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# A Novel Evolutionary-Swarm Hybrid Algorithm for Optimizing Power Transfer Efficiency in Wireless Power Transfer Systems

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**ABSTRACT**

Achieving high stable Power Transfer Efficiency (PTE) in Wireless Power Transfer (WPT) systems remains challenging due to the nonlinear, multimodal nature of the optimization space. Conventional algorithms such as Genetic Algorithms (GA), Differential Evolution (DE), and Simulated Annealing (SA) often face premature convergence, sensitivity to parameter settings, and inconsistent performance across runs. To overcome these issues, this study introduces the Evolutionary-Swarm Hybrid Algorithm (ESHA), which integrates DE for directional exploration, GA crossover for population diversity, SA for adaptive convergence, and Lévy Flights for stochastic global search. ESHA was implemented on a WPT system with a fixed 20 cm transmission distance and compared with GA, DE, and SA using three performance indicators: PTE, convergence speed, and computational efficiency. Results show that ESHA achieved a maximum PTE of 97.18%, surpassing GA (96.81%), DE (96.65%), and SA (96.19%), while maintaining zero variance across independent runs. It converged in an average of 31.2 iterations, slightly faster than GA (33.15) and SA (32.1), and comparable to DE (31.3). Execution time was 0.4738 s, close to GA (0.4654 s) and only marginally higher than DE (0.4262 s) and SA (0.4329 s). Statistical validation confirmed significant improvements in PTE ($p < 0.05$).



## 1. INTRODUCTION

Wireless Power Transfer (WPT) is an energy transmission method that transfers power from a source to a load without direct contact, using electromagnetic fields. Unlike traditional wired transmission, which relies on physical connectors and cables, WPT eliminates the need for direct contact, reducing the risk of electrical sparks and improving system flexibility and mobility. These benefits have made it a key area of interest in energy transfer research [1]–[6]. The ability of WPT to enhance mobility and reduce maintenance requirements makes it highly attractive for a wide range of applications, including consumer electronics [7]–[11], medical devices [12]–[15], electric vehicles (EVs) [16]–[20], and industrial automation [21][22].

Despite significant progress over the past century, achieving high and stable Power Transfer Efficiency (PTE) remains a major challenge in WPT systems. The efficiency and stability of WPT systems are highly sensitive to key design parameters, including coil geometry, mutual inductance, operating frequency, and compensation topology. Optimizing these parameters is essential to maximize efficiency and maintain system stability, but the process is inherently complex due to the nonlinear, multimodal nature of the search space, which poses significant challenges for conventional optimization techniques [23]-[26].

Evolutionary algorithms have demonstrated effectiveness in solving complex, high-dimensional optimization problems. Genetic Algorithms (GA), Differential Evolution (DE), and Simulated Annealing (SA) are widely used in various optimization tasks due to their adaptability and ability to handle complex search spaces. GA mimics natural selection through mutation and crossover to explore the solution space, but it is

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prone to premature convergence and loss of population diversity, leading to suboptimal solutions [27]–[29]. DE generates mutant solutions based on the differences between existing candidates, improving search efficiency, but it struggles with early stagnation when the search landscape is complex [30][31]. SA employs a probabilistic acceptance criterion to escape local optima, but its performance is sensitive to initial conditions and cooling schedules, limiting its effectiveness in dynamic or high-dimensional search spaces [32][33].

In the context of WPT optimization, GA has been applied to optimize coil geometry and system configuration [34]–[36]. However, its susceptibility to premature convergence and high computational cost often results in inconsistent solutions. DE has demonstrated faster convergence but tends to get trapped in local optima when the search landscape is complex [37][38]. SA has shown some success in fine-tuning design parameters [39][40], but its sensitivity to initial conditions and high computational demand make it less practical for large-scale WPT systems. The limitations of these methods underscore the need for a more adaptive and robust optimization framework that balances exploration and exploitation while ensuring consistent, high PTE in WPT systems.

Hybrid optimization algorithms that combine the strengths of different search strategies have shown promise in WPT applications. For example, ANN-based hybrids have been applied to EV charging systems to improve efficiency and reliability [41], but their dependence on large training datasets and difficulty in adapting to new operating conditions limit robustness. In microwave WPT, hybrid beamforming strategies have improved power delivery precision [42], yet they remain highly sensitive to hardware non-linearities and require complex calibration. Eel foraging optimization has been adapted to suppress magnetic leakage [43], though its effectiveness diminishes under coil misalignment and varying load conditions. Likewise, hybrid precoding in mmWave MIMO-SWIPT systems has boosted spectrum and energy efficiency [44], but at the expense of increased computational overhead and reduced scalability to large arrays.

More recent studies also reveal persistent gaps. Memetic-based WPT strategies achieved ~90.78% efficiency in EV charging but remained sensitive to state-of-charge estimation and load variation [45]. Multi-objective coil design hybrids achieved ~94% efficiency with swarm-analytic tuning, but added significant model complexity and showed poor tolerance to frequency shifts and misalignment [46]. Nonlinear waveform optimization hybrids demonstrated powerful results for large-scale WPT antennas but incurred high computational cost and scalability issues in multi-frequency, multi-user settings [47].

These limitations underscore the need for a more balanced and adaptive algorithm. Therefore, this work addresses these gaps with the proposed Evolutionary-Swarm Hybrid Algorithm (ESHA), which integrates the strengths of GA, DE, and SA while countering their weaknesses. By combining exploitation, exploration, adaptive convergence control, and stochastic diversity, ESHA achieves not only higher efficiency and stability but also greater scalability and computational practicality across diverse WPT scenarios.

## 2. METHOD

The Evolutionary-Swarm Hybrid Algorithm (ESHA) addresses the limitations of single-method optimization by combining swarm intelligence and evolutionary computation within a structured framework. ESHA integrates four core mechanisms - Levy Flights, Differential Evolution (DE) mutation, Genetic Algorithm (GA) crossover, and Simulated Annealing (SA), to create a balanced optimization process that enhances both exploration and exploitation. Each mechanism contributes to a specific phase of the optimization process, ensuring improved search efficiency, diversity, and convergence stability. Hybrid metaheuristic approaches that combine multiple strategies have been shown to outperform single-method algorithms in complex search problems, particularly in high-dimensional and multimodal landscapes.

### 2.1. Structural Design of ESHA

The ESHA framework is divided into three dynamic and interdependent phases:

1. Adaptive Exploration Phase – Early search phase focused on maintaining diversity and global exploration using Levy Flights.
2. Evolutionary Refinement Phase – Intermediate search phase focused on refining solutions using DE mutation and GA crossover.
3. Self-Tuning Convergence Phase – Final phase focused on solution stabilization and convergence using Simulated Annealing.

### 2.2. Adaptive Exploration Phase

The initial phase of ESHA focuses on global exploration and maintaining population diversity. To prevent early stagnation, Lévy Flights are applied with a small probability (20%) during candidate generation, introducing long-tailed stochastic jumps scaled to the variable bounds. This allows the algorithm to occasionally escape local traps and explore less-visited regions of the design space, especially during early iterations.

#### 2.2.1. Levy Flights Mechanism

Levy Flights is a stochastic process that generates step sizes using a heavy-tailed probability distribution [48]:

$$S = \frac{U}{|V|^{1/\lambda}} \tag{1}$$

where: $U \sim N(0, \sigma^2)$ and $V \sim N(0,1)$ are normally distributed random variables. $\lambda$ is the Levy exponent, typically chosen between 1.5 and 2. σ is given by [49]:

$$\sigma = \left(\frac{\Gamma(1+\lambda)\sin(\pi\lambda/2)}{\Gamma((1+\lambda)/2)\lambda 2^{(\lambda-1)/2}}\right)^{1/\lambda} \tag{2}$$

ESHA applies Lévy Flights~~,~~ with a 20% probability during candidate generation. When triggered, the generated step is scaled to the problem bounds and added to the current solution as follows [50]:

$$x_i = x_i + \text{step} \tag{3}$$

This allows the algorithm to introduce long-range perturbations that promote escape from local optima and encourage deeper exploration of the search space. Since Lévy steps are more likely early in the search, they enhance diversity at the start while naturally fading in impact as the population converges [51].

### 2.3. Evolutionary Refinement Phase

Once promising regions of the search space are identified, the algorithm enters a refinement phase in which exploitation becomes more dominant. The goal here is to improve the precision of candidate solutions without sacrificing diversity. To achieve this, ESHA combines Differential Evolution (DE) mutation and Genetic Algorithm (GA) crossover, both applied adaptively throughout the run. DE enables directional improvement using scaled vector differentials, while GA crossover introduces controlled variation through parent blending. These operations are applied probabilistically, ensuring a dynamic balance between exploration and exploitation as the search progresses.

#### 2.3.1. Differential Evolution (DE) Mutation

DE mutation introduces directional improvements to candidate solutions by generating a mutant vector from the difference between randomly population vectors. The mutation step is defined as [52]:

$$X_i' = X_r1 + F(X_r2 - X_r3) \tag{4}$$

Where $X_r1$, $X_r2$, $X_r3$ are randomly selected vectors from the population, and F is the scaling factor controlling mutation intensity. In the ESHA implementation, F is linearly decayed from 0.8 to 0.3 over the course of iterations:

$$F = 0.8 - (0.8 - 0.3)\frac{k}{k_{max}} \tag{5}$$

Where $k$ is the current iteration, and $k_{max}$ is the maximum number of iterations. This decay ensures strong exploration early on and smoother convergence later. DE mutation enables ESHA to maintain search diversity while focusing refinement on promising areas of the solution space.

#### 2.3.2. Genetic Algorithm (GA) Crossover

GA crossover is used to maintain genetic diversity and prevent stagnation. ESHA uses an arithmetic crossover method [53][54]:

$$X_{new} = \alpha X_1 + (1 - \alpha) X_2 \tag{5}$$

Where α is a random weight ( $0 \leq \alpha \leq 1$ ) and $X_1, X_2$ are selected parent solutions. This mechanism preserves useful genetic traits while introducing controlled variation into the population. In the implemented ESHA, arithmetic crossover is applied selectively, with a 50% probability during each iteration to maintain a balance between innovation and stability in the evolving population.

### 2.4. Self-Tuning Convergence Phase (Simulated Annealing (SA) Mechanism)

The final stage of ESHA is focused on fine-tuning solutions and stabilizing convergence. Simulated Annealing (SA) is employed to ensure that the algorithm does not become trapped in local optima. SA accepts worse solutions with a decreasing probability based on a temperature-controlled criterion [55]:

$$P = \exp\left(-\frac{\Delta E}{T}\right) \tag{6}$$

Where $\Delta E = f(x_{new}) - f(x_{current})$ is the difference in fitness between the current and new solution. If the new solution is worse, it is accepted with probability P; if it is better, it is accepted outright. The temperature T decreases over time according to the geometric cooling schedule [55]:

$$T = T_0 \cdot \beta^k \tag{7}$$

Where $T_0$ is the initial temperature, β is the cooling rate ( $0.85 \leq \beta \leq 0.99$ ), and k is the iteration number. As the temperature drops, the algorithm becomes more selective, gradually shifting from exploration to exploitation. By enabling temporary acceptance of worse solutions early on, SA improves global convergence reliability and helps ESHA escape local traps in the final optimization stretch.

### 2.5. Parameter Settings

The internal parameters of ESHA were fine-tuned through extensive empirical testing to ensure effective balance between exploration, exploitation, and convergence. Table 1 summarizes the key control parameters used in the final implementation, including Lévy Flight, Differential Evolution (DE), Genetic Algorithm (GA), and Simulated Annealing (SA) settings, along with stopping and transition criteria.

Table 1. Parameter Settings

| Component | Parameter | Value / Range | Notes |
|---|---|---|---|
| Population | Population size | 30 | Fixed across all runs |
| | Max iterations | 100 | Stopping criterion |
| Levy Flights | Injection probability | 20% | Applied randomly during early iterations |
| | Levy exponent (λ) | 1.5 | Controls tail-heaviness of jumps |
| Differential Evolution (DE) | Scaling factor (F) | 0.3 – 0.8 | Chosen adaptively per iteration |
| Genetic Algorithm (GA) | Crossover coefficient (α) | 0 – 1 | Random per crossover event |
| Simulated Annealing (SA) | Initial temperature ($T_0$) | 1.0 | Determines initial acceptance probability |
| | Cooling rate (β) | 0.95 | Controls temperature decay |
| | Temperature update | $T = T_0 \cdot \beta^k$ | Updated per iteration k |

### 2.6. Algorithmic Flow of ESHA

The execution flow of ESHA is illustrated in Figure 1. The algorithm starts with population initialization, followed by Levy Flight-based exploration, DE mutation and GA crossover for refinement, and SA for fine-tuning and convergence.

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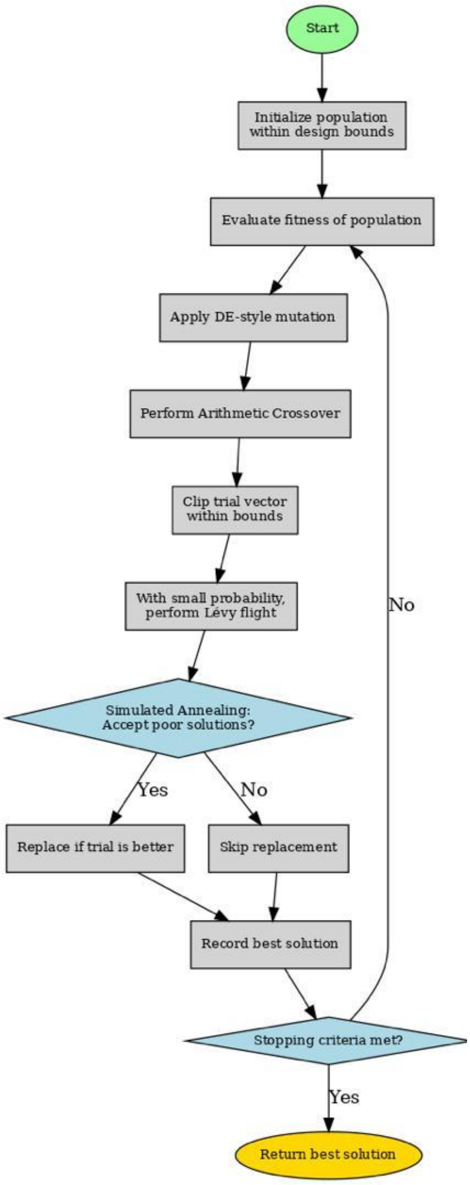


Figure 1. Flowchart of the Evolutionary-Swarm Hybrid Algorithm (ESHA)

### 2.7. Implementation Environment and Reproducibility

All experiments were conducted in Python (v3.11) using NumPy and SciPy. Each algorithm was executed 30 independent times with fixed random seeds to ensure reproducibility. All algorithms were evaluated under the same number of iterations (100) and population size (30). Each algorithm's parameters were individually tuned based on literature and preliminary sensitivity analysis to ensure fairness. Execution time was measured using Python's time module, and no runs or data points were excluded from the analysis.

## 3. THEORETICAL BASIS

The theoretical framework outlines the design of the transmitter and receiver coils and the selection of the Series-Series (SS) compensation topology. The coil geometry and topology are optimized to improve coupling efficiency, stability, and overall power transfer performance.

### 3.1. Coil Geometry and Topology

The transmitter (Tx) and receiver (Rx) coils in this work are designed as circular planar coils, offering high coupling efficiency and ease of fabrication, making them ideal for applications such as electric vehicle (EV) charging, medical implants, and consumer electronics. The Series-Series (SS) compensation topology was chosen because of its superior performance under varying load and misalignment conditions. Compared to other configurations like Series-Parallel (SP), Parallel-Series (PS), and Parallel-Parallel (PP) topologies, the SS topology offers several advantages, including higher power transfer efficiency through improved impedance matching [56], greater stability under misalignment and load variation [57], and simpler tuning since both the Tx and Rx sides resonate at the same frequency [58]. The SS topology also reduces sensitivity to detuning caused by environmental changes or component tolerances [59]. In this configuration, capacitors are placed in series with the Tx and Rx coils to cancel out inductive reactance at resonance, minimizing system impedance and maximizing PTE. This results in more stable and efficient power transfer.

### 3.2. Resonant Frequency and Compensation

The resonant frequency ($f_r$) of the WPT system is determined by the inductance (L) of the coils and the compensation capacitance (C). For each coil (Tx and Rx), the resonant frequency is given by:

$$f_r = \frac{1}{2\pi\sqrt{LC}} \tag{8}$$

To ensure that both the transmitter and receiver coils resonate at the same frequency, the compensation capacitors $C_1$ and $C_2$ are selected based on the inductances $L_1$ and $L_2$ of the Tx and Rx coils:

$$C_1 = \frac{1}{{w_r}^2 L_1} \tag{9}$$

$$C_2 = \frac{1}{{w_r}^2 L_2} \tag{10}$$

The resonant frequency, selected between 6.78 MHz and 13.56 MHz, falls within the Industrial, Scientific, and Medical (ISM) bands, which are approved for WPT with minimal regulatory restrictions. Higher frequencies enable smaller coils and improved coupling while reducing electromagnetic interference (EMI).

### 3.3. Mathematical Model

The efficiency of the WPT system is determined by several key electrical parameters, including mutual inductance, self-inductance, AC resistance, and quality factor.

#### 3.3.1. Mutual Inductance

The mutual inductance (M) between the Tx and Rx coils is a key determinant of coupling strength and, consequently, PTE. For two circular planar coils, mutual inductance is calculated using an elliptic integral-based model:

$$M = \frac{\mu_0}{2}\sum_{i=1}^{N_a}\sum_{j=1}^{N_b}\sqrt{a_i b_j}\left(\frac{2}{k_{ij}} - k_{ij}\right)K\left(k_{ij}^2\right) - \frac{2}{k_{ij}}E\left(k_{ij}^2\right) \tag{11}$$

where:
$N_a, N_b$ is the number of turns in the Tx and Rx coils.
$a_i = r_{inner,tx} + (i-1)(w_{tx} + p_{tx})$.
$b_j = r_{inner,rx} + (j-1)(w_{rx} + p_{rx})$.
$K(k^2)$ and $E(k^2)$ are the complete elliptic integrals of the first and second kind.
$k_{ij}$ is the coupling coefficient between the i-th turn of Tx and the j-th turn of Rx and is given as $k_{ij} = \sqrt{\frac{4a_i b_j}{(a_i+b_j)^2+d^2}}$, where d is the coil separation distance.

#### 3.3.2. Self-Inductance (L) Calculation

The self-inductance of a circular planar coil is:

$$L = \left(\frac{N^2(D_o - N(w+p))^2}{16D_o + 28N(w+p)}\right) \times \left(\frac{39.37}{10^6}\right) \tag{12}$$

Where $D_o$ is the outer diameter of the coil. N is the number of turns. w is the wire diameter and p is the turn spacing.

#### 3.3.3. AC Resistance ($R_{AC}$) Calculation

The AC resistance of the loosely wound coils (where $p \geq 2w$), is :

$$R_{AC} = \frac{R_{DC} w}{4\delta} \tag{13}$$

Where:

$$\delta = \frac{1}{(\pi\sigma f \mu_0)^{\frac{1}{2}}} \tag{14}$$

$$R_{DC} = \frac{l}{\pi\sigma {r_0}^2} \tag{15}$$

$$l = 2\pi[Nr_{inner} + \sum_{2}^{N-1}(w + p)] \tag{16}$$

$\mathbf{R_{DC}}$ is the DC resistance. $\mathbf{l}$ is the length of the wire used for the circular flat spiral coil, $\boldsymbol{\mu_0}$ is the permeability of free space, The skin depth is denoted by $\boldsymbol{\delta}$ and $\boldsymbol{\sigma}$ is the conductivity of the conductor, and **w** is the diameter of the wire.

### 3.3.4. Quality Factor (Q)

The quality factor **(Q)** of the coil is given by:

$$Q = \frac{w_r L}{\mathbf{R_{AC}}} \tag{17}$$

### 3.3.5. Power Transfer Efficiency (PTE) Calculation

The Power Transfer Efficiency (PTE) is:

$$PTE = \frac{Q_{tx} Q_{rx} K^2}{(1+\sqrt{1+Q_{tx}Q_{rx}K^2})^2} \tag{18}$$

Where K is the coupling coefficient. This PTE equation serves as the objective function for the optimization process.

## 3.3. Optimization Problem Formulation for ESHA

The WPT system design is framed as a constrained optimization problem to maximize Power Transfer Efficiency (PTE), as given in equation (18). The ESHA algorithm tunes key geometric and electrical parameters within defined bounds to ensure practical, physically realizable solutions. These constraints reflect real-world limitations and are detailed in Table 2 below. Each candidate solution generated by ESHA is evaluated using the PTE equation, and any violation of physical or geometric constraints is penalized through fitness degradation.

Table 2. Table of parameter bounds

| Variable | Description | Lower Bound | Upper Bound |
|---|---|---|---|
| $N_{tx}$ | No. of turns in Transmitter | 15 | 20 |
| $N_{rx}$ | No. of turns in Receiver | 15 | 20 |
| $r_{inner,tx}$ | Inner radius of Transmitter | 0.028 m | 0.03 m |
| $r_{inner,rx}$ | Inner radius of Receiver | 0.018 m | 0.02 m |
| w | Wire Diameter | 0.001 m | 0.0012 m |
| $p_{tx}$ | Pitch of Transmitter | 0.0025 m | 0.003 m |
| $p_{rx}$ | Pitch of Receiver | 0.0025 m | 0.003 m |
| f | Frequency | 6.78 MHz | 13.56 MHz |

The WPT system design follows key geometric and physical constraints to ensure optimal performance. The outer radii of the transmitter and receiver coils are computed based on the inner radii, number of turns, wire width, and pitch as:

$$r_{outer,tx} = r_{inner,tx} + N_{tx}(w + p) \tag{19}$$

$$r_{outer,rx} = r_{inner,rx} + N_{rx}(w + p) \tag{20}$$

The separation distance between coils is fixed at 20 cm, and the coil pitch (p) must satisfy the condition $p \geq 2w$ for loosely wound coils. Positive definiteness is enforced for all parameters to ensure physically valid solutions. Boundary constraints are enforced using a penalty-based method. If a candidate solution violates these bounds, it is either clamped to the nearest valid value or penalized through fitness degradation.

## 4. RESULTS AND DISCUSSION

The performance analysis of the Evolutionary-Swarm Hybrid Algorithm (ESHA) in optimizing Power Transfer Efficiency (PTE) in a Wireless Power Transfer (WPT) system is presented here. The performance of ESHA is evaluated against three benchmark algorithms: Genetic Algorithm (GA), Differential Evolution (DE), and Simulated Annealing (SA). The analysis focuses on three key performance indicators: Power Transfer Efficiency, Convergence Speed, and Computational Efficiency. A rigorous statistical analysis, including t-tests and Wilcoxon signed-rank tests, is employed to determine the reliability and consistency of the results. The findings demonstrate that ESHA achieves higher efficiency and more stable convergence than the benchmark algorithms, without incurring high computational costs. The results underscore the effectiveness of ESHA's hybridized approach in balancing exploration and exploitation to improve WPT system performance.

### 4.1.1. Performance Comparison of ESHA with Other Algorithms in WPT Optimization

A comparative analysis was conducted to evaluate ESHA's performance relative to GA, DE, and SA. The evaluation focuses on three critical metrics: PTE, convergence speed, and computational efficiency. The results of the optimization process are presented in Table 3.

Table 3. Results of the Optimization process

| Algorithm | Mean PTE | Std PTE | Best PTE | Mean Execution Time | Std Execution Time | Mean Convergence Speed | Std Convergence Speed |
|---|---|---|---|---|---|---|---|
| ESHA | 0.971794 | 0 | 0.971794 | 0.473834 | 0.132558 | 31.2 | 8.23 |
| GA | 0.963374 | 0.002861 | 0.968152 | 0.465419 | 0.164669 | 33.15 | 10.83 |
| DE | 0.965763 | 0.00031 | 0.96652 | 0.42622 | 0.115469 | 31.3 | 11.31 |
| SA | 0.943397 | 0.011838 | 0.961865 | 0.432933 | 0.15876 | 32.1 | 10.47 |

### 4.1.2. Power Transfer Efficiency (PTE) Comparison

The primary objective of this study was to maximize PTE while maintaining system constraints. The best PTE values obtained during optimization indicate that ESHA achieved **97.18%**, outperforming GA (**96.81%**), DE (**96.65%**), and SA (**96.19%**). Although the absolute differences in PTE may appear small, they are statistically significant when analyzed across multiple independent runs. ESHA maintained a **mean PTE of 97.18%** with zero variance, demonstrating its ability to consistently converge to the same optimal solution. In contrast, GA and SA exhibited higher variance, suggesting that these methods are more prone to local optima and less consistent in their convergence outcomes. The higher variability in GA and SA indicates that their performance is less reliable across different runs, while ESHA consistently achieves a high PTE value.

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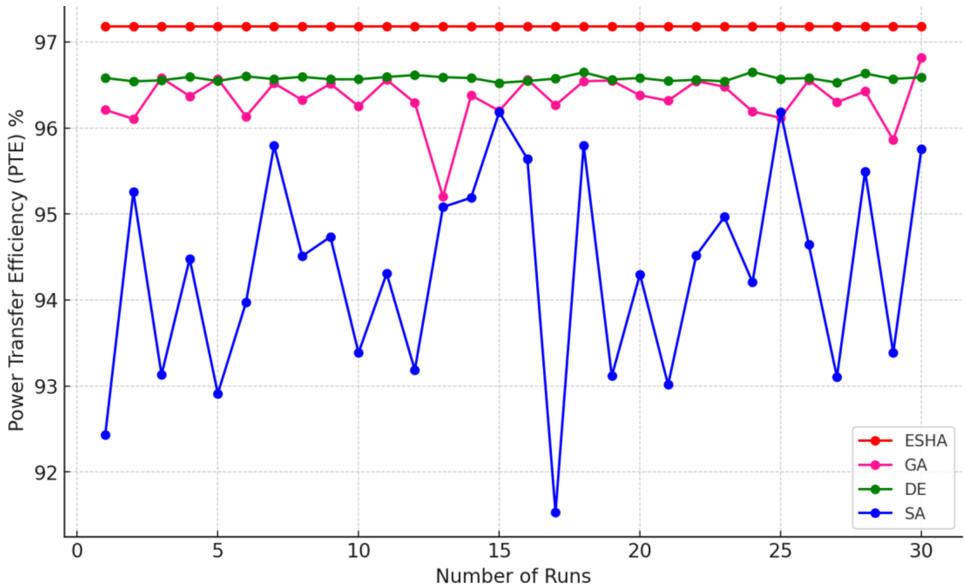


Figure 2. PTE (%) vs Number of Runs for all Algorithms

#### 4.1.3. Convergence Speed Analysis

Convergence speed is a key indicator of an optimization algorithm's ability to efficiently find optimal solutions. ESHA reached an optimal solution in an average of 31.2 iterations, marginally outperforming DE (31.3 iterations) and converging faster than GA (33.15 iterations) and SA (32.1 iterations). The faster convergence of ESHA relative to GA and SA reflects its effective balance between exploration and exploitation. DE's slightly slower convergence suggests a weaker exploration dynamic compared to ESHA's hybrid structure. The low standard deviation in ESHA's convergence speed further confirms its reliability and stability across multiple runs.

While these trends suggest that ESHA offers convergence advantages in typical scenarios, the statistical significance of these differences is examined in detail in Section 4.1.4.

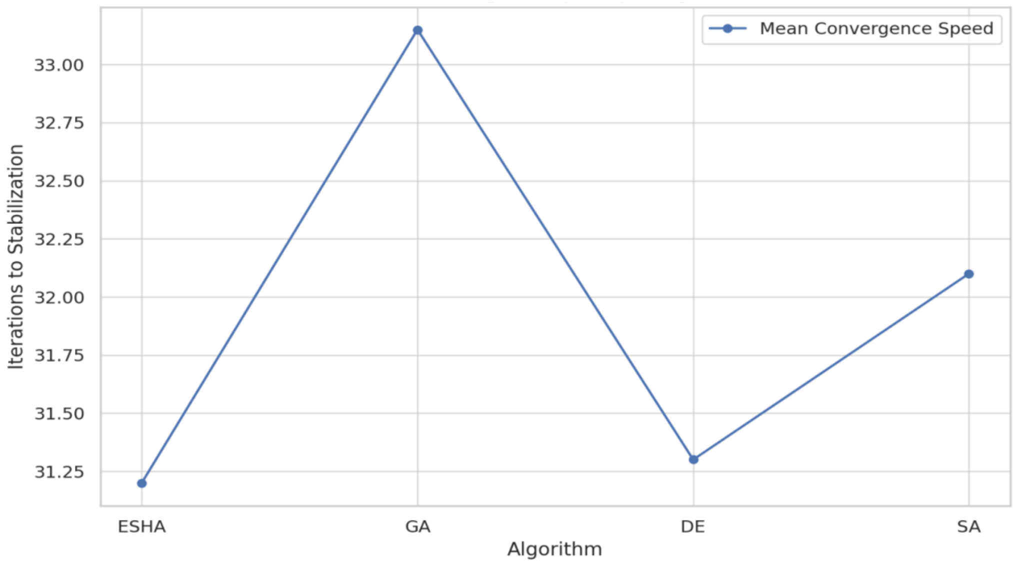


Figure 3. Convergence Speed Comparison Among Algorithms

#### 4.1.4. Computational Efficiency: Execution Time Comparison

The computational efficiency of the algorithm was evaluated based on the time required to reach an optimal solution. ESHA had an average execution time of 0.4738 seconds, which is comparable to GA (0.4654 s) and slightly higher than DE (0.4262 s) and SA (0.4329 s). The slight increase in ESHA's execution time is attributed to the added computational cost of combining DE, GA, Lévy Flights, and SA. However, this increase is negligible compared to the significant gains in PTE, stability, and convergence reliability. ESHA's hybrid nature allows it to optimize PTE effectively without imposing an undue computational burden.

#### 4.1.5. Statistical Validation of Performance Differences

To determine whether the observed performance differences are statistically significant, t-tests and Wilcoxon signed-rank tests were conducted.

Table 4. Statistical Comparison of ESHA and Benchmark Algorithms (GA, DE, and SA)

| Comparison | T-Test PTE (p-value) | Wilcoxon PTE (p-value) | T-Test Exec Time (p-value) | Wilcoxon Exec Time (p-value) | T-Test Conv Speed (p-value) | Wilcoxon Conv Speed (p-value) |
|---|---|---|---|---|---|---|
| ESHA vs GA | 8.02E-16 | 1.86E-09 | 0.8597 | 0.9563 | 0.5255 | 0.8124 |
| ESHA vs DE | 6.10E-39 | 1.86E-09 | 0.2334 | 0.2162 | 0.9747 | 0.6872 |
| ESHA vs SA | 1.48E-13 | 1.86E-09 | 0.3822 | 0.2943 | 0.7643 | 0.6215 |

The statistical analysis confirms that ESHA's improvements in Power Transfer Efficiency (PTE) over GA, DE, and SA are statistically significant, with p-values well below the 0.05 threshold. A p-value below 0.05 indicates that the probability of observing the result by random chance is less than 5%, supporting the rejection of the null hypothesis and confirming that the differences are not due to random variation. In contrast, the p-values for execution time and convergence speed exceed 0.05, suggesting no statistically significant difference between ESHA and the other methods in these areas. This means that while ESHA shows promising speed in typical runs, its convergence advantage cannot be generalized with high statistical confidence across all scenarios. Therefore, claims about superior convergence speed are limited to empirical trends rather than confirmed statistical differences. However, this confirms that ESHA achieves superior PTE without sacrificing computational efficiency or convergence speed, reinforcing the reliability of its hybridized optimization approach.

### 4.4. Discussion of Findings

The findings from this study strongly demonstrate ESHA's superiority in optimizing WPT efficiency while maintaining reliable convergence and computational efficiency. A detailed analysis of the results reveals key insights into ESHA's performance and effectiveness:

1. Consistent Performance: ESHA consistently achieved a PTE of 97.18% with zero variance across multiple runs, highlighting its ability to avoid premature convergence and local optima through a well-balanced exploration-exploitation mechanism.
2. Balanced Convergence and Stability: The integration of DE mutation, GA crossover, Lévy Flights, and SA allows ESHA to maintain high diversity during the early exploration phase while effectively refining solutions during the late-stage convergence. This ensures faster convergence and greater solution accuracy compared to single-method approaches.
3. Computational Efficiency: Despite incorporating multiple optimization techniques, ESHA's computational demand remains within practical limits. Its average execution time of 0.4738 seconds is comparable to GA and only marginally higher than DE and SA, confirming that the enhanced performance does not come at the cost of increased computational complexity.
4. Robust Statistical Significance: The statistical analysis, including t-tests and Wilcoxon signed-rank tests, confirms that ESHA's improvements in PTE are statistically significant ($p < 0.05$). However, the differences in execution time and convergence speed between ESHA and the other algorithms were not statistically significant, reinforcing the algorithm's reliability and computational efficiency.

## 5. CONCLUSION AND LIMITATION

This study introduced the Evolutionary-Swarm Hybrid Algorithm (ESHA), a novel metaheuristic framework designed to enhance Power Transfer Efficiency (PTE) in Wireless Power Transfer (WPT) systems. ESHA combines Levy Flights for adaptive exploration, Differential Evolution (DE) mutation, and Genetic Algorithm (GA) crossover for solution refinement, and Simulated Annealing (SA) for fine-tuning and convergence control. This hybrid structure effectively balances exploration and exploitation, leading to improved optimization performance in complex search spaces.

ESHA was rigorously evaluated against GA, DE, and SA using three key metrics: PTE, convergence speed, and computational efficiency. ESHA achieved a maximum PTE of 97.18%, surpassing the benchmark algorithms, with fast and stable convergence in an average of 31.2 iterations. Its execution time of 0.4738 seconds was comparable to GA and slightly higher than DE and SA. Statistical validation confirmed that ESHA's improvements in PTE were significant ($p < 0.05$), while differences in execution time were not, despite ESHA's hybrid structure, which combines multiple optimization strategies. This demonstrates that ESHA effectively balances exploration and exploitation without incurring a notable computational cost, reinforcing its efficiency and practicality for real-world applications.

Beyond WPT, ESHA's hybrid structure makes it highly adaptable to complex optimization problems across various fields. Its ability to balance exploration and exploitation while maintaining convergence stability makes it suitable for applications in electric vehicle charging, medical implants, and industrial automation. Additionally, ESHA's adaptability makes it a promising tool for machine learning, financial modeling, logistics, and network optimization, where complex search landscapes demand both precision and efficiency. Future work will explore multi-objective optimization, real-time deployment, and hardware-based validation to enhance ESHA's applicability in practical systems. A recent study [60] demonstrated a similar approach, applying hybrid swarm-based optimization techniques to tune AVR controllers, further underscoring the value of these integrated strategies in today's power and control engineering landscape.

Despite its strong performance, ESHA has limitations. Its multi-component structure introduces parameter complexity and may require careful retuning for different problem domains. There is also a potential risk of overfitting to the specific simulation environment, especially in the absence of real-world disturbances. Most importantly, the current evaluation is based solely on simulation results, which do not capture practical challenges such as electromagnetic interference, hardware misalignment, or environmental losses.

Future work will focus on hardware prototyping, noise-resilient optimization, and multi-objective extensions that address real-world trade-offs, ultimately strengthening ESHA's applicability in practical wireless power transfer systems.

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