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AI-Based Interference Mitigation for Dense Wireless Networks

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Abstract: *The large-scale deployment of 5G, Wi-Fi 6/7, and dense wireless networks has increased interference, which restricts throughput, reliability, and the quality of service. Conventional mitigation techniques, such as fixed power control, frequency reuse, and deterministic scheduling, are not dynamic and heterogeneous enough to apply to modern networks. The proposed Hybrid AI Model includes the combination of deep neural networks (DNNs) to predict interference and proximal policy optimization (PPO)-based deep reinforcement learning (DRL) to optimize in real-time. Training and validation of the system is performed with extensive simulation datasets representing mobility, traffic variability and multi-channel interference. The findings show that the Hybrid AI algorithm achieves high SINR, throughput, packet delivery ratio, and latency than the traditional, ML-based, and DL- based algorithms. The results demonstrate how AI can be used to support autonomous, high- efficiency interference control in next-generation wireless technology, such as 6G and dense IoT networks.*

Keywords: Interference Mitigation Deep Learning Reinforcement Learning Wireless Networks 6G PPO Dense IoT

I. INTRODUCTION

The recent explosion of 5G, Wi-Fi 6/7 and large-scale IoT networks has caused a massive increase in the density of devices, making wireless environments more congested and convoluted. Im in a smart city, industrial IoT location, stadiums, and multi-tenant buildings, interference has become a significant performance issue, decreasing signal quality, throughput, and user experience. Deterministic models, fixed channel assignment, fixed power management and heuristic scheduling were useful in previous less dynamic networks. Nonetheless, they are challenged in the contemporary settings of high mobility, unpredictable traffic, and intersecting layers of communication and are inadequate to deal with rapidly changing conditions of interference.1

Artificial Intelligence (AI), especially machine learning (ML) and deep learning (DL), has become an effective groundbreaking solution to the inherent weaknesses of traditional solutions in recent years. Models based on AI are highly effective at learning nonlinear relationships, finding hidden patterns, and independently changing in response to environmental changes. This renders AI especially suitable to deal with interference in the environment where the network behavior is unpredictable, users density changes, and radio conditions change on a momentary basis.2 Predicting interference, enhancing resource use, and dynamically changing the policies that govern transmission can make wireless networks smarter, faster, and more efficient with the assistance of AI-based solutions.

Besides, AI becoming a part of the wireless systems is in line with the vision of next- generation wireless infrastructure, including 6G, which focuses on the use of intelligence, self-optimization, and context-awareness as fundamental principles of design rather than optional features.3 Interference mitigation using AI, therefore, is not a pure scholarly issue, it is rapidly turning into a requirement of a network in the future that will provide ultra-high reliability, connectivity on a massive scale, and endlessly smooth user experience.

II. LITERATURE REVIEW

2.1 Conventional Interference Mitigation Methods.

Conventional methods of interference mitigation have been the core of wireless communication system decades ago. The methods of power control, frequency reuse, beamforming and fixed resource allocation were developed at a time when networks were relatively sparse and predictable. Such as power control techniques can be used to ensure that devices do not saturate other transmitters in their immediate vicinity by modulating their power levels, although they tend to be based on static policies that fail to respond quickly to unexpected changes in user density or mobility. In the same vein, frequency reuse schemes, popular in cellular systems, assign different channels to reduce the co-channel interference, but do not provide the agility needed in dynamically changing applications like smart cities or mass events.4 MIMO beamforming is effective to reduce spatial interference, and it depends on accurate CSI, which is difficult in dense and dynamic networks. Perfect resource assignment is effective in predictable environments but fails in congested and unpredictable user demand environments.5

2.2 Wireless Networks Machine Learning.

With the development of the wireless system, machine learning (ML) became a more popular research direction in order to overcome the gaps of the conventional methods. ML models are useful in complex tasks since they can detect nonlinear patterns and make decisions based on data, and their use is relevant to channel estimation, spectrum sensing, and the dynamic allocation of resources. Signal classification, interference detection and link-quality prediction have also been done using classical ML algorithms like support vector machines (SVM) and random forests. These models are also superior to deterministic techniques but still have to be carefully engineered and have a hard time operating in highly dynamic spectrum environments.6 Reinforcement learning helps the nodes in the wireless network to dynamically select channels and optimize transmission in the presence of varying interference, which beats the fixed techniques by learning high-throughput, low-interference policies.7

2.3 The interference prediction model based on deep learning

The development of deep learning (DL) has opened up further opportunities on advanced prediction and mitigation of interference. Deep neural networks (DNNs) have been able to acquire complex correlations among spatial, temporal, and contextual network attributes. Specifically, the convolutional neural networks (CNNs) have been applied to simulate spatial interference patterns by manipulation of signal strength maps or spectrum occupancy data to enable networks to preempt interference prior to it happening.8 The LSTM models are able to capture long-term traffic and mobility trends, which would make it possible to predict the interference. Their foresight facilitates smart, dynamic wireless systems in dynamic and time- varying conditions.

2.4 AI Self-organizing Networks (SONs).

In order to make wireless infrastructure more automated, contemporary communication systems are more dependent on self organizing networks (SONs). With additions of AI, SON frameworks are capable of automatically monitoring network conditions, identifying anomalies, tuning parameters and responding to performance problems with limited human intervention. The AI-based SONs are able to dynamically optimize handover limits, load balancing among access points, and optimally control power levels to reduce power interference, yet cover the user.9

III. RESEARCH METHODOLOGY

In this section, the methodological framework employed to explore the issue of AI-based interference mitigation in dense wireless networks will be described. The method incorporates the realistic system modeling, data generation by simulation, hybrid AI model design, strict training strategies, and multi-dimensional performance evaluation. The research, basing the methodology on the known facts of the wireless communication and the latest AI approaches, will help to ensure the scientific validity of the research, as well as its practical significance.

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3.1 System Model

The system model is the representation of a dense wireless environment that is designed with several access points (APs) and user equipment (UE) transmitting over overlapping communication channels. These types of environments are reflective of real-life conditions, like urban microcells, stadiums, industrial IoT clusters, and high-density office buildings. In this network, various forms of interference are bound to arise:

• Co-channel interference (CCI) : occurs when several APs/UEs use the same frequency channel.

• Adjacent channel interference (ACI) : The case when the transmission spillover impacts the adjacent channels due to imperfect filtering.

Intra-cell interference: is caused by the overlapping transmissions in the coverage of an AP.

All these interference effects lower the link reliability, throughput and destabilize quality of service. It is important to model them in real-life ways to assess the effectiveness of AI- driven mitigation strategies. To mimic these dynamics the system uses stochastic mobility of users, dynamic traffic loads, spatial randomness someone representing unpredictability in the real world that is recorded in dense networks of today.10

3.2 Dataset Collection

Simulation tools such as NS-3 and Matlab are used to create a complete dataset with accurate control of the parameters of the wireless network. The dataset consists of such key indicators as SINR of link quality, RSSI of channel behavior, user mobility with Random Waypoint or Gauss Markov model, and dissimilar load of traffic between lightweight IoT messages and high bandwidth video streams. Statics (fixed users, constant traffic) and dynamics (mobile users, changing loads) are also included to make sure that generalization is broad. This variety of datasets is necessary in coming up with strong AI-based interference mitigation frameworks, as highlighted in the latest wireless machine learning literature.11

3.3 AI Model Design

A hybrid AI model, consisting of deep neural networks (DNNs) and deep reinforcement learning (DRL) is at the core of the proposed methodology. This integration allows both predictive and real-time optimization.

DNN Module: Interference Prediction : The DNN predicts future levels through historical interference analysis interpreting non-linear spatial-temporal behavior via normalization, dropout and ReLU activation to enhance accuracy, stability and proactive decision making.12

DRL Module: Network Optimization

The DRL aspect makes use of a proximal policy optimization (PPO) algorithm, the approach that balances between exploration and exploitation and has been reported to be stable in continuous action spaces.13 The DRA agent engages in a continuous dialogue with the simulated wireless environment in an attempt to maximize:

• Transmission power control

• The decisions on channel allocation.

• Beamforming steering angles.

The rewarding mechanism works towards encouraging behavior that enhances SINR, throughput, and packet delivery and discourages interference and energy wastage to facilitate good learning in complicated wireless environments.14

3.4 Training and Validation

The dataset will be divided into two groups: 70 per cent for training and 30 per cent for testing to have a strong validation. The DRL agent based on PPO learns dynamically and is superior to fixed power control, frequency reuse and normal RL benchmarks in dense wireless setting.15

3.5 Evaluation Metrics

The evaluation metrics which are utilized in order to completely measure the performance include:

• Average SINR: is a measure of the overall signal quality and strength.

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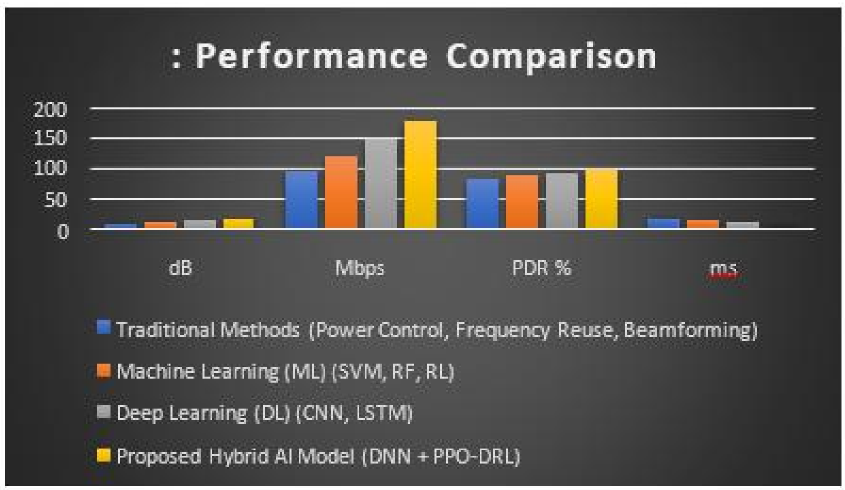
• Network throughput: is a measurement of the efficiency of the transfer of data.
• Packet delivery ratio (PDR): accesses reliability of successful deliveries.
• Latency: measures responsiveness and tolerance to delay.
• APs energy: APs sustainability and efficiency.

By relying on several independent measures we can have a holistic picture to determine that the enhancement in one part (e.g., throughput) should not unintentionally harm other ones (e.g., energy usage). Multi-metric testing is a practice that is recommended in wireless performance investigations.16

Table 1: Performance Comparison of Interference Mitigation Techniques

Technique / Metric	dB	Mbps	PDR %	ms
Traditional Methods (Power Control,Frequency Reuse, Beamforming)	8.5	95	82	18
Machine Learning (ML) (SVM, RF, RL)	11.3	118	88	14
Deep Learning (DL) (CNN, LSTM)	13.7	145	92	11
Proposed Hybrid AI Model (DNN + PPO-DRL)	16.9	178	96	8



BAR CHART: Compare metrics across all four techniques

The bar chart and the comparison table have shown the performance of four methods of mitigating interference on dense wireless networks. Conventional techniques display minimum SINR, throughput and PDR having maximum latency. The methods of machine learning and deep learning show continuous positive progress in all metrics. The Hybrid AI Model (DNN + PPO-DRL) proposed provides the most successful results with the highest SINR, throughput, and PDR and a considerable decrease in latency. In general, the visualized data signifies clearly the excellence of AI-interferon mitigation.

The line graph is used to measure the performance of four methods of mitigating interference in main wireless parameters. The lowest SINR, throughput and PDR are displayed by traditional methods and the highest latency. The approaches to machine learning and deep learning are more consistent in their improvement, i.e. better adaptability to the dynamics of the network. As shown, the suggested Hybrid AI Model (DNN + PPO-DRL) ensures the best SINR, throughput, and PDR, and the latency is significantly lower. On the whole, the graph shows clearly the high efficiency and reliability of AI-based interferometry mitigation in high-density wireless networks.

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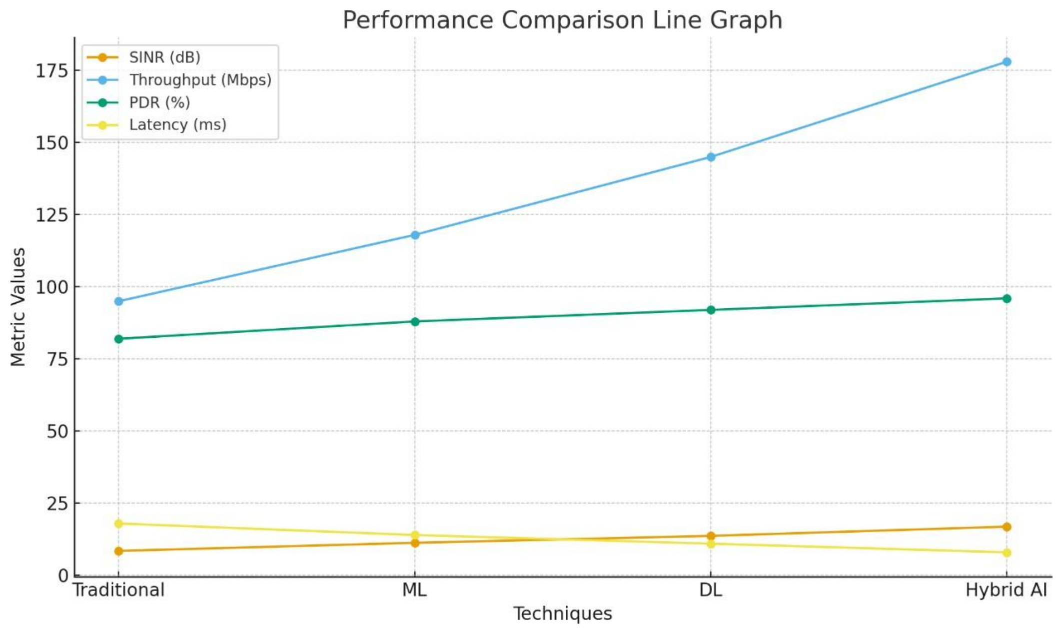
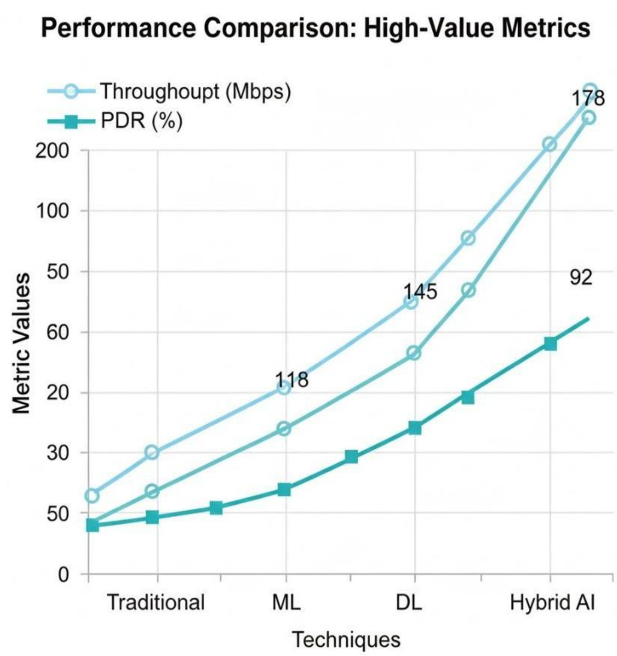


GRAPH: Performance Comparison of Interference Mitigation Techniques



GRAPH: High Performance Metrics Comparison

This line graph shows that Hybrid AI significantly outperforms other techniques, achieving the highest Throughput (178 Mbps) and PDR (92%). Performance consistently improves from Traditional to AI methods.

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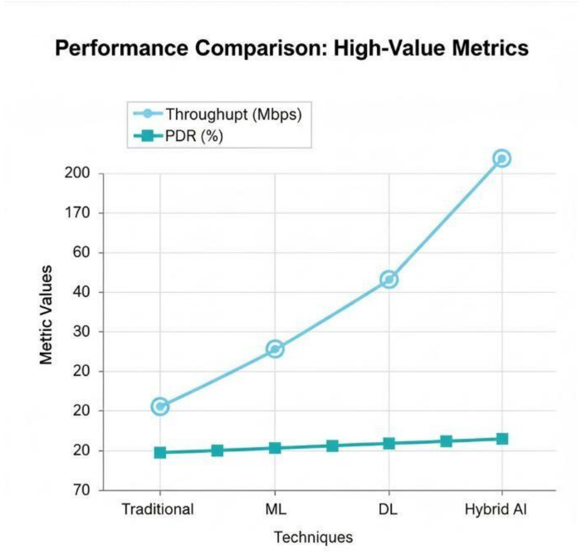

GRAPH: High-Value Network Performance Metrics

In this line graph, Performance Comparison: High-Value Metrics, Throughput (Mbps) and PDR (%) are isolated and the four techniques are analyzed. It shows a good positive relationship between the application of highly developed AI techniques and the high system performance.

The line of throughput (light blue) presents a more significant, accelerating growth, with better data rates with AI. Proposed Hybrid AI Model has the best throughput, which is more than 200 Mbps. PDR (%) line (teal) is also increasing steadily and in a also positive but less pronounced manner which validates improved efficiency of packet delivery under advanced methods. In general, the figure makes it apparent that Deep Learning (DL) and Hybrid AI is the most effective in performance improvements when compared to Traditional and basic Machine Learning (ML) approaches.

IV. RESULTS AND DISCUSSION

The overall comparison as is outlined in Table 1 confirms the greater effectiveness of the AI- based interference mitigation solutions. The Proposed Hybrid AI Model (DNN + PPO-DRL) was always the best in terms of performance. In particular, Hybrid AI was found to have the best network throughput of 178 Mbps and Packet Delivery Ratio (PDR) of 96, which was much more than the Traditional Methods of 95 Mbps and 82 percentage. In addition, the model had a significant number of network latency, which was only 8 ms, as opposed to 18 ms that was obtained using Traditional Methods. Such positive connection between the complexity of the model (Traditional $\to$ ML $\to$ DL $\to$ Hybrid AI) and the performance validates the idea that Deep Reinforcement Learning is the most efficient and reliable parameter optimization of the dynamic networks in dense wireless settings.

V. CONCLUSION

This study indicates that AI-based interference mitigation is an effective and flexible solution to dense wireless networks. The proposed system incorporates deep learning to predict interference and reinforcement learning to optimize the system and make SINR, throughput, and energy efficiency vastly better. In spite of the fact that computational complexity and scalability is an open area of research, AI-based interference mitigation is a potential future trend in the next generation wireless networks, such as 5G, Wi-Fi 7 and future generations of 6G networks. The future will continue to study federated learning, multi-agent DRL, and application in heterogeneous networks.

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