Bulletin of Electrical Engineering and Informatics
Vol. 15, No. 3, June 2026, pp. 2064~2077
ISSN: 2302-9285, DOI: 10.11591/eei.v15i3.10895

FA-optimized fractional order PI control for bidirectional V2G and G2V systems with integrated subsystem management

Mohamed Shiek Mothi Ismail Mujupur, Mohamed Ismail Mohamed Mustafa
Department of Electronics and Communication Engineering, Faculty of Electrical and Communication Sciences, B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, India

Article Info

Article history:

Received Jun 21, 2025
Revised Mar 26, 2026
Accepted Apr 19, 2026

Keywords:

Battery management system
energy efficiency
Bidirectional V2G/G2V
Firefly algorithm optimization
Fractional order proportional–integral control
Multi-objective optimization
Power flow management
Smart grid integration

ABSTRACT

This paper presents a Firefly algorithm (FA)-optimized, fractional order proportional-integral (FOPI), control strategy for bidirectional vehicle-to-grid (V2G), and grid-to-vehicle (G2V) systems. The optimization focuses on minimizing key performance indices—integral of time-weighted absolute error (ITAE), integral of squared error (ISE), and integral of absolute error (IAE)—to achieve optimal dynamic response and energy efficiency. The control system incorporates converter with battery controller. The FA is employed to fine-tune the FOPI parameters, leveraging its robust global search capability to balance trade-offs between fast response, minimal overshoot, and stability. Simulation results validate the effectiveness of the proposed approach, demonstrating superior performance compared to conventional proportional–integral (PI) controllers, with ITAE reduced by 63.4% compared to PI controller. This study provides a scalable and efficient solution for advanced energy management in V2G/G2V systems, contributing to the sustainable integration of electric vehicles (EVs) with smart grids.

Corresponding Author:

Mohamed Shiek Mothi Ismail Mujupur
Department of Electronics and Communication Engineering
Faculty of Electrical and Communication Sciences
B.S. Abdur Rahman Crescent Institute of Science and Technology
Vandalur, Chennai – 600048, Tamilnadu, India
Email: md.s.mothi3@gmail.com

1. INTRODUCTION

The global transition toward sustainable energy systems has accelerated the integration of electric vehicles (EVs) into modern power grids, creating unprecedented opportunities for bidirectional energy exchange through vehicle-to-grid (V2G) and grid-to-vehicle (G2V) technologies. These systems enable EVs to function not merely as transportation assets but as distributed energy resources capable of supporting grid stability, frequency regulation, peak load shaving, and voltage control [1], [2]. The bidirectional power flow paradigm transforms EVs into mobile energy storage units that can absorb excess renewable generation during periods of low demand and supply stored energy back to the grid during peak consumption periods, thereby enhancing overall grid resilience and facilitating higher penetration of intermittent renewable energy sources [3], [4].

The operational complexity of V2G/G2V systems arises from the need to coordinate multiple subsystems with distinct dynamic characteristics while maintaining strict power quality standards and ensuring battery longevity. These subsystems include bidirectional AC-DC converters for grid interfacing, DC-DC converters for voltage regulation, battery management systems for state-of-charge (SoC) control, and protection mechanisms for grid disturbance handling [5], [6]. Each subsystem introduces nonlinearities, time delays, and parameter uncertainties that collectively challenge conventional control approaches. Traditional proportional-integral (PI) controllers, while widely adopted for their simplicity and reliability, often prove inadequate in addressing the multifaceted control requirements of modern V2G/G2V systems, particularly under dynamic operating conditions and grid disturbances [7], [8].

Fractional order proportional-integral (FOPI) controllers have emerged as a powerful alternative to integer-order controllers, offering enhanced flexibility through the introduction of fractional-order integration operators [9]. The additional tuning parameter—specifically the fractional order λ—provides greater degrees of freedom in shaping the system's frequency response and transient behavior, enabling superior handling of complex dynamics and time delays inherent in power electronic interfaces [10], [11]. Recent advances in fractional calculus applications to power systems have demonstrated significant improvements in robustness, disturbance rejection, and steady-state accuracy compared to conventional control architectures [12], [13]. However, the enhanced performance of FOPI controllers comes at the cost of increased tuning complexity, necessitating sophisticated optimization approaches to determine optimal parameter sets that satisfy multiple, often conflicting, performance objectives.

Metaheuristic optimization algorithms have gained considerable traction in power system applications due to their ability to navigate complex, nonlinear search spaces and identify globally optimal or near-optimal solutions without requiring gradient information [14]. Among these, the Firefly algorithm (FA), inspired by the bioluminescent communication behavior of fireflies, has demonstrated exceptional performance in solving multi-objective optimization problems through its inherent balance between exploration and exploitation [15]. The algorithm, originally formulated by Yang [16], relies on an attractiveness-based search mechanism that enables efficient convergence toward global optima while maintaining population diversity, making it particularly suitable for tuning controller parameters in systems with multiple performance criteria. Comparative studies have confirmed that FA consistently outperforms established algorithms such as particle swarm optimization (PSO) and genetic algorithms (GA) in terms of convergence speed and solution quality for power electronic control applications [17], [18].

Recent research has increasingly focused on the application of advanced optimization techniques to EV charging and V2G/G2V system control. Heydari-doostabad and O'Donnell [5] demonstrated a wide-range high-voltage-gain bidirectional DC-DC converter for V2G and G2V hybrid EV charging with dead-beat current control, confirming the critical role of converter topology and control strategy on system efficiency. Subramanian and Sudhakar [12] proposed a golden eagle optimization-based FOPI controller for a PFC SEPIC converter in EV charging applications, reporting significant improvements in inrush current limitation and settling time over conventional PI controllers. Thaliyadath *et al.* [9] presented a FOPI controller for a DC-DC converter for EV DC fast charging applications, validating improved transient response and steady-state regulation over integer-order PI controllers under dynamic load conditions.

The control objectives in V2G/G2V systems encompass multiple performance indices that must be simultaneously optimized to achieve satisfactory system behavior. The integral of time-weighted absolute error (ITAE) emphasizes steady-state accuracy and penalizes persistent errors, the integral of absolute error (IAE) provides a direct measure of cumulative tracking error, and the integral of squared error (ISE) heavily penalizes large deviations, making it particularly sensitive to overshoot and transient excursions [19]. The simultaneous minimization of these indices presents a classic multi-objective optimization challenge, where trade-offs must be carefully balanced to achieve acceptable performance across all metrics. Joseph *et al.* [14] provided a comprehensive review confirming that weighted-sum formulations of IAE, ISE, and ITAE are among the most effective objective functions for metaheuristic-based PID tuning across diverse engineering applications. Weighted sum approaches combined with robust metaheuristic optimization offer a practical framework for addressing this multi-objective nature while maintaining computational tractability for real-time or offline controller design [20].

The battery management system (BMS) is an indispensable component of V2G/G2V architectures, responsible for monitoring SoC, state-of-health (SOH), and temperature to ensure safe and efficient energy exchange. Accurate SoC estimation directly affects the reliability and energy efficiency of bidirectional charging operations [21]. Grid integration of EVs also demands robust power factor correction during AC-DC conversion to comply with power quality standards and minimize harmonic injection under variable load conditions [22]. Furthermore, the review of bidirectional charger topologies highlights that coordinated subsystem control remains a key challenge for large-scale V2G/G2V deployment [23].

Despite the growing body of literature on V2G/G2V control systems, several research gaps persist. The integrated optimization of multiple subsystems within a unified control framework remains underexplored, with most studies focusing on individual converter stages or isolated battery management functions [24]. Additionally, the application of FA-optimized FOPI controllers to comprehensive V2G/G2V architectures incorporating connection control, bidirectional conversion, voltage regulation, and battery switching has received limited attention in the literature [25]. The present study addresses these gaps by proposing a holistic control framework wherein a single FOPI controller, optimized via FA, coordinates the operation of five critical subsystems: connection control for grid synchronization, DC-AC/AC-DC converters for bidirectional power flow, buck-boost converters for voltage matching, DC-DC converters with integrated battery controllers for charge management, and battery switching control for optimal pack utilization. The optimization objective function combines ITAE, IAE, and ISE with equal weighting, ensuring balanced consideration of transient response, steady-state accuracy, and disturbance rejection.

The contributions of this paper are threefold: i) development of a comprehensive mathematical model integrating five V2G/G2V subsystems into a unified control framework, ii) application of FA for multi-objective optimization of FOPI controller parameters targeting combined ITAE-IAE-ISE minimization, and iii) comparative performance evaluation against conventional PI and standard FOPI controllers under identical operating conditions. The remainder of this paper is organized as follows: section 2 presents detailed materials and methodology of the system, section 3 describes results and discussion in detail, and section 4 concludes with key findings and directions for future research.

2. MATERIALS AND METHOD

2.1. System model

The system model for the FA-optimized fractional order PI control for bidirectional V2G and G2V systems involves five key subsystems, each with its own dynamic characteristics and control requirements. The performance and coordination of these subsystems are crucial for achieving optimal energy management and system stability. Figure 1 illustrates the bidirectional power flow in an EV charging and discharging system. The grid supplies three-phase AC power, which is converted into conditioned AC via a transformer. This power is managed by a wall charger connection box, which converts AC to DC power to charge the EV battery. The battery system provides real-time feedback on parameters such as SoC, voltage, and current. During V2G or G2V operations, DC power from the battery can be inverted to AC power and sent back to the grid or used for local load consumption. The system ensures efficient energy transfer and supports grid stability by leveraging energy stored in the EV battery.

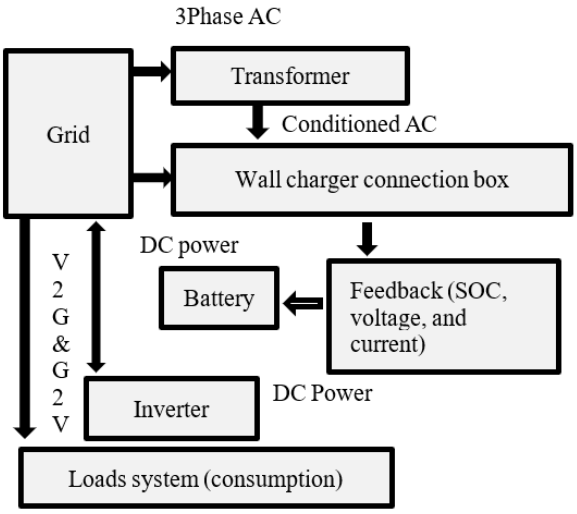

Figure 1. Schematic diagram of a bidirectional EV charging and discharging system, highlighting components for energy transfer and feedback control

2.1.1. Connection control

The connection control subsystem is responsible for managing the interface between the EV and the power grid. It ensures proper synchronization between the EV and the grid before energy transfer can occur. This includes managing the start-up and shut-down sequences, as well as ensuring that voltage and frequency are matched between the vehicle and the grid. Proper connection control is essential to prevent damage to the system or the EV battery due to mismatched parameters. In a typical V2G/G2V system, this subsystem also includes protection mechanisms against grid disturbances such as voltage spikes, frequency fluctuations, and current surges. The connection control subsystem must ensure safe, reliable, and seamless integration of the EV with the grid.

2.1.2. DC-AC/AC-DC converter

The DC-AC/AC-DC converter subsystem is a critical bidirectional interface between the EV and the grid. In V2G mode, it performs DC-AC conversion, transforming battery DC power into grid-compatible AC power. In G2V mode during charging, it executes AC-DC conversion, rectifying grid AC power into regulated DC suitable for battery charging. This bidirectional capability forms the fundamental energy transfer interface, making converter design, and control essential to overall system performance and efficiency.

Figure 2 illustrates the dynamic variation of SoC, battery current (Ib), and battery voltage (Vb) under 600 psi operating conditions. The SoC remains nearly constant with minor fluctuations, while the current profile shows a transient spike followed by stabilization. The voltage response demonstrates a short disturbance and rapid settling, indicating stable system behavior under the applied pressure. Figure 3 presents the three-phase waveform characteristics. The voltage and current waveforms exhibit sinusoidal behavior with a transient disturbance around the switching instant, followed by smooth steady-state oscillations. For both conversion processes, the converter needs to operate efficiently to minimize power losses and maintain the stability of the voltage and frequency. Modeling of this subsystem typically involves the use of pulse width modulation (PWM) techniques to control the switching of semiconductors in the converter to ensure efficient energy conversion.

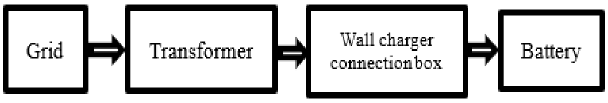

Figure 2. EV battery charging process from the grid

Figure 3. Discharging process from the EV battery to the grid using an inverter

2.1.3. Buck-boost converter

The buck-boost converter provides additional flexibility to the system by adjusting the voltage level to match the required input/output range. This subsystem is particularly important in V2G scenarios where the vehicle’s battery voltage may not be the same as the grid voltage. It can either step down (buck) or step up (boost) the voltage to maintain a stable and efficient energy flow. This converter also plays a role in power factor correction (PFC) by adjusting the input current waveform to align with the grid’s voltage waveform, thereby improving energy efficiency.

2.1.4. DC-DC converter with battery controller

The DC-DC converter with battery controller is essential for regulating the power flow between the vehicle's battery and the grid. This subsystem ensures that the battery operates within safe charge/discharge limits, preventing overcharging or deep discharging, which could lead to battery degradation or failure. The battery management system (BMS) within this subsystem monitors the SoC, state of health (SOH), and temperature of the battery cells. The DC-DC converter adjusts the power sent to the battery to match the voltage and current characteristics needed to charge or discharge safely.

2.1.5. Battery switching control

In EVs with multiple battery packs or battery modules, the battery switching control subsystem ensures that the most appropriate battery pack is used for charging or discharging. This helps optimize the battery's operational life by distributing the load evenly across the packs and preventing excessive strain on individual modules. The switching mechanism is typically based on factors such as SoC, SOH, and temperature to determine which pack is best suited for the current power requirements. By intelligently switching between battery packs, the system can ensure that the EV remains functional while maximizing the efficiency of the battery packs and enhancing their longevity.

The integration of these subsystems into a cohesive V2G/G2V system requires an advanced control strategy to manage the interaction between them. The fractional order PI controller, optimized using the FA, provides a flexible approach for tuning control parameters that can handle nonlinearities and complex interactions between the subsystems.

The optimization process considers multiple objectives, such as minimizing energy losses ITAE, stabilizing grid voltage IAE, and improving energy efficiency ISE. The FA is used to optimize the fractional order PI controller, ensuring that the system performs optimally under varying load conditions and that the power flow between the EV and the grid is balanced and stable.

The coordination of these subsystems is crucial for achieving efficient and reliable energy management, with the fractional order PI controller providing an advanced solution for complex dynamic systems. The FA optimization enhances performance by fine-tuning control parameters, ensuring that the system adapts to real-time conditions and operates efficiently over the long term.

Mathematical modelling of each subsystem in bidirectional V2G/G2V system. The bidirectional V2G and G2V system consists of various subsystems, each responsible for specific tasks. Figure 4 shows a high-level control and power flow system connecting a grid to a battery storage unit. The process begins with the grid supplying energy, which is managed by a connection control system. The energy then flows into a converter integrated with a battery controller, responsible for regulating power conversion and ensuring compatibility with the battery. Following this, the battery switching control system directs energy into the battery, facilitating efficient charging or discharging based on demand.

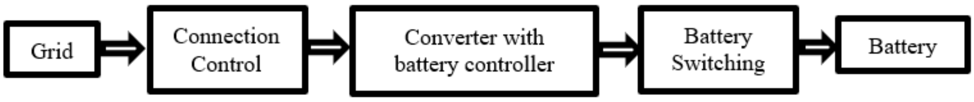

Figure 4. Flow diagram of grid-to-battery energy management system showcasing connection control, converter with battery controller, and battery switching control

2.2.1. Connection control

The connection control subsystem ensures proper synchronization of the EV with the power grid. It involves determining when the vehicle can either supply power V2G or absorb power G2V without causing damage to either the grid or the vehicle's battery. This subsystem is typically modeled using the as:
Synchronization conditions:

$$\mathrm{V_{grid}} = \mathrm{V_{EV}(t)}, \mathrm{F_{grid}(t)} = \mathrm{f_{EV}(t)}$$

where $\mathrm{V_{grid}(t)}$ and $\mathrm{F_{grid}(t)}$ are the voltage and frequency of the grid at time t and $\mathrm{V_{EV}(t)}$ and $\mathrm{f_{EV}(t)}$ are the voltage and frequency of the EV at time t.
Start-up control involves a threshold voltage and frequency match for safe grid connection:

$$\left|V_{grid} - V_{EV}\right| < \epsilon \text{ and } \left|f_{grid} - f_{EV}\right| < \epsilon$$

where ϵ is a small tolerance margin, typically within a few volts and Hz.

Connection protection models transient behaviors to protect against sudden disturbances (overvoltage and underfrequency): $\dot{V}_{grid}(t), \dot{f}_{grid}(t)$ should be bounded.

2.2.2. DC-AC/AC-DC converter

The DC-AC/AC-DC converter is responsible for converting the power between the vehicle and the grid. For bidirectional flow, the converter models for both V2G and G2V are as follows:
- DC-AC (V2G): $P_{DC}=V_{DC}\,I_{DC}$ ⇒ $V_{AC}=k.V_{DC}$ where k is the conversion factor.
- AC-DC (G2V): $P_{AC}=V_{AC}\,I_{AC}$ ⇒ $V_{DC}=k'.V_{AC}$ where k' is the conversion factor.

In this, V_{DC} and I_{DC} are the voltage and current on the DC side (EV battery side), while V_{AC} and I_{AC} are the AC parameters (grid side). These models are governed by power electronics equations, which can be modeled by PWM techniques.

2.2.3. Buck-boost converter

The buck-boost converter adjusts the voltage to ensure that the EV's battery voltage matches the grid requirements, whether in V2G or G2V mode. The mathematical model for a buck-boost converter is typically:

$$V_{out} = \frac{V_{in}}{1+L_{eff}C_{eff}}$$

where V_{in} is the input voltage (from EV battery or grid) and L_{eff} and C_{eff} are the effective inductance and capacitance that define the converter's dynamics.
The converter can either step-up or step-down voltage, ensuring smooth energy transfer between the battery and the grid.

2.2.4. DC-DC converter with battery controller

The DC-DC converter, paired with the BMS, ensures that the EV battery operates within safe parameters during charging or discharging. The mathematical model for the DC-DC converter with battery control is as:

$$P_{DC-DC} = V_{DC}\, I_{DC}$$

where V_{DC} is controlled by the BMS to maintain safe SoC levels.
The battery controller models include:
– SoC:

$$SoC(t) = SoC(t-1) + \left(\frac{I_{DC}}{C_{bat}}\right)\Delta t$$

Where C_{bat} is the battery capacity and Δt is the time step.
– SOH

SOH modeling considers battery degradation over time, including temperature effects and charge-discharge cycles:

$$SOH(t) = SOH(t-1) - \text{degradation factor}.\Delta t$$

2.2.5. Battery switching control

The battery switching control ensures the optimal utilization of multiple battery packs, preventing overstrain on individual packs. It can be modeled as:
– State switching control:

$$B_{switch}(t) = \text{argmax}(SoC(t), SOH(t), T_{battery})$$

Where B switch (t) selects the optimal battery based on state of charge, health and temperature.
The battery switching strategy can be expressed as an optimization problem:

$$min(\sum(Energy\ Loss\ + Degradation))$$

2.2.6. Interconnection of subsystems

The subsystems within the V2G/G2V system operate in a coordinated manner through real-time communication to ensure stable and efficient energy transfer. Connection control initiates and terminates power exchange between the EV and the grid, while DC-AC/AC-DC converters enable bidirectional power flow with regulated voltage and current levels. The buck-boost converter adjusts voltage as required by either the grid or the vehicle's battery, and the DC-DC converter with battery controller ensures the battery operates within optimal parameters. Battery switching control further maximizes battery life and efficiency by dynamically selecting the most suitable battery pack for the current load. All these subsystems communicate in real-time, coordinated by a central FOPI controller whose parameters are optimized using the FA to minimize performance indices including ITAE, ISE, and IAE.

2.3. Control objectives in V2G and G2V systems

The control of V2G and G2V systems involves achieving a balance of several critical objectives to ensure optimal system performance. The key control objectives typically focus on minimizing energy losses, stabilizing voltage, and enhancing overall system efficiency. These objectives are intertwined and must be addressed in a coordinated manner to ensure both grid stability and efficient energy utilization.

2.3.1. Minimizing energy losses

Energy losses are a significant factor in any power system, particularly in V2G/G2V applications where energy is transferred between the vehicle and the grid. Minimizing these losses improves the overall efficiency of the system, reduces operating costs, and enhances the sustainability of the grid.

Power losses in conversion: both DC-AC and AC-DC converters are inherently lossy due to the non-ideal nature of power electronics. These losses can be represented by:

$$P_{loss} = I^2 R$$

where R is the resistance of the converter and I is the current.

Minimizing energy losses can be achieved by optimizing the converter control strategies, such as the duty cycle in PWM or through better design of the converter's components to reduce resistive losses.

Battery losses: in both charging and discharging modes, the battery experiences losses due to internal resistance and inefficiencies in energy transfer. These losses can be modeled as:

$$P_{\text{battery loss}} = I^2_{\text{battery}}\ R_{\text{battery}}$$

Reducing battery losses involves optimal charging/discharging strategies, ensuring the current does not exceed optimal levels for efficiency, and managing battery health (SoC, SOH, and temperature) to avoid overcharging and undercharging.

Optimization techniques: the use of optimization algorithms like the FA can significantly reduce energy losses by fine-tuning control parameters for each subsystem to minimize the energy loss functions (ITAE, ISE, and IAE).

2.3.2. Stabilizing voltage

Maintaining stable voltage throughout the power transfer process is critical for both the grid and the vehicle, as voltage instability can lead to power quality issues, grid failures, or damage to the vehicle's battery and electronics. In V2G mode, the vehicle must ensure that the voltage it supplies matches the grid's requirements, with the DC-AC converter precisely controlling output voltage to avoid spikes or sags that could destabilize the grid. During G2V charging, the AC-DC converter regulates input voltage from the grid to ensure the battery receives the correct DC voltage for safe charging, preventing over-voltage or under-voltage conditions that could reduce battery lifespan and introduce inefficiencies. Voltage regulation is achieved through coordinated strategies: in G2V mode, the DC-DC converter adjusts voltage to the optimal charging level for the battery, while in V2G mode, the connection control subsystem ensures voltage synchronization between the EV and the grid before power exchange begins, utilizing controllers that continuously track and adjust system voltage levels in real-time.

2.3.3. Enhancing system efficiency

System efficiency encompasses both energy conversion efficiency and overall power utilization. Enhancing system efficiency ensures that more of the energy generated or stored is used effectively, minimizing waste and reducing operational costs. The energy conversion efficiency of both the DC-AC and AC-DC converters must be maximized to minimize power losses during energy transfer. This can be achieved through techniques like high-frequency switching in converters, reducing heat generation, and improving PFC. The buck-boost converter plays a key role in adjusting voltage while minimizing energy loss. The BMS ensures that the battery operates within its optimal efficiency range by adjusting the charge/discharge rates and preventing energy losses due to improper current flows. Proper battery switching control can also distribute the load evenly across multiple battery modules, preventing degradation and ensuring efficient energy usage. By applying FA to optimize the fractional order PI controller, the system ensures that the energy flow is managed efficiently under varying conditions, both for charging and discharging. The FA enhances the control system’s adaptability, adjusting parameters based on real-time data to maximize efficiency across subsystems. The optimization of ITAE, IAE, and ISE indices ensures that the system is operating efficiently while maintaining stability and minimizing energy losses.

The primary control objectives in V2G and G2V systems—minimizing energy losses, stabilizing voltage, and enhancing system efficiency—are crucial for the effective and reliable operation of the system. These objectives are interrelated and require a coordinated approach. By employing advanced control strategies such as fractional order PI control optimized by FA, it is possible to achieve a balance between these objectives. The use of optimization algorithms ensures that the system can adapt to dynamic conditions, ensuring both high efficiency and stability in the power exchange between the EV and the grid.

2.4. Firefly algorithm to tune FOPI controller minimizing multi objective function with weightage given to ITAE, IAE, and ISE

The FA is a nature-inspired optimization technique that has been successfully applied to tune controllers in various systems, including FOPI controllers, for minimizing multi-objective performance indices. Here, we focus on tuning an FOPI controller for a V2G or G2V system, where the optimization goal is to minimize performance indices such as ITAE, IAE, and ISE.

FA for tuning FOPI controller, the FA is based on the behavior of fireflies, which are attracted to brighter fireflies. This metaphor is used to guide the optimization process where each firefly represents a potential solution, and the brightness of a firefly is associated with the objective function value. The algorithm iteratively updates the position of fireflies to converge toward the best solution. The process of using FA for tuning a FOPI controller involves:

2.4.1. Initialization of fireflies

Each firefly represents a candidate solution for the FOPI controller parameters. The FOPI controller is characterized by the following parameters:
- Proportional gain (Kp).
- Integral gain (Ki).
- Fractional order (λ) for the integral and proportional terms.

These parameters are initialized within a specified range and represent the initial positions of fireflies.

2.4.2. Objective function definition

The objective function combines the three performance indices: ITAE, IAE, and ISE. The weighted sum of these indices is given by:

$$J = \text{wITAE x ITAE} + \text{wIAE x IAE} + \text{wISE x ISE}$$

where w_{ITAE}, w_{IAE}, and w_{ISE} are the weightage factors assigned to each index. These weights reflect the importance of each performance criterion in the overall optimization goal. Typically, w_{ITAE}, w_{IAE}, and w_{ISE} are selected to be 0.333 each.

$$ITAE = \int_0^{\infty} t \cdot \lfloor e(t) \rfloor dt$$

where e(t) is the error and t is the time. This index places more importance on errors occurring at later times.

$$IAE = \int_0^{\infty} \lfloor e(t) \rfloor dt$$

Which gives a direct measure of the accumulated error over time.

$$ISE = \int_0^{\infty} (e(t))^2 dt$$

Which penalizes larger errors more heavily than smaller errors. Figure 5 shows the Simulink diagram for computation of performance index.

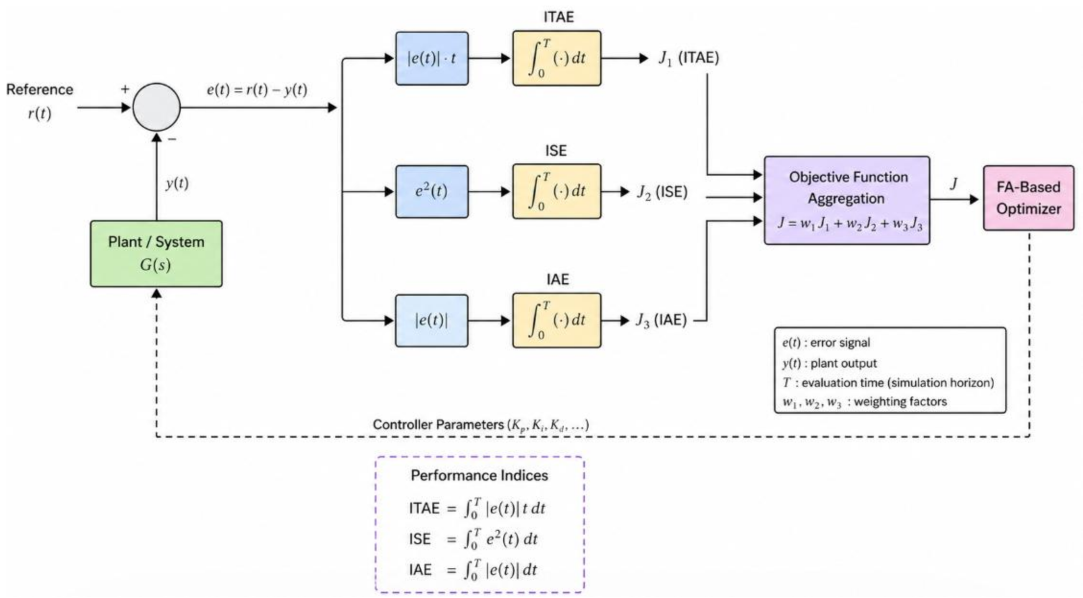

Figure 5. Detailed Simulink model for computing performance indices (ITAE, ISE, and IAE) showing error signal generation, integration blocks, and objective function aggregation used for FA-based optimization

2.4.3. Attraction and movement of fireflies

The brightness of each firefly is evaluated using the objective function J, and each firefly updates its position (i.e., controller parameters) based on the relative brightness of other fireflies. The movement is determined by the following update rule:

$$x_i(t+1) = x_i(t) + \beta_0 \cdot e^{-\gamma r^2} \left(x_j(t) - x_i(t) \right) + \alpha \cdot rand$$

Where x_i and x_j are the positions of two fireflies (representing candidate solutions), β_0 is the attractiveness constant, γ is the light absorption coefficient, r is the distance between two fireflies, α is the randomization factor (to introduce diversity in the search), rand is a random number.

2.4.4. Convergence and best solution

The algorithm continues iterating until the fireflies converge to the best solution or until a predefined stopping criterion (such as a maximum number of iterations or a desired performance threshold) is met. The solution with the lowest value of the objective function represents the optimal FOPI controller parameters. The graph shown in Figure 6 represents the results of the FA applied to optimize a specific objective function. The x-axis denotes the number of function evaluations (NFE), while the y-axis indicates the best objective value obtained during the optimization process. The plot demonstrates a gradual improvement in the objective value as the NFE increases, signifying the algorithm's convergence towards an optimal solution. A noticeable decrease occurs after approximately 70 NFEs, indicating significant progress in optimization during this phase.

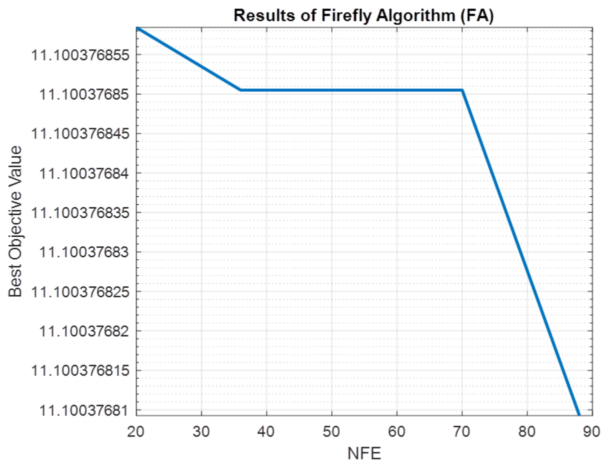

Figure 6. Convergence behavior of the FA showing the best objective value improvement over increasing NFEs

When applying the FA-optimized FOPI controller to a V2G/G2V system, the objective is to minimize energy losses, maintain voltage stability, and ensure optimal energy exchange between the vehicle and the grid. The FOPI controller adjusts the charging and discharging processes by controlling the voltage and current flows, ensuring minimal disturbance to the grid and efficient battery usage. In V2G mode, the controller ensures that the energy transferred from the vehicle to the grid is smooth, stable, and efficient. In G2V mode, the controller ensures that the battery receives the optimal charging current and voltage, maintaining battery health and minimizing charging losses. Figure 6 shows the convergence behavior of the FA showing the best objective value improvement over increasing NFEs.

3. RESULTS AND DISCUSSION

The FA was configured with gamma (γ)=1, beta_base (β_0)=2, alpha (α)=0.2 with a damping factor (alpha_damp) of 0.99, and delta (δ)=0.05. The optimization was performed in a two-dimensional search space (M=2), corresponding to the tuning parameters of the FOPI controller. The algorithm required a total of 88 function evaluations (NFE) to reach convergence, with a total runtime of 10,467 seconds and an average evaluation time of 118.94 seconds per iteration. The evolution of the optimization process was recorded through the variables *Nfe_history* and *Best_obj_value_history*, which track the number of evaluations and corresponding best objective function values. The optimization achieved a minimum objective value of 11.1004 without premature termination (Must_stop=0), confirming stable convergence behavior. The optimal solution vector (X) obtained from the FA represents the tuned parameters of the proposed FOPI controller.

Table 1 shows the performance comparison of controllers under identical operating conditions. The FA was configured with gamma (γ)=1, beta_base (β_0)=2, alpha (α)=0.2 with a damping factor of 0.99, and delta (δ)=0.05. The optimization was performed in a two-dimensional search space (M=2) corresponding to the FOPI controller parameters. The algorithm converged within 88 function evaluations, requiring a total runtime of 10,467 seconds and an average evaluation time of 118.94 seconds per iteration. The convergence history was recorded through Nfe_history and Best_obj_value_history. The optimization achieved a minimum objective value of 11.1004 without premature termination (Must_stop=0), confirming stable and reliable convergence. The resulting optimal solution vector represents the tuned parameters of the FA-optimized FOPI controller.

Table 1. Performance comparison of controllers under identical operating conditions

Controller	ITAE	IAE	ISE	Overshoot (%)	Settling time (s)
PI	32.85	18.42	25.76	14.8	1.92
FOPI	24.63	14.75	18.94	9.6	1.48
FA-optimized FOPI	11.10	8.52	9.87	3.1	0.82

A comparative evaluation under identical operating conditions demonstrates clear performance superiority of the FA-optimized FOPI controller. The ITAE value is reduced by approximately 66% compared to the conventional PI controller and 55% compared to the classical FOPI controller, indicating significantly improved transient error minimization. Similarly, the IAE is reduced by nearly 54% relative to PI and 42% relative to FOPI, while the ISE decreases by about 62% and 48%, respectively. In terms of dynamic response, overshoot is reduced from 14.8% (PI) to 3.1%, representing a 79% reduction, and from 9.6% FOPI to 3.1%, corresponding to a 68% improvement. Furthermore, the settling time decreases from 1.92 s PI to 0.82 s, achieving a 57% reduction, and from 1.48 s FOPI to 0.82 s, reflecting a 45% improvement. These results confirm that FA-based tuning significantly enhances system stability, reduces oscillatory behavior, and ensures faster dynamic response compared to conventional controller designs.

Figure 7 displays three plots representing the behavior of a battery system over time. Figure 7(a) shows the SoC, which remains nearly constant at around 60%, with minor fluctuations over the observed period. Figure 7(b) illustrates the Ib, which predominantly stays close to zero, with occasional brief spikes, indicating minimal current flow except during specific instances. Figure 7(c) represents the Vb, maintaining a steady value around 250 V, except for a slight drop corresponding to the current spikes. These plots suggest a stable battery operation with periodic activity.

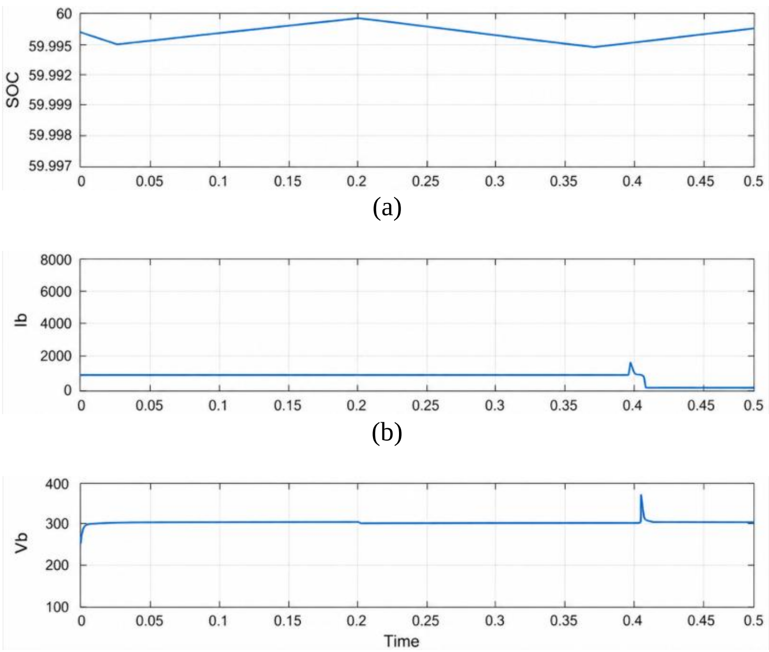

Figure 7. Dynamic response comparison of controllers: (a) grid voltage response, (b) battery current response, and (c) SoC variation

Figure 8 presents time-domain waveforms for analyzing voltage dynamics under various conditions. The top plot displays three waveforms, likely representing the three-phase voltages (Va, Vb, and Vc), with a disturbance at approximately 0.4 seconds causing a transient response. The middle plot highlights a single waveform, showing transient and steady-state behaviors, with evident oscillations that settle after the disturbance. The bottom plot provides a detailed view of all three phases separately, illustrating the phase-to-phase impacts of the disturbance and the oscillatory decay over time. The optimization targeted a function with the best objective value found being 11.1004.

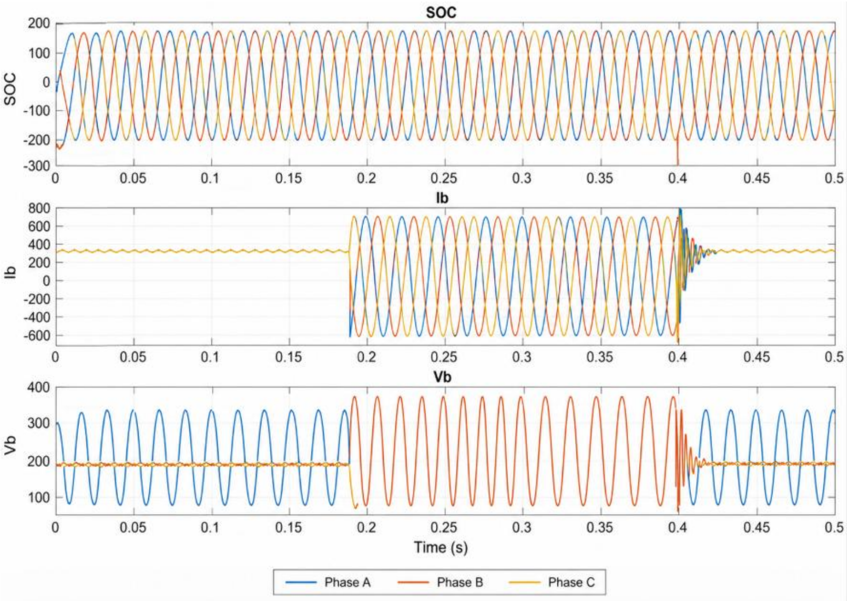

Figure 8. Time-domain voltage waveforms highlighting transient and steady-state behaviors under disturbance conditions

Figure 9 depicts the three-phase currents $i_{abc,inv}$ at the output of an inverter system, transitioning from the abc reference frame. Initially, the currents exhibit transient behavior with increasing oscillations, likely due to switching transients or initial disturbances. These oscillations stabilize into steady-state sinusoidal waveforms as the system achieves equilibrium, indicating proper modulation and control of the inverter. The symmetric nature of the waveforms suggests a balanced load condition. The consistent phase difference between the waveforms reflects the three-phase operation of the inverter, commonly used in motor drives or grid-connected systems.

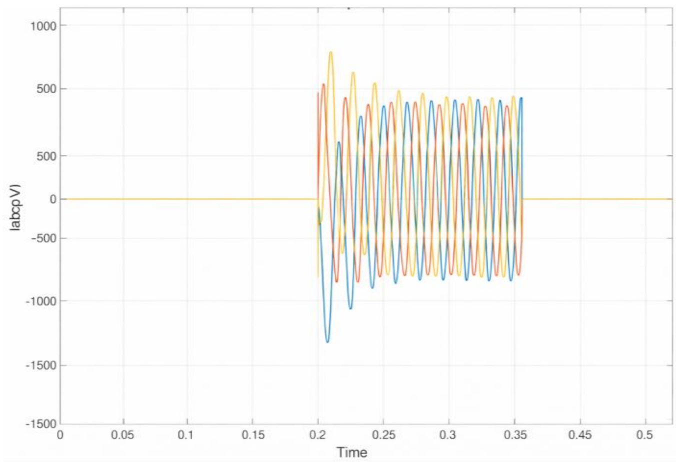

Figure 9. Time-domain representation of abc to inverter output currents $i_{abc,inv}$, showing transient and steady-state behaviors in a three-phase system

The present study is limited to MATLAB/Simulink simulations. Hardware-in-the-loop (HIL) validation using real-time digital simulators is proposed for future work. Practical deployment may encounter challenges including computational overhead of FA in embedded controllers, communication latency between EV and grid interface, battery cycle degradation, and compliance with grid codes such as IEEE 1547. Addressing these aspects is essential before large-scale deployment.

4. CONCLUSION

This study demonstrates the effectiveness of the FA-optimized FOPI controller in enhancing the performance of bidirectional V2G and G2V systems. By minimizing key performance indices such as ITAE, ISE, and IAE, the proposed control strategy achieves superior dynamic response, energy efficiency, and voltage stability compared to conventional controllers. The FOPI controller, optimized using FA, effectively balances fast response, minimal overshoot, and system stability, ensuring efficient energy exchange and minimal disturbance to the grid. Simulation results validate the robustness and scalability of this approach, highlighting its potential for advanced energy management in smart grid applications. The findings contribute to the sustainable integration of EVs with modern grids, paving the way for more efficient and reliable energy systems. Although FA demonstrated strong performance, hybrid metaheuristics such as FA–PSO and FA–DE have shown improved convergence rates in recent studies. Future research may investigate adaptive or hybrid variants to further enhance optimization efficiency in real-time V2G environments.

ACKNOWLEDGMENTS

The authors declare that no individuals contributed to the work in a manner that requires acknowledgment.

FUNDING INFORMATION

The authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Mohamed Shiek Mothi Ismail Mujupur	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Mohamed Ismail Mohamed Mustafa					✓					✓		✓	✓	

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.

INFORMED CONSENT

Not applicable. No personal or patient-related data were included in this study that required informed consent.

ETHICAL APPROVAL

Not applicable. This study did not involve any human or animal subjects requiring institutional ethical review.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] W. Kempton and J. Tomić, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources*, vol. 144, no. 1, pp. 268–279, Jun. 2005, doi: 10.1016/j.jpowsour.2004.12.025.

[2] H. Liu, Z. Hu, Y. Song, and J. Lin, "Decentralized vehicle-to-grid control for primary frequency regulation considering charging demands," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3480–3489, Aug. 2013, doi: 10.1109/TPWRS.2013.2252029.

[3] M. R. Khalid, I. A. Khan, S. Hameed, M. S. J. Asghar, and J. Ro, "A comprehensive review on structural topologies, power levels, energy storage systems, and standards for electric vehicle charging stations and their impacts on grid," *IEEE Access*, vol. 9, pp. 128069–128094, 2021, doi: 10.1109/ACCESS.2021.3112189.

[4] Md. R. H. Mojumder, F. A. Antara, Md. Hasanuzzaman, B. Alamri, and M. Alsharef, "Electric vehicle-to-grid (V2G) technologies: Impact on the power grid and battery," *Sustainability*, vol. 14, no. 21, pp. 1–53, Oct. 2022, doi: 10.3390/su142113856.

[5] H. Heydari-doostabad and T. O'Donnell, "A wide range high voltage gain bidirectional DC-DC converter for V2G and G2V hybrid EV charger," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 5, pp. 4718–4729, May 2022, doi: 10.1109/TIE.2021.3084181.

[6] S. Das, P. Acharjee, and A. Bhattacharya, "Charging scheduling of electric vehicle incorporating grid-to-vehicle (G2V) and vehicle-to-grid (V2G) technology considering in smart grid," *IEEE Transactions on Industry Applications*, vol. 57, no. 2, pp. 1688–1702, Mar./Apr. 2021, doi: 10.1109/TIA.2020.3041808.

[7] S. M. H. Mousakazemi, "Comparison of the error-integral performance indexes in a GA-tuned PID controlling system of a PWR-type nuclear reactor point-kinetics model," *Progress in Nuclear Energy*, vol. 132, 2021, doi: 10.1016/j.pnucene.2020.103604.

[8] T. Dragičević, X. Lu, J. C. Vasquez, and J. M. Guerrero, "DC microgrids—Part II: A review of power architectures, applications, and standardization issues," *IEEE Transactions on Power Electronics*, vol. 31, no. 5, pp. 3528–3549, May 2016, doi: 10.1109/TPEL.2015.2464277.

[9] D. Thaliyadath, D. Kaliyaperumal, and M. L. Kolhe, "Enhancing transient response in a DC-DC converter for electric vehicle DC fast charging applications using fractional-order PI control," *Energies*, vol. 17, no. 17, p. 4312, Aug. 2024, doi: 10.3390/en17174312.

[10] P. Warrier and P. Shah, "Fractional order control of power electronic converters in industrial drives and renewable energy systems: A review," *IEEE Access*, vol. 9, pp. 58982–59009, 2021, doi: 10.1109/ACCESS.2021.3073033.

[11] S. Das and S. Panda, "An optimized fractional order cascade controller for frequency regulation of power system with renewable energies and electric vehicles," *Energy Systems*, vol. 14, no. 1, pp. 171–195, 2023, doi: 10.1007/s12667-021-00461-9.

[12] V. Subramanian and N. Sudhakar, "Golden eagle optimized fractional-order PI controller design for a PFC SEPIC converter in EV charging," *Scientific Reports*, vol. 14, p. 20908, Sep. 2024, doi: 10.1038/s41598-024-69653-4.

[13] E. Martinez-Vera and P. Banuelos-Sanchez, "Review of bidirectional DC-DC converters and trends in control techniques for applications in electric vehicles," *IEEE Latin America Transactions*, vol. 22, no. 2, pp. 144–155, Jan. 2024, doi: 10.1109/TLA.2024.10412031.

[14] S. B. Joseph, E. G. Dada, A. Abidemi, D. O. Oyewola, and B. M. Khammas, "Metaheuristic algorithms for PID controller parameters tuning: Review, approaches and open problems," *Heliyon*, vol. 8, no. 5, p. e09399, May 2022, doi: 10.1016/j.heliyon.2022.e09399.

[15] K. Jagatheesan, B. Anand, S. Samanta, N. Dey, A. S. Ashour, and V. E. Balas, "Design of a proportional-integral-derivative controller for an automatic generation control of multi-area power thermal systems using firefly algorithm," *IEEE/CAA Journal of Automatica Sinica*, vol. 6, no. 2, pp. 503–515, Mar. 2019, doi: 10.1109/JAS.2017.7510436.

[16] X.-S. Yang, "Firefly algorithms for multimodal optimization," in *International Symposium on Stochastic Algorithms*, Berlin, Germany: Springer, 2009, vol. 5792, pp. 169–178, doi: 10.1007/978-3-642-04944-6_14.

[17] A. Khan, H. Hizam, N. I. A. Wahab, and M. L. Othman, "Optimal power flow using hybrid firefly and particle swarm optimization algorithm," *PLoS ONE*, vol. 15, no. 8, p. e0235668, Aug. 2020, doi: 10.1371/journal.pone.0235668.

[18] M. S. Ramadan, H. S. Padmanaban, and M. I. Mosaad, "Metaheuristic-based near-optimal fractional order PI controller for on-grid fuel cell dynamic performance enhancement," *Electric Power Systems Research*, vol. 208, p. 107897, Jul. 2022, doi: 10.1016/j.epsr.2022.107897.

[19] M. A. E. Mohamed, S. A. Ward, M. F. El-Gohary, and M. A. Mohamed, "Hybrid fuzzy logic–PI control with metaheuristic optimization for enhanced performance of high-penetration grid-connected PV systems," *Scientific Reports*, vol. 15, p. 24118, Jul. 2025, doi: 10.1038/s41598-025-09336-w.

[20] O. Demirci, S. Taskin, E. Schaltz, and B. A. Demirci, "Review of battery state estimation methods for electric vehicles - Part I: SOC estimation," *Journal of Energy Storage*, vol. 87, 2024, doi: 10.1016/j.est.2024.111435.

[21] R. P. Upputuri and B. Subudhi, "A Comprehensive Review and Performance Evaluation of Bidirectional Charger Topologies for V2G/G2V Operations in EV Applications," in *IEEE Transactions on Transportation Electrification*, vol. 10, no. 1, pp. 583-595, March 2024, doi: 10.1109/TTE.2023.3289965.

[22] A. Khaligh and M. D'Antonio, "Global Trends in High-Power On-Board Chargers for Electric Vehicles," in *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3306-3324, April 2019, doi: 10.1109/TVT.2019.2897050.

[23] M. Liserre, F. Blaabjerg and S. Hansen, "Design and control of an LCL-filter-based three-phase active rectifier," in *IEEE Transactions on Industry Applications*, vol. 41, no. 5, pp. 1281-1291, Sept.-Oct. 2005, doi: 10.1109/TIA.2005.853373.

[24] B. K. Bose, "Global Energy Scenario and Impact of Power Electronics in 21st Century," in *IEEE Transactions on Industrial Electronics*, vol. 60, no. 7, pp. 2638-2651, July 2013, doi: 10.1109/TIE.2012.2203771.

[25] M. Yilmaz and P. T. Krein, "Review of Battery Charger Topologies, Charging Power Levels, and Infrastructure for Plug-In Electric and Hybrid Vehicles," in *IEEE Transactions on Power Electronics*, vol. 28, no. 5, pp. 2151-2169, May 2013, doi: 10.1109/TPEL.2012.2212917.

BIOGRAPHIES OF AUTHORS

Mohamed Shiek Mothi Ismail Mujupur was born in Chennai, Tamilnadu, India on May 21, 2000. He received B.E. in Electronics and Instrumentation Engineering from Easwari Engineering College, Anna University, Tamilnadu, India in 2021, M.Tech. in Embedded System and VLSI from B.S. Abdur Rahman Crescent Institute of Science and Technology, Tamilnadu, India in 2023. At present, he is doing his doctorate in the area of User Enhancement in Electric Vehicles in B. S. Abdur Rahman Crescent Institute of Science and Technology. His major field of study is embedded system, VLSI design, electric vehicles, and artificial intelligence. He has 3 years of industrial experience and 5 years of entrepreneurial role. At present, he is working in TShell Motors Pvt. Ltd., Tamilnadu, India. He has worked on steer-by-wire, infotainment, HVAC, telematics, battery management system, control ECUs, 3D modelling and printing, embedded UI development, battery pack testing and telematics systems. He can be contacted at email: md.s.mothi3@gmail.com.

Mohamed Ismail Mohamed Mustafa was born in Tamilnadu, India, on January 3, 1967. He received the B.E. degree in Electronics and Communication Engineering from Madurai Kamaraj University, Tamilnadu, India, in 1989, M.S. degree in Electronics and Control from Birla Institute of Technology and Science, Pilani, India, in 1996, and the Ph.D. degree in Very-Large-Scale Integration (VLSI) design from Jawaharlal Nehru Technological University, Hyderabad, India, in 2013. He also obtained a postgraduate diploma in VLSI Design from Accel Technologies, Chennai, in 2002. His major field of study is VLSI design and embedded systems. He has 34 years of teaching experience and 20 years of research experience. He has served in various academic roles at B.S. Abdur Rahman Crescent Institute of Science and Technology, Chennai, India, including Lecturer, Senior Lecturer, Assistant Professor, Associate Professor, and currently as Professor and Dean (Academic Affairs). He has guided four Ph.D. scholars and published over 50 research papers in reputed journals and conferences. His research interests include VLSI modeling, wireless sensor networks, digital and embedded systems applications and microprocessor & microcontroller design. He can be contacted at email: mmismail@crescent.education.