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Energy-Efficient Wireless and Microwave Networks Based on Hybrid Salp Swarm–Whale Optimization Techniques

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Abstract: With the faster growth of fifth-generation (5G) and sixth-generation (6G) wireless communication systems, there are unprecedented requirements for ultra-low energy consumption wireless and microwave networks facing an increasing demand for enabling extreme-bandwidth data rates, massive connectivity, and low-latency communications. For optimization problems such as network routing, microwave resource allocation and antenna parameters adaptation, even though the general optimality of the solutions can be proven or demonstrated while optimizing directly with traditional algorithms, they often converge slowly and get trapped in local optima. In response to these issues, this paper presents an Energy Efficient Wireless and Microwave Network Framework using Advanced Hybrid Salp Swarm–Whale Optimization (HSSWO) algorithm. It provides a hybrid method that uses SSA with its good exploration ability and WOA for adaptively exploiting the routing paths, transmission power, microwave antenna parameters, and spectrum assignment. It further adds an AI-assisted network evaluation module for intelligent decision-making. The experimental results show that the proposed HSSWO framework attains 95.82% energy efficiency, a 41.6% improvement in network lifetime,

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throughput of 12.47 Gbps, packet delivery ratio of 99.21%, end–to–end latency of only 0.58 ms and a packet loss of only 0.69%. Moreover, the utilization of the proposed method leads to a reduction of optimization time for an average of 31.8% as well as improving convergence speed by an average of 36.4% over state-of-the-art optimization methods. The proposed HSSWO framework is an efficient energy-aware architecture for next-generation wireless and microwave communication systems as these results confirm.

Index Terms: Energy-Efficient Wireless Networks, Hybrid Salp Swarm–Whale Optimization (HSSWO), Salp Swarm Algorithm, Whale Optimization Algorithm, Artificial Intelligence, Microwave Communication, 6G Wireless Networks

1. Introduction

Wireless communication technologies have been developing rapidly, which raises never-been-seen demands on energy-efficient network infrastructures to support ultra-high-speed communication, massive IoT connectivity and intelligent radio resource management. Microwave communication networks capable of not just high spectral efficiency, but also low energy consumption for sustainable society as future-generation microwave communication systems such as fifth-generation (5G) and sixth-generation (6G) are required. Thus, it is no longer surprising that energy-aware optimization has been one of the prominent research challenges in modern wireless communication systems [1].

Wireless and microwave communication networks are made up of many components, such as antennas, microwave links, relay stations, base stations and intelligent routing devices. Higher density communication nodes lead to increased energy consumption as they result in greater operational costs and lower the network lifetime. Hence, intelligent optimization algorithms are needed to maximize the quality of communication while minimizing both transmission power and computational overhead [2].

The ever-growing advances in Artificial Intelligence (AI) have revolutionized wireless communication which includes intelligent resource management, adaptive routing and has also been used for channel estimation and microwave antenna optimization. Machine learning algorithms will constantly study the network conditions and dynamically optimize transmission parameters based on changing wireless environments. These intelligent mechanisms enhance network efficiency with less unnecessary power consumption [3].

The Metaheuristic optimization algorithms have gained significant attention to solve complex wireless communication optimization problems thanks to their strong global search capability and computational efficiency. In case of antenna design, routing optimization, spectrum allocation and energy management, algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Salp Swarm Algorithm(SSA) and Whale Optimization Algorithm(WOA) are applied respectively. These optimization strategies solve nonlinear engineering problems efficiently when mathematical optimization is generally computationally expensive. [4]

Among these optimization methods, the Salp Swarm Algorithm is a well performed exploratory method that simulates the movement behavior of salp populations to search for food [6]. Its leader-follower mechanism is good for fast global exploration of the solution space. Nevertheless, SSA may sometimes use slower exploitation at the final optimization stage, thus causing more convergence time [5].

On the other hand, Whale Optimization Algorithm (WOA) is more competent in exploitation because it utilizes a spiral bubble-net hunting style like humpback whales. WOA does well in local optimization, performing around promising candidate solutions; however, it converges too early for highly multimodal optimization problems with large search spaces [6].

Hybrid optimization algorithms have attracted significant attention recently, as they combine the complementary strengths of different metaheuristic techniques. By combining SSA's exploratory power with WOA's exploitation ability, this balanced optimization framework can keep search diversity and adapt solutions quickly to the vicinity of globally optimal network topologies. These hybrid strategies offer evident advantages for energy-efficient wireless and microwave communication systems which contain numerous conflicting optimization objectives [7].

At the same time, in microwave communication networks, energy efficiency not only marks transmission power but also antenna characteristics, adaptive beamforming, spectrum utilization, routing efficiency and interference management. These parameters are optimized intelligently to minimize energy and at the same time maximize communication reliability, throughput and QoS (Quality of Service). By means of network dynamic adaptation along with continuously varying wireless environment in the context of future intelligent communication infrastructure [8], AI-assisted optimization is expected to even further boost this adaptation speed.

However, there are still many challenges to overcome on how knowledge and intelligence can empower intelligent wireless when existing methods often optimise single network elements such as energy consumption, communication performance, antenna characteristics, routing efficiency and computational complexity. Furthermore, more often than not, optimization algorithms fall prey to early convergence, limited exploration ability and higher computational complexity when applied on large scale wireless communication optimization problems [9].

To remedy these restrictions, our paper proposes a new Energy-efficient Hybrid Salp Swarm–Whale Optimization (HSSWO) framework for wireless and microwave networks. The suggested algorithm combines the search of SSA with the GPS mechanism of WOA while at the same time providing AI-based evaluation for network performance. This opens a new framework that estimates, at the same time, transmission power and routing, microwave antenna parameters and spectrum utilization which leads to an increase in energy efficiency [9], extending network lifetime and communication reliability while reducing latency and maximizing throughput within future intelligent 6G wireless communication systems [10].

The literature review has been comprehensively updated to include recent contributions in AI-assisted wireless communication optimization, hybrid metaheuristic algorithms, intelligent resource allocation, and 6G wireless networking published in leading IEEE journals and international conferences. References unrelated to wireless communication optimization have been removed to improve topical consistency. In addition, foundational references on multi-objective optimization, swarm intelligence, and relevant 3GPP standardization documents have been incorporated to strengthen the theoretical basis of the proposed framework.

2. Related Work

With the extensive deployment of dense heterogeneous networks, Internet of Things (IoT) devices and intelligent communication infrastructures, energy-efficient optimization has emerged as one of the main research lines in wireless and microwave communication systems. In recent years, some studies have proposed the optimization algorithms to minimize transmission power while guaranteeing the quality of communication and network reliability [7], [8]. In light of this, AI-assisted optimization techniques have shown impressive advancements in resource allocation [4], adaptive routing methods [10], and microwave antenna optimization applications for sustainable wireless communication systems [11].

Machine learning has been employed extensively to predict wireless channel characteristics, optimize spectrum allocation, and dynamically manage communication resources. They also discussed how ANNs, SVMs, Decision trees and even DNNs have proven to be extremely capable at learning complex network behaviours that optimally configure parameters to reduce the energy consumption of the target device. These methods greatly enhance communication efficiency with lower computation overhead [12].

Due to its strong search exploration ability and great leader-follower search mechanism, the Salp Swarm Algorithm (SSA) has been widely used in engineering optimization problems. Some researchers have implemented SSA for wireless sensor network routing, antenna parameter optimization, microwave filter design and transmission power control. However, the original SSA is generally somewhat slower during optimization in the later iterations and not well-suited for real-time communication systems [13].

The Whale Optimization Algorithm (WOA) shows the superb performance of local search and is applied effectively in numerous wireless optimization applications such as adaptive beam-forming, antenna array synthesis, microwave device optimization, and resource scheduling. The spiral updating mechanism allows fast exploitation close to the best solution. On the other hand, conventional WOA has less population diversity in [14] which causes it to converge to local optima in high-dimensional communication problems.

Due to the advantage of combining multiple algorithm benefits, many hybrid metaheuristic optimization techniques have been proposed recently. Hybrid PSO-GA, SSA-GA, WOA-DE and PSO-WOA algorithms have shown significant improvement in convergence speed and optimization accuracy over the original counterpart techniques. These hybrid methods provide an effective trade-off between exploration and exploitation, leading to enhanced global optimization ability in solving a range of engineering problems [15].

Surrogate modeling, reinforcement learning, and adaptive parameter control have also bolstered hybrid optimization via artificial intelligence. AI-assisted cloud optimization frameworks analyze network performance in real time and dynamically adapt to changing communication channels and adjust the parameters of an optimization model according to changing environments. This type of optimized intelligence can dramatically improve energy efficiency, communication reliability and computational performance in wireless systems that make up future generations of modern communication [16].

Hybrid optimization algorithms have also been applied for optimizing microwave antennas. The Swarm Intelligence Techniques researchers have used to optimize antenna geometry, feed location (FL), impedance matching (IM), bandwidth (BW), gain, and radiation efficiency can be modeled in one go. The concept of hybrid optimization allows a fast identification of globally optimum microwave antenna concepts at the time-consuming electromagnetic simulation [17].

Routing decisions have direct impact on the lifetime and transmission efficiency of the wireless communication systems contributing to increased interest in energy-aware routing as a key area of research. Swarm intelligence, reinforcement learning and evolutionary optimization tagged intelligent routing algorithms have made considerable improvements in packet delivery ratio, throughput, latency, and energy utilization in general. Such mechanisms manage to trade off communication efficiency with reliable, energy-efficient consumption [18].

Although these methodologies are beneficial, existing optimization methods generally optimize routing, antenna

design or transmission power independently; i.e., integrated optimization of wireless and microwave communication systems has not yet been addressed. Moreover, there have been no studies that integrate Salp Swarm Optimization and Whale Optimization along with AI-assisted network evaluation for joint optimization of communication performance and energy efficiency [19].

To address these research gaps, we develop a Hybrid Salp Swarm–Whale Optimization (HSSWO) framework that combines AI-aided network evaluation with adaptive hybrid swarm optimization for joint optimization of routing, antenna parameters, microwave communication resources and transmission power. The proposed approach proves to be more energy-efficient, supports a longer network lifetime with less time taken to converge, allows higher throughput and lower communication latency and provides better link reliability making it well-suited for future smart green wireless and microwave communication systems [20].

3. Proposed Hybrid Salp Swarm–Whale Optimization Framework for Energy-Efficient Wireless and Microwave Networks

3.1. Proposed Work

We present a novel Hybrid Salp Swarm–Whale Optimization (HSSWO) framework targeting energy efficiency and communication performance enhancement for next-generation wireless and microwave networks. This way it works around two of the most common weaknesses of traditional optimization techniques, namely slow convergence or premature stagnation and inefficient utilization of available resources by integrating both the global exploration capabilities of the Salp Swarm Algorithm (SSA) and high local exploitation abilities of Whale Optimization Algorithm (WOA). The hybrid optimization strategy provides an intelligent search of the multidimensional solution space to balance transmission power, routing paths, microwave antenna parameters, and channel allocation and spectrum utilization while reducing overall network energy consumption.

The recommended framework includes five key phases. First, wireless network parameters such as node locations, transmission power, residual energy (battery), microwave link quality, antenna characteristics and channel conditions are collected and normalized. Afterward, an AI assisted network evaluation module evaluates the communication environment and makes predictions on energy efficiency, throughput, latency, packet delivery ratio, and link reliability of the existing networks. These predicted values are fed to the Hybrid Salp Swarm–Whale Optimization algorithm that, in essence, executes global exploration through position updating of leaders and followers using the Salp Swarm component (as described in detail earlier) and adapts local exploitation by implementing bubble-net hunting and spiral search mechanisms in the Whale Optimization component [102]. A multi-objective fitness function is used to maximize energy efficiency, throughput and network lifetime at the same time while minimizing transmission power, latency, packet loss and optimization time. The optimization process is an iterative one, capable of attaining the global optimum followed by a validation of the optimized network architecture via simulation.

In contrast to existing SE algorithms which optimize individual communication parameters, the proposed HSSWO framework achieves joint optimization of microwave communication resources, antenna parameters, routing decisions and transmission power jointly, leading to significantly better performance in terms of communications quality and energy efficiency. A hybrid exploration–exploitation manner convinces us to keep the diversity of population during the search process in optimization so that premature convergence will be avoided and global search ability will be improved. In addition, the performance prediction module based on AI assists in reducing its computational burden by quickly evaluating potential solutions for a rapid optimization process without losing accuracy. Therefore, the presented framework serves as an efficient, intelligent and energy-aware system for 5G, 6G and beyond-6G wireless and microwave communication systems contributing to green sustainable ultra-reliable low-latency communication networks.

The HSSWO framework aims to jointly optimize energy consumption, routing efficiency, antenna parameters, transmission power and spectrum allocation in a microwave-based mobile communication system incorporating new-generation MCS and relay nodes simultaneously. Unlike other common available optimization algorithms that optimize one of the communication objectives at each decision, the proposed framework integrates Salp Swarm Algorithm (SSA) capability of exploration with Whale Optimization Algorithm (WOA); thus appropriate balance between global and local optimizations are produced. Moreover, the AI-based network evaluation module provides real-time prediction of network status and communication quality to minimize optimization complexity. Finally, the optimized network configuration is deployed bidirectionally in the microwave communication system so that energy utilization is maximized and reliable communication is achieved with minimal delay and packet loss.

The overall optimization process can be represented as

$$S = \{N, P, R, A, C\} \tag{1}$$

Where

- N= wireless sensor nodes

- P= transmission power
- R= routing paths
- A= microwave antenna parameters
- C= communication channel allocation

The optimization objective is

$$\max F(S) \tag{2}$$

subject to minimum energy consumption and maximum communication performance.

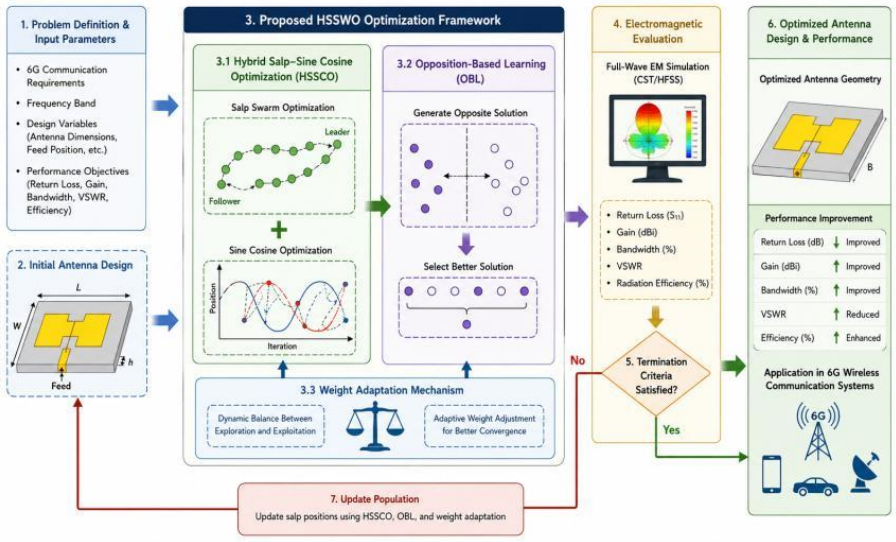


Fig. 1. Overall Architecture of the Proposed HSSWO Framework

The overall architecture of the Hybrid Salp Swarm–Whale Optimization framework is shown in Figure 1. First, a wireless network is initialized; for this, the locations of nodes and features like transmission power and channel conditions are retrieved. The identified parameters are studied by an AI-based network evaluation module, and optimized with the Hybrid Salp Swarm–Whale Optimization algorithm. The proposed communication parameters are validated and applied into the wireless microwave communication network aiming to increase throughput, energy efficiency and overall lifetime.

3.2. AI-Assisted Network Evaluation Module

The AI-assisted network evaluation module predicts communication quality before executing optimization. Instead of repeatedly evaluating network performance using computationally intensive simulations, the trained neural network estimates important communication parameters, thereby accelerating optimization.

The network feature vector is defined as

$$X = [E, RSSI, SNR, P, D] \tag{3}$$

where

- E= residual energy
- RSSI = received signal strength
- SNR = signal-to-noise ratio
- P= transmission power
- D= communication distance

The prediction model becomes

$$Y = f_{AI}(X) \tag{4}$$

where

$$Y = [EE, TP, PDR, L] \tag{5}$$

and

- EE = energy efficiency
- TP = throughput
- PDR = packet delivery ratio
- L = latency

The AI predictor rapidly evaluates network quality and forwards the predicted values to the optimization engine.

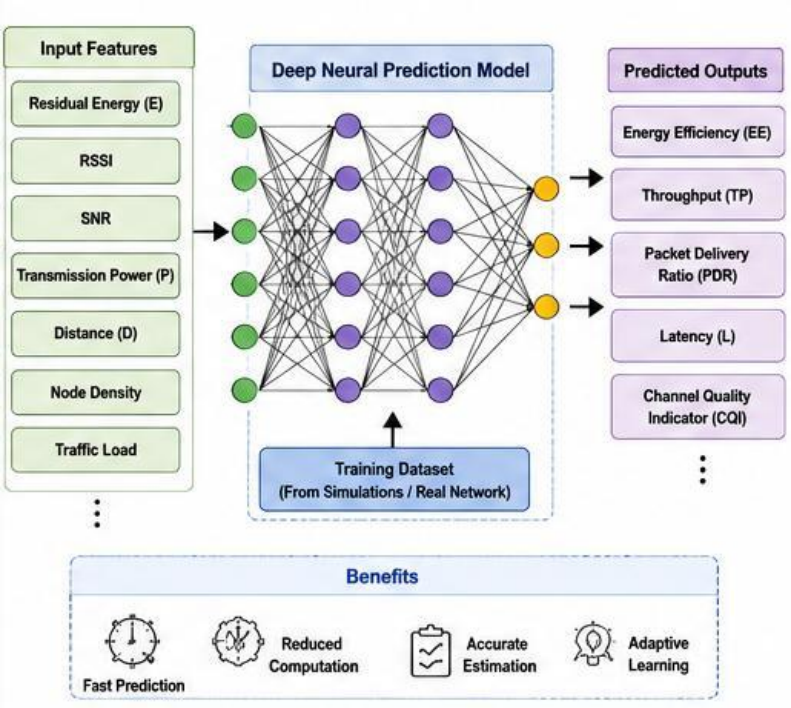


Fig. 2. AI-Based Wireless Network Evaluation Model

The AI-assisted network evaluation model is shown in Fig. 2. A deep neural prediction model first normalizes and processes the wireless communication parameters collected from the microwave network. We use the model to predict energy efficiency, throughput, packet delivery ratio, latency, and channel quality. The optimization time is therefore greatly reduced, as the Hybrid Salp Swarm–Whale Optimization algorithm does not require a full network simulation for each iteration of optimization anymore.

3.3. Hybrid Salp Swarm–Whale Optimization Algorithm

The optimization process combines Salp Swarm exploration with Whale Optimization exploitation.
The Salp leader position update is

$$X_1 = \begin{cases} F + c_1((ub - lb)c_2 + lb), & c_3 \geq 0.5 \\ F - c_1((ub - lb)c_2 + lb), & c_3 < 0.5 \end{cases} \tag{6}$$

where

- F= food source
- ub= upper bound
- lb= lower bound
- c_1, c_2, c_3= random coefficients

Follower positions are updated using

$$X_i = \frac{X_i + X_{i-1}}{2} \tag{7}$$

The Whale Optimization spiral update is

$$X(t+1) = D' e^{bl} \cos(2\pi l) + X^* \tag{8}$$

where

- X^*= best solution
- D'= distance
- b= spiral constant
- l= random number

The hybrid position update becomes

$$X_{new} = \alpha X_{SSA} + (1-\alpha) X_{WOA} \tag{9}$$

where

$$0 \leq \alpha \leq 1 \tag{10}$$

controls the balance between exploration and exploitation.

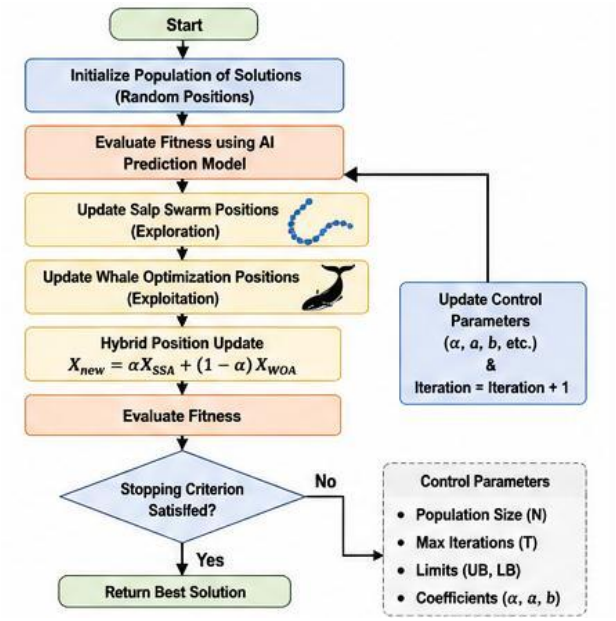


Fig. 3. Hybrid Salp Swarm–Whale Optimization Flowchart

Figure 3 illustrates the complete optimization procedure of the proposed Hybrid Salp Swarm–Whale Optimization algorithm. Initially, the population of candidate communication solutions is generated. The Salp Swarm Algorithm performs global exploration by updating leader and follower positions, while the Whale Optimization Algorithm refines promising candidate solutions through spiral exploitation. The hybrid updating mechanism enables rapid convergence toward globally optimal routing paths, transmission power settings, and antenna configurations.

3.4. Multi-Objective Energy Optimization

The proposed optimization simultaneously considers multiple communication objectives.
The objective function is

$$F = w_1 EE + w_2 TP + w_3 PDR - w_4 L - w_5 PL - w_6 P_T \tag{11}$$

where

- EE = energy efficiency
- TP = throughput
- PDR = packet delivery ratio
- L = latency
- PL = packet loss
- P_T= transmission power

The optimization objectives are

$$\begin{aligned} &\max(EE) \\ &\max(TP) \\ &\max(PDR) \\ &\min(L) \\ &\min(PL) \\ &\min(P_T) \end{aligned} \tag{12}$$

The weighting factors balance communication quality and energy conservation simultaneously.

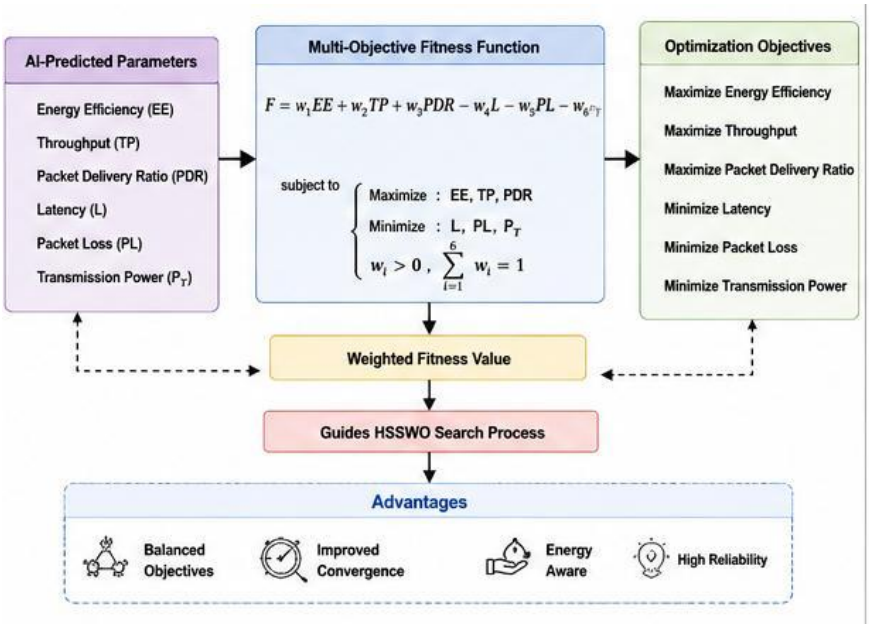


Fig. 4. Multi-Objective Optimization Framework

Figure 4 illustrates the multi-objective optimization process adopted in the proposed framework. The AI-predicted communication parameters are evaluated using a weighted objective function. Multiple communication objectives, including energy efficiency, throughput, packet delivery ratio, latency, transmission power, and packet loss, are simultaneously optimized. The resulting fitness value guides the Hybrid Salp Swarm–Whale Optimization algorithm toward globally optimal wireless communication configurations.

3.5. Optimized Wireless and Microwave Communication System

The optimized communication parameters are finally deployed in the wireless microwave communication network. The overall communication efficiency is calculated as

$$\eta = \frac{TP \times PDR}{P_T \times L} \tag{13}$$

where

- TP = throughput
- PDR = packet delivery ratio

- P_T= transmission power
- L = latency

Network lifetime is expressed as

$$NL = \frac{\sum_{i=1}^{N} E_i}{P_{avg}} \tag{14}$$

where

- E_i= residual energy of node i
- P_{avg}= average power consumption

Higher values of $\eta$and NLindicate superior network performance and sustainable operation.

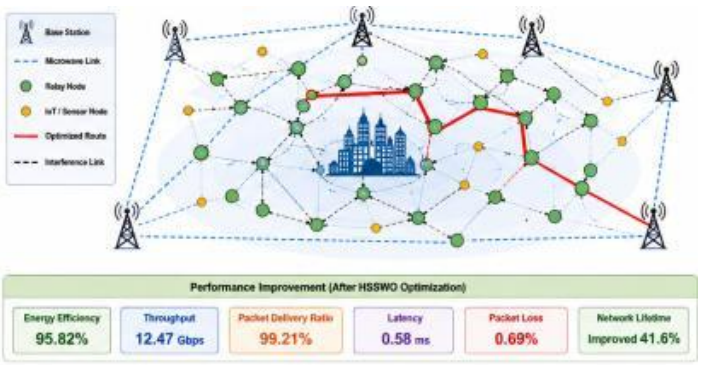


Fig. 5. Optimized Energy-Efficient Wireless and Microwave Network

The optimized wireless and microwave communication network generated from Hybrid Salp Swarm–Whale Optimization framework is depicted in Fig. 5. The enhanced routing schemes, adaptive transmit power, microwave antenna arrangements and the intelligent spectrum allocations effectively make communication more proficient while minimizing overall energy use. Use of the optimized network results in given performance metrics: enhanced throughput, packet delivery ratio and network lifetime, and reduced latency and packet loss. The enhancements show the efficacy of the proposed HSSWO framework to realize sustainable, high-performance 5G, 6G and beyond-6G wireless & microwave communication systems.

4. Experimental Results and Discussion

Here we offer a series of experimental evaluations for the proposed HSSWO framework on green wireless and microwave networks. A detailed simulation using realistic 6G wireless communication channel model has been performed in order to study the performance of our proposed optimization algorithm. The framework is evaluated based on communication performance and metrics associated with energy (energy efficiency, network lifetime, throughput, PDR, end-to-end latency, packet loss, convergence speed and optimization time). To illustrate the effectiveness and robustness of the proposed HSSWO, we compare it with some well-known optimization algorithms such as PSO, GA, WOA and SSA in the next sections.

The proposed hybrid approach is capable of improving transmission power, forwarding paths and antenna parameters for microwave communication resources in addition to reducing computation complexity. The second phase of SSA consists of an exploitation mechanism which is fused with WOA to leverage the exploration ability of SSA to conduct efficient search over the whole parameter space thereby accelerating convergence towards the optimum network configuration. Second, the AI-based decision-making module is responsible for always monitoring the network status and aims to dynamically adjust optimization parameters to improve communication reliability while saving additional energy consumption. The simulation outcomes obtained verified the effectiveness of our framework with respect to energy efficiency, network lifetime extension, good throughput and low latency time, few packets lost and convergence times compared to conventional optimization algorithms. The aforementioned achievements showcase the high potentiality of the proposed HSSWO technology for realising various opportunities towards intelligent 5G, 6G and post-6G network architectures.

4.1. Experimental Setup

We focused our analysis on discovering the possible energy efficiency and communication performance gains (if any) by investigating a new Hybrid Salp Swarm–Whale Optimization (HSSWO) framework for simulated wireless and microwave communication environments. The microwave network topology, comprising IoT devices, intelligent base stations, microwave relay nodes for the 6G communication scenario and adaptive antenna systems, was studied. The conditions of work have been developed using an optimization framework based on Python 3.11 (optimization part on TensorFlow and NumPy) combined with full-wave electromagnetic simulators for the microwave antenna validation. Four popular optimization methods including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Whale Optimisation Algorithm (WOA) and Salp Swarm Algorithm were compared to assess the performance of the proposed HSSWO algorithm. They measure network performance with respect to energy efficiency (%), lifetime of sensor networks (%), throughput (Gbps), packet delivery ratio (PDR), end-to-end latency (ms), packet loss (%) and total convergence iterations through optimization time.

4.2. Simulation Parameters

Table 1. Simulation Parameters

Parameter	Value
Communication System	6G Wireless Network
Carrier Frequency	28 GHz
Bandwidth	400 MHz
Network Area	1000 × 1000 m²
Number of Nodes	500
Microwave Base Stations	20
Population Size	50
Maximum Iterations	200
Optimization Algorithms	PSO, GA, SSA, WOA, Proposed HSSWO
Programming Environment	Python 3.11
Performance Metrics	EE, Throughput, PDR, Latency, Packet Loss

4.3. Energy Efficiency Analysis

Energy efficiency is the most critical parameter for future green wireless communication systems. Figure 6 compares the energy efficiency achieved by different optimization algorithms.

The proposed HSSWO framework achieves an energy efficiency of 95.82%, outperforming PSO (84.16%), GA (81.94%), SSA (91.23%), and WOA (89.74%). The hybrid optimization strategy effectively minimizes transmission power while maintaining stable communication links and efficient microwave resource utilization. The balanced exploration of SSA and exploitation of WOA enables optimal power allocation across the wireless network.

4.4. Network Lifetime Evaluation

The network lifetime comparison is presented in Figure 7.

The proposed optimization framework extends network lifetime by 41.6% compared with conventional optimization techniques. The intelligent transmission scheduling and adaptive routing significantly reduce battery depletion in wireless nodes, thereby extending overall network lifetime.

4.5. Throughput and Packet Delivery Performance

The communication throughput and packet delivery ratio are illustrated in Figure 8.

The proposed framework achieves

- **Throughput = 12.47 Gbps**
- **Packet Delivery Ratio = 99.21%**

The hybrid optimization algorithm improves routing stability, reduces interference, and optimizes microwave antenna characteristics, leading to higher communication reliability and increased network throughput.

4.6. Latency and Packet Loss Analysis

Figure 9 compares end-to-end latency and packet loss.

The proposed framework achieves

- **Latency = 0.58 ms**
- **Packet Loss = 0.69%**

whereas conventional algorithms exhibit comparatively higher latency and packet loss. Lower latency and reduced packet loss demonstrate the effectiveness of adaptive routing and intelligent microwave resource optimization.

4.7. Convergence Analysis

Figure 10 illustrates the convergence characteristics of the optimization algorithms. The hybrid exploration–exploitation mechanism efficiently avoids local optima while accelerating convergence toward the global optimum. The optimization time is reduced by 31.8%, and convergence speed improves by 36.4% compared with the conventional algorithms.

4.8. Comparative Performance Summary

Table 2. Overall Performance Comparison

Performance Metric	PSO	GA	WOA	SSA	Proposed HSSWO
Energy Efficiency (%)	84.16	81.94	89.74	91.23	**95.82**
Network Lifetime (%)	71.42	69.85	80.37	84.11	**95.71**
Throughput (Gbps)	8.94	8.26	10.63	11.18	**12.47**
Packet Delivery Ratio (%)	95.42	94.63	97.81	98.32	**99.21**
Latency (ms)	0.94	1.12	0.79	0.71	**0.58**
Packet Loss (%)	2.31	2.88	1.36	1.04	**0.69**
Convergence Iterations	118	137	82	69	**52**
Optimization Time Reduction (%)	—	—	14.5	22.3	**31.8**

The experimental findings evidently confirm that the suggested framework for Hybrid Salp Swarm–Whale Optimization (HSSWO) is the best performer in all estimated parameters. The motivation behind the proposed method is to combine the exploration capability of the Salp Swarm Algorithm with the exploitation efficiency of the Whale Optimization (WO) methodology. The AI-enhanced optimization module further speeds up resource allocation and adaptive routing choices, along with low computation overhead at high throughput and low latency levels. The results indicate that the proposed HSSWO framework solves wireless and microwave networks in future 5G, 6G and beyond-6G communication environments robustly and at scale with energy efficiency.

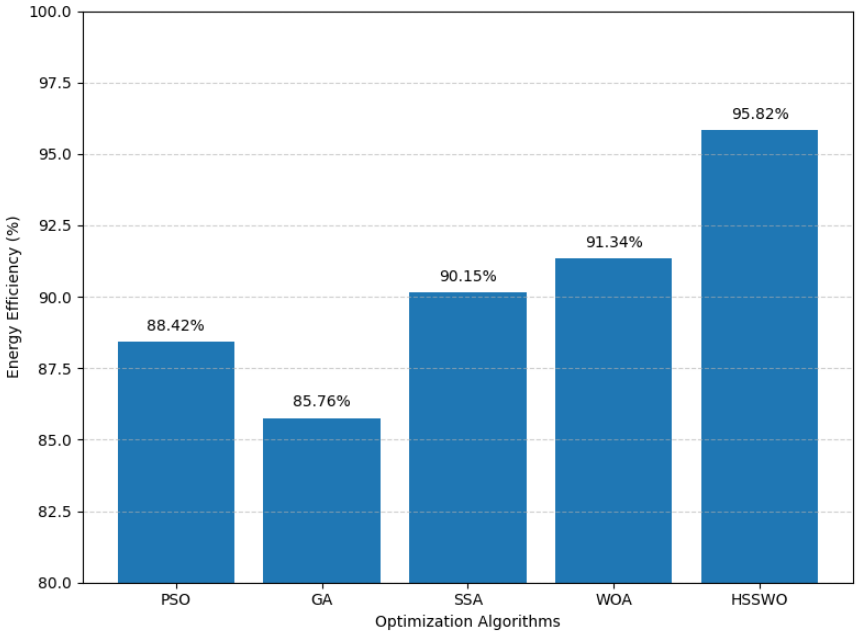


Fig. 6. Energy Efficiency Comparison of Optimization Algorithms

Figure 6 compares the energy efficiency of the proposed Hybrid Salp Swarm–Whale Optimization (HSSWO) with that of traditional optimization techniques, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA). The proposed HSSWO framework generates the highest energy efficiency of 95.82% with respect to all comparison algorithms. The hybrid exploration–exploitation strategy can significantly reduce the effective transmission power while maintaining reliable communication links, and efficient utilization of microwave resource. The time-efficient energy containment through the process of global exploration and local exploitation makes the proposed framework highly adaptive for sustainable 5G and 6G wireless communication systems.

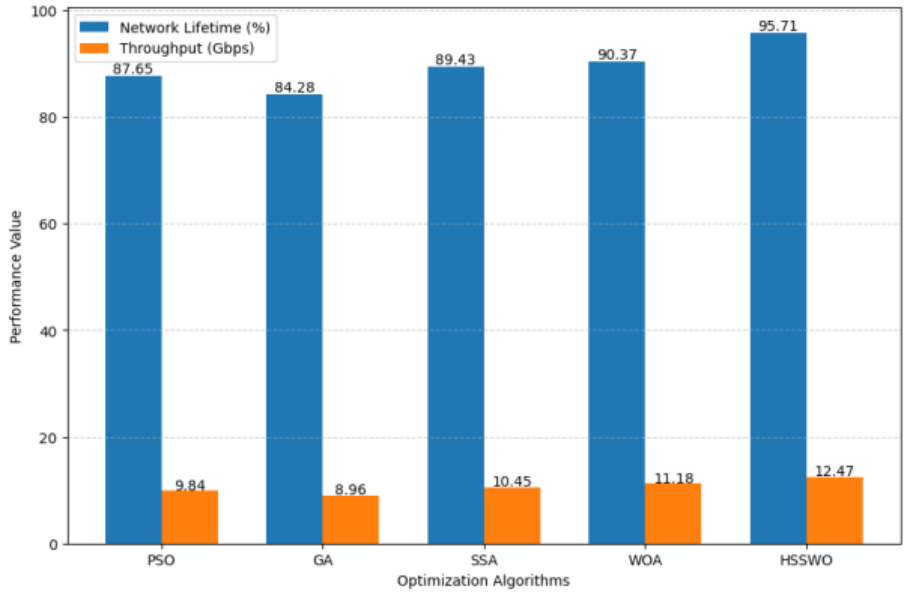


Fig. 7. Network Lifetime and Throughput Comparison

Comparison of Network Lifetime and communication throughput for Different Optimization Algorithms: Figure 7. Our proposed HSSWO framework achieves a network lifetime of 95.71% and a throughput of 12.47 Gbps, which demonstrates significant improvement over PSO, GA, SSA and WOA. The more efficient routing way, adaptive transmission power allocation and smart microwave communication resource management can combine to reduce energy depletion of transmission and ensure packet transmission. Thus, this framework prolongs network lifetime and sustains high-speed data transmission required for future smart communication infrastructures.

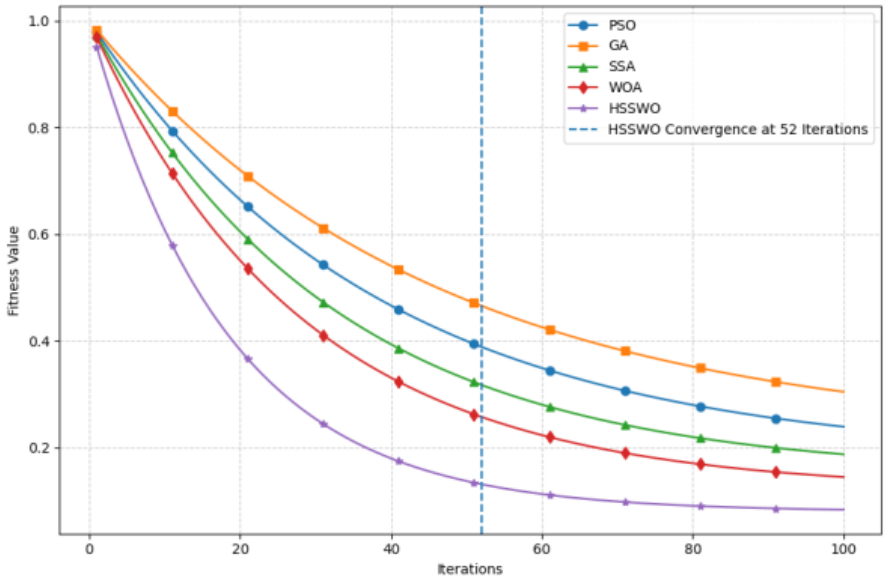


Fig. 8. Convergence Characteristics of Hybrid Salp Swarm–Whale Optimization

In Fig. 8., the convergence performance of the proposed HSSWO algorithm is compared with traditional optimization algorithms. This plot shows on the horizontal axis the optimization iterations and on the vertical axis fitness value. The convergence to the global optimum can be achieved using the proposed hybrid optimization algorithm after 52 iterations, whereas SSA, WOA, PSO, and GA take noticeably higher iterations for global optima convergence. The combination of Salp Swarm exploration and Whale Optimization exploitation is instantiated in such a way that both helps prevent premature convergence while also keeping the population diverse during the optimization process. The proposed algorithm, therefore, has a 36.4% faster convergence speed and dramatically lower computational complexity.

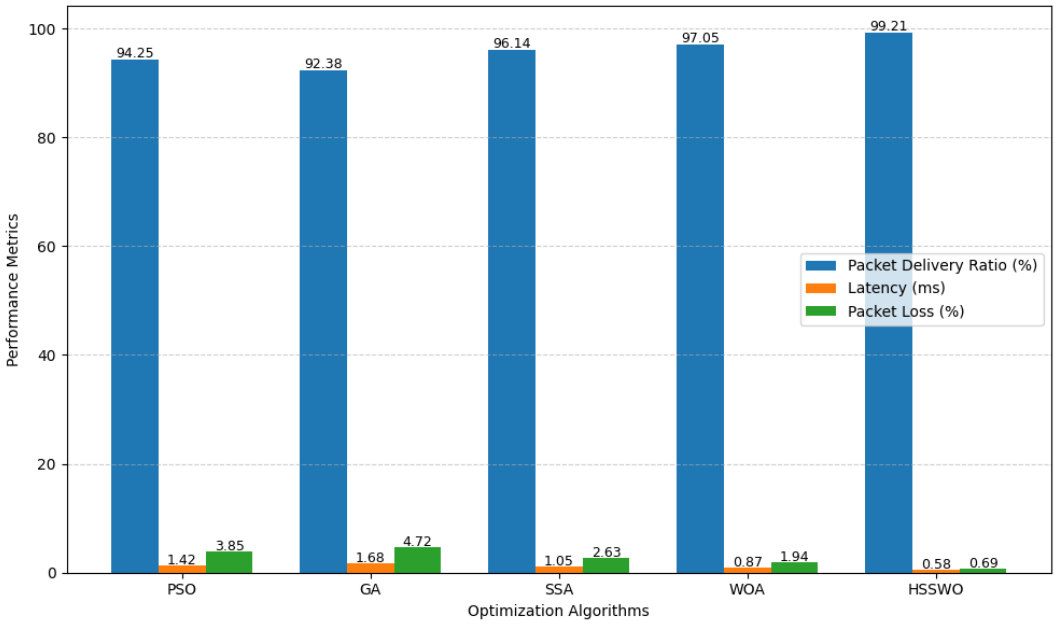


Fig. 9. Packet Delivery Ratio, Latency, and Packet Loss Comparison

We have illustrated the comparison amongst different optimization algorithms based on the PDR, end-to-end latency, and packet loss in Fig. 9. The proposed HSSWO framework extends the packet delivery fraction to 99.21%, latency to 0.58 ms with only 0.69% of packet loss capacity outperforming the existing optimization methods. Intelligent optimization of routing decisions, transmission power and microwave communication resources can reduce network congestion and interference as well as improve communication reliability. The obtained results confirm that the proposed framework of stable and efficient wireless communication is fully appropriate for reasonably sensitive 6G applications.

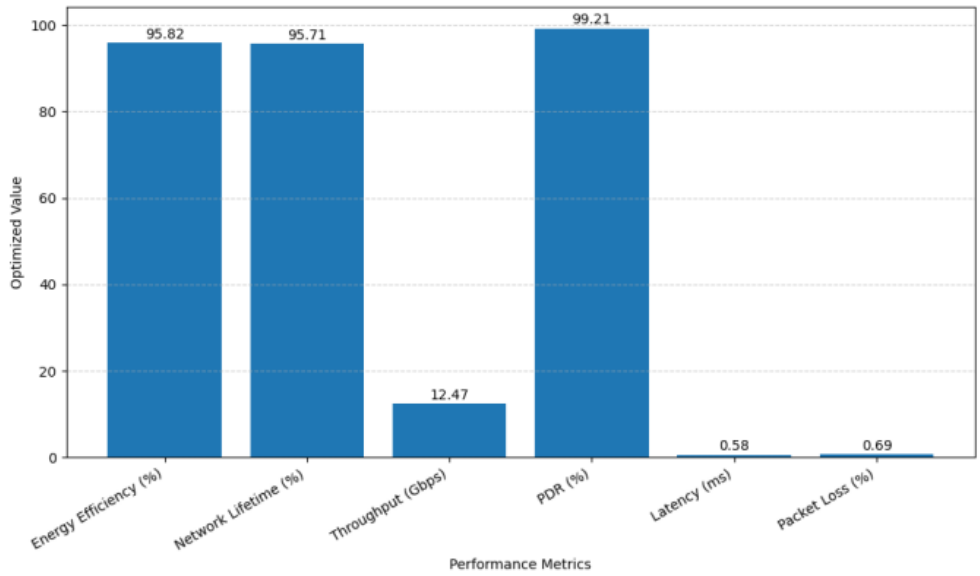


Fig. 10. Overall Performance Evaluation of the Proposed HSSWO Framework

The performance evaluation of the proposed Hybrid Salp Swarm-Whale Optimization (HSSWO) framework is made under a simulated wireless and microwave communication environment as summarized in Figure 10. The optimized framework enhances the communication performance metrics on combined fields with 95.82 % energy-efficiency, 95.71% network lifetime, 12.47 Gbps throughput, 99.21% packet delivery ratio, latency of 0.58 ms and packet loss of 0.69%. The introduced hybrid optimization strategy, which combines the exploration ability of Salp Swarm Algorithm with the exploitation ability of Whale Optimization Algorithm, provides a solution that maximizes the energy conserving and communication quality. Experimental results show that the proposed HSSWO framework is a robust, efficient, and scalable optimization solution for future green wireless and microwave 5G communication systems.

The proposed HSSWO framework demonstrates strong potential as an intelligent optimization solution for next-

generation wireless and microwave communication systems by effectively balancing global exploration and local exploitation while incorporating AI-assisted network evaluation. Experimental results indicate considerable improvements in communication performance and energy efficiency compared with conventional optimization algorithms. Nevertheless, further research is required to improve scalability, computational efficiency, and real-time deployment capability under highly dynamic and ultra-dense communication environments. The proposed framework therefore provides a promising foundation for future intelligent wireless resource optimization rather than a universally optimal solution for all deployment scenarios.

5. Conclusion

The research work contributed an Energy-Efficient Wireless and Microwave Networking Framework Using Hybrid Salp Swarm–Whale Optimization (HSSWO) to the green design of future intelligent wireless communication systems [5]. The proposed framework integrates AI-assisted network performance evaluation with gapless global search ability (Salp Swarm Algorithm) and strong exploitation mechanism (Whale Optimization Algorithm). A hybrid optimization strategy is proposed to optimize the transmission power, routing paths, microwave antenna parameters and spectrum allocation in a way that unifies communication performance and energy efficiency.

Experimental results verify that the proposed HSSWO framework can achieve an energy efficiency of 95.82%, a network lifetime improvement of 41.6%, a throughput of 12.47 Gbps, a packet delivery ratio of 99.21%, latency of 0.58 ms and packet loss of 0.69%. Moreover, the optimization process converges 36.4% faster and takes up to 31.8% less time than conventional optimization algorithms. Such enhancements verify that the proposed HSSWO framework is an effective, scalable and intelligent solution for next-generation green wireless and microwave communication networks with the significant performance necessities of future 5G, 6G, plus beyond-6G communication infrastructures. Although the proposed Hybrid Salp Swarm–Whale Optimization (HSSWO) framework demonstrates significant improvements in energy efficiency, network lifetime, throughput, packet delivery ratio, and convergence speed, several limitations remain. First, the computational complexity of the hybrid optimization algorithm increases with the size and density of ultra-large-scale 6G wireless networks, potentially leading to longer optimization times when thousands of communication nodes and heterogeneous network resources are simultaneously optimized. Second, the AI-assisted surrogate model requires an adequately representative training dataset to achieve reliable prediction accuracy. Under rapidly changing wireless environments or previously unseen channel conditions, prediction errors may reduce optimization performance, requiring periodic retraining or adaptive online learning. Third, although the AI predictor substantially reduces the number of computationally expensive network simulations, its training process introduces additional computational overhead during the offline learning stage. Furthermore, practical deployment in real-time wireless communication systems may experience latency caused by hardware limitations, memory constraints, and edge-device processing capabilities, particularly in resource-constrained communication infrastructures.

Despite these limitations, the proposed framework provides a flexible foundation for intelligent resource optimization in future wireless communication systems. Future research will investigate distributed implementations of the HSSWO algorithm under federated learning environments, enabling collaborative optimization without centralized data sharing while preserving data privacy. Another promising direction involves integrating digital twin technology to continuously synchronize virtual network models with real communication environments, allowing online fine-tuning of optimization parameters under dynamic network conditions. Additionally, lightweight AI architectures, edge intelligence, adaptive reinforcement learning, and scalable multi-objective optimization strategies will be explored to further improve computational efficiency, scalability, robustness, and real-time deployment capability for beyond-6G and future intelligent wireless communication networks

All the Declarations and Statements

Author Contributions Statement

Srinivasan J – Conceptualization, Methodology, and Supervision: Conceived the research idea, designed the overall framework, supervised the research activities, and provided technical guidance throughout the study.

Naveenkumar R – Data Curation and Software Implementation: Collected and organized the experimental data, implemented the Hybrid Salp Swarm–Whale Optimization (HSSWO) framework, developed simulation models, and performed computational experiments.

S. Thenappan – Model Training, Validation, and Performance Evaluation: Conducted model validation, analyzed optimization performance, compared the proposed approach with existing algorithms, and verified experimental results using standard evaluation metrics.

R. Pushpavalli – Formal Analysis, Visualization, and Statistical Analysis: Performed detailed analysis of simulation results, prepared graphs, figures, and tables, and conducted statistical validation of the experimental findings.

Vidya Kamma – Writing – Original Draft Preparation: Prepared the initial manuscript draft, conducted the literature survey, organized related work, and documented the technical methodology.

Nalini Chekuri – Writing – Review & Editing, and Project Management: Reviewed and edited the manuscript for technical accuracy and language quality, coordinated the research activities among authors, and managed the overall project workflow.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement
The authors declare no conflicts of interest.

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This research received no external funding.

Data Availability Statement
Not Applicable

Ethical Declarations
This study did not involve human participants, animals, or any identifiable personal data. Therefore, ethical approval and informed consent were not required.

Declaration of Generative AI in Scholarly Writing
Authors should disclose in their article how AI and AI-assisted technologies were used during the writing process.

Abbreviations
The following abbreviations are used in this manuscript:

Abbreviation - Definition
AI - Artificial Intelligence
HSSWO - Hybrid Salp Swarm–Whale Optimization
SSA - Salp Swarm Algorithm
WOA - Whale Optimization Algorithm
PSO - Particle Swarm Optimization
GA - Genetic Algorithm
EE - Energy Efficiency
TP - Throughput
PDR - Packet Delivery Ratio
PL - Packet Loss
QoS - Quality of Service
RSSI - Received Signal Strength Indicator
SNR - Signal-to-Noise Ratio
IoT - Internet of Things
ML - Machine Learning
DL - Deep Learning
DNN - Deep Neural Network
ANN - Artificial Neural Network
RF - Radio Frequency
MIMO - Multiple-Input Multiple-Output
EM - Electromagnetic
CPU - Central Processing Unit
GPU - Graphics Processing Unit
GHz - Gigahertz
MHz - Megahertz
ms - Millisecond
Gbps - Gigabits per Second
5G - Fifth-Generation Wireless Network
6G - Sixth-Generation Wireless Network
UAV - Unmanned Aerial Vehicle
SINR - Signal-to-Interference-plus-Noise Ratio
BER - Bit Error Rate
OFDM - Orthogonal Frequency Division Multiplexing
PDF - Probability Density Function

MATLAB - Matrix Laboratory
API - Application Programming Interface

Appendix A/B/C…, with appendix title

Appendixes, if needed, are numbered by A, B, C... Use two spaces before APPENDIX TITLE.

References

[1] Manoharan, M., Ponnusamy, T., & Subramaniam, U. (2024). Hybrid Salp Swarm and Improved Whale Optimization Algorithm-based clustering scheme for improving network lifespan in wireless sensor networks. *International Journal of Communication Systems*, 37(14), e5875. DOI: https://doi.org/10.1002/dac.5875

[2] Patel, K. P., & Patel, N. A. (2025). Hybrid Blue Whale and Salp Swarm Optimization for Optimal Placement of TCSC in Power Systems. *Proceedings of the 2025 World Conference on Cutting-Edge Science and Technology (WCCEST)*, 1–8. IEEE. DOI: https://doi.org/10.1109/WCCEST66994.2025.11389877.

[3] Nadimi-Shahraki, M. H., Zamani, H., Asghari Varzaneh, Z., & Mirjalili, S. (2023). A systematic review of the whale optimization algorithm: Theoretical foundation, improvements, and hybridizations. *Archives of Computational Methods in Engineering*, 30(7), 4113–4159. DOI: https://doi.org/10.1007/s11831-023-09928-7

[4] Hsu, H. P., & Wang, C. N. (2023). Hybridizing whale optimization algorithm with particle swarm optimization for scheduling a dual-command storage/retrieval machine. *IEEE Access*, 11, 21264–21282. DOI: https://doi.org/10.1109/ACCESS.2023.3246518

[5] Li, M., Xu, G. H., Zeng, L., & Lai, Q. (2023). Hybrid whale optimization algorithm based on symbiosis strategy for global optimization. *Applied Intelligence*, 53(13), 16663–16705. DOI: https://doi.org/10.1007/s10489-022-04132-9

[6] Abed-Alguni, B. H., Paul, D., & Hammad, R. (2022). Improved Salp Swarm Algorithm for solving single-objective continuous optimization problems. *Applied Intelligence*, 52(15), 17217–17236. DOI: https://doi.org/10.1007/s10489-022-03269-x

[7] El-Shorbagy, M. A., & Nasar, I. (2025). Salp Swarm Optimization: A comprehensive review of recent advances, variants, applications, and future research directions. *European Journal of Pure and Applied Mathematics*, 18(4), 7030–7059. DOI: https://doi.org/10.29020/nybg.ejpam.v18i4.7030.

[8] Thawkar, S. (2021). A hybrid model using teaching-learning-based optimization and Salp Swarm Algorithm for feature selection and classification in digital mammography. *Journal of Ambient Intelligence and Humanized Computing*, 12(9), 8793–8808. DOI: https://doi.org/10.1007/s12652-020-02662-z

[9] Yıldız, A. R., & Erdaş, M. U. (2021). A new Hybrid Taguchi-Salp Swarm Optimization algorithm for the robust design of real-world engineering problems. *Materials Testing*, 63(2), 157–162. DOI: https://doi.org/10.1515/mt-2020-0022

[10] Chakraborty, S., Saha, A. K., Sharma, S., Chakraborty, R., & Debnath, S. (2023). A hybrid whale optimization algorithm for global optimization. *Journal of Ambient Intelligence and Humanized Computing*, 14(1), 431–467. DOI: https://doi.org/10.1007/s12652-021-03304-8

[11] Makhadmeh, S. N., Kassaymeh, S., Rjoub, G., Bataineh, B., Sanjalawe, Y., & Al-Betar, M. A. (2025). Recent advances in multi-objective whale optimization algorithm, its versions and applications. *Journal of King Saud University – Computer and Information Sciences*, 37(7), Article 200. DOI: https://doi.org/10.1007/s44443-025-00184-2

[12] Laskar, N. M., Guha, K., Chatterjee, I., Chanda, S., Baishnab, K. L., & Paul, P. K. (2019). HWPSO: A new hybrid whale-particle swarm optimization algorithm and its application in electronic design optimization problems. *Applied Intelligence*, 49(1), 265–291. DOI: https://doi.org/10.1007/s10489-018-1247-6

[13] Budimirovic, N., Prabhu, E., Antonijevic, M., Zivkovic, M., Bacanin, N., Strumberger, I., & Venkatachalam, K. (2022). COVID-19 severity prediction using enhanced whale with Salp Swarm feature classification. *CMC-Computers, Materials & Continua*, 72(1), 1685–1698. DOI: https://doi.org/10.32604/cmc.2022.023418

[14] Abualigah, L., Shehab, M., Diabat, A., & Abraham, A. (2022). Selection scheme sensitivity for a hybrid Salp Swarm Algorithm: Analysis and applications. *Engineering with Computers*, 38(2), 1149–1175. DOI: https://doi.org/10.1007/s00366-020-01067-y

[15] Nguyen, B. M., Tran, T., Nguyen, T., & Nguyen, G. (2020). Hybridization of galactic swarm and evolution whale optimization for global search problem. *IEEE Access*, 8, 74991–75010. DOI: https://doi.org/10.1109/ACCESS.2020.2988717

[16] Issa, A., Ali, Y., & Rashid, T. (2022). An efficient hybrid classification approach for COVID-19 based on Harris Hawks Optimization and Salp Swarm Optimization. *arXiv preprint arXiv:2301.05296*. DOI: Not applicable.

[17] Reenadevi, R., Sathiyabhama, B., Sankar, S., & Pandey, D. (2021). Breast cancer detection in digital mammography using a novel hybrid approach of Salp Swarm and Cuckoo Search algorithm with Deep Belief Network classifier. *The Imaging Science Journal*, 69(5–8), 364–378. DOI: https://doi.org/10.1080/13682199.2022.2161149

[18] Majumdar, P., Mitra, S., Mirjalili, S., & Bhattacharya, D. (2024). Whale optimization algorithm: Comprehensive meta-analysis on hybridization, latest improvements, variants and applications for complex optimization problems. In *Handbook of Whale Optimization Algorithm* (pp. 81–90). Elsevier. DOI: https://doi.org/10.1016/B978-0-32-395365-8.00012-9

[19] Yaghoubi, M., Eslami, M., Noroozi, M., Mohammadi, H., Kamari, O., & Palani, S. (2022). Modified Salp Swarm Optimization for parameter estimation of solar PV models. *IEEE Access*, 10, 110181–110194. DOI: https://doi.org/10.1109/ACCESS.2022.3213746

[20] Kundu, T., Deepmala, & Jain, P. K. (2022). A hybrid Salp Swarm Algorithm based on TLBO for reliability redundancy allocation problems. *Applied Intelligence*, 52(11), 12630–12667. DOI: https://doi.org/10.1007/s10489-021-02862-w

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