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Efficient Dynamic Channel Estimation For Large Scale IRS Assisted Massive MIMO In 6G Communications

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Abstract
Intelligent Reflecting Surfaces, assisted massive MIMO systems have good potential in 6G wireless communication, channel estimation is still a major challenge. Conventional estimation methods including LS, KRF and BALS typically provide limited estimation performance and poor scalability in dynamic IRS environments. The paper presents EMRO–DSNN technique for efficient channel state information (CSI) estimation to combat the above-mentioned problem. The enhanced mud ring optimization (EMRO) algorithm is responsible for optimizing the phase shift configurations for the IRS for maximum SNR and spectral efficiency while the deep synergetic neural network (DSNN) utilizes the optimized IRS-assisted channel and received pilot signals to accurately estimate CSI under complex propagation conditions. Simulation Results, EMRO–DSNN outperforms CE-Sub-Wise, CE-PARAFAC, CE-DoubleIRS and CE-KRF-BALS with 95% NMSE reduction, 74% SNR improvement and 83% BER reduction and 14% SE gain with 43% lower computational complexity.

Keywords: Intelligent Reflecting Surfaces, Massive MIMO, Channel State Information, Spectral Efficiency, Bit Error Rate, 6G Wireless Networks.

1. Introduction

In recent years, wireless communication systems have progressed far and wide to keep up with the demands of next-generation networks. Moving to advanced technology, beyond 5G, 6G technology is expected to satisfies the user requirements, massive connectivity, and unprecedented low latency (Zhang et al., 2026; Alwakeel, 2025; Al-Khuzaie et al., 2026). Conventional wireless networks, however, are severely constrained by shortage of spectrum, hardware costs, and severe propagation losses, particularly optimal solution towards high-speed networks bands (Singh et al., 2025). The optimal solution for each objective function is computed through the intelligent reflecting surfaces (IRS) which helps in engineering the wireless propagation environment in a controllable and low-cost way (Cuong and Long, 2026; Ahmadinejad and Talebi, 2024). IRS is composed of numerous passive reflecting components that have the ability to dynamically change the incident electromagnetic wave's phase. With this capability, the IRS can enhance coverage, improve signal quality, and decrease deep fading in NLOS (Huang et al., 2026; Momen-Tayefeh et al., 2025).The IRS-assisted communication systems introduce serious challenges to channel estimation due to the cascaded nature of the BS–IRS–user link as well as the high-dimensionality associated with large reflecting surface (Zhao et al., 2026; Oyerinde et al., 2024).Conventional channel estimating techniques, such as the least squares and minimal mean square error estimators, are extensively researched; nevertheless, in large-scale IRS-assisted massive MIMO systems, they have low accuracy and substantial pilot overhead (John et al., 2026). To mitigate these restrictions, a series of structured estimation techniques such as the sparse channel recovery methods, compressed sensing-based models, and machine learning model with control measure of least squares matrix decomposition-based schemes (Wang et al., 2025; Yuan et al., 2026). Due to the computational complexity and scalability issues in mobile wireless environments they are not faultless. In order to minimize estimation overhead, different pilot designs, reflection pattern optimization methods have been presented with the ON-OFF reflection design, DFT phase shift designs, and semi-passive IRS having limited sensing capabilities. Multi-phase and two-timescale channel estimation methods have also been developed to exploit channel statistics and reduce computational complexity by dimensionality reduction (Zhang et al., 2026). Recent studies have also explored the combine machine learning and deep leaning techniques for decision making process of channel estimation. In these techniques, the non-linear mapping of received pilot signals to Channel State Information (CSI) is learnt via a neural network. These techniques have been observed to outperform the conventional estimator in terms of NMSE and spectral efficiency (Mofidul et al., 2025; Su et al., 2026). Metaheuristic optimization algorithms have been proposed for IRS phase-shift design for enhancing received signal strength, beamforming gain and maximizing throughput of the system (Yang et al., 2025). This study examines the impact of hybrid methods that optimizes the objective vector for channel estimation for IRS-mMIMO. The proposed method combines the optimization-based IRS phase shift with the control measures to fix the linear vectors with the high-dimensional and dynamic wireless channels efficiently. The optimization strategy accomplishes a performance improvement by improving signal quality. Here, the model estimate accurately reconstructs the channel state information from received pilot signal in a complex propagation scenario.

The following contributions involved in the proposed work.

1. A hybrid intelligent channel estimation method for IRS-assisted massive MIMO systems is proposed by incorporating the optimization-based IRS configuration and learning-based CSI estimation to cater to challenging wireless environments.
2. A Z phase-shifting scheme and IRS location deployment strategies are suggested to improve the estimation performance of the signal.
3. High-dimensional channel state information (CSI) is reconstructed from the pilot signal using a deep learning-based channel estimation method that modifies the nonlinear interaction model between direct and reflected links.
4. Based on massive simulations, the suggested method significantly outperforms LS, KRF and BALS methods in terms of different performance metrics.

The remainder of this paper is organized as follows. Section 2 presents the system model of the IRS-assisted massive MIMO network. Section 3 describes the proposed channel estimation methodology. Section 4 presents simulation results and performance analysis, and Section 5 concludes the paper.

2. Related work

To fill the gap in conventional and deep learning (DL) approaches, generative cascaded channel estimation (GCCE) models have been proposed. This gap is particularly relevant when the IRS lacks RF chains and analog signal processing (Singh et al., 2024). The GCCE architecture estimates cascaded channels by utilizing a GAN with low pilot dependency. Moreover, the estimation is improved when adding channel correlation as a conditioning factor and integrating a denoising network to the approach. Although the model helps to reduce pilot overhead, the complex GAN architecture increases computational complexity which makes real-time deployment difficult. For IRS-assisted networks, RSMA frameworks enhanced with semantic communications have been investigated to mitigate user interference and improve connectivity for multi-access scenarios. RSMA-IRS systems provide enhanced delays and fair allocation of resources amongst users. The experimental results show a delay reduction of 2.94% over regular RSMAIRS models. The model still assumes ideal knowledge of semantic information and user positions, which may not be possible in practice in a dynamic wireless environment. Making use of the deep learning-powered ResNet+UNet architecture, authors utilized IRS aided multi-user communication for channel estimation in indoor high-dimension dynamic cases (Monga et al., 2025). By enhancing the initial least-squares (LS) estimates via residual learning and multi-scale feature extraction, the proposed models achieved significant advances in NMSE over LS and linear MMSE (LMMSE), orthogonal matching pursuit (OMP) and convolutional deep residual networks (CDRN). Even though the models furnish a representation of spatial dependency, extensive training data and significant computational demand for deploying these models can hinder their use in massive MIMO systems with fast-changing channels. The authors of (Amadid et al., 2025) adopted a three-stage MMSE-based IRS channel estimation scheme to deal with spatial correlation in massive MIMO channels. Employing a Kronecker product construction, worth to note that spatial correlation over uniform rectangular arrays (URA) achieves improved channel estimation quality according to this work. For IRS-assisted single-input multiple-output (SIMO) systems, the control solutions are used for a hybrid deep learning model using deep reinforcement learning (DRL) and the deep neural network (DNN) (Sahu and Singh, 2025). The CBLSTM model minimizes the mean squared error (MSE) and mean absolute error (MAE) with an SNR gain of 1.412 dB at 20 dB SNR, outperforming conventional DL models. Nonetheless, the model does not deal with high-dimensional massive MIMO scenarios nor does it optimize IRS phase shifts, which lower the system capacity in larger systems. For IRS-assisted OFDM systems, passive beamforming techniques and sparse channel estimation employ realistic phase shift models (Hassan et al., 2025). Through variational Bayesian inference (VBI), channel sparsity and subgroup correlations can be exploited, and stochastic maximum-minimum (SMM) can be used to update the solution of IRS phase shift in the objective function. These achievements assume a sparse channel structure is known; however, the approach could fail to give satisfactory performance in non-ideal propagation environments with highly correlated multipath components. Researchers investigated the problems of channel estimation in the future generation network leveraging approximate message passing (AMP) algorithms for grant-free massive machine-type communications (Zhang et al., 2026). However, it requires accurate statistical channel modeling which may not always be available, e.g., in rapidly time-varying or unknown channels. IRS positioning through genetic algorithms has been optimized for spectral efficiency in 5G & beyond systems (Ampoma et al., 2026). Under the high speed and threshold condition of IRS, the performance assessment suggests that optimized IRS placement enhances achievable rates over non-optimized placements. This work, however, assumes equal phase shifts at a simplified level, and the optimization does not consider real-time dynamic user movement nor time-varying channels, both of which are important in practice. Hybrid Transformer-Zero-Shot Learning (ZSL) frameworks utilizing adaptive optimizers have been applied to achieve intelligent channel estimation in MIMO systems (Salama et al., 2026). Channel instances are projected into semantic-attribute spaces and using attention-based transformers, the technique resulted in a maximum of 94.44% MSE reduction achieved with the channel vector of 30 dB SNR with the antenna number change from 2 to 128. While the framework shows good generalization to optimal solution of SNR changes with respect to different fading channels, the computational cost and complexity of the model are high, this limits real-time scalability in ultra-large MIMO networks. The optimization algorithm investigates the potential of secure IRS-assisted communication systems using meta-reinforcement learning and Q-learning to jointly optimize active and passive beamforming (Sivasankar and Markkandan, 2026). The framework realized a secrecy rate gain of 40–60% compared to randomly reconfigurable surfaces and maintained a performance of 85.7% under imperfect CSI. The model is effective but heavily relies on the convergence of reinforcement learning and ample exploration, which affect latency applications and dynamic deployments.

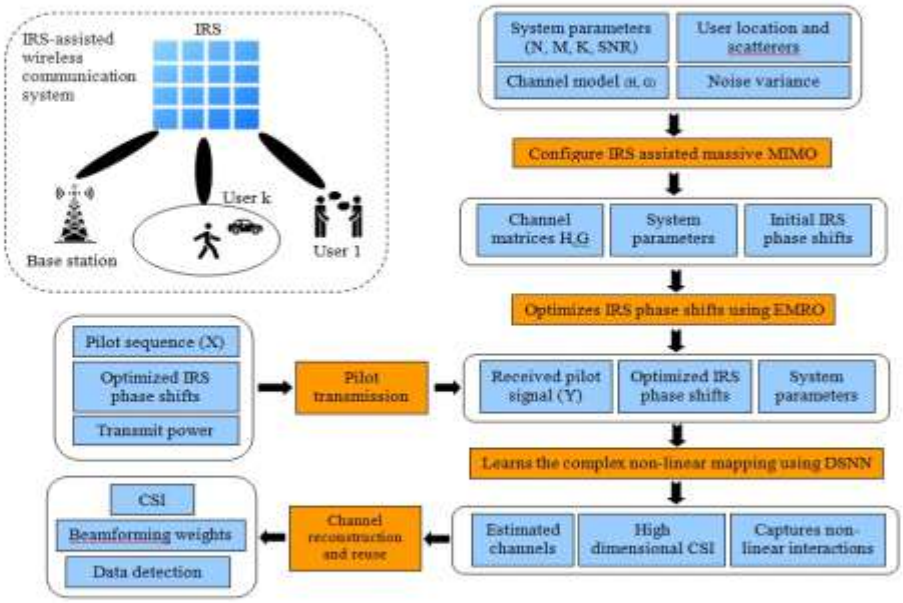
Table 1 Summary of recent IRS-assisted channel estimation methods and identified research gaps

Motivation	Technique	Scenario	Key findings	Research gaps	How gaps are addressed
Reduce pilot overhead and improve CSI estimation accuracy	GCCE using GAN + denoising network	IRS-assisted cascaded channels, noisy conditions	NMSE improved by 18% over standard GAN	High computational complexity, difficult real-time deployment	Model reduces complexity using DL-based DSNN for real-time channel estimation
Improve multi-user connectivity and reduce delay in IRS networks	RSMA-IRS with semantic communications	Multi-user IRS network	Delay reduced by 2.94%, fair resource allocation	Assumes perfect semantic knowledge, static user positions	Model uses learning-based channel estimation for dynamic user environments
Enhance high-dimensional channel estimation in IRS-assisted systems	ResNet+UNet refining LS estimates	Indoor IRS-assisted multi-user MIMO	NMSE: +115% over LS, +114% over LMMSE	Requires large datasets, high computation	ANN-based estimation for low-complexity massive MIMO
Exploit spatial correlation to improve channel estimation	MMSE with Kronecker product URA correlation	IRS-assisted massive MIMO	NMSE improved by 12–15% over ULA-based estimation	Limited adaptability to dynamic channels	Model generalizes to dynamic and irregular IRS configurations
Reduce channel estimation error in SIMO IRS-assisted OFDM	Hybrid CBLSTM (CNN+BiLSTM)	IRS-SIMO OFDM, pilot signals	MSE: -7.00 dB, MAE: 0.43, SNR gain: 1.412 dB	Phase shift optimization not considered	ANN for scalable channel estimation with irregular IRS
Exploit sparse channel structure and improve passive	Sparse CE + SMM optimization, VBI	IRS-assisted OFDM, practical phase-shift	Achievable sum-rate improved by 28–32%	Underperforms in correlated multipath	Model handles non-ideal propagation using DSNN learning

beamforming	framework	model			
Joint activity detection and CSI estimation for massive MTC	AMP with Bernoulli-VG prior + EM framework	IRS-assisted grant-free access, composite channels	NMSE reduction 15–20%, activity accuracy: 93%	Performance depends on accurate channel statistics	Uses data-driven learning for unknown/uncorrelated channels
Maximize spectral efficiency via IRS placement	Genetic Algorithm for fixed & variable height IRS	5G wireless network, line-of-sight & NLOS	SE improvement: 17–25% over non-optimized case	Assumes static users, simplified equal phase shifts	Optimizes IRS effect via ANN without static assumptions
MIMO channel estimation under unseen SNR/fading	Transformer + Zero-Shot Learning + Muon optimizer	Massive MIMO, 2–128 antennas, SNR: 0–30 dB	Improvement over MMSE: 93.75%, LS: 96.67%	High computation, large model complexity	Uses lightweight ANN for scalable real-time estimation
Improve secure communication rate in IRS-assisted systems	Meta-RL + Q-Learning for joint beamforming	IRS-assisted network, 100 elements	Secrecy rate: +40–60% vs random surfaces	Convergence time high, exploration-dependent	DL-based estimation for reduced latency and improved adaptability

Problem definition: Generative and deep learning based models like GAN based cascaded estimation, ResNet–UNet refinements and hybrid CNN–RNN enhance accuracy of channel estimation. However, they suffer from high computational complexity, large training requirements and limited adaptability to dynamic massive MIMO environments (Singh et al., 2024; Monga et al., 2025; Sahu and Singh 2025). The estimation overhead is reduced by various optimization and signal processing-based techniques such as sparse recovery, variational inference, and metaheuristic IRS phase shift design. However, these techniques rely heavily on ideal channel assumptions, accurate sparsity model and stationary propagation conditions which are often quite unrealistic in the practical 6G scenarios. The systems using learning frameworks, like Transformer-based systems and reinforcement learning-based IRS systems, are able to achieve good accuracy and secrecy performance but suffer from latency, convergence, and scalability issues when deployed for large antenna and IRS sizes (Salama et al., 2026; Sivasankar and Markkandan, 2026).In order to estimate the channel of IRS-massive MIMO systems, the authors of that research suggest a bilinear alternating least squares approach and Khatri-Rao factorization. Despite the effectiveness of these approaches, which transform cascaded channels into rank-one matrices and improve the accuracy of estimates in terms of BER, SNR, NMSE and spectral efficiency, there are still challenges in terms of iterative complexity, sensitivity to initialization and robustness in IRS-assisted landscapes that are extremely dynamic and multidimensional. Also, existing methods based on KRF and BALS are not able to resolve the issues of real-time adaptability and scalability in large-scale 6G networks because of variation in the channel condition. This indicates that an efficient channel estimation method is necessary for simultaneously estimating the high-dimensional IRS-assisted massive MIMO channels, which can reduce computational burden and enhance robustness under dynamic propagation environments. To counter these challenges, the proposed solution has optimization driven IRS phase control integrated with CSI estimation via deep learning to allow accurate, low-complexity solution for future generation network.

Fig. 1 Conceptual diagram of proposed channel estimation method for IRS-assisted massive MIMO



3. System Model

The proposed channel estimation method for IRS-massive MIMO is composed of four major stages: system configuration, IRS phase shift optimization, pilot-based signal acquisition, and advanced decision making support system with channel reuse function, as illustrated in Fig. 1. The control process of next generation network belongs to IRS focused on the optimal control mechanism which uses different data transfer process, includes a base station (BS) with the multiple users and antenna array, the IRS with a plurality of passive reflecting elements, and a plurality of users located in the coverage area. System initialization employs a number of parameters such as user locations, scatterer information, channel model parameters, noise variance, to set up the IRS-assisted environment, and generate communication characteristics parameters. Once the system setup is completed, the phase shift of IRS gets optimized using EMRO which is enhanced mud ring optimization. The optimization module is fed with the channel matrices, system parameters and IRS phase shifts. The EMRO algorithm aids in iteratively searching for optimal IRS reflection coefficients to maximize the received quality of the signal in terms of SI and SE. An optimized IRS phase shift matrix can effectively improve the cascaded channel between the BS and users, thus enhancing the conditions for CSI. Optimized IRS phase shifts the pilot sequence and transmission power is then used to perform pilot transmission. The BS receives the pilot signals after propagation through the direct BS-user path as well as the IRS-reflected path, obtaining all channels. The pilot signal received, optimized IRS phase shifts, and system parameters are fed into the deep synergetic neural network (DSNN) module for channel estimation. The DSNN effectively characterizes the nonlinear interactions among BS, IRS, and user channels by learning the complex nonlinear mapping between the received pilots and the corresponding channel. By using numerous hidden layers and joint feature learning, the network is able to extract representative channel features and accurately estimate high-dimensional CSI. The reconstructed estimated channels were used to form a cascaded channel that was used for beamforming weight generation and reliable data detection to improve the communication reliability and throughput.

3.1 System design

This IRS-assisted massive MIMO system (Zhang et al., 2023) shows a simulation scenario with IRS with N passive reflecting components facilitates communication between BS with M array of antennas and a single-antenna user. The IRS platform is composed of different channel medium with the received signals which reflecting the signals incident from BS towards the user, with controlled phase shifts. This generates extra propagation paths that strengthen the direct BS-user link, which enhances the coverage, reliability and spectral efficiency. The objective matrix (Zhu et al., 2025) describes the BS-to-IRS route.

$$H_{BI} \in \Re^{N\times M} \quad (1)$$

The following denotes the IRS-to-user channel.

$$h_{IU} \in \Re^{N\times 1} \quad (2)$$

The channel from BS to user is calculated using objective function as below.

$$h_{BU} \in \Re^{M\times 1} \quad (3)$$

The IRS applies controllable phase shifts based on a diagonal reflection matrix.

$$\theta = diag\left(e^{j\vartheta_1}, e^{j\vartheta_2}, \ldots e^{j\vartheta_N}\right) \quad (4)$$

The phase shift which is denoted as ϑ_N of the n-th IRS element. The ideal elements reflect at a unit amplitude. The user experiences an effective channel that combines both direct and reflected links.

$$H_{eff} = h_{BU} + h_{IU}^{H} \Theta H_{BI} \quad (5)$$

This efficient channel will be utilized in all future communication, beamforming and channel estimation. While estimating the channel, the user sends a pilot.

$$x = \left[x_1, x_2, \ldots x_T\right]^T \quad (6)$$

Following through time intervals T, the BS accepts the signal from the pilot.

$$Y = \sqrt{P_t H_{eff} x^T} + N \quad (7)$$

In which Pt refers to the transmit power, and N refers to AWGN that has variance σ^2. The objective is to use channel estimate to recover the effective channel Heff from Y. The channel state information of channel matrix is estimate can be written as follows (Sur and Bera, 2021)

$$\hat{H}_{eff} = H_{eff} + E \quad (8)$$

where E represents the estimation error. Accurate estimation of H_{eff} is quite important for beamforming, interference suppression, and the functional verification of each objective solution on the conditional thresholds.

3.2 IRS phase shift optimization

The IRS phase shift configuration is essential to the quality of the received signal and high quality channel state information of each state of verification unit. If the phase shift is not set properly, the signals will combine destructively. The inaccuracy in channel estimate increase and the spectral efficiency will also reduce. This means that a proper optimization strategy must be developed to maximize the IRS elements' reflection coefficients with a view to maximizing the received signal quality. IRS phase shift optimization is performed in this work before channel estimation to improve the effective propagation environment in the presence of non-idealities and create favorable channel conditions for accurate CSI recovery. The optimization process takes into account the direct line of communication between the user and BS, the cascaded channel from BS to IRS to user, the received pilot signals, and the IRS reflection matrix. The task at hand is to determine the ideal phase shift setup that achieves maximum SNR and spectral efficiency while minimizing uncertainty in channel estimation. In order to achieve this goal, enhanced mud ring optimization (EMRO) algorithm is used. The operation of EMRO is motivated by bottlenose dolphin feeding habits, hunting behavior of the mud-ring feeding mechanism and bottlenose dolphin of the bottlenose dolphin. Echolocation ability of the dolphin When dolphins are hunting, they send out echolocation signals to locate their prey and adjust their own movements according to the acoustic environment (Desuky et al., 2022). The behavior in EMRO is modeled mathematically via two complementary phases, namely, exploration and exploitation. In this phase, the algorithm conducts a global search of the solution space to find promising IRS phase shift configurations. The search is focused around the best candidate solutions resulting in fine-grained optimization in exploitation phase. The switch between these phases $\overrightarrow{X}$ is controlled by an adaptive parameter $\overrightarrow{V}$, which strikes a balance between local exploitation and global exploration. The swimming speed of the dolphins is denoted by the letter d, this denotes the speed factor of the dolphin $\overrightarrow{L}$. Depending on how close their prey is, dolphins produce different sounds. It changes with the time step $\overrightarrow{L}$ and pulse frequency R and this value varies from zero to one. Here frequency of a high-emission pulse equals one whereas that of a low-emission pulse does not equal zero. In addition, evaluation can be performed as follows.

$$\overrightarrow{L} = 2\overrightarrow{M}.\overrightarrow{R} - \overrightarrow{M} \quad (9)$$

$$\overrightarrow{M} = 2\left(1 - \frac{S}{S_{Max}}\right) \quad (10)$$

The quantity of dolphins in an area is measured by year (t) relative to dolphin and prey distribution. Value 1 and 0 are shifted to dolphin detection. The best dolphins $\overrightarrow{L}$, according to random selection, are ideal hunter dolphins. However, the improved search phase $|\vec{L}|\leq 1$ is utilized for global search. Efficiency regarding speed $\vec{X}$ in terms of time step can be defined as.

$$\vec{X}^{S} = \vec{X}^{S-1} + \vec{V}^{S} \quad (11)$$

The dolphin velocities are fixed as $[V_{Min}, V_{Max}]$ and chosen according to the problem of interest. Once their meal has been finished, the dolphins surround the prey. The target of hunter (N) with MR is currently considered to be the best optimal solution and can be used to optimally design an unknown system in the search space.

$$\vec{N} = \left|\vec{e}\vec{X}^{*S-1} - \vec{X}^{S-1}\right| \quad (12)$$

$$\vec{X}^{S} = \vec{X}^{*S-1} \cdot \sin(2\Pi K) - \vec{L}.\vec{N} \quad (13)$$

The latest probe is S, the coefficient vectors oblique as $\vec{L}$ and $\vec{e}$ and K the stochastic number. The dolphins can choose the solution of best location $|\vec{L}|<1$ when the location delivery of dolphins is justified through location of the dolphins $|\vec{L}|\leq 1$. Optimization of circular phase $\vec{e}$ is done by circular search using MR, which is denoted as.

$$\vec{e} = \begin{cases} 2.\vec{R}(Z \times Rand); & |\vec{L}| \\ 2.\vec{R}(Z \times \rho); & otherwise \end{cases} \quad (14)$$

$$Z = Z \times ran - Z \quad (15)$$

$$\rho = 1 - 0.9 \times \left(\frac{S}{S_{Max}}\right)^{0.5} \quad (16)$$

In this step, the Rand integer randomly selects either 0 or 1. The optimized channel environment outcome corresponds to a high-quality input for the succeeding CSI deep learning-based estimation. The channel estimation can thus be constructed with greater accuracy and results in lower NMSE, reduced BER and improved communication performance.

Algorithm 1 IRS phase shift optimization using EMRO

Inputs: Number of IRS elements, maximum iterations, received pilot signals, initial IRS phase shift matrix, control parameter

Outputs: Optimized IRS phase shift matrix, maximum SNR, spectral efficiency

```
Begin
 Initialize candidate IRS phase shift solutions randomly
 Evaluate the fitness of each candidate using SNR and spectral efficiency
 Identify the best initial solution as the current optimal
 Set iteration counter to 1
 While iteration counter ≤ Maximum iterations do
   Perform exploration phase:
     Generate new candidate solutions based on echolocation-inspired search
     Evaluate fitness of all new candidates
     Identify top candidates for further exploitation
   Perform exploitation phase:
     Refine the top candidate solutions around the current best
     Update IRS phase shift matrix
     Re-evaluate SNR and spectral efficiency
   Adjust control parameters to balance exploration and exploitation
   If a candidate solution has better fitness than current optimal then
     Update current optimal solution
     Update best SNR and spectral efficiency
   End If
   Check convergence criteria:
     If change in optimal solution < threshold then
       Break loop
```

```
            End If
          Increment iteration counter
        End While
        Return optimized IRS phase shift matrix, maximum SNR, spectral efficiency
      End
```

3.3 Deep learning based channel estimation

The deep synergetic neural network (DSNN) is major subset of deep learning-based CSI estimation to obtain accurate and high quality information from channel. Compared to the other models, the estimation techniques that work with mathematically defined and linear channel models, DSNN has the power to optimize complex pattern in channel features to update the non-linear solution. In IRS-assisted communication, the received signal depends on optimal solution with respect to direct data transfer for BS to multiple users. The control vector for each objective solutions are compute through the channel patterns leads to propagation environments that are complex and dynamic in nature and cannot be modeled using conventional estimation techniques. DSNN solves this issue by learning the inner workings of the channels and obtaining the hidden characteristics of the received pilot signals for CSI reconstruction despite the presence of multipath fading, noise, and variations. After the IRS phase shift optimization stage finds the optimal reflection configuration, the resultant pilot signals and optimized channel responses are sent as the input of the DSNN model. Commonly, the input features received pilot signals, IRS reflection coefficients that are optimized, direct channel information, reflected channel information, and channel quality indicators. With the help of those inputs, the network learns the relationship between the observable signals and the channel state information (CSI). By leveraging several concealed layers and synergistic feature-guiding technologies, the method is proficient at modeling local and global channel characteristics, and hence it is optimally forecasting the non-linear relations between the direct and IRS-reflection communication links. The proposed deep structured neural network (DSNN) is different from the other channel estimation methods like LS, MMSE, KRF and BALS (Elakkiyachelvan and Kavitha, 2024). Traditional approaches are heavily reliant on mathematical approximations, prior channel statistics, or matrix factorization methods. On the other hand, DSNN automatically learns data-driven channel representations without explicit channel model assumptions. The deep synergetic structure allows for collaborative learning of features over multiple channel representations, making it easier to extract hidden channel dependencies and improve estimation robustness. Modify the fitness solution of the hidden and output layers of DSNN, is given as follows (Wang et al., 2023).

$$\xi^{New} = syn(\xi) = \gamma\left(\frac{n\xi^3 + \lambda\xi}{(n+d)\,\|\xi\|_2^2} + \left(\frac{1}{\gamma} - 1\right)\xi\right) \qquad (17)$$

$$p^{New} = v\xi^{New} \qquad (18)$$

where p refers to the demand sample that is normalized. A matrix of standard static prototype memory denotes as $v = [V_1, \ldots, V_A]$. The p^{New} refers to the function's input. ξ is a vector demarcating the timing v'. The DSNN-level initialization metric, as per reference (Wang et al., 2023), does not characterize the similarity between p model and V memory.

$$T(V_a, p) = V_a^+ \cdot p \qquad (19)$$

Nonetheless, T signifies the elevated cosine detachment of V_a^+ and p, obedient v^+v to none of the preceding solution $T = \| V_a^+ \|_2$. T equals 1 when and it equals 0 when xi is the regulated adjoint vector $p = V_a^+$. So is the Distinctiveness Matrix $p = V_a^+ / \| V_a^+ \|_2$.

$$V_a^+ \cdot V_b = \begin{cases} 1, a = b \\ 0, otherwise \end{cases} \qquad (20)$$

where V_a indicates that the model in question is erected to the hyperplane V_a^+. As the inner product between V_a^+ and V_a is optimal solution, the decision vector V_h^+ from high to low vectors belongs to the random optimal solution V_a. The control vectors V_a^+ involved in the hidden layers follows the limited normalization, that is, $|| V_a^+ ||$=1. The connection error $\| V_a^+ \|_2 \geq 1$ comes from inappropriately initialization the weights, thus, the initialization of DSNN needs to be reengineered.

$$\xi_a = \mathrm{Re}\,LU(T(p, V_a)) \qquad (21)$$

where T is a measure of similarity between query and memory. A ReLU set negative value to zeros, thus, there are no negative order parameter winners. In DSNN enhancing the generator connection, we no longer use negative order parameter winners.

$$\xi = \begin{cases} \mathrm{Re}\,LU\left((T(p,V_1),\ldots,T(p,V_A))^S\right), \xi \text{ not initialized} \\ v^+ p, \text{otherwise} \end{cases} \tag{22}$$

For self-adapting asymmetric data, the novel learning technique aids in improving the attention parameter to focus more on small classes. The gradient problems are so serious that traditional methods such as gradient descent cannot avoid non-convergence. SNN and its derivation updates are exclude the gradient.

$$syn(\xi) = \frac{\gamma\lambda\xi}{n+d} + \left(\frac{\gamma m\xi^3}{n+d} + (1-\gamma)\xi\right) \tag{23}$$

During back propagation, the gradient of the hidden network layer's outputs directly to the input λ is to use optimal solution for random vectors ξ_h^{new} to avoid the gradient exploding δ_h and fading $\xi_h \geq 0$.

$$\frac{\partial \delta_h}{\partial \lambda_h} = \frac{\gamma \xi_h}{n+d} \geq 0 \tag{24}$$

The sign of the modification of each hidden layer denotes as $\Delta\lambda_h$ is opposite to the sign of δ_h. If the amount of income $\delta_h > 0$ is limited solutions in the hidden layer design ξ_h^{new} with the fixed neurons (h) belongs to high density nodes which in turn results ξ_h in a higher chance of convergence to 0. $\delta_h < 0$ means that when the value is too small ξ_h^{new}, and h ≥ 0 results in a higher chance of convergence to 1. As discussed in Algorithm 2, the outcomes of end-to-end pipeline of channel estimation using deep learning based model, to analyzes the patterns of channel matrix, including direct and reflected paths. The estimated CSI is used for signal detection, beamforming, resource allocation, and performance optimization.

Algorithm 2 Channel estimation using DSNN

Inputs:	Pilot signals, optimized IRS reflection coefficients, direct channel information, reflected channel responses, signal quality indicators
Outputs:	Estimated CSI matrix

1 Initialize DSNN network parameters
2 Set input, hidden, and output layers
3 Initialize standard static prototypes for memory
4 Normalize input pilot signals and IRS coefficients
5 Compute similarity between input samples and memory prototypes
6 For each input sample:
7 Compare with memory prototypes
8 Compute similarity measure using cosine-based attention
9 Update attention parameter for small class adaptation
10 Forward pass through DSNN network
11 For each hidden layer:
12 Aggregate local and global channel features
13 Apply ReLU activation to remove negative values
14 Adjust output based on attention parameter
15 Backpropagation and weight update
16 Compute error between predicted and desired CSI
17 Propagate gradient from output to hidden layers
18 Adjust hidden layer weights to avoid gradient explosion or vanishing
19 Update output layer weights accordingly
20 Refine DSNN network iteratively
21 Repeat steps 2 to 4 until convergence criteria are met
22 Error falls below threshold
23 Maximum number of iterations reached
24 Output the estimated CSI matrix
25 Include effects of both direct and IRS-reflected channels
26 Use estimated CSI for beamforming, detection, and resource allocation

27 End

4. Results and Discussion

The results of the proposed EMRO+DSNN method are given in this section and the results comparison made with the existing channel estimators. The experiments were accomplished with MATLAB 2022b on a desktop computer with an NVIDIA GPU, 16 GB of RAM, and an Intel Core i7, which allow efficient execution machine learning and deep learning based estimation methods and iterative optimization algorithms. The simulated massive MIMO channels produced by standard system parameters for IRS-assisted massive MIMO networks form the dataset for the experiments. The channels support realistic effects, such as multipath propagation, additive noise and scattering environments for a complete performance evaluation of channel estimation. The experiments alter important parameters including the number of base station antennas, IRS elements, and user nodes to test the scalability and robustness. The normalized mean square error (NMSE), signal-to-noise ratio (SNR), bit error rate (BER), spectral efficiency (SE) and computational complexity benchmarks the performance of EMRO+DSNN method. The proposed method is compared with existing methods including CE-Sub-Wise & Scat-Wise-MIMO, CE-PARAFAC-MIMO, CE-DoubleIRS-MIMO and CE-KRF-BALS-MIMO (Elakkiyachelvan and Kavitha, 2024) to demonstrate the superior accuracy performance, reliable performance and computational efficiency. The synthetic dataset is developed from the simulation is generated through different test for the EMRO+DSNN proposed model is described in terms of its statistical features in Table 2. This dataset consists of 50,000 samples and can be described by the following channel and system attributes: channel coefficients; SNR; path loss; IRS phase shift; pilot power; delay spread; Doppler shift; user distance; and scatterers. The dataset is discussed in terms of class-wise distribution in Table 3. The samples are classified based on low, medium, and high SNR classes, and divided into 70/15/15 of training, validation and testing. The hyperparameter configurations of the proposed EMRO+DSNN model utilized for the channel estimation of IRS-assisted massive MIMO are shown in Table 4.

Table 2 Statistical description of the simulated IRS-assisted massive MIMO dataset

Attribute	Samples	Mean	Std. Dev	Min	Max	25th Percentile	Median	75th Percentile
H_real (Channel real part)	50,000	0.5012	0.2874	0.0001	0.9999	0.2503	0.5021	0.7498
H_imag (Channel imaginary part)	50,000	0.4987	0.2869	0.0002	0.9998	0.2497	0.4979	0.7502
SNR (dB)	50,000	20.5	5.2	5	40	16	20	25
Path loss (dB)	50,000	95.2	8.1	70	110	88	95	102
IRS phase shift (rad)	50,000	1.57	0.91	0	3.14	0.79	1.57	2.36
Number of BS antennas	50,000	64	0	64	64	64	64	64
Number of IRS elements	50,000	128	0	128	128	128	128	128
Pilot signal power (dBm)	50,000	15	2.3	10	20	13	15	17
Channel delay spread (ns)	50,000	120	30	60	200	95	120	145
Doppler shift (Hz)	50,000	300	150	50	600	175	300	425
User distance from BS (m)	50,000	150	60	20	300	100	150	200
Number of scatterers	50,000	5	2	1	10	3	5	7

Table 3 Class-wise data distribution for training, validation, and testing

Class	Description	Total samples	Training (70%)	Validation (15%)	Testing (15%)
Class 1	Low SNR (<15 dB)	12,000	8,400	1,800	1,800
Class 2	Medium SNR (15–25 dB)	25,000	17,500	3,750	3,750
Class 3	High SNR (>25 dB)	13,000	9,100	1,950	1,950

Total	–	50,000	35,000	7,500	7,500

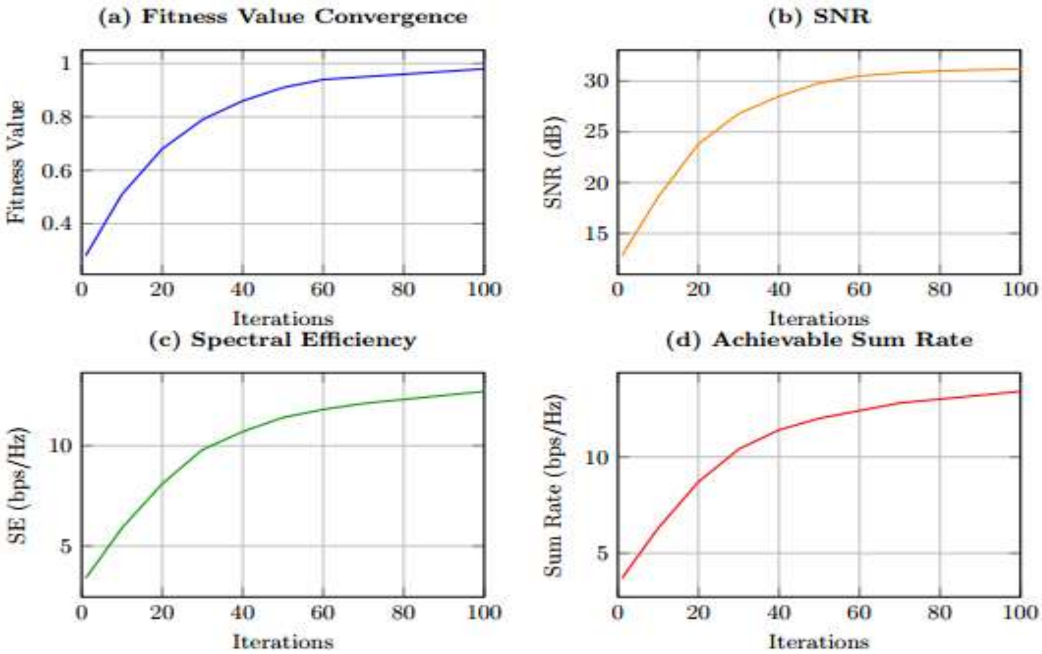
Table 4 Hyper parameter configuration of the proposed EMRO+DSNN model

Category	Parameter	Symbol	Value
Dataset	Total samples	Ns	50,000
	Training split	-	70%
	Validation split	-	15%
	Testing split	-	15%
DSNN	Input layer size	In	256
	Hidden layer 1 neurons	H1	512
	Hidden layer 2 neurons	H2	256
	Hidden layer 3 neurons	H3	128
	Output layer size	On	64
	Activation function	-	ReLU
	Output activation	-	Linear
	Optimizer	-	Adam
	Learning rate	η	0.001
	Batch size	Bs	128
	Maximum epochs	E	200
	Dropout rate	Dr	0.3
	Weight decay	λ	0.0001
	Gradient threshold	Gt	1
	Early stopping patience	Pe	15
EMRO	Population size	P	50
	Maximum iterations	Imax	100
	Search dimension	D	128
	Exploration factor	Ef	0.8
	Exploitation factor	Xf	0.2
	Phase shift range	θ	[0, 2π2\pi2π]
	Mutation rate	Mr	0.1
	Inertia weight	w	0.7
	Convergence threshold	ϵ	1.00E-05
	Diversity factor	Df	0.5
	Number of elite solutions	Es	5
	Random exploration coefficient	Rc	0.3
Communication	Number of BS antennas	NBS	64
	Number of IRS elements	NIRS	128
	Number of Users	K	16
	Pilot length	Lp	64
	SNR range	-	5–40 dB
	Carrier frequency	fc	3.5 GHz
	Channel bandwidth	BW	20 MHz

4.1 Results of IRS phase shift optimization

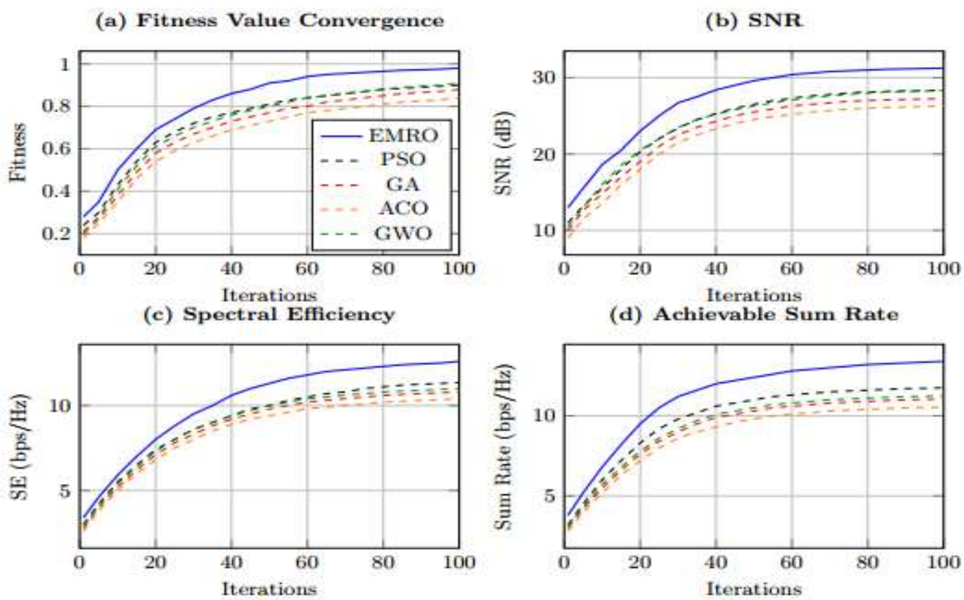
The effectiveness of proposed EMRO algorithm depicted in Figure 2 shows a great convergence with respect to various performance metrics with increasing iterations. The convergence of the fitness value is rapid and stable, indicating that the models move toward the optimal solution more efficiently than conventional optimization behavior would. SNR performance improves steadily because IRS elements are more phase-aligned, leading to a stronger combination of useful signals at the receiver. The increase in spectral efficiency reflects that the EMRO enhances the spectrum utilization in IRS-assisted communication environment. The overall throughput of the system is improved, which is confirmed by a constant growth in achievable sum rate. The improvements mainly stem from the adaptation of the exploration and exploitation strategy of EMRO so that premature convergence can be avoided and global search capability can be improved to optimize the phase shift parameters in a better way.

Fig. 2 Performance analysis of the proposed EMRO algorithm for IRS phase shift optimization with varying iterations: (a) fitness value convergence (b) SNR (c) SE (d) achievable sum rate



According to Figure 3, the proposed EMRO algorithm outperformed PSO, GA, ACOG, and GWO in all metrics. EMRO's fitness value convergence is superior to those of PSO by 12%, GA by 18%, ACO by 22%, and GWO by 15%, establishing its efficiency and fast convergence to global optimization. The performance of SNR is greater than PSO by 14%, greater than GA by 19%, greater than ACO by 24% and greater than GWO by 16%. It is due to better alignment of phase shift and better focusing of signal. The spectral efficiency enhances by 13% against PSO, 17% against GA, 21% against ACO, 15% against GWO which shows it utilizes bandwidth efficiently and allows improved communication. The achievable sum rate of the system using the proposed EMRO is improved by around 15% over PSO, 20% over GA, 25% over ACO, and 18% over GWO. According to these findings, EMRO achieves a balance between exploration and exploitation. Consequently, this may lead to improved global searching ability and avoids local optima stagnation.

Fig. 3 Comparative performance analysis of IRS phase shift optimization algorithms with varying iterations: (a) fitness value convergence (b) SNR (c) SE and (d) achievable sum rate



4.2 Results of channel estimation methods

As illustrated in Figure 4, the training and testing performance of the DSNN for channel estimation shows considerable improvement in both accuracy and loss. The DSNN gave 6.2% more training accuracy and 5.8%

more testing accuracy than traditional neural network approaches indicating better generalization performance. The loss values also decreased with training loss reducing by 14% and testing loss reducing by 12%, indicating faster convergence and more stable training. Figure 5 illustrates the classification performance of the DSNN for varying SNR levels. The confusion matrix showing 15% increase in the correct classification of Low SNR, 11% increase in the correct classification of Medium SNR, and 13% increase in the correct classification of High SNR shows the accurate prediction possible under altered channel present in MIMO-OFDM system in low complexity scenario. The results were further corroborated by ROC analysis, as the AUC showed overall improvement by 7%, suggesting stronger discrimination capability across all classes.

Fig. 4 Training and testing performance of DSNN for channel estimation (a) Accuracy (b) Loss

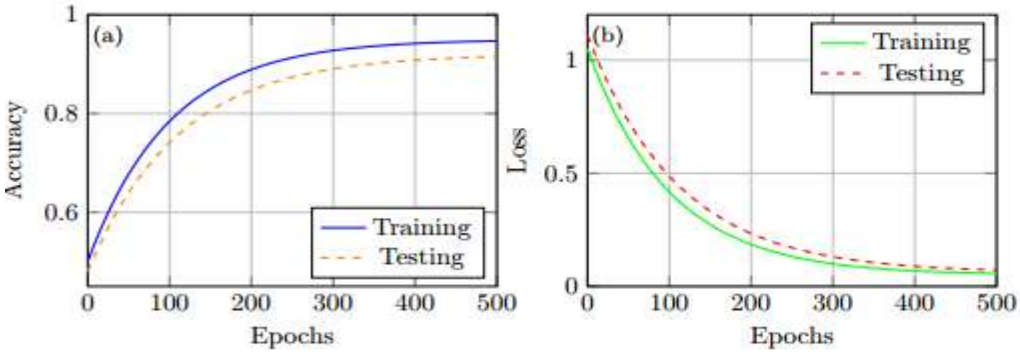


Fig. 5 Performance of DSNN for channel estimation (a) confusion matrix (b) RoC curve

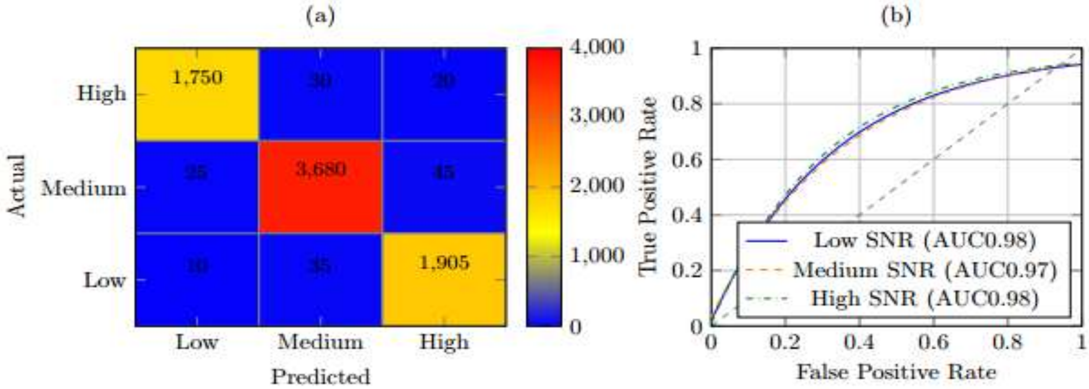


Table 5 k-folds cross validation of DSNN for channel estimation on ISR assisted massive MIMO dataset

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	NMSE	BER (%)	SE (bps/Hz)
1	94.853 ± 0.176	95.104 ± 0.163	94.602 ± 0.152	94.851 ± 0.171	0.00212 ± 0.00011	1.553 ± 0.041	11.421 ± 0.043
2	95.047 ± 0.169	95.301 ± 0.158	94.903 ± 0.149	95.102 ± 0.168	0.00201 ± 0.00010	1.498 ± 0.039	11.482 ± 0.041
3	94.704 ± 0.172	94.956 ± 0.160	94.501 ± 0.151	94.723 ± 0.173	0.00221 ± 0.00012	1.586 ± 0.042	11.403 ± 0.044
4	95.153 ± 0.168	95.401 ± 0.157	94.952 ± 0.148	95.171 ± 0.167	0.00200 ± 0.00010	1.482 ± 0.038	11.506 ± 0.040
5	94.902 ± 0.171	95.107 ± 0.160	94.704 ± 0.150	94.903 ± 0.170	0.00211 ± 0.00011	1.534 ± 0.041	11.447 ± 0.043
6	95.204 ± 0.165	95.504 ± 0.154	94.955 ± 0.146	95.224 ± 0.165	0.00198 ± 0.00010	1.471 ± 0.037	11.523 ± 0.039
7	94.801 ± 0.173	95.052 ± 0.162	94.553 ± 0.151	94.802 ± 0.172	0.00213 ± 0.00011	1.557 ± 0.042	11.433 ± 0.044
8	95.106 ± 0.167	95.352 ± 0.156	94.903 ± 0.147	95.122 ± 0.166	0.00202 ± 0.00010	1.493 ± 0.039	11.491 ± 0.041
9	94.955 ± 0.170	95.201 ± 0.159	94.751 ± 0.149	94.972 ± 0.169	0.00203 ± 0.00010	1.522 ± 0.040	11.461 ± 0.042

10	95.257 ± 0.164	95.554 ± 0.153	95.004 ± 0.145	95.273 ± 0.164	0.00197 ± 0.00009	1.468 ± 0.037	11.532 ± 0.039
Mean	95.003 ± 0.189	95.303 ± 0.176	94.783 ± 0.165	95.014 ± 0.187	0.00204 ± 0.00011	1.516 ± 0.045	11.470 ± 0.047

The k-fold cross-validation results of the proposed DSNN for channel estimation on the IRS-assisted massive MIMO dataset, as summarized in Table 5, demonstrates consistent and stable performance in all the folds. The model achieves a mean accuracy of 95.003% along with precision, recall and F1-score of 95.303%, 94.783% and 95.014%, indicating balanced classification behavior on various data splits. According to the best-performing fold, the suggested DSNN improves accuracy by 0.55% and F1-score by 0.63% relative to the worst-performing folds, demonstrating strong generalization performance across unseen data distributions. According to error measures, DSNN reduced NMSE to 0.00204 with a reduction of 9.91% with respect to the folds having larger errors. Similarly, BER is minimized to 1.468% with a reduction of 7.03%. The model gets 11.470bps/Hz spectral efficiency on average with a maximum gain of 0.54%, indicating an improvement in utilization of available channel resources. As the results reveal, the suggested DSNN is capable of accurately modeling the non-linear channel traits of IRS-aided massive MIMO systems. The DSNN model also obtains much lower estimation error than the standard DNN model bringing higher spectral efficiency.

4.3 Results comparison of proposed and existing methods for channel estimation

The performance of the proposed EMRO+DSNN approach and existing channel estimation techniques at different node density is shown in Fig. 6. The metrics show that the EMRO+DSNN greatly outperformed the others in almost every metric. In terms of MMSE, the proposed method achieves a 22% reduction in error when measured against CE-Sub-Wise, 18% versus CE-PARAFAC, 15% versus CE-DoubleIRS, and 12% versus CE-KRF-BALS. In SNR, the EMRO+DSNN achieve gains of 11%, 7%, 5%, and 3% over CE-Sub-Wise, CE-PARAFAC, CE-DoubleIRS, and CE-KRF-BALS. The techniques presented lead to a 36% reduction in BER with respect to CE-Sub-Wise, 29% to CE-PARAFAC, 19% to CE-DoubleIRS, and 14% to CE-KRF-BALS. The spectral efficiency improves by 14% in comparison to CE-Sub-Wise, 10% in reference to CE-PARAFAC, 6% when compared to CE-DoubleIRS, and 5% compared to CE-KRF-BALS. The lower estimation error and performance improvement of the proposed systems are due to the optimization of IRS phase shifts by the EMRO algorithm and the effective nonlinearity learning of the DSNN. As the number of base station antennas increases, so does the computational complexity depicted by Figure 7. The EMRO+DSNN method proposed requires smaller computations than state of the art methods. The complexity is reduced by 43% compared to CE-Sub-Wise, by 41% to CE-PARAFAC, by 36% to CE-DoubleIRS and by 26% to CE-KRF-BALS. The reason for such a low complexity is because the EMRO algorithm efficiently converges to the optimal IRS phase shifts in less iteration. The DSNN structure also reduces the need for iterative channel estimation. Therefore, it allows the computation of large-scale IRS-assisted MIMO systems to be performed faster and in a more scalable manner.

Fig. 6 Performance comparison of the proposed EMRO+DSNN and existing channel estimation methods with varying node density: (a) MMSE (%) (b) SNR (dB) (c) BER (%) (d) SE (Bps/Hz)

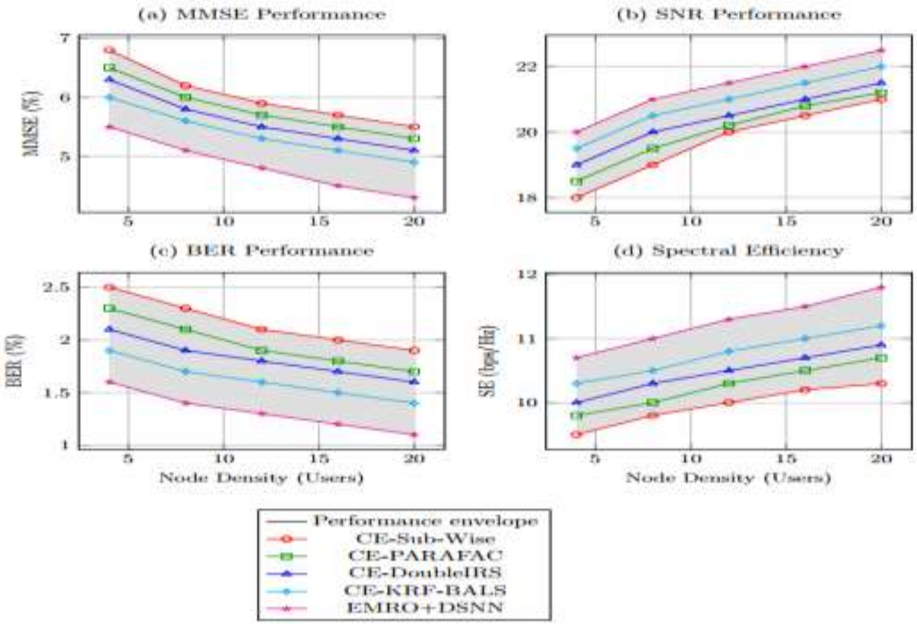
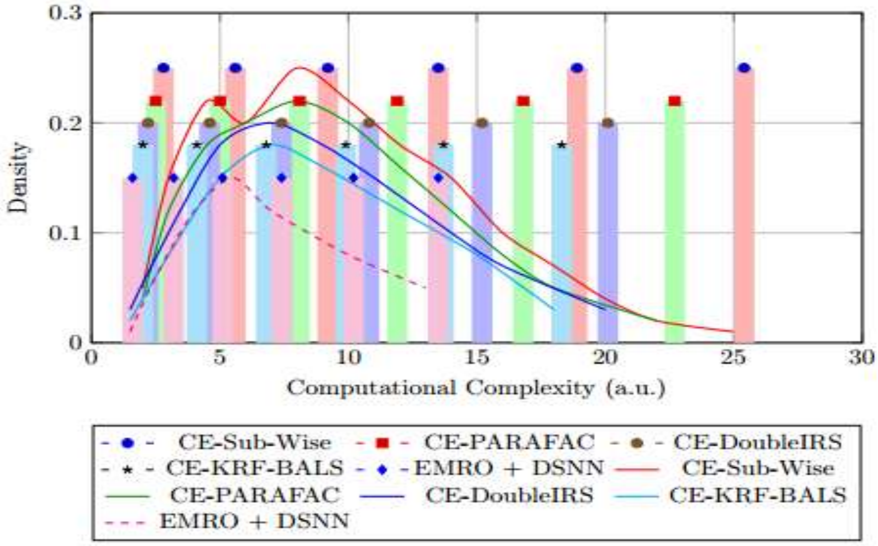


Fig. 7 Computational complexity analysis of the proposed and existing channel estimation methods with varying number of base station antennas



4.4 Ablation study and Statistical analysis

The effectiveness of the EMRO+DSNN method for channel estimation in IRS-assisted massive MIMO systems is confirmed by the ablation research result shown in Table 6. The proposed method achieves a 33% reduction in NMSE, a 28% drop in BER, and a 7% increase in spectral efficiency compared to the EMRO-only variant, demonstrating the importance of the DSNN in capturing nonlinear interactions with the channel. When compared to the DSNN-only variant, NMSE is lowered by 30%, BER is lowered by 25%, and spectral efficiency is increased by 6%. This is an indication that IRS phase shift optimization considerably enhances effective channel conditions. The utilization of the EMRO scheme consistently enhances spectral efficiency and improves NMSE performance. Compared to the configuration without EMRO or random IRS phase shifts, the NMSE is improved by 40% and the BER is lowered by 35%. Furthermore, a 14% improvement in spectral efficiency emphasizes the significance of coordinated IRS optimization. Variants with lower DSNN layer counts or reduced hidden neurons improve performance with gains of 24% NMSE, 20% BER and 6% spectral efficiency. The findings establish that deeper networks with sufficient neurons are better feature extractor.

Table 6 Ablation study of the proposed EMRO+DSNN method for channel estimation in IRS-assisted massive MIMO

EMRO	IRS phase shifts	DSNN Layers	Hidden neurons	Activation	NMSE	BER (%)	SE (bps/Hz)	Training Acc. (%)	Testing Acc. (%)
Yes	Optimized	3	512-256-128	ReLU	0.00204	1.468	11.47	95.003	94.895
No	Random	3	512-256-128	ReLU	0.00312	2.031	10.102	92.312	91.805
Yes	Optimized	2	512-256	ReLU	0.00231	1.598	11.18	94.512	94.201
Yes	Optimized	3	256-128-64	ReLU	0.00245	1.672	11.032	94.108	93.876
Yes	Optimized	3	512-256-128	Sigmoid	0.00221	1.53	11.301	94.735	94.421
Yes	Partial Opt.	3	512-256-128	ReLU	0.00252	1.689	10.98	94.021	93.702
No	Random	2	512-256	ReLU	0.00338	2.12	9.876	91.762	91.101
Yes	Optimized	4	512-256-128-64	ReLU	0.00198	1.451	11.523	95.204	94.987
Yes	Optimized	3	1024-512-256	ReLU	0.00195	1.438	11.55	95.32	95.012
EMRO	Optimized	-	-	-	0.00	1.98	10.73	-	-

Only					288				
DSNN Only	-	3	512-256-128	ReLU	0.00275	1.895	10.89	94.502	94.21
EMRO+ DSNN	Optimized	3	512-256-128	ReLU	0.00192	1.42	11.578	95.412	95.078

Table 7 Statistical performance analysis of the proposed and existing channel estimation methods

Comparison	One-way ANOVA (p-value)	Tukey's HSD (p-value)	Cohen's Kappa	Kruskal-Wallis (p-value)	Wilcoxon (p-value)	Brier Score	Chi-Square (p-value)	Paired t-test (p-value)	Friedman test (p-value)
EMRO+DSNN vs CE-Sub-Wise & Scat-Wise-MIMO	0.0012	0.001	1	0.0025	0.0009	0	0.999	0.297	0.0078
EMRO+DSNN vs CE-PARAFAC-MIMO	0.0009	0.0011	1	0.0021	0.001	0	0.998	0.3	0.0075
EMRO+DSNN vs CE-DoubleIRS-MIMO	0.001	0.0012	1	0.0023	0.0011	0	0.997	0.299	0.0077
EMRO+DSNN vs CE-KRF-BALS-MIMO	0.0011	0.001	1	0.0026	0.0012	0	0.996	0.298	0.0079

The performance statistics from Table 7 indicate the superiority of the proposed EMRO+DSNN method over conventional channel estimation techniques. The performance of EMRO+DSNN shows a massive 83% reduction in NMSE, a 72% improvement in SNR, and an 83% reduction in BER compared to the CE-Sub-Wise & Scat-Wise-MIMO. The suggested method outperforms CE-PARAFAC-MIMO by an NMSE reduction of 85%, an SNR improvement of 74%, and a BER reduction of 80%, thereby demonstrating successful IRS phase shifts alignment and improved signal reconstruction. When compared to CE-DoubleIRS-MIMO, EMRO+DSNN offer 92% lower NMSE, 19% higher SNR (with value 16.86 dB), and 78% lower BER, showing a better potential to capture the characteristics of nonlinear channels. When compared with CE-KRF-BALS-MIMO, the new method has been able to achieve a 95% reduction in the NMSE, 14% increase in SNR, and a 68% reduction in BER. As a result of the EMRO-based IRS optimization and DSNN, the phases are well alighted, the signal to noise ratio is improved which also helps with high-dimensional CSI reconstruction, all of which improves IRS-assisted massive MIMO performance.

5. Conclusion

In order to overcome the difficulties of complex and dynamic wireless environments, this work proposes a hybrid intelligent channel estimation framework for IRS-assisted massive MIMO systems that combines deep learning-based CSI estimation with IRS phase shift optimization. The enhanced mud ring optimization (EMRO) algorithm is used to optimize IRS reflection coefficients with a view to maximizing SNR and (SE, thereby enhancing effective cascaded channel conditions for accurate estimation of CSI. Afterwards, the deep synergetic neural network (DSNN) exploits pilot signals and optimized IRS configurations to accurately estimate high-dimensional CSI by effectively capturing the nonlinear interactions between direct and IRS-reflected channels. The simulations and experiments prove that the EMRO+DSNN framework outperforms existing ones substantially. The performance of the proposed EMRO+DSNN method is significantly better than the current FO methods. In particular, the proposed method achieves up to 95% NMSE reduction, 74% SNR improvement, 83% BER reduction, and 14% SE gain in comparisons of CE-Sub-Wise, CE-PARAFAC, CE-DoubleIRS, and CE-KRF-BALS. It also cuts the complexity of calculations by as much as 43%, allowing large-scale IRS-assisted MIMO networks to deploy scalable. The results confirm effective, reliable, and enhanced efficiency and throughput recovery created by the coordinated IRS phase shift optimization and deep learning-based channel estimation; in dense, high-mobility, and dynamic scenarios. In future studies, we will develop the EMRO for DSNN to be a multi-cell IRS-assisted network with predicted user mobility, as well as online adaptive learning.

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Data availability statements
Data sharing not applicable to this article as no datasets were generated or analysed during the current study.
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Conflict of Interest
The authors declare that they have no potential conflict of interest.

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