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Real-time Dynamic Adaption-centric Multi-dimensional Antenna Design Optimization Using MPS-OOA for 6G-Enabled Wireless Networks

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Abstract

Objectives: A Massive Multiple-Input-Multiple-Output (MIMO) antenna has emerged as a cornerstone in 6G-wireless networks. However, prior studies have not focused on real-time adaptive optimization. Hence, this article proposes an innovative design for real-time adaptive optimization of MIMO antenna systems that dynamically adjust to varying network conditions. **Methods:** Firstly, the design parameters are initialized to set up and optimize a massive MIMO antenna. Thereafter, the non-linear relationships between each parameter are captured. Further, the trade-offs are balanced to diminish the conflicting objectives. Here, the proposed Multi-Phase Search Orangutan Optimization Algorithm (MPS-OOA) is employed to optimize the antenna design. In real-time communication, the antenna operates under dynamic conditions. From the collected data, the Gaussian Extended Approximation Kalman Filter (GEAKF) is used to monitor the network fluctuations. **Findings:** Based on the observed variations, data is grouped and then subjected to the MPO-OOA antenna design optimization. **Novelty:** The proposed work ensures continuous adaption of the antenna with 97.02% efficiency.

Keywords: Antenna Design Optimization (ADO); Multiple-Input-Multiple-Output (MIMO); Antenna Systems (AS); Real-time Dynamic Adaption (RDA); 6G-Wireless Networks (6G-WN); Exponential Fuzzy Hyperbolic Tangent Interference System (EFHTIS); Pareto Linear Interpolation Front Analysis (PLIFA)

1 Introduction

In the era of 6G-wireless networks, MIMO antenna systems play a vital role in offering high data speed (THz)[1],[2]. 6G communications provide beneficial characteristics, such as low latency, high reliability, denser connection, and high throughput[3],[4]. Massive MIMO schemes support the networks to perform multiple computing, multiple sensing, and multiple-stream communications concurrently via the wireless medium[5],[6]. An optimal antenna design is fundamental to obtaining impressive performance and efficiency[7].

By optimizing the antenna parameters, MIMO systems achieve improved signal clutch and better utilization of wireless resources[8]. The existing studies introduced machine learning algorithms like random forest and DNN to fine-tune the design parameters of the antenna[9]. Further, bio-inspired optimization techniques like red panda optimization and ant colony optimization were employed in recent studies to perform optimal antenna design[10].

1.1 Problem statement

The limitations faced by the existing studies are stated below,

- Real-time adaptive optimization for massive MIMO antenna designs remained underexplored in the prevailing frameworks.
- The existing[11] failed to reduce the over-optimization risk during the multi-dimensional antenna design optimization.
- The traditional[12] did not focus on balancing the trade-offs among the different optimization metrics.
- Many conventional frameworks struggled to efficiently explore the entire search space due to the growing number of design parameters.

1.2 Objectives

The core objectives of the proposed work are given further,

- A robust GEAKF is established to enable the adaptive monitoring of the dynamic network conditions.
- The proposed EFHTIS is employed to capture the non-linear relationships between the design parameters, thereby reducing the risk of over-optimization.
- Trade-off analysis is done using the proposed PLIFA to improve the optimization quality.
- A novel MPS-OOA is utilized to perform ADO, thus enhancing communication efficiency.

The paper is organized as: Section 2 investigates the existing studies, Section 3 illustrates the proposed system, Section 4 evaluates the proposed work's performance, and Section 5 concludes the article.

In earlier studies[11],[12],[13],[14], designed an optimal O-shape fractal antenna for 6G-assisted mobile communication devices. The developed O-shape two-port MIMO antenna design had high gain and broad bandwidth. However, this model had a risk of over-optimization due to the lack of non-linear relationship analysis. Here, antenna arrays were optimally designed by considering the unique performance index, thus increasing the number of multiplexed parallel sub-channels. Nevertheless, this framework failed to handle the trade-offs. They also proposed a Deep Neural Network (DNN)-based antenna design for millimetre-wave applications. Particle swarm optimization and an improved gravitational search algorithm were utilized to optimize the hyper-parameters of the DNN. Subsequently, optimized DNN was used to design the main beam pattern of the uniform circular antenna module significantly. However, this model had scalability issues. Further an optimal super-wideband MIMO antenna system was proposed with four symmetric monopole-radiating elements[15],[16],[17],[18],[19],[20]. Here, a square ring was placed within the radiation elements. This developed antenna system had a high diversity gain. But this framework had high design complexity and fabrication issues.

2 Proposed System for Real-time Dynamic Adaption-based Antenna Design Optimization

The proposed framework aims to implement real-time adaptive design optimization, non-linear relationship mapping, and trade-off handling for massive MIMO antennas. The proposed work's architecture is presented in Figure 1.

2.1 Design parameter initialization

Primarily, the values for antenna design variables, such as antenna geometry (patch shape, slot position, and fractal layout), number of elements, return loss $(\Re)$, size (Sz), substrate material, frequency band, gain (G), bandwidth (B), efficiency (χ), and side lobe level (δ) are initialized to optimize the massive MIMO antennas. An appropriate initialization enhances the convergence efficiency in the optimization.

$$\partial\alpha_i \quad \overset{initialize}{\rightarrow} \quad \|\partial\alpha_1, \partial\alpha_2, \ldots\ldots \partial\alpha_I\| \text{ where, } i \;= 1 to I \tag{1}$$

Here, I exhibits the number of initialized design parameters $\partial\alpha_i$.

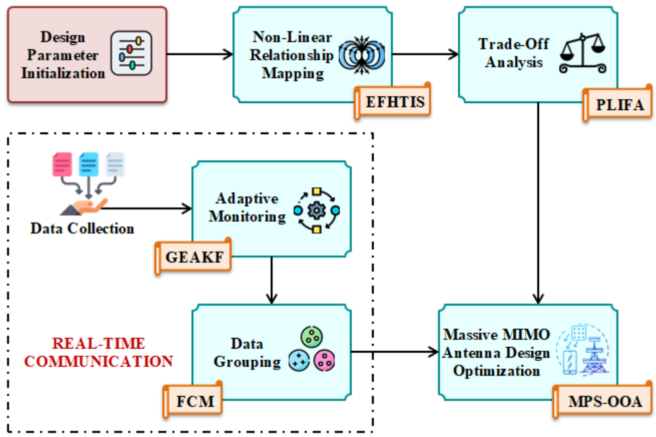

Fig 1. Block diagram of the research methodology

2.2 Non-linear relationship mapping

Thereafter, the non-linear complex relationships between antenna parameters $\partial\alpha_i$ are mapped via the proposed EFHTIS, reducing the issue of over-optimization for specific conditions. The Fuzzy Inference System (FIS) significantly handles high-dimensional issues while maintaining computational efficiency. Yet, the FIS has suboptimal optimization results owing to the improper membership function design. Therefore, the proposed approach introduces the Exponential Hyperbolic Tangent (EHT) membership function to improve the mapping efficiency. Firstly, the crisp input values $\partial\alpha_i$ are converted into fuzzy values (Fz) using the EHT membership function (γ_{eht}) that assigns the membership degree regarding the fuzzy set.

$$\gamma_{eht}(\partial\alpha_i) = \frac{1}{1+\exp(-\upsilon(\partial\alpha_i - Rf))} \cdot \tan h(\varsigma(\partial\alpha_i - Rf)) \to Fz \tag{2}$$

Where,(υ, ς) denotes the shaping parameters and Rf indicates the reference point. Next, the fuzzy rules (X_{base}) are generated to determine the relationship between the parameters.

$$X_{base}(Fz) = \begin{cases} If(G = high\&B = wide), Then\chi = moderate \\ If(\delta = low\&\chi = high), ThenG = high \\ If(B = wide\&\delta = high), ThenG = moderate \\ If(Sz = small\&G = high), ThenB = narrow \\ If(\Re = low\&\chi = high), ThenSz = medium \\ If(\chi = high\&\delta = low), ThenB = moderate \end{cases} \tag{3}$$

The efficiency is moderate when the gain is high and the bandwidth is wide. In such a way, the non-linear relationship is mapped between the design parameters. In the fuzzy inference unit, the fuzzy rules are evaluated via the fuzzy operators. Next, all the fuzzy results are merged to form a single fuzzy output, followed by defuzzification (D_{fuzz}).

$$D_{fuzz} = Fz \overset{convert}{\to} \partial\alpha_i \tag{4}$$

Subsequently, the non-linear relationship mapped data $(N\nabla)$ is subjected to the trade-off handling.

2.3 Trade-off handling

Here, the trade-off analysis is done in $N\nabla$ using the proposed PLIFA to balance the conflicting design objectives. For example, minimizing side lobe levels requires maximum energy, thus reducing the antenna gain. The trade-off handling helps to improve optimal antenna performance. The Pareto Front Analysis (PFA) had high flexibility; also, it improved the overall performance of the model. However, the PFA had biased results due to the inappropriate weighting decisions. Therefore, the proposed method introduces Linear Interpolation (LI) to diminish the risk of bias.

Initially, the multiple objective functions $\left(Ob_q\right)$ are defined according to the problem. Accordingly, a set of solutions $\left(Sn_p\right)$ is generated.

$$\left(Ob_q, Sn_p\right) \rightarrow \left(\left(Ob_1, Sn_1\right), \left(Ob_2, Sn_2\right) \ldots Ob_Q, Sn_P\right) \text{ Here, } q, p = 1 to Q, P \tag{5}$$

Here, Pareto dominance is used to compare the solutions. Pareto dominance reveals the solution, which is better or equal to another in all objectives and strictly better in at least one objective. Likewise, the Pareto front is identified to reveal a set of non-dominated solutions. The proposed work introduces the LI to weighting decisions.

$$L_i = \sum_{q,p=1}^{Q,P} (1-wt) Ob_q\left(Sn_p\right) + wt Ob_q\left(Sn_p\right) \tag{6}$$

Where, L_i depicts the interpolated objective vector and wt denotes the weight factor. Finally, the preferred solution is selected from the weighted set.

$$\tau\infty_y = \langle \tau\infty_1, \tau\infty_2, \ldots\ldots \tau\infty_Y \rangle \tag{7}$$

The trade-off handled data is mentioned as $\left(\tau\infty_y\right)$.

2.4 Design optimization

Further, the $\tau\infty_y$ is inputted to the proposed MPS-OOA, which optimizes the massive MIMO antenna design. The Orangutan Optimization Algorithm (OOA) had high adaptability and proficiently handled multi-dimensional optimization issues. However, the OOA had pre-mature convergence issues owing to the improper balancing between exploration and exploitation. Therefore, the proposed method employs the multi-phase search strategy to maintain a good balance nature. The OOA imitates the natural behaviors of orangutans (members). The proposed MPS-OOA's flow chart is given in Figure 2.

Here, the $\tau\infty_y$ is considered as the population member. Primarily, the position of each orangutan in the search zone is determined below,

$$\tau\infty_{y,z} = lw_z + \emptyset.\left(\mu\rho_z - lw_z\right); z = 1 \; to \; Z \tag{8}$$

Where, Y exhibits the number of members $\tau\infty_{y,z}$, Φ indicates the random value taken from 0 to 1, $\ell\omega_z$ and $\mu\rho_z$ depict the lower bound and upper bound, respectively, and $z = 1 to Z$ shows the problem variables. Thereafter, the best candidate solution $\left(\tau\infty_{y,z}{}^{Best}\right)$ is recognized by considering the multi-objectives, such as maximum gain, maximum bandwidth, maximum radiation efficiency, maximum strength, minimum side lobe level, minimum mutual coupling, minimum interference, and minimum latency. In the exploration phase, the position of each orangutan is updated by mimicking the foraging behavior.

$$\tau\infty_{y,z}{}^{\Omega} = \tau\infty_{y,z} + \Phi \cdot \left(\tau\infty_{y,z}{}^{Best} - \kappa \cdot \tau\infty_{y,z}\right) \tag{9}$$

$$\tau\infty_{y,z} = \begin{cases} \tau\infty_{y,z}{}^{\Omega}, \mathfrak{I}^{\Omega} \leq \mathfrak{I} \\ \tau\infty_{y,z}, else \end{cases} \tag{10}$$

Here, $\mathfrak{I}$ indicates the fitness value, κ exhibits the random integer taken from the set {1, 2}, and $\tau\infty_{y,z}{}^{\Omega}$ and $\mathfrak{I}^{\Omega}$ demonstrate the new member position and updated fitness in the exploration, respectively. In the exploitation, the new member's location $\left(\tau\infty_{y,z}{}^{\Theta}\right)$ is obtained by simulating the movements towards the tree.

$$\tau\infty_{y,z}{}^{\Theta} = \tau\infty_{y,z} + (1-2\Phi) \cdot \frac{\left(\mu\rho_z - l\omega_z\right)}{T_{\max}} \tag{11}$$

$$\tau\infty_{y,z} = \begin{cases} \tau\infty_{y,z}{}^{\Theta}, \mathfrak{I}^{\Theta} \leq \mathfrak{I} \\ \tau\infty_{y,z}, else \end{cases} \tag{12}$$

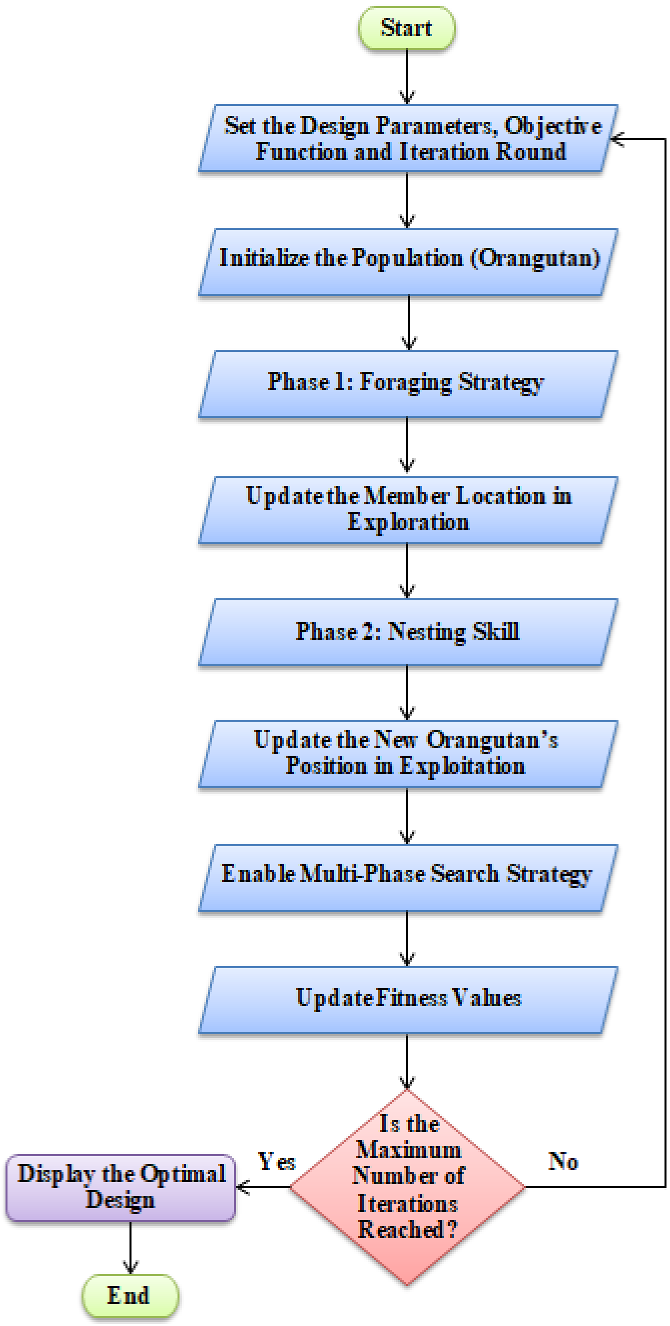

Fig 2. The flow chart of the proposed MPS-OOA

Where, $T_{\max}$ depicts the maximum iteration and $\mathfrak{I}^{\Theta}$ demonstrates the updated fitness value in the exploitation. The probability of switching (Ξ) between exploration and exploitation is computed below,

$$\Xi = Fn\left(\tau\infty_{y,z}, T\right) \tag{13}$$

At each iteration (T), the update rule is framed.

$$\tau\infty_{y,z}(\Xi) = \begin{cases} \tau\infty_{y,z}(T-1) + \tau\infty_{y,z}{}^{\Omega}, IF \tau\infty_{y,z}{}^{\Omega} is active \\ \tau\infty_{y,z}{}^{Best} + \tau\infty_{y,z}{}^{\Theta}, IF \tau\infty_{y,z}{}^{\Theta} is active \end{cases} \tag{14}$$

Thus, the search process is continued until the optimal antenna design $(\varphi\Lambda)$ is obtained. The pseudo-code of the proposed MPS-OOA is given below,

Input: Trade-off handled data $\tau\infty_y$
Output: Optimal antenna design $(\varphi\Lambda)$
Begin
 Initialize $\tau\infty_y$, Y, $\ell\omega_z$, $\mu\rho_z$, T and $T_{\max}$
 Set $(T = 1)$
 While $(T \leq T_{\max}())$ do,
  Determine population position,
  $\tau\infty_{y,z} = \ell\omega_z + \Phi \cdot (\mu\rho_z - l\omega_z); z = 1 to Z$
  Evaluate multi-objective functions
  #exploration
  Update orangutan's location
  IF $(\mathfrak{I}^{\Omega} \leq \mathfrak{I})$
  {
  $\tau\infty_{y,z}{}^{\Omega} = \tau\infty_{y,z} + \Phi \cdot \left(\tau\infty_{y,z}{}^{Best} - \kappa \cdot \tau\infty_{y,z}\right)$
  }
  ELSE
  {
  $\tau\infty_{y,z}$
  }
  End IF
  Update member's position in the exploitation
  IF $(\mathfrak{I}^{\Theta} \leq \mathfrak{I})$
  {
  $\tau\infty_{y,z}{}^{\Theta} = \tau\infty_{y,z} + (1 - 2\Phi) \cdot \frac{(\mu\rho_z - l\omega_z)}{T_{\max}}$
  }
  ELSE
  {
  $\tau\infty_{y,z}$
  }
  End IF
  Enable multi-phase search strategy,
  $\tau\infty_{y,z}(\Xi) = \begin{cases} \tau\infty_{y,z}(T-1) + \tau\infty_{y,z}{}^{\Omega}, IF \tau\infty_{y,z}{}^{\Omega} is active \\ \tau\infty_{y,z}{}^{Best} + \tau\infty_{y,z}{}^{\Theta}, IF \tau\infty_{y,z}{}^{\Theta} is active \end{cases}$
  Repeat until converge
 End While
Return
End

The $\varphi\Lambda$ efficiently improves the communication speed.

2.5 Data collection

In real-world communication, factors (K_e) like signal-to-noise-ratio, signal-to-interference-ratio, user mobility pattern, signal strength, path loss, and interference index are gathered to ensure optimal signal performance.

2.6 Adaptive monitoring

Subsequently, the GEAKF is used to estimate and predict variations in K_e over time by ensuring the dynamic adjustment of the antenna configurations. The Extended Kalman Filter (EKF) accurately handled nonlinear models in complex environments. However, the EKF was sensitive to the choice of initial conditions. Therefore, the proposed work introduces the Gaussian distribution approximation to estimate the initial state (M_0) and covariance (Cov).

$$M_0 \approx \eta\iota\left(mn_0, vr_0^2\right) \tag{15}$$

Where, $\eta\iota$ denotes the Gaussian distribution, and mn_0 and vr_0 indicate the mean and variance, respectively. Thus, the updated state estimate (M_1) is shown below,

$$M_1 = M_0 + Kg\left(\frac{mn_0^2\alpha\mu + mn_1^2 M_0}{mn_0^2 + mn_1^2}\right) \tag{16}$$

Here, Kg denotes the Kalman gain, $\alpha\mu$ represents the actual measurement, and mn_1^2 indicates the variances of the measurement. Next, the updated covariance $(Co\tilde{v})$ is obtained as follows,

$$Co\tilde{v} = \left(I_{\max}()\frac{mn_0^2 mn_1^2}{mn_0^2 + mn_1^2}\right) \tag{17}$$

Where, $I_{\max}$ denotes the identify matrix and Jn indicates the Jacobian of the measurement.

The pseudo-code of the proposed GEAKF is given below,

Input: Environmental factors K_e
Output: Estimated state M_1
Begin
  InitializeK_e,M_0,M_1 and $Co\tilde{v}$
    For each time step,
      #Gaussian distribution approximation
      Determine$M_0 \approx \eta\iota\left(mn_0, vr_0^2\right)$
      Update state estimate,

$$M_1 = M_0 + Kg\left(\frac{mn_0^2\alpha\mu + mn_1^2 M_0}{mn_0^2 + mn_1^2}\right)$$

      Update covariance

$$Co\tilde{v} = \left(I_{\max}()\frac{mn_0^2 mn_1^2}{mn_0^2 + mn_1^2}\right)$$

    End For
ReturnM_1
End

The M_1 helps to perform dynamic adjustment of antenna parameters.

2.7 Data grouping

Based on M_1, the K_e is grouped by using the Fuzzy C-Means (FCM) clustering with respect to similar time variations. FCM proficiently handled the ambiguous or complex relationships between data points. Initially, the number of clusters and the fuzziness parameter (Fp) are determined. Thereafter, the cluster centres and membership matrix are randomly initialized. Afterward, the new centroid (Cd) is computed based on the membership values and data points.

$$Cd = \frac{\sum_{e=1}^{E} \left(Mem_e{}^{Fp}\right) \cdot K_e}{\sum_{e=1}^{E} \left(Mem_e{}^{Fp}\right)} \tag{18}$$

Where, $e = 1 to E$ indicates the number of K_e and Mem_e depicts the membership value. The membership values are updated below,

$$Mem_e = \frac{1}{\sum_{e=1}^{E} \left(\frac{dis(K_1, Cd)}{dis(K_e, Cd)}\right)^{2/(Fp-1)}} \tag{19}$$

Here, dis depicts the distance. The data point with a high membership value is assigned to the cluster.

$$G\nabla = \{G\nabla_1, G\nabla_v, \ldots G\nabla_V\} \tag{20}$$

Then, the $v = 1 to V$ number of grouped data $(G\nabla)$ is subjected to the MPS-OOA antenna design optimization process, ensuring continuous adoption of the antenna to achieve maximum gain and minimum interference in real time. The proposed 6G-powered massive MIMO antenna systems enhance the Tbps speeds with superior signal clutch.

3 Results and Discussion

To showcase the system's efficacy, the performance of the research methodology is validated in this section. The experimentation of the proposed system is done on the MATLAB platform.

3.1 Performance assessment

The significance of the proposed work is evaluated by comparing it with related techniques.

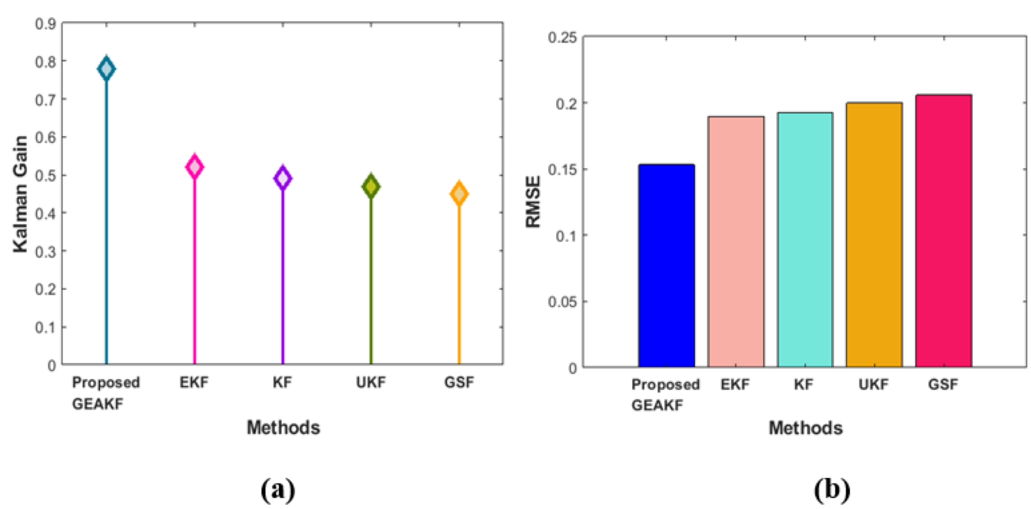

Fig 3. Performance analysis for adaptive monitoring according to (a) Kalman gain and (b) RMSE

In Figure 3, the performance of the proposed GEAKF is compared with traditional techniques like EKF, Kalman Filter (KF), Unscented Kalman Filter (UKF), and Gaussian Sum Filter (GSF). The proposed GEAKF obtained Kalman gain and Root Mean Squared Error (RMSE) of 0.78 and 0.1532, respectively. Likewise, the existing EKF had 0.52 Kalman gain and 0.1896 RMSE. Therefore, the proposed methodology had higher supremacy in adaptive monitoring due to the presence of Gaussian approximation.

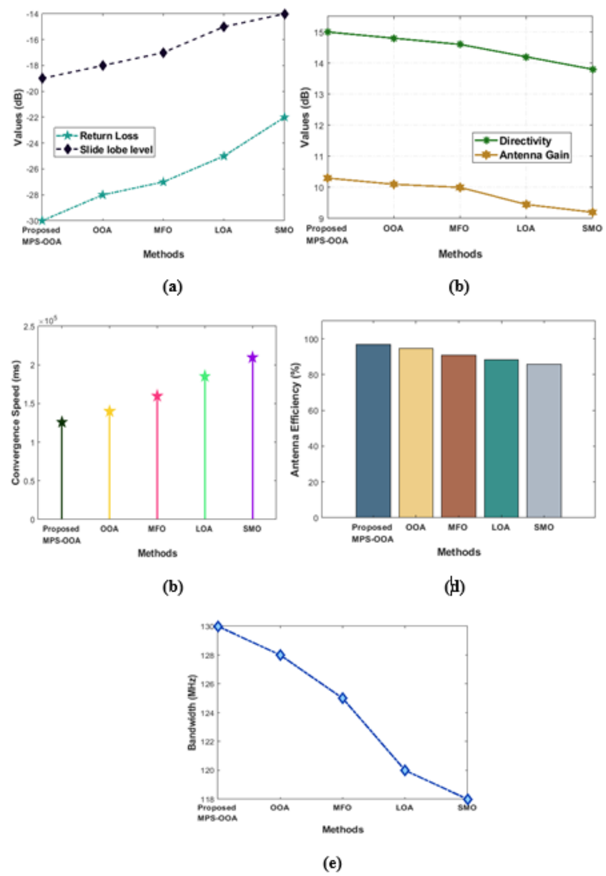

Fig 4. Performance analysis for design optimization regarding (a) return loss and side lobe level, (b) directivity and antenna gain, (c) convergence speed, (d) antenna efficiency, and (e) bandwidth

Figure 4 validates the performance of the proposed MPS-OOA and the existing algorithms like OOA, Moth Flame Optimization (MFO), Lion Optimization Algorithm (LOA), and Spider Monkey Optimization (SMO) according to design optimization. The proposed MPS-OOA achieved return loss, side lobe level, directivity, antenna gain, convergence speed, antenna efficiency, and bandwidth of -22dB, -19dB, 15dB, 10.3dB, 125896ms, 97.02%, and 130MHz, respectively. However, the existing techniques had poor performance due to the premature convergence issue. Thus, the proposed work had impressive performance owing to the inclusion of a multi-phase search strategy.

Table 1. Interference rate

Techniques	Interference rate (dB)
Proposed MPS-OOA	-28.95
OOA	-22.48
MFO	-18.31
LOA	-15.08
SMO	-10.96

The interference rate of the proposed MPS-OOA and the conventional algorithms is evaluated in Table 1. The proposed MPS-OOA had an interference rate of -28.95dB, whereas the existing methods obtained an average interference rate of -16.70dB. Therefore, the proposed work had higher prominence.

The performance of the proposed EFHTIS is validated in Figure 5 by comparing it with associated algorithms like FIS, trapezoidal-fuzzy, Gaussian-fuzzy, and Decision Rule (DR). Due to the utilization of the EHT membership function, the proposed EFHTIS achieved fuzzification time, defuzzification time, and rule generation times of 1896ms, 1775ms, and 1103ms,

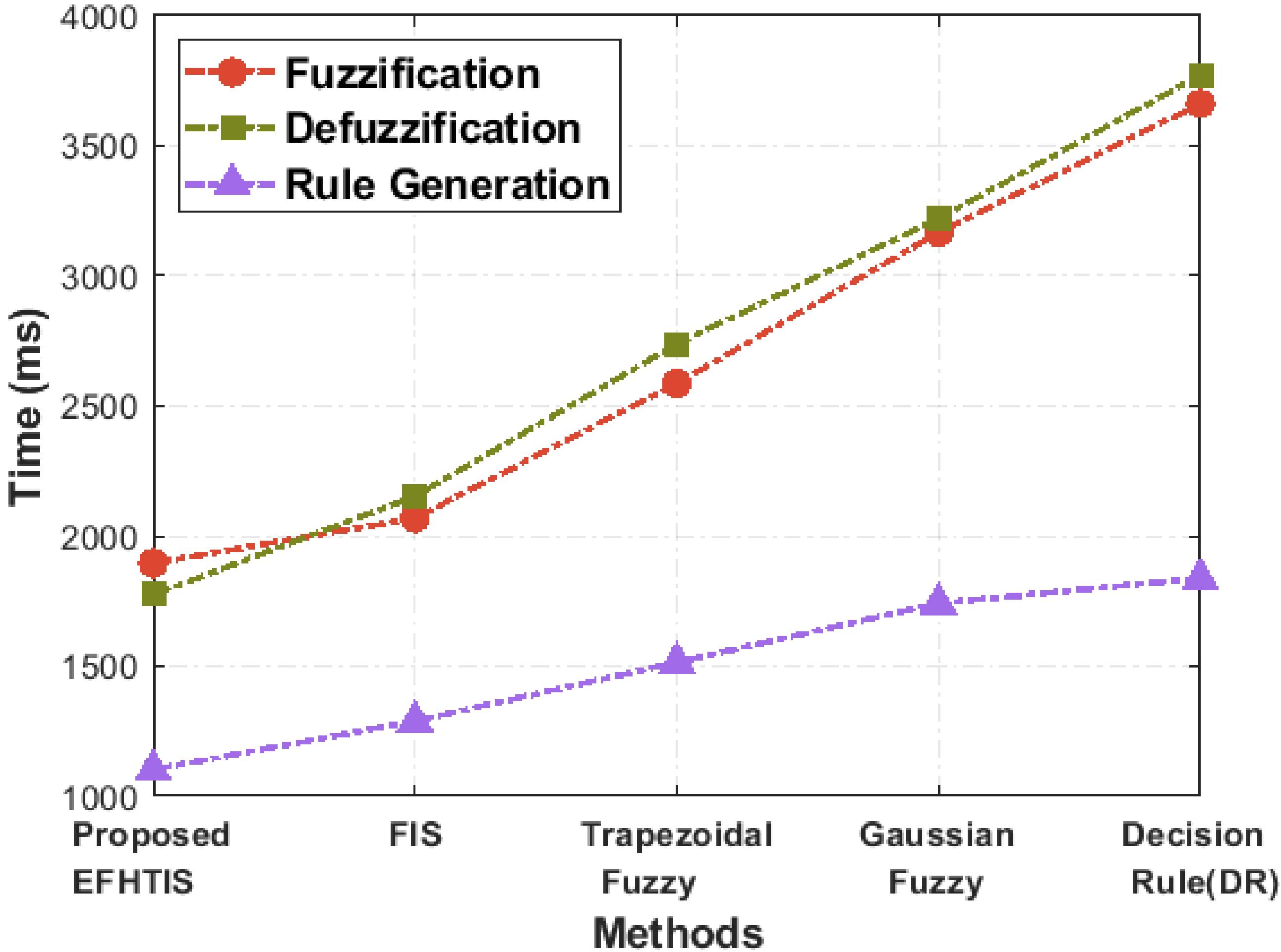

Fig 5. Performance validation for non-linear relationship mapping

respectively. Yet, the DR obtained fuzzification time, defuzzification time, and rule generation time of 3662ms, 3772ms, and 1838ms, respectively. Hence, the low time complexity of the proposed work was evidenced.

Table 2. Comparative analysis for trade-off handling

Algorithms	Convergence rate (%)
Proposed PLIFA	95.63
PFA	93.25
NSGA-II	90.19
SPEA2	88.67
ABC	85.43

Tables 2 and 3 show the comparative analysis of the proposed PLIFA regarding trade-off handling. Here, the existing techniques like PFA, Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), and Artificial Bee Colony (ABC) were compared with the proposed PLIFA. The proposed PLIFA had 95.63% convergence rate and 98.39% computational efficiency. However, the conventional ABC obtained a convergence rate and computational efficiency of 85.43% and 89.68%, respectively. Due to the presence of Linear Interpolation (LI), the performance of the proposed work was improved.

Table 3. Computational efficiency

Algorithms	Computational Efficiency (%)
Proposed PLIFA	98.39
PFA	96.58
NSGA-II	94.17
SPEA2	92.87
ABC	89.68

3.2 Comparative validation

Here, the performance of the proposed work is compared with the several related models.

Table 4. Comparative assessment

Reference	Techniques	Antenna gain (dB)	Directivity (dB)
Proposed approach	MPS-OOA	10.3	15
(21)	Mathematically-inspired MIMO antenna geometry	1.0	-
(22)	Hybrid ant colony African buffalo optimization	9.34	13.02
(4)	Machine learning models	8.09	-
(23)	Genetic algorithm	8.28	9.77
(24)	Defected Ground Structure (DGS) and multiple coupling effects	5.17	-

The performance of the proposed methodology is compared with the related studies in Table 4. The proposed MPS-OOA achieved antenna gain and directivity of 10.3dB and 15dB, respectively. But, the conventional genetic algorithm (Singh et al., 2021)[23] had 8.28dB antenna gain and 9.77dB directivity. Therefore, the supremacy of the proposed work was proved.

4 Conclusion

This article proposed a real-time dynamic adaption-centric multi-dimensional antenna design optimization using MPS-OOA for 6G-powered wireless networks. The proposed MPS-OOA significantly optimized the design of massive MIMO. Further, the non-linear relationship mapping and trade-off handling were done to reduce the over-optimization issue and conflicting objectives, respectively. Also, the proposed approach obtained Kalman gain and antenna efficiency of 0.78 and 97.02%, respectively. The proposed work was generalized well enough to offer adaptive monitoring, thus improving the network's resilience.

Future scope: In the future, this work will focus on handling the environmental noises during the antenna design optimization.

References

1) Haque A, Ahammed S, Socheatra S, Ananta RA, Nirob JH, Singh NSS, et al. Machine learning based compact MIMO antenna array for 38 GHz millimeter wave application with robust isolation and high efficiency performance. *Results in Engineering*. 2025;25:1–14. 10.1016/j.rineng.2025.104006.
2) Khaleel SA, Hamad EK, Parchin NO, Saleh MB. MTM-inspired graphene-based THz MIMO antenna configurations using characteristic mode analysis for 6G/IoT applications. *Electronics*. 2022;11(14):1–21. 10.3390/electronics11142152.
3) Shi Y, Lian L, Shi Y, Wang Z, Zhou Y, Fu L, et al. Machine learning for large-scale optimization in 6G wireless networks. *IEEE Communications Surveys & Tutorials*. 2023;25(4):1–39. 10.1109/COMST.2023.10198239.
4) New WK, Wong KK, Xu H, Wang C, Ghadi FR, Zhang J, et al. A tutorial on fluid antenna system for 6G networks: Encompassing communication theory, optimization methods and hardware designs. *IEEE Communications Surveys & Tutorials*. 2024;p. 1–53. 10.1109/COMST.2024.10753482.
5) Qi Q, Chen X, Khalili A, Zhong C, Zhang Z, Ng DWK. Integrating sensing, computing, and communication in 6G wireless networks: Design and optimization. *IEEE Transactions on Communications*. 2022;70(9):1–15. 10.1109/TCOMM.2022.9828481.
6) Sharma P, Tiwari RN, Singh P, Kumar P, Kanaujia BK. MIMO antennas: Design approaches, techniques and applications. *Sensors*. 2022;22(20):1–25. 10.3390/s22207813.
7) Jain R, Thakare VV, Singhal PK. Design and comparative analysis of THz antenna through machine learning for 6G connectivity. *IEEE Latin America Transactions*. 2024;22(2):1–10. 10.1109/TLA.2024.10412032.
8) Raj T, Mishra R, Kumar P, Kapoor A. Advances in MIMO antenna design for 5G: A comprehensive review. *Sensors*. 2023;23(14):1–34. 10.3390/s23146329.
9) Narayanaswamy NK, Alzahrani Y, Penmatsa KKV, Pandey A, Dwivedi AK, Singh V, et al. Machine Learning Aided Tapered 4-Port MIMO Antenna for V2X Communications with Enhanced Gain and Isolation. *IEEE Access*. 2025;13:1–13. 10.1109/ACCESS.2025.3543183.
10) Basherlou HJ, Parchin NO, See CH. Antenna Design and Optimization for 5G, 6G, and IoT. *Sensors*. 2025;25(5):1–6. 10.3390/s25051494.

11) Patel SK, Baz A. O-shape fractal antenna optimized design with broad bandwidth and high gain for 6G mobile communication devices. *Fractal and Fractional*. 2024;8(1):1–16. 10.3390/fractalfract8010017.
12) Pinchera D, Migliore MD, Schettino F. Optimizing antenna arrays for spatial multiplexing: Towards 6G systems. *IEEE Access*. 2021;9:1–16. 10.1109/ACCESS.2021.3070198.
13) Montaser AM, Mahmoud KR. Deep learning based antenna design and beam-steering capabilities for millimeter-wave applications. *IEEE Access*. 2021;9:1–9. 10.1109/ACCESS.2021.3123219.
14) Khurshid A, Dong J, Ahmad MS, Shi R. Optimized super-wideband MIMO antenna with high isolation for IoT applications. *Micromachines*. 2022;13(4):1–13. 10.3390/mi13040514.
15) Jain K, Kushwah VS, Bhatia R. A low Profile Ultra-Wideband Hexagonal Patch Antenna for UAV-Based Applications. *International Journal of Electronics Letters*. 2024;p. 1–13. 10.1080/21681724.2024.2349970.
16) Kushwah VS, Reddy MR, Charyulu MLN, Sastry PN, Goyal S. Design and Analysis of Frequency Tunable LP to CP Convertor Loaded Silicon-Graphene based MIMO Array Antenna in THz regime. *Journal of Optics*. 2024;p. 1–15. 10.1007/s12596-024-01783-4.
17) Reddy MR, Charyulu MLN, Kushwah VS, Sastry PN, Kumar R. Design and Investigation on Two Port Circularly Polarized Graphene-Silicon Based MIMO Antenna with High Isolation for THz Wireless Applications. *Journal of Optics*. 2024 Apr;p. 1–9. 10.1007/s12596-024-01821-1.
18) Dwivedi SA, Sharma R, Kushwah VS. Design and Optimization of MIMO Dielectric Resonator Antenna with High Gain and Circular Polarization Features using Machine Learning Algorithms. *International Journal of Microwave and Wireless Technologies*. 2025;17(2):287–296. 10.1017/S1759078725101694.
19) Sant A, Bhatia R, Kushwah VS. Two-port ceramic array antenna with metasurface suspension for wireless 5G applications in mm-wave regime. *Electromagnetics*. 2025 Apr;p. 1–12. 10.1080/02726343.2025.2496919.
20) Sant A, Bhatia R, Kushwah VS. Two-Port Circularly Polarized Printed Radiator with High Gain and Isolation Features for Sub-6GHz 5G Applications. *International Journal of Communication Systems*. 2025 Apr;38(9):1–16. 10.1002/dac.70113.
21) Chouhan S, Malviya L, Panda DK. Mathematically inspired MIMO antenna with enhanced isolation for wireless applications. *International Journal of Communication Systems*. 2024;37(7):1–16. 10.1002/dac.5730.
22) Kumar P, Shilpi S, Kanungo A, Gupta V, Gupta NK. A novel ultra wideband antenna design and parameter tuning using hybrid optimization strategy. *Wireless Personal Communications*. 2021;122(2):1–24. 10.1007/s11277-021-08942-x.
23) Singh M, Singh S, Islam MT. .
24) Amraoui Y, Halkhams I, Alami RE, Jamil MO, Qjidaa H. High gain MIMO antenna with multiband characterization for terahertz applications. *Scientific African*. 2024;26:1–15. 10.1016/j.sciaf.2024.e02380.