SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I11P102

Volume 12 Issue 11, 12-24, November 2025

Original Article

Di-Strategy Based Secretary Bird Optimization Algorithm for Electric Vehicle Using Bi-Directional DC-DC Converter

Poonam Nanjibhai Parmar[1], Deepali V. Bavlecha[2]

[1,2]Department of Electrical Engineering, Government Engineering College, Rajkot, Gujarat, India.

[1]Corresponding Author : parmarpoonam.88@gmail.com

Received: 02 September 2025 Revised: 04 October 2025 Accepted: 03 November 2025 Published: 28 November 2025

Abstract - *Electric Vehicles (EVs) provide a sustainable transportation solution by minimizing carbon emissions and dependence on non-renewable energy sources, which contribute to enhanced energy efficiency and lower operational costs. However, EVs suffer from inefficiencies of power conversion due to losses in electronic elements like switches and inductors that result in reduced system performance. In this research, the Di-Strategy based Secretary Bird Optimization Algorithm (DS-SBOA) is proposed for EV application utilizing a Bi-directional DC-DC converter. In conventional SBOA, diffusion mechanism and adaptive β hill climbing strategies are incorporated to enhance the population diversity, avoid local optima, and contribute to the search space for better solutions. A Photovoltaic (PV) system in EVs extends driving range by harnessing solar energy to charge the battery, which minimizes dependency on external charging stations and improves sustainability. A bidirectional DC-DC converter is employed to provide effective energy transfer between the load and the battery, which enhances battery life in EV applications. The proposed DS-SBOA obtains a better Total Harmonic Distortion (THD) of 2.32% in source current and 15.48% in load current compared to existing methods, such as DSTATCOM with an ANFIS controller.*

Keywords - *Bidirectional DC-DC converter, Diffusion mechanism, Electric vehicle, Photovoltaic, Secretary bird optimization algorithm.*

1. Introduction

Electric Vehicle (EV) provides a promising transportation solution to achieve low-carbon emissions, which has enhanced their popularity in the global market. Various countries enhance the EV market by substantial investments and by providing incentives that result in more than 16.5 million EVs on the road in 2021 [1]. The increasing demand for effective and sustainable energy systems has prompted important advancements in power electronics, especially in Direct Current (DC) to DC converters. These converters play a significant role in numerous applications that contain energy storage management, renewable energy integration, and EV power systems [2].

DC-DC transfers power across multiple voltage levels effectively within the vehicle by stepping voltage down or up as needed [3]. DC-DC converters are primarily classified into two types based on non-isolated and isolated. Isolated converters employ a transformer to provide isolation, whereas non-isolated converters operate without a transformer. Which are utilized in numerous applications and generation systems, depending on Renewable Energy Source (RES) like Photovoltaic (PV) and fuel cells, have been of concern because of the rapid depletion of environmental pollution and fossil fuels problems [4-6]. RESs are primarily used with Energy Storage Units (ESUs), owing to their intermittent power generation, like supercapacitors and batteries, for providing an uninterrupted and stable power flow to loads [7, 8]. PV contains two distinct categories: off-grid PV and grid-connected PV systems [9]. The extracted configuration represents a hybrid arrangement combining PV-generated electricity with the conventional power grid [10, 11]. Simultaneously, the latter depends entirely on PV as an energy source and is equipped with battery charging abilities [12, 13].

The PV grid utilizes solar energy during availability and depends on electricity in unavailability. Charging an EV places an augmented burden on the electrical system because of significant present demands, especially during fast charging [14, 15]. Furthermore, PV power has the potential to be transmitted to the grid, which results in financial gains even in the absence of a vehicle [16]. An off-grid PV system is an independent arrangement that only shows the required electrical energy to charge an EV without any external support from a utility provider [17]. Moreover, the PV has an adequate size for accommodating the varying demands of the necessary number of vehicles over time [18]. Generally, a PV system comprises PV panels coupled in series and parallel structures to provide the required power to the load. However, PV modules associated with series obtain various levels of sunlight exposure during the day, which impacts the non-linear Power-Voltage (P-V) curve that specifically has Maximum Power Point (MPP) over the constant environmental situations [18, 19].

Nevertheless, EV suffer from inefficiencies of power conversion because of losses in electronic elements like switches and inductors that result in reduced system performance. Despite significant progress in topologies of converters and EV control strategies, numerous technical limitations remain unsolved. Moreover, the existing bidirectional DC-DC converters often experience conduction losses and high switching, regulation capability, limited voltage, and improved THD under dynamic and non-linear load conditions.

Furthermore, traditional optimization algorithms like BOA, DBO, and standard SBOA frequently suffer from poor adaptability, premature convergence, and slow response to dynamic changes in PV-generated power. These challenges hinder effective power handling and reliable bidirectional energy flow in EV systems combined with natural energy resources. Hence, there occurs a significant research gap in evolving an adaptive and robust optimization strategy which having the capability to improve converter efficiency, mitigate THD, and enhance overall energy quality in solar power EV applications. To address this issue, the Di-Strategy based Secretary Bird Optimization Algorithm (DS-SBOA) is proposed in EV application by optimizing the bi-directional DC-DC converter, which solves power conversion inefficiencies. The converter minimizes losses in inductors and switches, which results in enhanced energy transfer and less THD. The major contribution of this research is as follows:

- The diffusion mechanism and adaptive β hill climbing strategy are two distinct di-strategies incorporated in traditional SBOA to enhance population diversity, prevent local optima, and provide better solutions that minimize THD in EV applications.
- The combination of Photovoltaic (PV) systems with EV charging minimizes dependency on the source of external power and enhances sustainability by effectively harnessing solar energy for battery charging.
- By decreasing power losses in electronic elements like inductors and switches, the proposed DS-SBOA ensures better voltage regulation and enhanced EV system performance.

This research paper is organized as follows: Section 2 follows the literature review, and Section 3 contains a brief discussion of the proposed method. Section 4 analyzes experimental results, and Section 5 presents the overall conclusion of the paper.

2. Literature Survey

Seyed Reza Mousavi-Aghdam et al. [20] established an improved voltage gain bidirectional DC-DC converter depending on the Voltage Multiplier Cell (VMC) for EV based on boost and buck converters. This converter contained a low device, less switching power loss, a simple structure, step-down and step-up again. Moreover, the established converter involves a primary ground between the input and output ports that prevents additional devices. However, VMC increases voltage gain, which introduces additional circuit complexity and losses because of parasitic elements, resulting in overall effectiveness.

William Christopher I et al. [21] presented a bidirectional DC-DC converter for Renewable Energy Source (RES) in EV applications. The presented converter contained 2 identical Zero Voltage Transmission (ZVT) cells with a capacitor, a supplementary switch, and 2 resonant inductors integrated with a 3-level topology, which enabled both boost and buck operating systems. This bidirectional DC-DC converter involved ripple frequency of inductor current and DC link voltage stress reduction. Nevertheless, frequently switching between charging and discharging introduced losses because of switching transients and conduction losses that minimize the overall performance.

Ranjan Pramanik and B.B. Pati [22] introduced a simpler logic control circuit with a capacitor and battery. Initially, mathematical modeling was applied with parasitic in each action model. To manage DC-DC, the small signal model was applied for buck and boost processes, utilizing linearization and the averaging model. Next, a logic circuit controller was established for acquired signals to determine the converter performance in boost and buck mode operation. However, a simpler logic control circuit struggled to dynamically balance power among the battery and supercapacitor, which resulted in inefficient voltage regularization.

Md Mujahid Irfan et al. [23] developed a shunt active power filter by utilizing a neuro-fuzzy control model (ANFIS) to reduce the harmonic performance in grid-interactive solar EV systems. The DSTATCOM was presented depending on Voltage Source Converter (VSC) based on ANFIS to determine the model performance.

The data was trained by applying a back-propagation model and decisions occupied by a fuzzy expert system. Nevertheless, ANFIS highly depends on the quality of input data and parameters, which makes it challenging to vary in grid connection and potentially results in suboptimal performance. K. Mounika Nagabushanam et al. [24] suggested a switched capacitor for interfering with the battery and propulsion system through DC. The passive components were designed to evaluate loss and effectiveness in steady-state analysis. However, switched capacitors lack precise voltage control and suffer from inherent charge redistribution loss that minimizes stability and effectiveness.

In the overall assessment, it is observed that the current existing bidirectional DC-DC converter topologies and control methodologies have significantly advanced power transfer capability and voltage gain; however, most of the methods are still accompanied by major disadvantages, including a rise in switching losses, poor THD, and the capability of voltage regulation under non-linear loads. Also, the optimization techniques employed have exhibited poor convergence speed and have gotten stuck in local optima in some studies, like DBO, ANFIS, and BOA-based control, which has led to suboptimal energy processing in EV systems. Thus, this research outlines a clear need for an advanced adaptive optimality procedure that is designed to handle with exploitation and exploration while improving power quality and reducing THD. Therefore, this paper proposes a DS-SBOA method that utilizes adaptive hill climbing and diffusion to enhance converter stability and efficiency in solar Electric Vehicle (EV) applications.

3. Proposed Methodology

In this research, the DS-SBOA is proposed for EV application utilizing a bi-directional DC-DC converter. Charger contains individual docks for the EV and grid, whereas the grid inverter, chopper, and DC EV charger are associated with the primary DC. DSTATCOM is applied to overcome the harmonics and power factor, which serve as a load compensator, voltage controller, and filter. Figure 1 depicts the primary structure of the EV charging system.

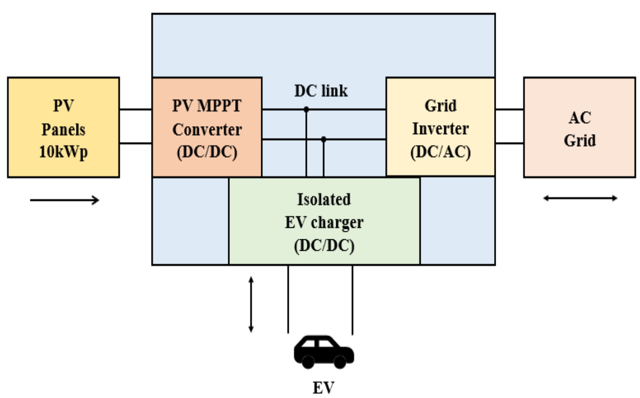


Fig. 1 Primary structure of EV system

3.1. PV Module

A PV module system in an EV combines solar panels for harnessing solar energy, which minimizes the dependency on external charging. It increases vehicle efficiency by supplying battery power and extends driving range, which is crucial for sustainable energy use, minimizing emissions, and operational costs. The mathematical equation for current is expressed in Equation (1),

$$I = I_{pv} - I_0 \left[e \frac{(v+Rs.I)q}{\alpha v_k} \right] - \frac{(v+Rs.I)}{R_p} \tag{1}$$

Where I_{pv} indicates photocurrent, V_k denotes thermal voltage, I_O Represents cell saturation of dark current, T determines the working temperature of the cell, α illustrates the ideality factor, R_p defines shunt resistance, and R_s Denotes series resistance. A PV current varies with temperature, irradiation, and the number of arrays, which is represented in Equation (2),

$$I = I_{pv} - I_0 \left[exp \frac{(v+Rs.I)q}{\alpha kT.Ns} - 1 \right] - \frac{(v+Rs.I)}{R_p} \tag{2}$$

Where Ns represents series-connected cells, then the PV panel output is passed through a bidirectional DC-DC converter. The overall block diagram of the proposed system is shown in Figure 2.

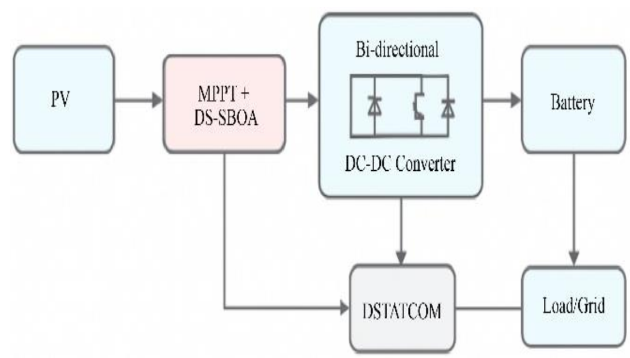


Fig. 2 Overall block diagram of the proposed system

3.2. Bidirectional DC-DC Converter

A main aim of DC-DC power conversion is to attain bidirectional power flow between two voltage levels during abnormal and normal conditions. Figure 2 represents a non-isolated bi-directional DC-DC converter that integrates step-up and step-down DC voltage. Converter executes in step-up mode as boost and step-down mode as buck. In Figure 3, V_{DB} represents voltage at high voltage, V_{BT} indicates low voltage, R_{DB} and R_{BT} denotes internal resistance of V_{BT} and V_{DB}.

Moreover, the circuit involves components of energy storage, like an input capacitor. C_H, two switches Q_1 and Q_2 with resistance R_{dson}, inductor L, output capacitor C_L, and R_{LP} Represents the inductor parasitic resistance. The two switches are connected in anti-parallel diodes. D_1 and D_2 respectively. This converter majorly processes with 2 operational modes: step-up and step-down with continuous current conduction, which is explained in the following subsections.

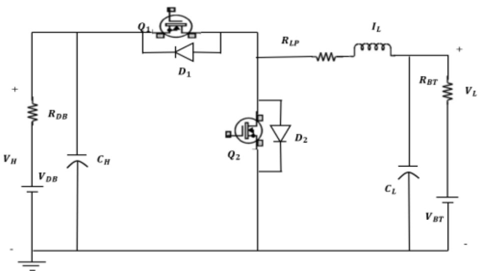


Fig. 3 Structure of bidirectional DC-DC converter

3.2.1. Buck Mode

During this process, the power flow is considered from the end of high voltage to low voltage (source to load), whereas the battery gets charged. In the overall evaluation, switch $Q_1$is ON and the remaining switches are off. Initially, Q_1 is ON and remaining Q_2, D_1, and $D_2$are OFF while the inductor and output capacitor C_L It is charged from the bus voltage. Moreover, D_2 acts as a freewheeling diode while Q_1 and Q_2 Both are OFF. Meanwhile, the inductor current I_L Does not instantly alter. Therefore, the output voltage overloads R_{BT} Minimizes compared to the input supply voltage. By applying KCL and KVL, dynamics are attained using Equations (3) to (6)

$$\frac{di_L}{DT} = \frac{R_{PT}I_L}{L} = \frac{V_L}{L} \tag{3}$$

$$\frac{dV_H}{dt} = \frac{V_H}{R_{DB}C_H} + \frac{V_{BS}}{R_{DB}C_H} \tag{4}$$

$$\frac{dV_L}{dt} = \frac{I_L}{C_L} + \frac{V_{BT}}{R_{BT}C_L} - \frac{V_L}{R_{DB}C_H} \tag{5}$$

$$\begin{bmatrix} i_L \\ V_H \\ V_L \end{bmatrix} = \begin{vmatrix} \frac{-R_{PT}}{L} & \frac{1}{L} & \frac{-1}{L} \\ \frac{-1}{C_H} & \frac{-1}{R_{DB}C_H} & 0 \\ \frac{1}{C_L} & 0 & \frac{-1}{R_{BT}C_L} \end{vmatrix} \begin{vmatrix} I_L \\ V_H \\ V_L \end{vmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \frac{1}{R_{DB}C_H} \\ \frac{1}{R_{BT}C_L} & 0 \end{bmatrix} \begin{bmatrix} V_{BT} \\ V_{DB} \end{bmatrix} \tag{6}$$

3.2.2. Boost Mode

The switch Q_1 is OFF and Q_2 is ON, respectively; hence, the battery supplies power to the load with high voltage. A D_1 and Q_2 executes conduction when Q_1 and $D_2$is OFF in step-up operational mode. Initially, Q_2 The remaining ON and the remaining components are off, which results in the inductor charging by the battery source. Therefore, the I_L is linearly increased till the switch Q_2 remains OFF. During this mode, another side D_1 is in reverse bias, while the switch Q_1 is OFF, no current is passed via the switch Q_1. Next in 2nd step, Q_1 and Q_2 If it remains OFF, the circuit is assumed to be an open circuit. Based on circuit topology, the mathematical formula of boost mode for KVL and KCL is expressed using Equations (7) to (12).

$$\frac{dI_L}{dt} = -\frac{R_{PT}I_L}{L} - \frac{V_L}{L} \tag{7}$$

$$\frac{dV_H}{dt} = -\frac{V_H}{R_{DB}C_H} + \frac{V_{DB}}{R_{DB}C_H} \tag{8}$$

$$\frac{dV_L}{dt} = \frac{I_L}{C_L} + \frac{V_{BT}}{R_{BT}C_L} - \frac{V_L}{R_{BT}C_L} \tag{9}$$

$$\begin{bmatrix} i_L \\ V_H \\ V_L \end{bmatrix} = \begin{vmatrix} \frac{-R_{PT}}{L} & \frac{D}{L} & \frac{-1}{L} \\ 0 & \frac{-1}{R_{DB}C_H} & 0 \\ \frac{1}{C_L} & 0 & \frac{-1}{R_{BT}C_L} \end{vmatrix} \begin{vmatrix} I_L \\ V_H \\ V_L \end{vmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & \frac{1}{R_{DB}C_H} \\ \frac{1}{R_{BT}C_L} & 0 \end{bmatrix} \begin{bmatrix} V_{BT} \\ V_{DB} \end{bmatrix} \tag{10}$$

Therefore, equating the state space average DC model is

$$0 = \begin{vmatrix} \frac{-R_{PT}}{L} & \frac{D}{L} & \frac{-1}{L} \\ -\frac{D}{C_H} & \frac{-1}{R_{DB}C_H} & 0 \\ \frac{1}{C_L} & 0 & \frac{-1}{R_{BT}C_L} \end{vmatrix} \begin{vmatrix} I_L \\ V_H \\ V_L \end{vmatrix} \begin{bmatrix} 0 & 0 \\ 0 & \frac{1}{R_{DB}C_H} \\ \frac{1}{R_{BT}C_L} & 0 \end{bmatrix} \begin{bmatrix} V_{BT} \\ V_{DB} \end{bmatrix} \tag{11}$$

Equating the state-space averaged AC is

$$\frac{d}{dt} \begin{bmatrix} \widehat{I_L} \\ \widehat{V_H} \\ \widehat{V_L} \end{bmatrix} = \begin{vmatrix} \frac{-R_{PT}}{L} & \frac{D}{L} & \frac{-1}{L} \\ -\frac{D}{C_H} & \frac{-1}{R_{DB}C_H} & 0 \\ \frac{1}{C_L} & 0 & \frac{-1}{R_{BT}C_L} \end{vmatrix} \begin{vmatrix} \widehat{I_L} \\ \widehat{V_H} \\ \widehat{V_L} \end{vmatrix} + \begin{bmatrix} 0 & \frac{1}{L} & 0 \\ -\frac{1}{C_H} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} I_L \\ V_H \\ V_L \end{bmatrix} \hat{d} \tag{12}$$

For addressing the high voltage gain problem that is observed in conventional bidirectional DC-DC converters, the proposed DS-SBOA includes an adaptive control optimization mechanism that maintains switching patterns and duty cycles. Traditional converters face excessive voltage stress and component heating when gain is not correctly controlled, which leads to decreased efficiency and unstable output. The DS-SBOA monitors converter output in a continuous manner and adaptively regulates control variables by its diffusion and hill-climbing strategies for regulating optimal gain levels.

This adaptive tuning guarantees that the voltage step-up ratio leaves out a stable operational range, which prevents overshoot by safeguarding high efficiency. Moreover, optimized inductor current balancing and decreased switching losses contribute to reducing voltage ripples. Therefore, the converter obtains smooth energy transfer among the PV source, battery, and load without imposing extra voltage stress on semiconductor components, which mitigates the high voltage gain problem and helps guarantee stable performance in differing load conditions.

Thus, the converter in EV enables efficient power flow between the battery and other components by supporting bi-directional energy transfer. This improves energy effectiveness, maximizes battery life, and enhances the overall performance of the vehicle.

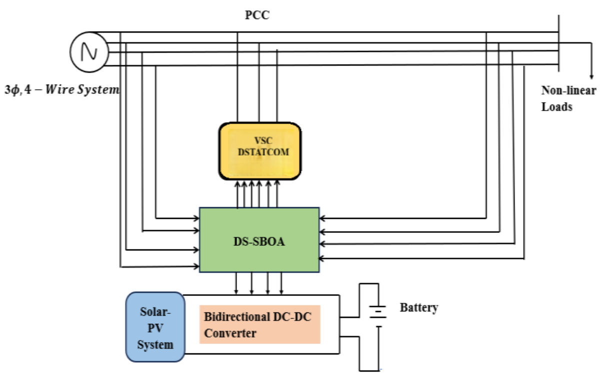


Fig. 4 Structure of proposed DS-SBOA

3.3. DSTATCOM Device

The employment of power equipment or devices represents fluctuating loads that result in distortions in power systems, such as reactive power components, harmonics, and so on. Moreover, the outputs are obtained with the heating of machines, low power factor, minimized efficiency, and misfire of devices that are highly sensitive. An extra power quality problem is due to the deployment of single or 3-phase nonlinear or unbalanced loads, which leads to excessive current flowing via the neutral wire.

Thus, the generation of negative sequence current element is minimized when the torque is reduced in the electric drive. These quality problems are addressed by utilizing power devices like DSTATCOM, DVR, and so on, where DSTATCOM is appropriate for reactive power problems and harmonic current mitigation on the distribution side, compared to other devices. For operating VSC, 6 gating pulses are used for the power switch, which is an IGBT. These pulses are generated by the proposed model, which offers a better response by minimizing high-order disturbance. The system speed is minimized due to the use of more training data and fewer memberships. The proposed DS-SBOA is to enhance the power quality of 3-phase 4W, which is represented in Figure 4. The proposed model operates in a 3-phase balanced action mode by addressing non-linear and unbalanced loads. The system involves a 4-leg IGBT-based VSC, DC-DC converter, solar PV array, and DC bus capacitor.

Therefore, the load does not draw any harmonics from the grid, which minimizes losses in neutral grid wire and maximizes the 3P4W system of power quality in unbalanced loading conditions.

3.4. Proposed DS-SBOA

After the converter, DS-SBOA is performed in the EV application to enhance PV system effectiveness. Compared to conventional optimization methods such as Dung Beetle Optimization (DBO) and Bobcat Optimization Algorithm (BOA), the SBOA [25] is used, which enhances global search ability and minimizes the premature convergence problem.

Its dynamic adaptive behavior ensures better Maximum Power Point Tracking (MPPT) under varying solar conditions and enhances energy harvesting. SBOA's effective management of non-linear optimization issues makes it ideal for EV applications, which leads to enhanced effectiveness, extended range, and increased sustainability of solar-powered EV systems.

Initialization: SBOA is a population-based meta-heuristic method that randomly produces a candidate solution set44999++ in the search space. A mathematical equation of the secretary bird's initial solution is expressed in Equation (13).

$$x_{i,j} = \left(ub_j - lb_j\right) \times r_1 + lb_j \tag{13}$$

Where $x_{i,j}$ indicates the initial value ofi^{th} candidate solution inj^{th} decision variable,lb_jandub_j denotes the minimum and maximum boundary, and r_1 represents a random number in the (0,1) range.

Exploration: The secretary bird's hunting behavior contains three phases: prey searching P_1, exhausting P_2, and prey attacking P_3. Secretary bird looks for prey during the stage of prey searching; once it is recognized, the prey enters the exhausting phase, where it increases the prey's stamina. It initiates the attack once the stamina of the prey is depleted sufficiently, using Equations (14) and (15).

$$x_{i,j}^{new1} = \begin{cases} P_1 : x_{i,j} + r_2 \times (x_{r1} - x_{r2}), & if\ iter < \frac{1}{3}T \\ P_2 : x_{best} + \exp\left(\left(\frac{iter}{T}\right)^4\right) \times (RB - 0.5) \times \left(x_{best} - x_{i,j}\right) & if\ \frac{1}{3}T < iter < \frac{2}{3}T \\ P_3 : x_{best} + \left(1 - \frac{iter}{T}\right)^{\left(2 \times \frac{iter}{T}\right)} \times X_{i,j} \times RL & else \end{cases} \tag{14}$$

$$X_i = \begin{cases} X_i^{new1}, & if\ F_i^{new1} < F_i \\ X_i, & else \end{cases} \quad (15)$$

Where $iter$ represents the present iteration number, T denotes a high number of iterations, X_i^{new1} illustrates a new state of i^{th} Secretary bird in the initial phase, x_{r1} and x_{r2} determines a random solution, X_i^{new1} denotes the position information of j^{th} dimension, and F_i^{new1} depicts the objective function fitness value.

Exploitation: Secretary birds look for attacks from predators to steal the food. One stage is split into two kinds: one involves running or flying to escape.S_1 whereas others include utilizing environmental structures or colors for camouflage S_2 which enables the challenge predators for identification using Equations (16) and (17).

$$x_{i,j}^{new2} = \begin{cases} S_1: x_{best} + (2 \times RB - 1) \times \left(1 - \frac{iter}{T}\right)^2 \times x_{i,j}, & if\ q < r_3 \\ S_2: x_{i,j} + r_4 \times \left(x_{rand} - 1 \times x_{i,j}\right), & else \end{cases} \quad (16)$$

$$X_i = \begin{cases} X_i^{new2}, & if\ F_i^{new2} < F_i \\ X_i, & else \end{cases} \quad (17)$$

The pseudocode of this proposed DS-SBOA is given in the following Algorithm 1

Algorithm 1: Di-Strategy Secretary Bird Optimization Algorithm (DS-SBOA)

```
Inputs:
    - Objective function f(x) (e.g., THD + weighted loss metric)
    - Search space bounds: x_min, x_max
    - Population size N, Max iterations T_max
    - Diffusion parameters: σ (Gaussian std), diffusion_prob
    - Adaptive hill-climbing parameters: q_max, a_start, a_end
Outputs:
    - x_best (optimal control parameters/switching pattern)
    - f_best (objective value)

1:  Initialize iteration t ← 0
2:  Initialize population P = {x_i | i = 1..N} uniformly in [x_min,x_max]
3:  Evaluate fitness f(x_i) for all x_i in P
4:  Set x_best ← argmin_i f(x_i); f_best ← f(x_best)
5:  while t < T_max do
6:     /* Exploration: secretary bird search (prey search & exhausting) */
7:     for each individual x_i in P do
8:         Generate candidate x_rand (random exploration)
9:         x_explore ← x_i + r1 * (x_rand - x_i)   // r1 ~ U(0,1)
10:        Project x_explore into bounds [x_min,x_max]
11:        Evaluate f(x_explore)
12:        if f(x_explore) < f(x_i) then
13:            x_i ← x_explore
14:        end if
15:    end for
/* Diffusion mechanism (increases diversity) */
18:        for each individual x_i in P with probability diffusion_prob do
19:          Δ ← Normal(0, σ^2) vector, i.e., a zero mean Gaussian with standard deviation σ
20:       x_diff ← x_best + Δ * (1 + rand()) // new particle around global best
21:        Project x_diff into bounds
22:        Evaluate f( x_diff)
23:        if f( x_diff) < f( x_i) then
24:            x_i ← x_diff
25:        end if
26:    end for
27:
28:    /* Exploitation: adaptive hill-climbing */
29:     a_t ← a_start - ( (a_start - a_end) * t / T_max ) // adaptive coefficient
30:    for each individual x_i in P do
31:       rN ← Normal(0,1) vector, i.e., a standard normal random vector
32:        x_hc ← x_i + a_t * rN * (x_best - x_i)
33:        Project x_hc into bounds
34:        Evaluate f( x_hc)
35:        if f( x_hc) < f( x_i) then
36:            x_i ← x_hc
37:        end if
38:    end for
39:
40:    /* Update global best */
41:    for each x_i in P do
42:        if f( x_i) < f_best then
43:            x_best ← x_i
44:            f_best ← f( x_i)
45:        end if
46:    end for
47:
48:    /* Optional local refinement counter q */
49:    if (t mod some_interval == 0) then
50:          perform additional local search around x_best (e.g., small Gaussian perturbations) until q > q_max
51:    end if
52:
53:    t ← t + 1
54: end while
55: Return x_best, f_best
```

3.4.1. Improved Di-Strategy

Exploration and exploitation do not provide a significant performance in searching global optima and solving local optima; the algorithm still has a certain search space that it cannot reach. Therefore, di-strategy is incorporated in those stages, namely, the diffusion process (exploration) and adaptive β hill climbing (exploitation).

The diffusion process provides more solutions by dissolving the population, which enhances the population's diversity and avoids stagnation and local optima. Adaptive β hill climbing explores continuously, which contributes to searching for finer solutions. Diffusion strategy: An original particle generates new particles randomly around it, which is expressed in Equation (18).

$$x_i = Gaussain\left(Bestposition,\ \varepsilon, m\right) + \sigma \times (Bestposition - x_i) \quad (18)$$

Where x_i indicates new particle position generated by diffusion mechanism, $Gaussain(Bestposition, \varepsilon, m)$ Represents a random matrix in a Gaussian distribution, $Bestposition$ denotes the global optima position, σ denotes a random number between 0 and 1, and m depicts the determinant of the generated matrix form.

Adaptive β hill climbing: The provisional solution is defined in each iteration and enhanced utilizing η and β operator. The η operator primarily plays a role in the exploitation stage, and β is similar to the uniform mutation operator, which is performed in the exploration stage. The η employs a random walk using Equation (19).

$$s_i' = s_i \pm U(0,1) \times \eta \quad (19)$$

Where s_i indicates the present solution, s_i' Represents a new solution, $U(0,1)$ depicts a random number with normal distribution, and η determines the adaptive coefficient, which is determined by the distance between s_i and s_i'. To balance the exploration and exploitation stages, η requires a high value. Therefore, it is minimized in each iteration from one to zero based on Equation (20)

$$n_t = 1 - \frac{t^{\frac{1}{p}}}{T^{\frac{1}{p}}} \quad (20)$$

Where t and T denote the number of present and the maximum number of iterations, p represents a constant. This research sets p value obtained by η, which is applied as the present solution and the new solution. s''utilizing β in Equation (21).

$$s'' = \begin{cases} s_k, & r \leq \beta \\ s_i' & otherwise \end{cases} \quad (21)$$

Where k illustrates a random number chosen from a range i, equation (21) defines that if r is not higher than β, then an individual from the present population is selected for replacing the individual; else, it is unchanged. The β is calculated linearly based on β_{max} (0.1) andβ_{min} (0.01) using Equation (22).

$$\beta_t = \beta_{min} + \frac{t}{T} \times [\beta_{max} - \beta_{min}] \quad (22)$$

The proposed Di-strategy-based SBOA efficiently combines the diffusion mechanism and adaptive hill climbing techniques into the essential SBOA position update rule. Basically, in the standard BOA, the I^{th} The secretary bird position at iteration t is modernized as $X_i^{t+1} = X_T^I + \alpha(X_{rand}^t - X_I^t)$, where α is an arbitrary exploration coefficient that commands the prey searching process. In the improved DS-BOA, this equation is computed to incorporate two corrective terms demonstrating the double strategies that are mathematically computed as shown in Equation (23)

$$X_i^{t+1} = X_i^t + \alpha(X_{rand}^t - X_I^t) + \beta\Delta_{diff} + \gamma\Delta_{hc} \quad (23)$$

Where, $\Delta_{diff} = N(0, \alpha^2)(1 + \mathrm{rand})I$ is the stochastic Gaussian perturbation derived from the Diffusion mechanism, which is Equation 18, and $\Delta_{hc} = a_t N(0,1)(X_{best} - X_i^t)$ is the adaptive step alteration generated by the hill climbing phase, as demonstrated by Equations (19-22). The β and γ adaptively regulate the exploration and exploitation degree as iterations progress. This formulation mathematically fuses both techniques into the actual SBOA motion dynamics, allowing the algorithm to instantaneously expand the hunt space while filtering convergence near promising regions.

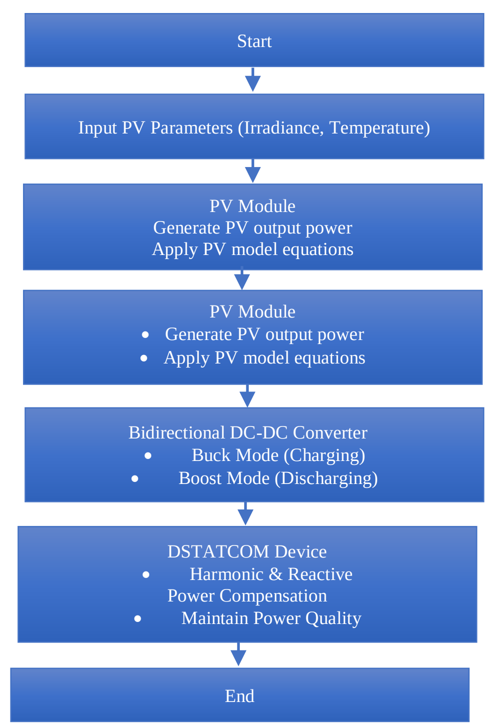


Fig. 5 Overall methodology flowchart for the DS-SBOA-based PV–EV power system

Similarly, the DS-SBOA attained quicker global convergence, enhanced precision in local hunt, and more reliable control enhancement for the EV bidirectional converter. Thus, the diffusion strategy in SBOA enhances the convergence speed in early iterations, which makes rapid optimal power tracking for PV systems in EVs. The adaptive β hill climbing improves model performance in later iterations, which provides robustness against dynamic environmental changes. Together, these enhancements improve PV effectiveness in EV applications. The Overall methodology flowchart for the DS-SBOA-based PV–EV power system is illustrated in Figure 5.

3.5 Functional Role of the Proposed DS-SBOA in PV MPPT Control

The suggested DS-SBOA efficiently improves the PV system MPPT. The algorithm comprises altering the duty ratio of the DC–DC converter in real time, which takes the PV array to the optimal voltage and current per the Maximum Power Point (MPP). The conventional algorithms, mainly Perturb and Observe (P&O) and Incremental Conductance (INC), are overwhelmed by steady-state oscillations and poor performance under partial shading and varying conditions. However, the DS-SBOA is different because it uses both diffusion and an adaptive hill climbing strategy, resulting in a balancing of exploration and exploitation. During its diffusion phase, the DS-SBOA not only provides diversity to the hunt process to avoid premature convergence, but it is also able to escape local maxima created under partial shading. To converge quickly and accurately to the true global MPP, the adaptive hill-climbing phase optimizes the value of the best solution. This hybrid functionality promotes a fast responsivity to rapid changes in solar irradiance and temperature, mitigating tracking time and maximizing energy harvesting. The algorithm-intelligent optimization of the converter control parameters reduces voltage oscillations and switching losses, enhancing total system efficiency and stability. Therefore, DS-BOA's consideration of the MPPT control loop enables the PV system to operate in a strong and energy-efficient manner regardless of environmental conditions.

4. Simulation Results

This section shows the performance analysis of the DS-SBOA for EV applications. The proposed DS-SBOA is simulated using MATLAB 2020b with a system configuration of 128 GB RAM, an Intel i7 processor, and Windows 10 operating system. Table 1 represents a parameter for a bi-directional DC-DC converter. Further to assure fair reproducibility and benchmarking, the overall simulation setup utilized for implementing the proposed DS-SBOA-based PV-EV system is illustrated in Table 2.

The simulation parameters are segregated into three groups: (i) DS-SBOA algorithmic parameters that define the search dynamics and convergence behavior, (ii) PV system parameters demonstrating environmental and module characteristics, and (iii) bidirectional DC–DC converter parameters that illustrate the power stage configuration and control operating conditions. These simulations were evaluated in MATLAB/Simulink (R2020b) by using a fixed step solver with a step size of 1 µs.

Table 1. Parameters for a bi-directional DC-DC converter

Parameters	Values
R_{DB} (ohm)	15
R_{BT} (ohm)	8
$L\ (\mu H)$	7
$C_L(\mu F)$	20
$C_H(\mu F)$	20
$F_{sw}(KHZ)$	70
R_{dson} (milli ohm)	36
$V_H(v)$	42
$V_L(v)$	14
R_{lp} (milli ohm)	36

Table 2. Simulation setup including DS-SBOA algorithm configuration, PV array specifications, and bidirectional DC–DC converter parameters used for performance evaluation

Category	Parameter	Symbol	Value	Description
A. DS-SBOA Parameters	Population size	N	50	Determines the number of candidate solutions
	Maximum iterations	T_{max}	200	Termination limit for the algorithm
	Diffusion probability	P_{diff}	0.3	Probability of diversity update

	Gaussian standard deviation	σ	0.1	Used in the diffusion process
	Adaptive coefficient (start–end)	$a_{start} - a_{end}$	0.9–0.01	Controls exploitation intensity
	Objective function	—	THD + Power Loss	Minimization target
	Random seed	—	12345	Ensures reproducibility
B. PV System Parameters	Irradiance	G	1000 W/m²	STC solar condition
	Temperature	T	25 °C	Ambient condition
	Module power	p_{mp}	300 W	Rated maximum power
	Voltage at MPP	V_{mp}	30 V	Module output voltage
	Current at MPP	I_{mp}	8 A	Module output current
	Series/Parallel modules	N_s/N_p	12 / 5	Defines total PV array rating
	PV model	—	Single-diode	Used for simulation modeling
C. DC–DC Converter Parameters	High-side voltage	V_H	400 V	Bus voltage (boost mode)
	Low-side voltage	V_L	48 V	Battery nominal voltage
	Inductance	L	500 µH	Main inductor value
	Inductor resistance	R_L	36 mΩ	Winding parasitic resistance
	DC link capacitance	C_{dc}	4700 µF	Energy buffer
	Output capacitance	C_{out}	2200 µF	Filtering capacitor
	Switching frequency	F_{sw}	20 kHz	PWM operation
	Control update period	C_{ctrl}	50 µs	Sampling period for control
	Operating mode	—	Continuous conduction	Buck and boost operation

4.1. Performance Analysis

Figure 6 shows a simulated result of V_{dc} (V), i_{sn} (A), i_{Ln}(A), and IV_{scn} (A) for the proposed DS-SBOA. This graph reflects that the harmonic current required by the load is neutral, which is compensated by 4th leg of the converter.

This compensation ability eliminates the requirement for input neutral for distributing the harmonic component of load-neutral current, which ensures enhanced system performance.

The input current (i_{sn}), converter-neutral current (i_{vsn}), and load-neutral current (i_{ln}) exhibit stable characteristics under dynamic conditions, which provides better power quality, enhanced reliability, and minimised system losses. The graphical evaluation in this graph shows the behavior of DC link voltage and neutral currents, which validate the system's effectiveness. These results provide the converter's ability to maintain a balanced power flow and enhanced harmonic compensation.

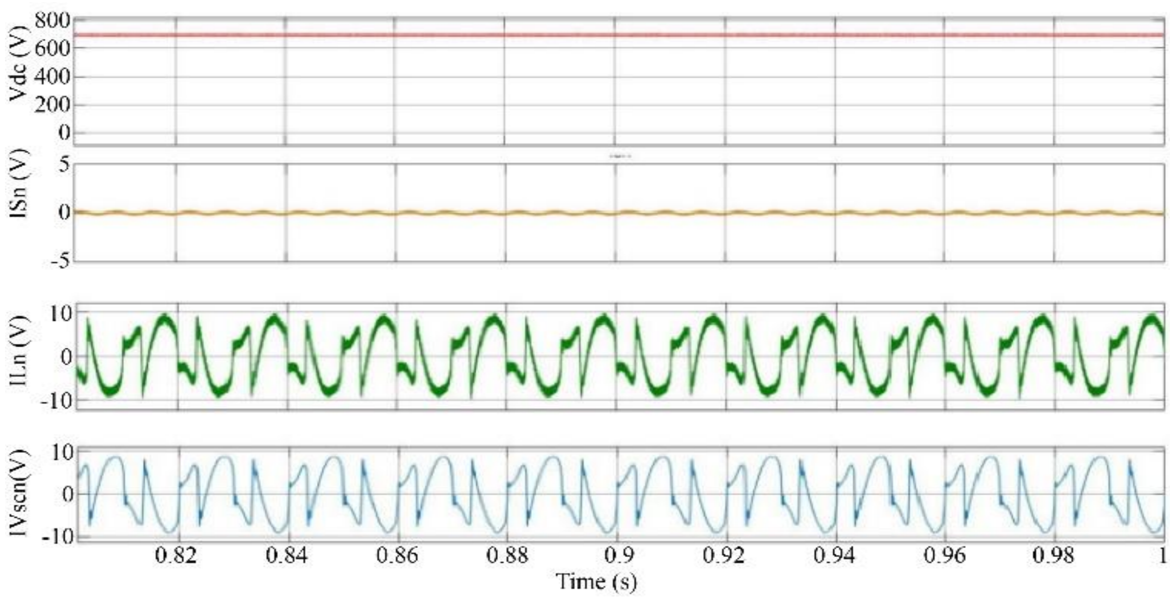
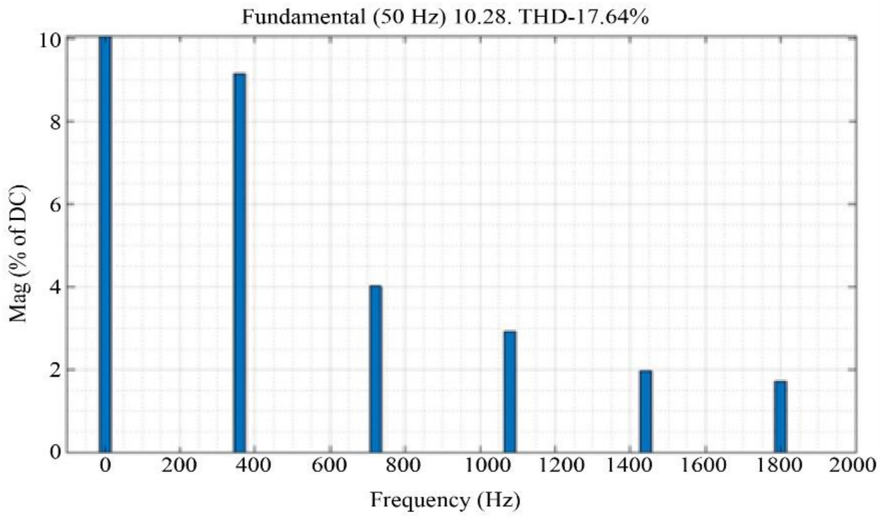
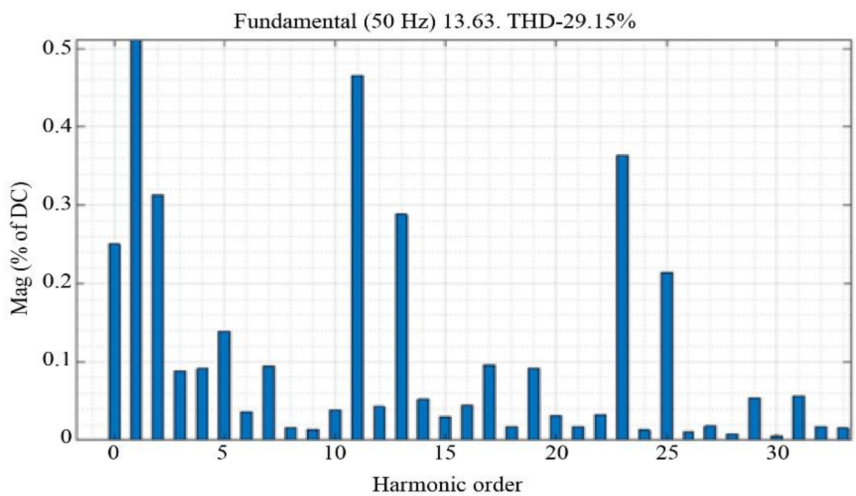


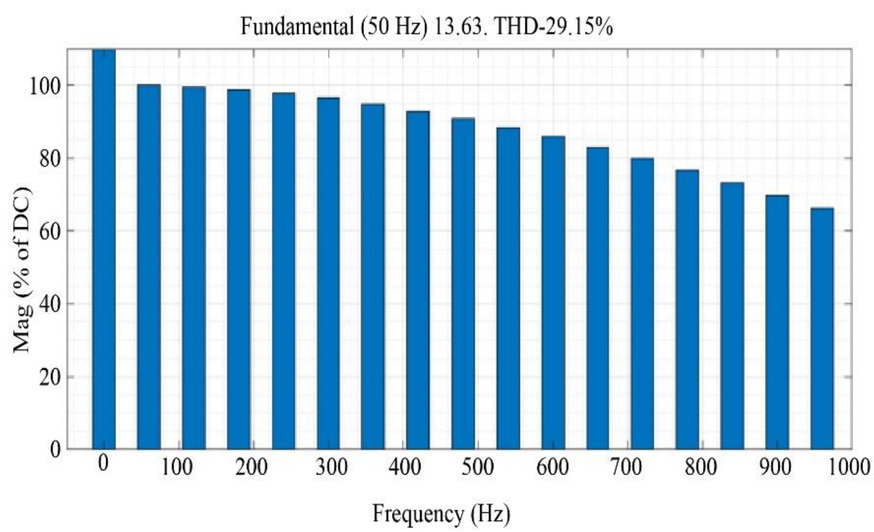
Fig. 6 Analysis of Vdc: DC link voltage, i_{Ln}: load neutral current, i_{Sn}: input neutral current, and IV_{scn}: compensator neutral current



(a)



(b)



(c)

Fig. 7 Analysis of three-phase unbalanced load current THD, (a) R-phase load current, (b) Y-phase load current, and (c) B-phase load current.

Figure 7 indicates a performance analysis of THD for three phases of unbalanced load by varying distortion levels. The R-phase load current has a THD of 17.64% which indicates moderate distortion. Y-phase load current represents the highest THD at 29.15%, which shows a significant harmonic interference; whereas B-phase load current obtains the lowest THD of 4.32%, which provides better power quality, which contributes to enhanced system efficiency and overall performance. Table 3 demonstrates the performance analysis of THD with different optimization methods. The existing methods, such as DBO, BOA, and SBOA, are compared with the proposed DS-SBOA methods. Compared to these methods, the proposed DS-SBOA obtains a better THD of 2.3% in source current and 15.4% in load current because of its effective management of harmonic distortion in the EV system. Its search method provides optimized control parameters that result in enhanced power quality. Moreover, minimized non-linear effects and better load balancing contribute to less harmonic interference. This leads to effective power conversion and more stability, which enhances overall system performance.

Table 3. Analysis of THD with different optimizations

Methods	THD (%)	
	Source current	Load current
DBO	9.5	29.5
BOA	7.2	25.7
SBOA	6.7	23.6
DS-SBOA	2.3	15.4

4.2. Comparative Analysis

Table 4 indicates a comparative analysis of THD with existing methods. When compared to [22-24], the proposed DS-SBOA obtains a lower THD of 2.32% in source current and 15.48% in load current due to its enhanced search strategy that effectively controls parameters and optimizes switching patterns. Its adaptive exploration and exploitation balance make accurate harmonic suppression by adjusting load variations dynamically. By minimizing switching losses, the proposed DS-SBOA improves current waveform quality, which results in minimal harmonic distortions. Moreover, it effectively manages non-linear loads and reduces voltage fluctuations that ensure stable power flow compared to existing methods. The main reason for achieving these superior results is that the proposed DS-SBOA comprises a dual strategy innovation consisting of adaptive and diffusion hill-climbing processes. This advanced and hybrid mechanism improves both exploitation and exploration abilities, enabling the converter to attain lower THD and mitigate switching losses under changing load conditions. The combination of this algorithm with bidirectional DC–DC converter control demonstrates a novel contribution that fills the gap of optimization theory and real-time power quality improvement in EV systems.

Table 4. Comparative analysis of THD with existing methods

Methods	THD (%)	
	Source Current	Load Current
Simpler digital control-based circuit [22]	5.32	23.87
DSTATCOM with ANFIS controller [23]	3.54	19.74
Switched capacitor-based BDC [24]	6.49	7.31
Proposed DS-SBOA	2.32	15.48

4.3. Discussion

The proposed Di-Strategy-based Secretary Bird Optimization Algorithm (DS-SBOA) is helpful for obtaining superior results when compared to existing optimization methods, and the reason is its effective balance between exploration and exploitation. The diffusion mechanism helps in enhancing population diversity by avoiding premature convergence and permitting broader search space exploration for optimal converter parameters. At the same time, the adaptive hill climbing strategy fine-tunes the solution by adjusting step sizes, enhancing local search precision in a dynamic manner in differing conditions. This combination allows the DS-SBOA to reduce harmonic distortions and obtain stable voltage regulation in EV applications. The obtained THD of 2.32% in source current and 15.48% in load current helps demonstrate a significant improvement over DSTATCOM-ANFIS, BOA, DBO, and conventional SBOA models. Moreover, optimized switching control decreases conduction losses, improves current waveform quality, and enhances reactive power compensation. The combined PV system also contributes to better energy utilization and sustainability. In general, the DS-SBOA guarantees high power quality, effective energy conversion, and enhanced performance compared to previously reported approaches.

5. Conclusion

This research proposed DS-SBOA for EV application using a bi-directional DC-DC converter. A deployment of this converter extends battery life and improves power transfer, whereas PV integration minimises dependence on external charging stations. The diffusion mechanism and adaptive strategies are incorporated in SBOA, which solves local optima and convergence speed in early iterations, making rapid optimal power tracking for PV systems in EV applications. The proposed DS-SBOA provides better voltage regulation and increased EV system performance by minimizing losses in electronic components such as switches and inductors.

The experimental results show that the proposed DS-SBOA obtains a lower THD of 2.32% in source current and 15.48% in load current compared to existing methods like DSTATCOM with an ANFIS controller. These advancements contribute to the growing adaptation of EVs in pubic, personal, and industrial applications. Unlike its effectiveness, this work only involves simulation analysis, and no physical hardware implementation was performed. Moreover, this simulation analysis, although useful for algorithmic validation, cannot fully capture real-time factors like sensor noise, converter switching fluctuations, and testing a real-time hardware platform. Therefore, in future work, this research incorporates designing and testing a real-world DS-SBOA-based bidirectional converter prototype on DSP/FPGA hardware platforms. This approach will allow experimental validation of power quality enhancement, THD mitigation under varying load conditions, and converter efficiency, assuring the algorithms' strength in real-time EV applications.

5.1. Limitations and Future Scope

Although the proposed Di-Strategy-based Secretary Bird Optimization Algorithm (DS-SBOA) illustrates superior performance in harmonic reduction and voltage regulation, there are specific limitations that are present. The study aims at simulation-based validation by the utilization of MATLAB, without experimental hardware implementation. Real-time hardware testing in differing load and environmental conditions provides more accurate insights into system reliability and converter performance. In addition, the proposed method is evaluated using a single bi-directional DC-DC converter topology; the outcomes differ from those with other converter architectures and multi-level systems. The algorithm's convergence speed is influenced by large-scale parameter differences in highly dynamic EV environments. Future research can explore the combination of DS-SBOA with adaptive neural control and fuzzy-based hybrid strategies for faster convergence and real-time optimization. Furthermore, implementing the model on FPGA and DSP platforms could help in allowing practical validation and real-world deployment in electric vehicle charging stations. The consideration of battery degradation modelling and grid interaction studies will be helpful for further improvement of system adaptability and efficiency.

5.2. Ethical Considerations

This research adheres to the ethical standards and integrity guidelines that are prescribed for academic and scientific publications. All data that were exploited in this study were generated by simulation using MATLAB and did not incorporate any human participants, animals, or personally identifiable information. Hence, no ethical approval and informed consent were necessary. The research regulates transparency in methodology, guarantees originality, and prevents fabrication, falsification, and plagiarism. All external sources are correctly acknowledged and cited based on the journal's referencing standards. The study also prevents any form of self-citation or citation manipulation to maintain scholarly neutrality. The proposed Di-Strategy-based Secretary Bird Optimization Algorithm (DS-SBOA) has been presented mainly for academic and research purposes by following responsible research and publication practices.

References

[1] Jeong Lee, and Jehyuk Won, "Multifunctional Onboard Charger for Electric Vehicles Integrating a Low-Voltage DC-DC Converter and Solar Roof," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 12, no. 1, pp. 283-294, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Arvind R. Singh et al., "A High-Efficiency Poly-Input Boost Dc-Dc Converter for Energy Storage and Electric Vehicle Applications," *Scientific Reports*, vol. 14, no. 1, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] Wagner Coelho Leal et al., "Cascaded Interleaved Dc-Dc Converter for a Bidirectional Electric Vehicle Charging Station," *IEEE Transactions on Industrial Electronics*, vol. 71, no. 4, pp. 3708-3717, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Yiliang Li et al., "Design and Optimization of High-Gain Bidirectional DC-DC Converter for Electric Vehicles," *IEEE Transactions on Power Electronics*, vol. 38, no. 9, pp. 11221-11232, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Noah Dias, Anant J. Naik, and Vinayak N. Shet, "A Novel Tri-Mode Bidirectional DC-DC Converter for Enhancing Regenerative Braking Efficiency and Speed Control in Electric Vehicles," *World Electric Vehicle Journal*, vol. 15, no. 1, pp. 1-30, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Tahsin Koroglu, Elanur Ekici, and M. Mustafa Savrun, "Five-Port Isolated Bidirectional DC-DC Converter for Interfacing a Hybrid Photovoltaic-Fuel Cell-Battery System with Bipolar DC Microgrids," *Electronics*, vol. 13, no. 6, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] K.S. Kavin, and P. Subha Karuvelam, "PV-Based Grid Interactive PMBLDC Electric Vehicle with High Gain Interleaved DC-DC SEPIC Converter," *IETE Journal of Research*, vol. 69, no. 7, pp. 4791-4805, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Alok Jain, and Suman Bhullar, "An Extensive Analysis of Power Converter Architectures for Grid-Connected Solar Photovoltaic Driven Electric Vehicles (EVs)," *Engineering Science and Technology, an International Journal*, vol. 58, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Truong Hoang Bao Huy, Huy Truong Dinh, and Daehee Kim, "Multi-Objective Framework for a Home Energy Management System with the Integration of Solar Energy and an Electric Vehicle using an Augmented E-Constraint Method and Lexicographic Optimization," *Sustainable Cities and Society*, vol. 88, pp. 1-24, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Sinem Hisoglu, Anu Tuominen, and Aapo Huovila, "An Approach for Selecting Optimal Locations for Electric Vehicle Solar Charging Stations," *IET Smart Cities*, vol. 5, no. 2, pp. 123-134, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Chaouki Ghenai, Fahad Faraz Ahmad, and Oussama Rejeb, "Artificial Neural Network-Based Models for Short Term Forecasting of Solar PV Power Output and Battery State of Charge of Solar Electric Vehicle Charging Station," *Case Studies in Thermal Engineering*, vol. 61, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Abhishek Pratap Singh et al., "Development of Artificial Intelligence-Based Adaptive Vehicle to Grid and Grid to Vehicle Controller for Electric Vehicle Charging Station," *Ain Shams Engineering Journal*, vol. 15, no. 10, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Rahat Redwan et al., "Design Analysis and Techno-Economic Assessment of a Photovoltaic-Fed Electric Vehicle Charging Station at Dhaka-Mawa Expressway in Bangladesh," *Energy Conversion and Management: X*, vol. 24, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Satyabrata Behera et al., "A Dual Control Strategy for Improved Power Quality in Grid-Tied Off-Board Bidirectional Electric Vehicle Charger," *Electric Power Systems Research*, vol. 236, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Manuel S. Mathew et al., "Data Driven Approach for the Management of Wind and Solar Energy Integrated Electrical Distribution Network with High Penetration of Electric Vehicles," *Journal of Cleaner Production*, vol. 421, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] P. Justin Raj et al., "Solar Powered Charging of Fuzzy Logic Controller (FLC) Strategy with Battery Management System (BMS) Method Used for Electric Vehicle (EV)," *International Journal of Fuzzy Systems*, vol. 25, no. 7, pp. 2876-2888, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] R.J. Venkatesh et al., "An Optimization Approach Control of EV Solar Charging System with Step-Up DC-DC Converter," *Analog Integrated Circuits and Signal Processing*, vol. 119, no. 2, pp. 215-232, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohd Bilal, Fareed Ahmad, and M. Rizwan, "Techno-Economic Assessment of Grid and Renewable Powered Electric Vehicle Charging Stations in India using a Modified Metaheuristic Technique," *Energy Conversion and Management*, vol. 284, pp. 1-27, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Neeraj Priyadarshi et al., "High-Power DC-DC Converter with Proposed HSFNA MPPT for Photovoltaic Based Ultra-Fast Charging System of Electric Vehicles," *IET Renewable Power Generation*, vol. 19, no. 1, pp. 1-13, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[20] Seyed Reza Mousavi-Aghdam, Armineh Dastgiri, and Majid Hoseinpour, "An Improved Voltage Gain Bidirectional DC/DC Converter based on Voltage Multiplier Cell for Electric Vehicle Application," *International Journal of Modelling and Simulation*, pp.1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] I. William Christopher et al., "A Bidirectional DC/DC Converter for Renewable Energy Source-Fed EV Charging Stations with Enhanced DC Link Voltage and Ripple Frequency Management," *Results in Engineering*, vol. 24, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Ranjan Pramanik, and B.B. Pati, "Modelling and Control of a Non-Isolated Half-Bridge Bidirectional DC-DC Converter with an Energy Management Topology Applicable with EV/HEV," *Journal of King Saud University-Engineering Sciences*, vol. 35, no. 2, pp. 116-122, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Md Mujahid Irfan et al., "Enhancing the Power Quality of the Grid Interactive Solar Photovoltaic-Electric Vehicle System," *World Electric Vehicle Journal*, vol. 12, no. 3, pp. 1-13, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] K. Mounika Nagabushanam et al., "Development of High-Gain Switched-Capacitor Based Bi-Directional Converter for Electric Vehicle Applications," *Journal of Energy Storage*, vol. 82, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Yu Zhu et al., "Secretary Bird Optimization Algorithm based on Quantum Computing and Multiple Strategies Improvement for KELM Diabetes Classification," *Scientific Reports*, vol. 15, no. 1, pp. 1-24, 2025. [CrossRef] [Google Scholar] [Publisher Link]