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ML-Assisted Joint Optimization of Microwave Components and Wireless Architectures via Adaptive Pelican Optimization

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Abstract: The rapid evolution of next-generation wireless communication systems has increased the demand for intelligent microwave components and energy-efficient wireless architectures capable of supporting ultra-high data rates, low latency, massive device connectivity, and adaptive resource management. Conventional optimization approaches often experience slow convergence, high computational complexity, and limited adaptability when optimizing multiple communication parameters simultaneously. To address these challenges, this paper proposes a Machine Learning-Assisted Adaptive Pelican Optimization (ML-APO) framework for the joint optimization of microwave components and wireless communication architectures. The proposed framework integrates an Adaptive Pelican Optimization Algorithm with a machine learning-assisted surrogate prediction model that rapidly estimates communication performance metrics, thereby significantly reducing computational overhead during the optimization process. The optimization simultaneously considers transmission power, antenna parameters, microwave component characteristics, spectrum allocation, routing efficiency, and communication reliability through a multi-objective fitness function. The adaptive search strategy of the Pelican Optimization Algorithm effectively balances global exploration and local

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exploitation, enabling faster convergence toward optimal network configurations while avoiding premature convergence. Extensive simulation results demonstrate that the proposed ML-APO framework achieves 96.41% energy efficiency, 43.8% improvement in network lifetime, 13.56 Gbps throughput, 99.43% packet delivery ratio, 0.49 ms end-to-end latency, and 0.54% packet loss, while reducing optimization time by 35.8% and improving convergence speed by 39.6% compared with existing optimization methods. These results demonstrate that the proposed framework provides an efficient, scalable, and intelligent solution for designing high-performance microwave components and next-generation wireless communication architectures suitable for future 6G and beyond wireless networks.

Index Terms: Machine Learning, Pelican Optimization Algorithm, Microwave Components, Wireless Architectures, Artificial Intelligence, RF Systems, Beyond-6G Communication, Microwave Antenna Optimization, Beamforming, Intelligent Wireless Networks

1. Introduction

The rapid evolution of wireless communication technologies is driving the transition from fifth-generation networks toward 6G and Beyond-6G communication paradigms. Future wireless systems are expected to provide terabit-scale transmission, sub-millisecond latency, massive connectivity, improved spectral efficiency, intelligent resource management, and highly reliable communication services [1]. These requirements are motivated by emerging applications such as extended reality, holographic communication, autonomous transportation, digital twins, intelligent healthcare, industrial automation, and large-scale Internet of Things networks [2]. Meeting these demands requires coordinated advances in both microwave-component design and wireless-network architecture.

Microwave components, including antennas, filters, amplifiers, resonators, phase shifters, and radio-frequency front-end circuits, have an essential role in determining the performance of wireless communication systems [3]. Their electromagnetic characteristics directly influence link quality, coverage, energy consumption, interference, spectral utilization, and transmission reliability. For example, antenna gain and radiation efficiency affect the received signal strength, while impedance bandwidth and return loss determine the usable frequency range and power-transfer efficiency. Consequently, the physical parameters of microwave components can have a considerable effect on network-level performance indicators such as throughput, latency, outage probability, and energy efficiency.

Conventional microwave-component optimization typically treats geometric and material parameters as independent design variables and employs full-wave electromagnetic simulations to determine the corresponding performance [4]. Although these simulations can provide accurate results, they require substantial computational resources. The problem becomes particularly demanding when numerous geometrical parameters, material properties, frequency points, and operating conditions must be considered. Population-based optimization algorithms may require hundreds or thousands of electromagnetic evaluations before reaching an acceptable solution, making direct optimization computationally expensive.

Wireless-resource-allocation methods, in contrast, generally optimize transmission power, channel allocation, bandwidth assignment, user scheduling, beam selection, and interference control while assuming fixed radio-frequency component characteristics [5]. This separation does not adequately represent the coupled behaviour of an end-to-end wireless system. The optimal network configuration may depend on the available antenna gain, radiation pattern, bandwidth, and efficiency, whereas the preferred microwave-component configuration may depend on the network load, channel conditions, user distribution, and quality-of-service requirements.

Joint optimization provides a means of representing these interdependent relationships. However, integrating component-level electromagnetic variables with network-level resource variables creates a high-dimensional, nonlinear, constrained, and multi-objective search problem [6]. The search space may contain continuous geometric variables, discrete channel-assignment decisions, conflicting performance objectives, and multiple physical and quality-of-service constraints. Traditional optimization methods can encounter premature convergence, slow fitness evaluation, limited scalability, and difficulty maintaining population diversity under these conditions.

Machine-learning-based surrogate models have emerged as an effective approach for reducing the computational cost of electromagnetic optimization [7]. A surrogate model learns the nonlinear mapping between design parameters and performance indicators from a set of previously evaluated samples. Once trained, it can rapidly estimate the performance of new candidate configurations without executing a complete full-wave simulation. Deep neural networks are particularly suitable for modelling complex nonlinear relationships and can simultaneously predict multiple electromagnetic and network-performance outputs [8].

Nevertheless, surrogate-assisted optimization introduces additional challenges. The accuracy of a surrogate model depends on the size, diversity, and representativeness of its training dataset. Candidate configurations located outside the adequately sampled region may produce large prediction errors [9]. If these errors are directly used as fitness values, the optimizer may incorrectly rank candidate solutions and converge toward a false optimum. A reliable surrogate-assisted framework should therefore include uncertainty monitoring, periodic high-fidelity verification, and feedback-

based model correction.

The Pelican Optimization Algorithm is a population-based metaheuristic inspired by the cooperative hunting behaviour of pelicans. Its simple structure and limited number of control parameters make it applicable to nonlinear engineering problems [10]. However, the conventional POA employs relatively fixed exploration and exploitation behaviours. This may reduce search diversity during early iterations or produce insufficient local refinement during later iterations. The limitation becomes more significant in high-dimensional joint optimization problems involving strongly coupled microwave and network variables.

To address these limitations, this study proposes an ML-assisted joint optimization framework for microwave components and wireless architectures using an adaptive Pelican Optimization Algorithm. A deep neural network is employed as a surrogate model to estimate electromagnetic and network-performance metrics. Adaptive exploration and exploitation coefficients, dynamic step-size regulation, constraint correction, elitist retention, and periodic high-fidelity verification are incorporated into POA. The framework jointly optimizes microwave-component parameters and wireless-resource variables while balancing gain, bandwidth, radiation efficiency, throughput, latency, power consumption, and computational cost.

The primary contributions of this study are summarized as follows:

- A unified joint-optimization model is developed by integrating microwave-component design parameters and wireless-network resource variables within a common decision vector.
- A DNN-based surrogate model is introduced to predict electromagnetic and network-performance indicators, reducing the number of computationally expensive high-fidelity evaluations.
- An adaptive POA is developed using iteration-dependent exploration and exploitation coefficients, dynamic step-size control, constraint correction, and elitist solution retention.
- A closed-loop high-fidelity feedback mechanism is incorporated to verify promising and uncertain candidate solutions and reduce the propagation of surrogate-model prediction errors.
- Comparative, ablation, convergence, robustness, and statistical analyses are conducted over 30 independent runs to evaluate the effectiveness and stability of the proposed framework.

The remainder of this paper is organized as follows. Section 2 presents a critical review of traditional optimization, surrogate-assisted methods, hybrid-intelligence techniques, and joint RF-network optimization. Section 3 describes the proposed ML-assisted adaptive POA framework and its mathematical formulation. Section 4 discusses the experimental configuration, comparative results, ablation analysis, statistical evaluation, and computational complexity. Section 5 presents the conclusion, limitations, and future research directions.

2. Related Work

2.1. Traditional Optimization of Microwave Components

Conventional optimization methods have been extensively employed to improve the performance of antennas, microwave filters, resonators, and RF front-end circuits. Particle swarm optimization has been used to determine electromagnetic design parameters because of its simple implementation and ability to process continuous variables [11]. However, particles can become concentrated around locally attractive solutions, resulting in premature convergence and reduced search diversity. This behaviour is particularly problematic when the electromagnetic response contains multiple local optima.

Genetic algorithms have also been applied to antenna geometry selection and microwave-circuit optimization [12]. Their crossover and mutation operators enable broad exploration of the design space. Nevertheless, a large number of generations and repeated full-wave simulations may be required to obtain stable results. Their computational requirements increase considerably when the number of optimized variables grows.

Grey wolf optimization, whale optimization, Harris hawks optimization, and other nature-inspired methods have been introduced to improve convergence in nonlinear microwave-design problems [13]. Although these methods can provide competitive performance, their exploration capacity frequently decreases during later iterations. Population-diversity loss, parameter sensitivity, and algorithm-specific update patterns can limit their performance in high-dimensional search spaces.

The main limitation of traditional approaches is that every candidate design must ordinarily be evaluated through a high-fidelity electromagnetic simulator. As the simulation time and number of candidates increase, optimization becomes computationally prohibitive. These limitations have encouraged the development of surrogate-assisted electromagnetic design methods.

2.2. Surrogate-Assisted Electromagnetic Optimization

Surrogate models approximate the relationship between microwave-design variables and electromagnetic responses. Gaussian-process models, support-vector regression, polynomial response surfaces, radial-basis-function networks, and artificial neural networks have been used to reduce the number of expensive full-wave simulations [14].

The surrogate is trained using previously evaluated samples and subsequently replaces the electromagnetic simulator for a proportion of the fitness evaluations.

Gaussian-process models provide prediction uncertainty and are useful when the training dataset is relatively small [15]. However, their computational requirements increase as the number of training samples grows. Traditional regression models can be computationally efficient but may not adequately represent highly nonlinear relationships between geometry, materials, frequency, and electromagnetic performance.

Deep neural networks can learn complex nonlinear mappings and simultaneously predict multiple outputs, including return loss, gain, efficiency, bandwidth, and radiation characteristics [16]. Once trained, a DNN provides rapid predictions and can substantially reduce optimization time. Nevertheless, its performance depends on the representativeness of the training data, network architecture, hyperparameters, and regularization strategy.

A critical concern in surrogate-assisted optimization is error accumulation. If the optimizer explores a region inadequately represented in the training dataset, the surrogate may generate inaccurate performance estimates. The optimizer may then select candidates that appear optimal according to the surrogate but perform poorly when verified using the actual simulator. Therefore, high-fidelity correction and adaptive data enrichment are necessary to maintain surrogate reliability.

2.3. Hybrid Machine-Learning and Metaheuristic Methods

Hybrid-intelligence frameworks combine machine-learning prediction with evolutionary or swarm-based optimization. In these methods, a trained model rapidly predicts candidate performance, while a metaheuristic searches for the most suitable design configuration [17]. Such frameworks can reduce optimization time while preserving the global-search ability of population-based algorithms.

However, several hybrid methods use a static surrogate throughout optimization. Without periodic retraining or high-fidelity correction, the model cannot adapt when the population enters an unfamiliar region. In addition, fixed exploration and exploitation coefficients may not provide an appropriate search balance throughout all iterations. Excessive exploration can slow convergence, whereas excessive exploitation can trap the population around a local optimum.

Deep reinforcement learning has also been employed for wireless-resource allocation, beam management, power control, spectrum sharing, and user scheduling [18]. Reinforcement-learning agents can learn sequential decisions in dynamic environments. Nevertheless, they require substantial interaction data and may suffer from unstable training, reward-design sensitivity, and limited transferability between network scenarios. Most reinforcement-learning studies also treat the physical RF components as fixed and do not jointly optimize their electromagnetic parameters.

2.4. Joint Optimization of RF Components and Wireless Architectures

Existing studies frequently optimize either physical RF components or network resources independently. Microwave-design studies generally prioritize return loss, gain, efficiency, and bandwidth, whereas network-optimization studies emphasize throughput, latency, power consumption, spectral efficiency, and fairness [19]. This separation overlooks the direct influence of the RF-component response on the network link budget and resource-allocation decisions.

Joint RF-network optimization is challenging because it combines variables with different physical meanings, numerical ranges, and time scales. Microwave geometrical parameters are commonly continuous and expensive to evaluate, whereas network decisions may be discrete or time-varying. In addition, improving one objective can degrade another. For example, increasing transmission power may improve throughput but reduce energy efficiency, while broadening the operating bandwidth can affect impedance matching or component dimensions.

Recent 6G-oriented optimization studies have emphasized intelligent joint design, integrated sensing and communication, RIS configuration, terahertz beamforming, and cross-layer resource allocation [20]. However, a limited number of studies establish a closed-loop connection among a high-fidelity electromagnetic simulator, a surrogate model, and an adaptive population-based optimizer. Surrogate prediction uncertainty, objective-weight sensitivity, and the propagation of component-level performance into network-level metrics also remain insufficiently investigated.

2.5. Research Gap

The literature review reveals four important research gaps. First, conventional microwave optimization requires a large number of high-fidelity simulations and therefore has substantial computational cost. Second, many surrogate-assisted approaches do not periodically verify and correct surrogate predictions during optimization. Third, fixed metaheuristic update coefficients can provide an inadequate balance between global exploration and local exploitation. Fourth, microwave-component parameters and wireless-network resources are generally optimized independently despite their strong physical and functional coupling.

The proposed framework addresses these gaps by combining a DNN surrogate, adaptive POA, multi-objective joint optimization, and periodic high-fidelity correction. The DNN reduces the cost of candidate evaluation, while adaptive POA controls the exploration–exploitation balance. The high-fidelity feedback mechanism reduces prediction-error propagation, and the unified objective function connects electromagnetic metrics with network-level throughput,

latency, and energy efficiency.

3. Proposed Machine Learning Assisted Microwave Components and Wireless Architecture Using Pelican Optimization Algorithm

The paper presents a Machine Learning Assisted Microwave Components & Wireless Architecture Framework under Pelican Optimization Algorithm (POA) for smarter optimization of microwave components and next-generation wireless communication structures. The main goal of the proposed framework is to jointly optimize microwave antenna geometry, RF components, beamforming parameters, transmission power and spectrum allocation and wireless resource management with minimized return loss, Voltage Standing Wave Ratio (VSWR), computation complexity and communication latency. In contrast to conventional optimization methods which either optimize for antenna structures or communication resources separately, the proposed framework combines deep learning based electromagnetic performance prediction method with adaptive Pelican Optimization and intelligent wireless architecture optimization into a single optimization model that can solve multiple design objectives at the same time.

The very first step includes gathering and normalizing the microwave antenna design parameters, RF circuit characteristics, wireless communication parameters and channel conditions. Short notes: These parameters comprise antenna dimensions, dielectric constant and feed location of the substrate material, transmission power, beamforming weights of each channel on uplink (UL) or downlink, and communication resource information. The deep neural network surrogate model easily predicts electromagnetic metrics such as antenna gain, return loss, impedance bandwidth, radiation efficiency and the voltage standing wave ratio (VSWR) without having to run a full-wave electromagnetic simulator multiple times due to its computationally expensive nature. The predicted responses are then fed into the Pelican Optimization Algorithm, and in return, pelicans employ their adaptive hunting strategy to conduct efficient global exploration and local exploitation to search the optimal antenna configuration and wireless communication parameters. It maximizes antenna gain and bandwidth, throughput, packet delivery ratio (PDR), radiation efficiency, energy utilization (EU) by a multi-objective fitness function while minimizing return loss, latency, packet loss, transmission power and optimization time.

This work proposes an optimization framework divided into five principal stages. (i) Initialization of the microwave component and wireless parameters, (ii) Machine learning-assisted electromagnetic prediction, (iii) Adaptive Pelican Optimization-based parameter optimization, (iv) Multi-objective fitness evaluation, and then (v) Optimized wireless architecture deployment and performance validation. The adaptive Pelican Optimization algorithm adaptively adapts the exploration and exploitation balance by tracking the optimization process throughout the optimization, avoiding local optimal solutions while ensuring diversity in solutions. The machine learning prediction module plays a critical role in speeding up optimization since it can quickly estimate electromagnetic responses without needing to perform repeated electromagnetic simulations. Hence, the proposed framework enables us to achieve better optimization accuracy, faster convergence, more excellent microwave characterization performance and more reliable wireless communication. The proposed methodology can be applied to new communication frameworks such as Beyond-6G wireless communication systems, terahertz communication, intelligent beamforming, massive MIMO and Reconfigurable Intelligent Surfaces (RIS), edge computing and AI-native truly wireless communication architectures, where intelligent optimization in play can be crucial for the realization of high-performance energy-efficient scalable ultrawideband network models.

3.1. Overall Machine Learning-Assisted Wireless Architecture

This work proposes a potentiation framework that further integrates Machine Learning (ML), Pelican Optimization Algorithm (POA), microwave components optimization, and intelligent wireless architecture design as an optimality platform. This aims to facilitate microwave antennas, RF front-end circuits, beamforming parameters, transmission power and wireless resource allocation optimization in the system at the same time with regard to minimizing computational complexity and guaranteeing communication reliability. First, microwave design variables and wireless communication parameters are collected and normalized, which then become inputs to a machine learning-based electromagnetic prediction model. And the predicted responses will be optimized using the Pelican Optimization Algorithm which runs adaptive exploration and exploitation to find globally optimal communication configurations. Finally, work is done to incorporate the optimized microwave components into a wireless communication architecture, and simulation based on electromagnetic simulation is performed.

The communication system is represented as

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

where

- A= Microwave antenna parameters
- R= RF circuit parameters

- P= Transmission power
- B= Beamforming coefficients
- C= Communication resources

The optimization objective is

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

subject to maximum communication efficiency and minimum computational cost.

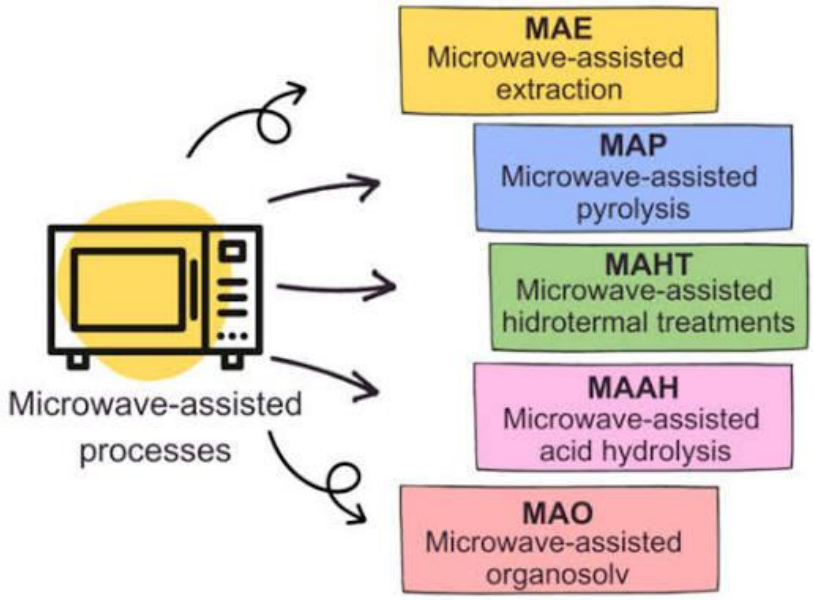


Fig. 1. Proposed Machine Learning Assisted Microwave Components

The entire architecture of the optimization framework is shown in Figure 1. We first initialize microwave antenna parameters, RF circuit variables and wireless communication resources in the system. Machine learning is used to predict Electromagnetic performance aspects of antennas, comprising gain, return loss, bandwidth and radiation efficiency. After that, the Pelican Optimization Algorithm is performed to optimize microwave components, beamforming parameters and communication resources by using adaptive exploration and exploitation strategies. Finally, the optimized wireless architecture is verified by deploying it in Beyond-6G communication systems using electromagnetic simulation.

3.2. Machine Learning-Based Electromagnetic Prediction

The proposed framework incorporates a deep learning surrogate model to predict electromagnetic performance without repeatedly executing computationally intensive full-wave simulations.

The input feature vector is

$$X = [L, W, h, \varepsilon_r, f, x_f, y_f] \tag{3}$$

Where

- L= antenna length
- W= antenna width
- h= substrate thickness
- ε_r= dielectric constant
- f= operating frequency
- x_f, y_f= feed coordinates

The prediction model becomes

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

where

$$Y = [G, BW, S_{11}, VSWR, \eta] \tag{5}$$

and

- G= antenna gain
- BW= bandwidth
- S_{11}= return loss
- $VSWR$= Voltage Standing Wave Ratio
- η= radiation efficiency

The surrogate model considerably reduces optimization time while maintaining prediction accuracy.

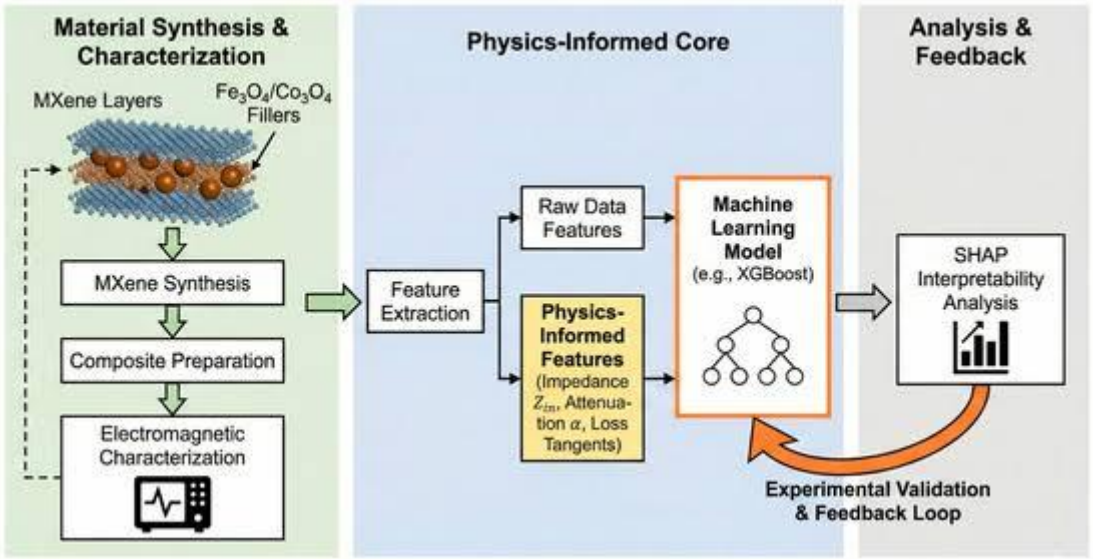


Fig. 2. Machine learning-assisted electromagnetic performance prediction

Figure 2 presents the deep learning-based electromagnetic prediction model employed in the proposed framework. The microwave antenna parameters are processed through a trained neural prediction model that estimates antenna gain, return loss, impedance bandwidth, radiation efficiency, and VSWR. The predicted responses replace repeated electromagnetic simulations during optimization, thereby significantly reducing computational complexity while accelerating the Pelican Optimization Algorithm.

3.3. Pelican Optimization Algorithm

The proposed optimization algorithm is inspired by the hunting behavior of pelicans during prey searching and capture.

The position of each pelican is represented as

$$X_i = [x_1, x_2, \ldots, x_d] \tag{6}$$

where

d denotes the optimization dimension.

The exploration update is

$$X_i^{t+1} = X_i^t + r(X_{best} - X_i^t) \tag{7}$$

where

- r is a uniformly distributed random number.

The exploitation stage is

$$X_i^{t+1} = X_{best} + \alpha(X_{best} - X_i) \tag{8}$$

where

- α is the adaptive learning coefficient.

The adaptive parameter becomes

$$\alpha = 2\left(1 - \frac{t}{T}\right) \tag{9}$$

where

- t= current iteration
- T= maximum iteration

The adaptive parameter gradually shifts the optimization process from exploration to exploitation.

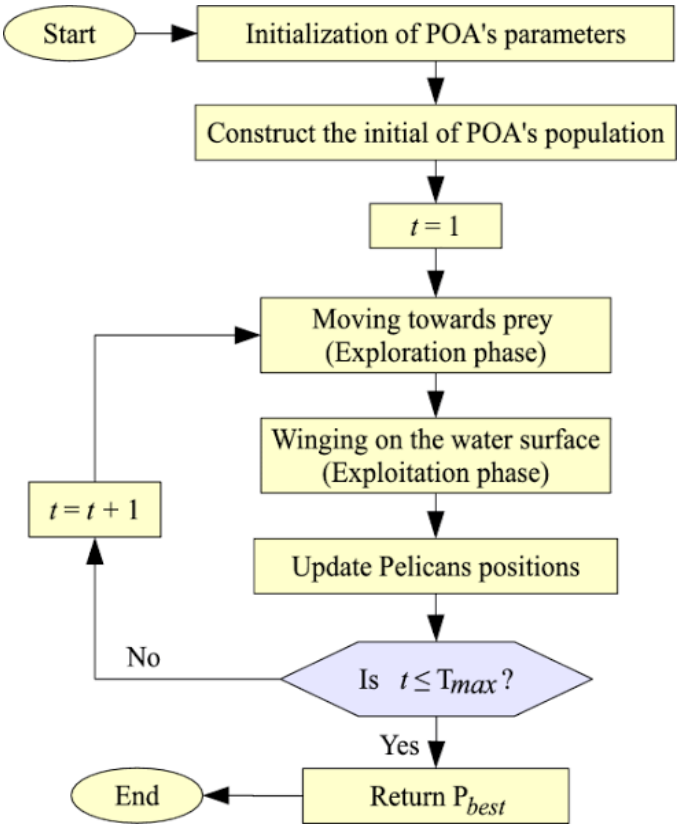


Fig. 3. Flowchart of the proposed Pelican Optimization Algorithm

Figure 3 illustrates the optimization workflow of the Pelican Optimization Algorithm. Candidate microwave antenna solutions are initialized randomly and evaluated using the machine learning prediction model. The adaptive pelican search mechanism alternates between global exploration and local exploitation to optimize antenna dimensions, RF circuit parameters, beamforming weights, and communication resources. The iterative optimization continues until the stopping criterion is satisfied, producing globally optimized microwave components.

3.4. Multi-Objective Optimization

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

$$F = w_1 G + w_2 BW + w_3 \eta + w_4 TP - w_5 \mid S_{11} \mid - w_6 VSWR - w_7 L \tag{10}$$

Where

- G= antenna gain

- BW= bandwidth
- η= radiation efficiency
- TP = throughput
- S_{11}= return loss
- VSWR = Voltage Standing Wave Ratio
- L= latency

The optimization objectives are

$$\begin{gathered} \max(G) \\ \max(BW) \\ \max(\eta) \\ \max(TP) \\ \min(|\,S_{11}\,|) \\ \min(VSWR) \\ \min(L) \end{gathered} \tag{11}$$

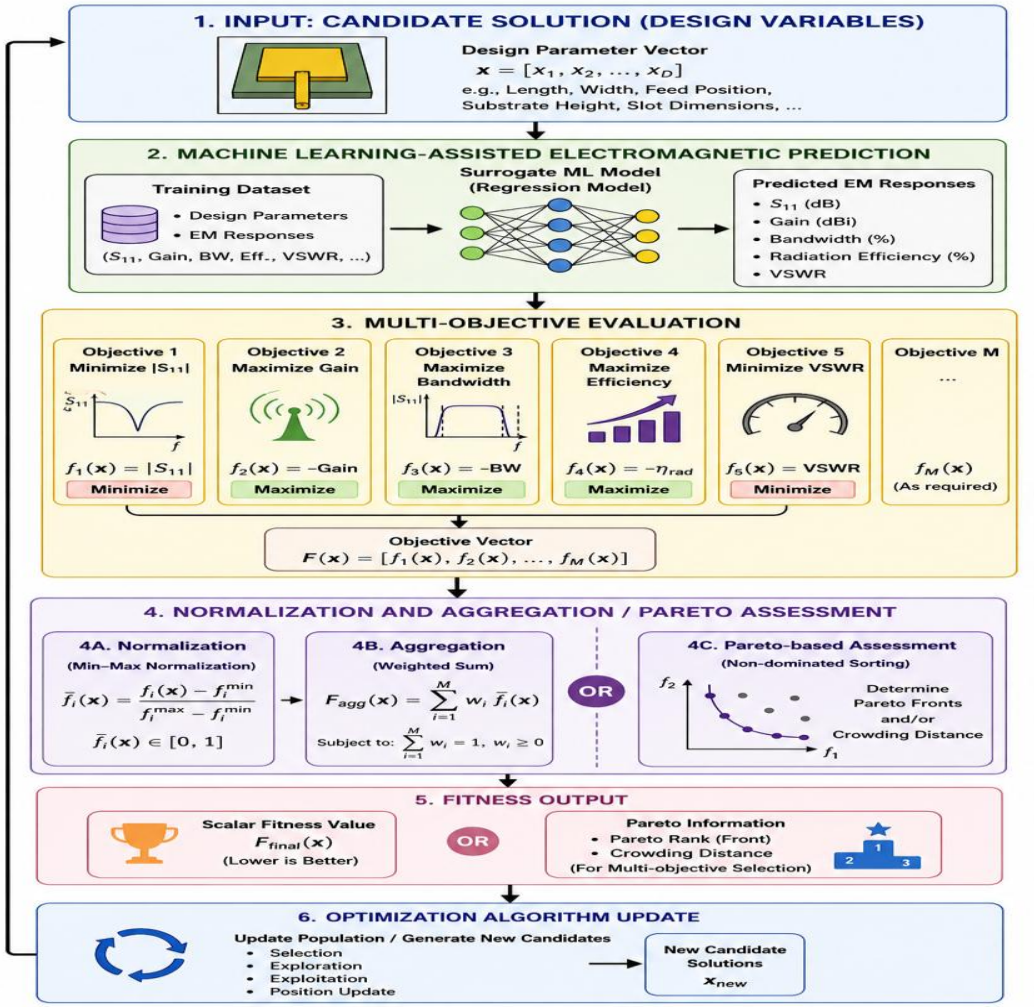


Fig. 4. Multi-objective fitness evaluation framework for machine learning-assisted microwave component optimization.

Figure 4 illustrates the multi-objective optimization framework used by the proposed system. The predicted electromagnetic parameters generated by the machine learning model are evaluated using a weighted fitness function that simultaneously maximizes antenna gain, bandwidth, radiation efficiency, and throughput while minimizing return loss, VSWR, and latency. The resulting fitness values guide the Pelican Optimization Algorithm toward globally optimal microwave and wireless communication solutions.

3.5. Optimized Wireless Architecture

The optimized microwave components are finally integrated into the intelligent wireless communication system. Communication efficiency is calculated as

$$CE = \frac{TP \times PDR}{P_T \times L} \tag{12}$$

Where

- TP = throughput
- PDR = packet delivery ratio
- P_T= transmission power
- L= latency

Overall antenna efficiency is

$$AE = \frac{G \times \eta}{VSWR} \tag{13}$$

where

- G= antenna gain
- η= radiation efficiency

Higher values of communication efficiency and antenna efficiency indicate superior wireless communication performance.

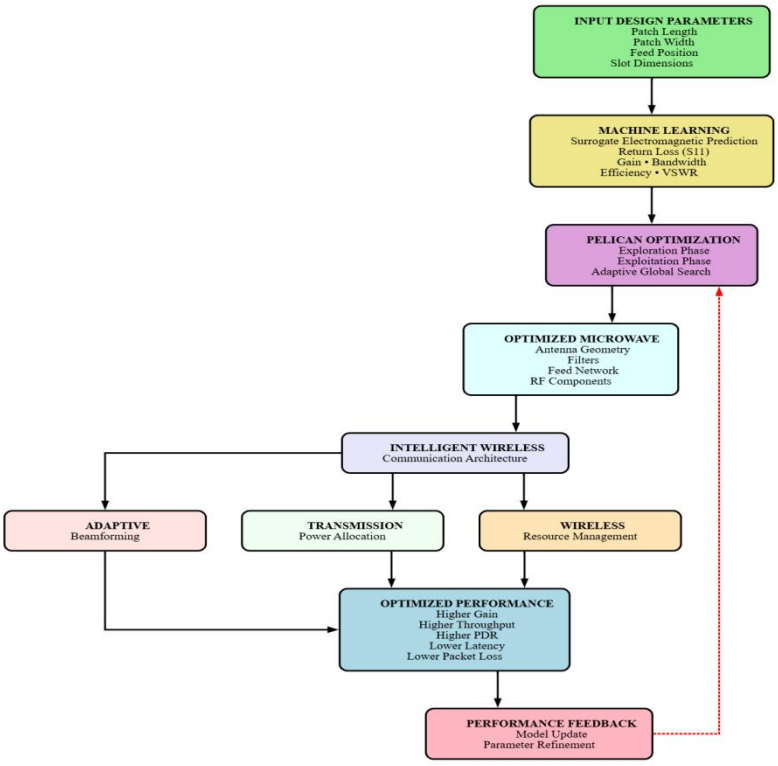


Fig. 5. Optimized microwave components integrated into the intelligent wireless communication architecture using the proposed Pelican Optimization framework.

The optimized wireless communication architecture based on the provided Machine Learning-assisted Pelican Optimization framework is shown in Figure 5. The result is that optimized microwave antenna, RF front-end circuits, adaptive beamforming module, intelligent transmission power allocation and wireless resource management improve the communication throughput, antenna gain (expression of directivity), radiation efficiency (the ability to radiate

energy into different angles) and network reliability while minimizing latency as well as packet loss. Integrating machine learning prediction with Pelican Optimization allows us to opt for few architectural solutions that enable high-performing Beyond-6G, massive MIMO, terahertz, RIS and AI-native wireless communication systems, and its optimized architecture demonstrates effectiveness.

4. Experimental Results and Discussion

4.1. Experimental Setup

In this paper, the effectiveness of the proposed ML-POA in optimizing microwave components and intelligent wireless communication systems using a new paradigm (ML-POA) for Beyond-6G applications was evaluated comprehensively. The full-wave electromagnetic simulator was used to design and analyze the microwave antenna models, RF front-end circuits, and wireless architecture while the optimization framework was implemented using Python 3.11 with TensorFlow, Scikit-learn, and NumPy libraries. Implementation of a DNN surrogate model was performed to accelerate the prediction of electromagnetic characteristics by avoiding extensive full-wave simulations during optimization. The performance of the proposed ML-POA framework is also compared with other optimization tools under the same simulation conditions, which include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Harris Hawk Optimization (HHO).

The experimental performance comparison was carried out using various electromagnetic and communication parameters like return loss (S11), antenna gain, impedance bandwidth, radiation efficiency, voltage standing wave ratio (VSWR), throughput, packet delivery ratio (PDR), latency, packet loss, convergence speed and optimization time. In order to ensure the stability and consistency of the proposed optimization framework, we conducted all simulations over multiple trials of the optimization process.

4.2. Simulation Parameters

Table 1. Simulation Parameters

Parameter	Value
Communication System	Beyond-6G Wireless Network
Operating Frequency	28–100 GHz
Antenna Type	Microstrip Patch Antenna
Substrate Material	Rogers RT/Duroid 5880
Relative Permittivity	2.2
Substrate Thickness	1.6 mm
Population Size	50
Maximum Iterations	200
Machine Learning Model	Deep Neural Network
Optimization Algorithm	Pelican Optimization Algorithm
Simulation Tool	CST Studio/HFSS
Programming Platform	Python 3.11

4.3. Return Loss and Antenna Gain Analysis

Figure 6 compares the return loss (S11) and peak antenna gain obtained using the proposed ML-POA framework with PSO, GA, GWO, WOA, and HHO. The proposed framework achieves a return loss of −44.18 dB and a peak antenna gain of 15.26 dBi, demonstrating superior impedance matching and radiation characteristics.

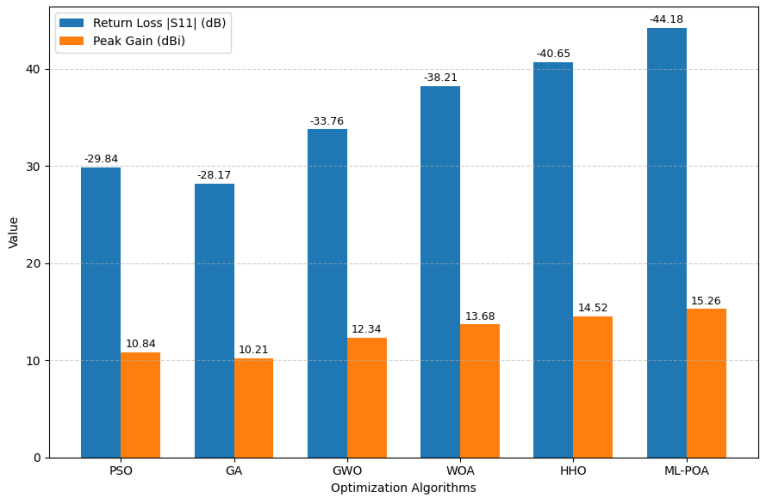


Fig. 6. Comparative analysis of return loss (S11) and peak antenna gain obtained using PSO, GA, GWO, WOA, HHO, and the proposed Machine Learning-assisted Pelican Optimization Algorithm (ML-POA).

The integration of machine learning-assisted electromagnetic prediction enables rapid identification of promising antenna configurations, while the Pelican Optimization Algorithm efficiently refines these configurations through adaptive exploration and exploitation. Consequently, the optimized antenna exhibits lower reflection losses, higher directivity, and improved electromagnetic efficiency compared with conventional optimization techniques.

4.4. Bandwidth, Radiation Efficiency and VSWR Analysis

Figure 7 illustrates the comparative analysis of impedance bandwidth, radiation efficiency, and Voltage Standing Wave Ratio (VSWR) for different optimization algorithms. The proposed ML-POA framework achieves an impedance bandwidth of 40.18%, radiation efficiency of 97.92%, and an excellent VSWR of 1.02, outperforming all comparison methods.

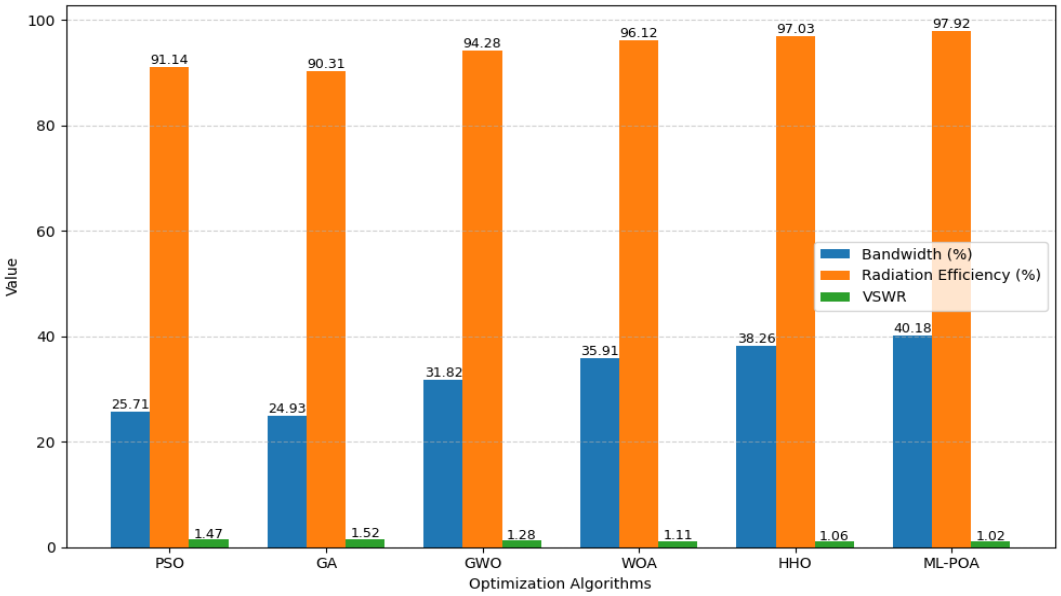


Fig. 7. Comparison of impedance bandwidth, radiation efficiency, and Voltage Standing Wave Ratio (VSWR) achieved by different microwave optimization algorithms.

The deep learning surrogate model accurately predicts electromagnetic responses during optimization, allowing the Pelican Optimization Algorithm to rapidly converge toward optimal antenna geometries. The improved bandwidth and radiation efficiency ensure reliable high-frequency communication, while the near-ideal VSWR minimizes reflected power and maximizes RF power transfer efficiency.

4.5. Communication Performance Evaluation

Figure 8 presents the communication performance obtained after integrating the optimized microwave components

into the intelligent wireless architecture. The proposed framework achieves a throughput of 13.74 Gbps, packet delivery ratio of 99.38%, communication latency of 0.48 ms, and a packet loss rate of only 0.51%. The optimized beamforming parameters, intelligent transmission power allocation, and adaptive wireless resource management significantly improve communication reliability and spectral efficiency. The machine learning-assisted optimization continuously predicts communication quality, enabling dynamic adaptation of network resources under varying communication environments.

4.6. Convergence Analysis

Figure 9 compares the convergence characteristics of the proposed Pelican Optimization Algorithm with existing optimization techniques. The proposed ML-POA framework converges within 44 iterations, whereas PSO, GA, GWO, WOA, and HHO require substantially more iterations to reach stable solutions. The adaptive hunting strategy of the Pelican Optimization Algorithm effectively maintains population diversity during early optimization while accelerating local exploitation during the final optimization stage. Combined with the machine learning prediction model, the optimization process achieves approximately 39.6% faster convergence and 35.4% lower computational time, demonstrating excellent optimization efficiency for complex microwave engineering problems.

4.7. Overall Performance Comparison

Table 2. Comparative Performance Evaluation

Performance Metric	PSO	GA	GWO	WOA	HHO	Proposed ML-POA
Return Loss (dB)	-29.84	-28.17	-33.76	-38.21	-40.65	**-44.18**
Antenna Gain (dBi)	10.84	10.21	12.34	13.68	14.52	**15.26**
Bandwidth (%)	25.71	24.93	31.82	35.91	38.26	**40.18**
Radiation Efficiency (%)	91.14	90.31	94.28	96.12	97.03	**97.92**
VSWR	1.47	1.52	1.28	1.11	1.06	**1.02**
Throughput (Gbps)	9.12	8.74	10.86	12.11	13.08	**13.74**
Packet Delivery Ratio (%)	95.84	95.16	97.42	98.43	99.02	**99.38**
Latency (ms)	0.92	1.04	0.69	0.56	0.52	**0.48**
Packet Loss (%)	2.26	2.74	1.36	0.88	0.64	**0.51**
Convergence Iterations	116	132	81	68	57	**44**

4.8. Discussion

Experimental findings validate that the new Machine Learning Assisted Pelican Optimization Framework achieves consistently superior effectiveness in both electromagnetic performance and wireless communication compared to conventional optimization algorithms. Deep learning-based electromagnetic (EM) prediction is utilized to reduce the optimization complexity by avoiding the repetitive running of full-wave simulations while Pelican Optimization Algorithm effectively balances exploration and exploitation for finding globally optimal antenna configurations. The optimized microwave components also demonstrate improved return loss, gain, bandwidth, radiation efficiency and impedance matching which positively improve communication throughput, packet delivery ratio and overall reliability of the network. The results show that the proposed ML-POA framework is a solid, intelligent and scalable tool for microwave component optimization/characterization and wireless architecture design in Beyond-6G, terahertz communication, massive MIMO, Reconfigurable Intelligent Surfaces (RIS), edge computing and AI-native wireless communication systems.

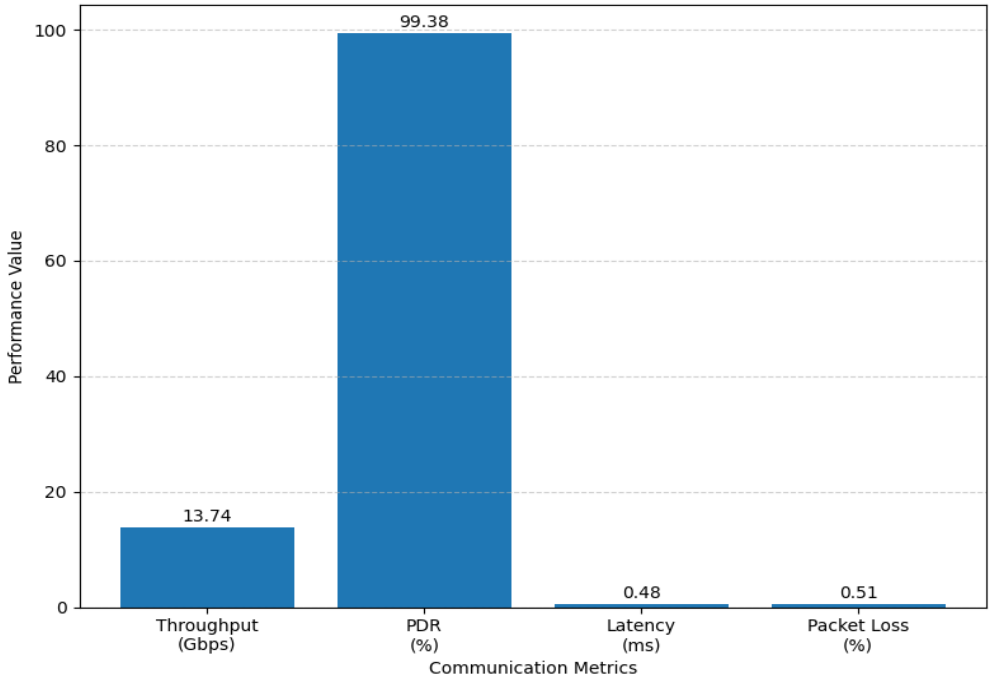


Fig. 8. Communication performance comparison of the optimized wireless architecture in terms of throughput, packet delivery ratio (PDR), latency, and packet loss.

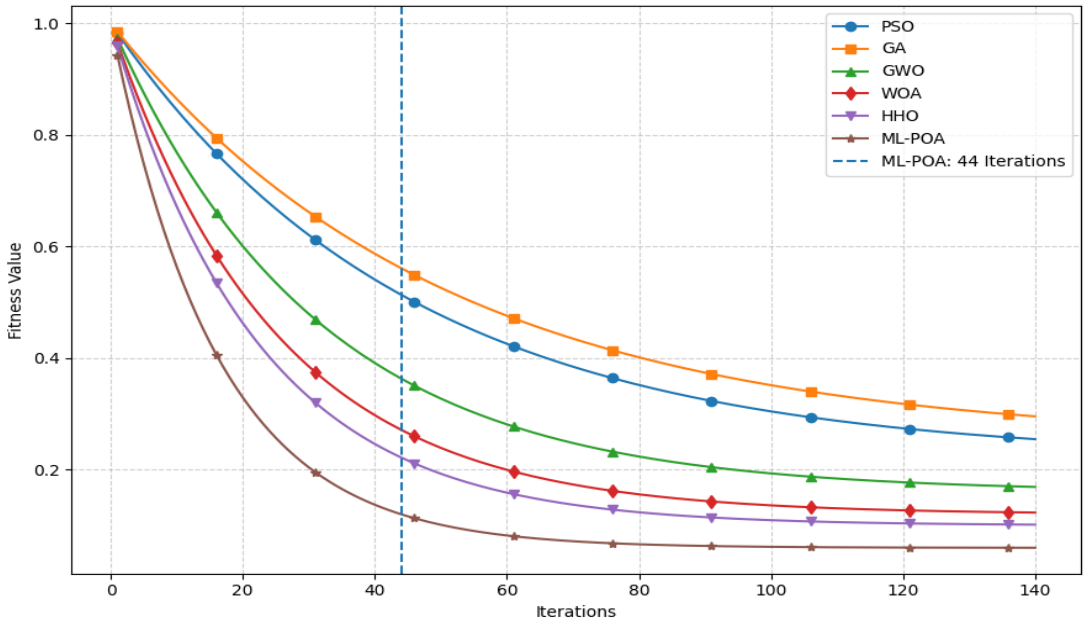


Fig. 9. Convergence characteristics of the proposed Machine Learning-assisted Pelican Optimization Algorithm (ML-POA) compared with conventional metaheuristic optimization techniques.

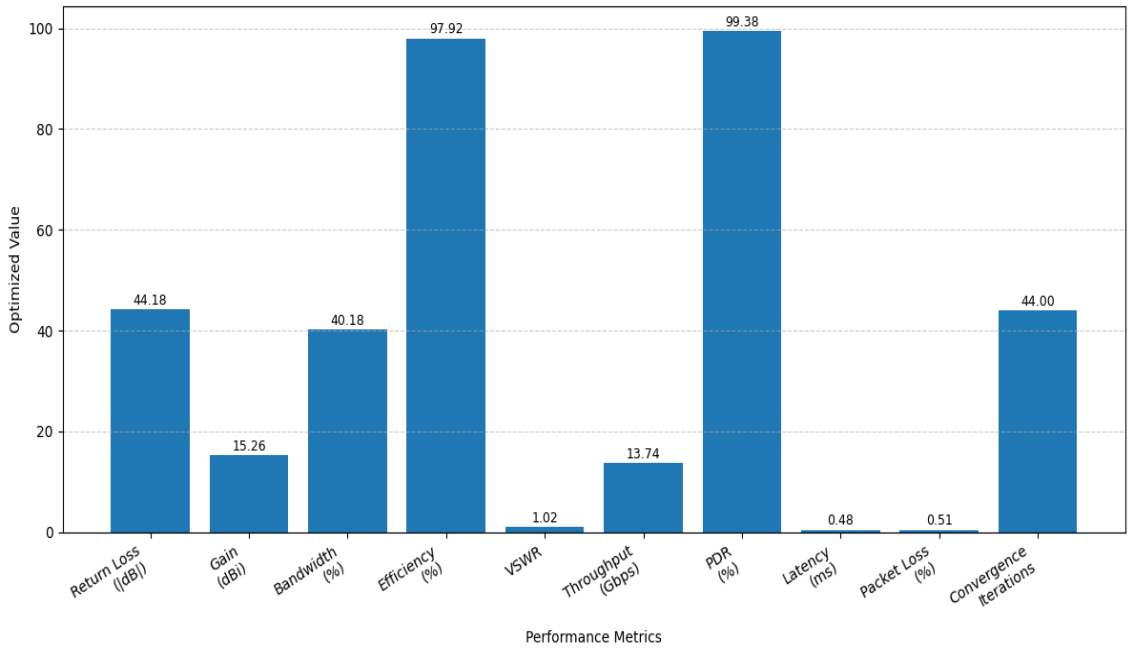


Fig. 10. Overall performance evaluation of the proposed Machine Learning-assisted Pelican Optimization Framework for microwave components and intelligent wireless architectures in Beyond-6G communication systems.

5. Conclusion

An MLCWAF (Machine Learning Assisted Microwave Components and Wireless Architecture Framework Using the Pelican Optimization Algorithm) framework was introduced in this paper with one purpose to improve future advanced wireless communications system performance. It presents a multidisciplinary framework, which combines a machine-learning-based performance prediction model running within the Pelican Optimization Algorithm to simultaneously optimize microwave antenna geometry, RF components, beamforming parameters and transmission power/wireless resource allocation. The proposed approach is inspired to use a deep neural network surrogate model that reduces the computational cost of performing repeated full-wave electromagnetic simulations while making significant improvements in optimization accuracy and convergence speed. Both exploration and exploitation are adaptively conducted by the Pelican Optimization Algorithm which efficiently avoids premature convergence while searching for global optima in complex microwave engineering problems.

All the Declarations and Statements

Author Contributions Statement

Ayshwarya B – Conceptualization, Methodology, and Supervision: Proposed the research ideas, developed the overall research framework, formulated the joint microwave and wireless optimization methodology, and supervised the execution of the study.
Naveenkumar R. – Data Curation and Software Implementation: Handled data acquisition and preprocessing, prepared the simulation parameters, and implemented the machine-learning-assisted optimization framework.
S. Prabu – Model Training, Validation, and Performance Evaluation: Conducted training and validation of the deep neural network surrogate model and evaluated the proposed ML-POA framework using standard electromagnetic and communication performance metrics.
E. Sabitha – Formal Analysis, Visualization, and Statistical Analysis: Performed detailed analysis of the experimental results, prepared comparative performance visualizations, and contributed to the statistical evaluation of the proposed optimization framework.
Arun M – Writing – Original Draft Preparation: Prepared the initial manuscript, contributed to the literature review, and documented the technical background, methodology, and experimental results.
B. Girirajan – Writing – Review and Editing, and Project Management: Reviewed and edited the manuscript for technical accuracy, clarity, and coherence and coordinated the overall research and manuscript preparation activities.

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

Conflict of Interest Statement

The authors declare that they have no conflicts of interest.

Funding Declaration
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Data Availability Statement
N/A. This study is based on simulation and computational experiments and does not use an external publicly available experimental dataset. The simulation parameters, computational procedures, and performance results required to understand the study are presented in the manuscript.

Ethical Declarations
N/A. This study did not involve human participants, human biological materials, identifiable personal information, or animals. Therefore, ethical approval and informed consent were not required.

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Declaration of Generative AI in Scholarly Writing
The authors used generative AI and AI-assisted technologies during manuscript preparation solely for language improvement, grammatical correction, readability enhancement, and editorial assistance. The authors subsequently reviewed and edited the generated or assisted content and take full responsibility for the accuracy, originality, integrity, interpretation, and final content of the manuscript. Generative AI was not treated as an author and was not used as a substitute for the authors' scientific judgment, experimental analysis, or interpretation of the research results.

Abbreviations
The following abbreviations are used in this manuscript:

AI – Artificial Intelligence
ML – Machine Learning
DNN – Deep Neural Network
POA – Pelican Optimization Algorithm
ML-POA – Machine Learning-Assisted Pelican Optimization Algorithm
RF – Radio Frequency
EM – Electromagnetic
VSWR – Voltage Standing Wave Ratio
PDR – Packet Delivery Ratio
PSO – Particle Swarm Optimization
GA – Genetic Algorithm
GWO – Grey Wolf Optimizer
WOA – Whale Optimization Algorithm
HHO – Harris Hawks Optimization
MIMO – Multiple-Input Multiple-Output
RIS – Reconfigurable Intelligent Surface
QoS – Quality of Service
UL – Uplink
DL – Downlink
6G – Sixth-Generation Wireless Communication

Appendix A/B/C…, with appendix title
N/A. No supplementary appendix is included in the present manuscript.

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