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Research paper

Multi-objective optimization of PI controller for BLDC motor speed control and energy saving in Electric Vehicles: A constrained swarm-based approach

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A B S T R A C T

Proportional Integral Derivative (PID) controllers are widely employed in industrial applications due to their effectiveness, simplicity, and versatility. Within the automotive sector, one notable application of the Proportional Integral (PI) controller is in the realm of electric motors, particularly the Brushless Direct Current (BLDC) motors powering Electric Vehicles (EVs). The precision of speed control over BLDC motors, renowned for their efficiency and reliability, is paramount for optimizing vehicle performance and ensuring energy efficiency. PIDs must be tuned each time they are used in an application to optimize performance. A well-known empirical hit and trial tuning strategy is the Ziegler–Nichols method, which results in sub-optimal performance in the presence of locally optimal solutions of large-dimensional search spaces. Existing Artificial Intelligence methods tailored for PID controller tuning often focus on singular optimization aspects, neglecting potential performance gains achievable through multi-objective considerations. Furthermore, prevalent swarm-based PID optimization methods typically initialize the population randomly without imposing any bounds on input parameters, thus rendering them susceptible to inconsistent, unreliable, sub-optimal solutions in unconstrained search environments. In our research endeavors, we mathematically model the multi-objective optimization of BLDC motor speed control, energy usage, and efficiency using constrained Differential Evolution and Particle Swarm Optimized PID controllers. The Ziegler–Nichols tuning method is used to ascertain the initial PI parameters and define bounds within the input space. Our methodology addresses a critical gap by integrating real-time road gradient data into the EV control system, enhancing precision and minimizing energy consumption, especially during challenging road conditions. The proposed approach significantly improves motor speed control and energy efficiency in EVs. With our proposed swarm-based optimization over 30 iterations, MSE decreased by approximately 95.4% (from 3.8834 to 0.1809), while energy consumption reduced by about 3.1% (from 1.015 kWh to 0.984 kWh). These results highlight the effectiveness of our method in enhancing both speed control precision and energy efficiency. In addition, code related data is available at Github.

1. Introduction

The increasing global concern for environmental issues and the growing demand for fossil fuel resources have propelled the integration of electric vehicle (EV) technology. Electric vehicles (EVs) utilize electricity instead of employing on fossil fuel which paved a way to offer new technologies for energy saving and contribute towards carbon emissions reduction (Shirkhani et al., 2023; Zhang et al., 2023b). Recently, EVs have gathered substantial attention due to their exceptional efficiency, cost-effective maintenance, and user-friendly operation (Veysi et al., 2020), Sun et al. (2019). This surge in EV popularity has contributed to significant reductions in pollution

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and an enhancement of sustainability. The propulsion system stands out as the pivotal part that demands careful control to ensure the remarkable performance of EVs Naqvi et al. (2024a). This aspect has garnered substantial research interest from industrial and academic circles (Ehsani et al., 1997). Focused investigations are essential to ensure optimal performance and effective energy management of EVs Naqvi et al. (2024b). A key objective is developing a controller capable of achieving maximum speed while minimizing tracking errors and energy consumption (Baidya et al., 2023).

In this context, the significance of achieving optimal motor control cannot be overstated, as it profoundly influences EVs’ performance, efficiency, and overall sustainability. To attain this level of control, Proportional–Integral–Derivative (PID) controllers form a robust foundation for EV control strategies (Dantas et al., 2018). PID controllers have evolved into critical controllers for effectively regulating motor speed within the domain of EV control. However, the challenge lies in the manual calibration of PID controller parameters. This complexity often leads to sub-optimal performance and inaccurate propulsion system control. These inaccuracies, in turn, can significantly compromise the energy efficiency of EVs (Arya, 2019). Numerous techniques have been suggested for fine-tuning PID controllers. One widely recognized classical method is the Ziegler–Nichols method. This approach often proves effective for a broad spectrum of real-world control processes, yielding satisfactory results in many cases (Patel, 2020). Nevertheless, there are instances where this method falls short, leading to substantial overshooting in the system’s response. Consequently, in practical control applications, it is common to require reevaluation and adjustment of this method before its implementation for process control (Bassi et al., 2011; Jamil et al., 2022; Wang et al., 2023b). In addition, it is required to optimize the existing controllers for enhancing their capabilities to deal with adaptive control processes (Fei et al., 2024; Wang et al., 2022a). In addition, Hou et al. (2017) proposed an optimization strategy to enhance energy efficiency of the EVs by reducing the cost associated with battery charging. Incorporating Artificial Intelligence (AI) alongside PID controllers brings about a notable improvement in the traditional PID controller’s functionality, enriched by its self-tuning capabilities (Vishal et al., 2014). By merging the optimization techniques such as Genetic Algorithm (GA) (El-Deen et al., 2015), Particle Swarm Optimization (PSO) (Sharaf and EI-Gammal, 2010), and Differential Evolution (DE) (Jigang et al., 2019) with PID control, an optimal PID controller can be designed that can result in more adaptive and dynamic control mechanisms. This fusion allows the system to learn and adjust its control parameters in real-time, effectively responding to environmental variations and uncertainties.

Optimized PID tuning remains a central focus in control engineering, enhancing control techniques, system stability, and overall performance in various applications. Table 1 presents the most recent developments in this area and offers a thorough overview of current methods. Below, we provide a comprehensive summary of the research that has been highlighted in Table 1, summarizing the state of the art in the field. Issa (2023), introduced an enhanced optimization method, AOA-HHO, combining the Arithmetic Optimization Algorithm (AOA) with Harris Hawk Optimization (HHO) for optimal PID controller tuning. AOA-HHO is capable of estimating PID parameters for DC motor regulation and three fluid-level sequential tank systems, demonstrating superior performance over comparative algorithms. Zadehbagheri et al. (2023), proposed an approach using Genetic Algorithm (GA) and PSO for PID controller design in power networks. The proposed approach demonstrated improved control efficiency and effectiveness in single-machine systems, validated through simulations in MATLAB. Hemeida et al. (2023), utilized AOA to optimize PID controller parameters to enhance transient stability in the Western System Coordinating Council (WSCC) power system. Simulation results demonstrated improved damping of low-frequency oscillations and enhanced transient stability during three-phase short-circuit faults. Similarly, Zhang et al. (2022a) suggested a multi-objective optimization strategy based on PSO to optimize the load dispatch of the micro-grid containing EVs. Their approach demonstrated significant reductions in total cost and microgrid load variance, particularly with ordered charging–discharging strategies and distributed power output scheduling, thereby enhancing grid safety and economy. In addition, in (Zhang et al., 2023a), the authors presented a two-stage optimization strategy based on PSO to optimize the charging–discharging demands of the EVs. The results show a substantial reduction in charging costs (40% to 110%) and distribution network load variance (19% to 100%), indicating significant benefits for grid operators and EV users. Ghith and Tolba (2023), introduced HAOAGTO, a hybrid algorithm merging the AOA and Artificial Gorilla Troop’s Optimization (AGTO) for optimizing PID parameters which is then applied in micro-robotics systems. Compared with other algorithms, including Seagull Optimization Algorithm (SOA) and Parasitism-predation Algorithm (PPA), the hybrid approach (HAOAGTO) demonstrates superior performance, achieving optimal PID parameters and reducing error metrics such as Integral Square Time multiplied square Error (ISTES).

Furthermore, in Raj et al. (2023), tackled automated load frequency control (LFC) in multi-area power networks by enhancing PID controllers’ performance using the Bald Eagle-Sparrow Search Optimization (BESSO) technique. The results demonstrate reduced settling times and improved stability, showcasing the efficacy of the developed controller for enhanced power system operation and stability in multi-area networks. Wang et al. (2017) and Hu et al. (2024) suggested multi-objective optimization using evolutionary methods for enhancing energy efficiency and reliability of energy systems. Intidam et al. (2023), employed PSO-PI-ANFIS controller. These controllers are evaluated for their ability to maintain the desired speed, considering the effect of load torque disturbances and parameter variations. This controller performs better than classical PI and PI-ANFIS controllers, offering enhanced tracking accuracy, reduced overshoot, and improved settling time. Similarly, Liang et al. (2023a) and Shao et al. (2023) introduced an energy-aware controllers based on torque-vector and signal modelling for EVs. Baidya et al. (2023), introduced a Dandelion Optimization (DO) based PID controller for precise speed control of DC motors in EVs. Jassim et al. (2023), proposed an optimized PID controller for EVs using PSO and Multi-Verse Optimization (MVO) algorithms. These controllers effectively regulate the EV’s speed, demonstrating superior performance with minimal steady-state error and overshoot compared to traditional methods. Santos et al. (2022), proposed the NSGA-II algorithm to tune three PI controllers for a DC motor drive with control loops for armature current, speed, and position. Simulation results demonstrate the algorithm’s effectiveness in achieving optimal controller tuning, enhancing the performance of electric drives in various operating conditions. Parkar et al. (2023), proposed a modified PSO methodology in optimizing the energy management strategies for Range Extended EVs, significantly reducing fuel consumption and nitrogen oxide emissions. The approach achieved significant reductions in both fuel consumption (12%) and NOx emissions (35%) individually, and when employing multi-objective optimization, it achieves a simultaneous reduction of 9.4% in fuel consumption and 7.9% in NOx emissions compared to baseline models using rule-based power management strategies.

In addition, Zhang et al. (2022b) proposed an adaptive control strategy to improve control accuracy in EVs through investigating the hybrid energy source system. Simulation and prototype experiments demonstrated fast response, reduced error, and robust stability under hybrid driving conditions, highlighting the effectiveness of the proposed approach for EV applications. Similarly in Zhang et al. (2020), the authors presented L2-gain robust adaptive controller to enhance tracking control of the hybrid energy source system in EVs. Liang et al. (2023b) and Liang et al. (2024) introduced moment and shared controllers to enhance stability margin of EVs but these controllers are not efficient to deal with non-linear and dynamics control challenges. Wang et al. (2024) proposed an optimal controller based on double
loop paradigm to reduce the speed error of the BLDC motor. The proposed method effectively handles disturbances and parameter changes, ensuring fast response, high performance, and stability. Compared to traditional methods like PID and sliding mode control, it shows superior performance in EV applications, validated through prototype implementation.

Most of the work in motor speed control of EVs has focused on improving single parameters, such as decreasing speed error. However, there is still much to learn about the comprehensive optimization of PID controllers with multi-objectives, particularly speed control and energy consumption reduction. To fill this gap, this study examines how Brushless DC (BLDC) motors in EVs are controlled at different speeds, focusing on minimizing energy usage. Our study improves the PI controller by utilizing the swarm intelligence methods PSO and DE, providing an integrated perspective considering energy efficiency and speed accuracy in EV motor control. In contrast to traditional PID controllers utilizing proportional, integral, and derivative gains, our approach focuses solely on the proportional $K_p$ and integral $K_i$ gains. This strategy is chosen after extensive testing and analysis, revealing the significant influence of these components on the motor’s speed response. The derivative term, while adding complexity, does not substantially enhance performance in our application context.

Simplifying the control architecture aligns with the characteristics of BLDC motor systems. Given their smoother reactions compared to more complex systems requiring accurate differentiation, the proportional and integral terms play a crucial role in achieving steady and responsive speed control. Through focused optimization of these critical factors, control can be simplified without compromising efficiency (Elkholy and El-Hay, 2020; Sayed et al., 2024).

The noteworthy contributions of our study are presented as follows:

- Implement an intelligent Proportional-Integral (PI) controller based on swarm intelligence for controlling the motor speed of EVs.
- Employ PSO and DE as swarm intelligence algorithms to automate the tuning process of the PI controller, ensuring precise speed control and energy efficiency of BLDC motors used in EVs.
- Develop a simulation prototype using Simulink to validate the speed control and energy efficiency precision of BLDC motors.
- Employs extensive simulations and comparisons to demonstrate the superior performance of the swarm-based constrained optimized PI controller considering the multi-objective optimization problem.

The rest of the paper is organized as follows: The system overview of the proposed model, along with the Multi-objective optimization problem, is described in Section 2. Section 3 presents the results and comparative analysis of the architecture. Section 4 concludes the paper and offers future directions of the study.

2. Methodology

In order to develop understanding of the proposed method, we discuss the problem related to non-optimized tuning of PI controller which leads us to the requirement of optimization of PI controller for efficient motor speed control and energy economy. The methodology for achieving precise speed control of BLDC motors in EVs involves a well-coordinated system of interconnected components. Initially, all

Table 1

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Application</th>
<th>Optimization Method</th>
<th>Optimization Type</th>
<th>Performance Index</th>
<th>Challenges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isa (2023)</td>
<td>DC Motor Regulation, Three Fluid Level Sequential Tank Systems</td>
<td>AOA combined with HHO</td>
<td>Single Objective Optimization</td>
<td>Integral Absolute Error (IAE)</td>
<td>Comprehensive analysis and comparison of the performance metrics are required for the comparison of the two optimization approaches.</td>
</tr>
<tr>
<td>Zadebbagheri et al. (2023)</td>
<td>Grid Control within Power Networks</td>
<td>Genetic Evolutionary Algorithm (GEA) and PSO</td>
<td>Single Objective Optimization</td>
<td>Overshoot, Settling Time, Rise Time, Stability Index</td>
<td>Designing PID controllers for multivariable systems can be significantly more complex than for single-variable systems.</td>
</tr>
<tr>
<td>Hemeida et al. (2023)</td>
<td>Transient Stability Enhancement in Power Systems</td>
<td>AOA</td>
<td>Single Objective Optimization</td>
<td>Integral Time Absolute Error (ITAE)</td>
<td>Computational complexity and scalability when applied to complex power systems.</td>
</tr>
<tr>
<td>Ghith and Tolba (2023)</td>
<td>Micro-Robotics systems (drug delivery inside the human body)</td>
<td>Hybrid AOA and AGTO</td>
<td>Single Objective Optimization</td>
<td>IAE and Integral of Time Multiplied by Square Error (ITSE)</td>
<td>The choice of parameters for the hybrid optimization algorithm might be challenging.</td>
</tr>
<tr>
<td>Raj et al. (2023)</td>
<td>LFC in complex multi-source power systems</td>
<td>BESSO</td>
<td>Single Objective Optimization</td>
<td>ITAE</td>
<td>Accurate modeling and simulation of multi-source power systems can be challenging.</td>
</tr>
<tr>
<td>Intidam et al. (2023)</td>
<td>Speed Control of a BLDC Motor in Fuel Cell EV</td>
<td>PSO</td>
<td>Single Objective Optimization</td>
<td>ITAE</td>
<td>The controller’s effectiveness may be affected by real-world implementation challenges.</td>
</tr>
<tr>
<td>Baidya et al. (2023)</td>
<td>Speed Control of DC Motors in EVs</td>
<td>Dandelion Optimization (DO)</td>
<td>Single Objective Optimization</td>
<td>Integral Square Error (ISE), IAE, Integral Error, Integral Time Square Error, Integral Time Absolute Error</td>
<td>Disturbances or uncertainties inherent in real-world EV operating conditions are not considered.</td>
</tr>
<tr>
<td>Jassim et al. (2023)</td>
<td>EV speed regulation by minimizing the error between measured and reference speed</td>
<td>PSO and MVO</td>
<td>Single Objective Optimization</td>
<td>Steady-State Error, Overshoot, Settling Time, Rising Time</td>
<td>Disturbances or uncertainties inherent in real-world EV operating conditions are not taken into account.</td>
</tr>
<tr>
<td>Dos Santos et al. (2022)</td>
<td>PI controller for an electric drive system, specifically a DC motor drive</td>
<td>NSGA-II (Non-Dominated Sorting Genetic Algorithm II)</td>
<td>Multi-Objective Optimization</td>
<td>Response time, Stability, and Efficiency of the electric drive system</td>
<td>Optimization complications due to non-linearity caused by anti-Windup circuits</td>
</tr>
<tr>
<td>Parkar et al. (2023)</td>
<td>Energy and Power management strategies for hybrid electric power-trains</td>
<td>Modified PSO (Modified PSO)</td>
<td>Multi-Objective Optimization</td>
<td>Reduction in fuel consumption and nitrogen oxide emission</td>
<td>Computational complexity due to high-dimensional optimization problems</td>
</tr>
</tbody>
</table>
the components for modeling the motor and PI controller are discussed using the block diagram without applying any optimization (termed as manual tuning). Next, the exact position within the block diagram where the optimization component can be integrated to control the PI controller efficiently is identified. To maximize the BLDC motor’s energy economy and speed control performance, singular objective functions are formulated and modeled mathematically. These two performance objectives contradict each other and must be optimized concurrently. Considering this requirement, the problem is mathematically formulated for multi-objective optimization for both motor speed and energy efficiency. A fair amount of detail is provided for solving all the variants of the problem as follows (in separate subsections): (1) Non-optimized method for tuning PI controller, (2) Optimization of PI controller for motor speed control as a singular objective problem, (3) Optimization of PI controller for energy efficiency as a singular objective problem, and (4) Multi-objective Optimization of PI controller for both motor speed and energy efficiency. For singular objective formulation, the input and output variables for the objective functions with corresponding constraints are identified. For each singular motor speed and energy efficiency objective, two separate block diagrams are drawn for a concrete understanding of the empirical modeling. In the later part of the section, swarm-based methods (namely: PSO and DE) are designed to solve singular and multi-objective optimization problems.

2.1. Non-optimized PI controller for speed control in EVs

This section presents an overview of the non-optimized PI controller using the Ziegler–Nichols method to control the speed of BLDC motors commonly used in EVs. The detail of components used in modeling and operational workflow of the entire system is illustrated using the block diagram in Fig. 1. As illustrated in the setup, the desired speed acts as an input reference, while the Hall effect sensor provides precise feedback on the measured speed. By comparing these speeds, an error signal is generated and processed by the PI controller. The Ziegler–Nichols method is employed to adjust the PI controller’s proportional and integral gain parameters. The PI controller then utilizes the optimized \( K_p \) and \( K_i \) gains to generate a control signal, resulting in optimal speed control of the BLDC motor in EVs. The input to the optimization module is the speed error of the EV, calculated by subtracting the vehicle’s measured speed from the desired speed. The optimization algorithms optimize the PI controller’s proportional \( K_p \) and integral \( K_i \) gain parameters. The PI controller then utilizes the optimized \( K_p \) and \( K_i \) gains to generate a control signal, resulting in optimal speed control performance. By utilizing these optimization techniques, the aim is to overcome the limitations of the non-optimized approach (presented in Section 2.1) and achieve superior speed control accuracy and energy efficiency in EV applications. In further subsections, focus is placed on formulating objective functions tailored for efficient speed control of BLDC motors in EVs. The mathematical modeling process is meticulously detailed, wherein a singular objective function is designed to encapsulate the key performance metrics essential for optimizing BLDC motor speed control.

2.2. Optimized PI controller for speed control in EVs

In this section, the Constrained Swarm-Based Approach is examined, utilizing PSO and DE as effective optimization techniques for improving the performance and efficiency of BLDC motor speed control in EVs. Constrained optimization methods are employed to fine-tune the parameters of the PI controller. Fig. 2 illustrates the optimization module incorporated in the basic block diagram shown in Fig. 1 for optimal speed control of the BLDC motor in EVs. The input to the optimization module is the speed error of the EV, calculated by subtracting the vehicle’s measured speed from the desired speed. The optimization algorithms optimize the PI controller’s proportional \( K_p \) and integral \( K_i \) gain parameters. The PI controller then utilizes the optimized \( K_p \) and \( K_i \) gains to generate a control signal, resulting in optimal speed control performance. By utilizing these optimization techniques, the aim is to overcome the limitations of the non-optimized approach (presented in Section 2.1) and achieve superior speed control accuracy and energy efficiency in EV applications. In further subsections, focus is placed on formulating objective functions tailored for efficient speed control of BLDC motors in EVs. The mathematical modeling process is meticulously detailed, wherein a singular objective function is designed to encapsulate the key performance metrics essential for optimizing BLDC motor speed control.

2.2.1. Objective function for speed control in EVs

Continuing our investigation into optimizing the PI controller for speed control in EVs, this subsection explores the creation of objective function for speed control of BLDC motors in EVs. These functions are customized to improve the efficiency and performance of the BLDC motor speed control system.

Our methodology tackles the challenge of accurate speed control in EVs during demanding road conditions, particularly uphill climbs and downhill descents. Traditionally, control methods have overlooked the complexities of terrain, neglecting their impact on speed control precision and energy consumption (Xiao et al., 2023; Wang et al., 2023a). To address this, our study integrates real-time road gradient data into the EV control system, enabling adaptive speed control that adjusts to the road’s slope. The road gradient is calculated using GPS technology that measures changes in altitude over a specific horizontal distance. The data points are then utilized to determine the slope, allowing real-time adjustments in the control system.

A key aspect is introducing a weight function \( \alpha(t) \) that modulates speed control errors based on the road slope.

- Steeper uphill gradients receive higher weights, emphasizing precise speed control in EVs.
Fig. 2. Block diagram of BLDC motor speed control using optimized PI controller.

- Moderate weights are assigned to downhill gradients, ensuring controlled deceleration.

This adaptive approach enhances speed control accuracy and maximizes energy efficiency, contributing to a more robust vehicle control system.

Objective Function 1:
The objective function $f_1(K_p, K_i)$ is formulated to minimize the integrated squared error between the reference and measured speed over a given time duration $T$. The proportional gain $K_p$ and integral gain $K_i$ of the PI controller are optimized to achieve this objective, ensuring optimal speed control performance.

Objective 1: $f_1(K_p, K_i) = \int_0^T (u(t) \cdot (\text{Reference Speed} - \text{Measured Speed})^2) \, dt$ (1)

\[ u(t) = \begin{cases} 
\text{High Weight} & \text{if Gradient}(t) > \text{Threshold (Uphill)} \\
\text{Medium Weight} & \text{if Gradient}(t) < \text{Threshold (Downhill)} \\
\text{Low Weight} & \text{otherwise} 
\end{cases} \]

Constraints:
Constraints are imposed on $K_p$ and integral gain $K_i$ to keep them within allowable ranges, initially set using the Ziegler–Nichols tuning method. Additionally, constraints are placed on the rate of change of the reference speed to ensure smooth acceleration, as well as on the total energy consumption of the vehicle to limit it within a specified range. These constraints further contribute to the efficient operation of the EV.

$K_p^{\text{min}} \leq K_p \leq K_p^{\text{max}}$

$K_i^{\text{min}} \leq K_i \leq K_i^{\text{max}}$

Where $K_p^{\text{min}}, K_p^{\text{max}}, K_i^{\text{min}},$ and $K_i^{\text{max}}$ represent the allowable range for the proportional and integral gains and are set initially using Ziegler–Nichols tuning method.

$\left| \frac{d}{dt} (\text{Reference Speed}(t)) \right| \leq \text{Max Acceleration Rate}$

This ensures smooth changes in reference speed, limiting the acceleration rate.

$\int_0^T (\text{Power}(t)) \, dt \leq \text{Max Energy}$

This limits the total energy consumption of the vehicle within a specified range.

- $f_1(K_p, K_i)$: Objective function representing the integrated squared error between reference and measured speed.
- $K_p$: Proportional gain of the PI controller.
- $K_i$: Integral gain of the PI controller.
- Reference Speed(t): Desired vehicle speed at time $t$.
- Measured Speed(t): Actual measured vehicle speed at time $t$.
- $T$: Total time duration of the control operation.

For uphill conditions:

Threshold (Uphill) = Baseline Gradient + Uphill Threshold Value

(2)

For downhill conditions:

Threshold (Downhill) = Baseline Gradient − Downhill Threshold Value

(3)

In Eqs. (2) and (3):
- Baseline Gradient represents the baseline or flat road gradient (0%).
- Uphill Threshold Value represents the additional gradient percentage considered as uphill.
- Downhill Threshold Value represents the gradient percentage considered as downhill.

The gradient of the road, denoted as Gradient(t), serves as a critical parameter in our adaptive speed control system. We meticulously analyzed the vehicle’s response to varying gradients through extensive Simulink simulations, enabling us to determine the optimal thresholds for classifying road conditions. The Uphill Threshold, set at 3%, delineates uphill gradients, while the Downhill Threshold, established at −3%, identifies downhill slopes.

The formulation of the objective function and associated constraints is informed by extensive analysis of the vehicle’s response to varying gradients through Simulink simulations. Optimal thresholds for
classifying road conditions, such as uphill and downhill segments, are determined based on observed vehicle performance under diverse scenarios. This ensures the accuracy of our approach in real-world driving situations.

2.3. Optimized PI controller for energy efficiency in EVs

This section covers the optimization technique for improving the energy efficiency of EVs using a tuned PI controller. To improve total energy usage in EVs, we emphasize integrating the PI controller into energy management systems, building upon the efficient energy optimization in EVs. Fig. 3 illustrates the optimization module incorporated in the basic block diagram shown in Fig. 1 for optimal energy consumption in EVs. We utilized the PI controller’s parameters within an energy optimization framework, where the PI controller gains $K_p$ and $K_i$ are dynamically adjusted based on the objective function formulated in Section 2.3.1 for efficient energy conservation in EVs. To accurately assess the energy consumption of the EV propulsion system, we employ a measuring technique that intercepts the three-phase power output from the inverter powering the BLDC motor. This measured power output is then integrated over time to represent the energy utilized during vehicle operation. The optimization algorithms employed within our Constrained Swarm-Based approach utilize this energy consumption measure as a critical fitness function, guiding the dynamic adjustment of the PI controller’s parameters. Through iterative optimization processes, we seek to achieve an optimal configuration of the PI controller to minimize energy consumption.

2.3.1. Objective function for energy efficiency in EVs

This subsection introduces the objective function formulation for optimizing energy consumption in EVs by highlighting the importance of minimizing total energy consumption to enhance the efficiency of EVs. This objective function is tailored to adjust the optimization process dynamically based on real-time driving conditions, ensuring optimal energy usage across various scenarios. The formulation of the objective function $f_2(K_p, K_i)$ is presented, where $K_p$ and $K_i$ represent the proportional and integral gains of the controller, respectively. This objective function aims to minimize the integral of energy consumption over time, incorporating a dynamic weight function $\omega(t)$ to adapt to changing driving conditions.

**Objective Function 2:**

The objective function is defined as the integral of energy consumption weighted by the dynamic weight function $\omega(t)$ over the duration of the control operation $T$.

$$\text{Objective 2: } f_2(K_p, K_i) = \int_0^T (\omega(t) \cdot \text{Energy Consumption}(t)) \, dt \quad (4)$$

The dynamic weight function, $\omega(t)$, is pivotal in adapting the optimization process according to the electric vehicle’s real-time operating conditions. For example, in challenging scenarios such as uphill climbs or high-speed driving, $\omega(t)$ can prioritize minimizing energy consumption, allowing the controller to focus on optimizing energy usage during periods of higher power demand. This real-time adjustment ensures the controller’s responsiveness to varying situations, making the objective function highly adaptive. By dynamically prioritizing energy optimization efforts, the controller achieves efficient and responsive performance, contributing significantly to the electric vehicle’s energy-saving goals.

The calculation of energy consumption accounts for motor efficiency and power consumption over time. Total energy consumption is obtained by integrating energy consumption over the entire duration of the control operation.

$$\text{Energy Consumption}(t) = \frac{1}{\text{Motor Efficiency}} \cdot \text{Power Consumption}(t)$$

$$\text{Total Energy Consumption} = \int_0^T \text{Energy Consumption}(t) \, dt$$

**Constraints:**

Constraints are imposed on the $K_p$ and $K_i$ gains, ensuring they fall within permissible ranges. Additionally, constraints are placed on the rate of change of the reference speed to limit acceleration, maintaining vehicle stability.

$$K_p^{\text{min}} \leq K_p \leq K_p^{\text{max}}$$

$$K_i^{\text{min}} \leq K_i \leq K_i^{\text{max}}$$

$$\left| \frac{d}{dt}(\text{Reference Speed}(t)) \right| \leq \text{Max Acceleration Rate}$$

Reference Speed($t$) $\leq$ Max Attainable Speed

Where:

- $f_2(K_p, K_i)$ represents the objective function for minimizing energy consumption.
- $K_p$ and $K_i$ are the proportional and integral gains of the controller, respectively.
- $\omega(t)$ is a dynamic weight function based on real-time driving conditions.
- Energy Consumption($t$) represents the energy consumption of the vehicle at time $t$.
- $T$ is the total time duration of the control operation.
2.4. Multi-objective optimization of PI controller for both motor speed and energy efficiency

This section provides a framework that combines our optimized speed control methodology and energy consumption optimization technique into a unified multi-objective optimization framework. This new technique is motivated by the realization that great energy economy and excellent speed control are two requirements for EVs nowadays. This section discusses the crucial requirement to balance speed control and energy efficiency goals in real-time operations. Our multi-objective optimization scenario aims to find the best compromise between energy conservation and speed control accuracy. To reach this balance, the vehicle has to react quickly to demands for acceleration and speed while utilizing as little energy as feasible. Our technique minimizes needless energy use while dynamically adjusting the PI controller parameters to guarantee that the vehicle runs at the ideal speed in response to the driver’s inputs. Fig. 4 represents the scenario diagram for the optimization-based speed control of EVs employing a Proportional-Integral (PI) controller to enhance the performance of EVs by achieving precise speed control while minimizing energy consumption. Vehicle input data is acquired based on time and speed. This data serves as the foundation for controlling the EV speed and includes the reference speed of the vehicle. The acquisition of vehicle input data, including extensive parameters such as Vehicle speed, road gradient, altitude, latitude, longitude, EngineRPM, and RoadType, lays the groundwork for robust speed and energy management. The measured speed of the EV is determined based on the BLDC motor’s actual performance. This value serves as a feedback signal for the control system, enabling it to adjust the control inputs in real-time. The simulated vehicle data, including the measured speed, reference speed, and time, is transmitted from the Simulink model to MATLAB. In MATLAB, the MSE and energy consumption are calculated based on these parameters, which serve as the objective function for the PSO and DE algorithms. The two swarm-based optimization algorithms play a pivotal role in this scenario by optimizing the gains of the PI controller (\(K_p\) and \(K_i\)). These gains are then transferred to the Simulink model from the Matlab workspace at each iteration to compute MSE between desired and measured vehicle speed and the energy consumption. This process continues for the set iterations and yields optimal \(K_p\) and \(K_i\) gains, resulting in minimum MSE for vehicle speed and energy efficiency.

**Multi-Objective Problem:**

Minimize: \(F(K_p, K_i) = o_1 \cdot f_1(K_p, K_i) + o_2 \cdot f_2(K_p, K_i)\)  

In this multi-objective problem, \(o_1\) and \(o_2\) are weights representing the importance of each objective. Assigning a higher weight \(o_1\) to the speed control objective serves a crucial purpose. In many real-world applications, precise speed control is paramount as it directly impacts electric vehicle safety and user experience. The control system aims to minimize the mean square error between the reference and measured speeds by prioritizing speed control accuracy with a higher weight. This emphasis aligns with the primary focus on achieving accurate and stable speed control, addressing our core objective of ensuring optimal vehicle performance.

2.5. Optimization solutions for multi-objective optimization problem

The main stages of PSO and DE optimization algorithms for speed and energy efficiency are shown in Figs. 5 and 6, respectively. Initial parameters are first set to adjust the control system. Two objective functions, precise speed control and energy consumption minimization, are simultaneously optimized. The iterative process illustrates the constant improvement of PI controller gains \(K_p\) and \(K_i\) to attain optimal performance, capturing the dynamic adjustments made by the control system. This summarizes the methodology of this work by showing how multi-objective optimization is integrated with the EV model in Simulink to provide the optimal, finely-tuned control strategy. The proposed multi-objective optimization module has several benefits. First, it can improve the performance of the motor speed control system by optimizing the \(K_p\) and \(K_i\) gains of the PI controller. This can improve speed tracking, reduce error, and improve energy efficiency. Second, the proposed optimization module is relatively simple and can be used with various motor speed control systems.

2.5.1. Particle swarm optimization

PSO is a swarm intelligence nature-inspired optimization algorithm that simulates the social behavior of birds flocking or fish schooling. In PSO, a group of particles (potential solutions) moves through the search space to find the optimal solution. Each particle adjusts its position and velocity based on its own experience (Pbest) and the group’s best-known position (Gbest) (Iqbal et al., 2022, 2021). Random values and acceleration coefficients influence the movement (Shami et al., 2022).

The velocity and position of each particle are updated iteratively using the Eqs. (6) and (7)

\[
v_{i,d}(t + 1) = v_{i,d}(t) + c_1 r_1 (P_{i,d}(t) - x_{i,d}(t)) + c_2 r_2 (G_{best}(t) - x_{i,d}(t)) \quad (6)
\]

\[
x_{i,d}(t + 1) = x_{i,d}(t) + v_{i,d}(t + 1) \quad (7)
\]

The pseudo-code for the PSO optimization problem is provided in Algorithm 1.

**Algorithm 1: PSO Algo. for PI Controller Optimization of Motor Speed and Energy Efficiency**

1. Initialize swarm particles and velocities;
2. Define the swarm size \(S\) and total dimensions \(D\);
3. for each particle \(i \in [1..S] \) do
4. Randomly initialize position \(X_i\) and velocity \(V_i\);
5. Evaluate fitness \(f(X_i)\) for the initial position;
6. using Eq. (5);
7. Set \(P_{best} = X_i\);
8. Set \(f(P_{best}) = f(X_i)\);
9. if \(f(P_{best}) < f(G_{best})\) then
10. Set \(G_{best} = P_{best}\);
11. Set \(f(G_{best}) = f(P_{best})\);
12. for each iteration \(t\) until maximum iterations do
13. for each particle \(i \in [1..S] \) do
14. Update velocity \(V_{i}(t + 1)\) using Eq. (6);
15. Update position \(X_{i}(t + 1)\) using Eq. (7);
16. Evaluate fitness \(f(X_{i}(t + 1))\) using Eq. (5);
17. if \(f(X_{i}(t + 1)) < f(P_{best})\) then
18. Update \(P_{best} = X_{i}(t + 1)\);
19. Set \(f(P_{best}) = f(X_{i}(t + 1))\);
20. if \(f(P_{best}) < f(G_{best})\) then
21. Update \(G_{best} = P_{best}\);
22. Set \(f(G_{best}) = f(P_{best})\);
23. Return \(G_{best}\);

We utilized PSO in our work to optimize a multi-objective function about the speed control and energy efficiency of BLDC motors in EVs. The goal was to optimize the controller gains, \(K_p\) and \(K_i\), to balance precise speed control and energy efficiency. We adopted the PSO algorithm for our specific problem by considering the following parameters:

- **Swarm Size (S):** The number of particles in the swarm was set to 15, providing diverse potential solutions.
- **Maximum Iterations (MaxIt):** We range MaxIt from 10 to 30, allowing the PSO algorithm to explore the solution space iteratively.
Fig. 4. Proposed framework for BLDC motor speed control and energy efficiency with optimized PI controller.

- Search Space: The search space for each parameter, $K_p$ and $K_i$, was defined within specified bounds ($K_p^{\text{min}}, K_p^{\text{max}}, K_i^{\text{min}}, K_i^{\text{max}}$) determined through Ziegler–Nichols tuning.
- Crossover Probability (pCR): The crossover probability was set to 0.2, influencing the probability of accepting changes in the parameter values during the PSO iterations.

Fig. 5 describes how the PSO algorithm was included in the adaptive speed control system. The PI controller’s performance was simulated under actual driving circumstances as part of the fitness test. The PSO algorithm changed the PI controller's settings $K_p$ and $K_i$ at each iteration to find optimal speed and energy usage combinations. In real-time simulations, the adaptive speed control system performed better when the PI controller settings were improved. By including dynamic weighting based on road grade, the controller could easily adjust to both uphill and downhill circumstances, maximizing energy efficiency and preserving accurate speed control.

2.5.2. Differential evolution

Differential Evolution (DE) is an evolutionary optimization algorithm designed for continuous optimization problems. DE employs a population of candidate solutions and iteratively refines them to find the optimal solution. It was introduced by Storn and Price in 1997 (Storn and Price, 1997). In DE, a population of candidate solutions, often vectors, has evolved over generations. Each vector is represented by a set of parameters that define a potential solution to the optimization problem. The algorithm uses mutation, crossover, and selection operations to create new candidate solutions and improve the overall population.

The core steps of the DE algorithm are as follows:

1. Initialization: Randomly initialize a population of vectors with appropriate parameter values.
2. Mutation: Generate trial vectors by perturbing and combining existing vectors. One common mutation strategy is the difference vector strategy.
3. Crossover: Recombine trial vectors with the target vectors to create a new population of candidate solutions.
4. Selection: Choose the best vectors from the current and new populations based on their fitness values.
5. Termination: Repeat the mutation, crossover, and selection steps for a predefined number of generations or until convergence criteria are met.

The equations for the mutation and crossover steps in DE are given by:

\[
\text{Mutation: } V_{i, \text{new}} = X_{i1} + F \cdot (X_{i2} - X_{i3}) \tag{8}
\]

\[
\text{Crossover: } U_{i, \text{new}} = \begin{cases} V_{i, \text{new}} & \text{if } \text{rand()} \leq CR \text{ or } j = j_{\text{rand}} \\ X_{i, \text{old}} & \text{otherwise} \end{cases} \tag{9}
\]

where $X_{i1}, X_{i2},$ and $X_{i3}$ are randomly selected vectors, $F$ is the scaling factor, $CR$ is the crossover rate, and $j_{\text{rand}}$ is a randomly chosen index.

The pseudocode for the DE optimization algorithm is presented in Algorithm 2.

In our work, to enhance the speed control precision of BLDC motors in EVs, we strategically employed DE, a sophisticated optimization algorithm inspired by the principles of natural evolution. This optimization approach involves evolving a population of solutions, each representing a set of crucial parameters for our motor control system. Specifically, the parameters include the Proportional $K_p$ and Integral $K_i$ gains of the Proportional-Integral (PI) controller. The DE algorithm iteratively refines these parameters using crossover, mutation, and selection operations. We initialized the population with randomly selected values for $K_p$ and $K_i$ and let DE explore the solution space, dynamically adjusting these gains to improve speed control precision and energy efficiency. The DE optimization process is detailed in Fig. 6.

3. Results and discussion

The methodology described in the preceding section establishes the foundation for precisely controlling the speed of BLDC motors while
minimizing the energy consumption in EVs. We combine optimization approaches to improve the performance and efficiency of the PI controller after having a solid understanding of the system design. In this section, we explore the outcomes of our methodology, presenting empirical results and engaging in a comprehensive discussion of their implications. We first clarify the effectiveness of the non-optimized Ziegler–Nichols methodology for PI controller tuning. We then explore the optimization of the PI controller as single-objective problems for energy efficiency and motor speed control. In addition, we investigate the complexities of multi-objective optimization with the goal of optimizing motor speed and energy efficiency at the same time. We analyze the lessons gained from each strategy and have an engaged discussion about their importance in improving EV speed control and energy efficiency using simulation analysis and results.

In the context of this work, the Ziegler–Nichols method served as an initial tuning approach for setting the initial values of $K_p$ and $K_i$ in the speed control of the BLDC motor within the EV system. These initial parameters provided a stable starting point and established the lower and upper bounds for $K_p$ and $K_i$ gains in PSO and DE algorithms, facilitating fine-tuning the PI controller for enhanced speed control and energy efficiency.

![Flowchart for PSO-based Multi-objective Optimization of Motor Speed and Energy Efficiency](image)

**Algorithm 2:** DE Algo. for PI Controller Optimization of Motor Speed and Energy Efficiency

1. Initialize a population of individuals with random solutions;
2. Define the population size $N$, total dimensions $D$, and scaling factor $F$;
3. for each individual $i \in \{1..N\}$ do
   4. Randomly initialize a solution vector $X_i$;
   5. Evaluate fitness $f(X_i)$ for the initial solution;
4. for each iteration $t$ until convergence do
   5. for each individual $i \in \{1..N\}$ do
      6. Randomly select three distinct individuals $a, b, c \in \{1..N\}$;
      7. Generate trial vector $V_i(t)$ using the mutation strategy (e.g., $V_i(t) = X_i + F \cdot (X_b - X_a)$);
      8. Clip elements of $V_i(t)$ to ensure they are within the solution space;
      9. Perform binomial crossover between $X_i$ and $V_i(t)$ to produce the offspring $U_i(t)$;
      10. Evaluate fitness $f(U_i(t))$ using Eq. (5);
      11. if $f(U_i(t)) \leq f(X_i)$ then
          12. Update individual $X_i$ with the offspring $U_i(t)$;
   6. Update Position
   7. Update Velocity
   8. Stop criteria met
   9. End Algorithm
10. Return the best solution found during the optimization process;

3.1. Results of non-optimized PI controller for speed control in EVs

During the manual tuning stage outlined in Section 2.1, the Simulink model was configured to furnish the Proportional–Integral (PI) controller with the EV’s speed reference over time, as illustrated in Fig. 1. The process involved tuning the proportional $K_p$ and integral $K_i$ gains using the PID Tuner App in Simulink. Initially, the integral and derivative gains were set to zero to establish a baseline for subsequent adjustments. Subsequently, the $K_p$ gain was incrementally increased until the control loop’s output stabilized at a consistent pace. To mitigate the steady-state error between the measured and reference vehicle speeds, the integral term $K_i$ was introduced, and both gains were fine-tuned based on the tuner App’s response.

Following this manual tuning procedure, the $K_p$ and $K_i$ parameters were set, and the simulation was executed with the chosen speed reference throughout the duration. A Hall Effect Sensor was employed to monitor the vehicle’s speed at each time step in the simulation model. The observed speed was fed into the three-phase inverter to adjust the motor speed accordingly. Throughout the simulation, the measured vehicle speed from the Hall Effect Sensor was compared with the speed reference to evaluate the performance of the manually adjusted PI controller. The results depicting the actual and measured speeds of the vehicle over the given period are presented in Fig. 7.

Concerns regarding the efficacy of the manually adjusted PI controller were raised upon calculating the mean square error between the actual and measured vehicle speeds, yielding an approximate value of 3.8 throughout the entire duration. This observation underscores the inherent limitations of manual tuning methods, particularly in dynamically changing road conditions. As road conditions vary, the manually optimized parameters may no longer be optimal, leading to sub-optimal control performance and increased energy consumption.

The significant mean square error observed, particularly during road conditions involving uphill climbs and downhill descents, highlights the challenge posed by varying terrain. The Ziegler–Nichols method, employed in the manual tuning approach, struggled to adequately adjust the PI controller parameters to accommodate these changing conditions. This inadequacy resulted in a sub-optimal response to sudden
fluctuations in vehicle speed, leading to inaccuracies in speed control and a large MSE. Specifically, Fig. 7 shows significant discrepancies between the actual and measured speed are evident during two distinct time spans: from 1 to 10 and from 50 to 60. These discrepancies are indicative of the inefficiency of the Ziegler–Nichols method in accurately tuning the PI controller to match varying road conditions.

Consequently, the manual tuning approach proved inefficient in managing these fluctuations, resulting in increased energy usage. Hence, a more adaptable control approach is necessary in light of these limitations. Subsequent sections of this work propose the application of optimization techniques to fine-tune the settings of the PI controller, addressing these challenges and enhancing speed control accuracy and energy efficiency. Specifically, optimization techniques like PSO and DE offer superior performance by dynamically adjusting the PI controller parameters based on real-time driving conditions, thereby optimizing speed control accuracy and energy efficiency in diverse scenarios.

3.2. Results of optimized PI controller for speed control in EVs

In this section, to improve the speed control precision of EVs, the results obtained after optimizing the PI controller parameters using PSO and DE. The main aim is to minimize the MSE of vehicle speed, considering dynamic weighting based on driving conditions, as detailed in Objective Function 1. The optimization process utilized PSO and DE to parameterize the PI controller gains, focusing on reducing MSE between actual and measured vehicle speed from simulation environment in simulink. Notably, the dynamic weighting scheme adjusted the emphasis on speed deviation reduction based on road gradient, ensuring optimal control in varying terrains. Three scenarios were considered to examine the controller’s performance under various road conditions, with iterations ranging from 10 to 30. For validation, specific time spans from the graph in Figs. 8(a), 8(b) and 8(c) were chosen, representing time spans of (0 to 1.5), (10 to 10.4), (51 to 51.5), and (114 to 114.7). It is evident from the figures that as the number of iterations increased, the results obtained from the optimized PI controller improved. Moreover, the results obtained from the DE-based PI controller were superior to its counterpart, the PSO-based PI controller. There was a significant decrease in error at all four points when comparing results between PSO and DE, highlighting DE’s superior performance in these settings.

3.3. Results of optimized PI controller for energy efficiency in EVs

To enhance the energy efficiency of Electric Vehicles (EVs), an energy management strategy was implemented, utilizing Objective Function 2: “Minimize Energy Consumption with Dynamic Weighting” (Eq. (4)). This function adapts the optimization process in real-time based on driving conditions, prioritizing energy conservation during demanding situations. Simulation results depicted in Fig. 9 showcase the impact of optimization techniques on energy consumption. Compared to manual tuning, both PSO and DE optimizations effectively minimized energy usage. Notably, DE demonstrated lower consumption, especially in challenging driving scenarios. These results highlight the effectiveness of optimization algorithms in dynamically adjusting PI controller settings to achieve superior energy efficiency across various driving conditions.

The simulation environment ran from time 0 to 150, during which the proposed energy management strategy for EVs performed very well. The results of DE were better than PSO throughout the simulation period. A dip in the graph from (120 to 140) simulation time indicates the change in road conditions from uphill to downhill, resulting in reduced energy consumption. When comparing Figs. 8 and 9, it is evident that the dip in energy consumption in Fig. 9 corresponds with a decrease in the speed of the EV during the same time period of the simulation.

3.4. Results of multi-objective optimization of PI controller for both motor speed and energy efficiency

This section presents the outcomes of our framework that integrates optimized speed control methodology and energy consumption optimization into a unified multi-objective optimization framework. This approach balances the dual objectives of enhancing speed control accuracy and minimizing energy consumption in EVs. Our methodology dynamically adjusts the parameters of the PI controller based on real-time vehicle input data to achieve optimal speed control while conserving energy. The simulated vehicle data, including measured speed, reference speed, and time, is processed in MATLAB, where the Mean Squared Error (MSE) between desired and measured vehicle speed and energy consumption is calculated as the objective function for swarm-based optimization algorithms.

A comprehensive analysis of the performance of the PI controller under various optimization configurations, are summarized in Table 2. Different optimization techniques (DE and PSO) and iteration counts (10, 20, and 30) are explored to determine their impact on PI parameters and performance metrics. The findings demonstrate that DE consistently yields PI parameter values conducive to improved energy
Fig. 7. Comparison of actual vs. measured speed with non-optimized PI controller (Ziegler–Nichols Method).

Fig. 8. Comparison of optimized controller using proposed multi-objective PSO vs. DE based on speed control.

(a) 10 iterations of PSO and DE  
(b) 20 iterations of PSO and DE  
(c) 30 iterations of PSO and DE

Fig. 9. Comparison of optimized controller using proposed multi-objective PSO vs. DE based on energy efficiency (30 iterations).
Table 2
Comparison of different methods (with learned Kp, Ki values) based on vehicle speed error (MSE) and energy consumption (kWh).

<table>
<thead>
<tr>
<th>Algorithm Configuration</th>
<th>PI Parameters</th>
<th>Performance Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Proportional Gain (Kp)</td>
<td>Integral Gain (Ki)</td>
</tr>
<tr>
<td>Without Optimization</td>
<td>0.0141</td>
<td>0.1891</td>
</tr>
<tr>
<td>PSO Optimization (10 Iterations)</td>
<td>0.2</td>
<td>4.72</td>
</tr>
<tr>
<td>DE Optimization (10 Iterations)</td>
<td>0.2761</td>
<td>4.7914</td>
</tr>
<tr>
<td>PSO Optimization (20 Iterations)</td>
<td>0.212</td>
<td>4.83</td>
</tr>
<tr>
<td>DE Optimization (20 Iterations)</td>
<td>0.2347</td>
<td>4.9873</td>
</tr>
<tr>
<td>PSO Optimization (30 Iterations)</td>
<td>0.24</td>
<td>5.0146</td>
</tr>
<tr>
<td>DE Optimization (30 Iterations)</td>
<td>0.2207</td>
<td>5.3746</td>
</tr>
</tbody>
</table>

Fig. 10. Comparison of optimized PI Controller using proposed multi-objective DE vs. PSO based on MSE of vehicle speed (with different iterations).

Similarly, the energy consumption comparison graph, depicted in Fig. 11, contrasts the energy consumption between PSO and DE across 10, 20, and 30 iterations. As shown in the graph, both PSO and DE exhibit a decreasing trend in energy consumption as the iteration count increases, reflecting the iterative refinement process. However, notable differences emerge in their performance: PSO yields energy consumption values of 1.006, 0.993, and 0.992 kWh for 10, 20, and 30 iterations, respectively. In contrast, DE achieves significantly lower energy consumption values of 1.004, 0.9857, and 0.984 kWh for the same iteration counts. This substantial discrepancy underscores DE’s superior ability to minimize energy consumption, consistently outperforming PSO across all iterations. Such efficiency in energy conservation highlights DE’s potential to enhance energy efficiency in EV applications.

In the existing BLDC motor controller, the efficiency in terms of speed control is typically measured by the MSE between the desired and actual speed of the motor. For our comparison, we have considered the Ziegler–Nichols method as the baseline method, and we denote the MSE of this baseline method as $MSE_{baseline}$. For the proposed method, denoted as $MSE_{proposed}$, we have observed an improvement in speed control efficiency. The improvement percentage is calculated using the formula:

\[
\text{Improvement Percentage} = \frac{MSE_{baseline} - MSE_{proposed}}{MSE_{baseline}} \times 100
\]
various applications. The challenges associated with achieving precise and efficient speed control using a swarm-based approach, our study contributes to overcoming the field of control systems. By optimizing the PI controller settings, our proposed multi-objective constrained swarm-based simulations and comparative analyses with the conventional Ziegler–Nichols baseline method. It is noteworthy that for the proposed method, the percentage improvement in energy efficiency is calculated as:

\[
\text{Energy Efficiency Improvement (\%)} = \frac{\text{Energy}_{\text{baseline}} - \text{Energy}_{\text{proposed}}}{\text{Energy}_{\text{baseline}}} \times 100
\]

By applying these calculations to our experimental results, we demonstrate the effectiveness of our approach compared to the Ziegler–Nichols baseline method. It is noteworthy that for the proposed method, we have chosen the values of DE with 30 iterations, which represent the best results achieved.

Future research directions include addressing the acknowledged limitations of the study. This entails exploring the integration of advanced machine learning techniques like deep learning or reinforcement learning to enhance BLDC motor speed control. Neural networks, in particular, are deep learning algorithms that can extract complex patterns and representations from massive amounts of information. Deep learning models can be trained on enormous volumes of motor operational data in the context of BLDC motor speed control to identify complex characteristics and correlations that might not be readily apparent using conventional approaches automatically. Based on the motor’s present operating circumstances, these models can forecast the best control signals or modify the controller’s settings in real-time. Researchers can create more precise and adaptable speed control techniques that enhance overall motor performance and efficiency by utilizing deep learning. A subfield of machine learning called reinforcement learning (RL) focuses on discovering the most effective standards for making decisions by experimenting and interacting with the environment. RL algorithms can be trained to optimize control actions in the context of BLDC motor speed control by engaging directly with the motor system and getting feedback on the obtained performance. RL agents have the ability to investigate many control techniques, adjust to fluctuating operating circumstances, and optimize long-term performance goals like energy efficiency or precision in speed regulation. Future studies can investigate novel and adaptive control strategies that gradually enhance the performance of BLDC motor speed control by utilizing RL algorithms.

Additionally, there is a potential to apply the proposed optimization approach to other electric vehicle control areas, such as battery management or regenerative braking systems. For battery management, the proposed optimization methods can be applied to develop dynamic charging strategies, improve State of Charge (SoC) and State of Health (SoH) estimation accuracy, optimize thermal management, and enhance cell balancing techniques. Similarly, in regenerative braking systems, optimization techniques can maximize energy recovery during braking, enable adaptive control based on real-time factors, and integrate with vehicle dynamics for enhanced performance. By implementing these advanced control strategies, researchers can improve overall vehicle efficiency, range, and sustainability.

Fig. 11. Comparison of optimized PI Controller using proposed multi-objective DE vs. PSO based on energy consumption (with different iterations).

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Furthermore, it is essential to conduct experimental validation to evaluate the real-world effectiveness of the proposed decentralized control strategies. This involves testing the optimized control algorithms in practical EV systems to validate their performance under various operating conditions and scenarios. Additionally, addressing scalability issues is crucial to ensure that the control strategies can be efficiently implemented in large-scale electric vehicle fleets. By conducting experimental validation and addressing scalability concerns, researchers can further enhance EV technology by ensuring that the proposed control
strategies are robust, reliable, and scalable for widespread adoption in the automotive industry.

**CRediT authorship contribution statement**

**Syed Shehryar Ali Naqvi**: Writing – original draft, Validation, Software, Investigation, Conceptualization. **Harun Jamil**: Methodology. **Naeem Iqbal**: Conceptualization. **Salabat Khan**: Project administration, Investigation. **Dong-In Lee**: Resources. **Youn Cheol Park**: Funding acquisition. **Do Hyeun Kim**: Supervision.

**Declaration of competing interest**

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Do Hyeun Kim reports financial support was provided by Jeju National University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Data availability**

I have shared the link of Github repository for my code and data.

**Acknowledgments**

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**Appendix A**

**PID Controller**

A proportional–integral–derivative controller (PID controller) is a feedback control mechanism commonly utilized in industrial control systems and several other applications that require constantly modulated control. The system takes in two main pieces of information: Input r(t): This is the desired value or target you want the system to achieve, like a specific temperature or speed. Output y(t): This is the current measured value of the system, such as the actual temperature or speed.

**Importance of using BLDC Motor in EV**

In the context of electric vehicle (EV) propulsion, the choice of the electric motor plays a pivotal role in determining the overall performance, efficiency, and user experience of the vehicle. Among the five common electric motor types, the details of which are listed in Table 3, the BLDC motor emerges as an optimal choice due to its alignment with specific performance requirements and efficiency. With a high power density and efficient torque production across a broad range of speeds, BLDC motors can offer the desired acceleration, speed, and responsiveness required for modern EVs.

- **High Efficiency**: BLDC motors exhibit high efficiency across various operating conditions, ensuring effective energy utilization and minimizing losses.
- **Power Density**: The design of BLDC motors allows for a compact size and lightweight construction, leading to a high power-to-weight ratio.
- **Long Lifespan**: The absence of brushes in BLDC motors eliminates mechanical wear, contributing to longer operational lifespans and reduced maintenance requirements.
- **Regenerative Braking**: BLDC motors facilitate regenerative braking, converting kinetic energy into electrical energy during deceleration, thereby enhancing energy recuperation.

**Analysis of BLDC Motor in EV**

A BLDC motor is analyzed with a series of simplifying assumptions to maintain a balance between accuracy and computational feasibility. Collectively, these assumptions provide a foundation for creating a mathematical model that adequately represents the motor’s behavior. The BLDC motor is considered to operate in a region where magnetic saturation effects are negligible. This implies that the magnetic properties of the motor’s core material remain linear under the applied magnetic field. It is assumed that the resistances of all stator windings are identical. This assumption eases calculating the current distribution among the different phases and simplifies the overall analysis. Both self-inductance (inductance of a winding concerning itself) and mutual inductance (inductance between different windings) are constants throughout the motor’s operational range. This simplification allows for consistent modeling of the motor’s electromagnetic behavior. The electronic switches within the motor’s inverter, typically made from semiconductors, are ideal. This implies that they have no losses and switch instantaneously, simplifying the analysis of the inverter’s impact on motor performance. The back electromotive force (back-EMF) waveforms produced in all motor phases are considered identical. This simplifying assumption helps streamline the analysis of the motor’s behavior, as it assumes uniformity in the electrical characteristics of different motor phases.

In motor dynamics, the fundamental voltage equation is expressed as follows (Abkenar et al., 2014):

$$V = Ri + L \frac{di}{dt} + E$$  \hspace{1cm} (10)

where $V$ represents the voltage applied to the motor terminals, $R$ denotes the resistance, $L$ signifies the inductance, $i$ represents the current, $\frac{di}{dt}$ denotes the rate of change of current with respect to time, and $E$ stands for the back electromotive force (EMF).

Assuming a standard 3-phase Brushless DC (BLDC) motor with phases A, B, and C, the voltage equations for each phase are given by:

$$V_A = R_Ai_A + L_A \frac{di_A}{dt} + M_A \frac{dE_A}{dt} + E_A$$  \hspace{1cm} (11)

$$V_B = R_Bi_B + L_B \frac{di_B}{dt} + M_B \frac{dE_B}{dt} + E_B$$  \hspace{1cm} (12)

$$V_C = R_Ci_C + L_C \frac{di_C}{dt} + M_C \frac{dE_C}{dt} + E_C$$  \hspace{1cm} (13)

where $V_A$, $V_B$, and $V_C$ denote the phase voltages of the three stator windings; $R_A$, $R_B$, and $R_C$ represent the stator winding resistances; $L_A$, $L_B$, and $L_C$ signify the stator self-inductances; $i_A$, $i_B$, and $i_C$ denote the phase currents; $M_A$, $M_B$, $M_C$, $M_A$, and $M_C$ represent the mutual inductances between stator windings; and $E_A$, $E_B$, and $E_C$ denote the trapezoidal back electromotive forces (EMFs) in the stator windings.

The relationship between the currents in the individual phases in a balanced three-phase stator winding system ensures that the sum of all phase currents is zero:

$$i_A + i_B + i_C = 0$$  \hspace{1cm} (14)

The Eqs. (11) to (13) can be rewritten as Abkenar et al. (2014):

$$V_A = R_Ai_A + L_A \frac{di_A}{dt} + M_A \frac{dE_A}{dt} + E_A$$  \hspace{1cm} (15)

$$V_B = R_Bi_B + L_B \frac{di_B}{dt} + M_B \frac{dE_B}{dt} + E_B$$  \hspace{1cm} (16)

$$V_C = R_Ci_C + L_C \frac{di_C}{dt} + M_C \frac{dE_C}{dt} + E_C$$  \hspace{1cm} (17)
Each parameter in the Eqs. (10) to (19) is defined and explained as follows:

- $V$: Applied voltage
- $R$: Resistance of the motor winding
- $L$: Inductance of the motor winding
- $E$: Back electromotive force (EMF) generated by the motor
- $i$: Current flowing through the motor winding
- $M$: Mutual inductance between motor windings
- $\theta$: Rotor angular position
- $\omega$: Angular velocity of the rotor

The voltage Eqs. (15) to (17) can be expressed in state space as:

$$
\begin{bmatrix}
V_A \\
V_B \\
V_C
\end{bmatrix} = 
\begin{bmatrix}
R & 0 & 0 \\
0 & R & 0 \\
0 & 0 & R
\end{bmatrix} 
\begin{bmatrix}
i_A \\
i_B \\
i_C
\end{bmatrix} + 
\begin{bmatrix}
(L - M) & 0 & 0 \\
0 & (L - M) & 0 \\
0 & 0 & (L - M)
\end{bmatrix} 
\begin{bmatrix}
in_A \\
in_B \\
in_C
\end{bmatrix} + 
\begin{bmatrix}
E_A \\
E_B \\
E_C
\end{bmatrix}
$$

(18)

The mechanical variables of the BLDC motor, namely rotor angular position $\theta$ and angular velocity $\omega$, are related by the equation:

$$
\omega = \frac{d\theta}{dt}
$$

(19)

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\end{bmatrix} = 
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0 & 0 & R
\end{bmatrix} 
\begin{bmatrix}
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i_B \\
i_C
\end{bmatrix} + 
\begin{bmatrix}
(L - M) & 0 & 0 \\
0 & (L - M) & 0 \\
0 & 0 & (L - M)
\end{bmatrix} 
\begin{bmatrix}
in_A \\
in_B \\
in_C
\end{bmatrix} + 
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\end{bmatrix}
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References

Abkenar, A.T., et al., 2014. BLDC Motor Drive Controller for Electric Vehicles (Doctor of Philosophy Thesis). Faculty of Science, Engineering and Technology Swinburne University of Technology.


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i_A \\
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\end{bmatrix} + 
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(L - M) & 0 & 0 \\
0 & (L - M) & 0 \\
0 & 0 & (L - M)
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\begin{bmatrix}
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in_C
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E_B \\
E_C
\end{bmatrix}
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- $\theta$: Rotor angular position
- $\omega$: Angular velocity of the rotor

Table 3

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Motor</th>
<th>Performance Measure</th>
<th>Cost</th>
<th>Efficiency</th>
<th>Advantages</th>
<th>Disadvantages</th>
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<tbody>
<tr>
<td>Yang et al. (2020)</td>
<td>Induction Motor (IM)</td>
<td>Basic performance</td>
<td>Lower</td>
<td>&gt;90</td>
<td>&gt;90</td>
<td>Simple design, Robust, Lower Cost</td>
</tr>
<tr>
<td>Ulu et al. (2017)</td>
<td>BLDC Motor</td>
<td>High power, Efficiency</td>
<td>Moderate</td>
<td>&gt;95</td>
<td>70–80</td>
<td>High efficiency, High power density, Long lifespan</td>
</tr>
<tr>
<td>Hashemnia and Aseai (2008)</td>
<td>Switched Reluctance Motor (SRM)</td>
<td>Basic performance</td>
<td>Lower</td>
<td>&lt;95</td>
<td>&gt;90</td>
<td>Robust design, Simple structure, Lower manufacturing cost</td>
</tr>
<tr>
<td>Aneku et al. (2013)</td>
<td>Synchronous Reluctance Motor (SynRM)</td>
<td>Balanced performance</td>
<td>Moderate</td>
<td>&gt;92</td>
<td>80–85</td>
<td>High efficiency, Improved performance at high speeds, Lower rotor losses</td>
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<tr>
<td>Bianchi et al. (2016)</td>
<td>BLDC Motor</td>
<td>High power, Efficiency</td>
<td>Moderate</td>
<td>&gt;95</td>
<td>70–80</td>
<td>High efficiency, High power density, Precise control.</td>
</tr>
</tbody>
</table>

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V_B \\
V_C
\end{bmatrix} = 
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0 & R & 0 \\
0 & 0 & R
\end{bmatrix} 
\begin{bmatrix}
i_A \\
i_B \\
i_C
\end{bmatrix} + 
\begin{bmatrix}
(L - M) & 0 & 0 \\
0 & (L - M) & 0 \\
0 & 0 & (L - M)
\end{bmatrix} 
\begin{bmatrix}
in_A \\
in_B \\
in_C
\end{bmatrix} + 
\begin{bmatrix}
E_A \\
E_B \\
E_C
\end{bmatrix}
$$