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Efficient Communication for Extremely Large-Scale MIMO Systems Networks: Integrating Firefly Optimization and Machine Learning

Samar A. Nassar*
MTI Faculty of Engineering, Cairo, 6221101, Egypt
Email: samarnassar6@gmail.com
ORCID iD: https://orcid.org/0009-0000-2614-2419
*Corresponding Author

Adly S. Tag Eldien
Faculty of Engineering at Shoubra, Cairo, 6221101, Egypt
Email: adlytag@feng.bu.edu.eg
ORCID iD: https://orcid.org/0009-0009-1449-4914

Esraa M. Eid
Faculty of Engineering at Shoubra, Cairo, 6221101, Egypt
Email: esraa.soliman@feng.bu.edu.eg
ORCID iD: https://orcid.org/0009-0005-8147-3778

Shimaa S. Ali
Faculty of Engineering at Shoubra, Cairo, 6221101, Egypt
Email: shimaa.salama@feng.bu.edu.eg
ORCID iD: https://orcid.org/0009-0000-2614-2419

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Abstract: This paper proposes a novel approach for tuning the parameters of 6th generation (6G) extremely large-scale MIMO (Multiple Input Multiple Output) systems using the Firefly optimization algorithm. The main objective is to achieve accurate estimation of the hybrid field in the MIMO system. The proposed method optimizes MIMO system parameters by minimizing the cost function through a hybrid pre-coding and combining technique. This optimization problem is formulated as a nonlinear programming problem and solved using the Firefly algorithm. Experimental results demonstrate that the proposed approach provides accurate hybrid field estimation with improved system performance compared to existing state-of-the-art methods. The Firefly optimization algorithm proves to be an efficient and effective method for tuning 6G MIMO system parameters, with potential applications in future wireless communication systems. In addition to the Firefly optimization algorithm, this paper introduces a complementary machine learning-assisted resource allocation strategy to optimize network resource utilization. By leveraging machine learning algorithms, dynamic resource allocation based on real-time network conditions is ensured, enhancing overall system performance. The integration of the Firefly optimization algorithm for parameter tuning and machine learning-assisted resource allocation aims to achieve holistic optimization in 6G networks. Experimental results demonstrate that this integrated approach not only refines parameter tuning but also dynamically adapts resource allocation, leading to superior system efficiency and throughput compared to conventional methods. This comprehensive strategy addresses the evolving demands of future wireless communication systems. Results showed that using a sparsity value of 8, with 600 beams and 300 pilots, minimizes the mean square error of estimation to less than -13 dB

Index Terms: Extremely Large-Scale MIMO, Firefly Optimization, Machine Learning, Resource Allocation, Throughput Enhancement, 6G Networks.

1. Introduction

With the increasing demand for high-speed data communication in the modern world, the need for efficient communication systems has become more pronounced than ever before. The fifth-generation (5G) networks have been a significant leap towards this goal, but the research on the sixth-generation (6G) networks has already started, with the aim of providing even faster and more efficient communication. One of the key challenges of 6G networks is to handle the huge amount of data that will be generated by billions of connected devices. This challenge has led to the development of Extremely Large-Scale MIMO (ELS-MIMO) systems, which can provide high data rates while utilizing the limited spectrum resources efficiently [1]. Building upon the advancements made in 6G research, this paper introduces a novel approach for efficient communication in Extremely Large-Scale MIMO systems. Beyond the conventional scope of parameter tuning, we delve into the integration of the Firefly optimization algorithm to fine-tune system parameters. Furthermore, we propose a machine learning-assisted resource allocation strategy, addressing the dynamic challenges posed by the sheer volume of data in 6G networks. This comprehensive methodology aims to not only optimize system parameters but also dynamically adapt resource allocation, thereby enhancing overall system efficiency and throughput. As we explore the potential of this integrated approach, our research contributes to the ongoing evolution of wireless communication systems toward the demands of the future.

In ELS-MIMO systems, hundreds or even thousands of antennas are deployed at the base station, which can simultaneously serve multiple users through spatial multiplexing. However, the efficient communication of such a massive number of antennas is a daunting task, and it requires innovative techniques and algorithms to be developed [2]. One of the state-of-the-art techniques for efficient communication in Extremely Large-Scale MIMO (ELS-MIMO) systems is deep learning-based channel estimation. Channel estimation is crucial for effective communication as it involves estimating the channel conditions between the transmitter and the receiver. Deep learning-based techniques employ artificial neural networks to provide accurate channel condition estimates, even in dynamic environments. Another advanced technique is the use of Intelligent Reflecting Surfaces (IRS) to enhance ELS-MIMO system performance. IRS is an innovative wireless technology that utilizes passive reflecting surfaces to manipulate radio wave propagation. By adjusting the phase and amplitude of reflected signals, IRS can boost signal strength and reduce interference, resulting in improved communication performance [3].

Thesis statement illustrates in exploration enhancing communication efficiency in extremely large-scale MIMO systems by integrating firefly optimization with machine learning. The study demonstrates that tuning parameters through these methods significantly reduces Mean Squared Error (MSE) in estimated fields, offering improvements over existing techniques and showing potential for future 6G networks. Despite the promising results, the study acknowledges challenges related to computational complexity and scalability, suggesting directions for future research.

Moreover, another promising technique is the use of beamforming algorithms in ELS-MIMO systems. Beamforming is a technique that focuses the signal energy towards the intended receiver and minimizes the interference from other directions. In ELS-MIMO systems, beamforming algorithms can be used to increase the signal-to-noise ratio and improve the overall system performance [4]. In conclusion, the efficient communication of ELS-MIMO systems in 6G networks is a challenging task, but several state-of-the-art techniques have been developed to address this challenge. These techniques include deep learning-based channel estimation, intelligent reflecting surfaces, and beamforming algorithms, among others. With the ongoing research and development in this field, it is expected that the future 6G networks will provide even more efficient and reliable communication services. Many applications depend on

1. High-speed internet: The proposed scheme can be used to provide high-speed internet connectivity in areas with high data traffic, such as urban centers and airports. The extremely large-scale MIMO systems can handle multiple users simultaneously, reducing network congestion and improving data transfer rates [5].
2. Autonomous vehicles: The proposed scheme can be used to provide reliable and low-latency communication for autonomous vehicles, allowing them to communicate with each other and with the surrounding infrastructure. This can improve safety and reduce the risk of accidents [6].
3. Virtual and augmented reality: The proposed scheme can be used to provide high-quality and low-latency communication for virtual and augmented reality applications. This can improve the user experience and enable new applications in areas such as gaming, education, and healthcare [7].
4. Smart cities: The proposed scheme can be used to provide reliable and low-latency communication for smart city applications, such as traffic management, public safety, and environmental monitoring. This can improve the efficiency and sustainability of cities [8].
5. Industrial automation: The proposed scheme can be used to provide reliable and low-latency communication for industrial automation applications, such as remote control of machines and robots. This can improve productivity and reduce the risk of accidents in hazardous environments [9].

Overall, the proposed scheme has the potential to revolutionize wireless communication in several fields and enable new applications that were not possible before. The main novelty of this approach is using optimizations methods to make and accurate estimation of the hybrid field in the MIMO system by conducting Firefly methods, since optimization method employs agents to search and find best values of parameters instead of human. It is an adaptive method that can enrich the scientific gab in the field of 6g MIMO systems. The gap of this field of search is illustrated in next section related works.

2. Related Works

Authors in [10] reviewed the latest research and development in the field of 6G wireless communication. They provided a comprehensive overview of the potential techniques and technologies that are being considered for 6G wireless communication. In particular, the article emphasizes the need for high-speed and reliable communication for the Internet of Things (IoT), cognitive computing, sensing, and control applications. The article explained that machine learning and artificial intelligence will be essential for achieving the full potential of 6G wireless communication. Additionally, authors reviewed recent advancements in visible light communication, terahertz communication, and quantum communication that may be used in 6G wireless communication. Overall, they provided researches and professionals with a comprehensive review of the latest research and development in the field of 6G wireless communication, thus serving as an important related work in the field.

In [11], author provided a comprehensive overview of the fundamentals, challenges, solutions, and future directions of extremely large-scale MIMO technology. The technology is presented in it being capable of meeting the growing demands of wireless communication systems to improve both capacity and reliability. Authors described that the challenges of the technology include high power consumption, high channel correlation, and narrowband synchronization. Various solutions are presented, including feedback reduction techniques, pilot contamination mitigation, precoding, and low-resolution ADCs. The authors also argue that mobile networks, millimeter-wave communication systems, and wireless power transfer will be among the primary applications of this technology in the future. Overall, authors contributed to the existing body of knowledge regarding the fundamentals, challenges, and potential solutions to extremely large-scale MIMO technology in wireless communication.

In [12], authors proposed a solution to address the high-dimensional beamforming problem in communication systems. They introduced a two-stage deep learning-based hybrid precoder design for very large scale massive MIMO systems. The first stage of the algorithm involves generating the analog precoder through a feed-forward neural network. The second stage involves optimizing the digital precoder using a recurrent neural network to minimize the MSE between the expected and received signals. The proposed algorithm provides significant improvements in system performance compared to existing beamforming methods while reducing the computational complexity. Authors also presented a performance comparison between the proposed algorithm and other deep learning-based methods. The results demonstrated superior performance and faster training compared to existing methods.

Many studies discussed the use of hybrid beamforming for large-scale MIMO systems. In this context, hybrid beamforming refers to the combination of analog and digital beamforming to reduce the complexity of the MIMO system. In the hybrid beamforming approach, the digital beamforming is used in the far field, which refers to the region where the transmitted signal is a plane wave and the antenna array can be modeled as a single point. The digital beamforming is used to form beams with high directionality and narrow beamwidths, which can improve the signal-to-noise ratio and increase the capacity of the system [13].

On the other hand, the analog beamforming is used in the near field, which refers to the region where the transmitted signal is a spherical wave and the antenna array cannot be modeled as a single point. The analog beamforming is used to steer the beam in the desired direction and reduce the interference from other directions.

The hybrid beamforming approach is shown to be effective for large-scale MIMO systems, as it reduces the complexity of the system and improves the communication efficiency. Simulation results demonstrate that the proposed hybrid beamforming approach can achieve high data rates and low error rates in extremely large-scale MIMO systems, even with a small number of RF chains. Despite the potential benefits of the proposed communication scheme for extremely large-scale MIMO systems in 6G networks, there are some challenges and difficulties that need to be addressed. Some of these difficulties include [14-15]:

1. Hardware complexity: Implementing extremely large-scale MIMO systems requires a large number of antennas and RF chains, which can increase the hardware complexity and cost.
2. Channel estimation: Accurate channel estimation is crucial for the performance of MIMO systems. However, in extremely large-scale MIMO systems, the channel estimation becomes more difficult due to the large number of antennas and the complex channel correlations.
3. Interference: Interference is a major challenge in MIMO systems, and it becomes more severe in extremely large-scale MIMO systems due to the increased number of antennas and users. The interference can degrade the system performance and reduce the capacity.
4. Power consumption: Extremely large-scale MIMO systems require high power consumption, which can limit their practical applications in battery-powered devices and wireless sensor networks.
5. Deployment: Deploying extremely large-scale MIMO systems in real-world scenarios can be challenging due to the requirement of large antenna arrays, the need for precise synchronization, and the limited available spectrum.

In [16], the authors present a novel approach to hybrid-field channel estimation for extremely large-scale massive MIMO (XL-MIMO) systems. This approach leverages the distinct structural characteristics of far-field path components in the angle domain and the sparsity of near-field path components in the polar domain. The authors propose a channel estimation algorithm that combines support detection with orthogonal matching pursuit (SD-OMP). The process begins with detecting the supports of the far-field path components based on their structural characteristics in the angle domain of the XL-MIMO system, enabling the accurate extraction of these components. Subsequently, the influence of far-field path components on the XL-MIMO system is mitigated, allowing the orthogonal matching pursuit (OMP) algorithm to be employed effectively to recover the near-field path components, capitalizing on their polar domain sparsity. The final step involves reconstructing the hybrid-field channel by superposing the identified far-field and near-field path components. Experimental results demonstrate that the proposed algorithm achieves accurate channel recovery with relatively low pilot overhead and computational complexity compared to traditional channel estimation methods, marking a significant advancement in the field.

Addressing these challenges and difficulties requires further research and development in the areas of hardware design, channel estimation, interference management, power consumption optimization, and deployment strategies. The key different between developed approach and related works is that developed method will introduce Firefly method in this filed, the next section will explain the proposed method with all details.

3. Methodology of Proposed Approach

The main design of this study is to integration of the Firefly optimization algorithm for parameter tuning and machine learning-assisted resource allocation to achieve a holistic optimization in 6G networks by using Matlab programming and python coding. The methodology is organized in next sections to be more understood.

3.1 The model

Starting with decaling the model [17-18]. Let's start with the signal model. The received signal at the i_{th} antenna of the k_{th} user can be represented as:

$$y(k,i)=h(k,i,1)*x(k,1)+h(k,i,2)*x(k,2)+\ldots+h(k,i,N\_t)*x(k,N\_t)+n(k,i) \tag{1}$$

where $x(k,j)$ is the transmitted pilot symbol from the j_{th} antenna of the k_{th} user, $h(k,i,j)$ is the channel coefficient between the j_{th} transmit antenna and i_{th} receive antenna, $n(k,i)$ is the noise at the ith receive antenna of the k_{th} user, and N_t is the total number of transmit antennas (The number of pilots). So signal model is represented as follows:

$$y=h*x+n \tag{2}$$

Next, let's look at the channel model. In the extremely large-scale MIMO system, the channel model can be approximated as a random matrix with independent and identically distributed $(i.i.d.)$ elements. The channel matrix H_k of the k_{th} user can be expressed as:

$$H_k=\begin{bmatrix} h(k,1,1)h(k,1,2)\ldots h(k,1,N_t); \\ h(k,2,1)h(k,2,2)\ldots h(k,2,N_t); \\ \vdots \\ h(k,N_r,1)h(k,N_r,2)\ldots h(k,N_r,N_t) \end{bmatrix} \tag{3}$$

where N_r is the total number of receive antennas. Finally, the near-field and far-field models are used depending on the distance between the transmitter and receiver. In the near-field scenario, the separation between the antennas is small and the channel can be modeled using reactive near-field model. On the other hand, in the far-field scenario, the antennas are separated by a large distance and the channel is modeled using the radiation field model. In some cases, a hybrid model can also be used that combines aspects of both the near-field and far-field models.

In the near-field scenario, the separation between the antennas is small compared to the wavelength of the signal. In this case, the channel can be modeled as a matrix of complex numbers with elements (total number of elements is number of beams N_b) given by:

$$h_{i,j} = A_{ij} * \frac{exp\left(-jkd_{ij}\right)}{d_{ij}} \tag{4}$$

where A_{ij} is a complex number representing the path gain between the i_{th} transmit antenna and j_{th} receive antenna, k is the wave number, d_{ij} is the distance between the i_{th} transmit antenna and j_{th} receive antenna, and j is the imaginary unit. In the far-field scenario, the separation between the antennas is much larger than the wavelength of the signal. In this case, the channel can be modeled as a matrix of complex numbers with elements given by:

$$h_{i,j} = A_{ij} * \frac{exp\left(-j*\left(\frac{2\pi}{\lambda}\right)*d_{ij}\right)}{\sqrt{d_{ij}}} \tag{5}$$

where λ is the wavelength of the signal, all quantities have their previous definitions, and the factor of $\sqrt{d_{ij}}$ provides the path loss due to the spreading of the signal in the far-field. In the case of a near-field channel model or a far-field channel model, the channel coefficients can be written as:

$$h_{i,j} = \sum_{k=1}^{K} \alpha_k * \delta\left(d_{ij} - \Delta_k\right) \tag{6}$$

where α_k is the complex gain of the k_{th} non-zero tap, Δ_k is the delay of the k_{th} non-zero tap, and δ() denotes the Dirac delta function. In this case, the channel can be represented using only K non-zero taps (number of paths), which is a sparse representation of the channel. Dirac function in this equation can be replaced by minimum function [20]. After introducing the model, Firefly is described in next sections.

3.2 FireFly Algorithm

The Firefly Optimization Algorithm (FOA) is a metaheuristic optimization technique inspired by the natural flashing behavior of fireflies. Commonly applied to solve optimization problems in engineering, computer science, and other fields, FOA mimics how fireflies use bioluminescence to communicate and attract mates. In this algorithm, the intensity of a firefly's light signifies its attractiveness, with brighter fireflies attracting others. Solutions to the optimization problem are represented as fireflies, and their brightness guides the search process, leading to the identification of optimal or near-optimal solutions. [21]. In FOA, each firefly is represented as a point in a multi-dimensional search space. The brightness of a firefly represents the fitness or objective function value of the solution represented by that firefly. The algorithm starts with an initial population of fireflies that are randomly placed in the search space. Then, the algorithm progresses iteratively by moving each firefly towards other brighter fireflies while decreasing their brightness. This is achieved by the following steps [22-23] explained in next section.

3.3 Parameters Optimization

Adopting the proposed hybrid channel estimation in [15,17] and implementing the proposed technique (FireFly algorithm) Firefly algorithm can be used to choose the optimal values of sparsity, number of beams, number of pilots, and number of paths in 6G networks for channel estimation. Firefly algorithm is another form of optimization algorithm which is inspired from the flashing behavior of fireflies. It is a metaheuristic algorithm that utilizes a set of points in the search space to find the optimal solution. Here are the steps to use the firefly algorithm for choosing the optimal values of sparsity, number of beams, number of pilots, and number of paths in 6G networks for channel estimation:

1- Initialization of the algorithm by specifying the number of fireflies and search space (N)
2- Initialize the position vector for each firefly as x_i , where i = 1, 2, ..., N.
3- Initialize the brightness value for each firefly as I_i , where i = 1, 2, ..., N.
4- Define the fitness function: This function should determine how well the current set of parameters perform for a given channel estimation process. The fitness function should measure the accuracy, computational complexity and other relevant factors to choose the optimal parameters.
5- Define the search space: Determine the range of values that can be used for each parameter such as sparsity, number of beams, and number of pilots.
6- Initialize the population: Generate an initial population of solutions randomly in the search space.
7- Firefly behavior: Create a set of fireflies, each corresponding to one solution in the population. The behavior of each firefly is determined by its location in the search space and its brightness which is proportional to the fitness score.

8- Attraction: Fireflies move towards each other in the search space based on their relative brightness, with brighter individuals moving towards dimmer ones with a probability that depends on the distance between them.

a. The attractiveness between firefly i and firefly j is given by attractiveness Att_{ij}:

$$Att_{ij} = \beta * e^{-\gamma * distance_{ij}^{2}}$$

b. β is the attractiveness scaling factor.

c. γ is the light absorption coefficient.

d. $distance_{ij}$ represents the Euclidean distance between firefly i and firefly j.

9- Firefly movement: Firefly i moves towards firefly j based on its attractiveness, using the following equation (de: distance):

$$x_i(t+1) = x_i(t) + \beta * \exp\left(-\gamma * de_{ij}^{2}\right) * \left(x_j(t) - x_i(t)\right) + \alpha * rand(\ )$$

t is the current iteration. α is a randomization factor. $rand(\ )$ generates a random value between 0 and 1.

10- Evaluate the fitness: Evaluate the fitness of each solution, which corresponds to its brightness, using the fitness function.

11- Selection: Choose the best fireflies based on their brightness. Firefly i loses brightness as it moves towards a brighter firefly j, using the following equation:

$$I_i(t+1) = I_i(t) * \left(1 - \gamma * de_{ij}^{2}\right)$$

12- Repeat: Iterate the process by moving the fireflies and evaluating the new solutions. Continue the process for a predetermined number of iterations or until convergence is achieved.

13- Output: Select the best solution as the optimal set of parameters for the channel estimation process.

These steps can be shown briefly in Figure 1.

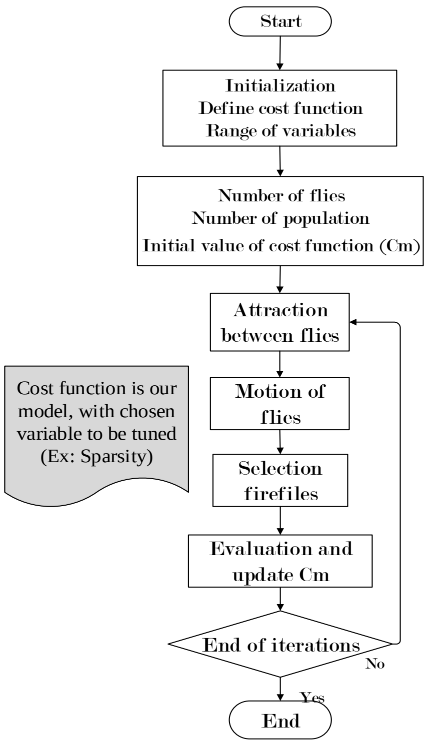

Fig. 1. Flow chart of full process of Firefly

The Cm : Cost function or optimization function is defined as follows: first a true hybrid field is generated suppose it THF and then the estimated hybrid field is calculated during the optimization EHF

$$Cm_{sample} = \Sigma\left(\left|THF - EHF\right|\right)^2 \tag{7}$$

$$Cm = \frac{mean\left(Cm_{samples}\right)}{mean\left(Energy\right)} \tag{8}$$

At the end of optimization, the best parameters are chosen the resulted in minimum Cm

3.4 Machine learning approach

The machine learning-assisted resource allocation can be described by the following equations:

1- Far Field Channel Matrix H_{far}

$$H_{far} = \frac{1}{\sqrt{N_{far}}} \sum_{i=1}^{N_{far}} \alpha_{far,i} a_{far,i} b_{far,i}^{H}$$

2- Near Field Channel Matrix H_{near}

$$H_{near} = \frac{1}{\sqrt{N_{near}}} \sum_{i=1}^{N_{near}} \alpha_{near,i} a_{near,i} b_{near,i}^{H}$$

3- Hybrid Field Channel Matrix H_{hybrid}

$$H_{hybrid} = \sqrt{\rho} H_{far} + \sqrt{1-\rho} H_{near}$$

Mathematical Framework for Resource Allocation:

Far Field Channel Matrix (H_{far}):

The far field channel matrix represents the contributions from antennas in the far field. By employing the sum of scaled beamforming vectors ($a_{far,i}$ and $b_{far,i}$) weighted by the corresponding channel gains ($\alpha_{far,i}$), the matrix H_{far} characterizes the channel response in the far field. This formulation enables a detailed understanding of the spatial characteristics of the communication channel.

1- Near Field Channel Matrix (H_{near}):

Similar to the far field, the near field channel matrix (H_{near}) captures the contributions from antennas in proximity. The summation of scaled beamforming vectors ($a_{near,i}$ and $b_{near,i}$) weighted by the corresponding channel gains ($\alpha_{near,i}$) provides insights into the spatial dynamics of the near-field communication channel. This allows for a nuanced examination of channel behavior in close proximity.

Hybrid Field Channel Matrix (H_{hybrid}):

The hybrid field channel matrix (H_{hybrid}) synthesizes contributions from both the far and near fields, offering a balanced perspective on the communication channel. The parameter ρ governs the weight assigned to each field, enabling dynamic adaptation to changing network conditions. The hybrid approach acknowledges the distinct characteristics of the far and near fields, allowing for flexibility in resource allocation. By leveraging the spatial characteristics of the far and near fields, and dynamically adjusting the hybrid field based on real-time network conditions, our approach aims to optimize resource allocation in 6G networks. This comprehensive methodology not only refines system parameters but also adapts resource allocation dynamically, enhancing overall system efficiency and throughput.

4. Results and Discussion

Authors in [17], worked with frequency 30 GHz, in our case the frequency was set to 1 and 0.5 THz since 6G networks requires these frequencies or high frequencies in general to match real time conditions. starting with optimizing of Sparsity. After running the algorithms. Sparsity at the end of these iterations was 8. Setting the sparsity then to 8 and start to optimize number of beams and after got the tuned value, number of pilots is changed by Firefly to be tuned. The best values are shown below in Table 1.

Table 1. Final optimizations result of tuning parameters

Parameter	Value
Sparsity	8
Number of beams	600
Number of pilots	300

The simulation parameters are Sparsity, Number of beams and number of pilots. These are tested and tuned and the results in next experiments show how the error changes. The results with explanation are shown below. Each figure from figures below show the results of MSE of estimated hybrid field according to Equations (7-8).

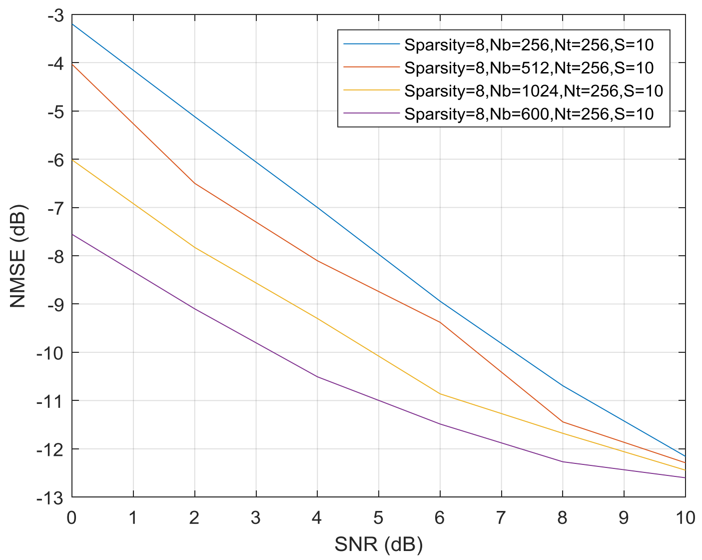

Fig. 2. Results of experiment when changing Number of beams

When value of sparsity is set to the value from FOA 8, FOA is tuning N_b, 4 values of N_b are plotted Figure 2-5, the estimated MSE are changed but best results (minimum MSE) are when $N_b = 600$. When value of sparsity is set to the value from FOA 8, and value of N_b is set to the value from FOA 600, FOA is tuning N_t, 2 values of N_t are plotted below, the estimated MSE are changed but best results (minimum MSE) are when $N_t = 300$.

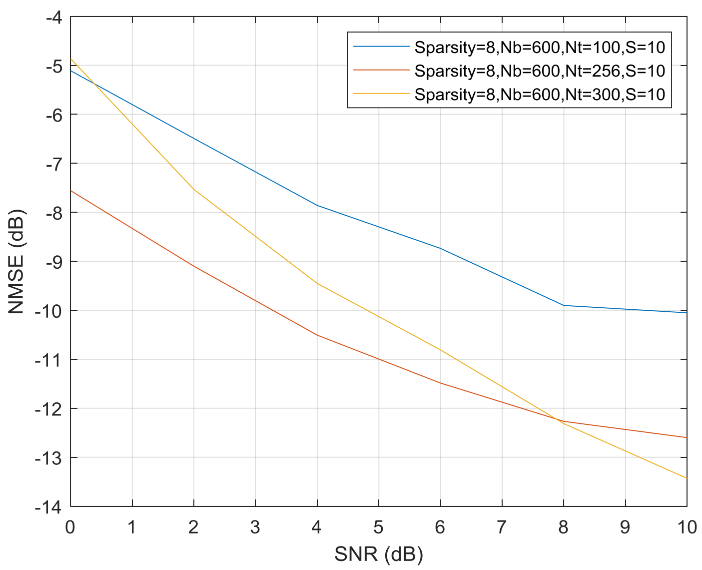

Fig. 3. Results of experiment when changing Number of pilots

Previous results were run for 10 samples. When running for 100 and 1000 samples with values obtained from FOA for all parameters, the results are in figure below

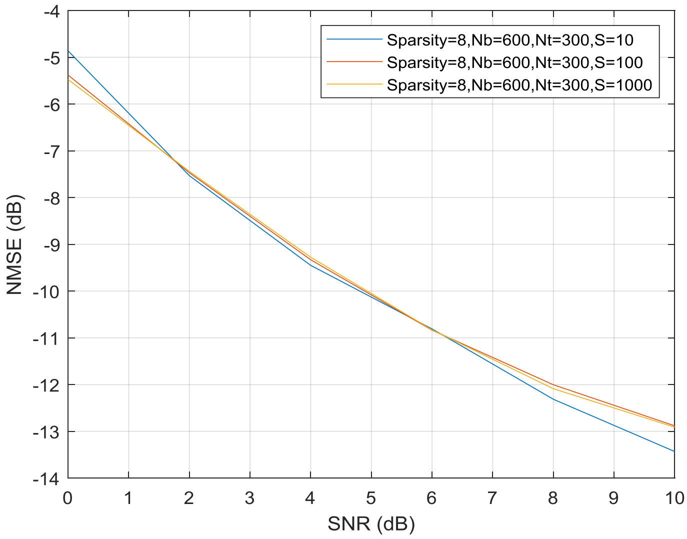

Fig. 4. Results of experiment when changing Number of samples

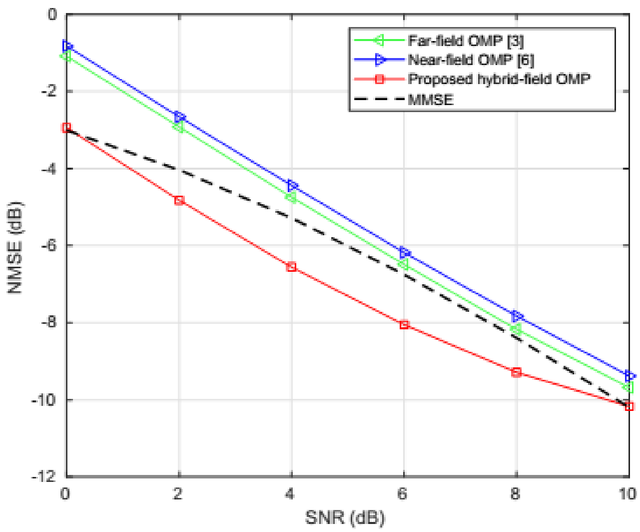

Fig. 5. Results from [17]

Figures above illustrates that tuning parameters has an effective impact on MSE of estimated fields, since the MSE is decreased to reach minimum value. Figure 5 shows results from the study [15]. Figure 4 shows final results of proposed method when changing samples, as the number of samples increased, this will be more likely real time simulation, 1000 samples were testing as max number of samples to compare with study [17], since authors adopted 1000 samples in their research. Results (the orange line Figure 4) are better than results in [15] (red line in Figure 5), near and far field with these values are almost the same. The Cost function error was changed during optimization as in Figure 5 (just for 10 iterations). Another comparing was made in figure 5 the frequency was 30 GHz when increasing frequency since the 6G network works till 1 THz, so this comparison made in Figure 7 and Figure 8, in case of frequency 1THz and 500. The result is that 1 THz is better than 500 GHz. Because the near field and far field are matched more than case 500 GHz.

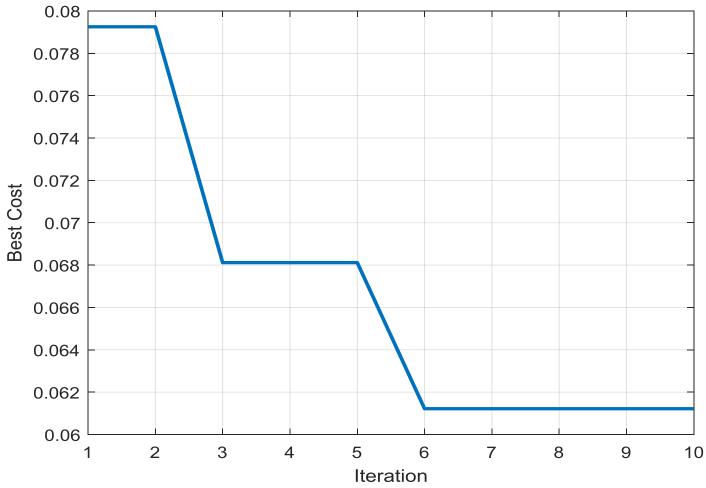

Fig. 6. Cost function curve during the process of FireFly

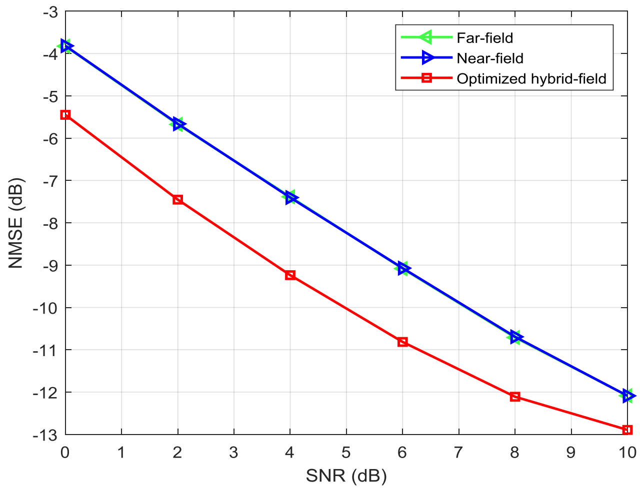

Fig. 7. Values from table 1 with $samples = 1000,\ fc = 1THz$

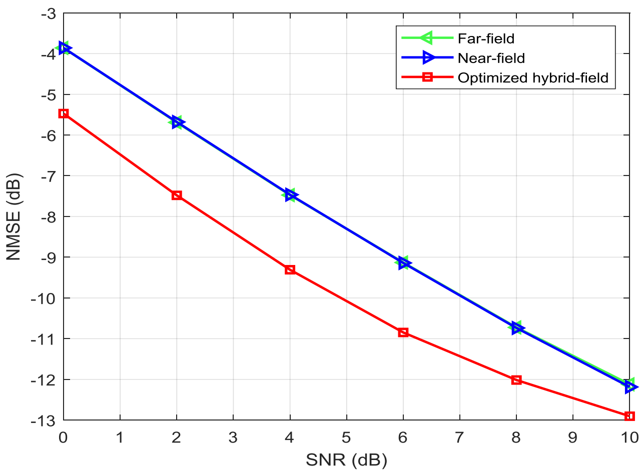

Fig. 8. Values from table 1 with $samples = 1000,\ fc = 0.5THz$

When varying the number of samples, our method approaches real-time simulation, achieving optimal results with 1000 samples—the same number used in [17] for comparability. This indicates that our method not only performs better but also maintains efficiency at higher sample volumes. Additionally, Figure 6 highlights the dynamic changes in the cost function error over just 10 iterations, underscoring the rapid convergence of our optimization process.

Further comparisons were made at different frequencies, notably 30 GHz, 500 GHz, and 1 THz, as depicted in Figures 7 and 8. The results show that at 1 THz, the near field and far field align more closely than at 500 GHz, affirming the potential of higher frequencies in 6G networks which operate up to 1 THz. This suggests that our method can effectively leverage higher frequency bands to enhance communication performance.

However, these results should be critically examined considering potential limitations. The computational complexity associated with the firefly optimization and machine learning integration could pose challenges for large-scale implementation. Additionally, while our method shows promising results with up to 1000 samples, real-world scenarios may require even larger datasets, which could impact performance and necessitate further optimization.

Future research should focus on addressing these limitations by developing more efficient algorithms that can handle larger datasets and exploring hybrid optimization techniques to enhance scalability. Additionally, investigating the impact of different environmental factors and network conditions on the performance of the proposed method would provide a more comprehensive understanding of its applicability in various real-world scenarios.

The integration of firefly optimization and machine learning in extremely large-scale MIMO systems can significantly enhance the performance and efficiency of various practical applications and real-world applications. One prominent use case is in 5G and beyond wireless networks, where these technologies can improve channel estimation and prediction, optimizing resource allocation dynamically. Beamforming optimization can be achieved through firefly algorithms, ensuring better signal quality and reduced interference. Furthermore, the management of massive device connectivity in high-density networks can be streamlined, ensuring reliable and low-latency communication for numerous connected devices.

In smart cities, efficient communication is crucial for traffic management systems and the coordination of IoT devices. Firefly optimization can enhance the performance of traffic signal control systems, allowing for real-time data transfer and adaptive traffic management. Similarly, the vast array of IoT devices used for environmental monitoring, public safety, and utility management can communicate more effectively, improving the overall functionality and responsiveness of smart city infrastructure.

The industrial Internet of Things (IIoT) also benefits greatly from optimized communication networks. In smart manufacturing environments, the integration of firefly optimization and machine learning ensures timely data exchange for real-time monitoring and automation. Predictive maintenance models rely on efficient communication networks to collect and analyze data promptly, preventing equipment failures and reducing downtime.

Autonomous vehicles and V2X (Vehicle-to-Everything) communication require highly reliable and low-latency networks. Optimizing communication protocols and resource allocation enhances the safety and efficiency of autonomous vehicle operations. This includes critical applications like collision avoidance and traffic signal warnings, which depend on rapid and accurate data transmission.

Despite the promising applications, integrating firefly optimization and machine learning for extremely large-scale MIMO systems networks faces several limitations, including computational complexity, scalability challenges, and the need for real-time processing capabilities. The algorithms may require substantial computational resources, which can hinder their practical implementation in large networks. Additionally, ensuring scalability and adapting to dynamic network conditions remain significant challenges. Future research should focus on developing more efficient algorithms, exploring hybrid optimization techniques, and leveraging advancements in hardware acceleration, such as GPUs and specialized processors, to enhance real-time processing and scalability of these integrated approaches.

5. Conclusion

In summary, the optimization algorithm successfully identified optimal values, leading to the best estimation of the hybrid channel in 6G MIMO systems. This methodology holds versatility, applicable to various network structures or models. Users need only comprehend the relevant parameters and their ranges, enabling the algorithm to iteratively refine the system and obtain values that minimize a specific term. The introduced approach, enriched by the integration of machine learning-assisted resource allocation, marks a significant stride toward enhancing the adaptability and efficiency of wireless communication systems in the era of 6G networks. The potential applications and contributions of this method extend to shaping the landscape of future wireless technologies.

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Authors' Profiles

Samar A. Nassar got her B.Sc. degree in Electrical Engineering and Communication from Ain Shams University in 2014 and her M.Sc. in Communication Engineering in The Vulnerability of Free Space Optical Communication Systems Against Severe Weather Conditions from Shoubra, Benha University in 2018. She is currently Teaching Assistant at Electrical Engineering Department, Electronic and Communications Division, Faculty of Engineering at Modern University for Technology and Information. Her research interests include Mobile communication, networks, Deep Learning and machine learning.

Adly S. Tag Eldien received the B.Sc., M.Sc.,and Ph.D. degrees from Benha University, Egypt, in 1984, 1989, and 1993, respectively. He is currently the Ex-Head of the Network and Information Center and the Head of the Electrical Engineering Department, Faculty of Engineering at Shoubra, Benha University. His research interests include robotics, networks, and mobile communication.

Esraa M. Eid got her B.Sc. degree in Electrical Engineering and Communication from Benha University in 2008 and her M.Sc. in Communication Engineering in Multicast Security in Long Term Evolution (LTE) Networks from Benha University in 2014 and she got her Ph.D. in Communication Engineering in Multiple Access Techniques in Mobile Next Generation Network from Benha University in 2019. She is currently an Assistant professor at Electrical Engineering Department, Electronic and Communications Division, Faculty of Engineering at Shoubra, Benha University. Her research interests include Mobile communication, machine learning, IoT.

Dr. Shimaa S. Ali obtained her PhD in Cloud Computing from the Faculty of Engineering at Shoubra in 2018. She is currently an assistant professor in the Department of Communication Engineering at the University of Benha. Her research interests include issues related to Cloud Computing, Deep Learning approaches, and RIS.

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