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# Particle-Swarm-Optimised Neural Interference Management for MIMO Architectures in Next-Generation Wireless Network

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**ABSTRACT:** The interlinked nature of mobile users and terminals has been significantly impacted by Wireless Communication System (WCS). A hybrid Particle-Swarm-Optimized Artificial Neural Network (PSO-ANN) framework is presented in this paper for proactive downlink interference mitigation in multi-cell Orthogonal Frequency Division Multiple Access (OFDMA) systems. Large-scale route loss, instantaneous Signal-to-Interference-Plus-Noise Ratio (SINR), user mobility vectors, and neighboring-cell power budgets are all included in the compact feature vector that is taken from live radio measurements and fed into a multilayer artificial neural network. PSO globally adjusts the network's initial weights and biases prior to traditional back-propagation refinements in order to avoid poor local minima and speed up convergence. Simulations are conducted and the proposed PSO-ANN outperforms standalone neural networks and traditional reuse schemes in terms of signal quality, network throughput, and interference suppression. The method is resilient across a broad range of user mobility and traffic volumes while maintaining inference delays that are consistent with ultra-reliable low-latency communication needs. According to the results, PSO-ANN is a scalable and effective option for managing radio resources in future wireless infrastructures while taking interference into account.

**Keywords:** Wireless Communication System, MIMO, OFDMA, Artificial Neural Network, SINR, NMSE.

## 1. Introduction

The explosive growth in wireless data demand, driven by mobile internet, Internet of Things (IoT), and emerging applications such as augmented reality and autonomous systems, necessitates the development of more efficient and robust WCS [1]. Multiple Input - Multiple Output (MIMO) technology has emerged as a cornerstone of modern wireless architectures, offering significant improvements in spectral efficiency, link reliability, and data throughput. The ever-increasing demand for high-speed, reliable, and energy-efficient wireless communication is driving the evolution of next-generation wireless systems, including 5G and the emerging 6G paradigm [2-3]. Among the various enabling technologies, MIMO has established itself as a foundational pillar due to its ability to significantly improve spectral efficiency, system capacity, and signal robustness. By utilizing multiple antennas at both the transmitter and receiver ends, MIMO systems support simultaneous data streams, leading to enhanced throughput without requiring additional bandwidth or transmit power [4]. However, as MIMO systems scale to support massive antenna arrays and operate in increasingly dense and dynamic environments, the challenge of interference management becomes more critical [5]. Interference in MIMO systems arises from various sources, including inter-user interference in Multi-User MIMO (MU-MIMO), inter-cell interference in heterogeneous networks, and hardware-induced distortions. Machine Learning (ML) and Deep Learning (DL) play pivotal roles in interference management for MIMO architectures in next-generation wireless networks [6-7]. In this case, Custom Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) these networks become increasingly complex, conventional interference management techniques often fall short due to their inability to adapt dynamically or scale efficiently [8-9]. These impairments significantly degrade system performance, particularly in 5G and beyond wireless standards, where ultra-reliability and low latency are required [10]. So, efficient classification and integrated optimization techniques are essential to overcome these downsides. Hence, this paper develops a PSO-ANN framework for proactive downlink interference mitigation in multi-cell OFDMA systems. The following objectives are explored in this work:

- To minimize unnecessary signal suppression and improve spatial reuse by using an interference estimation module.
- To predict the noises of NMSE and MSE, NN - based prediction is employed.
- To increase throughput and adjust the network parameters, using the ANN algorithm.
- To estimate the SINR and SNR values, the PSO-ANN technique is utilized.

This paper's remaining sections are organized as follows. The recent works are presented in Section II. The proposed system is described in Section III. Section IV provides experiments and simulations with findings. Section V is the conclusion part.

## 2. Recent Works

**Ignacio Santamaria *et al* (2025) [11]** have presented a two-stage approach for passive and active beamforming in MIMO Interference Channels (ICs) assisted by a Beyond-Diagonal Reconfigurable Intelligent Surface (BD-RIS). It manages signal propagation and enables more general reflection transformations. It consumes more power.

**Zhouyou Gu *et al* (2024) [12]** have proposed a design an Actor-Critic Graph Representation Learning (AC-GRL) algorithm for contention and interference management in wireless networks. It is more flexible and robust than static embedding methods. However, it led to increased training time and memory usage.

**To Truong An *et al* (2023) [13]** have developed a Threshold Autoencoder Denoiser Convolutional Neural Network (TADCNN) to achieve high classification performance. It mitigates over-smoothing, a common problem in DLs. Moreover, it lacks strong theoretical grounding for convergence or performance guarantees.

**Md Habibur Rahman *et al* (2023) [14]** have developed a Hybrid Deep Neural Network (HyDNN) and a Bi-Directional Long Short-Term Memory (BiLSTM) model for multiuser uplink channel estimation. It offers higher performance on tasks that require understanding the full context of a sequence. However, it is not used for real-time or streaming tasks where future inputs aren't available yet.

**Jin Kwan Kim *et al* (2024) [15]** have proposed an improved self-interference cancellation receiver with Successive Interference Cancellation (SIC)-based channel estimation for the WCS. It is highly effective for tasks like sentiment analysis and speech tagging, where understanding both preceding and succeeding elements matters. It is less practical due to its larger size and latency.

## 3. Proposed Work Explanation

Initially, the base station provides the data to downlink interference in WCS. In Figure 1, the proposed block diagram is presented.

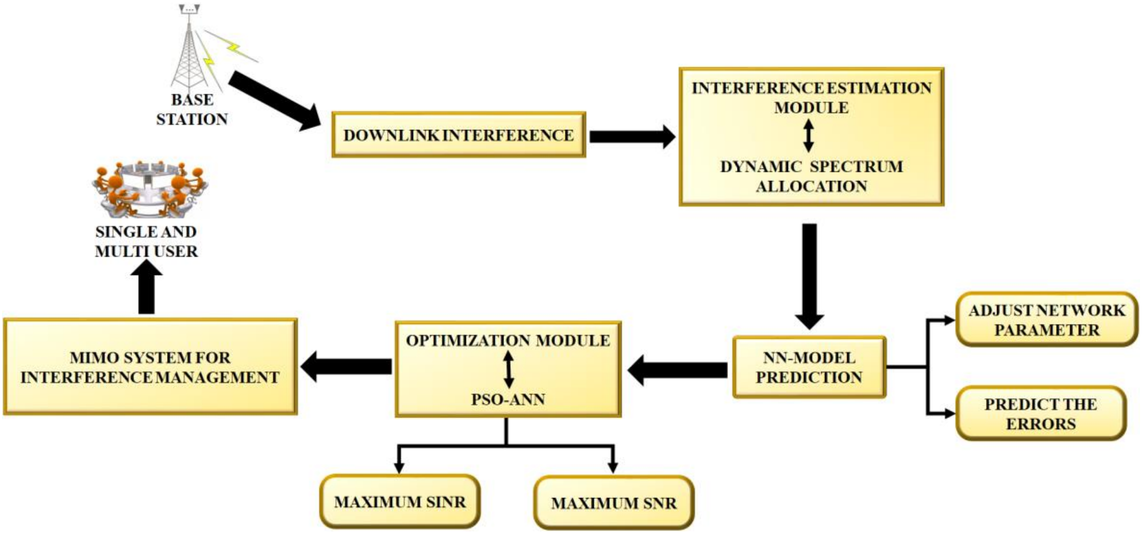


**Figure 1:** *Block Diagram for Proposed System*

The downlink interference is used for the transmission from the Base Station (BS) to the User Equipment (UE). Following that, transmit signals are moved to the interference estimation, which is handled by dynamic spectrum allocation. It measures the interference power at a receiver or across the network and provides real-time data for decision-making in resource management. After that, transmit signals are allowed to NN-based prediction model is used by ANN classification for time-series prediction and predict the various noises of NMSE and MSE. Finally, ANN with the optimization technique of PSO is used for estimating the SINR and SNR, improving spectrum efficiency, reducing losses, and enhancing overall network performance in single / multi-user MIMO scenarios.

## 3.1 Wireless Network Interference

A source node is the device that initiates communication by generating and sending data packets to the destination node in the network. Unlike traditional networks with fixed infrastructure, Mobile Ad Hoc Network (MANETs) are decentralized and composed of dynamically changing topologies, where each node moves freely and independently. When a source node wants to send data, it must first determine a valid route to the destination, often by initiating a route discovery process through protocols. Since nodes in a MANET also serve as routers, the source node relies on neighboring nodes to forward packets across multiple hops until the data reaches its destination. The mobility and limited resources of nodes in MANETs add complexity to this process, requiring the source node to be adaptive and resource-efficient in managing communication.

### *3.1.1 Downlink MIMO Interference*

Downlink MIMO interference refers to signal interference occurring during transmission from a base station to UE in a MIMO wireless system. It's a major challenge in LTE, 5G, and other modern communication networks due to their complex and dense deployment. The downlink MIMO interference is presented in Figure 2.

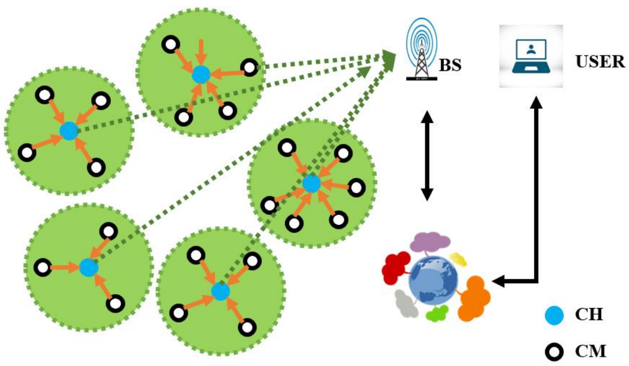


**Figure 2:** *The downlink MIMO interference*

In cellular networks such as LTE and 5G, where base stations use multiple antennas to simultaneously serve multiple users, interference arise both within the same cell and from inter-cell interference. Intra-cell interference typically happens in multi-user MIMO scenarios when multiple users are served on the overlapping spatial channels. Inter-cell interference, on the other hand, occurs when signals from adjacent base stations interfere with the intended downlink signal of a UE, especially near cell boundaries. Additionally, challenges such as imperfect channel state information, pilot contamination in massive MIMO systems, and hardware limitations contribute to further interference. This interference reduces throughput, increases latency, and worsens the overall quality of service.

### 3.2 Interference Estimation Module

An Interference Estimation Module is a crucial component in WCSs, particularly in MIMO, LTE, and 5G networks. Its primary function is to analyze and quantify the interference levels affecting a given user or cell, enabling the network to make intelligent decisions for resource allocation, beamforming, and interference mitigation. This module is responsible for analyzing real-time and historical network data to estimate the level and sources of interference affecting users. Using these inputs, the module applies analytical models, statistical techniques, or machine learning algorithms to quantify interference on a per-user or per-resource-block basis. The resulting interference metrics help in making decisions related to beamforming, power control, scheduling, and resource allocation.

### 3.3 NN model prediction

A Neural Network (NN) model used for prediction plays a key role in intelligent network management, particularly for tasks like interference mitigation, resource allocation, and channel estimation. When applied to prediction, the NN model is trained on large datasets that may include CSI, historical user traffic, signal quality metrics and spatial-temporal patterns. Once trained, the model is quickly inferring or predict outcomes in real time. For instance, in an interference management system, the NN model predicts future interference levels at different user locations based on mobility and usage patterns, allowing the network to proactively adjust transmission parameters such as beamforming vectors, frequency assignments, or scheduling decisions.

### 3.4 PSO - ANN Optimization

PSO-ANN optimization refers to a hybrid approach where PSO is used to train or optimize an ANN to enhance the training and performance of neural models, especially in complex and dynamic environments such as WCS. The ANN architecture is represented in Figure 3.

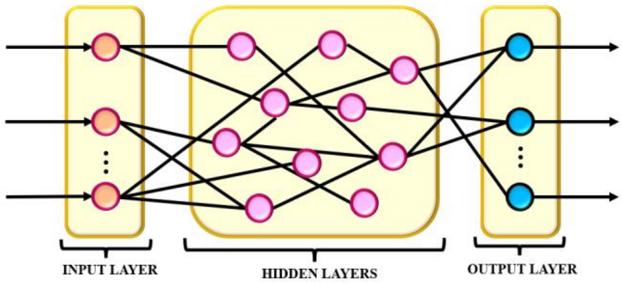


**Figure 3:** *The ANN architecture*

An ANN is a model composed of layers of interconnected neurons that learns complex input-output mappings from data. In typical applications, an ANN’s performance depends heavily on its weights and biases, which are often optimized using gradient-based methods like backpropagation.

In this method, PSO is employed to optimize the parameters of an ANN typically its weights and biases by simulating a swarm of particles that search for the optimal solution within the parameter space. Each particle represents a potential configuration of the neural network, and its performance is evaluated using a predefined fitness function, such as prediction accuracy or interference minimization. Unlike traditional gradient-based training methods like backpropagation, PSO does not rely on derivatives and is better at escaping local minima, making it particularly effective for non-convex optimization problems.

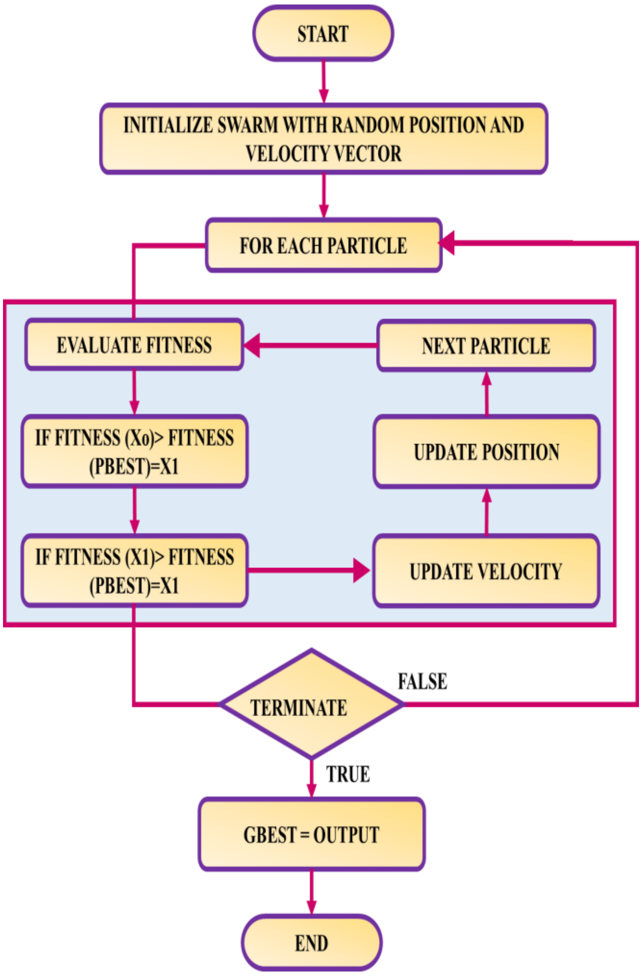


**Figure 4:** *Flowchart of the PSO*

Figure 4 displays the flowchart of the PSO optimization. In applications such as MIMO downlink interference management, PSO-ANN models predict optimal transmission strategies by learning complex patterns in channel state information and user behavior, ultimately improving system performance in terms of throughput, signal quality, and resource allocation efficiency. It provides a robust and flexible framework for solving optimization problems in real-time, data-driven communication networks.

## 4. Results and Discussion

In this work, a hybrid PSO-ANN framework is implemented and the outcomes of the simulation results are provided.

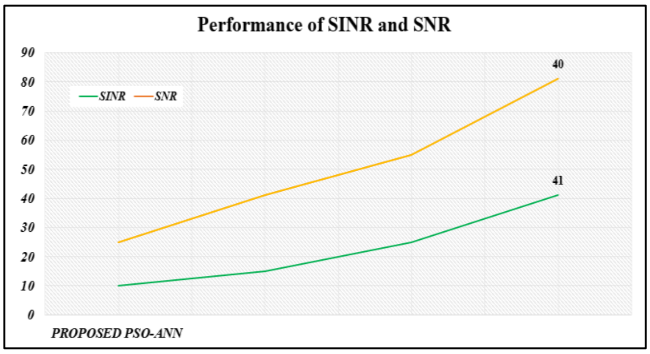


**Figure 5:** *Performance of SINR and SNR*

Figure 5 displays the performance of SINR and SNR values of the proposed work. In this plot, an SINR value of 41 dB and an SNR value of 40 dB are attained.

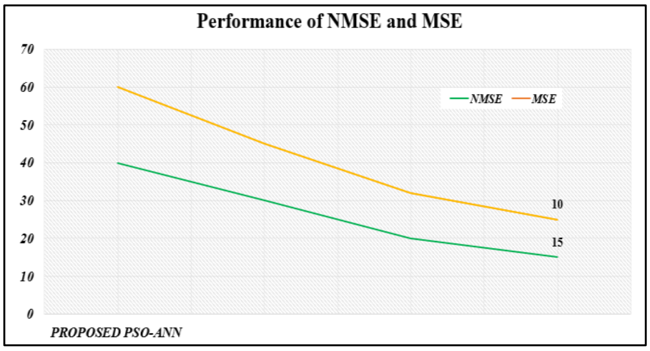


**Figure 6:** *Performance of NMSE and MSE*

Figure 6 illustrates the performance of NMSE and MSE for the proposed work. The NMSE value is obtained at 15dB, and the MSE value is obtained at 10 dB.

**Table 1:** *Performance of Comparative Analysis*

| Optimizations | Parameters (dB) | | | |
|---|---|---|---|---|
| | SINR | SNR | NMSE | MSE |
| Custom CNN [11] | 20 | 10 | 25 | 25 |
| CNN [13] | 25 | 20 | 20 | 25 |
| CNN - BILSTM [14] | 25 | 22 | 16 | 20 |
| Proposed PSO-ANN | 41 | 40 | 15 | 10 |

The parameter and its specifications are shown in Table 1. When compared to a variety of other approaches, the proposed PSO-ANN offers the best parameter outcomes.

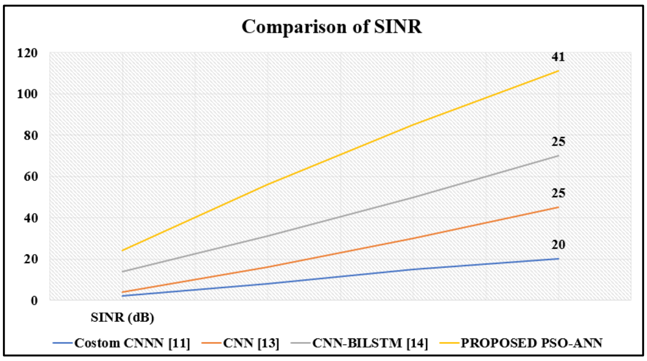


**Figure 7:** *Comparison of SINR*

The comparison of SINR values is shown in Figure 7. In this plot, the proposed PSO-ANN achieved the highest SINR values of 41 dB, indicating a stronger and clearer signal and leading to better data rates. In other methods, the minimum SINR value is attained with poor performance.

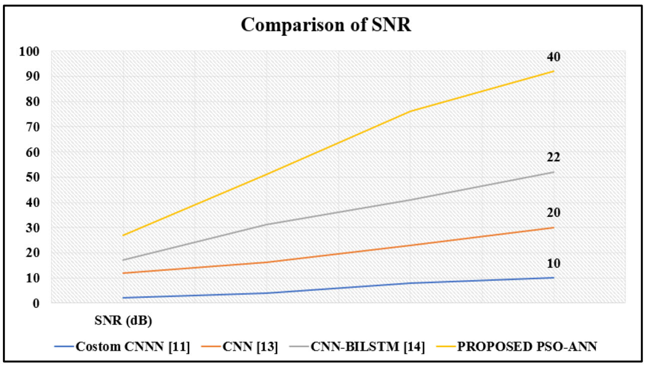


**Figure 8:** *Comparison of SNR.*

The comparison of SNR seen in Figure 8. In this instance, a proposed SNR value of 40 dB is reached. Likewise, previous techniques are custom. CNN is 10 dB, CNN is 20 dB, and CNN-BILSTM is 22 dB of SNR values.

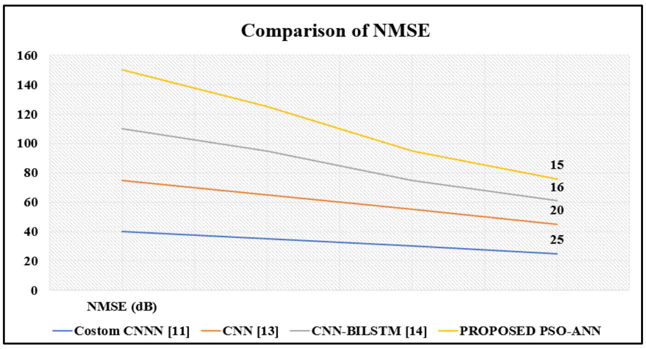


**Figure 9:** *Comparison of NMSE*

Figure 9 illustrates a comparison of different classifications of NMSE values. In the graph, the proposed classification is an NMSE of 15 dB, and the previous classifications of custom CNN provide a highest NMSE value of 25 dB, CNN is 20 dB, and CNN-BILSTM is 16 dB of SNR values, respectively.

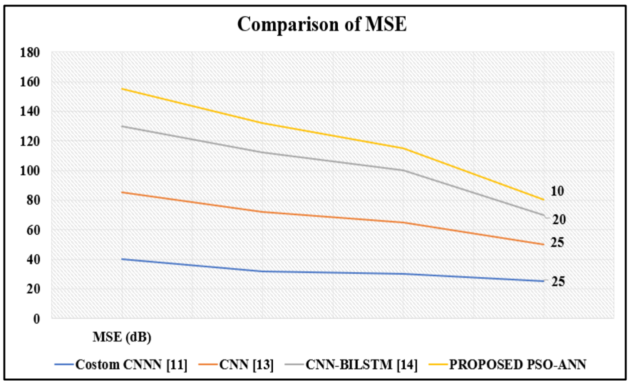


**Figure 10:** *Comparison of MSE*

Figure 10 illustrates a comparison of different classifications of MSE values. The graph demonstrates that it offers a minimum value of MSE compared to other methods. When the error value is low, the performance and efficiency are enhanced.

## 5. Conclusion

This paper presents a hybrid framework that integrates PSO with NN-based interference management strategies for MIMO architectures in next-generation wireless networks. PSO is employed to optimize the NN's parameters, enabling faster convergence and improved adaptability to varying channel conditions. This method effectively mitigates inter-user and inter-cell interference, significantly enhancing spectral efficiency and signal reliability. Simulation results confirm that the PSO-optimized neural approach outperforms conventional techniques in noise ratio of SINR, SNR and overall errors of NMSE and MSE. These findings highlight the promise of intelligent optimization-driven solutions in addressing the complexity and performance demands of future WCSs.

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