IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5568~5580
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp 5568-5580

Deep learning-based direction of arrival estimation using optimized sparse array configuration

Anughna Narayanaswamy[1], Ramesha Muniyappa[2], Anne Gowda Aleri Byregowda[3], Babu Nallur Venkateshappa[4]

[1]Department of Electronics and Communication Engineering, Amity University, Bengaluru, India
[2]Department of Electrical, Electronics and Communication Engineering, GITAM School of Technology, GITAM (Deemed to be University), Bengaluru, India
[3]Department of Electronics and Communication Engineering, Sri Venkateshwara College of Engineering, Visvesvaraya Technological University, Bengaluru, India
[4]Department of Electronics and Communication Engineering, SJB Institute of Technology, Visvesvaraya Technological University, Bengaluru, India

Article Info

Article history:

Received Jun 19, 2025
Revised Aug 7, 2026
Accepted Aug 31, 2026

Keywords:

Deep learning
Direction of arrival
DLIA-OSAC-EDOA
Massive multiple-input multiple-output
Modern wireless communication

ABSTRACT

Accurate direction of arrival (DOA) estimation is a critical component in 5th-generation (5G) massive multiple-input multiple-output (MIMO) systems, essential for improving data rates, power savings, and link reliability. This paper presents a novel approach to DOA estimation that combines optimized sparse array configuration (OSAC) with a deep learning-based integrated architecture (DLIA), termed DLIA-OSAC-enhanced DOA (EDOA). The proposed method leverages the optimized redundancy property of OSAC to enhance degrees of freedom (DOF) and mitigate mutual coupling (MC) effects. At the same time, the DLIA utilizes a deep learning-based novel EDOA network to improve estimation accuracy by using raw received signals through addressing multiple issues in DOA estimation, utilizing the customized deep learning architecture for enhanced feature extraction. The integration of OSAC and EDOA addresses the limitations of traditional methods, providing superior accuracy, robustness, and computational efficiency. Simulation results demonstrate that the DLIA-OSAC-EDOA significantly outperforms existing techniques, achieving lower root mean square error (RMSE) across various signal-to-noise ratio (SNR) levels and array imperfections. This approach offers a highly effective solution for DOA estimation in 5G MIMO systems, meeting the stringent requirements of modern wireless communication and radar-based applications.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Anughna Narayanaswamy
Department of Electronics and Communication Engineering, Amity University
Bengaluru, India
Email: anughna_12@rediffmail.com

1. INTRODUCTION

Massive multiple-input multiple-output (MIMO) systems have garnered significant interest in wireless communications due to their ability to offer higher data rates, potential power savings, and improved link reliability. Accurate direction of arrival (DOA) information is crucial for harnessing the full benefits of massive MIMO systems, as base stations (BS) rely on precise DOA data for effective downlink beamforming. With hundreds of antennas in a massive MIMO system, it is essential to maintain a manageable computational load for real-time implementations. DOA estimation has been a focal point of

research in the array signal processing (ASP) community for many years due to its critical role in localization and its applications in location-aware communications, vehicular networks, and virtual reality. Unlike time of arrival/time difference of arrival (TOA/TDOA) methods, which require precise clock synchronization, DOA is preferred for localization. Additionally, DOA information enables orientation estimation at the user side in high-frequency communication systems [1]–[3].

DOA estimation algorithms are typically utilized in digital arrays; however, assigning a radio-frequency chain (RFC) to each antenna in high-frequency communication systems is impractical due to the large array size. To address this, hybrid analogue-digital architectures have been proposed in MIMO systems, incorporating phase shifters (PSs), switches, or lenses. While PS-based structures are commonly used in MIMO systems, switch-based architectures have gained attention due to their reduced complexity and low power consumption, which are crucial for mobile devices. In switch-based arrays, a small number of RFCs are associated with a subset of antennas. Given that the geometry of the selected subarray impacts DOA estimation, a performance-optimizing criterion must be applied to the antenna selection process. The issue of DOA estimation in underdetermined scenarios has raised significant concern in radar, wireless communications, and radio astronomy. Utilizing a sparse array instead of a (ULA) is a viable solution as it offers more degrees of freedom (DOFs), an extended array aperture, and mitigated mutual coupling (MC) from the perspective of the virtual coarray. The performance of DOA estimation is highly dependent on the positions of the array sensors, making careful array design crucial. This design must consider physical constraints such as field conditions that may prevent optimal geometries and the limited number of sensors that can be deployed [4]–[6]. There are many conventional high-resolution DOA estimation algorithms, such as multiple signal classification (MUSIC), estimation of signal parameters via rotational invariance techniques (ESPRIT), and Capon. In ideal scenarios, these spatial spectrum estimation algorithms perform well by acquiring signal and noise subspaces through eigen decomposition of the signal's covariance matrix. However, these methods face significant limitations in non-uniform and low signal-to-noise ratio (SNR) environments, where the accuracy and reliability of DOA estimation can be compromised. Additionally, these conventional methods are computationally intensive, requiring real-time complex calculations that demand substantial computational resources and hardware capabilities. This results in prolonged processing times for predicting DOAs, which can be impractical in time-sensitive applications. The complexity of these algorithms can also lead to increased power consumption, limiting their applicability in resource-constrained environments. In dynamic settings where the DOAs of signals change rapidly, slow prediction speeds can negatively impact overall system performance [7]–[10].

To address these challenges, various alternative approaches have been explored, with machine learning (ML) emerging as a particularly promising option. ML algorithms can learn and adapt from data, making them highly versatile and capable of handling complex and dynamic environments. Unlike conventional methods that rely on predefined mathematical models, ML algorithms can discover patterns in data, enabling more accurate, and robust predictions. ML approaches, especially neural networks (NNs), reduce computational complexity and allow for swift predictions once the initial training phase is completed, eliminating the need for intricate real-time computations. Moreover, ML methods can handle a wide range of input data formats, facilitating seamless integration with different types of sensors and signal sources. Convolutional neural networks (CNNs), in particular, have demonstrated their effectiveness in tasks such as object detection, image recognition, and semantic segmentation. It is reasonable to expect that CNNs can also excel in DOA estimation when appropriately applied for this purpose [8], [9]. Deep learning-based methods struggle with robustness in the presence of MC, varying gains, and antenna position perturbations, significantly degrading the accuracy of DOA estimation. These non-ideal arrays often suffer from limitations in effective DOF due to these imperfections. Additionally, deep learning methods must contend with increased redundancy in non-ideal arrays because of overlapping virtual elements in the coarray, which can impact their overall performance.

2. RELATED WORK

Several academic endeavors have significantly guided the progression of DOA estimation research. A seminal study presented in [11] introduced a NN-based smart antenna for tracking multiple sources. This foundational work paved the way for subsequent advancements in smart antenna technology through the integration of NNs. The efficacy of antenna (convolutional recurrent neural networks (CRNNs)) in challenging acoustic environments is explored in [12]. Studies such as [13] and [14] focus on the robustness, noise resistance, and applicability of CNNs in broadband DOA estimation and source counting. The research by Huang *et al.* [15] delves into high-resolution channel and DOA estimation within massive MIMO systems, providing insights into the application of deep learning for enhanced system performance. The work in [16] addresses the challenges posed by array imperfections by developing a DOA estimation method based on deep neural networks (DNNs) that is inherently robust to such imperfections. The study in [17] introduces

a deep convolutional neural network (DCNN) that leverages sparse knowledge for accurate estimations. Additionally, Massa *et al.* [18] offer a comprehensive review of the application of DNNs in electromagnetics and antennas, providing a panoramic understanding of this evolving field. The ML approach to DOA estimation in noisy environments presented in [19] addresses a critical challenge in real-world applications. Various studies, including [20], [21], have focused on minimizing the computational overhead and processing time of DOA estimation. While most existing literature concentrates on linear antenna arrays, only a few, such as [22], explore deeper configurations like circular or planar arrays to address the DOA estimation challenge in three-dimensional space. In study [22], a modification to conventional beamforming methods specifically designed for realistic linear antenna arrays is proposed, emphasizing practical applicability and spatial signal processing. A discretization-free sparse and parametric approach for linear ASP is introduced in [23], establishing its statistical reliability with a varying number of snapshots under uncorrelated sources. The application and evolving significance of CNNs for DOA estimation in linear antenna arrays is further explored in [24]. The study in [25] presents an exploration of 5th-generation (5G) ULAs, employing beamforming and spatial multiplexing for outdoor urban communication at various gigahertz (GHz) frequencies, showcasing a robust two-level approach. Research in [26] and [27] leverages deep networks for DOA estimation in low SNR scenarios, demonstrating the adaptability of deep learning techniques in antenna arrays. In study [28], there is a focus on near-field DOA estimation in MIMO systems using a complex ResNet framework.

The study in [29] proposes a new class of planar arrays sparsely located on a two-dimensional (2D) lattice to achieve the highest DOF for a given number of sensors. The researchers formulate an optimization problem to find a hole-free 2D sparse array with the fewest possible sensors, converting it into a nonlinear binary problem and then into a binary linear programming problem, which is solved efficiently using branch and bound programming. The generalized multicascaded subarrays configuration (GMC-SC) system discussed in [30] cascades a series of identical subarrays following an effective placement strategy, significantly improving the number of DOFs and the effective aperture to enhance DOA estimation accuracy. Finally, a novel relocating enhanced nested array (RENA) configuration was designed in [31]. A comprehensive comparative analysis of annealed polylactic acid (PLA), offering insights into the mechanical properties relevant for structural evaluations in signal processing hardware. Compared to most existing sparse array configurations, the proposed RENA features a hole-free difference co-array, simple closed expressions for array geometry and DOFs, and achieves more consecutive DOFs. This study also improves a root multi-signal classification algorithm based on pseudo-noise subspace root multiple signal classification (PNS-root-MUSIC) for DOA estimation, which has lower algorithm complexity and takes full advantage of the larger hole-free co-array, yielding higher accuracy in DOA estimation.

3. PROPOSED METHODOLOGY

3.1. DLIA-OSAC-EDOA system modelling

In this section of the study focus on the estimation issue for the DOA in a real-time system and propose a deep-learning framework. Figure 1 shows the architectural framework of the deep learning-based integrated architecture (DLIA)-optimized sparse array configuration (OSAC)-enhanced DOA (EDOA) model. This study considers M distant-field signals and the $m\text{-}th$ signal where $m = 0,1, \dots, M\text{-}1$ is shown as $u_m(v)$ belongs E with the DOA denoted as φ_m belongs $(\frac{-\pi}{2}, \frac{\pi}{2})$. A system of linear arrays having P antennas are utilized for receiving signals and evaluating the DOA, in which μ denotes the wavelength. Considering the extra noise $y_p(v)$ belongs E the received signal at the $p\text{-}th$ antenna where $p = 0,1, \dots, P\text{-}1$ is formulated as given in (1). Considering (1), the proposed method take the $0\text{-}th$ antenna as a reference, implying $f_0 = 0$, the location of the $p\text{-}th$ antenna is f_p and for a linear uniform array, the antenna position $f_p = p\mu(2)^{-1}$.

$$t_p(v) = y_p(v) + i\left(z_p(v) + \sum_{p' not\ equal\ \ p} \left| \ D_{p,p'} z_{p'}(v)\right.\right) \quad (1)$$

Furthermore, in (2).

$$z_p(v) = \sum_{m=0}^{M\text{-}1} \ (u_m(v))(C_p g^{l\theta_p} g^{l2\pi(f_p(\mu)^{-1})sinsin\ \varphi_m}) \quad (2)$$

3.2. Problem definition

In the signal that is received, we consider the following non-ideal scenario issues that are taken into account. Firstly, the effect of MC, where the antennas are not isolated, introduces an effect between the signals that are received. The coefficient of mutual coupling among he $p\text{-}th$ as wellas e$p'\text{-}th$ antenna is given

as $D_{p,p'}$ belongs E with $|D_{p,p'}|$ lesser than 1 in (1). Secondly, the perturbation location refers to the position of the antenna that is not particularly at the desired location and could result in phase errors for the signals that are received by the antennas in the specific vector. Thirdly, the varying gains imply that the radio frequency channels generally do not have similar amplifiers and will result in differences relating to amplitude between the signals that are received. The $p\text{-}th$ antenna channel gain is expressed as C_p is greater than 0. Furthermore, the varying stages show the distinction between the channels of radio frequency that results in delay as well as phase errors for the signals that are received. The $p\text{-}th$ antenna phase channel is expressed as θ_p. Lastly, the non-linear effect for the radio frequency channels, as well as analogue to digital conversion, introduces this effect and degrades the evaluation performance of the DOA. Furthermore, overlapping virtual elements between their direct and sum coarrays do not enhance the unique degrees of freedom (uDOFs). The coarray redundant ratio, defined as the percentage of overlapping virtual sensors to the total number of uDOFs, can be minimized by reducing redundant sensors.

3.3. DLIA-OSAC-EDOA architecture

A non-linear function is used for the operation of receiving channels that are denoted as $i(\cdot)$. Therefore, the gathered signals are expressed as a vector that is formulated as given in (3). The DOA estimation issue could be formulated in the form of a parameter estimation issue, as the signals received are denoted as t. Prior existing studies have considered techniques with a perfect array, where the proposed method use $i(\cdot)$ as a linear function, and the coupling coefficient is given as $D_{p,p'}$ which is zero, $C_p = 1$ and $\theta_p = 0$ and know the location. f_p of the antenna.

$$t \triangleq [t_0(v), t_1(v), \ldots, t_{P\text{-}1}(v)]^V \tag{3}$$

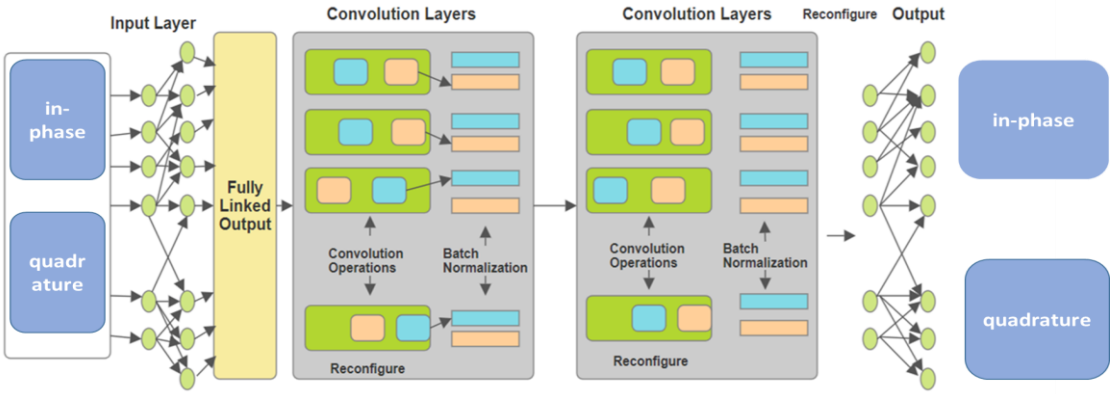

Figure 1. DLIA-OSAC-EDOA architecture

Although consider an array that is not perfect, its elements include the effect of MC, the varying stages, the varying gains, and the perturbations' location. Practically, the already existing DOA mechanisms do not outperform the traditional methods, wherein the DOA estimation mechanisms should contain perfect systems as well as an increased SNR. In this DLIA-OSAC-EDOA model aim to develop a robust upper solution for the DOA estimation with system effects that know from prior existing studies, where the DOA is estimated by calculating the highest score of spatial spectrums [16], [17]. This study proposes a deep learning EDOA network technique for estimating the DOA and term it as the EDOA. DOA network that includes more data and is trained more swiftly in comparison to the traditional matrix-based techniques. The architecture of the EDOA is shown in the Figure 1. Firstly, the signal is received, which is seen in (1), where it is denoted as a vector having in-phase as well as quadrature is shown in (4). Wherein the signal vector is received in (5). Here, the batch dimension is denoted as O_{batch}. the input signal is given as in (6).

$$a(v) \triangleq [[T^V\{t(v)\}, K^V\{t(v)\}]^V belongs\ T^{2P\times 1}] \tag{4}$$

$$t(v)=[t_0(v), t_1(v), \ldots\ldots, t_{P\text{-}1}(v)]^V belongs\ E^{P\times 1} \tag{5}$$

$$A \triangleq [a(0), a(1), \ldots\ldots, a(O_{batch}\text{-}1)]^V \tag{6}$$

The dimension is given as $O_{batch} \times 2P$. Further, as the DLIA-OSAC-EDOA network is based on a convolutional network, a fully linked layer is utilized as the input layer having an output size of $O_H O_K$, where the count of filters is expressed as O_H. For the layers of convolution and the inner dimension extension is expressed as O_K. After the initial layer, the size of the signal is $O_{batch} \times O_H O_K$ and the signal is reconfigured as a tensor expressed as $h_1(A)$ having size $O_{batch} \times O_H \times O_K$, in the function of the input layer is given as $h_1(\cdot)$. The tensor is sent to the layer of convolution, and the count of the layer is denoted as O_E. For every convolutional layer, a 1-dimensional convolution operation is performed, having the kernel dimension as $O_H \times O_M$. The dimension of the input is kept the same as the size of the convolutional output using the operation of padding. The output is given as $O_{batch} \times O_H \times O_K$. Further, the convolutional output has batch normalization implemented, and the output of normalization is expressed as $h_3(h_2(h_1(A)))$. The convolutional operation is expressed as $h_2(\cdot)$ and the operation of batch normalization is given as $h_3(\cdot)$ is shown in (7).

$$h_3(z)=(z\text{-}Mean\{z\})(Varience\{z\}+\omega)^{\frac{-1}{2}} \tag{7}$$

Here, the mean and variance of z are given as $Mean\{z\}$ and $Varience\{z\}$, respectively. For numerical stability, the proposed method adds a value ω to the denominator, which is equivalent to $\frac{1}{10^5}$. For every convolutional layer, the proposed method has a function rectified linear unit (ReLu), denoted as $h_4(\cdot)$ which is implemented to the batch normalization output and is expressed as given in (8). After the layers of convolution, a fully linked layer is utilized as output, with the dimensions of input as well as output given as $O_{batch} \times O_K O_H$ as well as $O_{batch} \times 2P$, respectively. The output of the DLIA-OSAC-EDOA network is given as in (9).

$$h_4(z)=maximum\ (0,z) \tag{8}$$

$$I=h_5(h_4\left(h_3\left(h_2\left(h_4(\dots h_4(\dots h_2(h_1(A))\dots)\dots)\right)\right)\right)) \tag{9}$$

Then, the expression in (10) can be obtained.

$$I \triangleq [i(0), i(1), \dots, i(O_{batch}\text{-}1)] belongs\ T^{2P \times O_{batch}} \tag{10}$$

The corresponding vector has high complexity and is taken from the output of the network $i(O)(O=0,1,\dots,O_{batch}\text{-}1)$ given as in (11). Considering in (10), the sub-vector of $i(O)$ is given as $i_{0:P\text{-}1}(O)$ having index ranging from 0 to P-1, $i_{P:2P\text{-}1}(O)$ expresses the range from P to $2P$-1. Having an output b from the DLIA-OSAC-EDOA network, the spatial spectrum is evaluated as in (12).

$$b(O) \triangleq i_{0:P\text{-}1}(O)+li_{P:2P\text{-}1}(O) \tag{11}$$

$$h_{Spec}(\chi)=|c^J(\chi)b|^2 \tag{12}$$

Here, χ is selected based on the detected area, such that it ranges from $\frac{-\pi}{2}$ to $\frac{\pi}{2}$. The DLIA-OSAC-EDOA DOA network introduces an ideal method in comparison to traditional approaches. Distinct from traditional approaches, the network uses sampled information that is raw for input and also uses layers of convolution for retrieval of features from this raw information. By the use of this raw information, which possesses all the data of the signals that are received, we attain a vector that is the output of the network. This vector is different from the DOA results or the spectrum utilized by prior methods. Specifically, the output vector dimension matches the count of antennas present in the array, which leads to a decreased dimension in comparison to the networks that produce the spectrum as output. However, the period for training has noticeably decreased. Further, we obtain the DOA by gaining the highest value of $h_{Spec}(\chi)$ from (12), which omits the issue of adopting the number of signals that are received within the network by utilizing the value of DOA as the output.

3.4. Optimized redundancy array

In many existing sparse array configurations [9], [31], overlapping virtual elements between their direct and sum coarrays do not enhance the uDOFs. The coarray redundant ratio, defined as the percentage of

overlapping virtual sensors to the total number of uDOFs, can be minimized by reducing redundant sensors. This research proposes a minimum redundancy array design using a two-level sparse array. To ensure minimum redundancy, the design follows specific strategies for direct and sum coarrays to avoid overlapping virtual sensors and holes.

3.5. Optimized array design

Let's consider a dual-level sparse array comprising. P=P_1+P_2 sensors characterized through N=$N_r UN_s$. To achieve the minimum redundancy, the designed array configuration aims to reduce the overlapping of sensors between difference coarray (DCA) and the sum coarray (SCA). The array comprises P sensors and is divided into three subarrays N_r, $N_s \wedge N_{s2}$. The equations at the first level are shown in (13). Here the DOF is provided as $4(P_1^2\text{-}P_1\text{+}2P_2)\text{+}1$. Similarly, at the second level, the MC effects are reduced, as shown in (14). Here the degree of freedom is given as $4(P_0^2\text{+}6P_0\text{-}3)$.

$$N_r=\{((n_s\text{-}1)P_1+\tfrac{P_2}{2})(n_s \in [P_{1,}1]\}$$
$$N_s=\{((P_1^2\text{-}1)P_1+P_2+n_s)(n_s \in [P_{1,}1]\} \quad (13)$$

$$N_r'=\{(1+(n_s\text{-}1)P_0)(n_s \in [P_{0,,}0]\}$$
$$N_s^{1\prime}=\{(P_0^2+P_0+n_s), n_s \in [2,\ldots 2p,\ldots .P_0\text{-}2]\}$$
$$N_s^{1\prime}=\{(P_0^2+n_s)+n_s), n_s \in [1,\ldots 3,\ldots 2p\text{+}1,\ldots .P_0\text{-}3, P_o\text{-}1]U(P_0))\} \quad (14)$$

The optimized sparse array configuration significantly reduces redundancy and increases the DOFs by carefully designing the sensor placement to avoid overlapping virtual elements in the coarray. By utilizing the sum-difference coarray (SDCA) concept, the framework ensures that there are no redundant lags between the DCA and SCA. This is achieved by configuring the sensor positions such that the longest consecutive segments of the DCA and SCA are geometrically continuous without any overlap. For the first level, this involves specific sensor placement rules that maximize the non-redundant virtual sensor positions, leading to a higher number of uniform DOFs. The second level builds on this by rearranging the dense subarrays of the second level to reduce MC effects while maintaining the minimum redundancy property. Further ensures that the virtual array maintains its integrity despite the changes. The result is an array configuration that maximizes the utilization of each sensor pair, enhancing the array's ability to resolve more sources with higher accuracy. This efficient use of the virtual array elements not only increases the DOFs but also improves the overall performance of the array in practical applications like DOA estimation.

3.6. DLIA-OSAC-EDOA model training

The training of the DLIA-OSAC-EDOA network $h_{Spec}(\chi)$. The spatial spectrum is taken from (15), and the spectrum that is referred to is given in (15). Here, Gaussian functions are utilized for spatial spectrum approximation. The value of the spectrum is denoted as C_m, the standard deviation is given as δ_I for the Gaussian function. For this study, the values of the standard deviation are set as given in (16). Considering the referred spectrum, the proposed method expressed the loss function as given in (17). In this case, $h_{RefSpec}(\chi)$ belongs $T^{\varrho\times 1}$ and $h_{Spec}(\chi)$ belongs $T^{\varrho\times 1}$ are vectors with $\rho\text{-}th$ entry where ρ=0,1, …, ϱ-1 being $h_{RefSpec}(\chi_\varrho)$ and $h_{Spec}(\chi_\varrho)$, respectively. Therefore, the proposed method express in (18).

$$h_{RefSpec}(\chi)=\sum_{m=0}^{M\text{-}1} C_m g^{\frac{\text{-}(\chi\text{-}\varphi_m)^2}{\delta_I^2}} \quad (15)$$

$$\delta_I=\frac{\delta_I}{P} \quad (16)$$

$$h_{loss}(\chi)=(\varrho)^{\text{-}1}\left(\left|\left|h_{RefSpec}(\chi)\text{-}h_{Spec}(\chi)\right|\right|_2^2\right) \quad (17)$$

$$\chi \triangleq [\chi_0,\ldots.,\chi_{\varrho\text{-}1}]^V \quad (18)$$

Here, the count of spatial angles that is discretized is denoted as ϱ. The DLIA-OSAC-EDOA network is trained to reduce the loss of function $h_{loss}(\chi)$ in (15) by the coefficients of the network. In the real-time system, the effect of MC, the non-linear effect, the varying gains, the varying stages, and the perturbation location are considered and taken into account while training the DLIA-OSAC-EDOA network. Algorithm 1 shows the steps while training the DLIA-OSAC-EDOA network.

Algorithm 1. The proposed training

Step 1: The signals that are received by utilizing the perfect array, omitting the imperfect effect, are implemented at the time of training.

Step 2: The signals received with *Perturbations location* are implemented. The *Perturbation location* is derived from Gaussian distribution where $Mean = 0$ and the standard deviation δ_{per} chosen via uniform distribution $\delta_{per}\ belongs\ \left[0, \delta_{maximum_{per}}\right]$. $\delta_{maximum_{per}}$ is set during simulation.

Step 3: The varying gains are introduced when the mean of Gaussian distribution is zero and the standard deviation δ_{gain} is $\delta_{gain}\ belongs\ \left[0, \delta_{maximum_{gain}}\right]$. $\delta_{maximum_{gain}}$ is defined during simulation.

Step 4: The varying stages are introduced when the mean of Gaussian distribution is zero and standard deviation δ_{stage} is $\delta_{stage}\ belongs\ \left[0, \delta_{maximum_{stage}}\right]$. $\delta_{maximum_{stage}}$ is defined during simulation.

Step 5: MC effect is defined using matrix D with entries that have a high complexity and the diagonal entries are equivalent to 1. The $p\text{-}th$ row entry as well as the $p'\text{-}th$ column is expressed as $D_{p,p'}=|D_{p,p'}|g^{l\alpha_{p,p'}}$

Step 6: A uniform distribution is used to determine $|D_{p,p'}|$ where $|D_{p,p'}|\ belongs\ [0, \delta_{couple}^{|p\text{-}p'|}]$ while $p\ is\ not\ equal\ p'$. The stage $\alpha_{p,p'}$ has a uniform distribution $l\alpha_{p,p'}\ belongs\ [0,2\pi)$. δ_{couple} is defined during simulation.

Step 7: A non-linear function is used to express this effect $h_{nonlinear}(z)$=$tanhtanh\ (z\delta_{nonlinear})$ The $\delta_{nonlinear}$ is particular to the simulation to manage the nonlinear effect. The function $tanhtanh\ (\cdot)$ is implemented as the non-linear function.

Step 8: Generally, various other activation functions could also be used, and the selection of the activation function has negligible impact on DOA estimation performance.

4. PERFORMANCE EVALUATION

DOA estimation is a critical component in 5G MIMO systems, essential for improving data rates, power savings, and link reliability. This paper presents a novel approach to DOA estimation that combines OSAC with a DLIA, termed DLIA-OSAC-EDOA. The DLIA-OSAC-EDOA method leverages the minimum redundancy property of OSAC to enhance DOF and mitigate MC effects. At the same time, the DLIA utilizes a deep learning-based EDOA to improve estimation accuracy by using raw received signals instead of covariance matrices. The integration of OSAC and EDOA addresses the limitations of traditional methods, providing superior accuracy, robustness, and computational efficiency. Simulation results demonstrate that the DLIA-OSAC-EDOA significantly outperforms existing techniques, achieving lower root mean square error (RMSE) across various SNR levels and array imperfections. This approach offers a highly effective solution for DOA estimation in 5G MIMO systems, meeting the stringent requirements of modern wireless communication and radar-based applications. The simulation settings used for training and testing are listed in Table 1.

Table 1. Simulation parameters of the DLIA-OSAC-EDOA model

Parameter	Value
DLIA-OSAC-EDOA_Batch_Size	128
DLIA-OSAC-EDOA_Layer	8
DLIA-OSAC-EDOA_filter	2
DLIA-OSAC-EDOA_LR (learning rate)	5×10^{-4}
DLIA-OSAC-EDOA_antenna_distance	0.5
MC_effect	0.06

The simulation parameters in Table 1 outline a detailed configuration of the system, showcasing the complexities involved in designing a robust antenna array for signal processing. The standard deviation in the Gaussian function is set to 100, indicating a wide data spread, which affects signal variability. A batch size of 64 strikes a balance between computational efficiency and gradient accuracy during NN training. With six convolution layers and two filters per layer, the network captures complex patterns while remaining lightweight. A kernel size of three ensures effective feature capture and computational efficiency. The learning rate is set to facilitate stable model convergence. Antennas are spaced at half-wavelength intervals (0.5 λ), balancing spatial resolution and array size. Position perturbation, inconsistent gain, and phase variability are capped at 0.15, 0.5, and 0.5, respectively, highlighting the need to manage these inconsistencies to maintain system performance. The MC effect is limited to 0.06, addressing antenna

interaction in dense arrays, indicating the significant impact of system nonlinearities on signal integrity. These parameters collectively underscore the intricate considerations necessary for effective antenna array system simulation and design.

4.1. Comparison algorithm

Existing methodologies, as in [32]–[35] for DOA estimation, include several notable approaches. The MUSIC method utilizes the covariance matrix derived from multiple snapshots and employs eigenvalue decomposition to estimate DOA. To enhance performance, a snapshot-based MUSIC algorithm uses a Hankel data matrix and Vandermonde decomposition. The atomic norm minimization (ANM), taking advantage of the sparsity of targets in the spatial domain to estimate DOA in the continuous domain, thus overcoming the off-grid problems associated with compressed sensing (CS) methods that use discretized spatial grids and dictionary matrices. The fast Fourier transform (FFT) method is popular in practical systems due to its low computational complexity, although its resolution is often unsatisfactory. Despite this, the FFT method remains robust against array imperfections. The orthogonal matching pursuit (OMP) method is another CS-based technique that uses discretized spatial angles for DOA estimation. It is favored for its relatively low computational complexity and effectiveness in sparse reconstruction problems.

4.2. Results

Figure 2 illustrates the relationship between the RMSE of DOA estimation and the SNR for seven different layers in a deep learning network. The analysis reveals that RMSE decreases as SNR increases for all layers, indicating that higher SNR levels lead to more accurate DOA estimations. Notably, Layer3 consistently demonstrates the lowest RMSE across all SNR levels, making it the most effective for accurate DOA estimation. In contrast, Layer1 and Layer2 perform well but are slightly less accurate than Layer3, while Layer4 through Layer7 exhibit higher RMSE values, indicating lower accuracy. At low SNR levels (0 to 10 dB), there is a significant improvement in RMSE, showing the network's capability to leverage better signal conditions. However, despite these improvements, none of the layers achieve the target RMSE of less than 0.2°, even at the highest SNR of 30 dB. This suggests the need for further optimization of the network, particularly focusing on Layer3, which shows the best performance.

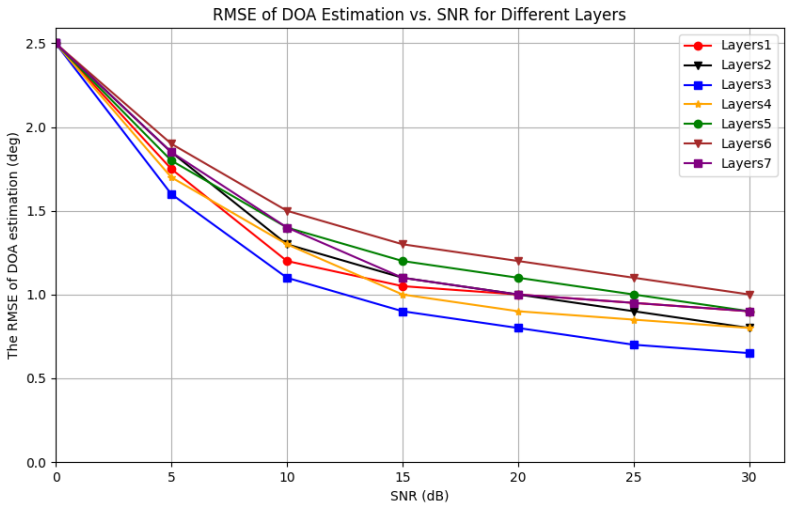

Figure 2. RMSE of DOA estimation versus SNR for the DLIA-OSAC-EDOA network with different numbers of convolutional layers (Layer1–Layer7)

Figure 3 shows that the DLIA-OSAC-EDOA method consistently achieves the lowest RMSE across all SNR levels, indicating superior accuracy in DOA estimation compared to ES1, ES2, and ES3. At low SNR levels (0 to 10 dB), the DLIA-OSAC-EDOA method significantly reduces RMSE under 1°, while ES1 and ES2 remain higher, and ES3 performs poorly with minimal improvement. At high SNR levels (20 to 30 dB), the DLIA-OSAC-EDOA method maintains an RMSE close to or under 0.5°, demonstrating its robustness, whereas ES1 and ES2 show RMSE values slightly above 1°, and ES3 remains ineffective with high RMSE.

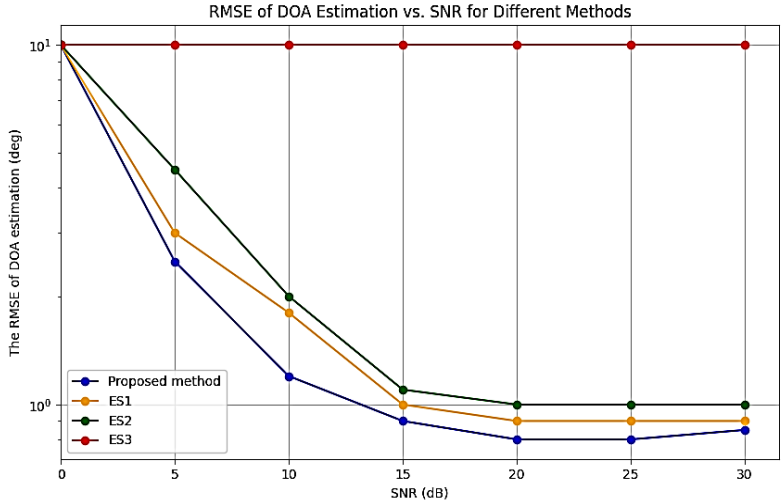

Figure 3. RMSE of DOA estimation versus SNR for the proposed DLIA-OSAC-EDOA method and the existing methods ES1, ES2, and ES3

Figure 4 shows the performance comparison of the DLIA-OSAC-EDOA method against three existing methods (ES1, ES2, and ES3) in terms of the RMSE of DOA estimation across various SNR levels. The DLIA-OSAC-EDOA method (red line) consistently exhibits the lowest RMSE across all SNR levels, demonstrating superior accuracy in DOA estimation. At lower SNR levels (0 to 10 dB), the DLIA-OSAC-EDOA method significantly reduces RMSE under 2°, while ES1, ES2, and ES3 remain above 2°. At higher SNR levels (20 to 30 dB), the DLIA-OSAC-EDOA method maintains an RMSE close to 1°, whereas the other methods show RMSE values between 1.5° and 2°. This analysis highlights the effectiveness and robustness of the DLIA-OSAC-EDOA method, making it a preferable choice for achieving high accuracy in DOA estimation for 5G MIMO systems.

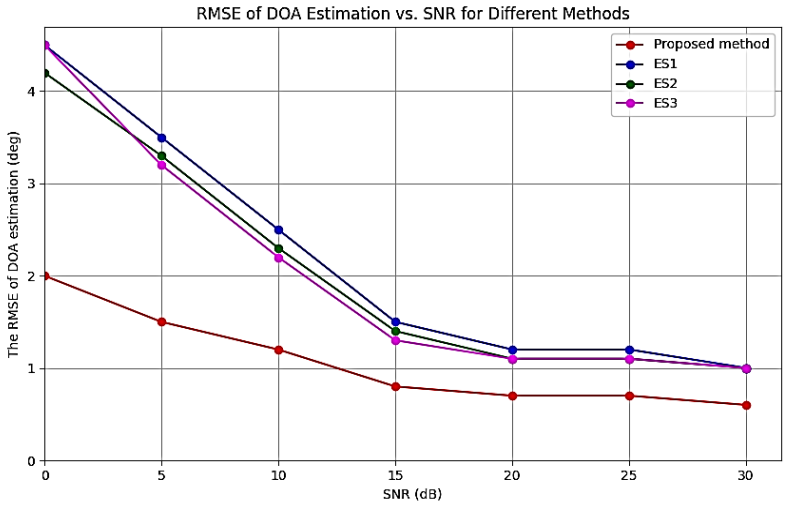

Figure 4. DOA estimation over various SNRs

Figure 5 demonstrates that the DLIA-OSAC-EDOA method consistently achieves the lowest RMSE across all levels of array imperfections, indicating superior robustness and accuracy compared to ES1, ES2, ES3, and ES4. As the imperfection factor increases, the RMSE of all methods rises, but the DLIA-OSAC-EDOA method maintains an RMSE under 1.0° even at the highest imperfection level, whereas other methods exceed 1.5°. This highlights the DLIA-OSAC-EDOA method's effectiveness in handling imperfections, though further optimization may be needed to achieve the target RMSE of less than 0.2° under high imperfection conditions.

The graph in Figure 6 shows that RMSE decreases as SNR increases for all filter configurations, indicating improved accuracy with higher SNR. The 6-filter configuration consistently achieves the lowest RMSE across all SNR levels, making it the optimal choice. Configurations with 2 and 4 filters perform well, especially at higher SNR levels, but are slightly less accurate than the 6-filter configuration. In contrast, configurations with 8 and 10 filters exhibit higher RMSE, suggesting that more filters do not necessarily improve accuracy and may slightly worsen it. Overall, the 6-filter configuration balances complexity and performance most effectively, achieving the highest accuracy in DOA estimation.

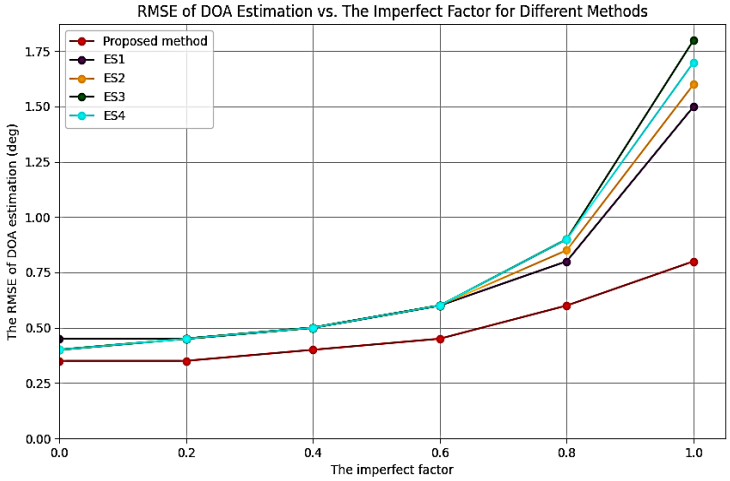

Figure 5. RMSE DOA comparison (factor)

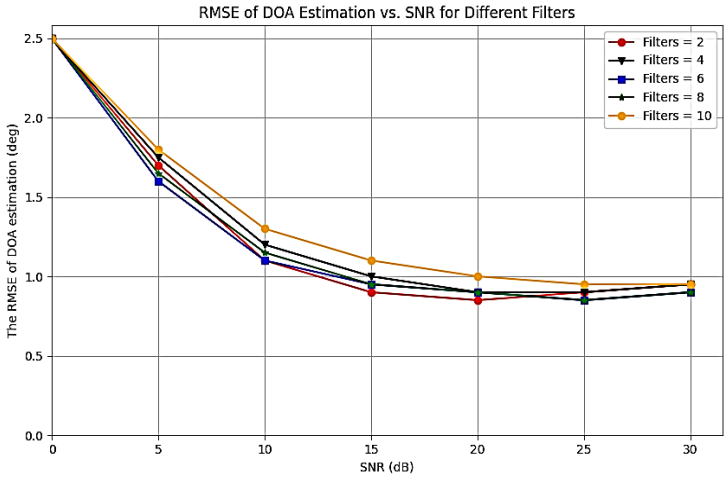

Figure 6. DOA versus different filters

4.3. Comparative analysis

The performance evaluation of the DLIA-OSAC-EDOA method demonstrates its significant superiority over existing DOA estimation methods, such as ES1, ES2, ES3, and ES4. The DLIA-OSAC-EDOA consistently achieves lower RMSE across various SNR levels, showcasing enhanced estimation accuracy. Notably, Layer3 of the deep learning network achieves the lowest RMSE, making it the most effective for accurate DOA estimation. When compared to ES1, ES2, and ES3, the DLIA-OSAC-EDOA method outperforms in all SNR conditions, significantly reducing RMSE under 1° at low SNR levels (0 to 10 dB) and maintaining an RMSE close to or under 0.5° at high SNR levels (20 to 30 dB). Furthermore, the DLIA-OSAC-EDOA method demonstrates superior robustness to array imperfections, maintaining an RMSE under 1.0° even at the highest imperfection levels, while other methods exceed 1.5°. Additionally, the evaluation of different filter configurations reveals that the 6-filter configuration achieves the lowest RMSE across all SNR levels, balancing complexity and

performance most effectively. Overall, the DLIA-OSAC-EDOA method provides enhanced accuracy, robustness, and computational efficiency, making it a superior solution for DOA estimation in 5G MIMO systems. This integrated approach addresses the stringent requirements of modern wireless communication and radar-based applications, pushing the boundaries of current DOA estimation technologies.

5. CONCLUSION

This research presents a novel approach for DOA estimation in 5G MIMO systems, combining OSAC with a DLIA, termed DLIA-OSAC-EDOA. The DLIA-OSAC-EDOA method effectively addresses the limitations of traditional DOA estimation techniques by leveraging the optimized redundancy property of OSAC to enhance DOF and mitigate MC effects. Concurrently, the deep learning-based EDOA improves estimation accuracy by using raw received signals through enhanced feature extraction. The methodology involves designing two-level sparse arrays to ensure minimum redundancy. The EDOA network, implemented as a CNN, processes the received signals and outputs a spatial spectrum, enabling accurate DOA estimation even in the presence of array imperfections. Performance evaluations demonstrate that the DLIA-OSAC-EDOA significantly outperforms existing techniques, achieving lower RMSE across various SNR levels and array imperfections. Specifically, the 6-filter configuration consistently achieves the lowest RMSE, indicating it as the optimal choice for balancing complexity and performance. The DLIA-OSAC-EDOA method maintains high accuracy and robustness, with superior performance in both low and high SNR conditions, as well as under varying levels of array imperfections. Future work may focus on further optimizing the network and array configurations to achieve even lower RMSE and exploring real-world implementations to validate the DLIA-OSAC-EDOA system's practical applicability.

ACKNOWLEDGEMENT

The authors would like to express our sincere gratitude to all those who have supported and contributed to this research project. Primarily, the authors extend our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process.

FUNDING INFORMATION

No funding is raised for this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Anughna Narayanaswamy	✓	✓	✓		✓	✓		✓	✓	✓	✓		✓	
Ramesha Muniyappa	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		
Anne Gowda Aleri Byregowda	✓	✓		✓	✓	✓		✓	✓	✓		✓		
Babu Nallur Venkateshappa	✓	✓	✓		✓	✓	✓		✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

DATA AVAILABILITY

No datasets utilized in this research.

REFERENCES

[1] A. M. Haimovich, R. S. Blum, and L. J. Cimini, "MIMO radar with widely separated antennas," *IEEE Signal Processing Magazine*, vol. 25, no. 1, pp. 116–129, 2008, doi: 10.1109/MSP.2008.4408448.

[2] W. Zhang, W. Liu, J. Wang, and S. Wu, "Joint transmission and reception diversity smoothing for direction finding of coherent targets in MIMO radar," *IEEE Journal on Selected Topics in Signal Processing*, vol. 8, no. 1, pp. 115–124, 2014, doi: 10.1109/JSTSP.2013.2285520.

[3] H. Chen, T. Ballal, and T. Y. A.-Naffouri, "DOA estimation with non-uniform linear arrays: a phase-difference projection approach," *IEEE Wireless Communications Letters*, vol. 10, no. 11, pp. 2435–2439, 2021, doi: 10.1109/LWC.2021.3102402.

[4] X. Zhan *et al.*, "Rapid phase ambiguity elimination methods for DOA estimator via hybrid massive MIMO receive array," *Chinese Journal of Electronics*, vol. 33, no. 1, pp. 175–184, 2024, doi: 10.23919/cje.2022.00.112.

[5] L. Tosi, P. Rocca, N. Anselmi, and A. Massa, "Array-antenna power-pattern analysis through quantum computing," *IEEE Transactions on Antennas and Propagation*, vol. 71, no. 4, pp. 3251–3259, 2023, doi: 10.1109/TAP.2023.3242128.

[6] D. Hu, Y. Zhang, L. He, and J. Wu, "Low-complexity deep-learning-based DOA estimation for hybrid massive MIMO systems with uniform circular arrays," *IEEE Wireless Communications Letters*, vol. 9, no. 1, pp. 83–86, 2020, doi: 10.1109/LWC.2019.2942595.

[7] N. Anughna and M. Ramesha, "Multiplicative basis function based adaptive DOA estimation in optimal MIMO sparse antenna reconfiguration model," *IETE Journal of Research*, vol. 70, no. 9, pp. 7219–7230, 2024, doi: 10.1080/03772063.2024.2351554.

[8] N. Amani, F. Jansen, A. Filippi, M. V. Ivashina, and R. Maaskant, "Sparse automotive MIMO radar for super-resolution single snapshot DOA estimation with mutual coupling," *IEEE Access*, vol. 9, pp. 146822–146829, 2021, doi: 10.1109/ACCESS.2021.3122967.

[9] Z. Zheng, W. Q. Wang, Y. Kong, and Y. D. Zhang, "MISC array: a new sparse array design achieving increased degrees of freedom and reduced mutual coupling effect," *IEEE Transactions on Signal Processing*, vol. 67, no. 7, pp. 1728–1741, 2019, doi: 10.1109/TSP.2019.2897954.

[10] S. Li and X. P. Zhang, "A new approach to construct virtual array with increased degrees of freedom for moving sparse arrays," *IEEE Signal Processing Letters*, vol. 27, pp. 805–809, 2020, doi: 10.1109/LSP.2020.2993956.

[11] A. H. E. Zooghby, C. G. Christodoulou, and M. Georgiopoulos, "A neural network-based smart antenna for multiple source tracking," *IEEE Transactions on Antennas and Propagation*, vol. 48, no. 5, pp. 768–776, 2000, doi: 10.1109/8.855496.

[12] S. Adavanne, A. Politis, J. Nikunen, and T. Virtanen, "Sound event localisation and detection of overlapping sources using convolutional recurrent neural networks," *IEEE Journal on Selected Topics in Signal Processing*, vol. 13, no. 1, pp. 34–48, 2019, doi: 10.1109/JSTSP.2018.2885636.

[13] S. Chakrabarty and E. A. P. Habets, "Broadband DOA estimation using convolutional neural networks trained with noise signals," *IEEE Workshop on Applications of Signal Processing to Audio and Acoustics*, pp. 136–140, 2017, doi: 10.1109/WASPAA.2017.8170010.

[14] T. N. T. Nguyen, W. S. Gan, R. Ranjan, and D. L. Jones, "Robust source counting and DOA estimation using spatial pseudo-spectrum and convolutional neural network," *IEEE/ACM Transactions on Audio Speech and Language Processing*, vol. 28, pp. 2626–2637, 2020, doi: 10.1109/TASLP.2020.3019646.

[15] H. Huang, J. Yang, H. Huang, Y. Song, and G. Gui, "Deep learning for super-resolution channel estimation and DOA estimation based massive MIMO system," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 9, pp. 8549–8560, 2018, doi: 10.1109/TVT.2018.2851783.

[16] Z. M. Liu, C. Zhang, and P. S. Yu, "Direction-of-arrival estimation based on deep neural networks with robustness to array imperfections," *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 12, pp. 7315–7327, 2018, doi: 10.1109/TAP.2018.2874430.

[17] L. Wu, Z. M. Liu, and Z. T. Huang, "Deep convolution network for direction of arrival estimation with sparse prior," *IEEE Signal Processing Letters*, vol. 26, no. 11, pp. 1688–1692, 2019, doi: 10.1109/LSP.2019.2945115.

[18] A. Massa, D. Marcantonio, X. Chen, M. Li, and M. Salucci, "DNNs as applied to electromagnetics, antennas, and propagation—a review," *IEEE Antennas and Wireless Propagation Letters*, vol. 18, no. 11, pp. 2225–2229, 2019, doi: 10.1109/LAWP.2019.2916369.

[19] X. Xiao, S. Zhao, X. Zhong, D. L. Jones, E. S. Chng, and H. Li, "A learning-based approach to direction of arrival estimation in noisy and reverberant environments," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, 2015, pp. 2814–2818, doi: 10.1109/ICASSP.2015.7178484.

[20] M. S. Saeed, R. Saurabh, S. B. Bhasme, and A. N. Nazarov, "Machine learning based intrusion detection system in cloud environment," *2022 VIII International Conference on Information Technology and Nanotechnology*, Samara, Russian Federation, 2022, pp. 1-6, doi: 10.1109/ITNT55410.2022.9848611.

[21] K. Wu, W. Ni, T. Su, R. P. Liu, and Y. J. Guo, "Recent breakthroughs on angle-of-arrival estimation for millimetre-wave high-speed railway communication," *IEEE Communications Magazine*, vol. 57, no. 9, pp. 57–63, 2019, doi: 10.1109/MCOM.001.1800966.

[22] Z. D. Zaharis, I. P. Gravas, P. I. Lazaridis, T. V. Yioultsis, C. S. Antonopoulos, and T. D. Xenos, "An effective modification of conventional beamforming methods suitable for realistic linear antenna arrays," *IEEE Transactions on Antennas and Propagation*, vol. 68, no. 7, pp. 5269–5279, 2020, doi: 10.1109/TAP.2020.2977822.

[23] Z. Yang, L. Xie, and C. Zhang, "A discretization-free sparse and parametric approach for linear array signal processing," *IEEE Transactions on Signal Processing*, vol. 62, no. 19, pp. 4959–4973, 2014, doi: 10.1109/TSP.2014.2339792.

[24] R. Saurabh, S. B. Bhasme, M. S. Saeed, C. Kumar, and A. Nazarov, "Masquerading email detection," *2022 VIII International Conference on Information Technology and Nanotechnology (ITNT),* Samara, Russian Federation, 2022, pp. 1-4, doi: 10.1109/ITNT55410.2022.9848745.

[25] J. Lota, S. Sun, T. S. Rappaport, and A. Demosthenous, "5G uniform linear arrays with beamforming and spatial multiplexing at 28, 37, 64, and 71 GHz for outdoor urban communication: a two-level approach," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 11, pp. 9972–9985, 2017, doi: 10.1109/TVT.2017.2741260.

[26] G. Papageorgiou, M. Sellathurai, and Y. Eldar, "Deep networks for direction-of-arrival estimation in low SNR," *IEEE Transactions on Signal Processing*, vol. 69, pp. 3714–3729, 2021, doi: 10.1109/TSP.2021.3089927.

[27] J. Yu and Y. Wang, "Deep learning-based multipath DoAs estimation method for mmWave massive MIMO systems in low SNR," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 6, pp. 7480–7490, 2023, doi: 10.1109/TVT.2023.3239402.

[28] N. Nagarajappa and N. K. Bhoganna, "DTPRA: Dynamic traffic and priority-aware resource allocation with admission control in highly dense heterogeneous wireless networks," *Engineering, Technology & Applied Science Research,* vol. 15, no. 6, pp. 28796–28803, Dec. 2025, doi: 10.48084/etasr.11694.

[29] M. Ebrahimi and S. Gazor, "Two-dimensional minimum sensor array: a new perspective to array design," *IEEE Sensors Journal*, vol. 23, no. 13, pp. 14685–14690, 2023, doi: 10.1109/JSEN.2023.3273401.
[30] S. K. Ojha, R. Saurabh, U. M. Andrabi, and K. Singh, "Optimizing data aggregation for energy efficiency in wireless sensor networks with neural network prediction models," *International Conference on Innovations in Data Science*, Cham, Switzerland: Springer, pp. 11–24, doi: 10.1007/978-3-032-19303-2_2.
[31] L. Zhou, K. Ye, J. Qi, and H. Sun, "DOA estimation based on pseudo-noise subspace for relocating enhanced nested array," *IEEE Signal Processing Letters*, vol. 29, pp. 1858–1862, 2022, doi: 10.1109/LSP.2022.3199149.
[32] W. Liao and A. Fannjiang, "MUSIC for single-snapshot spectral estimation: stability and super-resolution," *Applied and Computational Harmonic Analysis*, vol. 40, no. 1, pp. 33–67, 2016, doi: 10.1016/j.acha.2014.12.003.
[33] B. Sreevidya and K. N. Vidyasagar, "GAN and YOLOv8 deep learning integration for text extraction from scanned documents," *Discover Artificial Intelligence*, vol. 6, no. 1, pp. 1-31, 2026, doi: 10.1007/s44163-026-01395-w.
[34] Z. Wei, W. Wang, F. Dong, and Q. Liu, "Gridless one-bit direction-of-arrival estimation via atomic norm denoising," *IEEE Communications Letters*, vol. 24, no. 10, pp. 2177–2181, 2020, doi: 10.1109/LCOMM.2020.3000755.
[35] M. Lin *et al.*, "Single sensor to estimate DOA with programmable metasurface," *IEEE Internet of Things Journal*, vol. 8, no. 12, pp. 10187–10197, 2021, doi: 10.1109/JIOT.2021.3051014.

BIOGRAPHIES OF AUTHORS



Anughna Narayanaswamy is an assistant professor at Amity University, Bengaluru campus. She completed her B.E. from Sri Jagadguru Chandrashekaranatha Swamiji Institute of Technology, Chikkaballapur, affiliated with VTU, Belagavi, and her M.Tech. from the same college and her Ph.D. degree from GITAM University, Bengaluru, India. Her research interests are in the area of digital communication, signal processing, and next-generation wireless communication systems, especially on 5G technologies such as massive MIMO and mm-Wave. She has contributed to more than 15 research papers. Her research papers were published extensively in leading international journals and conferences. She can be contacted at email: anughna_12@rediffmail.com.



Ramesha Muniyappa is an assistant professor at GITAM University, Bengaluru campus. He completed his B.E. from VTU, Belagavi, and M.Tech. from Dayananda Sagar College of Engineering, Bangalore, and Ph.D. degrees from GITAM University, Visakhapatnam. His research interests are in the area of next-generation wireless communication systems with special emphasis on various 5G technologies such as massive MIMO, mm-Wave, OFDM, FBMC, and NOMA. He has contributed to more than 20 research papers and two Indian patents. His research papers were published extensively in leading international journals and conferences. He can be contacted at email: rameshmalur037@gmail.com.



Anne Gowda Aleri Byregowda is a Ph.D. scholar in the Department of Electronics and Communication Engineering at SJB Institute of Technology, Bengaluru, and is currently working as an assistant professor in the Department of Electronics and Communication Engineering at Sri Venkateshwara College of Engineering. He has approximately 10 years of teaching experience. He received his B.E. degree in Telecommunication Engineering from Dayananda College of Engineering and his M.Tech. degree in Signal Processing with distinction from SJCIT, Chickkaballapur, affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India. He has published 10 research papers in refereed international journals and the proceedings of various international conferences. His research areas include signal processing, wireless communications, and biomedical image processing. He can be contacted at email: annegowda_12@rediffmail.com.



Dr. Babu Nallur Venkateshappa is a professor in the Department of Electronics and Communication Engineering and academic dean at SJB Institute of Technology, Bengaluru, with 20 Years of academic and research experience. He received his B.E. from AIT, Chikkamagaluru, M.Tech. from Dr. MGR Education and Research Institute, and Ph.D. from Kuvempu University. He has published about 19 papers in indexed journals and international conferences with good impact and citations. Successfully executed one funded project from VGST and has 3 patents to his credit. He is a doctoral committee member for Ph.D. scholars and a reviewer for various Scopus- and WOS-indexed journals, international conferences, and the IEEE international conference, where he has served as publication chair. He is an IEEE senior member and a lifetime member of ISTE. His research areas include wireless sensor networks, wireless communication, VLSI and embedded systems, biosensors, and image processing. He can be contacted at email: nvbabu@sjbit.edu.in.