0	$-V_{cc}$	$+V_{cc}$	NC
II	1	0	1	NC	$+V_{cc}$	$-V_{cc}$
III	0	0	1	$+V_{cc}$	NC	$-V_{cc}$
IV	0	1	1	$+V_{cc}$	$-V_{cc}$	NC
V	0	1	0	NC	$-V_{cc}$	$+V_{cc}$
VI	1	1	0	$-V_{cc}$	NC	$+V_{cc}$

### III. PSO ADAPTATION INTO TRAPEZOIDAL COMMUTATION

PSO, a searching algorithm, can be adopted into the speed PI controller of Trapezoidal Commutation, to help search for the best proportional gain constant,  $K_p$ , and integral gain constant,  $K_i$ , allowing for the system to achieve efficient speed response. For PSO to work, random particles, known as a swarm, are initially generated and initialised within the search space. These particles in the swarm travel through the search space at random position and speed, based on the initial initialised position and speed. Each particle within the swarm offers a potential optimal solution for the optimization solution. In order to determine the optimal solution, a specific fitness function is applied to each particle through each iteration [10]. Fitness function is used to determine which of the solution provided by the particles are similar to the ideal solution [11]. The fitness function used to evaluate the cost of each particle for every iteration, is as shown below:

$$J = \left( \sum_{n=1}^N |\omega_m^{ref} - \omega_m(n)| \right)^2 + \beta \left( \sum_{n=1}^N |u(n) - u(n-1)| \right)^2 + \gamma \left( \sum_{n=1}^N |\zeta(n)| \right)^2 \quad (4)$$

where,  $\omega_m^{ref} - \omega_m(n) = e(\omega_m)$  represents the speed error,  $u(n)$  &  $u(n-1)$  indicates the output of the PI controller,  $\beta$  is the penalty factor for the control signal dynamics, and  $\gamma$  indicates the penalty factor for overshoot. Do note that the penalty factors,  $\beta$  &  $\gamma$ , are selected through a trial-and-error method.

After evaluating the particle's fitness, the solution with the least cost would be stored as global optimal particle,  $gbest$ . This information would be shared and distributed among all the particles, each of which retains its own previous ideal data,  $pbest^i$ . The data is then used to calculate and estimate the particle's position and velocity for the following iteration [10]. Each particle in the search space would dynamically change its velocity based on its current best location and the best position of its near surrounds [12]. Furthermore, evaporation mechanism and diversity mechanism are also introduced into the velocity equation. This is to allow for optimization by the PSO in a dynamic environment. The modified velocity equation is as shown below:

$$v_j(i+1) = k \left[ v_j(i) + \frac{\phi}{2} r_p \delta (x_j^{pbest} - x_j(i)) + \frac{\phi}{2} r_p \delta (x_j^{gbest} - x_j(i)) \right] \quad (5)$$

$$x_j(i+1) = x_j(i) + v_j(i+1) \quad (6)$$

$$k = \frac{2}{|2 - \phi - \sqrt{\phi^2 - 4\phi}|} \quad (7)$$

where,  $k$  is the constriction factor,  $\frac{\phi}{2} = 2.05$  represents the correction factor,  $\delta$  indicates swarm diversity (  $1 =$  swarm contract &  $-1 =$  swarm repels),  $i$  represents swarm iteration number,  $v_j$  indicates the speed of the  $j$ -th particle,  $x_j$  is the position of the  $j$ -th particle,  $x_j^{pbest}$  indicates the best solution of the  $j$ -th particle,  $x_j^{gbest}$  represents the best solution of the swarm, and  $r_p$  &  $r_g$  is a random number between 0 and 1, generated for each particle in every iteration.

As mentioned above, the minimum cost evaluated using the fitness function in equation (4) represents the ideal solution. The continuous update of the global and local best solution for every particle is done after every evaluation. The optimal fitness value of the swarm with its respective particle is updated as such [13]:

$$\begin{bmatrix} F_j(i+1) \\ x_j^{pbest} \end{bmatrix} = \begin{cases} \begin{bmatrix} \rho F_j(i) \\ x_j^{pbest} \end{bmatrix} & \text{if } \eta_{j+1} \geq \rho F_j(i) \\ \begin{bmatrix} \eta_{j+1} \\ x_j(i+1) \end{bmatrix} & \text{if } \eta_{j+1} < \rho F_j(i) \end{cases} \quad (8)$$

$$\eta_{j+1} = J(x_j(i+1)) \quad (9)$$

where,  $\rho$  represents evaporation constant,  $\eta_{j+1}$  indicates the current fitness value of the  $(j+1)$ -th particle,  $F$  is the global best fitness value,  $F(x_j^{gbest})$ ,  $J$  indicates the current fitness value of the  $j$ -th particle in the  $i$ -th iteration, and  $x_j(i+1)$  represents the update position of the  $j$ -th particle. Besides that, modified evaporation constant,  $\rho_1$  &  $\rho_2$ , has also been introduced into the PSO. This would allow for a more efficient PSO algorithm, where the ideal solution can be determined faster. The smaller evaporation constant,  $\rho_2$ , is employed to achieve a steady state when the process is stationary. By letting  $\rho = \rho_2 = 0.999$ , the system will have a better convergence. To find a new optimal solution more swiftly in a non-stationary environment, the system adjusts the evaporation constant to a larger value,  $\rho_1$ , where  $\rho = \rho_1 = 0.85$ , allowing the search for the ideal position and the transition to a stable state at a quicker rate [10]. The evaporation constant selection criteria is as shown below:

$$\rho = \begin{cases} \rho_1 & \text{if } J \geq (1+k)J_{op}(j) \text{ or } J \leq (1-k)J_{op}(j) \\ \rho_2 & \text{if } (1-k)J_{op}(j) < J < (1+k)J_{op}(j) \end{cases} \quad (10)$$

where,  $J$  represent the current fitness value, and  $J_{op}(j)$  indicates the  $j$ -th particle's historical optimal fitness value.

The diversity mechanism in PSO is introduced to allow the swarm to contract and disperse. Hence, the introduction of attraction and repelling mode. The swarm shrinks when it is in the attraction phase, and this causes the swarm's diversity to decline. This happens when the diversity,  $D_{dist}$ , is larger than the diversity threshold,  $D_{thold}$ , setting the swarm's behavioral coefficient,  $\delta$ , to  $\delta = 1$ . In contrary, the swarm's behavioral coefficient,  $\delta$ , is set to  $\delta = -1$ , when the swarm is in repelling mode. This mode is triggered when the diversity,  $D_{dist}$ , is lesser compared to the diversity threshold,  $D_{thold}$ , preventing the swarm from contracting till zero speed. The diversity,  $D_{dist}$ , and the swarm's behavioral coefficient,  $\delta$ , is determined as shown:

$$D_{dist} = \frac{x_{max}(i) - x_{min}(i)}{2} \quad (11)$$

$$\delta = \begin{cases} 1 & \text{if } \delta < 0 \text{ \& } D_{dist} > D_{thold} \\ -1 & \text{if } \delta > 0 \text{ \& } D_{dist} < D_{thold} \end{cases} \quad (12)$$

where,  $D_{dist}$  represents diversity,  $D_{thold}$  indicates diversity threshold,  $x_{max}(i)$  is the particle's maximum position in the  $i$ -th iteration,  $x_{min}(i)$  represents the particle's minimum position in the  $i$ -th iteration, and  $\delta$  is the swarm's behavioral coefficient.

#### IV. EXPERIMENT

Since the introduction of PSO into Trapezoidal Commutation control is a promising solution, experiments are to be conducted to determine if PSO can increase the efficiency of the BLDC speed controls with improvement of the speed response.

The simulation on the adaptation of PSO into Trapezoidal commutation can be summarized as follow:

- 1) The PSO simulation variables, initial swarm position and velocity, initial fitness value, and initial  $K_p$  and  $K_i$  are initialized.
- 2) The fitness value of each particle is evaluated.
- 3) The Pbest and Gbest of each particle of the swarm is evaluated.
- 4) The position and velocity of each particle is calculated and updated.
- 5) Step 2) to 4) is repeated for a set number of iterations.

TABLE II. SIMULATION PARAMETERS OF THE PSO ALGORITHM WITH TRAPEZOIDAL COMMUTATION CONTROLLER

Parameters	Symbol	Value
Number of Particles	$N$	5
Number of Iterations	$N_{iter}$	5 & 12
Evaporation constant	$[\rho_1, \rho_2]$	$[\frac{1}{0.85}, \frac{1}{0.999}]$
Diversity Threshold	$D_{thold}$	[0.1, 1]
Penalty factor for Control Signal Dynamics	$\beta$	0.01
Penalty factor for Overshoot	$\gamma$	50,000
Period (s)	$T_0$	0.4

TABLE III. BLDC MOTOR PARAMETERS

Parameters	Symbol	Value
Stator Resistance	$R_s$	0.72Ω
d-axis stator inductance	$L_{ds}$	0.0012 H
q-axis stator inductance	$L_{qs}$	0.0012 H
Moment of Inertia	$J$	0.000048 kgm <sup>2</sup>
Number of Pole pairs	$p$	4
Rated Speed	$\omega_m$	4000 RPM
Switching frequency	$f_{BLDC}$	20 kHz

With the initialization of the parameters as specified in TABLE II and TABLE III, the simulation is executed, and experiments are carried out to study the response of the PSO – Trapezoidal Commutation method. Simulation is done in MATLAB with the PSO algorithm executed in the MATLAB Script before Trapezoidal Commutation control operates in the Simulink. A step input is introduced into the system as the reference speed,  $\omega_{m,ref}$ , and the feedback speed response,  $\omega_{m,fb}$ , is measured, and they are compared to compute the error of the system, follow by the  $K_p$  and  $K_i$  values obtained for the PI Speed controller. The measured speed response of the BLDC motor would be measured in terms of percentage overshoot, %OS, settling time,  $t_s$ , and rising time,  $t_{rise}$ , in order to ascertain the system's efficiency.

A. Difference in number of Iterations for PSO algorithm

The PSO algorithm for BLDC motor with Trapezoidal Commutation control is put to the test by varying the number of iterations,  $N_{iter}$ , while keeping the other variables constant, as specified in TABLE II and TABLE III. Sufficient difference between the number of iterations is crucial to allow for observable difference in the system response. Hence, the number of iterations,  $N_{iter}$ , for the PSO – Trapezoidal commutation control integration is simulated at  $N_{iter} = 5$  and  $N_{iter} = 12$ .

B. Change in Rotor's Inertia

The PSO algorithm used in this research can adapt to the change in variables of the BLDC motor, and still produce the most suitable  $K_p$  and  $K_i$  value. Hence, an experiment is conducted for Trapezoidal Commutation with PSO, to observe if the PSO manage to adapt to the change in inertia,  $J$ , of the BLDC motor. Initially, the PSO algorithm would

run with inertia,  $J$ , set as  $J = 48e^{-6}kgm^2$ . After 6 iterations, the algorithm would change the rotor's inertia,  $J$ , to  $J = 3J_0 = 144e^{-6}kgm^2$ , where the algorithm would run for another 6 iterations. The speed response for the BLDC motor run with Trapezoidal commutation of both  $J = 48e^{-6}kgm^2$  &  $J = 3J_0 = 144e^{-6}kgm^2$  is simulated, and the response is observed and recorded.

C. Ordinary Trapezoidal Commutation versus Trapezoidal Commutation with PSO

The ordinary Trapezoidal Commutation control simulation is first simulated with the motor parameters stated in TABLE III. While maintaining the motor parameters, the PSO-Trapezoidal Commutation control adaptation is simulated for 12 iterations,  $N_{iter} = 12$ . The speed response between these two types of control is observed and recorded, depending on the  $K_p$  and  $K_i$  value determined for the PI Speed controller of each respective control system.

D. Field Oriented control versus Trapezoidal Commutation with PSO

Field Oriented Control is a motor commutation control that is much more efficient compared to that of Trapezoidal Control. Torque ripples are persistent at low speed for Trapezoidal Commutation and is reduced at high speed. This is not the case for Field Oriented Control, FOC, as FOC is suitable for both low and high speed with little ripple. Hence, with the introduction of PSO algorithm into Trapezoidal Commutation, the response of such integration is to much anticipation on whether it could perform better compared to Field Oriented control, FOC, commutation of BDLC motor. The simulation of the ordinary Field Oriented Control, FOC, is first simulated with the motor parameters stated in TABLE III. While maintaining the motor parameters, the PSO-Trapezoidal Commutation control adaptation is simulated for 12 iterations,  $N_{iter} = 12$ . The speed response between these two types of control is observed and recorded.

V. RESULTS AND DISCUSSION

A. Difference in number of Iterations for PSO algorithm

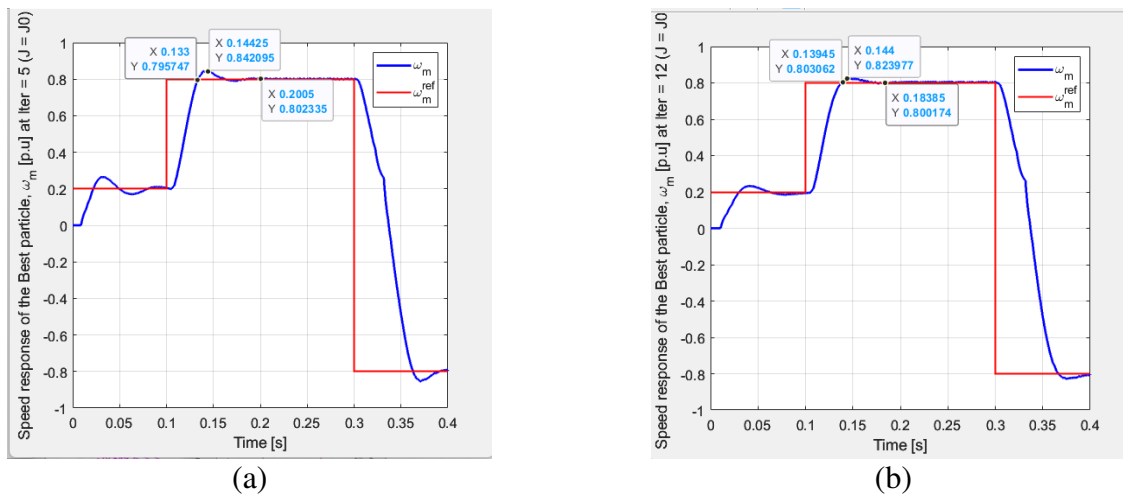


Fig. 2. Speed response of (a) PSO-Trapezoidal Commutation control adaptation at 5 iterations and (b) 12 iterations

The PSO-Trapezoidal commutation control adaption was run for 5 iterations and 12 iterations respectively. The speed response for both iterations were obtained and demonstrated in Fig. 2. It is observed that the speed response for (b) with  $t_{rise} = 0.14s$ ,  $\%OS = 2.98\%$ ,  $t_s = 0.18s$ , is better than (a) which has a  $t_{rise} = 0.13s$ ,  $\%OS = 4.96\%$ ,  $t_s = 0.2s$ . Hence, it can be determined that the PSO is working accordingly as it matches the understanding on PSO. The increase in the number of iterations of the PSO will increases the chances to obtain a promising solution achieved by the algorithm. In this case, it would be the fitness value of the  $K_p$  &  $K_i$  values of the PI Speed Controller determining the system performance. Based on the response in Fig. 2, it can be concluded that the  $K_p$  &  $K_i$  values obtained by the PSO with 12 iterations is the best solution found compared to that of 5 iterations.

B. Change in Rotor's Inertia

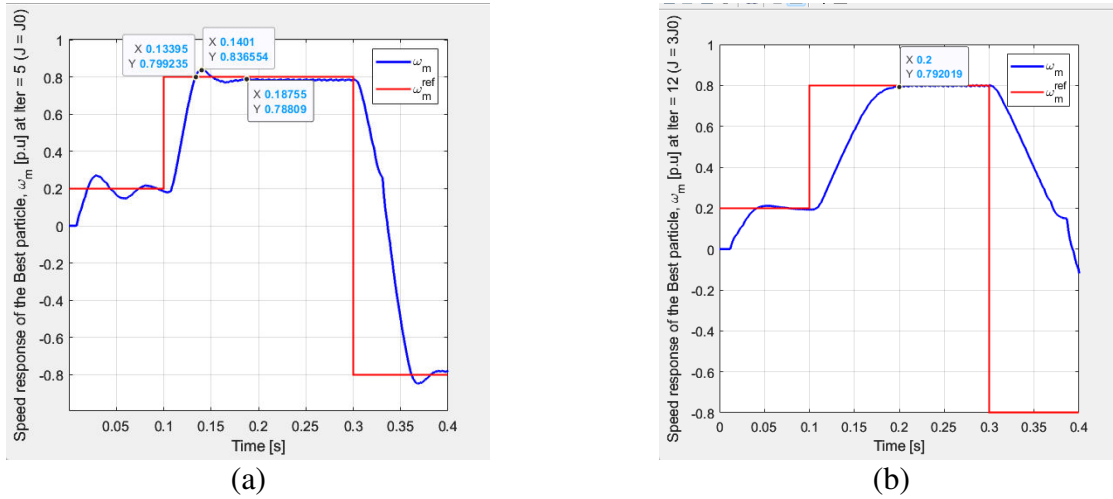


Fig. 3. Speed response of PSO-Trapezoidal Commutation control adaptation for (a)  $J = 48e^{-6}kgm^2$  and (b)  $J = 144e^{-6}kgm^2$

The PSO-Trapezoidal commutation control adaptation was run with a rotor inertia,  $J$ , of  $J = 48e^{-6}kgm^2$  and  $J = 144e^{-6}kgm^2$  respectively. The speed response for both simulations was obtained and demonstrated in Fig. 3. As expected, different speed responses are observed. As observed in Fig. 3, the speed response in (b) has a longer settling time,  $t_s$ , as compared to (a). This is due to the increase in rotor's inertia,  $J$ , by a multiple of 3, leading to a slower velocity response. Nonetheless, even with a change in the BLDC motors' inertia,  $J$ , the PSO-Trapezoidal commutation control adaptation was able to adjust the speed accordingly. Hence, the PSO algorithm was able to find the best  $K_p$  &  $K_i$  value for the PI Speed controller in a Trapezoidal Commutation control, even in a dynamic environment.

C. Ordinary Trapezoidal Commutation versus Trapezoidal Commutation with PSO

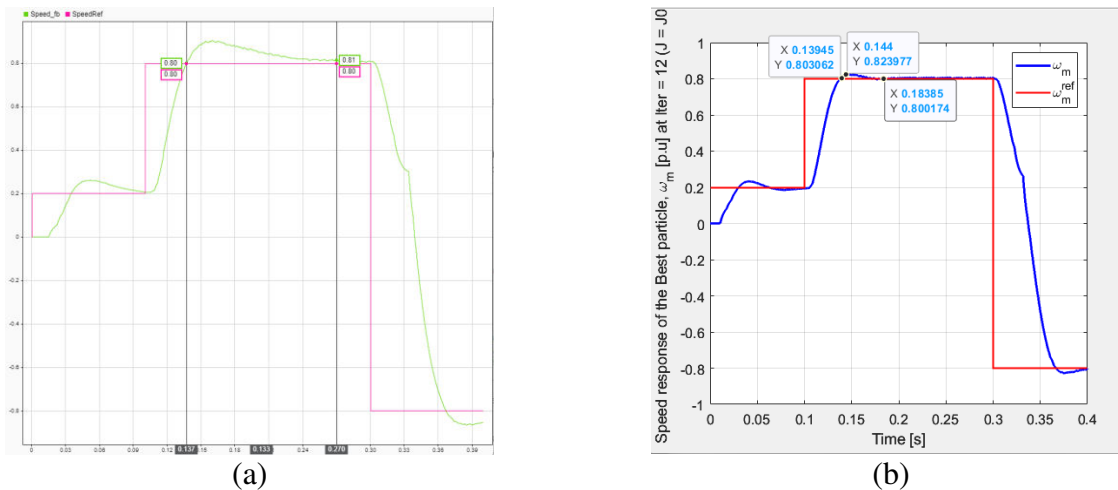


Fig. 4. Speed response of (a) Ordinary Trapezoidal Commutation and (b) Trapezoidal Commutation control with PSO

Two different BLDC speed control is simulated for this experiment, mainly the ordinary Trapezoidal commutation and the PSO-Trapezoidal Commutation control adaptation. The speed response for both simulations were obtained and shown in Fig. 4. By comparison, it is observed that the speed response for (b) with  $t_{rise} = 0.14s$ ,  $\%OS = 2.97\%$ ,  $t_s = 0.18s$ , is better than (a) which has a  $t_{rise} = 0.14s$ ,  $\%OS = 11.11\%$ ,  $t_s = 0.27s$ . The ordinary Trapezoidal commutation control uses Symmetrical Optimum (SO) to determine the best  $K_p$  and  $K_i$  values [14]. Symmetrical Optimum (SO) is a tuning criterion that compels the frequency response of the system to be as similar to that for a controller of low frequency [15]. Contrary to that, PSO is introduced to determine the best  $K_p$  and  $K_i$  values for the PSO-Trapezoidal commutation adaptation system. Hence, it can be determined that PSO is a better optimization



method to determine the best  $K_p$  and  $K_i$  values for the PI Speed controller of Trapezoidal Commutation control compared to that of Symmetrical Optimum tuning criterion used in Ordinary Trapezoidal Commutation control.

D. Field Oriented Control versus Trapezoidal Commutation with PSO

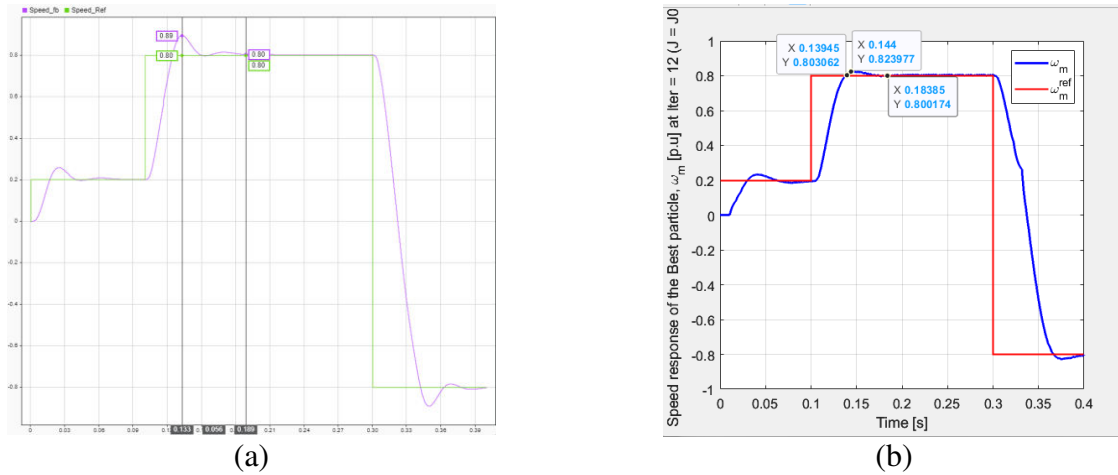


Fig. 5. Speed response of (a) Field Oriented Control, FOC [17], [18], and (b) Trapezoidal Commutation control with PSO

Two different BLDC speed control is simulated for this experiment, mainly the Field Oriented Control, FOC, and the PSO-Trapezoidal Commutation control adaptation. The speed response for both simulations were obtained and shown in Fig. 5. With reference to Fig. 5, it is observed that the speed response in (b), with  $t_{rise} = 0.14s$ ,  $\%OS = 2.97\%$ ,  $t_s = 0.18s$ , is better than (a), which has a  $t_{rise} = 0.12s$ ,  $\%OS = 11.25\%$ ,  $t_s = 0.19s$ . This is an unexpected response as FOC is a control technique that has higher efficiency compared to the rest of the commutation method. However, based on the response show in Fig. 5, it is observed that the introduction of PSO as a searching algorithm for the best  $K_p$  and  $K_i$  value for the PI speed controller produces better speed response compared to the FOC method. Hence, the implementation of PSO into BLDC speed control will greatly increase the speed response efficiency and proves the dominance of a PSO algorithm.

VI. CONCLUSION

Numerical experiments have been conducted to evaluate the PSO-Trapezoidal commutation control system. The change in the number of iterations for the PSO algorithm has been tested, and it is concluded that the increase in number of iterations would increase the accuracy of the search, leading to a better speed response. Furthermore, the PSO-Trapezoidal Commutation adaptation with varying rotor's inertia was successfully controlled using the PSO algorithm with evaporation and diversity mechanism coded into it. By comparing the speed performance of the PSO-Trapezoidal Commutation control adaptation with the ordinary Trapezoidal Commutation and Field Oriented Control, FOC, the improvement brought by the PSO algorithm to a BLDC speed control is shown. Therefore, it can be concluded that integrating PSO into BLDC speed control will significantly boost the speed response's effectiveness and demonstrate a PSO algorithm's superiority. In the future, PSO can also be implemented in other commutation method, such as Sinusoidal commutation control and Field oriented control. Also, the number of iterations of the PSO can be further increased, allowing for the algorithm to determine a better solution for the  $K_p$  and  $K_i$  value for the PI Speed controller, leading to a better speed response with higher efficiency.

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