

Optimal Tuning of PID Controller using Bio-Inspired Algorithm for Speed Control of Brushless DC Motor in Electric Vehicle

M. Sai Veeraj*
 *Professor, Department of Electrical and Electronics Engineering, S.R.K.R Engineering College
 Bhimavaram-534204, Andhra Pradesh, India
 msaiveeraj36@gmail.com

Abstract— The research and development trends in electric vehicles (EV) are gaining tremendous importance in the automotive sector as a result of the growing demand for technical advancements, sustainable energy consumption, and stringent environmental safety rules and regulations. An efficient motor with an intelligent control method is regarded to be essential for rapid advancement in EV technology. The efficiency of an electric motor necessitates automatic control of fundamental elements such as speed, position, and acceleration. Brushless DC (BLDC) motors are three-phase permanent magnet motors that employ direct current (DC) voltage as their power source. Because of its excellent efficiency and torque, this type of motor is often used in EV. Unfortunately, when used to an EV, the speed control mechanism of a BLDC motor is still somewhat complex. Because the BLDC motor in an EV undergoes various setpoints continuously. For making appropriate speed control, Proportional Integral Derivative (PID) controller is important and it cannot be tuned by a conventional method. If this controller is still used, the system response to steady-state will be too long, causing the motor to operate poorly. The speed management of a BLDC motor can be improved by employing Optimal PID tuning, which is a combination of PID and nature-inspired optimization approaches like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). The performance of the controller is evaluated using time-domain features and error functions such as Integral Square Error (ISE), Integral Absolute Error (IAE), and Integral Time Absolute Error (ITAE). Furthermore, it has been discovered that tuning PID with an optimization technique yields significantly better results than tuning PID with a conventional tuning technique.

Keywords— *Electric Vehicle, Motor, Speed, Optimization, Error, Time response.*

I. INTRODUCTION

EVs have been in use since the nineteenth century. Bikes, motorcycles, automobiles, and buses all fall under the same general group. In 1834, Thomas Davenport [1] created the first electric car. In recent years, there has been a renaissance of interest in electrical technology. This is likely to occur because of advancements in energy storage, batteries, electric motors, permanent magnets, and control approaches. The future of combustion technology in automobiles is also uncertain due to rapidly depleting fossil fuel resources such as petroleum. Furthermore, the cost of electrical energy is far cheaper than the cost of energy obtained from fossil fuels. Furthermore, because the cost of producing one kilowatt-hour of so-called green energy is now far more profitable and possible than it was a few decades ago, renewable electricity is

already playing a growing role in the global energy market. Furthermore, the growing need to protect the environment is pushing major energy and vehicle companies to adopt cutting-edge technology developments to continuously reduce pollution emissions, particularly in urban areas. This increase in population and vehicle numbers is predicted to continue until 2050 when the world's population is expected to exceed 10 billion. [2] If all vehicles are powered by internal combustion engines, it will take a long time for the gasoline and diesel oil to run out. As a result, there is a greater emphasis on energy conservation and environmental protection issues all over the world. Because of the aforementioned considerations, research into the creation of EVs is on the rise. EV development is influenced by battery storage capacity, electric motor efficiency, lightweight materials, and power electronics. EVs have recently gained popularity as a potential alternative to vehicles powered by traditional internal combustion engines. The unusual focus is due, most all, to environmental and economic worries over the use of fossil-based oil as fuel for internal combustion engines (ICE). The EV has emerged as the most promising replacement for the ICE.

EVs can employ regenerative braking to recycle energy from the brakes, which is unachievable in conventional internal combustion vehicles. To put it another way, when the vehicle's inertia causes the drive motor to switch to generator mode when braking, the energy is fed back into the battery pack. EVs are given braking force as a result of the battery being treated as a load in this model [3]. When compared to EVs that do not have regenerative braking, using regenerative braking in EVs can rise their range by up to 15%. (RBS). In some instances, such as when the battery is charged 100%, the vehicle must slow down using a resistive load rather than regenerative braking. As a result, the EV still needs a mechanical brake. The best electric motors for EVs are BLDC motors [4]. It offers various profits over brushed DC motors and induction motors [5]. Because BLDC motor brushes wear out so quickly, this type of motor is significantly more reliable. In addition to the previously mentioned dynamic response and efficiency, this design has higher speed ranges and higher power-to-weight ratios. For the BLDC motor drive's fast-breaking function and speed regulation, a speed controller was required. A flurry of tactics and algorithms for speed controlling BLDC motors have been developed by researchers.

The paper [6] runs and analyses the Bat Algorithm to discover the best value PID controller parameter for speed control of a BLDC motor. When analysing the performance,

robustness, max value, and steady-state when utilising a PID controller with support for the Bat-PID, the peak value and settling time for Bat-based PID are superior. The Fuzzy Logic Control approach performed effectively when used to BLDC in a study published in [7]. Even while a fuzzy logic controller improved the dynamic response of BLDC, it was unable to provide a clear benefit in steady-state performance. To overcome its limitations, the fuzzy controller was utilized in conjunction with several other control techniques. A comparison of all the controllers available for controlling the speed of a nonlinear hybrid EV reveals that the LQR Optimal controller provides the best results in every way. The greatest overshoot and settling time in reaching the required speed will be the shortest, implying that the current and torque will be the most efficient as well. This means that the battery performance of these vehicles will be optimal. According to the author [8], the LQR approach is the best and must-have for transient and steady-state responses. The LQR control method can be used for various nonlinear systems to improve their performance. The LQR optimum controller helps improve the efficiency of a car's drive system. The research [9] looks at the optimal control techniques for regulating the speed of an HEV. The output of the system's open-loop is unpredictable. PID and Fuzzy-PID are used to maintain the speed of HEVs. The response of the controller is determined by the values of its parameters. PSO and grey wolf optimization (GWO) are two strategies for improving controller performance. The performance of the controllers has been compared and analyzed. According to the statistics, the GWO tuned Fuzzy superior to other controllers in transient and steady-state response.

The study [10] offers an AI operating theory using an SRM drive. A hybrid ANN controller can be employed to maintain the speed of the SRM motor. And compare the hybrid ANN controller to a standard PID controller in this study to show that the suggested controller gives superior results to the regular PID controller in terms of performance and robustness. The simulation is carried out using MATLAB/Simulink. The article [11] describes a closed-loop control of the BLDC motor. It consists of the design and construction of an IR2130, an H bridge, motor rotation direction control, and a speed detecting circuit. Using the PID algorithm, one can improve a motor's performance by fine-tuning each parameter of the PID controller to get a predictable and consistent speed. Hardware and software control mechanisms have been demonstrated to be reliable, and the system's performance remains stable despite the addition of extra load. The recommended method of the author [12] was used to run the IGBTs in a converter. The produced signals of PWM were successfully tested for operating the inverter using a dsPIC30F4011 Digital Signal Controller. The motor runs at a consistent pace as a result of employing a peripheral pot fixed to the circuit to set the speed of the stator winding of the 48 V, 250 W, 3850 rpm BLDC motor. The software has been proven to be effective, and positive results have been produced using the hardware that was designed for it. The control and power circuit designed meets the application's requirements and performs as intended. The results of testing back up the developed drive designs.

The research tries to solve the issues in speed control of BLDC employed in EV with the help of the above-mentioned journals (Part I). The mathematical model of BLDC is identified using the first principal method (Part II), The tuning techniques and their working are studied (Part III),

Evaluation parameters are detailed with mathematical formula (Part IV), the BLDC performance on various PID tuning is discussed (Part V) and finally conclude which PID tuning is optimal for BLDC speed control.

II. MATHEMATICAL MODEL OF BLDC

The mathematical model of BLDC is detailed in this chapter. Figure 1 depicts the battery, inverter, controller, and electric motor. The battery is a critical component in an electric car that stores energy and powers the vehicle. A DC-DC converter can be used to change the voltages of the battery and motor driving systems. The inverter control pulse generator refers to the motor's feedback and speed profile. Taking into account the battery's state of charge at the time of conversion. A DC voltage converter to suit the inverter's requirements. The BLDC is controlled by a PID. The variance in speed between the required and obtained values determines the mistake in this scenario.

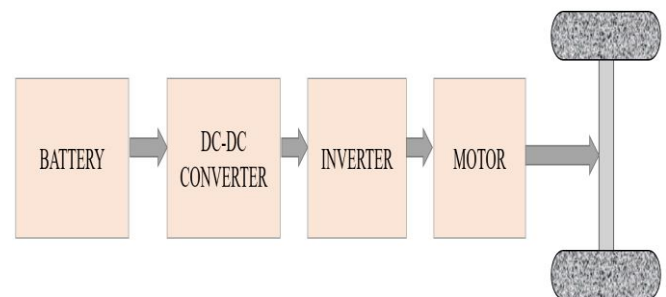


Fig. 1. EV block architecture

The BLDC motor's armature circuit is depicted in figure 2. Three star-shaped stator windings are connected to the rotor of this motor, which is permanently magnetized. Motors are typically powered by three-phase electricity. It is possible to use any wave-shaped input power. The following assumption [13] is used to establish the BLDC motor modelling: If the motor is not saturated, use the rated current. The resistance of the three stator windings is the same. The inductance is unaffected by the distance between two circuits. Iron and other stray materials aren't lost in great quantity. The three-phase equilibrium is unique. The air gap is consistent. Hysteresis and eddy's current losses are not taken into account. The best switches are those built of semiconductors.

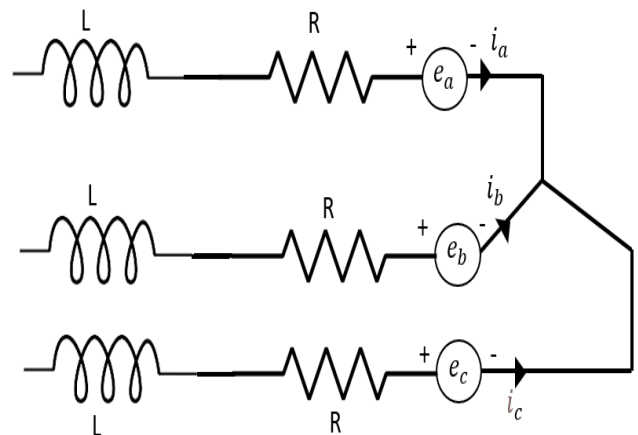


Fig. 2. Armature winding circuit diagram

Consider the armature winding model of a BLDC motor:

$$V_a = R_a i_a + L_a \frac{di_a}{dt} + e_a \quad [1]$$

$$V_b = R_b i_b + L_b \frac{di_b}{dt} + e_b \quad [2]$$

$$V_c = R_c i_c + L_c \frac{di_c}{dt} + e_c \quad [3]$$

Where:

$R_a = R_b = R_c = R \rightarrow$ Resistance (Ω)

$L_a = L_b = L_c = L \rightarrow$ Inductance (H)

$V_a, V_b, V_c \rightarrow$ Voltage (V)

$i_a, i_b, i_c \rightarrow$ Current (A)

$e_a, e_b, e_c \rightarrow$ Back emf (V)

A matrix can be used to represent the BLDC motor modelling equation:

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \begin{bmatrix} R + \frac{d}{dt}L & 0 & 0 \\ 0 & R + \frac{d}{dt}L & 0 \\ 0 & 0 & R + \frac{d}{dt}L \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} + \begin{bmatrix} e_a \\ e_b \\ e_c \end{bmatrix} \quad [4]$$

Each of the windings of a BLDC motor produces a volt called "Back EMF" (b-emf) when the motor is rotating, from Lenz's law. In this case, the voltage is in opposition to the primary volt given to the winding. The b-emf decreases in proportion to the increase in source voltage. Each phase has a 120-degree difference and is connected to the position of the rotor in the rotor. The rotor angular velocity, the generated magnetic field, and the total stator windings turn to contribute to the determination of the b-emf.

$$e_a = k \cdot w \cdot f(\theta) \quad [5]$$

$$e_b = k \cdot w \cdot f\left(\theta - \frac{2\pi}{3}\right) \quad [6]$$

$$e_c = k \cdot w \cdot f\left(\theta + \frac{2\pi}{3}\right) \quad [7]$$

Where:

$k \rightarrow$ Back EMF constant (v/rad/s)

$\theta \rightarrow$ Rotor angle (0)

$w \rightarrow$ Rotor speed (rad/s)

Laplace of equation 1,2,3

$$V_a(s) - e_a(s) = R I_a(s) + L s I_a(s) \quad [8]$$

$$V_b(s) - e_b(s) = R I_b(s) + L s I_b(s) \quad [9]$$

$$V_c(s) - e_c(s) = R I_c(s) + L s I_c(s) \quad [10]$$

The transfer function of equation

$$\frac{I_a(s)}{V_a(s) - e_a(s)} = \frac{1}{R + Ls} \quad [11]$$

$$\frac{I_b(s)}{V_b(s) - e_b(s)} = \frac{1}{R + Ls} \quad [12]$$

$$\frac{I_c(s)}{V_c(s) - e_c(s)} = \frac{1}{R + Ls} \quad [13]$$

The computation of every phase can reflect the total torque. In a conclusion, the entire torque formula looks like this:

$$T_e = \frac{i_a e_a + i_b e_b + i_c e_c}{\omega} \quad [14]$$

$$T_e = i_a \cdot K \cdot f(\theta) + i_b \cdot K \cdot f\left(\theta - \frac{2\pi}{3}\right) + i_c \cdot K \cdot f\left(\theta + \frac{2\pi}{3}\right) \quad [15]$$

Another method to represent the generation of electromagnetic torque is as follows:

$$T_e = J \frac{d\omega}{dt} + T_L + B\omega \quad [16]$$

Where:

$J \rightarrow$ Inertia (Kgm²)

$B \rightarrow$ Damping constant

$T_L \rightarrow$ Load torque (N-m)

Final transfer function using Laplace transformation:

$$\frac{\omega(s)}{T_e(s) - T_L(s)} = \frac{1}{Js + \theta} \quad [17]$$

III. CONTROLLER AND ITS TUNING TECHNIQUES

This section discusses PID control design and tuning methodologies for physical parameter control systems. The PID controller has been widely used in metallurgical, mechanical, chemical, and thermal process control applications for more than 50 years. Because of the simplicity, operability, and adaptability of its control structure, as well as its inherent robustness, PID is the most commonly employed control method. It has recently been developed and spread as a major and reliable technical project and instrument for industrial process control. PID parameter tuning is a major topic in PID control. It is customary to utilize a full set notion based on the mathematical model of the object to calculate PID parameters when tuning PID parameters. The precision with which parameters are described has a direct impact on the stability and resilience of the control system. Model parameters and model structure can change as a result of the complexity, diversity, unpredictability, and uncertainty of modern industrial processes. As a result, the system is unable to operate in its initial state, which is outside of the parameters of the control performance index. PID control is a technique that is commonly used in a variety of applications to regulate an output variable by modifying an input variable. PID control works by comparing the measured speed to the intended reference speed and calculating the control action accordingly. The difference in speed between the reference and measured speeds is analyzed using terms such as P, I, and D. Consider the current error, the accumulation of errors over some time, and the rate at which the error has changed since it was last recorded in the system. It is based on this knowledge that the P, I, and D expressions are derived. In this case, the three words are multiplied by factors that change the overall voltage contribution made by each phrase in turn. The three modifiable parameters of a PID controller are the three coefficients, which can be modified by practitioners to make the controller more aggressive or more conservative depending on the situation.

PID controllers are a popular choice for control algorithms because of their simplicity and ease of implementation, but their lack of sophistication limits their ability to properly regulate systems with many disturbances, time-varying delays, and temporal dynamics. The appropriate three terms must be selected to produce the best possible outcome. Due to the exponential complexity of the algorithm representing the system in question, it is required to use meta-heuristics to tackle the problem of optimizing the PID controller parameters to achieve a satisfactory result. It is advantageous to utilize meta-heuristics because they may be applied to a wide range of difficult optimization problems

without requiring significant or even drastic adjustments to the method. Stochastic optimization and local search are both examples of meta-heuristics that can be used. These optimization approaches require only a minimal amount of information about the problem being optimized to be effective. One of the most important things to consider is whether or not to optimize for one or more criteria (objective functions). ACO [14] and PSO[15] are two algorithms used in this work of metaheuristics that are inspired by natural processes.

A. ACO

Most academics are now focused on novel meta-heuristic algorithms to solve the challenges and drawbacks associated with existing tuning techniques. Metaheuristics have enabled the rapid identification of outstanding solutions to difficult and practical combinatorial optimization problems. The ACO evolved as a result of the ant's innate proclivity to seek food. These social insects employ pheromone, a volatile chemical, to communicate and to mark their path between the nest and the food. Those ants who spend the least amount of time traveling between the nest and the food storehouse have travelled the shortest distance. This path is more likely to be stolen because of the higher pheromone concentration and enhanced attractiveness to ants. Because it is more reinforced, the majority of the ants will eventually prefer this track over the others. The working of ACO is shown in a pictorial format in figure 3. The basic procedure is divided into three components[16].

- Initialize Process
- Constructing Process
- Updating Process

Initialize Process:The objective is to find the lowest Hamiltonian cycle in a network where each vertex represents a city. Can use it by d_{ij} and the pair to represent the distance between two places (i, j) . This is referred to as the edge between two points. The function τ_{init} , has been used to initialize the pheromone concentration on edges, after which each ant traverses the graph and constructs a sequence.

Constructing Process:During the process of constructing solutions, the ant must decide where to walk ahead, and this decision is reliant on the values of pheromones and relevant statistics that can assist it in discovering an optimal solution.

Updating Process: Each ant k leaves a trail of pheromones $\Delta\tau_{ij}^k$ along its route after developing a solution with the help of other ants. If the path (i, j) is in the ant's circle at any iterations, the quantity of pheromone that is produced on this path is

$$\Delta\tau_{ij}^k(t) = \frac{Q}{L^k(t)} \quad [18]$$

The number of pheromones to be provided is related to the solution's efficiency; the more pheromones provided, the stronger the solution. A low pheromone rate of evaporation is the greatest option for optimal effectiveness if the surroundings are stable or fluctuate slightly. On contrary, where the surroundings are particularly dynamic, a large rate of evaporation must be chosen.

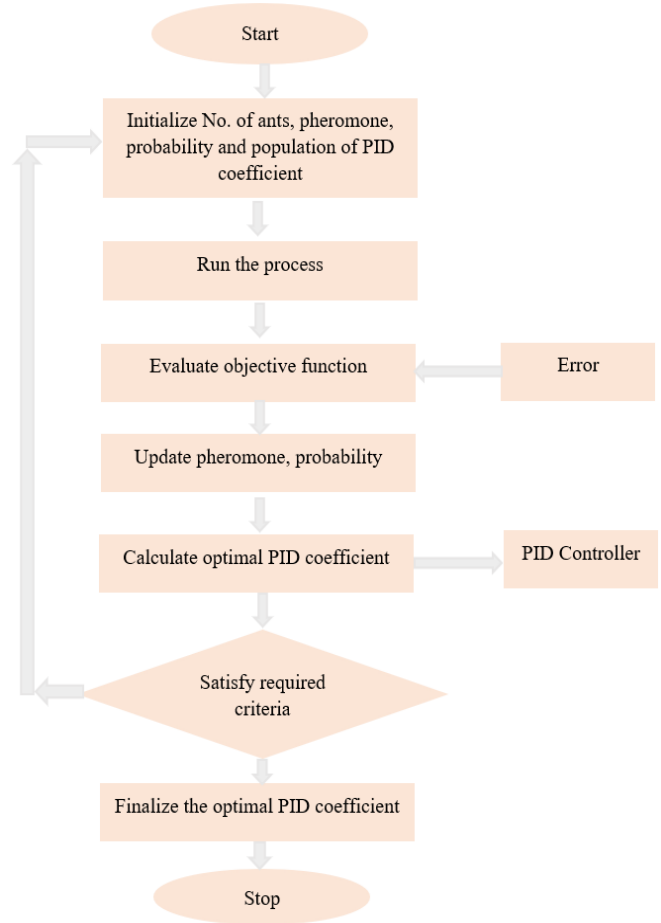


Fig. 3. ACO Flow chart

The advantages and disadvantages of ACOs are well examined [17].The following are some of the advantages of employing the ACO method: Positive feedback is responsible for the speedy identification of good answers. The greedy heuristic aids in the discovery of an acceptable solution early in the search process by preventing premature convergence via distributed computation.The disadvantages of ACO, on the other hand, are as follows: Convergence is lower than with other Heuristics. It performs poorly if the problem has more than 75 nodes. There is no centralized processor to guide the ACO to appropriate solutions.

B. PSO

The PSO algorithm is based on the idea that groups of people can learn from each other (SI). People who saw how animals, like birds and fish, behaved and interacted came up with the idea for the method. PSO is similar to the way fish look for food, which is to compete and work together. There are a lot of people in the swarm, called particles, and each particle has a different set of unknown parameters that need to be changed. A group of random solutions usually starts a "swarm." In this system, particles fly over a multidimensional search space. This is how it works: It moves all the time about the experience. All of the particles' main goal is to find a way out as quickly as possible. In this case, the particles swarm around and come together at the ideal function, which is called the fitting function. The algorithm then comes to a single min or max answer. A function has already been set up to measure how well a particle is doing. This means that how well the controller is tuned is based on how well the model is made. As

a result, the system model is very important. Most of this work is going to use the PSO that we're going to make to help us find the best settings for the PID controller that we're going to use for BLDC speed control. Figure 4 depicts the functioning of PSO in visual form.

Genetic operators are not employed in PSO. Individuals are known as particles, but on the other hand, they "evolve" by cooperating and warring with one another across generations. A particle is a possible solution to a problem. The way each particle flies varies as a result of its own and its companion's own flight experiences. D-dimensional space: Each particle is conceived of as a point in this space. The i^{th} particle is referred to as $X_I = (x_{i1}, x_{i2}, \dots, x_{iD})$. The best past position of any particle, which offers the lowest fitness value, is written down and shown as $P_I = (p_{i1}, p_{i2}, \dots, p_{iD})$ pbest is the term for this. People use the symbol g , which stands for gbest, to denote the best particle out of all the other particles in the group. It is shown that the particle's velocity, denoted by $V_I = (v_{i1}, v_{i2}, \dots, v_{iD})$, is equal to the velocity of I. The following equations are used to make sure that the particles keep up to date.

$$v_{id}^{n+1} = w \cdot v_{id}^n + c_1 \cdot \text{rand}(p_{id}^{n+1} - x_{id}^n) + c_2 \cdot \text{rand}(p_{gd}^n - x_{id}^n) \quad [19]$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \quad [20]$$

c_1 and c_2 are two positive constants that are always the same size. In Clerc's PSO, the constants are $c_1=c_2=1.494$, which is how they should be. The random function between 0 and 1 shows how many times it has been done. Calculating a particle's new velocity with Eq.19 takes into account how far it is from where it is now and where it has been before, as well as how far it is from the group's best experience. The particle then moves on to Eq. 20 and moves to a new place. Each particle's performance is measured by a fitness function (performance index) that is relevant to the problem that needs to be solved. The inertia weight, w , is added to the equation to make sure that the global and local search options work together.

Under a normal operating environment, the Stochastic Algorithm can be utilized to optimize PID controller gains for optimal control performance. PSO is used to tune PID gains and parameters offline. In the search area described by the matrix, PSO produces an early swarm of particles. Each article provides a potential PID parameter option with a value scale from zero to 100. Position and movement are described in this three-dimensional task utilising 3xSwarm-sized matrices. The number of particles in the swarm is defined as the swarm size, with 40 being deemed adequate. A well-chosen set of PID controller parameters may result in an improved response of the system and a reduced performance score.

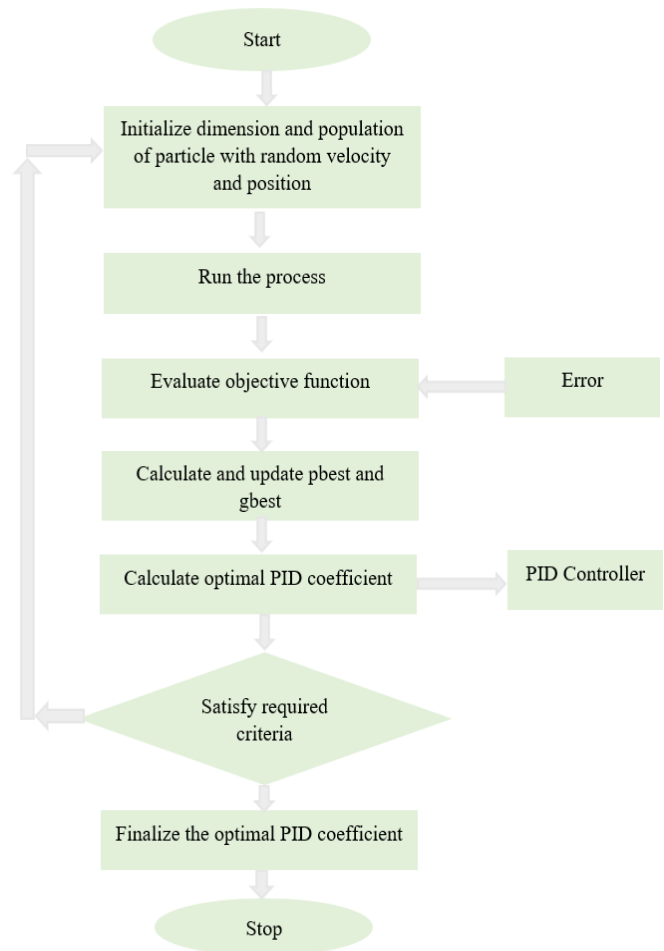


Fig. 4. PSO Flow chart

IV. CONTROLLER EVALUATION

The performance analysis of the system is very important. Because it is the main key for the process safety, productivity, product quality, and profit. The system performance analysis is evaluated and the controller is a design based on that. It is not possible to design a controller without this analysis. If so, do the system will become unstable. The performance helped to understand the dynamics of the system or plant. For performance analysis error and time-domain characteristics are taken. The error is used as an objective function for tuning and evaluating the PID controller. The time-domain characteristics are used to evaluate the PID. The fitness function under discussion here is generated using the error criteria. The objective function of this study is based on performance measures. A performance index, on the other hand, is defined as a statistical measurement used to evaluate the performance of a developed PID. This technique is widely used to construct an 'optimal system,' and a combination of PID parameters in the process can be modified to fulfill the desired specification. Three indices show the performance of a PID-controlled system: ISE, IAE, and ITAE. These are their definitions:

$$ISE = \int_0^{\infty} e^2(t)dt \quad [21]$$

$$IAE = \int_0^{\infty} |e(t)|dt \quad [22]$$

$$ITAE = \int_0^{\infty} t|e(t)|dt \quad [23]$$

The time characteristics are rise time, settling time, overshoot, peak value, and peak time. If the behaviour of the system's output is time-varying, then the output is called time response. There are two sections of the time response. One is the transient response and the other one is the steady-state response. Both are important for the system to analyze the performance. The transient response means the time taken to reach the steady-state of the system. And the time after the steady-state to infinity is called the steady-state response.

V. RESULTS AND DISCUSSION

The PID is employed for speed control of BLDC. Finding the appropriate value of PID is very difficult and these values decide the BLDC performance. In this research optimization method of finding the PID is projected. The ZN

tuning method was also used for comparing the results of the optimized tuning PID. Figure 5 shows the result obtained by 3 different tuning techniques namely ZN, PSO, and ACO. The EV is not always working at a constant speed, it usually undergoes different speeds based on the driver. To ensure whether the design PID is applicable for practical application three different set-points are given at different intervals. First, the setpoint of 300rpm is given at time 1 second (s). Next at the interval of 75s, the speed is reduced to 150rpm, and finally, at 150s the speed again increased to 200rpm. Figure 5 shows the response of 3 controllers at continuous varying setpoints. The ZN-PID response is shown in the blue graph, likewise PSO-PID, and ACO-PID is depicts responses in red and green colour.

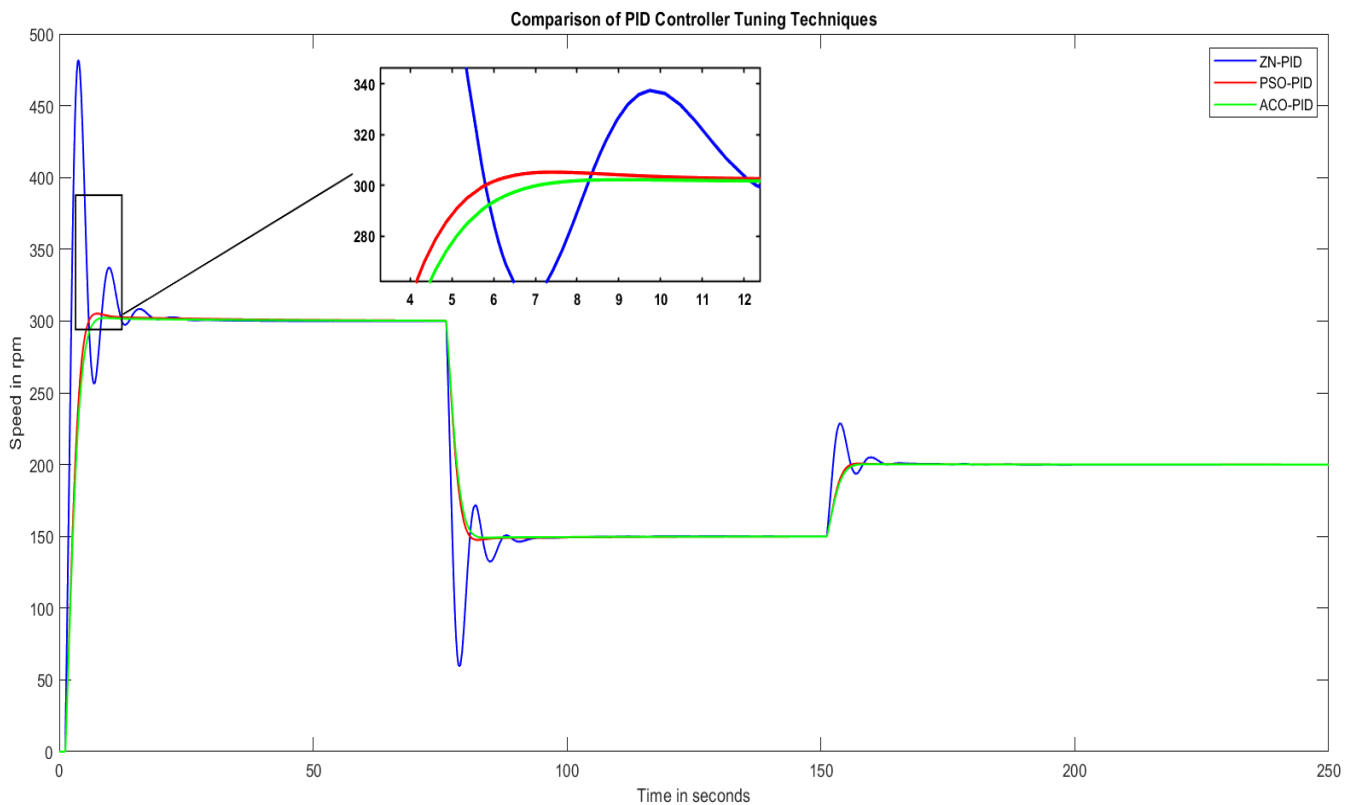


Fig. 5. PID Comparison on servo problem

It is not possible to identify the result by just visualizing the graph. For evaluating the controller performance mathematically, the time domain characteristics and error functions are used. The time characteristics of each controller are shown in Table I. The rise time of the BLDC is low for ZN-PID. The settling time is low for PSO-PID. Then the overshoot should be null for a good process. In this research, ZN-PID gives a high 140.75% overshoot, but the PSO-PID and ACO-PID provide low overshoot of 52.57% and 51.08%. The next characteristic is a peak value. The first setpoint is 300. But ZN-PID gives 481.48 as peak value which means if the user gives 300rpm, the EV goes up to 481rpm it is a really dangerous thing. But the designed PID gives 305.17rpm and 302.18rpm which is under the tolerable limit. Finally, the peak time of ZN-PID, PSO-PID, and ACO-PID are 3.6s, 7.4s, and 9.2s. The values stored in the table are

transferred to the bar graph for visual comparison and it is shown in figure 6.

TABLE I. TIME DOMAIN RESPONSE

Parameter	ZN-PID	PSO-PID	ACO-PID
Rise Time	0.6519	1.6299	1.5139
Settling Time	157.3122	145.0256	144.6138
Overshoot	140.7507	52.5708	51.0814
Peak	481.4861	305.172	302.1843
Peak Time	3.6491	7.4158	9.2188

Time Domian Characteristics of PID Controllers

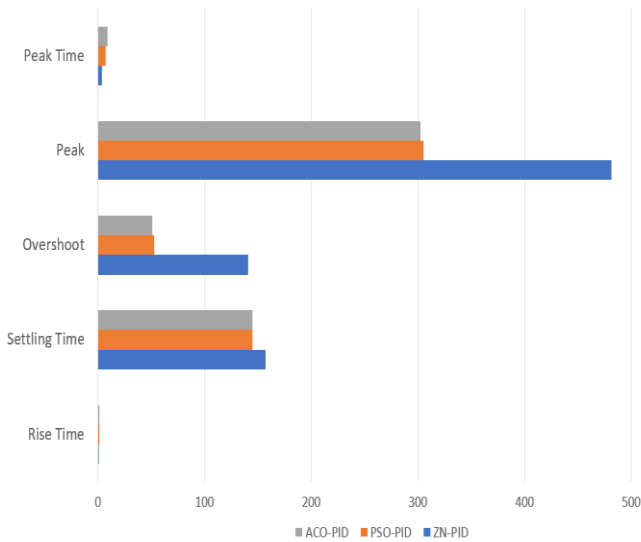


Fig. 6. Time-domain characteristics of PID controllers

Table II shows the error obtained by three PID controllers. Many error functions are available to evaluate the controller. In this research ISE, IAE, IATE is used. The table helps to identify which controller gives minimal error when compared to the other two controllers. The ISE of ZN-PID is $2.585e^5$ and it will be high when compared to PSO-PID and ACO-PID which yield errors of $2.32e^5$ and $2.172e^5$. The IAE of ZN-PID, PSO-PID, and ACO-PID is 1880, 1530, and 1548. The error of $7.7695e^4$, $6.327e^4$, and $6.297e^4$. Figure 7 shows the error comparison of three PID controllers. To differentiate the errors three different colours are used, orange for ISE, yellow for IAE, and green for ITAE. From the analysis all three error values of ZN-PID are high. Then ISE and ITAE are low for ACO-PID, and the IAE is lower in PSO-PID.

TABLE II. ERROR COMPARISON

Parameter	ZN-PID	PSO-PID	ACO-PID
ISE	$2.585e^5$	$2.32e^5$	$2.172e^5$
IAE	1880	1530	1548
ITAE	$7.7695e^4$	$6.327e^4$	$6.297e^4$

Error Comparison

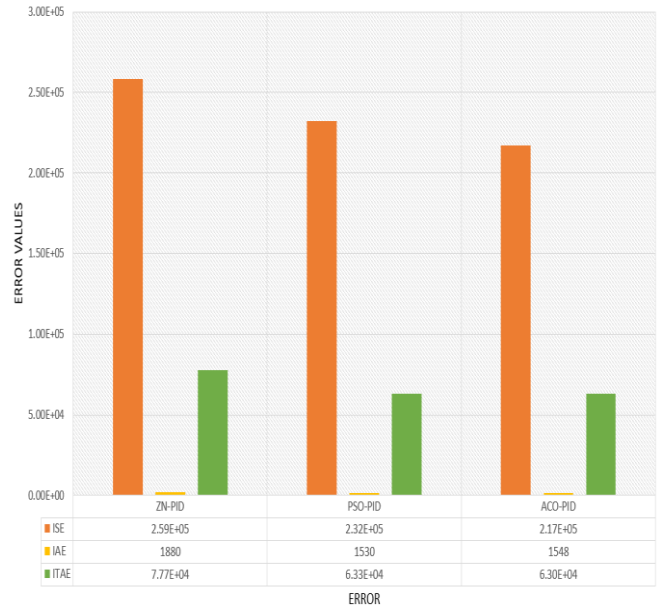


Fig. 7. Error analysis of PID controllers

VI. CONCLUSION

The EVs make significant strides into the automobile market, so modelling and simulation of EVs have piqued the interest of researchers. Controlling an EV is a difficult task because the design and operational aspects change depending on the driving conditions. One of the most important aspects to control on an EV is speed. Recently, BLDC has been widely used in EVs to acquire power from the controller and operate the vehicle. The BLDC transfer function model is being used for the research. It is discovered that the PID controller is simple and practical, with improved closed-loop performance. However, in PID, the selection of three parameters is critical. The study presents the design and PID tuning for BLDC speed control using several algorithms such as ZN, PSO, and ACO. Finally, the results of all PID controllers are compared. A comparison analysis was performed using its time-domain characteristics as well as performance indices. The optimal tuning method outperforms the standard method. When comparing the two optimal techniques, ACO will provide a little better response than PSO. The error numbers, such as ISE and ITAE, will be lower for ACO-PID, then the time domain characteristics are also quite good for the ACO-PID controller.

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