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Performance analysis of a battery-operated electric vehicle using metaheuristic optimization

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ABSTRACT

Battery-powered electric vehicles (BEVs) are gaining significant attention due to high energy efficiency, zero emissions, and advanced control systems. This article illustrates the performance analysis of a BEV, which consists of a high-voltage battery pack, a BEV controller, a motor driver, a gearbox, and a longitudinal driver. A conventional proportional-integral-derivative (PID) controller is used as a BEV controller. Several optimal algorithms are employed for tuning the PID controller, including the Ziegler-Nichols method (ZN method), particle swarm optimization (PSO), genetic algorithm (GA), grey wolf optimization (GWO), artificial bee colony algorithm (ABC), and artificial hummingbird algorithm (AHA). The proposed research framework was assessed in terms of vehicle efficiency, battery power consumption, vehicle mileage, motor speed, and battery state of charge (SOC). Metaheuristic algorithms with PID controllers outperform conventional PID and classical ZN-PID controllers. Among all algorithms, the PID-GWO controller achieves maximum vehicle mileage, low battery power consumption, improved battery SOC, and the highest vehicle efficiency.

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1. INTRODUCTION

Mounting worldwide alarm about environmental damage and air pollution has prompted a substantial paradigm shift towards sustainable transportation options, with electric vehicles emerging as an attractive alternative to traditional vehicles [1]. Eco-friendly and renewable energy sources are more eye-catching due to the increase in pollution. The transport sector is one of the major factors that cause environmental degradation. The rising concern about the deterioration of air quality and the rapid effects of greenhouse gas emissions has further increased the need for clean transportation alternatives. In this regard, electric vehicles have been recognized as a clean alternative to conventional internal combustion engine (ICE)-based vehicles. Increasing numbers of individuals in India are using electrically powered vehicles every single day. Electrically powered two-wheelers, three-wheelers, and four-wheelers are the main things that have led to this growth. About 20.26 lakh electric vehicles were registered in 2024–2025 [2], [3].

Hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and fuel–cell hybrid electric vehicles (FHEVs) are among the several types of electric vehicles available in the market. BEVs far exceed other vehicles in terms of cost-effectiveness, dependability, and operational safety [4]. Electric vehicles have a lot of assemblies, including the electrical drive system, electric motor, battery management system, power electronic systems, and motor control systems [5]. Electric vehicles use different types of motors, such as brushless direct current (BLDC) motors, permanent magnet synchronous motors (PMSMs), and direct current (DC) motors. The DC motor is still the best choice for some EV uses because it is more efficient, cheaper, easier to control, and has good torque-speed characteristics [6].

Proportional-integral-derivative (PID) controllers' simple layout, simplicity in operation, and reliable performance make them popular in a wide range of industries, not just the electric vehicle market. Due to their dependability and effectiveness, PID controllers have historically been used extensively for motor control. However, when it comes to nonlinear drive systems in electric vehicles, traditional PID controllers frequently break down. There are several optimization techniques that have been used to improve the traditional controller performance [7]. Conventional controllers can be tuned using a variety of methods. Classical techniques like the Cohen-Coon and Ziegler-Nichols methods are included in the first group. Statistical methods such as state-space modelling and frequency response analysis constitute the second category. The third category consists of optimization-based methods, which include algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization (ACO), and artificial neural network (ANN). The fourth approach, which usually relies on trial and error, involves empirical or manual tuning. Last but not least, a lot of contemporary control systems employ software-based auto-tuning, which automatically modifies controller settings for best results [8], [9].

Conventional PID controllers work well for linear systems, but they have trouble with non-linear systems, such as motors, batteries, and so on, which are used in automobiles powered by electricity [10]. As reported by the work of Nepal *et al.* [11], conventional PID controllers showed higher steady-state error than the PID-NN controller with a DC motor driving. Nippatla and Mandava [12] illustrated that the Ziegler-Nichols technique results in higher steady-state error when the DC motor operates in unstable states in an electric vehicle. Mohan *et al.* [13] report that an ANN-based PI controller for sensorless PMSM motors used in EVs shows a faster response time and a lower speed estimation error. Shamseldin *et al.* [14] presented a nonlinear PID controller whose parameters are tuned using the harmony search method for electric vehicle speed tracking, and it shows better performance than a traditional PID controller. Patil *et al.* [15] presented several types of algorithms for optimizing the PI controller, including GA, PSO algorithm, ACO algorithm, ANN, and fuzzy. Among all algorithms, the ANN and hybrid algorithms perform best for PI controller gains (K_p, K_i) in industrial and real-time applications for nonlinear systems [15]. Heybetli *et al.* [16] demonstrated how heuristic optimal algorithms for PID controller tuning can outperform traditional tuning techniques like the classical ZN method approach and other conventional strategies in the context of vehicle cruise control, particularly under changing operating conditions and disturbances.

Different controller algorithms are based on different behavior and different control strategy: The AHA algorithm is based on the fighting tactics and behavior of hummingbirds; the GWO algorithm is based on the hunting and leadership behavior of grey wolves; the ABC algorithm is based on the natural behavior of honey bee swarms; the GA algorithm is based on the principles of natural selection and genetics; and the PSO algorithm is based on the social behavior of fish schools or flocks of birds. [17]. In BEV, modern researchers give more focus on improving the motor controller using different metaheuristic algorithms like grey wolf optimization (GWO), PSO, GA, artificial hummingbird algorithm (AHA), and artificial bee colony (ABC). When it comes to lowering errors like integral time absolute error (ITAE), integral absolute error (IAE), integral square error (ISE), and integral time square error (ITSE), Mirjalili *et al.* [18] claim that metaheuristic algorithms perform better than conventional tuning techniques.

This article presents the MATLAB simulation of a battery-powered electric vehicle, which includes components like a speed controller using a PID controller, a high-voltage battery, a motor drive unit, a reduction gear, and a longitudinal vehicle body. In this research framework, a PID controller is incorporated into the battery electric vehicle's motor controller to improve overall performance through the integration of an automatic PID tuner and a metaheuristic optimization algorithm. The main objective of this study is to give a performance analysis of battery electric vehicles using PID with metaheuristic algorithms like the ZN method, PSO, GA, GWO, ABC, and AHA algorithms.

2. BATTERY-OPERATED ELECTRIC VEHICLE

The block diagram of a MATLAB/Simulink model of a battery electric vehicle (BEV) is shown in Figure 1. Real-time vehicle speed with respect to time is represented by the vehicle reference speed, which is regarded as the input signal to the BEV controller. Reference signals can be produced from several standardized driving cycles, such as FTP-74, FTP-75, New European Driving Cycle (NEDC), and Worldwide harmonized light vehicle test procedure (WLTP) [19]. This study represented the real-time BEV vehicle speed data over 100 seconds as the reference speed, which is illustrated in Figure 2.

Figure 3 represents the flow graph of a battery-operated electric vehicle with a PID controller optimized by metaheuristic algorithms. The battery electric vehicle (BEV) motor speed is estimated from the vehicle reference speed using the wheel rolling radius and gear reduction ratio, which are supplied to a standard PID controller. The motor speed passes through the 20 Hz low-pass filter to remove high-frequency noise and improve the control strategy. The PID controller receives the speed error signal, and a saturation block is applied to the controller's output. The motor torque command is represented by the resultant signal, which is then sent to the motor drive unit. A high-voltage lithium-ion battery pack is used in this investigation to model the system for storing energy [18], [20]. In this BEV, the motor driver receives power from the high-voltage battery pack output. The electrical torque converts into rotational motion, which is transmitted to the reduction gear. The torque in the transmission decreases the motor speed to reach the longitudinal vehicle. The longitudinal vehicle block receives reference control speed and vehicle dynamics as input and outputs the vehicle's actual speed and distance reached by the BEV for 100 seconds.

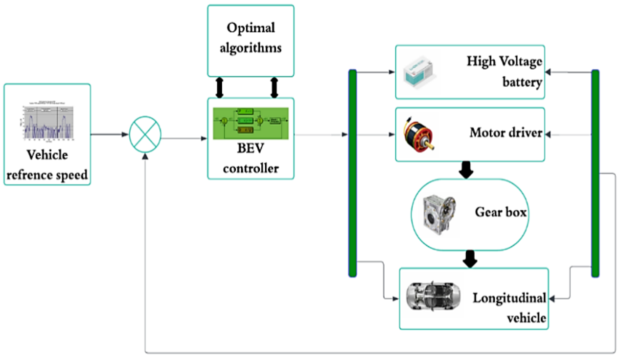

Figure 1. Schematic diagram of a battery-operated electric vehicle

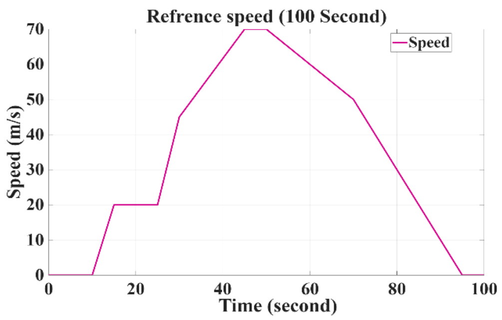

Figure 2. Graphical representation of reference speed input for a PID-based controller

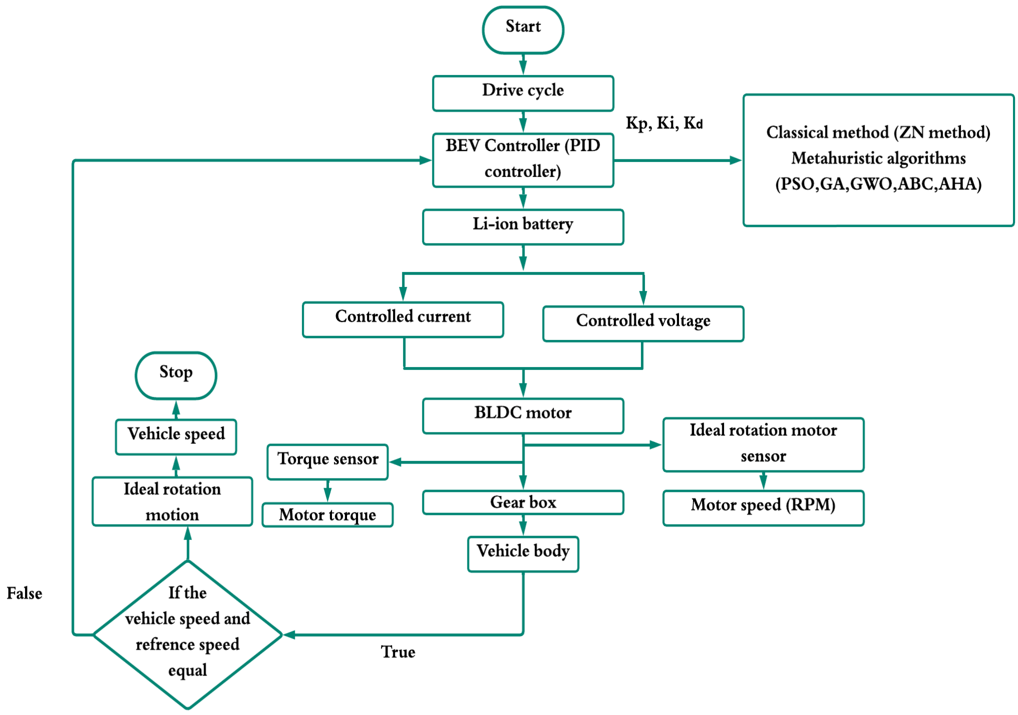

Figure 3. Flow chart of a battery-operated electric vehicle with a PID controller

2.1. Mathematical representation of the battery-operated electric vehicle
2.1.1. BEV controller (PID)

An electric vehicle motor controller controls the power flow from the battery to the electric motor. Conventional PID controllers constantly compare the input speed with the actual speed and adapt the motor input. Mathematical representation of BEV controller (PID):

$$\text{Wheel rotational speed (RPM)} = w_{wheel}(t) = \frac{V_{veh}(t)}{2\times\pi\times R} \quad (1)$$

Where $V_{veh}(t)$ = vehicle reference speed (m/s) and R = tire rolling radius (m).

$$\text{Motor reference speed (rpm)} = w_{motor}(t) = G \times w_{wheel}(t) \quad (2)$$

Inserting (1) in place of (2).

$$\text{Motor reference speed (rpm)} = w_{motor}(t) = G \times \frac{V_{veh}(t)}{2\times\pi\times R} \quad (3)$$

Where G = reduction gear ratio.

$$\text{Low- pass filter (20 Hz)} = G_f(s) = \frac{1}{\left(\frac{1}{2\times\pi\times f_c}\right)s+1} \quad (4)$$

Where, f_c = cut-off frequency (Hz).

$$w_f(s) = G_f(s) \times w(s) \quad (5)$$

$$\text{Speed error calculation } e(t) = w_{motor}(t) - w_f(t) \quad (6)$$

Where e(t) = error signal (rpm) and $w_f(t)$ = filtered motor speed (rpm). PID controller:

$$T_c(t) = K_p \times e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \quad (7)$$

$$T_S(t) = \begin{cases} T_{max} & T_c(t) > T_{max} \\ T_c(t) & -T_{max} \le T_c(t) \le T_{max} \\ -T_{max} & T_c(t) < -T_{max} \end{cases} \quad (8)$$

Where $T_S(t)$ = saturated torque (N.m), $T_c(t)$ = controlled output torque (N.m), K_p = proportional constant, K_i = integral constant, and K_d = derivative constant.

2.1.2. High voltage battery pack

A lithium-ion high-voltage battery pack is a main component of a battery-operated electric vehicle (BEV) that provides DC power to the power controller. The mathematical representation of the high-voltage battery pack is given by (9).

$$\text{Terminal voltage } (V_t) = \text{OCV- IR} \quad (9)$$

Where OCV = Open-circuit voltage of the battery (V), I = battery current (A), and R = internal resistance of the battery (Ω).

$$\text{Load power} = P_{load} = V_t I \quad (10)$$

Where V_t = terminal voltage (v). Battery current calculation:

$$RI^2\text{-OCVI}+P_{load} = 0 \quad (11)$$

$$\text{Battery power loss} = P_{loss} = I^2 \times R \quad (12)$$

Where P_{loss} = power loss in the battery pack (w).

$$\text{SOC update } Q_{new} = Q_{old} - I \times \left(\frac{dt}{3600}\right) \text{ A-Ah} \quad (13)$$

Where Q_{new} = battery charge (Ah) and Q_{old} = previous battery charge (Ah).

$$\text{Temp rise } \Delta T = \frac{P_{loss}\times dt}{\text{Thermal mass}} \quad (14)$$

Where ΔT = change in temperature (°C).

2.1.3. BEV motor driver

The motor driver receives control signals from PID controllers and converts them into the required voltage and current for the motor.

$$T(t) = T_{cmd}\,(1\text{-}\ e^{\frac{t}{\tau}}) \tag{15}$$

$$V(t) = K_e\omega + I(t)R \tag{16}$$

$$I(t) = \frac{T(t)}{K(t)} \tag{17}$$

$$P_{elec} = T \times \omega \tag{18}$$

$$\text{Mechanical power} = P_{mech} = T \times \omega \tag{19}$$

$$\text{Motor electrical losses} = P_{elec} - P_{mech} \tag{20}$$

$$\eta = \frac{P_{mech}}{P_{elec}} \tag{21}$$

Where T_{cmd} = command torque (N.m), τ = torque constant (sec.), $I(t)$ = motor current (A), $K(t)$ = torque constant (N.m), P_{elec} = electrical power (W), P_{mech} = mechanical power (W), η = efficiency of the motor.

2.1.4. Longitudinal vehicle

Longitudinal vehicle defines the vehicle movement in the forward and backward directions. The mathematical equations of the longitudinal vehicle are as follows:

$$F_{tractive} = \frac{T}{r} \tag{22}$$

$$\text{Rolling resistance force} = F_{rr} = mgC_{rr} \tag{23}$$

$$\text{Aerodynamic drag force} = F_{drag} = \frac{1}{2} \times \rho \times C_d \times AV^2 \tag{24}$$

$$\text{At constant speed } F_{tractive} = F_{rr} + F_{drag} \tag{25}$$

$$\text{In rad/sec } w_{axle} = \frac{V}{r} \tag{26}$$

Where r = tire rolling radius, m = vehicle mass, C_{rr} = rolling resistance coefficient, C_d = aerodynamic drag coefficient, A = frontal area, T = wheel torque, and w_{axle} = axial speed. Table 1 illustrates the battery-operated electric vehicle parameters.

Table 1. BEV specifications

S. No.	BEV parameters	Specifications	S. No.	BEV parameters	Specifications
1	Vehicle mass	2400 Kg	5	Motor torque	420 N.m
2	Tire rolling radius	0.34 m	6	Battery voltage	340 V
3	Motor type	BLDC	7	Battery nominal capacity	60 Kwh
4	Motor rated power	220 Kw			

2.2. Optimal algorithms for BEV controller

Figure 4 illustrates the designed optimization protocol for the PID controller in BEV. PID controller optimization methodologies are classified into different categories: classical rule-based methods, metaheuristic methods, and learning based method so on. In this research framework, the classical Ziegler-Nichols method is considered due to its simplicity and easy for application. In metaheuristic optimization techniques, especially PSO, GA, GWO, ABC, and AHA algorithms are implemented to reduce the errors in nonlinear and time-varying characteristics of the BEV. Table 2 illustrates the contrast between classical and metaheuristic optimal algorithms applied for PID controller parameter tuning, emphasizing their search behavior and main advantages.

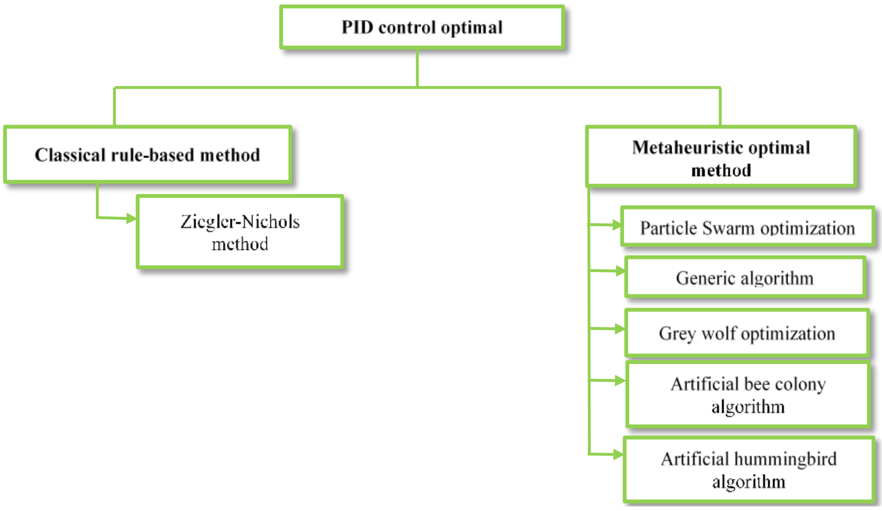

Figure 4. Proposed optimal algorithms for PID controller

Table 2. Comparison study of classical and heuristic algorithms for PID controller

Algorithms	Optimal categories	Algorithm behaviors	Key advantages	References
Ziegler-Nichol's method	Classical method	Deterministic, heuristic	Simple Easy application	[21]
Particle swarm optimization (PSO)	Metaheuristic (swarm-based optimization)	Searching movement	Simple Fast action High global searching capacity	[22]
Genetic algorithm (GA)	Metaheuristic (evolutionary algorithm)	Crossover and mutation	Strong global search capacity	[23]
Grey wolf optimization algorithm (GWO)	Metaheuristic (swarm intelligence algorithm)	Social hierarchy and hunting behavior	High convergence accuracy Fewer control parameters	[24]
Artificial bee colony (ABC)	Metaheuristic (swarm intelligence algorithm)	Food search and employed, onlooker, scout bees	Comprehensible algorithm structure Avoid local minimal	[25]
Artificial hummingbird algorithm (AHA)	Metaheuristic (nature-inspired method)	Dynamic switching behavior	Leading flight mechanism	[26]

3. RESULT AND DISCUSSIONS

Figure 5 illustrates the comparative graph analysis of vehicle speed using different classical and metaheuristic algorithms with a PID controller over 50 seconds. The classical (Zn-method) drastically increased the peak overshoot. The PID controller optimized using PSO and GA algorithms reduced the peak overshoot by 8% and improved performance compared to the classical method. Additionally, GWO, ABC, and AHA algorithms perform better compared to other heuristic and classical algorithms. Among all evaluations, the PID- GWO algorithm performs closer to the reference speed.

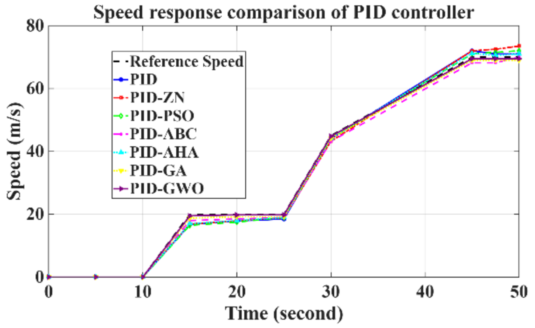

Figure 5. Vehicle speed response comparison with PID controller and optimal algorithms

Figure 6 illustrates the comparative graph analysis of the consumption of Li-ion battery power (Kw) with different classical and metaheuristic algorithms with a PID controller for over 50 seconds. The classical (ZN-method) power consumption from the battery peaks, but after 15 second power consumption is negative due to the underdamped behavior of the controller. The PID controller is optimized using PSO, GA, GWO, ABC, and AHA algorithms. The PSO control algorithm significantly decreased the power consumption from the battery and the underdamped behavior of the controller compared to the classical method. Among all evaluations, the PID-GWO algorithm consumes less power and provides smoother traction.

Figure 7 illustrates the comparison graph of Lithium-ion battery SOC in BEV with different classical and metaheuristic algorithms with a PID controller over 50 seconds. Initially, all controller algorithms maintain SOC at 70% under no-load conditions. After applying dynamic loads, there was a noticeable drop in SOC, which means the power consumption demand increased. The classical (ZN method) has high energy consumption, so the SOC is reduced to 65.5%. Furthermore, PID-GA, PID-ABC, and PID-AHA show moderate performance. Among all considered algorithms, PID-GWO maintains the highest SOC of 69.975%; it demonstrates reduced power consumption and increased energy efficiency.

Figure 8 demonstrates a comparison study of BEV motor speed using a PID controller with different optimal algorithms for 50 seconds. All controllers maintain 0 motor speed at no-load condition until 10 seconds. The traditional PID and classical method (PID-ZN) controllers have slower acceleration and a lower speed of 1820 rpm. PID-PSO controller improved the motor speed compared to the classical method. Furthermore, PID-GA, PID-ABC, and PID-AHA show moderate performance for motor speed in BEV. Among all optimal algorithms, PID-GWO enhances the motor speed, and a maximum motor speed of 1920 rpm means lower energy consumption.

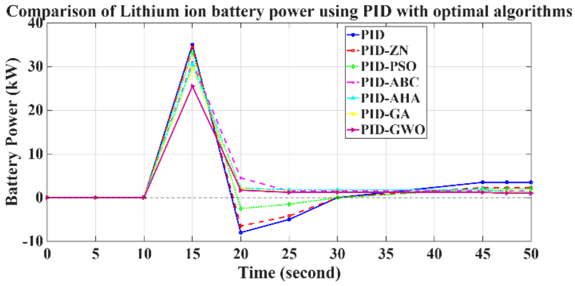

Figure 6. Li-ion battery power consumption with PID controller and optimal algorithms

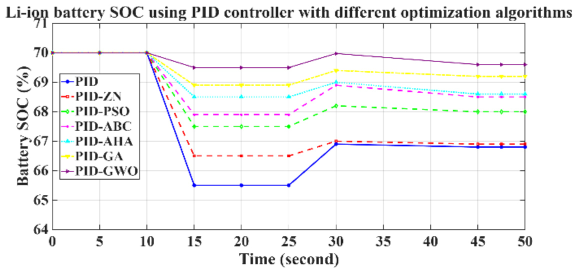

Figure 7. Li-ion battery SOC comparison with PID controller and optimal algorithms

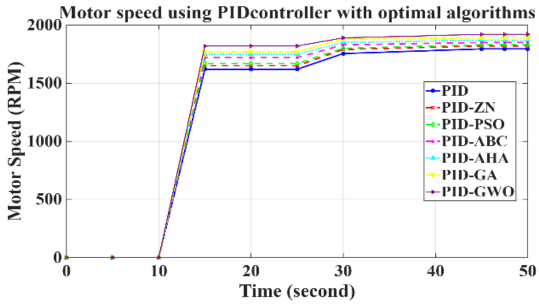

Figure 8. Comparison of motor speed using a PID controller with an optimal algorithm

Figure 9 demonstrates a comparison study of distance covered by BEV using a PID controller with different optimal algorithms over 50 seconds. The BEV is equipped with a traditional PID controller, which covers a distance of 0.0699 km. The classical (Zn-method) improved the vehicle mileage compared to the traditional PID controller, achieving a distance of 0.07 km. PID-PSO and PID-AHA algorithms show moderate performance improvement in vehicle mileage, achieving distances of 0.072 km and 0.0731 km. PID-ABC and PID-GA controller algorithms show better performance, achieving distances of 0.076 km and 0.0792 km. Among all algorithms, PID-GWO covered the maximum distance of 0.081 km.

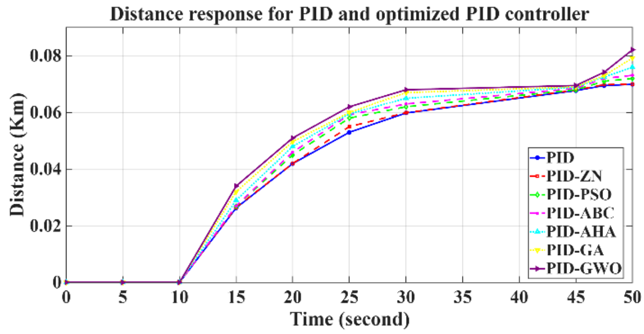

Figure 9. Comparison of distance covered by BEV using PID controller with optimal algorithm

Table 3 demonstrates the comparative analysis of battery-operated electric vehicles using traditional PID controllers with metaheuristic algorithms. It shows that optimal control algorithms enhance the vehicle performance in terms of vehicle efficiency, battery power, battery SOC, motor speed, mileage, and temperature of the BEV compared to the conventional PID controller and classical tuning (ZN-method). Among all optimal algorithms, the PID-GWO controller performs better than other algorithms (PID-ZN, PID-PSO, PID-GA, PID-AHA, PID-ABC). PID-GWO achieves the highest energy efficiency 97.5%, low battery power consumption 25.51 Kw, highest battery SOC 69.975%, highest motor speed (1920 rpm), and highest mileage 0.0821 km for 50 seconds. After optimization of the PID controller, the switching stress, harmonics, and total harmonic distortion are reduced, and the efficiency of the electric vehicle system is 97.5%. Battery temperature was reduced from 22 ℃ to 19℃ after applying PID with metaheuristic algorithms.

Table 3. Comparative analysis of BEV using PID and optimal algorithms

S.no	Parameters	PID	PID-ZN	PID-PSO	PID-AHA	PID-ABC	PID-GA	PID-GWO
1	Vehicle efficiency (%)	72.5	75	85	82.5	90	92.5	97.5
2	Maximum power consumption from battery (Kw)	35	34.5	33.2	31	30.5	29.5	25.5
3	Battery SOC (%)	66.9	67	68	68.5	68.6	69.2	69.975
4	Motor speed (RPM)	1795	1820	1830	1850	1870	1890	1920
5	Distance travelled (km)	0.0699	0.07	0.072	0.0731	0.076	0.0792	0.0821
6	Temperature (℃)	22	19	19	19	19	19	19

4. CONCLUSION

Battery-operated electric vehicles (BEVs) demonstrate high energy efficiency, zero emissions, and advanced optimization control techniques compared to traditional vehicles. This research framework investigated the effectiveness of classical and metaheuristic optimal methods for optimizing the PID controller in a BEV. A complete battery-operated electric vehicle MATLAB Simulation model was developed by combining a high-voltage battery pack, motor driver unit, gearbox, and longitudinal vehicle with a BEV controller. The suggested approach was evaluated using multiple metaheuristic optimization algorithms, namely the ZN method, PSO algorithm, AHA algorithm, ABC algorithm, GA algorithm, and GWO algorithm. Compared to traditional controller PID and classical PID-ZN method, PID-PSO meta heuristic algorithm perform superior. Compared with the PID-PSO algorithm, the AHA, ABC, and GA algorithms perform better. The comparison outcome shows that traditional PID and classical (ZN-method) offer high battery power consumption, decreased efficiency, and reduced vehicle mileage. Among all appraisals, the PID-GWO controller perform outstanding, achieving the highest vehicle efficiency of 97.5%, minimum peak battery power consumption of 25.51 kW, maximum battery SOC of 69.975%, and the largest distance covered by the vehicle of 0.0821 m. Overall, the proposed research work comes up with a simple and efficient way to improve the performance of BEV, which is helpful for controlling the battery electric vehicle. To extend this research framework, hybrid and learning-based optimal control strategies such as PSO-GA, ANN, LR, and fuzzy can be implemented. Additionally, real-time or standard drive cycles (FTP74, NEDC, and so on) to enhance the performance of the BEV. It can be additional experimental verification using (FOC, DTC, predictive controller) to drive the EV control strategy. In this research article, a BLDC motor is used; however, the proposed approach is also extendable to different types of motors (like PMSM and IM).

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data sharing does not apply to this study, as no datasets were generated or analyzed. The findings are based on MATLAB/Simulink simulations.

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