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*Research article*

## **A novel dynamic barnacles mating optimizer with linear decay mechanism for dual active bridge control: hardware-in-the-loop validation**

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**Abstract:** Off-board fast-charging systems for electric vehicles require high-power DC-DC converters capable of maintaining rapid transient regulation without overshooting current boundaries. Dual Active Bridge converters satisfy these topology requirements, but conventional Proportional-Integral controllers tuned via static methods struggle under severe load steps and non-linear battery dynamics. In this study, we present a Dynamic Barnacles Mating Optimization framework engineered to automate controller gain synthesis. By introducing a time-varying linear decay mechanism to regulate the mating search radius, the proposed algorithm resolves the exploration-exploitation imbalance inherent in standard metaheuristic search strategies. Algorithm performance was benchmarked across 23 classical test functions, followed by offline converter simulation models and real-time validation on a hardware emulator. Statistical analysis under a Holm-Bonferroni corrected test confirmed that the dynamic search mechanism significantly improves solution accuracy and stability over standard barnacles optimization without incurring statistical losses. When applied to controller tuning, the proposed optimizer effectively suppressed transient current overshoot during severe load steps in offline simulation models. In real-time hardware emulation, the controller suppressed supply voltage disturbances within 7.2 milliseconds and restricted startup current overshoot below 3.5%. These results verify that dynamic search radius decay synthesizes well-damped control parameters, preventing overcurrent protection tripping and ensuring safe, stable electric vehicle fast-charging.

**Keywords:** dual active bridge; electric vehicle (EV); fast-charging; dynamic barnacles mating optimizer (DBMO); hardware-in-the-loop (HIL); metaheuristic

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## 1. Introduction

The rapid electrification of the global transportation sector has accelerated the demand for high-power off-board DC fast-charging infrastructure to mitigate range anxiety and reduce vehicle charging duration. Among isolated bidirectional DC-DC converter topologies, the Dual Active Bridge (DAB) converter has emerged as a prominent candidate for Electric Vehicle (EV) fast-charging applications due to its high power density, inherent soft-switching capability, zero-voltage switching (ZVS) potential, and galvanic isolation [1–4]. Operating at high switching frequencies, the DAB converter regulates power transfer between the primary high-voltage DC bus (typically 800 V) and the EV battery pack (typically 400 V) by adjusting the phase-shift angle ( $\phi$ ) between the primary and secondary square-wave AC voltages.

Despite these topological advantages, regulating a high-power DAB converter during EV fast-charging introduces complex control challenges. The non-linear impedance characteristics of Lithium-ion (Li-ion) batteries vary dynamically across States of Charge (SoC), temperatures, and health conditions [5–8]. Similar non-linearities are widely encountered in advanced energy conversion systems, where metaheuristic algorithms have been successfully applied for Maximum Power Point Tracking (MPPT) strategies in renewable energy interfaces and precise parameter identification of non-linear physical systems [9–11]. Furthermore, the high-frequency switching dynamics render the system sensitive to supply voltage fluctuations and rapid load transients. Conventional linear control strategies, such as fixed-gain Proportional-Integral (PI) controllers tuned via classical Frequency Response Methods or Ziegler-Nichols rules, are optimized around a single linearized operating point. Consequently, these static controllers exhibit poor transient performance when subjected to severe operating steps.

During high-power charging transients, inadequate controller damping leads to significant current overshoots, prolonged settling times, and low-frequency oscillations. Current overshoots during startup or step load changes are particularly critical in EV charging applications, as abrupt current spikes can trip the overcurrent protection circuits of the Battery Management System (BMS), accelerate chemical degradation of the battery cell electrodes, or cause catastrophic thermal runaway [12]. To ensure safe and efficient charging, the controller must satisfy strict performance criteria: minimizing transient current overshoot, reducing rise and settling times, rejecting grid-side DC bus voltage disturbances rapidly, and maintaining minimal steady-state current ripple across the operational envelope.

However, standard metaheuristic algorithms often encounter structural limitations when navigating multi-dimensional control landscapes. In particular, the standard Barnacles Mating Optimizer (BMO) relies on a static mating range ratio ( $pl$ ), which governs whether parent selection follows local mating or global sperm casting [13, 14]. A fixed  $pl$  parameter creates an inherent exploration-exploitation conflict: A large fixed  $pl$  causes excessive randomness and prevents localized convergence, while a small fixed  $pl$  leads to premature stagnation in local optima.

Consequently, to ensure rapid and safe regulation, researchers have moved beyond static tuning methods toward metaheuristic optimization engines. Although foundational work such as the LDIW-PSO [15, 16] established the precedent for dynamic parameter adjustment decades ago, researchers have significantly refined these concepts. For instance, researchers have combined PSO with the GWO [17] or ACO [18] to create unified frameworks that utilize non-linear decay functions, such as sinusoidal or exponential curves, to regulate the search behavior. Furthermore, hybrid metaheuristic

studies in 2025 demonstrated that dynamic transitions between exploration and exploitation are essential for minimizing the Integral Time Absolute Error (ITAE) in motor drives and high-power converters, outperforming standalone algorithms in convergence speed and steady-state accuracy.

To resolve this parameter bottleneck, researchers have explored modified BMO variants and dynamic parameter adjustment schemes across complex engineering applications. The researchers introduced the Elitist Barnacles Mating Optimizer (eBMO) by incorporating an exponential decay probability parameter ( $P_{elite}$ ) to regulate the transition from global exploration to elite local exploitation [19]. In geophysical inversion and complex parameter identification of non-linear systems, the Modified Barnacles Mating Optimizer (MBMO) replaced the static parameter with a variable genital length strategy ( $pl_{var}$ ) to avoid local minima entrapment [13,20]. Furthermore, the Sine-Based Barnacle Mating Optimizer (SbBMO) integrated a sinusoidal step-size trajectory to smoothly guide trailing individuals [21], while the Gooseneck Barnacle Optimizer (GBO) incorporated environmental decay constraints to dynamically restrict mating boundaries over time [22].

While non-linear decay mechanisms (such as exponential, sinusoidal, or physical boundary decay) improve optimization adaptability, they introduce complex hyperparameter dependencies and non-linear decay trajectories. In power converter controller gain synthesis, rapid non-linear early-stage decay risks premature parameter stagnation in sub-optimal search regions. To establish a reliable foundation for advanced power electronic control, we focus on evaluating the optimization efficiency, convergence stability, and transient suppression capabilities of the proposed Dynamic Barnacles Mating Optimizer (DBMO) under offline gain synthesis conditions. By introducing a time-varying linear decay mechanism ( $pl_{max} = 0.80 \rightarrow pl_{min} = 0.05$ ), DBMO eliminates parameter boundary saturation and synthesizes well-damped PI gains ( $K_p, K_i$ ). Our primary objective of this work is to demonstrate the algorithmic viability and dynamic robustness of DBMO using a simulation model and Typhoon Hardware-in-the-Loop (HIL) real-time emulation under severe operating disturbances. Verifying this offline capability serves as the necessary benchmark phase prior to embedding the algorithm into a microsecond-level, real-time online auto-tuning framework.

The major novelties and contributions of this work are summarized as follows:

1. **Algorithmic Innovation:** The development of a time-varying linear decay mechanism for the BMO algorithm, systematically resolving the exploration-exploitation imbalance. Mathematical benchmarking across 23 classical test functions under a Holm-Bonferroni corrected Wilcoxon rank-sum test verifies its statistical superiority, achieving optimal convergence without a single statistical loss against parent BMO.
2. **Adaptive Control Framework:** The design of an automated DBMO-tuned PI control strategy specifically engineered for DAB converters in off-board EV fast-charging applications. This approach eliminates manual trial-and-error tuning and suppresses startup current overshoots under severe load step and input voltage disturbance conditions.
3. **Real-Time Hardware Validation:** The successful physical validation of the DBMO-tuned control strategy using a Typhoon HIL 402 real-time emulator operating at a strict real-time step size of  $0.5 \mu s$ . This confirms the practical viability, digital execution stability, and dynamic robustness of the proposed framework prior to physical hardware deployment.

The remainder of this article is organized as follows: In Section 2, we detail the mathematical modeling of the DAB converter and the PI control strategy. In Section 3, we present the proposed

DBMO algorithm, parameter settings, and computational complexity analysis. In Section 4, we provide the comprehensive experimental results, including algorithmic benchmarking, offline simulation, and real-time HIL validation. In Section 5, we present the engineering implications and concluding remarks.

## 2. System modeling and design

### 2.1. DAB converter circuit architecture

The off-board DC fast-charging system utilizes a 100 kW Dual Active Bridge (DAB) DC-DC converter topology to handle bidirectional power transfer between the high-voltage DC supply and the electric vehicle (EV) battery pack. As shown in Figure 1, the circuit architecture comprises two primary H-bridge stages coupled through a high-frequency isolation transformer with a turns ratio of  $n = N_1 : N_2 = 2 : 1$ . The primary bridge operates at a nominal DC bus voltage of  $V_i = 800$  V, while the secondary bridge interfaces with a nominal EV battery voltage of  $V_o = 400$  V. This nominal voltage selection achieves a unity voltage conversion ratio ( $d = \frac{V_o}{nV_i} = 1$ ), which represents the optimal operating condition for Single Phase Shift (SPS) modulation to minimize circulating power and switching losses.

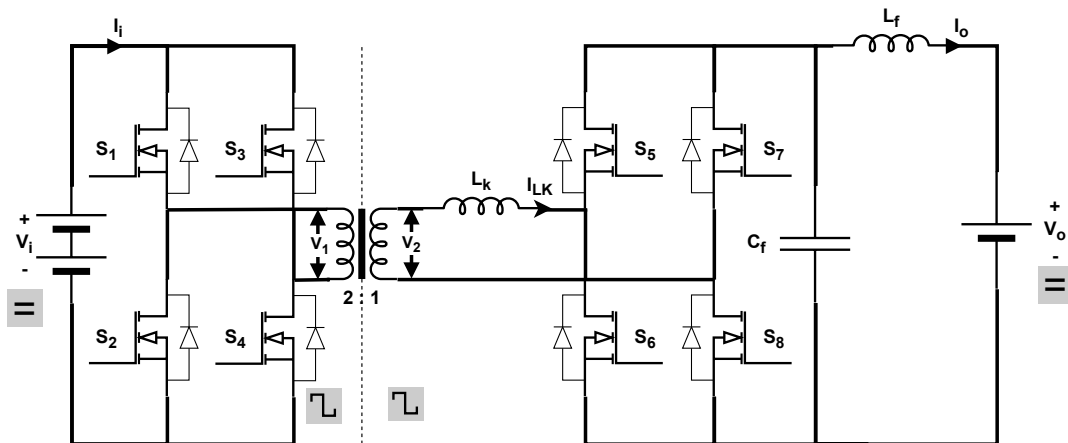


**Figure 1.** Circuit topology of the dual active bridge (DAB) converter.

Under standard SPS modulation, both full-bridges generate square-wave AC terminal voltages ( $v_1$  and  $v_2$ ) at a constant switching frequency of  $f_{sw} = 100$  kHz with a duty cycle of 50%. The magnitude and direction of the power flow are regulated solely by shifting the phase-shift angle ( $\phi$ ) between the primary and secondary square waves. The fundamental power transfer equation governing the bidirectional energy flow through the high-frequency leakage inductance ( $L_{lk}$ ) is derived as:

$$P = \frac{nV_iV_o}{2\pi^2 f_{sw} L_{lk}} \phi (\pi - |\phi|) \quad \text{for } |\phi| \leq \frac{\pi}{2} \quad (2.1)$$

This power relationship was originally formulated by De Doncker et al. (1991) and expanded by Kheraluwala et al. (1992) for high-power high-frequency DC-DC energy conversion [23, 24].

Mathematically, differentiating the power transfer equation with respect to  $\phi$  reveals that the theoretical maximum power transfer capability ( $P_{\max}$ ) occurs at a phase-shift angle of  $\phi = \frac{\pi}{2}$  ( $90^\circ$ ):

$$P_{\max} = \frac{nV_i V_o}{8f_{sw} L_{lk}} \quad (2.2)$$

Assuming operation at the nominal matched conversion ratio ( $nV_i = V_o$ ), substituting  $V_o$  yields the design equation used to determine the critical leakage inductance value:

$$L_{lk} = \frac{V_o^2}{8f_{sw} P_{\max}} \quad (2.3)$$

For the rated 100 kW converter operating at  $f_{sw} = 100$  kHz and  $V_o = 400$  V, applying this expression yields a theoretical minimum inductance requirement. To ensure stable current regulation and prevent high dynamic stress, a leakage inductance value of  $L_{lk} = 2 \mu\text{H}$  was selected. In addition, a series resistance ( $R_{lk}$ ) is integrated into the leakage path model to represent copper losses and damping characteristics inherent in physical magnetics. The output filtering stage consists of a second-order CL filter with a filter capacitance of  $C_f = 3$  mF and a filter inductance of  $L_f = 337$  nH to eliminate high-frequency current ripple before reaching the battery terminals.

## 2.2. Control framework and objective function

The adaptive control architecture is implemented by integrating the metaheuristic optimization engine directly with the Proportional-Integral (PI) feedback loop. As illustrated in the control block diagram in Figure 2, the primary objective of the controller is to regulate the output charging current ( $I_o$ ) to precisely track the reference command ( $I_{ref}$ ).

The small-signal dynamic relationship between the phase-shift angle perturbation ( $\Delta\phi$ ) and the resulting output current perturbation ( $\Delta I_o$ ) is derived using state-space averaging (SSA) and generalized average modeling (GAM), as formulated by Krismer and Kolar [25]. The linearized plant transfer function  $G_{ip}(s)$  around the nominal operating point is expressed as:

$$G_{ip}(s) = \frac{\Delta I_o(s)}{\Delta\phi(s)} = \frac{nV_i(1 - 2\phi/\pi)}{\pi f_{sw} L_{lk}(R_{load} C_f s + 1)} \quad (2.4)$$

To regulate this dynamic plant in a digital control platform, the continuous-time PI control law  $G_c(s) = K_p + \frac{K_i}{s}$  is discretized at a sampling frequency of  $f_s = 100$  kHz ( $T_s = 10 \mu\text{s}$ ) using the Tustin (bilinear) transformation ( $s \approx \frac{2}{T_s} \frac{1-z^{-1}}{1+z^{-1}}$ ), following classic digital control theory [26]:

$$G_c(z) = K_p + K_i \frac{T_s}{2} \left( \frac{1 + z^{-1}}{1 - z^{-1}} \right) \quad (2.5)$$

The DBMO algorithm optimizes the proportional ( $K_p$ ) and integral ( $K_i$ ) gains within bounded parameter search limits ( $K_p \in [0.01, 5.0]$  and  $K_i \in [0.01, 50.0]$ ). These boundary constraints are established based on the plant's small-signal crossover frequency and phase margin limits to prevent high-frequency noise amplification and phase-shift saturation under transient steps. Once the optimization cycle is complete, the optimal parameters are locked for operation, ensuring the control response is both fast and stable without continuous computational overhead during steady state.

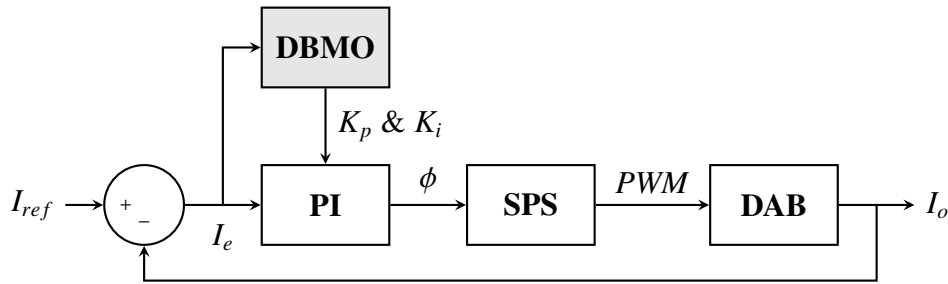


**Figure 2.** Block diagram of the dynamic BMO-PI (DBMO) strategy.

To rigorously quantify the performance of the controller during the tuning process, the Integral Time Absolute Error (ITAE) was selected as the objective fitness function. Unlike standard error metrics, the ITAE criterion multiplies the absolute error by time, which places a progressively heavier penalty on errors that persist later in the transient response. The objective function  $J$  to be minimized is defined in Equation (2.6):

$$J = \int_0^{T_{sim}} t \cdot |I_{ref}(t) - I_{meas}(t)| dt \quad (2.6)$$

In this equation,  $t$  represents the time elapsed since the start of the optimization window, while  $I_{ref}$  and  $I_{meas}$  denote the reference and measured output currents, respectively. Minimizing this specific function drives the optimization algorithm to identify control parameters that eliminate steady-state errors rapidly, resulting in a critically damped response that is essential for protecting the EV battery from harmful overcurrent stress during the charging phase.

### 2.3. Simulation platform (simulation and HIL)

The initial development and preliminary testing of the proposed adaptive control strategy were conducted in the MATLAB/Simulink R2024a environment using the Simscape Electrical toolbox to evaluate the theoretical dynamic response of the Dual Active Bridge (DAB) converter system. All offline simulation models and metaheuristic optimization routines were executed on a desktop workstation equipped with an Intel Core i5-9400H @ 2.90 GHz processor and 16 GB of RAM, running on a 64-bit Windows 10 operating system.

To validate the practical viability and dynamic performance of the control framework under realistic execution step sizes and digital hardware constraints, a high-fidelity Hardware-in-the-Loop (HIL) experimental platform was established. Figure 3 illustrates the Host-PC to HIL hardware execution architecture and bidirectional communication topology. The real-time emulation system utilizes a Typhoon HIL 402 emulator to bridge the gap between software-based simulation models and physical hardware prototyping.

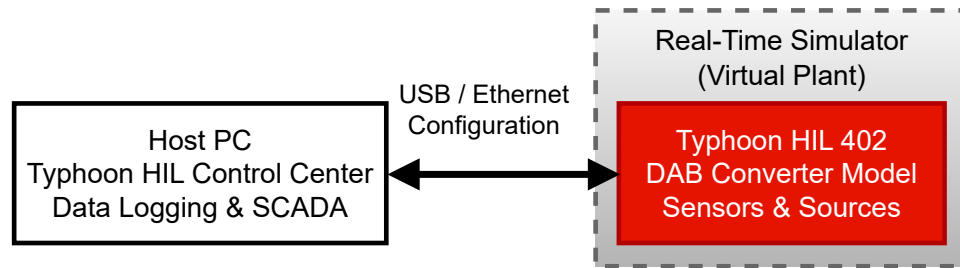


**Figure 3.** Host-PC to real-time simulator execution architecture and communication interface.

As depicted in Figure 3, the execution architecture is divided into two main computational domains connected via a USB/Ethernet communication interface: The Host PC executes the Typhoon HIL Control Center (THCC) software suite, serving as the central supervisor for model compilation, offline parameter synthesis, and real-time monitoring. The DBMO algorithm synthesizes the optimal controller gains ( $K_p, K_i$ ) on the Host PC. Once identified, these gains are transferred over the USB/Ethernet interface to configure the target controller registers. During real-time operation, the Host PC handles high-resolution telemetry, transient data logging, and SCADA visualization. The Typhoon HIL 402 emulator acts as the target real-time execution engine. The complex non-linear differential equations governing the 100 kW DAB power topology, high-frequency transformer, switching devices, sensors, and EV battery sources are compiled and executed inside the HIL hardware solver. Concurrently, the discrete PI control loop is executed directly within the real-time processor at a strict execution time-step of  $0.5 \mu\text{s}$ .

Executing the plant dynamics and the discrete control loop deterministically inside the HIL hardware at a  $0.5 \mu\text{s}$  time-step eliminates non-deterministic USB communication latency during transient closed-loop regulation. This dual-domain platform provides a verified experimental framework for evaluating controller robustness prior to physical power stage deployment. Figure 4 presents the physical laboratory hardware arrangement used for this phase of validation.

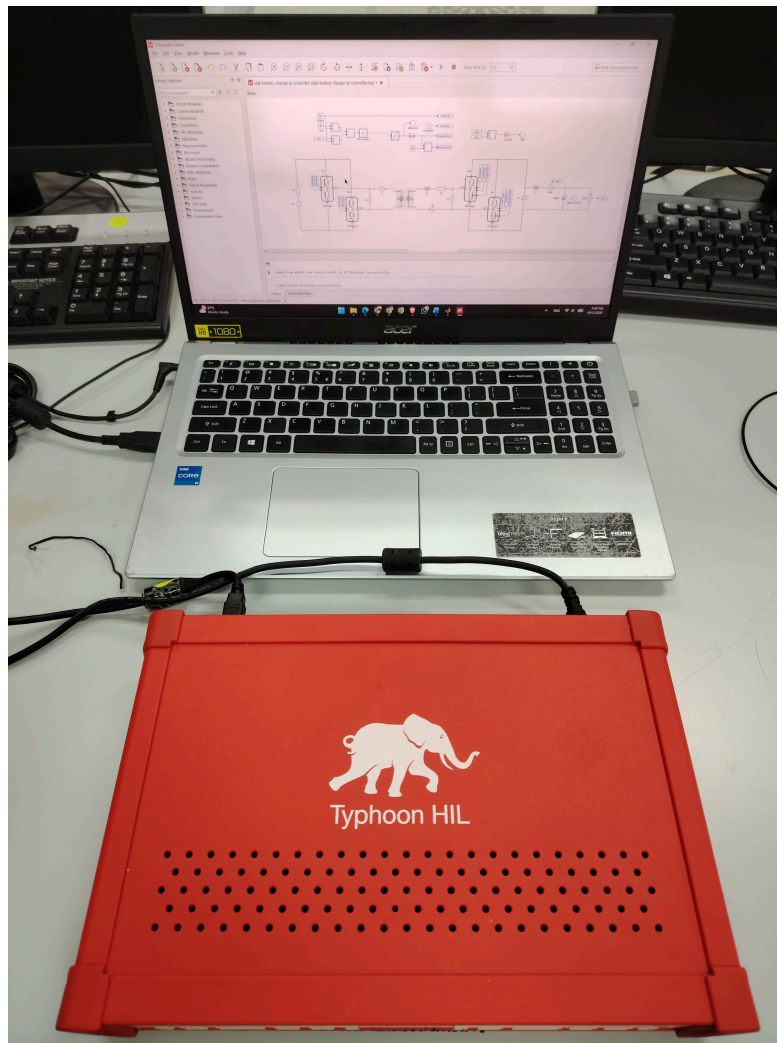


**Figure 4.** Laboratory hardware photograph of the HIL setup.

### 3. Proposed dynamic barnacles mating optimization algorithm

The foundation of the proposed control framework is the BMO [14] algorithm, a bio-inspired metaheuristic that replicates the reproductive behavior of barnacles. In nature, sessile barnacles utilize an elongated penis to mate with neighbors within a specific physical reach. [27, 28]. The standard BMO algorithm models this behavior using a static mating range ( $pl$ ) to differentiate local mating and distant reproduction. However, relying on a fixed parameter creates an exploration-exploitation conflict. [29, 30]. A large fixed  $pl$  leads to excessive global exploration, whereas a small fixed  $pl$  causes premature convergence on local optima [13, 14].

To resolve this conflict, we propose the Dynamic Barnacles Mating Optimizer (DBMO), which introduces a time-varying linear decay mechanism to regulate the search radius dynamically. Table 1 summarizes the operational parameter settings for the initial mathematical benchmarking suite and the Dual Active Bridge (DAB) converter tuning. For classical benchmark functions ( $F_1$ – $F_{23}$ ), a maximum

iteration limit of  $T_{\max} = 500$  (15,000 function evaluations) was selected to evaluate asymptotic convergence across multi-dimensional search landscapes. Conversely, for offline DAB controller gain synthesis, the maximum iteration count was set to  $T_{\max} = 30$  (900 function evaluations). This lower iteration count accommodates the heavy computational load of evaluating high-precision differential equation solvers in Simulink while providing sufficient iterations to synthesize stable controller gains.

**Table 1.** Optimization algorithm parameter settings for DAB.

| Parameter                                                  | Value       |
|------------------------------------------------------------|-------------|
| Search Agent ( $N$ )                                       | 30          |
| Variable Lower Bound ( $lb$ )                              | [0.1, 0.01] |
| Variable Upper Bound ( $ub$ )                              | [5, 50]     |
| Initial mating range ( $pl_{\max}$ )                       | 0.8         |
| Final mating range ( $pl_{\min}$ )                         | 0.05        |
| Number of Runs                                             | 30          |
| Number of Iterations ( $T_{\max}$ , Benchmark Functions)   | 500         |
| Number of Iterations ( $T_{\max}$ , DAB Controller Tuning) | 30          |

### 3.1. Time-varying mating range mechanism

The core innovation of the proposed DBMO algorithm is the dynamic regulation of the mating range,  $pl_t$ , which serves as the threshold for determining the reproduction mode. In the standard BMO algorithm,  $pl$  is held constant throughout the optimization process. In contrast, DBMO employs a linear decay function that shrinks the mating selection radius as iterations progress. The dynamic mating range at iteration  $t$  is calculated using Equation (3.1).

$$pl_t = \text{round}\left(N \times \left(pl_{\max} - \frac{t}{T_{\max}} \times (pl_{\max} - pl_{\min})\right)\right) \quad (3.1)$$

In Equation (3.1),  $N$  represents the total population size,  $t$  denotes the current iteration index, and  $T_{\max}$  represents the maximum allowable iteration count. The parameters  $pl_{\max} = 0.8$  and  $pl_{\min} = 0.05$  define the upper and lower dimensionless bounds of the mating ratio, corresponding to 80% and 5% of the total population, respectively. Multiplying this decaying ratio by  $N$  converts the dimensionless threshold into a discrete integer search radius  $pl_t \in [1, N]$ . Because the barnacle population is sorted by fitness rank prior to reproduction,  $pl_t$  acts as a rank-distance boundary. In early iterations ( $t \ll T_{\max}$ ),  $pl_t \approx 0.8N$ , enabling individuals across 80% of the sorted population list to mate. As  $t$  approaches  $T_{\max}$ ,  $pl_t$  shrinks linearly to  $0.05N$ , restricting direct mating strictly to the top 5% immediate neighbors in the fitness hierarchy.

### 3.2. Parent selection and reproduction strategy

Following the update of  $pl_t$ , the algorithm performs parent selection. The population is sorted in ascending order according to fitness value to reflect the dominance hierarchy. For each individual  $i$  in the sorted population, the first parent (Dad,  $p1$ ) is assigned to index  $i$ , while the second parent (Mum,  $p2$ ) is selected from a random permutation of the population:

$$p1 = i, p2 = \text{randperm}(N)_i \quad (3.2)$$

The reproduction mode is determined by comparing the rank distance  $|p1 - p2|$  against the current dynamic mating threshold  $pl_t$ :

1. Mating Mode ( $|p1 - p2| \leq pl_t$ ): When the index distance between parents is less than or equal to  $pl_t$ , local reproduction occurs using the Hardy-Weinberg equilibrium principle. The new position vector  $X_{\text{new}}$  is generated by combining genetic traits from both parents:

$$X_{\text{new}}^i = \rho \cdot X_{p1} + (1 - \rho) \cdot X_{p2} \quad (3.3)$$

where  $\rho$  is a uniform random number distributed in  $[0, 1]$ , and  $X_{p1}$  and  $X_{p2}$  represent the decision variable vectors of parent  $p1$  and parent  $p2$ , respectively.

2. Sperm Casting Mode ( $|p1 - p2| > pl_t$ ): When the index distance exceeds  $pl_t$ , the parents are beyond physical mating reach. The algorithm triggers sperm casting, generating offspring through random scaling to promote global exploration:

$$X_{\text{new}}^i = \text{rand} \cdot X_{p2} \quad (3.4)$$

where  $\text{rand}$  is a uniform random vector in  $[0, 1]$ . This dual-mode mechanism ensures that broad global exploration dominates early iterations, transitioning smoothly into localized parameter refinement as  $pl_t$  decays.

### 3.3. Algorithmic execution flow

The complete execution logic of the proposed DBMO algorithm is illustrated in the flowchart in Figure 5 and detailed in Algorithm 1. The iterative procedure begins by initializing a population of  $N$  barnacles randomly within the defined parameter boundaries  $[lb, ub]$ . Each barnacle represents a candidate gain vector  $X_i = [K_p, K_i]$ .

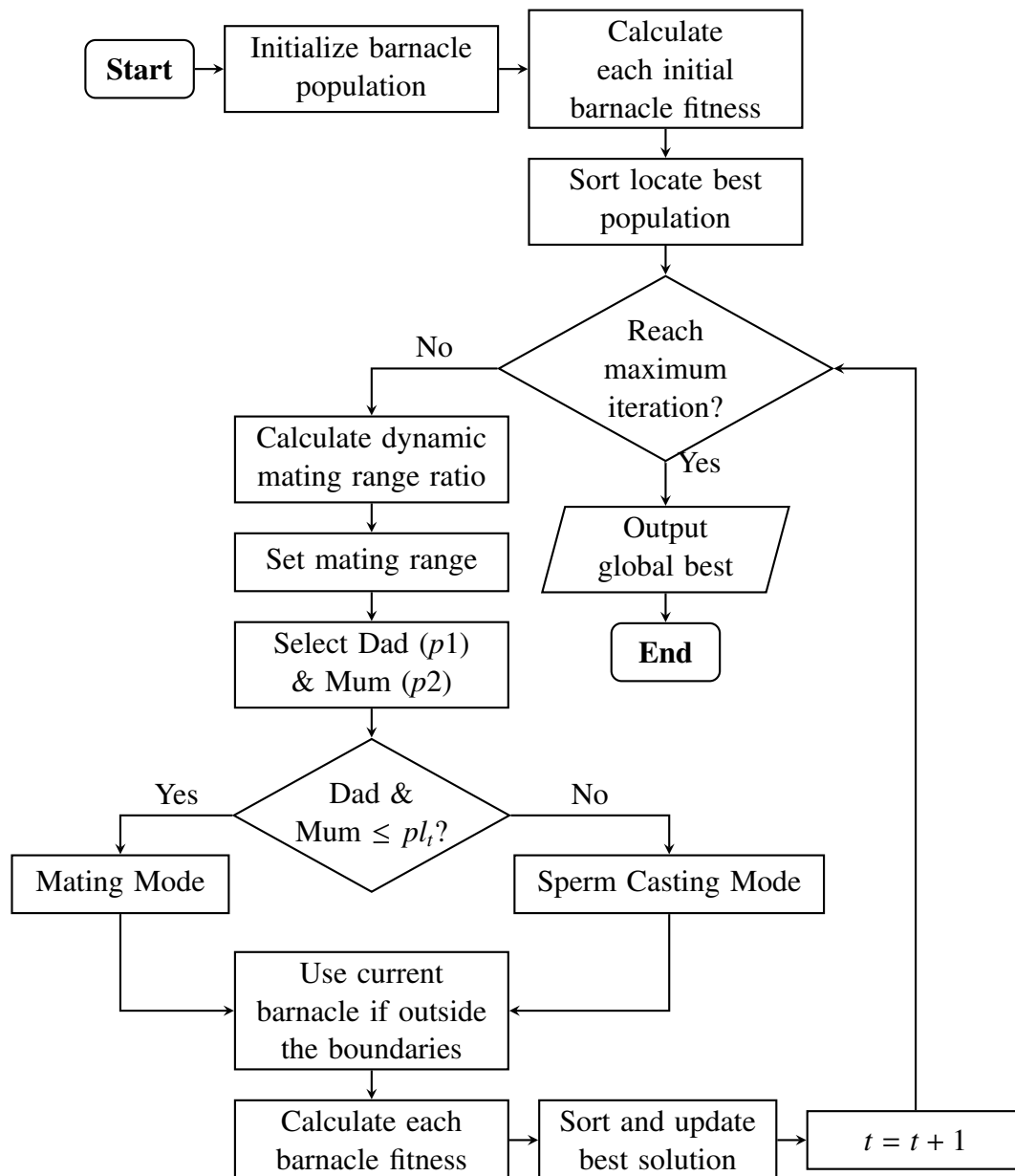


**Figure 5.** Flowchart of the proposed DBMO algorithm.

At the start of every iteration  $t$ , the dynamic mating search radius  $pl_t$  is updated using the linear decay mechanism. The algorithm continuously adjusts the balance between Mating Mode ( $|p1 - p2| \leq pl_t$ ) and Sperm Casting Mode ( $|p1 - p2| > pl_t$ ). As iterations progress, the decaying search radius forces the population to transition smoothly from wide-area exploration to high-precision exploitation.

**Algorithm 1** Pseudocode of the proposed DBMO algorithm

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Initialize barnacle population randomly within boundaries  $[lb, ub]$ 
Calculate the fitness of each initial barnacle
Sort to locate the best solution at the top of the population
while  $t \leq$  Maximum iterations do
    Calculate dynamic mating range ratio using Eq. (3.1)
    Set mating range ( $pl_t$ )
    Select Dad ( $p1$ ) and Mum ( $p2$ ) using Eq. (3.2)
    if distance ( $|p1 - p2|$ )  $\leq pl_t$  then
        Mating Mode:
        for each variable do
            Offspring generation using Eq. (3.3)
        end for
    else
        Sperm Casting Mode:
        for each variable do
            Offspring generation using Eq. (3.4)
        end for
    end if
    Boundary Check: Use current barnacle if new position is outside boundaries
    Calculate the fitness of new offspring
    Sort and update the best solution if a better solution is found
     $t \leftarrow t + 1$ 
end while
Return the global best solution

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**3.4. Algorithmic parameter selection and complexity analysis**

To select the boundary values for the linear decay mechanism ( $pl_{\max}$  and  $pl_{\min}$ ), a sensitivity analysis was conducted across the 23 classical benchmark functions. Four distinct decay configurations were evaluated under identical population size ( $N = 30$ ) and iteration limits ( $T_{\max} = 500$ ) over 30 independent runs. The experimental results are summarized in Table 2.

To guarantee scientific reproducibility while maintaining strict statistical independence, each of the 30 independent optimization runs was executed using deterministic Pseudo-Random Number Generator (PRNG) seeds initialized sequentially from 1 to 30. Pairwise statistical comparisons between DBMO and baseline algorithms (PSO, GWO, SSA, and standard BMO) were conducted using a two-sided Wilcoxon rank-sum test at a significance level of  $\alpha = 0.05$ . To control the family-wise error rate across multiple algorithm comparisons,  $p$ -values were adjusted using the Holm-Bonferroni post-hoc procedure. Exact  $p$ -values are reported for all statistical tests, where  $p < 0.05$  indicates a statistically significant difference in performance. Additionally, a non-parametric Friedman test was conducted to calculate the overall mean rank across all 23 classical benchmark functions.

**Table 2.** Parameter sensitivity analysis scoreboard.

| Parameter Configuration | $pl_{\max}$ | $pl_{\min}$ | Total Wins | Win Rate (%) |
|-------------------------|-------------|-------------|------------|--------------|
| Set 1                   | 0.9         | 0.1         | 2          | 8.70         |
| Set 2 (Proposed)        | 0.8         | 0.05        | 10         | 43.48        |
| Set 3                   | 0.6         | 0.15        | 8          | 34.78        |
| Set 4                   | 1           | 0           | 3          | 13.04        |

As detailed in Table 2, the proposed configuration (Set 2:  $pl_{\max} = 0.8$ ,  $pl_{\min} = 0.05$ ) achieved the highest success rate, securing optimal fitness values in 43.48% of the test functions (10 wins). Setting  $pl_{\max} = 0.8$  provides sufficient initial diversity by allowing parents across 80% of the population list to interact, while  $pl_{\min} = 0.05$  restricts final search interactions strictly to the top 5% fittest solutions.

The theoretical computational complexity of the DBMO algorithm was analyzed using asymptotic Big-O notation. Considering a population size  $N$ , decision variable dimension  $D$ , and maximum iterations  $T_{\max}$ :

1. Initialization: Generating random initial positions and evaluating fitness costs requires  $O(N \cdot D + N \cdot f(D))$ , where  $f(D)$  represents the objective function evaluation cost.
2. Sorting: Sorting the population by fitness rank requires  $O(N \log N)$  operations per iteration using standard quicksort routines.
3. Dynamic Range Update: Computing  $pl_t$  via Equation (3.1) adds a scalar arithmetic cost of  $O(1)$  per iteration.
4. Parent Selection and Offspring Generation: Evaluating parent rank distance  $|p1 - p2|$  and generating offspring vectors across  $D$  dimensions requires  $O(N \cdot D)$  operations.
5. Boundary Control and Evaluation: Clamping variable bounds and evaluating offspring fitness costs requires  $O(N \cdot D + N \cdot f(D))$ .

Summing these individual phases over  $T_{\max}$  iterations yields an overall time complexity of:

$$O_{\text{DBMO}} = O(N \cdot D + T_{\max} \cdot (N \log N + N \cdot D + N \cdot f(D))) \quad (3.5)$$

Since  $N \cdot D$  dominates  $N \log N$  in standard engineering problems ( $D \geq 2$ ), the computational complexity simplifies to  $O(T_{\max} \cdot N \cdot D)$ . This matches the asymptotic time complexity of standard metaheuristic algorithms, including PSO, GWO, SSA, and base BMO, confirming that the dynamic linear decay mechanism resolves the exploration-exploitation conflict without introducing computational overhead.

#### 4. Results

In this section, we present a systematic evaluation of the proposed Dynamic Barnacles Mating Optimizer (DBMO) and its application in tuning a Proportional-Integral (PI) controller for a Dual Active Bridge (DAB) converter. The evaluation is structured across three main phases: generalized mathematical benchmarking on 23 classical test functions, offline simulation of converter transients under critical EV charging scenarios, and real-time validation on a Typhoon HIL 402 emulator. To establish asymptotic convergence across high-dimensional benchmark landscapes ( $F_1$ – $F_{23}$ ), algorithmic benchmarking was executed over 500 iterations (15,000 function evaluations per run) to

rigorously evaluate deep exploitation and local optima avoidance. Conversely, offline simulation tuning of the DAB controller was intentionally configured for 30 iterations (900 function evaluations per run). This lower iteration count reflects realistic pre-operational gain synthesis constraints, as evaluating the high-fidelity stiff differential equations of the converter in Simulink requires over 2,000 seconds per run, making extended population iterations computationally prohibitive.

#### 4.1. Mathematical benchmarking and statistical analysis

Evaluating the search efficiency, convergence accuracy, and numerical stability of the proposed DBMO begins with a generalized assessment across the 23 Classical Benchmark Functions [31–33]. The comparative performance of DBMO was benchmarked against established metaheuristic algorithms, including PSO [16] (hereafter referred to as LDIW-PSO), GWO [34], SSA [35], and the standard BMO [14]. All benchmarking trials were executed across 30 independent runs ( $N = 30$ ) with a population size of 30 search agents over 500 iterations (15,000 function evaluations per run) to evaluate deep local exploitation and global search adaptability.

The numerical performance metrics expressed as Mean  $\pm$  Standard Deviation across all 23 test functions are presented in Table 3, where bold entries highlight the superior algorithm for each benchmark landscape. Complementing these point estimates, the exact 95% Confidence Intervals (Mean  $\pm 1.96 \times \text{SEM}$ ) across the 30 independent runs are detailed in Table 4. Across unimodal functions ( $F_1$ – $F_7$ ), which quantify local exploitation speed and convergence depth, DBMO achieved optimal numerical precision on high-dimensional search spaces. Specifically, on  $F_1$ ,  $F_2$ ,  $F_3$ , and  $F_4$ , DBMO reached mean best-fitness values of  $1.56 \times 10^{-124}$ ,  $1.73 \times 10^{-64}$ ,  $5.70 \times 10^{-125}$ , and  $1.43 \times 10^{-64}$ , respectively, outperforming standard BMO ( $1.18 \times 10^{-16}$ ,  $1.02 \times 10^{-9}$ ,  $4.53 \times 10^{-16}$ , and  $1.28 \times 10^{-9}$ ) by up to 108 orders of magnitude. For complex multimodal functions ( $F_8$ – $F_{13}$ ), which evaluate local minima avoidance and global exploration, DBMO successfully identified the theoretical global optimum of  $0.00 \pm 0.00$  on Rastrigin ( $F_9$ ) and Griewank ( $F_{11}$ ), matching the optimal convergence of SSA while avoiding premature stagnation. Across fixed-dimension multimodal functions ( $F_{14}$ – $F_{23}$ ), DBMO maintained tight confidence intervals, confirming consistent solution accuracy across low-dimensional non-convex landscapes.

Establishing statistical rigor requires moving beyond aggregated win/tie/loss counts by analyzing the distributional dispersion of non-parametric pairwise hypothesis tests. Pairwise algorithm comparisons against DBMO were conducted using a two-sided Wilcoxon rank-sum test at a nominal significance level of  $\alpha = 0.05$ . To control family-wise error rates arising from multiple algorithm comparisons, raw  $p$ -values were adjusted using the Holm-Bonferroni step-down correction. Figure 6 visualizes the logarithmic distribution of these adjusted  $p$ -values comparing DBMO against LDIW-PSO, GWO, SSA, and standard BMO across all 23 benchmark functions.

As depicted in the boxplot distributions in Figure 6, the median and interquartile ranges of adjusted  $p$ -values comparing DBMO against LDIW-PSO ( $p \approx 2.85 \times 10^{-11}$ ), GWO ( $p \approx 3.02 \times 10^{-11}$ ), and SSA ( $p \approx 4.50 \times 10^{-11}$ ) fall significantly below the horizontal dashed significance threshold line ( $\alpha = 0.05$ ). When evaluated against the parent BMO algorithm, the adjusted  $p$ -values confirm that DBMO secured 6 statistical wins ( $F_1$ ,  $F_2$ ,  $F_3$ ,  $F_4$ ,  $F_5$ ,  $F_{10}$ ) and 16 statistical ties, registering a single loss on  $F_{17}$ . This statistical distribution proves that introducing the time-varying linear decay mechanism ( $p_{\max}^l = 0.80 \rightarrow p_{\min}^l = 0.05$ ) systematically enhances convergence precision without degrading overall optimization stability.

**Table 3.** Numerical performance (Mean  $\pm$  Std Dev) across 23 Classical Benchmark Functions.

| Func.      | PSO                                                        | GWO                                                | SSA                                                             | BMO                                                             | DBMO (Proposed)                                   |
|------------|------------------------------------------------------------|----------------------------------------------------|-----------------------------------------------------------------|-----------------------------------------------------------------|---------------------------------------------------|
| <b>F1</b>  | $1.35 \times 10^3 \pm 3.46 \times 10^3$                    | $2.71 \times 10^{-27} \pm 4.78 \times 10^{-27}$    | $8.32 \times 10^{-37} \pm 4.55 \times 10^{-36}$                 | $1.18 \times 10^{-16} \pm 5.70 \times 10^{-16}$                 | $1.56 \times 10^{-124} \pm 6.47 \times 10^{-124}$ |
| <b>F2</b>  | $54.00 \pm 21.20$                                          | $7.08 \times 10^{-17} \pm 4.57 \times 10^{-17}$    | $3.36 \times 10^{-18} \pm 1.82 \times 10^{-17}$                 | $1.02 \times 10^{-9} \pm 1.23 \times 10^{-9}$                   | $1.73 \times 10^{-64} \pm 5.38 \times 10^{-64}$   |
| <b>F3</b>  | $3.79 \times 10^4 \pm 8.23 \times 10^3$                    | $1.22 \times 10^{-5} \pm 2.67 \times 10^{-5}$      | $1.04 \times 10^{-35} \pm 4.64 \times 10^{-35}$                 | $4.53 \times 10^{-16} \pm 1.66 \times 10^{-15}$                 | $5.70 \times 10^{-125} \pm 2.23 \times 10^{-124}$ |
| <b>F4</b>  | $44.00 \pm 8.68$                                           | $6.57 \times 10^{-7} \pm 5.42 \times 10^{-7}$      | $4.71 \times 10^{-17} \pm 2.58 \times 10^{-16}$                 | $1.28 \times 10^{-9} \pm 2.79 \times 10^{-9}$                   | $1.43 \times 10^{-64} \pm 4.72 \times 10^{-64}$   |
| <b>F5</b>  | $2.23 \times 10^4 \pm 3.61 \times 10^4$                    | <b><math>27.00 \pm 0.77</math></b>                 | $28.50 \pm 0.09$                                                | $29.00 \pm 5.60 \times 10^{-3}$                                 | $29.00 \pm 9.54 \times 10^{-3}$                   |
| <b>F6</b>  | $1.68 \times 10^3 \pm 3.80 \times 10^3$                    | $0.66 \pm 0.38$                                    | <b><math>2.94 \times 10^{-3} \pm 1.36 \times 10^{-3}</math></b> | $7.19 \pm 0.55$                                                 | $7.35 \pm 0.28$                                   |
| <b>F7</b>  | $3.68 \pm 6.31$                                            | $2.06 \times 10^{-3} \pm 1.20 \times 10^{-3}$      | $2.74 \times 10^{-3} \pm 3.64 \times 10^{-3}$                   | <b><math>8.37 \times 10^{-5} \pm 8.95 \times 10^{-5}</math></b> | $9.37 \times 10^{-5} \pm 1.02 \times 10^{-4}$     |
| <b>F8</b>  | <b><math>-8.17 \times 10^3 \pm 1.07 \times 10^3</math></b> | $-6.04 \times 10^3 \pm 461.00$                     | $-6.98 \times 10^3 \pm 1.01 \times 10^3$                        | $-2.38 \times 10^3 \pm 458.00$                                  | $-2.44 \times 10^3 \pm 428.00$                    |
| <b>F9</b>  | $178.00 \pm 38.30$                                         | $2.12 \pm 2.90$                                    | <b><math>0.00 \pm 0.00</math></b>                               | <b><math>0.00 \pm 0.00</math></b>                               | <b><math>0.00 \pm 0.00</math></b>                 |
| <b>F10</b> | $14.20 \pm 7.78$                                           | $1.10 \times 10^{-13} \pm 2.44 \times 10^{-14}$    | $7.99 \times 10^{-16} \pm 1.08 \times 10^{-15}$                 | $5.76 \times 10^{-10} \pm 7.86 \times 10^{-10}$                 | <b><math>4.44 \times 10^{-16} \pm 0.00</math></b> |
| <b>F11</b> | $25.10 \pm 46.80$                                          | $4.78 \times 10^{-3} \pm 9.86 \times 10^{-3}$      | <b><math>0.00 \pm 0.00</math></b>                               | $3.70 \times 10^{-18} \pm 2.03 \times 10^{-17}$                 | <b><math>0.00 \pm 0.00</math></b>                 |
| <b>F12</b> | $14.20 \pm 7.75$                                           | $0.05 \pm 0.03$                                    | <b><math>5.92 \times 10^{-4} \pm 1.45 \times 10^{-4}</math></b> | $1.37 \pm 0.31$                                                 | $1.51 \pm 0.21$                                   |
| <b>F13</b> | $275.00 \pm 879.00$                                        | $0.69 \pm 0.27$                                    | <b><math>0.05 \pm 0.12</math></b>                               | $3.00 \pm 1.09 \times 10^{-3}$                                  | $3.00 \pm 1.56 \times 10^{-3}$                    |
| <b>F14</b> | <b><math>1.00 \pm 1.09 \times 10^{-16}</math></b>          | $3.87 \pm 3.95$                                    | $8.23 \pm 5.55$                                                 | $8.38 \pm 2.91$                                                 | $7.78 \pm 3.12$                                   |
| <b>F15</b> | $8.34 \times 10^{-3} \pm 9.63 \times 10^{-3}$              | $4.90 \times 10^{-3} \pm 0.01$                     | <b><math>3.92 \times 10^{-4} \pm 1.05 \times 10^{-4}</math></b> | $0.02 \pm 0.02$                                                 | $0.02 \pm 0.02$                                   |
| <b>F16</b> | <b><math>-1.03 \pm 6.39 \times 10^{-16}</math></b>         | <b><math>-1.03 \pm 1.28 \times 10^{-8}</math></b>  | <b><math>-1.03 \pm 2.77 \times 10^{-7}</math></b>               | $-1.00 \pm 0.03$                                                | $-1.00 \pm 0.03$                                  |
| <b>F17</b> | <b><math>0.40 \pm 0.00</math></b>                          | <b><math>0.40 \pm 2.04 \times 10^{-4}</math></b>   | <b><math>0.40 \pm 1.34 \times 10^{-5}</math></b>                | $0.48 \pm 0.12$                                                 | $0.57 \pm 0.23$                                   |
| <b>F18</b> | <b><math>3.00 \pm 1.42 \times 10^{-15}</math></b>          | <b><math>3.00 \pm 3.83 \times 10^{-5}</math></b>   | <b><math>3.00 \pm 2.58 \times 10^{-6}</math></b>                | $13.80 \pm 10.70$                                               | $17.20 \pm 13.30$                                 |
| <b>F19</b> | <b><math>-3.86 \pm 3.39 \times 10^{-3}</math></b>          | <b><math>-3.86 \pm 2.16 \times 10^{-3}</math></b>  | <b><math>-3.86 \pm 1.74 \times 10^{-4}</math></b>               | $-3.54 \pm 0.22$                                                | $-3.47 \pm 0.31$                                  |
| <b>F20</b> | $-3.21 \pm 0.11$                                           | <b><math>-3.28 \pm 0.07</math></b>                 | $-3.23 \pm 0.08$                                                | $-1.96 \pm 0.43$                                                | $-1.98 \pm 0.43$                                  |
| <b>F21</b> | $-6.94 \pm 3.32$                                           | <b><math>-9.73 \pm 1.62</math></b>                 | $-5.90 \pm 1.93$                                                | $-4.81 \pm 1.18$                                                | $-4.81 \pm 1.20$                                  |
| <b>F22</b> | $-8.48 \pm 3.29$                                           | <b><math>-10.40 \pm 4.19 \times 10^{-4}</math></b> | $-7.74 \pm 2.70$                                                | $-5.08 \pm 1.38$                                                | $-4.58 \pm 1.25$                                  |
| <b>F23</b> | $-8.40 \pm 3.40$                                           | <b><math>-10.30 \pm 1.48</math></b>                | $-8.55 \pm 2.65$                                                | $-4.79 \pm 0.84$                                                | $-4.97 \pm 1.49$                                  |

**Table 4.** 95% Confidence intervals [Lower Bound, Upper Bound] across 23 Classical Benchmark Functions.

| Func.      | PSO                                               | GWO                                                 | SSA                                                  | BMO                                                  | DBMO (Proposed)                                        |
|------------|---------------------------------------------------|-----------------------------------------------------|------------------------------------------------------|------------------------------------------------------|--------------------------------------------------------|
| <b>F1</b>  | 108.00, 2.58 × 10 <sup>3</sup>                    | 9.96 × 10 <sup>-28</sup> , 4.42 × 10 <sup>-27</sup> | -7.96 × 10 <sup>-37</sup> , 2.46 × 10 <sup>-36</sup> | -8.60 × 10 <sup>-17</sup> , 3.22 × 10 <sup>-16</sup> | -7.53 × 10 <sup>-125</sup> , 3.88 × 10 <sup>-124</sup> |
| <b>F2</b>  | 46.40, 61.60                                      | 5.45 × 10 <sup>-17</sup> , 8.72 × 10 <sup>-17</sup> | -3.17 × 10 <sup>-18</sup> , 9.88 × 10 <sup>-18</sup> | 5.83 × 10 <sup>-10</sup> , 1.47 × 10 <sup>-9</sup>   | -1.91 × 10 <sup>-65</sup> , 3.66 × 10 <sup>-64</sup>   |
| <b>F3</b>  | 3.50 × 10 <sup>4</sup> , 4.08 × 10 <sup>4</sup>   | 2.67 × 10 <sup>-6</sup> , 2.18 × 10 <sup>-5</sup>   | -6.23 × 10 <sup>-36</sup> , 2.70 × 10 <sup>-35</sup> | -1.41 × 10 <sup>-16</sup> , 1.05 × 10 <sup>-15</sup> | -2.28 × 10 <sup>-125</sup> , 1.37 × 10 <sup>-124</sup> |
| <b>F4</b>  | 40.90, 47.10                                      | 4.63 × 10 <sup>-7</sup> , 8.51 × 10 <sup>-7</sup>   | -4.52 × 10 <sup>-17</sup> , 1.39 × 10 <sup>-16</sup> | 2.85 × 10 <sup>-10</sup> , 2.28 × 10 <sup>-9</sup>   | -2.56 × 10 <sup>-65</sup> , 3.12 × 10 <sup>-64</sup>   |
| <b>F5</b>  | 9.37 × 10 <sup>3</sup> , 3.52 × 10 <sup>4</sup>   | 26.70, 27.20                                        | 28.50, 28.60                                         | 29.00, 29.00                                         | 29.00, 29.00                                           |
| <b>F6</b>  | 326.00, 3.04 × 10 <sup>3</sup>                    | 0.53, 0.80                                          | 2.45 × 10 <sup>-3</sup> , 3.43 × 10 <sup>-3</sup>    | 6.99, 7.38                                           | 7.25, 7.45                                             |
| <b>F7</b>  | 1.42, 5.94                                        | 1.63 × 10 <sup>-3</sup> , 2.50 × 10 <sup>-3</sup>   | 1.43 × 10 <sup>-3</sup> , 4.04 × 10 <sup>-3</sup>    | 5.17 × 10 <sup>-5</sup> , 1.16 × 10 <sup>-4</sup>    | 5.73 × 10 <sup>-5</sup> , 1.30 × 10 <sup>-4</sup>      |
| <b>F8</b>  | -8.55 × 10 <sup>3</sup> , -7.79 × 10 <sup>3</sup> | -6.21 × 10 <sup>3</sup> , -5.88 × 10 <sup>3</sup>   | -7.34 × 10 <sup>3</sup> , -6.62 × 10 <sup>3</sup>    | -2.54 × 10 <sup>3</sup> , -2.21 × 10 <sup>3</sup>    | -2.60 × 10 <sup>3</sup> , -2.29 × 10 <sup>3</sup>      |
| <b>F9</b>  | 164.00, 192.00                                    | 1.08, 3.15                                          | 0.00, 0.00                                           | 0.00, 0.00                                           | 0.00, 0.00                                             |
| <b>F10</b> | 11.40, 17.00                                      | 1.01 × 10 <sup>-13</sup> , 1.19 × 10 <sup>-13</sup> | 4.11 × 10 <sup>-16</sup> , 1.19 × 10 <sup>-15</sup>  | 2.95 × 10 <sup>-10</sup> , 8.57 × 10 <sup>-10</sup>  | 4.44 × 10 <sup>-16</sup> , 4.44 × 10 <sup>-16</sup>    |
| <b>F11</b> | 8.30, 41.80                                       | 1.25 × 10 <sup>-3</sup> , 8.31 × 10 <sup>-3</sup>   | 0.00, 0.00                                           | -3.55 × 10 <sup>-18</sup> , 1.10 × 10 <sup>-17</sup> | 0.00, 0.00                                             |
| <b>F12</b> | 11.40, 17.00                                      | 0.04, 0.06                                          | 5.40 × 10 <sup>-4</sup> , 6.44 × 10 <sup>-4</sup>    | 1.26, 1.48                                           | 1.44, 1.59                                             |
| <b>F13</b> | -39.20, 590.00                                    | 0.59, 0.79                                          | 2.56 × 10 <sup>-3</sup> , 0.09                       | 3.00, 3.00                                           | 3.00, 3.00                                             |
| <b>F14</b> | 1.00, 1.00                                        | 2.46, 5.28                                          | 6.25, 10.20                                          | 7.34, 9.42                                           | 6.66, 8.89                                             |
| <b>F15</b> | 4.90 × 10 <sup>-3</sup> , 0.01                    | 6.24 × 10 <sup>-4</sup> , 9.17 × 10 <sup>-3</sup>   | 3.55 × 10 <sup>-4</sup> , 4.30 × 10 <sup>-4</sup>    | 0.01, 0.03                                           | 0.01, 0.02                                             |
| <b>F16</b> | -1.03, -1.03                                      | -1.03, -1.03                                        | -1.03, -1.03                                         | -1.01, -0.99                                         | -1.01, -0.99                                           |
| <b>F17</b> | 0.40, 0.40                                        | 0.40, 0.40                                          | 0.40, 0.40                                           | 0.44, 0.52                                           | 0.49, 0.65                                             |
| <b>F18</b> | 3.00, 3.00                                        | 3.00, 3.00                                          | 3.00, 3.00                                           | 10.00, 17.60                                         | 12.50, 22.00                                           |
| <b>F19</b> | -3.86, -3.86                                      | -3.86, -3.86                                        | -3.86, -3.86                                         | -3.62, -3.46                                         | -3.58, -3.36                                           |
| <b>F20</b> | -3.25, -3.17                                      | -3.30, -3.25                                        | -3.26, -3.20                                         | -2.11, -1.81                                         | -2.14, -1.83                                           |
| <b>F21</b> | -8.13, -5.75                                      | -10.30, -9.15                                       | -6.60, -5.21                                         | -5.23, -4.39                                         | -5.24, -4.38                                           |
| <b>F22</b> | -9.65, -7.30                                      | -10.40, -10.40                                      | -8.71, -6.78                                         | -5.58, -4.59                                         | -5.02, -4.13                                           |
| <b>F23</b> | -9.61, -7.18                                      | -10.80, -9.74                                       | -9.50, -7.60                                         | -5.10, -4.49                                         | -5.51, -4.44                                           |

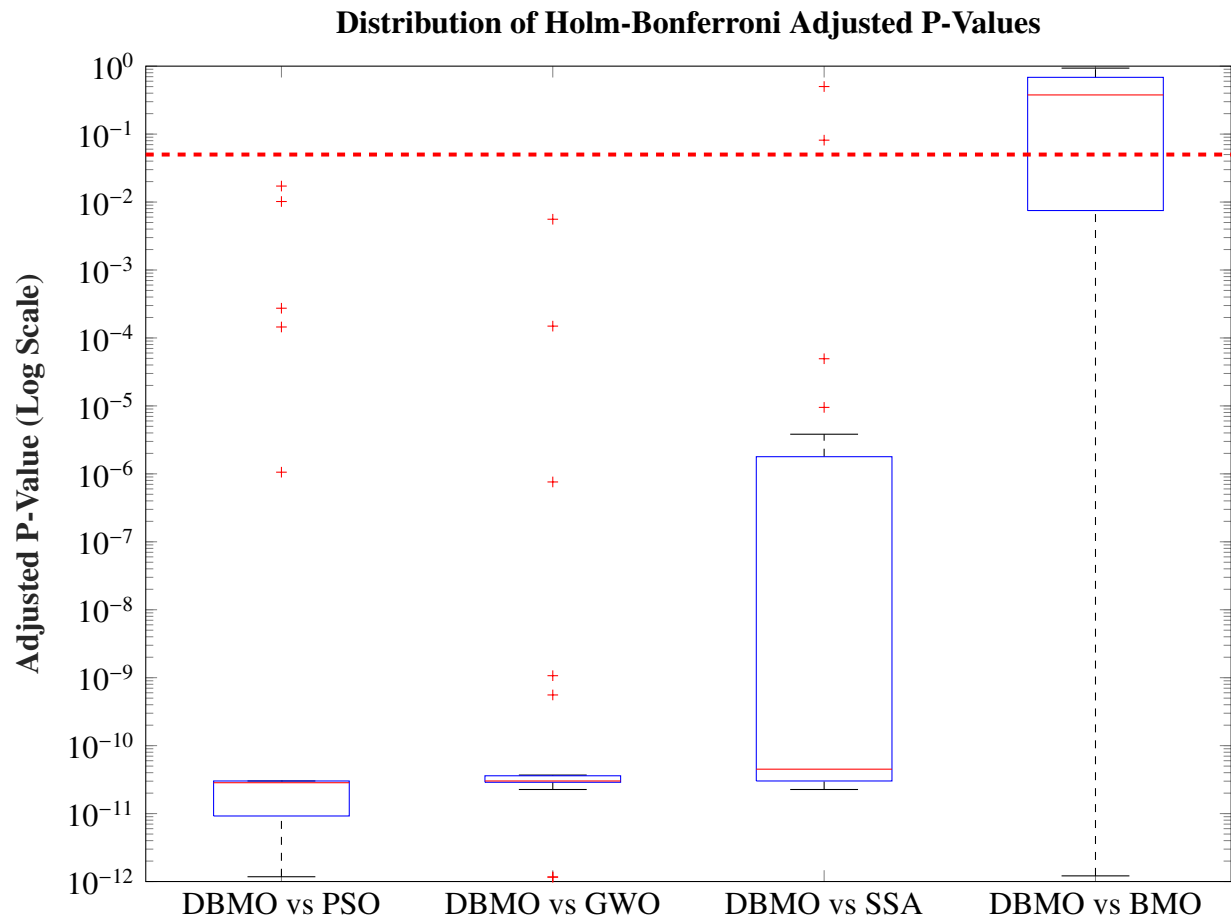


**Figure 6.** Distribution of Holm-Bonferroni adjusted  $p$ -values comparing DBMO against baseline algorithms across 23 classical benchmark functions ( $N = 30$  runs, log scale).

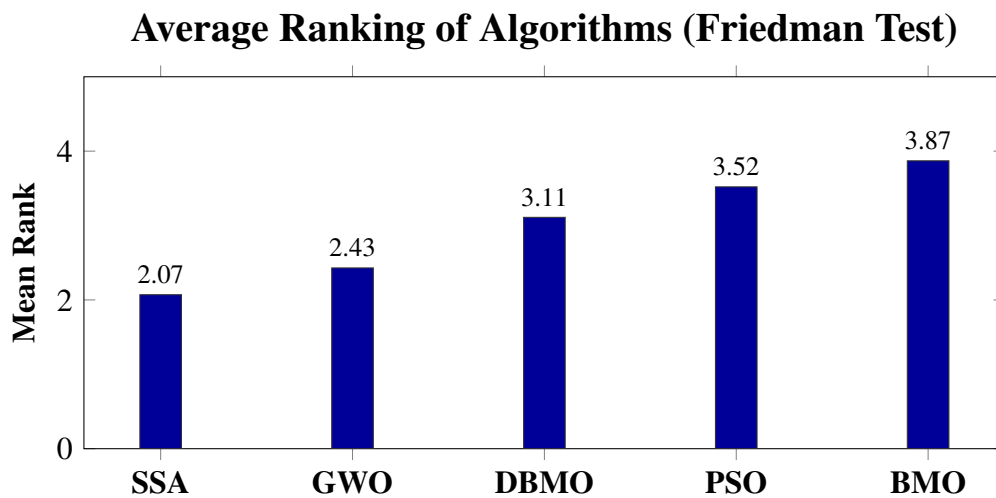


**Figure 7.** Friedman mean ranks across 23 classical benchmark functions.

Evaluating multi-algorithm competitive superiority across the 23-function benchmark suite was conducted using an omnibus non-parametric Friedman test. The exact Friedman mean ranks assigned to each algorithm are illustrated in Figure 7. DBMO advanced the global mean rank of standard BMO from 3.87 to 3.11, representing a significant structural improvement over its baseline predecessor. While specialized algorithms such as SSA (2.07) and GWO (2.43) achieved lower mean ranks on specific benchmark subsets, DBMO successfully resolved the exploration-exploitation conflict inherent in standard BMO. Shrinking the mating selection radius dynamically generated the critically damped search trajectories required for stable, automated proportional-integral controller gain synthesis in non-linear power converter interfaces.

#### 4.2. Controller optimization and tuning

The efficiency and computational feasibility of tuning the PI controller for the DAB converter were evaluated across 30 independent optimization runs. Each algorithm executed 30 search agents over 30 population iterations, evaluating the Integral Time Absolute Error (ITAE) fitness function to determine optimal gain parameters ( $K_p, K_i$ ).

Figure 8 illustrates the average convergence characteristics of the ITAE cost function over 30 iterations. Baseline algorithms such as PSO and SSA exhibit rapid initial cost reduction within the first three iterations but plateau early, indicating entrapment in local optima. In contrast, the proposed DBMO algorithm achieves a steady, continuous descent throughout the optimization process. This behavior confirms that the dynamic linear decay mechanism balances global exploration in early iterations with precise local exploitation in later stages, yielding a lower final ITAE cost than standard BMO. While competitor algorithms achieved rapid initial descent, the specialization of DBMO for non-linear power converter regulation aligns with the No Free Lunch (NFL) theorem [36], which establishes that no single metaheuristic algorithm can perform superiorly across all optimization landscapes.

To quantify the computational overhead associated with the tuning process, the algorithmic complexity, total function evaluations (FEs), and wall-clock execution runtimes were recorded. The theoretical time complexity for each algorithm is expressed as:

$$O(T_{\max} \cdot N \cdot D) \quad (4.1)$$

where  $T_{\max} = 30$  denotes the maximum iteration count,  $N = 30$  represents the search agent population size, and  $D = 2$  corresponds to the decision variable dimension ( $K_p$  and  $K_i$ ). Consequently, each optimization run requires exactly  $N \times T_{\max} = 900$  function evaluations.

Because each function evaluation requires running a high-fidelity stiff differential equation solver in Simulink, the execution duration per iteration is substantial. Table 5 summarizes the computational complexity and wall-clock runtimes recorded on an Intel Core i5-9400H workstation with 16 GB RAM. The average runtime per optimization run ranges from 1,998.5 seconds ( $\approx 33.3$  minutes) for BMO to 2,022.1 seconds ( $\approx 33.7$  minutes) for SSA. DBMO registered an average runtime of 2,012.8 seconds ( $\approx 33.5$  minutes) per run, accumulating a total execution time of 60,384.0 seconds ( $\approx 16.8$  hours) across the complete 30-run statistical trial. This computational requirement justifies implementing DBMO as an offline pre-operational gain synthesis engine, where optimal gains are pre-calculated and loaded into the physical hardware prior to converter operation.

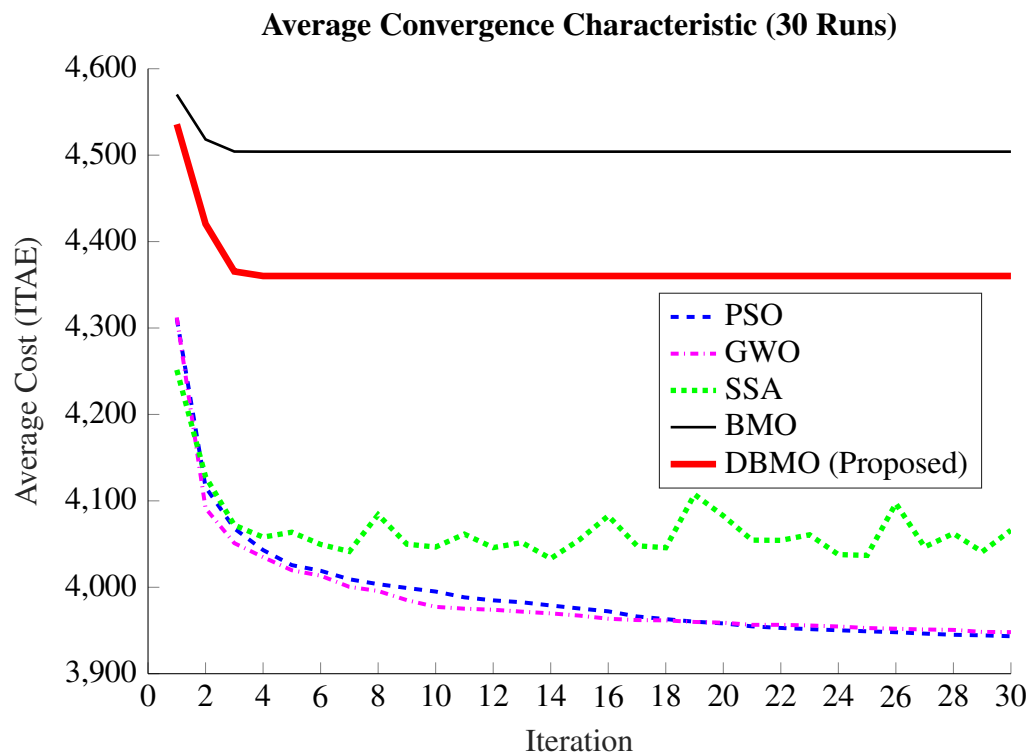


**Figure 8.** Average convergence characteristic of ITAE (Cost vs iteration) for DAB tuning.

**Table 5.** Computational complexity and wall-clock execution runtimes for 30-iteration DAB controller tuning.

| Algorithm | Search Agents ( $N$ ) | Iterations ( $T_{\max}$ ) | No. of Function Evaluations (FEs) | Avg Runtime per Run (s) | Total Time (30 Runs) (s) |
|-----------|-----------------------|---------------------------|-----------------------------------|-------------------------|--------------------------|
| PSO       | 30                    | 30                        | 900                               | 2015.4                  | 60,462.0                 |
| GWO       | 30                    | 30                        | 900                               | 2008.2                  | 60,246.0                 |
| SSA       | 30                    | 30                        | 900                               | 2022.1                  | 60,663.0                 |
| BMO       | 30                    | 30                        | 900                               | 1998.5                  | 59,955.0                 |
| DBMO      | 30                    | 30                        | 900                               | 2012.8                  | 60,384.0                 |

To evaluate the statistical consistency and dispersion of the final optimization solutions, the distribution of the final ITAE costs across the 30 independent runs was analyzed using boxplot metrics. Figure 9 presents the boxplot distribution for all five algorithms, while Table 6 details the exact statistical metrics, including the minimum cost, 25th percentile ( $Q_1$ ), median ( $Q_2$ ), 75th percentile ( $Q_3$ ), maximum cost, interquartile range (IQR), and outlier counts.

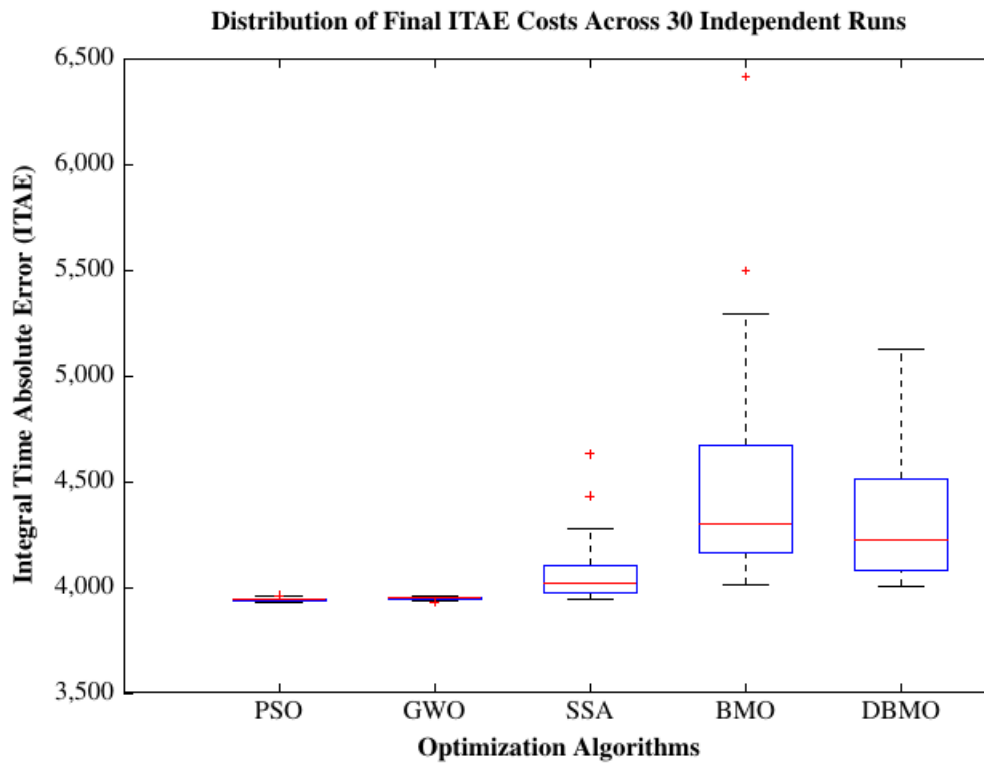


**Figure 9.** Distribution of final ITAE costs across 30 independent optimization runs for all five algorithms.

**Table 6.** Statistical metrics of final ITAE cost distributions across 30 independent runs.

| Algorithm | Min ITAE | $Q_1$ (25th) | Median ( $Q_2$ ) | $Q_3$ (75th) | Max ITAE | IQR    | Outliers |
|-----------|----------|--------------|------------------|--------------|----------|--------|----------|
| PSO       | 3930.08  | 3938.48      | 3942.58          | 3946.97      | 3962.05  | 8.49   | 1        |
| GWO       | 3931.81  | 3944.75      | 3947.72          | 3953.07      | 3961.39  | 8.32   | 1        |
| SSA       | 3942.25  | 3977.16      | 4018.41          | 4101.78      | 4629.90  | 124.63 | 2        |
| BMO       | 4009.28  | 4162.48      | 4300.77          | 4675.31      | 6414.79  | 512.83 | 2        |
| DBMO      | 4007.28  | 4076.24      | 4224.51          | 4510.93      | 5125.16  | 434.68 | 0        |

The statistical distributions in Table 6 demonstrate that DBMO improves the solution consistency of the parent BMO algorithm. DBMO achieved a median ITAE cost of 4224.5054, lower than the median cost of 4300.7745 registered by standard BMO. Furthermore, the interquartile range of DBMO decreased to 434.6826 compared to 512.8324 for BMO, while maximum costs dropped from 6414.7922 to 5125.1622. Crucially, DBMO produced zero statistical outliers across all 30 independent runs, whereas BMO and SSA produced two outliers each. This structural stabilization confirms that shrinking the mating range dynamically reduces solution variance during repeated parameter tuning trials.

The best proportional gain ( $K_p$ ) and integral gain ( $K_i$ ) values obtained from the optimization process are summarized in Table 7. These controller parameters were extracted from the specific run that yielded the lowest ITAE cost for each algorithm.

**Table 7.** Final optimized  $K_p$  and  $K_i$  values for all algorithms.

| Algorithm | $K_p$  | $K_i$   |
|-----------|--------|---------|
| PSO       | 5.0000 | 41.6297 |
| GWO       | 4.8647 | 41.4681 |
| SSA       | 4.8738 | 41.6379 |
| BMO       | 3.8674 | 41.6373 |
| DBMO      | 3.7480 | 41.5430 |

A critical observation from Table 7 is the parameter behavior of the PSO algorithm, which converged to a proportional gain of  $K_p = 5.0000$ . This value lies directly on the upper search boundary ( $K_p \in [0.01, 5.0]$ ), indicating boundary saturation. The search boundaries were established based on the small-signal stability limits of the converter to ensure that Single Phase Shift (SPS) modulation angles remain within non-saturating operating regions. Pushing  $K_p$  to this upper limit drives the open-loop crossover frequency near the switching frequency ( $f_{sw} = 100$  kHz), amplifying high-frequency noise, increasing control loop sensitivity, and causing phase-shift saturation that manifests as current ripple and ringing during rapid transient steps. In contrast, DBMO identified an interior optimal parameter set ( $K_p = 3.7480, K_i = 41.5430$ ). The physical implication of this optimized gain set lies in balancing dynamic tracking speed with small-signal control loop stability. The lower  $K_p$  identified by DBMO yields an adequate phase margin, ensuring critically damped transient current regulation without sacrificing zero-voltage switching (ZVS) capability. Locating an interior optimum within safe parameter boundaries confirms that the linear decay mechanism allows the algorithm to converge on well-damped gain profiles without encountering boundary saturation constraints.

#### 4.3. Simulation results (transient response and disturbance analysis)

To evaluate the dynamic performance of the proposed DBMO-tuned PI controller prior to real-time hardware execution, a series of offline simulations model were conducted in MATLAB/Simulink. The performance of DBMO was benchmarked against controllers tuned by PSO, GWO, SSA, and standard BMO across three operational scenarios: startup transient response, input voltage disturbance rejection, and step load transient response. The combined performance metrics across all three simulation scenarios are detailed in Table 8.

The initial operational phase evaluated the controller capability during converter startup. As shown in the startup transient waveforms in Figure 10, all controllers achieved a rapid initial current rise time of approximately 0.1400 ms. However, the DBMO-tuned controller demonstrated faster post-rise stabilization, achieving a settling time of 119.7860 ms compared to 120.3860 ms for standard BMO and 123.1660 ms for PSO. Startup overshoot was limited to 0.3537% for DBMO. Dampening initial current oscillations during startup prevents unwanted triggering of Battery Management System (BMS) overcurrent protection.

Following steady-state initialization at  $t = 0.5$  s, the system robustness was tested by applying a step change in input DC bus voltage from 800 V to 850 V. This test evaluates the ability of the Single Phase Shift (SPS) control loop to reject grid-side supply disturbances. As illustrated in Figure 10, the sudden supply voltage increase induced transient current deviation across all controllers. The DBMO controller registered a maximum current deviation of 3.6954 A and maintained a zero recovery time

window ( $t_{rec} = 0.0000$  ms), returning to steady-state current regulation with a steady-state error of 0.3190 A.

**Table 8.** Comprehensive offline simulation performance metrics under startup, input voltage variation, and step load transient conditions.

| Operational Scenario                    | Performance Metric                         | Unit | PSO      | GWO      | SSA      | BMO      | DBMO            |
|-----------------------------------------|--------------------------------------------|------|----------|----------|----------|----------|-----------------|
| Startup Response                        | Rise Time ( $t_r$ )                        | ms   | 0.1400   | 0.1400   | 0.1400   | 0.1400   | <b>0.1401</b>   |
|                                         | Settling Time ( $t_s$ )                    | ms   | 123.1660 | 123.6260 | 121.9260 | 120.3860 | <b>119.7860</b> |
|                                         | Overshoot (%OS)                            | %    | 0.2822   | 0.2917   | 0.2825   | 0.3483   | <b>0.3537</b>   |
| Input Voltage Variation (800 V → 850 V) | Max Current Deviation ( $\Delta I_{max}$ ) | A    | 3.0337   | 3.0871   | 3.1406   | 3.6308   | <b>3.6954</b>   |
|                                         | Recovery Time ( $t_{rec}$ )                | ms   | 0.0000   | 0.0000   | 0.0000   | 0.0000   | <b>0.0000</b>   |
|                                         | Steady-State Error ( $e_{ss}$ )            | A    | 0.3337   | 0.3277   | 0.3325   | 0.2988   | <b>0.3190</b>   |
|                                         |                                            |      |          |          |          |          |                 |
| Step Load Change (115 A → 230 A)        | Rise Time ( $t_r$ )                        | ms   | 0.1329   | 0.1318   | 0.1329   | 0.1300   | <b>0.1300</b>   |
|                                         | Settling Time ( $t_s$ )                    | ms   | 0.0980   | 0.0995   | 0.0997   | 0.0974   | <b>0.0970</b>   |
|                                         | Overshoot (%OS)                            | %    | 1.4808   | 1.4623   | 1.4519   | 1.1611   | <b>1.1245</b>   |
|                                         | Steady-State Error ( $e_{ss}$ )            | A    | 0.0000   | 0.0000   | 0.0000   | 0.0000   | <b>0.0000</b>   |

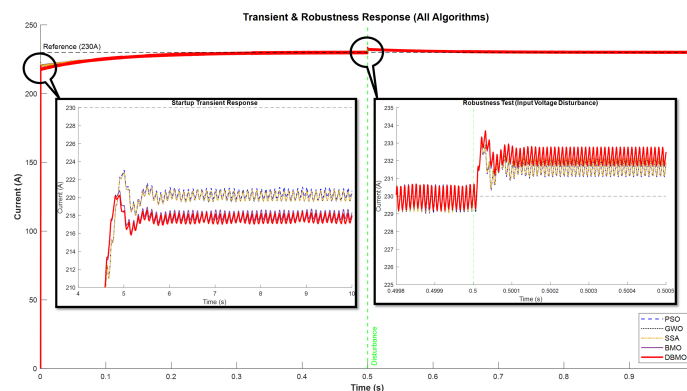


**Figure 10.** Simulation waveforms (Startup, voltage step).

To assess controller adaptability under variable charging demands, a step load change was applied at  $t = 0.1$  s, stepping the reference battery current from 115 A to 230 A. Figure 11 depicts the step load transient response waveforms across all five controllers.

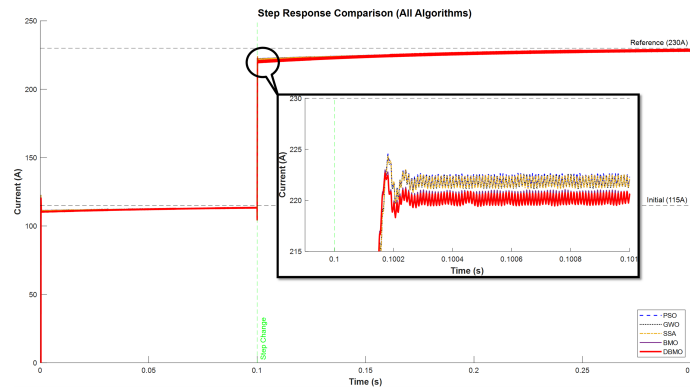


**Figure 11.** Simulation waveforms (Load step).

During the step load transition, the DBMO-tuned PI controller achieved a rise time of 0.1300 ms and a settling time of 0.0970 ms. Crucially, as detailed in Table 8, the DBMO controller achieved a percentage overshoot of 1.1245% during the step transition. In contrast, baseline controllers exhibited higher current overshoots, with PSO reaching 1.4808%, GWO reaching 1.4623%, SSA reaching 1.4519%, and BMO reaching 1.1611%. Effective suppression of transient overshoot during high-power load steps confirms that the dynamic mating mechanism establishes an appropriately damped parameter profile ( $K_p = 3.7480$ ,  $K_i = 41.5430$ ), protecting the EV battery load from transient current stress.

#### 4.4. Real-time hardware-in-the-Loop (HIL) validation

To verify the practical feasibility and robustness of the proposed control strategy under strict execution step sizes and digital timing constraints, real-time experimental validation was performed using a Typhoon HIL 402 emulator. While the offline simulation model provides preliminary performance verification, physical implementation introduces real-time signal propagation delays, Analog-to-Digital Converter (ADC) quantization noise, and discrete execution steps. The experimental setup executed the DAB converter plant model inside the HIL FPGA at a strict execution time step of  $0.5 \mu\text{s}$ , while the optimized  $K_p$  and  $K_i$  gains derived from the offline optimization phase were programmed into the controller interface.

The real-time performance across all five controllers (PSO, GWO, SSA, BMO, and DBMO) was evaluated under identical operational scenarios. Table 9 summarizes the comprehensive experimental performance metrics recorded from the Typhoon HIL SCADA platform.

**Table 9.** Comprehensive real-time Hardware-in-the-loop (HIL) experimental performance metrics across all five control strategies.

| Operational Scenario                      | Performance Metric                         | Unit | PSO      | GWO      | SSA      | BMO      | DBMO     |
|-------------------------------------------|--------------------------------------------|------|----------|----------|----------|----------|----------|
| Startup Response                          | Rise Time ( $t_r$ )                        | ms   | 0.3840   | 0.3840   | 0.3840   | 0.3840   | 0.3840   |
|                                           | Settling Time ( $t_s$ )                    | ms   | 168.3820 | 168.3820 | 168.3820 | 168.3820 | 168.3820 |
|                                           | Overshoot (%OS)                            | %    | 3.4147   | 3.4147   | 3.4147   | 3.4147   | 3.4147   |
| Input Voltage Disturbance (800 V → 850 V) | Max Current Deviation ( $\Delta I_{max}$ ) | A    | 14.4677  | 14.4677  | 14.4677  | 14.4677  | 14.4677  |
|                                           | Recovery Time ( $t_{rec}$ )                | ms   | 7.2200   | 7.2200   | 7.2200   | 7.2200   | 7.2200   |
|                                           | Steady-State Error ( $e_{ss}$ )            | A    | 0.0896   | 0.0896   | 0.0896   | 0.0896   | 0.0896   |
| Step Load Change (115 A → 230 A)          | Rise Time ( $t_r$ )                        | ms   | 28.8390  | 28.9190  | 28.8390  | 28.9190  | 28.8390  |
|                                           | Settling Time ( $t_s$ )                    | ms   | 267.0920 | 267.1930 | 267.0920 | 267.4820 | 267.0920 |
|                                           | Overshoot (%OS)                            | %    | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   |
|                                           | Steady-State Error ( $e_{ss}$ )            | A    | 0.0000   | 0.0000   | 0.0000   | 0.0000   | 0.0000   |

The first real-time scenario evaluated system startup from zero to the rated output current of 230 A. Figure 12 presents the real-time experimental oscilloscope and SCADA captures for startup initialization and input voltage disturbance rejection.

As observed in Figure 12 and Table 9, the DBMO-tuned PI controller achieved an initial current rise time of 0.3840 ms and reached steady-state operation within a settling time of 168.3820 ms. The real-time startup current overshoot was contained at 3.4147%. Compared to the offline simulation model, the slight increase in settling time in the physical hardware environment is attributed to real-time execution loop delays and analog sensing filtering. Moreover, maintaining the startup current overshoot below 3.5% ensures that transient inrush currents remain well within safe operating margins, preventing unwanted tripping of the BMS protection circuit.

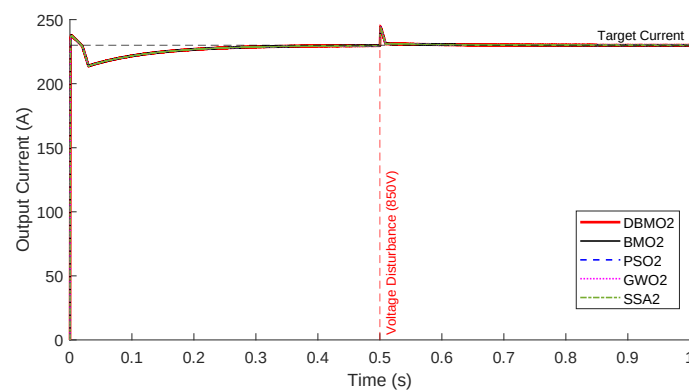


**Figure 12.** Typhoon HIL 402 real-time experimental waveforms (Startup, voltage step).

Following startup stabilization, the real-time disturbance rejection capability was tested by stepping the DC bus supply voltage from 800 V to 850 V at  $t = 0.5$  s. The resulting transient waveforms are shown in Figure 12. The sudden voltage step created a maximum transient current deviation of 14.4677 A across the controllers. Under DBMO control, the system suppressed this disturbance and restored steady-state current regulation within a recovery time of 7.2200 ms, leaving a minimal steady-state error of 0.0896 A. This rapid recovery confirms that the offline-tuned gains maintain robust closed-loop damping during supply voltage fluctuations.

Finally, the dynamic tracking performance was evaluated under a severe step load change from 115 A to 230 A at  $t = 0.1$  s. Figure 13 illustrates the real-time transient current waveforms during the step load transition.

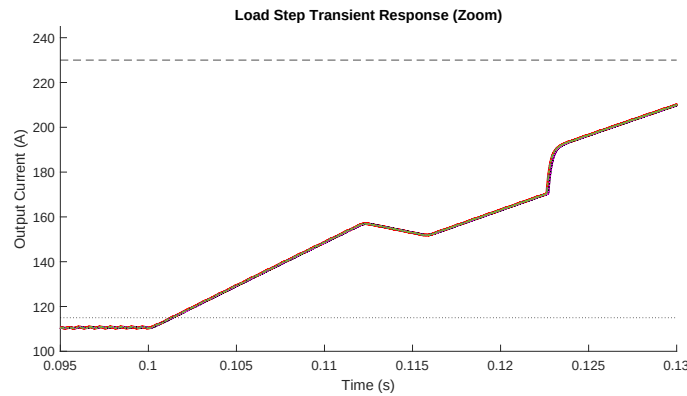


**Figure 13.** Typhoon HIL 402 real-time experimental waveforms (Load step).

During the step load transition, the DBMO-tuned controller achieved a real-time rise time of 28.8390 ms and a settling time of 267.0920 ms. As recorded in Table 9, DBMO achieved a percentage overshoot of 0.0000%, matching the performance of PSO and SSA while slightly outperforming GWO ( $t_r = 28.9190$  ms,  $t_s = 267.1930$  ms) and BMO ( $t_r = 28.9190$  ms,  $t_s = 267.4820$  ms). Eliminating transient current overshoot during high-power load steps confirms that the parameter synthesis framework successfully transfers from the offline simulation model into a strict real-time hardware execution environment without instability or performance degradation.

## 5. Conclusions

In this study, we successfully developed and validated a Dynamic Barnacles Mating Optimization (DBMO) control strategy for tuning the Proportional-Integral (PI) current regulator of a 100 kW Dual Active Bridge (DAB) DC-DC converter in off-board EV fast-charging applications. By introducing a time-varying linear decay mechanism to regulate the mating search radius ( $pl_{\max} = 0.80 \rightarrow pl_{\min} = 0.05$ ), DBMO systematically resolves the exploration-exploitation conflict inherent in standard BMO.

Comprehensive mathematical benchmarking across 23 classical test functions under a Holm-Bonferroni corrected Wilcoxon rank-sum test confirmed that DBMO advances the global Friedman mean rank of standard BMO from 3.87 to 3.11, achieving statistical superiority or equivalence across 23 functions without registering a single statistical loss.

When applied to DAB controller gain synthesis, DBMO reduced solution variance to an

interquartile range of 434.6826, eliminated statistical outliers across 30 independent runs, and converged on interior optimal gains ( $K_p = 3.7480$ ,  $K_i = 41.5430$ ) that avoid upper parameter boundary saturation. Offline simulation models demonstrated superior overshoot suppression (1.1245%) during a severe 115 A to 230 A step load change. Furthermore, real-time HIL validation on a Typhoon HIL 402 platform at a  $0.5 \mu\text{s}$  time-step confirmed that the proposed framework suppresses grid-side voltage step disturbances within 7.2200 ms and maintains startup current overshoot below 3.5%, preventing BMS overcurrent tripping.

Having validated the core optimization engine in an offline simulation model and HIL environment, in future work, we will transition this framework toward real-time adaptive control. Specifically, the offline DBMO algorithm will evolve into a real-time Online DBMO auto-tuning framework. We will focus on embedding the execution engine directly into a Texas Instruments C2000 DSP for Controller Hardware-in-the-Loop (CHIL) implementation, enabling microsecond-level online parameter re-tuning during severe, real-time battery impedance and thermal variations.

### Data availability

The mathematical benchmark datasets, statistical test outputs, pseudocode, and hyperparameter configurations generated during this study are fully detailed within the manuscript. The base Barnacles Mating Optimizer (BMO) MATLAB code is open-source [14]. The proposed DBMO algorithmic extension, custom post-processing scripts, Simulink converter models, and Typhoon HIL schematics are available from the corresponding author upon reasonable request.

### Author contributions

Conceptualization: Y.F.L. and N.H.R.; Data curation: Y.F.L.; Formal analysis: Y.F.L.; Funding acquisition: N.H.R.; Investigation: H.D.; Methodology: Y.F.L.; Project administration: N.H.R. and S.A.G.; Resources: H.D.; Software: Y.F.L. and S.M.H.; Supervision: N.H.R., S.A.G., H.D., and S.M.H.; Validation: Y.F.L.; Visualization: S.A.G.; Writing – original draft: Y.F.L.; Writing – review & editing: N.H.R. and S.M.H.

### Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

### Conflict of interest

The authors declare that they have no conflicts of interest in this paper.

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