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Hybrid optimization of dual-port converter for electric vehicles

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ABSTRACT

Vehicle-to-grid (V2G) technology, which cuts peak loads, levels load, and modulates voltages but generates power system instability, accelerated by the growing popularity of electric-powered vehicles. This research suggests a unique three-level full-bridge non-isolated buck-boost bidirectional direct current (DC)-DC converter that integrates solar (photovoltaic (PV)) systems, vehicle batteries, and the power grid to charge plug-in electric vehicles (EVs). This converter is combined with hybrid Tasmanian-hawk optimization (HTHO). By enabling EV batteries to be charged concurrently from PV systems and the grid, the converter improves charging flexibility and efficiency. The exploration and exploitation phases of HTHO, a new method that combines elements of the Harris hawks and Tasmanian devil algorithms for optimization. Using a 69-node test system, the suggested methodology, which is implemented in MATLAB/Simulink, evaluates power quality improvements in controlled and bidirectional charging operations. At a total harmonic distortion (THD) value of 1.768%, which indicates minimal harmonic distortion in the signal and exceeds conventional optimization techniques, the suggested converter, which integrates with HTHO, enhances charging flexibility and efficiency and helps to preserve overall power system stability. The research strengthens EV charging infrastructure through the seamless integration of natural renewable resources, multi-method optimization, and efficient grid operation strategies.

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1. INTRODUCTION

Electric vehicles (EVs) are receiving increasing attention because they offer a promising solution for reducing greenhouse gas emissions and energy dependency. Vehicle-to-grid (V2G) and grid-to-vehicle (G2V) technologies, which allow EVs to function as portable energy storage devices and help balance the load balance the electrical grid, have been developed as a result of the growing popularity of EVs [1]. However, large power demands from multiple EV chargers, nonlinear EV charger components, and heavy loads can result in voltage and frequency changes that can lead to power quality issues when V2G and G2V systems are combined [2]. Voltage source converters (VSCs) and other power electronics devices can help reduce power quality problems in V2G and G2V systems. The VSC's control algorithm is essential to preserving the electric grid's power quality.

Researchers have sought to enhance converter control strategies in several publications. While optimization methods enhance power quality in bidirectional lithium-ion cell charging systems [3], the criminal search optimization algorithm, which is restricted to single-objective optimization and limits flexibility under changing grid and load conditions, is accommodated by proportional–integral (PI) controller tuning [4]. Without taking into account harmonic distortion or overall power quality improvement, the self-adaptive multi-population elitist Jaya (SAMPE-JAYA) technique concentrates on energy loss reduction and voltage profile improvements [5]. References [6]–[8] are devoid of harmonic mitigation, bidirectional power flow, or multi-objective G2V/V2G converter optimization; instead, they concentrate on network-level coordinated charging, fleet-level behavior, load management, and transformer ageing from plug-in hybrid electric vehicle (PHEV) loads using linear programming. For grid-supportive V2G operation, Shaheen *et al.* [9] investigates high-level scheduling and cost/load optimization using metaheuristic techniques. Simulation results indicate that whale optimization algorithm (WOA) performs best in reducing charging costs. The authors [10], [11] use the expected energy not charged (EENC) metric to assess system reliability under plug-in electric vehicle (PEV) integration and analyze load modeling and distribution network impacts by taking into account variables like automobile type, standard sized battery, state of charge (SOC) status, driving patterns, distance and purposes, plug-in timing, charging frequency, power usage, and dynamic monetary pricing schemes. Zhou *et al.* [12] optimizes a high-power proton exchange membrane (PEM) fuel cell system using enhanced grey wolf optimization (GWO), while hybrid optimization techniques are proposed for VSC control in V2G and G2V systems, though metaheuristic methods can suffer from local optima and high computational costs. Utilizing voltage-dependent power flow (VDPF) analysis, studies [13]–[15] examine PEV integration, V2G scheduling, and photovoltaic (PV) maximum power extraction for effective solar power extraction. An adapted neural swarm optimization (NSO) method is used to enhance performance, along with a genetic algorithm for additional optimization, but their effectiveness is limited by load modelling assumptions, artificial neural network (ANN) prediction accuracy, and computational complexity.

The research [16]–[18] explores AI and optimization-based techniques for V2G and G2V systems, including Monte Carlo-based EV scheduling, opposition-based competitive swarm optimizer (OCSO), self-tuning filters, and sliding mode control, aiming to enhance energy management, efficiency, system stability, and grid power quality. However, practical implementation is challenged by high computational complexity, reliance on accurate system modelling and real-time data, and uncertainties in EV behavior, grid conditions, and battery state-of-charge, while hybrid methods like wild horse–particle swarm optimization (WHPSO) [19] also face difficulties in real-time deployment. These challenges highlight a requirement for reliable, adaptable control and mechanisms that can manage both system uncertainties and converter limitations in real-time V2G and G2V operations. A unit commitment framework for V2G-connected smart grids that considers PEV penetration, battery degradation, and controlled charging/discharging is proposed by Egbue *et al.* [20]. The practical limitations of direct current (DC)/alternating current (AC) converters, including conversion efficiency, voltage/current limits, and power quality problems during bidirectional energy flow, as well as the computational complexity of large-scale systems and reliance on precise EV availability and load projections, may limit the technique. Using methods like enhanced metaheuristic algorithms, optimization-based scheduling, simulation analyses, and probabilistic Monte Carlo assessments, researchers [21]–[25] concentrate on optimizing and analyzing V2G and G2V operations in residential networks to improve energy management, lower costs, integrate renewables, and assess impacts on grid stability, battery performance, and power quality. Effective deployment, however, may be hampered by practical constraints like high computational complexity, reliance on precise EV/grid data or simulation assumptions, difficulties in real-time implementation, and DC/AC converter problems, such as efficiency losses, voltage/current constraints, harmonics, and power quality impacts.

A three-level full-bridge based buck-boost converter for plug-in electric car charging in smart grid situations is presented in this research study. To enhance electrical quality, a hybrid Tasmanian-Hawk optimization (HTHO) technique is employed. Efficacy of the suggested approach is verified by contrasting it with aquila optimization (AQO), particle swarm optimization (PSO), golden eagle optimization (GEO), Harris hawk optimization (HHO), and Tasmanian devil optimization (TDO). The findings demonstrate that by using hybrid optimization for the converters, the suggested approach for grid-connected EVs can enhance power quality by stabilizing voltage, lowering harmonics, and increasing overall efficiency.

2. METHOD

With emphasis on combining PV systems, vehicle batteries, and the power grid, the study's suggested methodology centers on the creation and application of a unique bidirectional AC-DC converter designed especially for PEV charging. The persistent harmonics caused by EV charging impact the operations and functions of the power system. Utilizing converters with the HTHO technique, the objective is to minimize overall power quality degradation in the EV power system by lowering total harmonic distortion (THD), voltage deviation (V_D), and power loss (P_{loss}) while preserving system stability, efficiency, and operating restrictions. By charging the batteries of autonomous vehicles from PV systems and the grid, the converter uses the meta-heuristic algorithm technology HTHO to enhance the grid's power quality and boost charging efficiency and flexibility. Energy can be transferred between the grid and vehicle batteries using this converter through V2G and G2V functionality. In G2V operation, the converter functions similarly to an optimized buck converter, regulating the voltage and current to accomplish efficient battery charging. In V2G mode, it functions as an optimized boost converter, increasing the battery voltage to satisfy the requirements of the grid-connected AC-DC bidirectional converter. An innovative approach called HTHO, which incorporates aspects of the Tasmanian devil and HHO methods, is used to optimize the converter's gain functions and duty cycles. The goal of this hybrid optimization technique is to enhance the hybrid buck-boost converter's performance. Figure 1 depicts the general flow of the suggested EV charging converter.

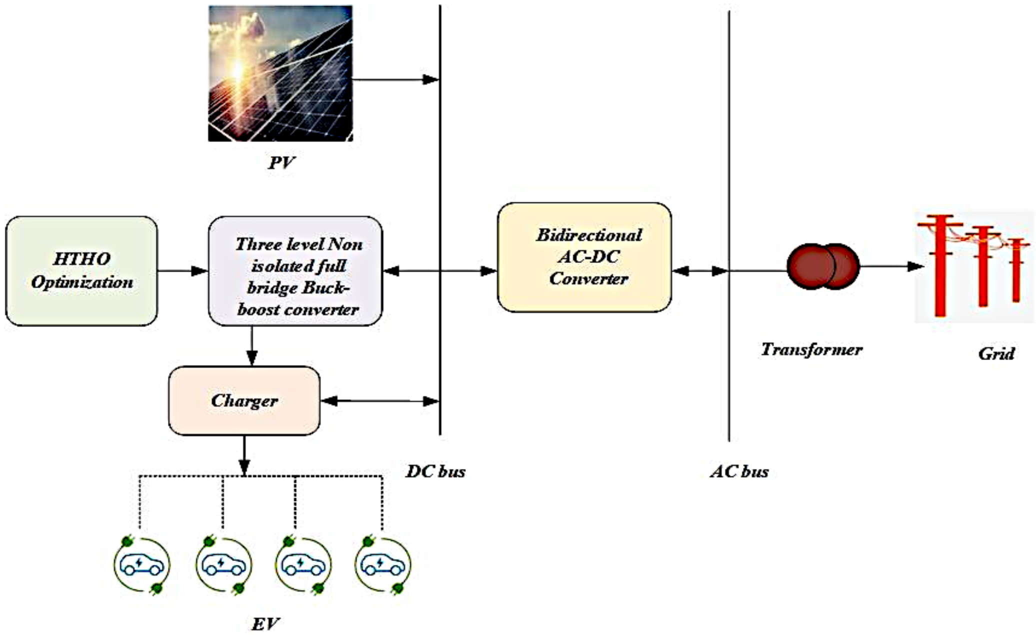

Figure 1. The envisioned work's overall flow

The overall architecture of the suggested process is depicted in the block diagram in Figure 2. The variable DC power generated by the PV array is managed using a three-level buck-boost DC-DC converter with maximum power point tracking (MPPT). Its output is connected to a shared DC bus that connects the bidirectional AC-DC converter, EV charger, and PV system. For both charging and V2G operations, the EV charger facilitates bidirectional power transfer. Controlled power exchange and voltage adjustment are made possible by the AC–DC converter, which connects the DC bus directly to the grid via an AC bus and transformer. When charging PEVs from different power sources, the HTHO technique improves the converter's overall efficacy, reliability, and efficiency by coordinating system operation through the delivery of control signals to maintain effective power flow and voltage stability. To achieve this, a unique hybrid optimization methodology uses two distinct optimization techniques: the Tasmanian devil and HHO [26], [27]. The Tasmanian devil's hunting activity serves as the model for the TDO algorithm, a naturalistic-inspired optimization technique that is renowned for its speedy exploration of the space and efficient identification of ideal solutions. On the other aspect, HHO is characterized by its efficient use of the areas of the inquiry space that show the greatest possibility and is modelled after the hunting behavior of Harris hawks. By integrating these two techniques, the suggested hybrid optimization approach for the converter aims to leverage the benefits of both approaches. Effective harmonic suppression results from HTHO's enhancement of the converter's ability to accurately trace harmonic currents, preserve DC-link stability, and produce precise switching signals. The optimization method tunes the PI controller parameters to achieve superior harmonic suppression compared to traditional PI control and demonstrates improved power quality and reduced harmonic distortion. The proposed algorithm is suitable for future smart grid applications, renewable-integrated EV charging infrastructure, and intelligent energy management systems.

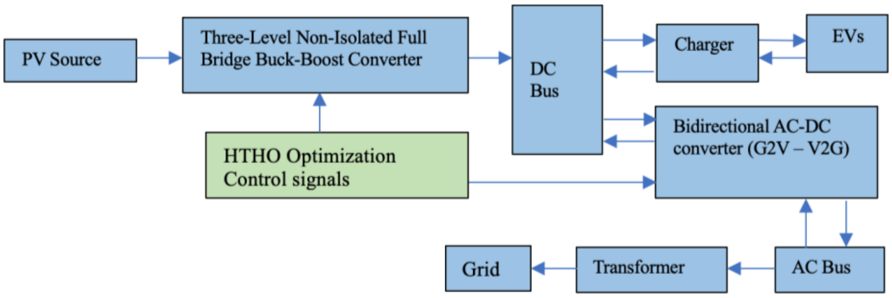

Figure 2. The proposed methodology's system-level block diagram

2.1. Mathematical model

2.1.1. Initialization phase

Tasmanian devils are used in a population-based stochastic framework to mimic the search agents in the suggested TDO method. The agent population is first initialized at random using the optimization problem's restrictions. Based on its current position, each member of the TDO population investigates the solution space and suggests potential values for the decision variables. Each member of the population is mathematically represented by the objective function (1), which is applied to determine the performance of each solution, which is expressed as a vector with dimensions equal to the number of decision variables in the issue.

$$min\, J(x_i) = \omega_1 P_{loss} + \omega_2 \Delta V + \omega_3 THD + \omega_4 Soc_{error} \tag{1}$$

The fitness value $J(x_i)$ guides both algorithms during the optimization process, where x is the control design variable optimized by HTHO. The objective considers the P_{loss} , V_D ΔV, and THD, SOC as an objective function. The TDO population is capable of being modeled using the matrix outlined in (2), including P_{loss}, V_D. THD as an objective function. In the given problem formulation, N signifies the number of respondents participating in the search, whereas M and Z reflect the total number of variables and the Tasmanian devil population, where Z_I corresponds to the ith solution and $z_{I,J}$ the decision value for the J^{th} variable.

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_I \\ \vdots \\ Z_N \end{bmatrix}_{N\times M} = \begin{bmatrix} z_{1,1} & \cdots & z_{1,J} & \cdots & z_{1,M} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ z_{I,1} & \cdots & z_{I,J} & \cdots & z_{I,M} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ z_{N,1} & \cdots & z_{N,J} & \cdots & z_{N,M} \end{bmatrix}_{N\times M} \tag{2}$$

2.1.2. Objective value computation

Throughout the optimization process, the objective function is assessed by examining the variable values connected to each potential solution. In (3), a vector that represents the final objective values. P_{loss}, V_D, THD, SOC are among the objective factors in this work that make up the vector H. The phrase H_I represents i-th candidate solution linked to a specified value of the objective function. These objective values can be used to assess the efficacy of each possible solution, and the solution that yields the ideal population member is determined by selecting the optimum goal function outcome.

$$H = \begin{bmatrix} H_1 \\ \vdots \\ H_I \\ \vdots \\ H_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} H(A_1) \\ \vdots \\ H(A_I) \\ \vdots \\ H(A_N) \end{bmatrix}_{N\times 1} \tag{3}$$

2.1.3. Exploratory optimization processes

The suggested technique looks for the most desirable potential candidate solutions in the search domain, drawing inspiration from the scavenging habits of Tasmanian devils, which look for carrion left by other predators. The TDO method searches several sections of the solution space to find interesting locations, demonstrating the algorithm's exploration capability. In (4) to (6), provide the mathematical expression for this scavenging behavior. The carrion locations linked to each Tasmanian devil are assumed to match the locations of other members of the population in the proposed TDO framework. As a result, the k-th habitant of the group is the ith Tasmanian devil's target carrion, where both i and k are picked at random from the population range of 1 to N.

$$D_I = \{Z_K \mid \mathrm{K} \in \{1, \ldots, N\}\{I\}\} \tag{4}$$

In which D_I symbolises the carcass targeted to be consumed by the Tasmanian devil. Upon determining the selected carrion, the Tasmanian carnivore updates its position within the search space. According to the behavioral model adopted in this strategy, the devil moves toward the carrion when the associated objective function value is superior; otherwise, it shifts away from it. In the final step of this process, the new position is accepted if it yields an improved objective function value; otherwise, the Tasmanian devil retains its previous position and $H_I^{New,S1}$ shows the objective function value of the chosen carrion. Based on the initial strategy, $Z_I^{New,S1}$ and $z_{I,J}^{New,S1}$ indicates its value for the I^{th} and J^{th} Tasmanian devil variable. R and G indicates an arbitrary and stochastic number bounded within [0, 1] alongside 1 or 2.

$$z_{I,J}^{New,S1} = \begin{cases} z_{I,J} + R.\left(d_{i,j} - G.z_{I,J}\right), H_{D_I} < H_I; \\ z_{I,J} + R.\left(z_{I,J} - d_{I,J}\right), otherwise, \end{cases} \tag{5}$$

$$Z_I = \begin{cases} Z_I^{New,S1}, H_I^{New,S1} < H_I; \\ Z_I, otherwise, \end{cases} \tag{6}$$

2.1.4. Conversion phase between exploration and exploitation

The HHO algorithm regulates E as escape energy factor, the transition between global and local search, which has the following definition (7). T denotes the maximum iteration limit, while E_0 denotes the initial energy value in the limit (-1, 1). When $|E| \geq 1$, HHO optimizer enters the exploratory stage, symbolizing the movement of individuals within the population towards the prey across the entire search space. The search phase will transition into the exploitation phase when $|E| < 1$.

$$E = 2.E_0.(1 - \tfrac{t}{T}) \tag{7}$$

2.1.5. Energy updated exploitation stage

Tasmanian devil can also secure food through predation, and its hunting behavior is typically characterized by two sequential stages. In the first phase, it scans the area, chooses the target, and initiates an attack. Local search is the process used in the exploitation phase. The Tasmanian devil will strike when it has surrounded their prey. The HHO algorithm uses various combinations of the escape energy factor E and random numbers $r \in (0, 1)$ to simulate the behavior of prey escaping, and the hunting tactics of hawks are utilized in this exploitation phase to attack and determine the prey. There is a chance for prey to flee. If r is less than 0.5, the escape is successful; if r is greater than 0.5, the escape is unsuccessful.

i) Soft besiege: the prey is energetic and tries to escape by jumping when $|E| \geq 0.5$ and $r \geq 0.5$, but ultimately, it is caught. The mathematical is shown in (8) to (10). The variable $rand$ is an arbitrary number between 0 and 1, and $\Delta z_{I,J}$ denotes the gap between the present individual and the optimal solution after completing the iteration. J is sprinting for his life, leaping ahead of his prey.

$$z_{I,J}^{new} = \Delta z_{I,J} - E.\left|J.F_I - z_{I,J}\right| \tag{8}$$

$$\Delta z_{I,J} = F_I - z_{I,J} \tag{9}$$

$$J = 2.(1 - rand) \tag{10}$$

ii) Hard besiege: when the prey lacks physical strength and can be directly captured, the formula (11) is as follows when $|E| < 0.5$ and $r \geq 0.5$. The Tasmanian devil determines whether the new location improves the objective function value after locating the prey and calculating the new location using either the soft besiege or hard besiege strategy. Whenever the newly created position improves the objective function value, it supersedes the prior one; if not, the current position is retained. The modelling of this process is displayed in (12). In (13), the technique for the second strategy, which involves updating the prior Tasmanian devil location when the newly created one enhances the objective function value, which formulates the process for the second strategy.

$$z_{I,J}^{new} = F_I - E.\left|\Delta z_{I,J}\right| \tag{11}$$

$$z_{I,J}^{new,S2} = \begin{cases} z_{I,J}^{new} + r.\left(f_{I,J} - G.z_{I,J}\right), H_{P_I} < H_I \\ z_{I,J}^{new} + r.\left(z_{I,J} - f_{I,J}\right), otherwise, \end{cases} \tag{12}$$

$$Z_I = \begin{cases} Z_I^{new,S2}, H_I^{new,S2} < H_I \\ Z_I, \quad otherwise \end{cases} \tag{13}$$

Where $Z_I^{new,S2}$ depicts the updated state of I^{th} Tasmanian under the second strategy, where $z_{I,J}^{new,S2}$ represents J^{th} component, $H_I^{new,S2}$ is its corresponding fitness value.

The following phase and the predation modelling are the main differences between this strategy and the first. The local hunt for the search space is analogous to the pursuit of prey near the attack location. The Tasmanian devil's behavior shows how the TDO algorithm progresses toward promising regions of the search space. In the pursuit phase, it tracks prey around the attack point, which serves as the center of the hunting area. The search radius, defined in (14), limits the exploration range, and the updated position is computed using (15). Overall, in (14) to (16) describe the prey-pursuit stage centered on Tasmania's location and its surrounding region. Whenever the newly generated position results in a higher target function output relative to the preceding one, the Tasmanian approves. A simulation is used in (16) to update the position of the Tasmanian devil.

$$R = 0.01\left(1 - \frac{t}{T}\right) \tag{14}$$

$$z_{i,j}^{new} = z_{i,j} + (2r - 1).R.z_{i,j} \tag{15}$$

$$Z_i = \{Z_i^{new}, H_I^{new} < H_I;\ Z_I, \quad otherwise, \tag{16}$$

Where Z_i^{new} and $z_{i,j}^{new}$ represents the I^{th} and J^{th} value of Z_i neighborhood, R and t defines the local search range of attack point, in which T gives the maximum iteration limit.

The HTHO algorithm's flowchart is depicted in Figure 3. To improve the hybrid buck-boost converter's performance when charging PEVs from various power sources, the HTHO optimization technique is used in this work. HTHO strives to enhance the efficiency, dependability, and comprehensive efficacy of bidirectional power transfer among EV batteries and the power grid by refining the duty cycle and gain function.

2.2. Grid-to-vehicle and vehicle-to-grid operation mode in bidirectional converter

This research uses a grid, eight 40 kW EVs, and a photovoltaic that is powered by standard test conditions of 1,000 W/m² of irradiance and 25 °C. The EVs are also linked to a DC-DC converter that operates bidirectionally with two ports, which allows for simultaneous charging from the solar panels and the main power source. Enabling reversible power transfer between the power grid and EV batteries is a key feature of the optimized hybrid three-level fully integrated buck-boost DC-DC converter described in this work. The converter operates as an optimized buck converter when in G2V mode. This means that the converter is designed to control both current and voltage during the charging process when the vehicle is receiving energy from the grid. This guarantees safe operating conditions and effective battery charging for the vehicle. In contrast, the converter performs as an optimized boost converter when it is in V2G operation mode. In this case, the converter primarily functions to step up the voltage of the vehicle batteries to an appropriate DC link level. This requirement is crucial to keep the full-bridge AC-DC bidirectional converter connected to several EVs operating successfully. The converter allows the EVs to be seamlessly integrated into the grid and to return power to it when needed by increasing the voltage.

2.2.1. Grid-to-vehicle mode of operation

The envisioned three-level non-isolated buck-boost bidirectional converter functions as an optimized buck converter in the G2V regime, with the aim of charging the batteries at different current and voltage stages. In order to charge the batteries at different current and voltage stages, the suggested three-level non-isolated buck-boost bidirectional converter operates as an optimized buck converter in G2V regime. The proposed three-level non-isolated buck-boost functions as an optimized buck converter in G2V mode, with the goal of charging the batteries at various current and voltage stages. The current reference (i_{ref}) and the power reference P_{dc} in this operating mode is acquired by the (17), where current and voltage in the batteries are v_b and i_b, and V_G is the grid voltage's root mean square (RMS) value.

$$i_{ref} = \frac{P_{dc}+i_b v_b}{V_G{}^2} V_G \tag{17}$$

2.2.2. Vehicle-to-grid operation mode

The V2G operating mode transfers stored battery energy to the grid; the buck-boost bidirectional converter operates as an optimized boost converter for continuous battery discharge; the AC-DC converter control used in this mode of operation is similar to that used in the G2V; and the AC-DC full-bridge bidirectional converter has sinusoidal current injection capabilities and functions as an inverter. Additionally, the predictive current control was utilized to synthesize the reference current. The primary distinction is the DC-DC operation, which functions as a boost converter in this case. The quantity of energy to be delivered to the power grid is specified by an external input parameter, current reference (i_{BT}) is calculated using the reference power (P_{BT}) and the battery voltage (v_{BT}) by the (18). While V2G mode allows the EV batteries to return power to the grid through optimized boost conversion, G2V mode makes it easier to charge the EV batteries from the grid using optimized buck conversion. EVs can be seamlessly integrated into the grid infrastructure due to their bidirectional operation, which supports both energy generation and consumption as needed.

$$i_{BT} = \frac{P_{BT}}{v_{BT}} \tag{18}$$

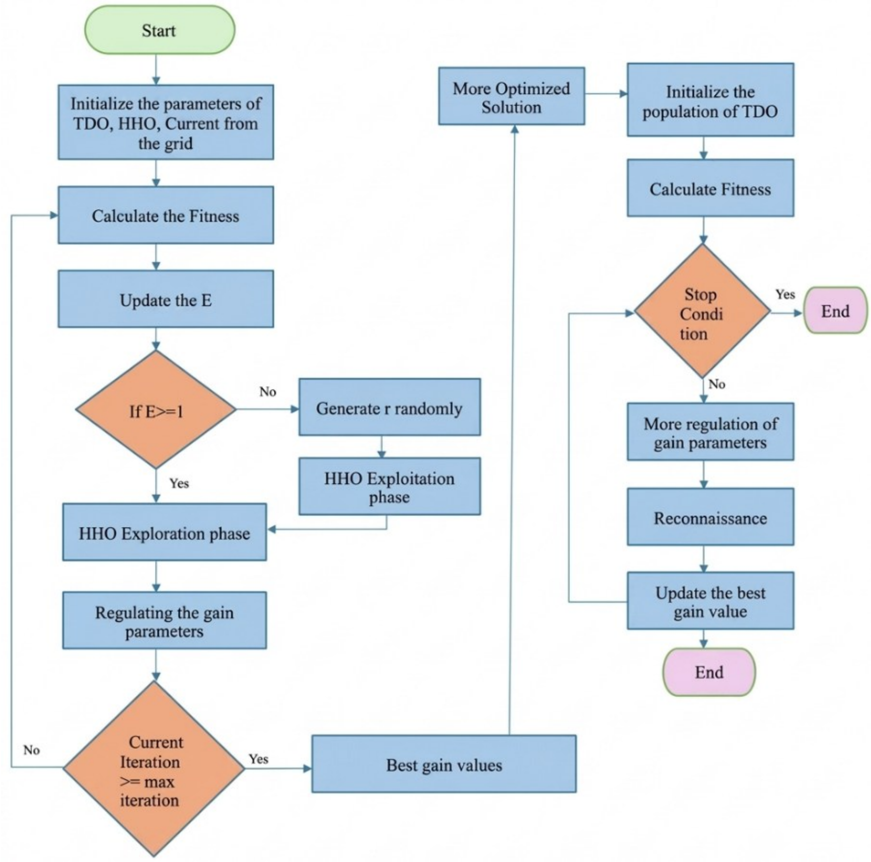

Figure 3. Flow chart of the hybrid HTHO algorithm

3. RESULTS AND DISCUSSION

MATLAB/Simulink in Figure 4 was utilized for implementing the proposed three-level non-isolated buck-boost regulator model. The distortion of harmonics at the coupling point has been minimized by refining the PI controller gains using the outlined HTHO technique was assessed using fast Fourier transform (FFT) analysis. The performance metrics analyzed include PV, sag fluctuation, and THD. The performance of the proposed model, which integrates PV, AC/DC converter, and battery systems within the IEEE 69-bus distribution network, is analyzed through an analysis of the simulation results.

3.1. Performance analysis

The performance of the PV and V2G operation, grid voltage fluctuation, inverter injected voltage, and charge/discharge output, and THD are evaluated. Figure 5 shows an evaluation of PV output, which includes PV power, PV current, and PV voltage. Figure 6 depicts a V2G operation.

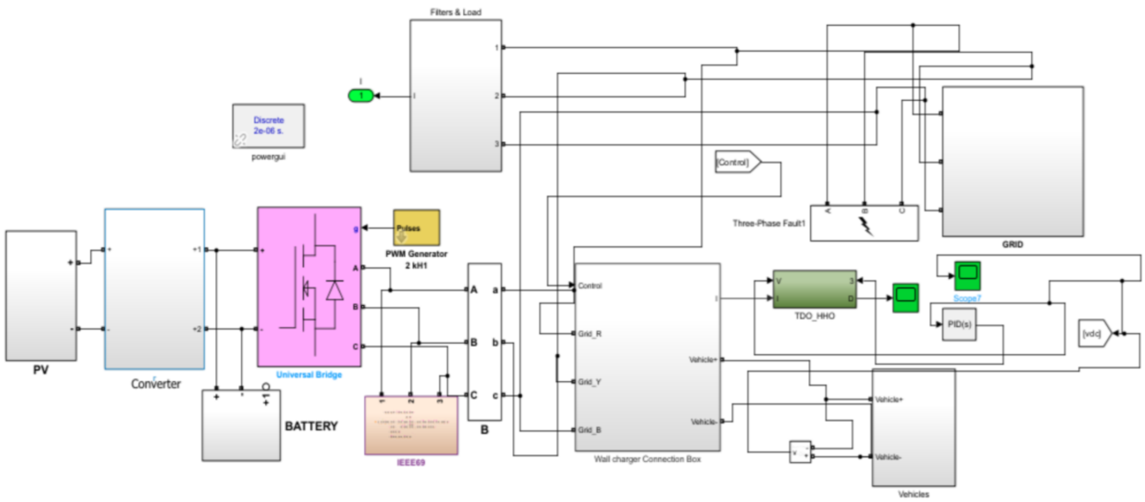

Figure 4. Simulink model of a bidirectional converter

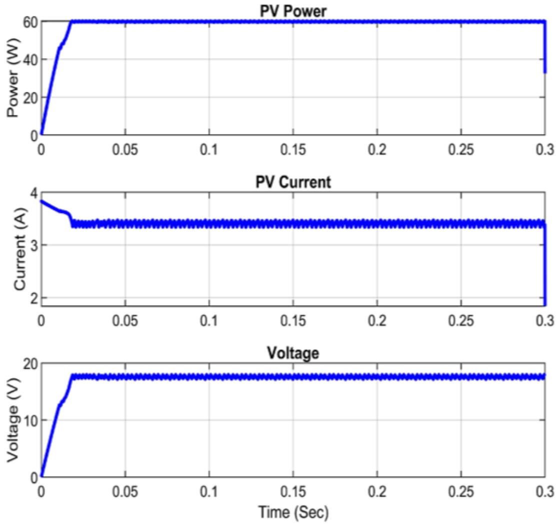

Figure 5. Analysis of PV output

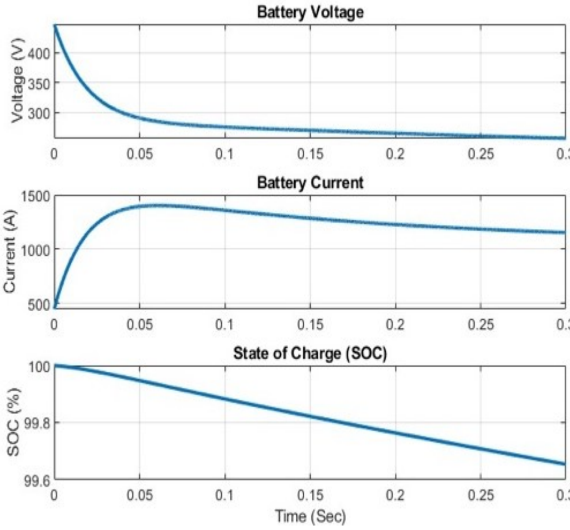

Figure 6. Analysis of V2G operation

Figure 7 depicts a G2V operation. The PV power output varies between 0 and 60 W before stabilizing at a constant value of 0.03 W. This fluctuation is most likely due to variations in sunlight intensity or environmental conditions that affect the effectiveness of the PV system. Concurrently, the PV current fluctuates between 3 and 4 A, indicating rapid fluctuations in the electrical current produced by the PV panels. Similarly, PV voltage differs from 0 to 19 V. These current and voltage fluctuations are typical of PV systems operating in variable environmental conditions, where factors such as sunlight intensity and temperature influence electrical output. SOC drops from 100% to a lower value as battery voltage drops and battery current rises. Figure 8 shows an analysis of grid voltage, inverter voltage, and charge and discharge voltage. The grid voltage, which ranges from -400 to 400 V, represents the voltage levels provided by the external power grid to the system, and sag is observed between 0.4 to 0.43 s.

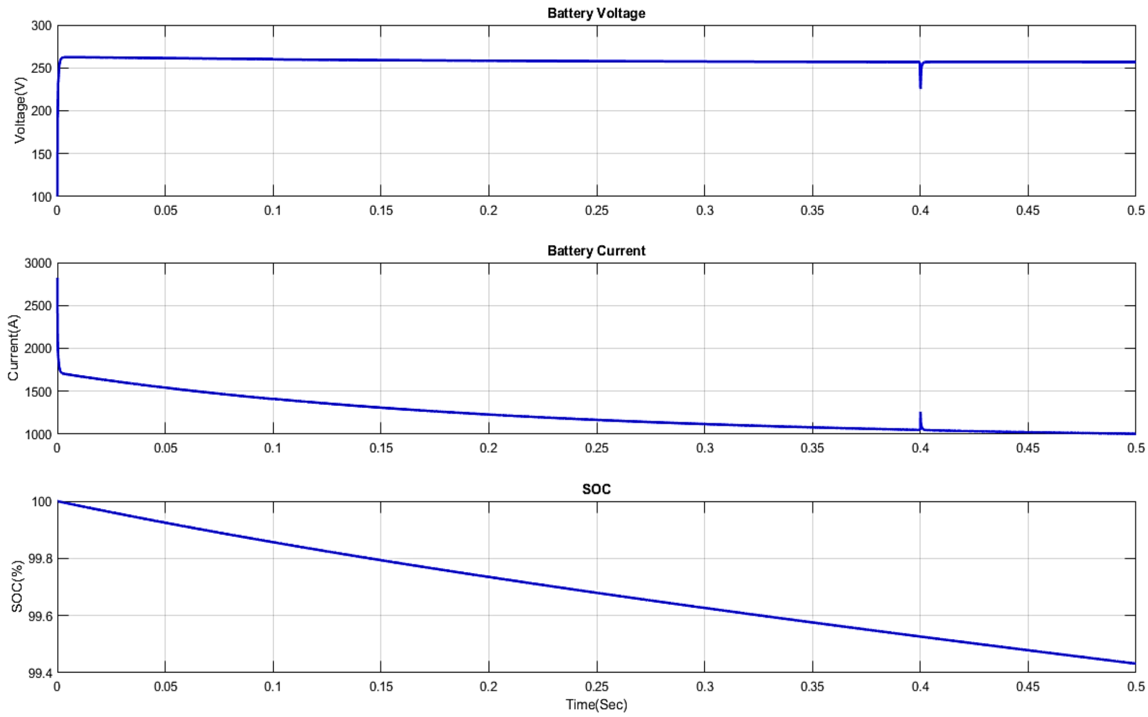

Figure 7. Analysis of G2V operation

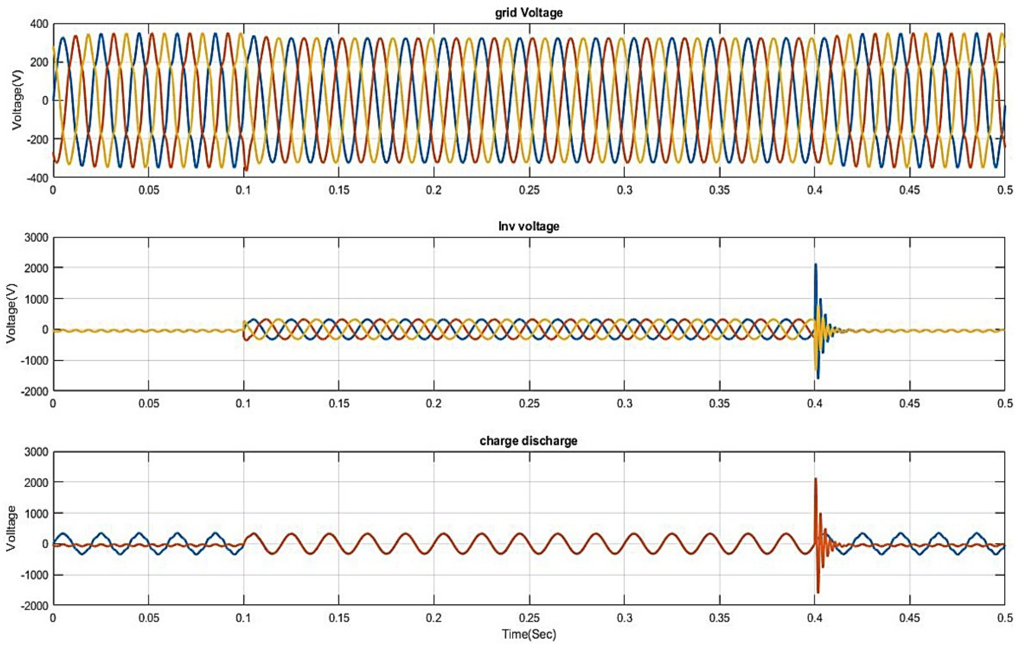

Figure 8. Simulation result of grid voltage, inverter injected voltage during sag, and charging and discharging voltage of battery with HTHO

Grid voltage fluctuations can be caused by a variation of factors, including load variations, grid disturbances, and voltage regulation mechanisms. Then the inverter voltage starts at zero and fluctuates between -200 and 200 V after 0.1 seconds, and the injected voltage is given at 0.4-0.43 seconds. In addition, the charge and discharge voltages of HTHO represent the voltage levels associated with the system's charging and discharging processes. Figure 9 displays the grid current THD analysis.

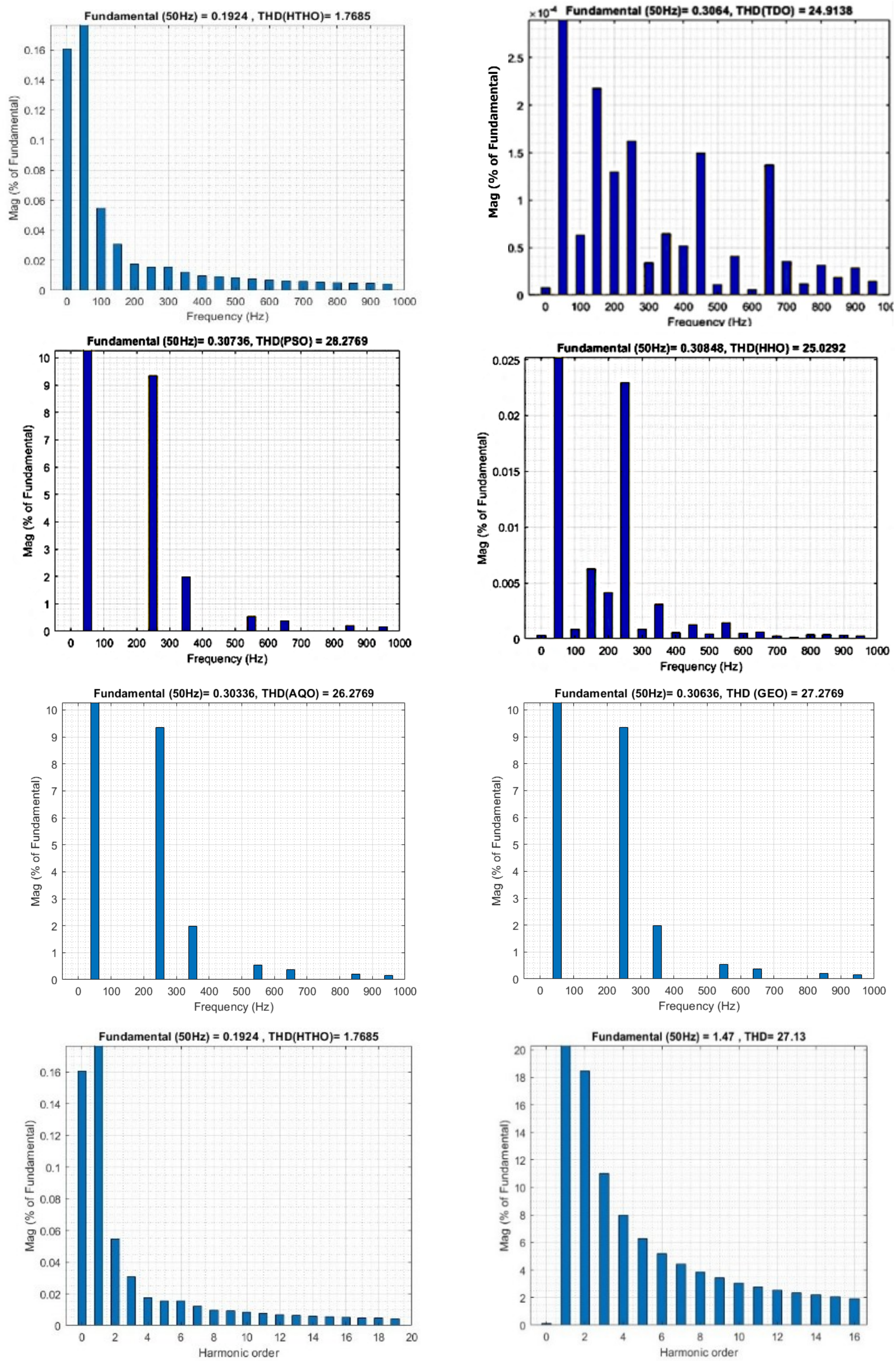

Figure 9. THD analysis of grid current when EVs are connected with various optimization techniques

The THD comparison between the suggested and current methods is shown in Table 1. THD is a metric that expresses how distorted a signal is in relation to its fundamental frequency. The proposed method THD value of 1.76855 indicates that the harmonic distortion in the signal, as calculated with the proposed method, accounts for approximately 1.76% of the total signal. As a result, the odd harmonics were effectively suppressed by the proposed algorithm when compared with conventional control methods such as PI controller.

Table 1. Grid current THD comparison of various optimization techniques

S. no	Optimization techniques	THD (%)
1	HTHO	1.76
2	TDO	24.91
3	HHO	25.02
4	GEO	27.27
5	AQO	26.27
6	PSO	28.27
7	PI	27.13

4. CONCLUSION

By developing an innovative bidirectional DC-DC converter which is intended for V2G connections and G2V based operations, this research makes a substantial contribution to the advancement of EV charging infrastructure. The proposed converter, which integrates PV systems, EV batteries, and the power grid, improves charging flexibility and efficiency while also helping to reduce peak load, level load, regulate voltage, and maintain overall power system stability. The implementation of the proposed methodology in MATLAB/Simulink shows significant power quality improvements in V2G and G2V operations. The THD analysis verifies the effectiveness of the suggested approach, with a THD value of 1.768% indicating minimal harmonic distortion in the signal, and the odd harmonics were successfully suppressed. The HTHO algorithm guarantees that the converter operates optimally, enabling successful integration of renewable sources with grid operations, indicating little harmonic distortion in the signal and successful suppression of the odd harmonics. The THD analysis validates the effectiveness of the suggested strategy. This study lays the groundwork for future advancements in EV charging infrastructure, which could find applications in smart grid systems and eco-friendly energy integration. With the objective to guarantee the performance and scalability of the suggested converter under various EV charging settings and grid contexts, further investigation will concentrate on experimental validation and practical deployment.

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Immanuel Selvakumar	✓	✓		✓	✓			✓		✓	✓	✓	✓	
Pandiyan Venkatesh Kumar	✓	✓		✓	✓		✓	✓		✓	✓	✓	✓	

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

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

This paper does not involve new data; therefore, data availability is not applicable.

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