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Proposed Explainable Interference Control Technique in 6G Networks Using Large Language Models (LLMs)

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Abstract: After the advent of 5th generation (5G) and 6th generation (6G) cellular networks, the complexity of managing real-time signal interference has increased in dense and dynamic environments. Traditional interference techniques, such as frequency reuse and allocation, while effective, lack robust adaptability and transparency needed to reduce interference in advanced communication networks. This paper introduces a novel approach that fuses large language models (LLMs) and Explainable Artificial Intelligence (XAI) to mitigate interference and enhance interference management in the mathematical foundations of 6G networks. The proposed approach provides accurate interference predictions, which the LLM balances with its complex architecture, necessary to meet the demands of beyond 5G and 6G networks, along with interpretable explanations to ensure transparency in decision-making. The proposed framework has been evaluated across various performance metrics. Interference latency consistently achieves lower rates of 0.95 s, compared to traditional techniques, which average around 1 s. Furthermore, the confidence score of the LLM shows a stable value of 0.87 throughout the system, compared to 0.85 in techniques without LLMs. Overall, the XAI-driven LLM demonstrates the potential of incorporating LLMs and XAI into wireless networks to improve resilience in next-generation networks. This proof of concept introduces a novel framework that offers new dimensions in wireless communication, particularly for interference management, prediction, and mitigation.

Keywords: AI/ML; LLM; intelligent communication; beyond 5G; 6G

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1. Introduction

Wireless communication technologies have advanced so fast that the world has seen the emergence of 5G networks, and the emergence of 6G is expected in a shorter time [1]. These next-generation networks are believed to provide ultra-reliable and low-latency communication for new-generation applications like smart cities, autonomous cars, and IoT [2]. However, the complexity and density of 6G networks create a new problem, namely interference between the signals [3]. Signal interference in densely populated regions or high-traffic networks can consequently cause the communication quality to diminish, data rate to decrease, and latency to rise, all of which influence the network [4].

The earlier generations of the wireless communication system are best addressed by the conventional interference management techniques that utilize static or semi-static models for signal propagation and interference detection. However, these methods are not suitable in dynamic environment of modern networks [5]. Moreover, traditional approaches provide minimal insights into the rationale behind interference mitigation techniques, which is problematic for network operators as they cannot easily understand or rely on the system's judgments, especially in critical applications [6].

AI and ML have opened new ways of handling interference in wireless networks [7]. Researchers have employed supervised learning and reinforcement learning algorithms to predict interference patterns, power control, and frequency allocation [8]. Although these models are more flexible and efficient than traditional approaches, they are basically 'black boxes' that make decisions that are hard to rationalize [9]. In mission-critical application scenarios such as emergency communication systems or self-driving cars, such a lack of interpretability can be a concern because network operators require an understanding of the reasoning behind the system's decisions for the safety and resilience of the network [10].

The problem of interpretability in machine learning has been solved by a new approach known as Explainable AI (XAI) [11]. XAI methods are designed to provide human-understandable reasoning for the actions taken by AI systems in order to enhance the trustworthiness of AI-based systems [12]. In wireless communication, XAI can help explain the reasons for signal interferences and the rationale behind the proposed measures to avoid them, thus providing the network operators with the information they need to take appropriate actions [13]. Including XAI in the large language models, including Llama v3, is one of the critical areas of interest for interference management in the 6G network. Why Llama_v3 and why not other models? Because Llama_v3 is highly customizable [14].

The recent success of LLMs in natural language processing tasks makes them suitable for processing large volumes of data and making contextual decisions [15]. In wireless networks, LLMs can be trained to learn the network's current status, forecast interference patterns, and recommend changes for interference management [16]. Integrating XAI techniques into LLMs improves their applicability by providing explainable outputs as to why specific actions were taken in addressing interference. This combination of predictive power and transparency provides a new way to improve interference management in a complex network environment, making interference mitigation more proactive, adaptive, and explainable [17].

Nevertheless, applying XAI-based LLMs to interference management has yet to be explored extensively. Previous work in this domain was mainly based on conventional signal processing methods or machine learning models that lacked interpretability. Given the continuous growth of wireless networks' complexity and the rising importance of explaining the functioning of AI-based systems, there is a need to study the possibility of using XAI-based LLMs to manage interference in 6G networks.

The rest of the paper is structured as follows: the proposed framework is presented in Section 3, and the experimental settings and results are covered in Sections 4 and 5. Finally, Section 6 concludes the study.

2. Literature Review

Interference is a critical challenge that impacts signal amplitude, network, and data transfer rate. Conventional interference management techniques, mainly founded on deterministic signal processing and statistical models, are operational and efficient but insufficient for today's communication context. The high density and complexity of the network with many interconnected devices, time-varying channel conditions, and real-time data transfer characterize these environments [18].

Current interference mitigation techniques include frequency hopping, power control, and channel allocation, which usually need to be more flexible to provide real-time adaptation to the constantly changing environment of the network [19]. Techniques such as game theory and reinforcement learning have been applied to attempt to introduce a level of adaptability [20]. Nevertheless, these methods enhance network reactivity to interference, but issues of transparency and interpretability need to be addressed. Executives and managers of the networks are frequently left with little idea of why some actions were made or taken, which makes it challenging to rely on the system's decision-making, especially in the application of self-driving cars, smart cities, and IoT environments [21–23].

XAI techniques are intended to explain the reasoning behind AI systems to human users. This is especially crucial in the case of the 6G networks, as the actions performed by

the interference management system can strongly impact the system's reliability and user satisfaction. Conventional approaches to AI reasoning, described as 'black box' systems, are not appropriate for contexts where the reasons for specific decisions are essential [24].

The use of LLMs, including the XAI-based Llama v3, for interference management is relatively uncommon. LLMs have been proven to be very successful across several domains, including natural language processing and predictive analytics. Due to their capability to handle large volumes of data and to produce context-aware predictions, they are suitable for the dynamic and often highly unpredictable conditions characteristic of most current wireless networks. Furthermore, using LLMs in conjunction with XAI techniques can give both accurate predictions of the interference and explain the cause of the interference, which would be helpful for the network operators to take necessary actions against the interference [25,26].

On the other hand, LLMs like Llama v3 can be programmed to infer interference patterns given a large amount of historical and real-time network data. This predictive capability enables interference management, where the system can change the network before considerable interference happens, enhancing the network's performance. Also, the models discussed here are explainable, meaning the network operators can understand how the system arrived at a particular decision.

The shift from 5G to 6G is an incredible challenge, where high population density, smart city, and IoT systems demand high bandwidth and low latency [27]. In such environments, the basic methods of interference management fail because they cannot respond quickly to network fluctuations. Integrating LLMs with interference management provides a possible solution by allowing networks to adapt parameters such as power control and frequency allocation according to actual conditions. In addition, XAI-based LLMs can assist network operators in comprehending and accepting these dynamic adjustments due to the explainability of the models.

One issue that has emerged in contemporary interference management is the ability to achieve the best result while maintaining the visibility of the process [28]. However, the traditional AI models used to enhance the network's performance commonly sacrifice interpretability. LLMs can solve the above problem since they can achieve high performance while being explainable. This is especially true in the case of 6G networks, where interference can have severe effects and operators require a reason for the system's behavior.

While various AI techniques such as supervised learning and reinforcement learning have been explored for interference management, these models often act as 'black boxes,' limiting interpretability and trust. In mission-critical scenarios, such as self-driving cars and emergency communication systems, understanding the reasoning behind AI decisions is essential for ensuring safety and reliability. Therefore, this study opts for Explainable AI (XAI) to bridge the gap between prediction accuracy and transparency. XAI not only enhances decision-making by providing interpretable outputs but also builds trust with network operators by explaining the rationale behind interference management strategies. The integration of AI, particularly with LLMs, enables real-time adaptability and contextual interference management, outperforming traditional static methods that lack flexibility in dynamic environments. The research gap is in the need for studies on how such XAI-based LLMs like Llama v3 can be applied to the problem of interference management. Conventionally used signal processing techniques are popular, but they could be more efficient regarding real-time reconfigurability and interpretability, particularly in the context of 6G. Existing approaches must offer the means for generating easily understandable and context-sensitive information about interference causes and countermeasures. The study reveals the demand for understanding how XAI-based LLMs can provide accurate interference detection and explainable solutions, thus establishing a significant gap in creating intelligent and transparent interference management systems.A comprehensive comparison of traditional and proposed techniques can be observed in Table 1.

Closing this gap, this research will address the following questions:

1. How can XAI-based LLMs, like Llama v3, enhance real-time signal interference detection in 6G networks?
   This research will investigate how large language models, particularly XAI-based models like Llama v3, can improve the detection of signal interference in real-time. It will explore the model's ability to predict interference patterns and suggest proactive measures to mitigate interference before it significantly impacts network performance.
2. What are the benefits of explainability in LLM-driven interference management compared to traditional methods?
   A central focus of this research will be understanding how the explainability provided by XAI-based LLMs can offer advantages over traditional interference management techniques. The study will assess how explainable outputs enhance decision-making, build trust with network operators, and provide actionable insights into network conditions and interference sources.
3. How effectively can LLMs like Llama v3 provide transparent and adaptive solutions for mitigating signal interference in complex communication environments?
   The research will evaluate the overall efficacy of LLMs in providing not only accurate but also transparent and adaptive solutions for interference management. By focusing on the ability of LLMs to adapt to varying network conditions while providing interpretable outputs, the study aims to establish these models as viable tools for next-generation wireless communication systems. By focusing on these research questions, this study aims to bridge the gap between traditional interference management techniques and modern, explainable AI-driven approaches, paving the way for more resilient, efficient, and transparent communication networks.

Table 1. Comparison between traditional and proposed techniques.

Parameter	Traditional Techniques	Proposed XAI-Driven LLM Approach
Interference Management	Frequency reuse, power control	Predictive LLM-based control
Adaptability	Limited	Real-time adaptability
Explainability	Minimal	High (SHAP values)
Latency	1 s	0.95 s
Confidence Score	0.85	0.87
Throughput	100 Mbps	107.5 Mbps
Transparency	Low	High

SHAP: SHapley Additive exPlanations.

With the emergence of 6G wireless communication, the density of the network and the frequency of the interference increases rapidly in the urban environment, smart cities, and IoT systems. Many conventional interference management techniques are insufficient to cope with such a type of network, as they do not possess real-time adaptability and transparency. This can lead to low-quality communication and a negative impact. Therefore, new techniques must be developed that not only identify and control interference but also offer understandable and explainable results to the network operators.

XAI-based LLMs, especially the new model, Llama v3, offer a new prospect. As data processing entities capable of context-aware predictions and providing explainable outputs, LLMs can potentially radically change interference management in wireless communication. Nevertheless, their use in this field has not been thoroughly investigated and is, therefore, a research area of interest.

Due to the complex and dense nature of 6G networks, more sophisticated, fast solutions are required for interference prediction and mitigation. Furthermore, after accurate mitigation and prediction, transparency is also key because deep learning models act as a 'black box' and dependence on the output of particular model can question the integrity of whole framework. Keeping in view this aforementioned issue, the following contributions have been proposed:

1. To develop a XAI-driven LLM for interference management in complex 6G networks.
2. To develop a dynamic interference mitigation model based on predictive models and XAI framework.
3. To make a formal comparison and analysis of the XAI-driven LLM interference mitigation technique with traditional methods.

3. Proposed Model

To build a general mathematical model for signal interference control based on an XAI-based LLM (Llama v3), we first establish the wireless communication system model and subsequently incorporate reinforcement learning, clustering, and XAI. The goal is to establish a smooth transition from simple signal transmission equations to complex optimization techniques and explain why each equation leads to the next. The proposed framework can be illustrated in Figure 1.

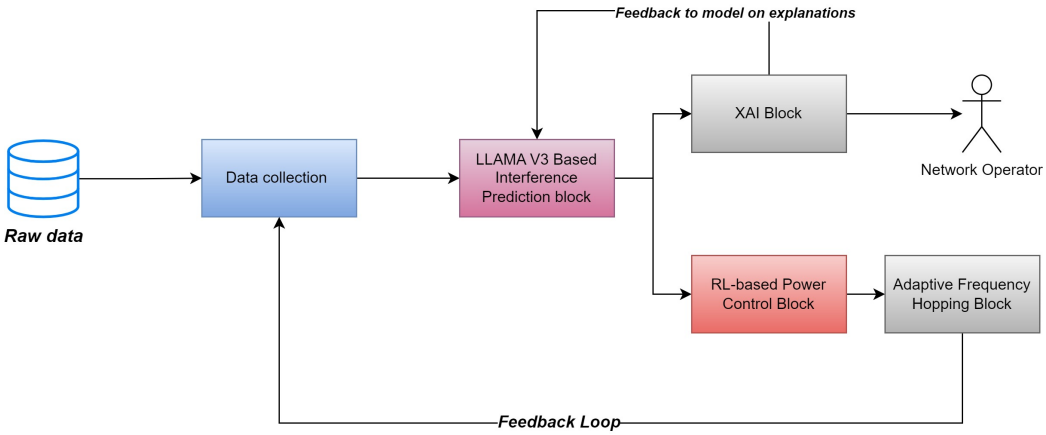


Figure 1. Proposed framework.

The transmitted signal from node i over frequency f at time t is given by the following:

$$x_i^f(t) = \sqrt{P_i^f(t)}\, s_i^f(t) \tag{1}$$

where $P_i^f(t)$ is the transmission power, and $s_i^f(t)$ is the unit-power symbol transmitted by node i. This equation describes the basic transmission process, where the signal power is scaled by the square root of the transmission power.

The effect of the communication channel between nodes must be considered next. The channel gain between nodes i and j over frequency f at time t is modeled as follows:

$$h_{i,j}^f(t) = \frac{G_{i,j}^f}{d_{i,j}^\gamma}\, e^{-\kappa_{i,j}^f(t)} \tag{2}$$

where $G_{i,j}^f$ is the antenna gain, $d_{i,j}$ is the distance between nodes, γ is the path loss exponent, and $\kappa_{i,j}^f(t)$ represents shadowing and fading effects. This captures the attenuation in signal strength over distance and the influence of environmental factors.

The received signal at node j from node i is affected by this channel and can be expressed as follows:

$$y_{j,i}^f(t) = h_{i,j}^f(t)\, x_i^f(t) + n_j^f(t) \tag{3}$$

where $n_j^f(t)$ represents the additive white Gaussian noise (AWGN) at node j. Here, we introduce the role of noise, an important aspect that contributes to the total received signal.

To understand interference, the total interference at node j over frequency f caused by other nodes in the network is calculated as follows:

$$I_j^f(t) = \sum_{k \in \mathcal{N}, k \neq i} h_{k,j}^f(t)\, x_k^f(t) \tag{4}$$

This equation sums the contributions of signals from all interfering nodes k to node j, demonstrating how interference from other transmitters affects the received signal.

Based on the received signal and interference, the Signal-to-Interference-plus-Noise Ratio (SINR) at node j when receiving from node i can be calculated as follows:

$$\mathrm{SINR}_{j,i}^f(t) = \frac{|h_{i,j}^f(t)|^2\, P_i^f(t)}{\sum_{k \in \mathcal{N}, k \neq i} |h_{k,j}^f(t)|^2\, P_k^f(t) + N_0} \tag{5}$$

where N_0 is the noise power spectral density. This ratio quantifies the quality of the signal by comparing the power of the desired signal to the sum of interference and noise.

The achievable data rate between nodes i and j over frequency f, which is directly related to the SINR, is given by

$$R_{j,i}^f(t) = B^f \log_2\left(1 + \mathrm{SINR}_{j,i}^f(t)\right) \tag{6}$$

where B^f is the bandwidth of frequency f. This expression represents the theoretical maximum data rate, linking SINR to the achievable transmission capacity.

To optimize network performance, we aim to minimize the total interference, which is expressed as follows:

$$\min_{P_i^f(t)} \sum_{j \in \mathcal{N}} \sum_{f \in \mathcal{F}} I_j^f(t) \tag{7}$$

This minimization is subject to power and SINR constraints, ensuring both efficiency and quality of communication. The power constraints are

$$0 \leq P_i^f(t) \leq P_{\max}^f, \quad \forall i \in \mathcal{N},\, f \in \mathcal{F} \tag{8}$$

and the SINR constraints ensure adequate signal quality:

$$\mathrm{SINR}_{j,i}^f(t) \geq \mathrm{SINR}_{\min}, \quad \forall (i,j) \in \mathcal{C},\, f \in \mathcal{F} \tag{9}$$

Next, we define the input feature vector for the LLM, which will predict interference based on current system states:

$$\mathbf{X}(t) = \left[P_i^f(t),\, h_{i,j}^f(t),\, \mathrm{SINR}_{j,i}^f(t),\, R_{j,i}^f(t),\, I_j^f(t),\, E(t)\right] \tag{10}$$

This vector includes relevant features such as transmission power, channel gain, SINR, and other factors affecting system performance.

The LLM predicts the interference at a future time $t + \Delta t$:

$$\hat{I}_j^f(t + \Delta t) = \mathrm{LLM}_\theta(\mathbf{X}(t)) \tag{11}$$

This prediction is achieved through a loss function that minimizes the difference between the predicted and actual interference:

$$\mathcal{L}(\theta) = \frac{1}{NF} \sum_{j=1}^{N} \sum_{f=1}^{F} \left(I_j^f(t + \Delta t) - \hat{I}_j^f(t + \Delta t)\right)^2 \tag{12}$$

To explain the influence of each feature in the LLM's prediction, the SHAP value for feature k is computed as follows:

$$\phi_k = \frac{1}{M!} \sum_{\mathcal{S} \subseteq \mathcal{F} \setminus \{k\}} \frac{|\mathcal{S}|!(M - |\mathcal{S}| - 1)!}{M!} \left[\hat{I}_j^f(\mathcal{S} \cup \{k\}) - \hat{I}_j^f(\mathcal{S}) \right] \tag{13}$$

This provides a measure of how much each feature contributes to the interference prediction.

Frequency allocation is then adapted based on the predicted interference

$$f_i^*(t + \Delta t) = \arg\min_{f \in \mathcal{F}} \hat{I}_i^f(t + \Delta t) \tag{14}$$

with a constraint on the amount of frequency hopping allowed

$$|f_i^*(t + \Delta t) - f_i(t)| \leq \Delta f_{\max} \tag{15}$$

The utility function for frequency hopping is defined to balance SINR improvements and frequency switching costs:

$$U_f(t) = \sum_{i=1}^{N} \log_2 \left(1 + \text{SINR}_{i,j}^f(t) \right) - \beta |f_i^*(t + \Delta t) - f_i(t)| \tag{16}$$

Power control is optimized similarly, with the goal of maximizing system utility while minimizing power consumption:

$$\max_{P_i^f(t)} \sum_{i=1}^{N} \log_2 \left(1 + \text{SINR}_{i,j}^f(t) \right) - \alpha \sum_{i=1}^{N} \sum_{f=1}^{F} P_i^f(t) \tag{17}$$

subject to power constraints.

The Lagrangian for this optimization is as follows:

$$\mathcal{L} = -\sum_{i=1}^{N} \log_2 \left(1 + \text{SINR}_{i,j}^f(t) \right) + \alpha \sum_{i=1}^{N} \sum_{f=1}^{F} P_i^f(t) + \sum_{i=1}^{N} \lambda_i \left(P_i^f(t) - P_{\max}^f \right) \tag{18}$$

and the KKT conditions for optimality are

$$\frac{\partial \mathcal{L}}{\partial P_i^f(t)} = 0, \quad \lambda_i \geq 0, \quad \lambda_i \left(P_i^f(t) - P_{\max}^f \right) = 0 \tag{19}$$

The reinforcement learning (RL) agent operates within this system, adjusting power and frequency. Workflow can be depicted in Figure 2. The agent's state at time t is given by

$$s(t) = \left[\mathbf{X}(t),\, f_i(t),\, P_i^f(t) \right] \tag{20}$$

and the agent takes actions $a(t)$ that adjust power and frequency as follows:

$$a(t) = \left[\Delta P_i^f(t),\, \Delta f_i(t) \right] \tag{21}$$

The reward function for the agent is

$$R(t) = \lambda_1 \Delta \text{SINR}(t) - \lambda_2 \Delta P(t) - \lambda_3 I_j^f(t) \tag{22}$$

and the policy is updated using

$$\theta \leftarrow \theta + \eta R(t) \nabla_\theta \log \pi_\theta(a(t)|s(t)) \tag{23}$$

The value function is updated as:

$$V(s(t)) = R(t) + \gamma V(s(t+1)) \tag{24}$$

and the Q-value is updated as follows:

$$Q(s(t), a(t)) \leftarrow Q(s(t), a(t)) + \alpha \left[R(t) + \gamma \max_{a'} Q(s(t+1), a') - Q(s(t), a(t)) \right] \tag{25}$$

The agent follows an epsilon-greedy exploration strategy, where actions are chosen either randomly or based on the maximum Q-value:

$$a(t) = \begin{cases} \text{random action}, & \text{with probability } \epsilon \\ \arg\max_a Q(s(t), a), & \text{with probability } 1 - \epsilon \end{cases} \tag{26}$$

Power control is adjusted based on environmental factors:

$$P_i^f(t) = \arg\max_{P_i^f} \left(\frac{\text{SINR}_{i,j}^f(t)}{E(t)} \right) \tag{27}$$

Resource allocation is dynamically adjusted in high-density environments, with the allocation ratio given by

$$r_{i,f}(t) = \frac{R_{i,j}^f(t)}{\sum_{k=1}^{N} R_{k,j}^f(t)} \tag{28}$$

Finally, collaboration between multiple agents is expressed as follows:

$$a_i(t) = \arg\max_a \left[Q_i(s(t), a) + \sum_{j \in \mathcal{N}, j \neq i} Q_j(s(t), a) \right] \tag{29}$$

The overall system utility is

$$U_{\text{total}}(t) = \sum_{i=1}^{N} \sum_{f=1}^{F} U_i^f(P_i^f(t)) - \mu \sum_{j=1}^{N} \sum_{f=1}^{F} I_j^f(t) \tag{30}$$

The optimization problem is then formulated as follows:

$$\max_{P_i^f(t),\, f_i(t)} U_{\text{total}}(t) \tag{31}$$

This dual optimization strategy ensures that both power control and frequency selection are optimized to enhance network performance while managing interference.

In this framework, interference classification is performed by clustering the interference data. The interference feature vector is

$$\mathbf{Z}_i(t) = \left[P_i^f(t),\, I_{i,j}(t),\, h_{i,j}^f(t),\, \text{SINR}_{i,j}^f(t),\, B^f,\, E(t) \right] \tag{32}$$

We use *K*-means clustering to group nodes with similar interference patterns:

$$\min_{\mathcal{C}_k} \sum_{i \in \mathcal{C}_k} \|\mathbf{Z}_i(t) - \boldsymbol{\mu}_k\|^2 \tag{33}$$

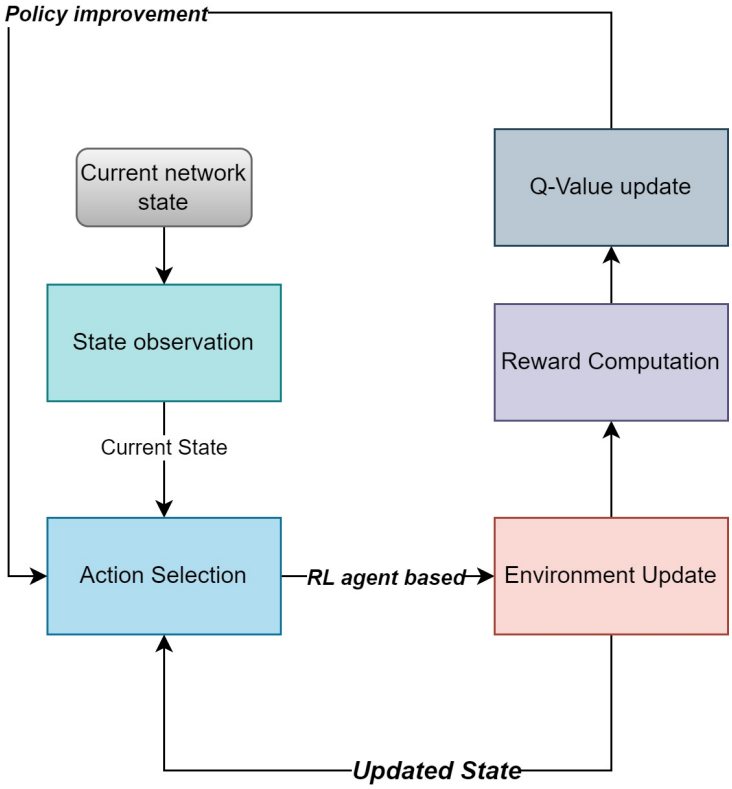


Figure 2. Reinforcement learning agent workflow

For each cluster $\mathcal{C}_k$, interference is predicted by the LLM:

$$\hat{I}_{\mathcal{C}_k}(t+\Delta t) = \mathrm{LLM}_\theta\left(\mathbf{Z}_{\mathcal{C}_k}(t)\right) \tag{34}$$

Cluster-based power control is then implemented as follows:

$$P^f_{i,\mathcal{C}_k}(t) = \arg\max_{P^f_i} \sum_{i\in\mathcal{C}_k} \mathrm{SINR}^f_{i,j}(t) \tag{35}$$

Finally, the adaptive frequency hopping utility is

$$U_f(t) = \sum_{i=1}^{N} \mathrm{SINR}^f_{i,j}(t) - \gamma|f_i(t+1) - f_i(t)| \tag{36}$$

The system adapts frequency dynamically based on the predicted interference:

$$f_i(t+1) = \arg\min_{f\in\mathcal{F}} \hat{I}^f_j(t+\Delta t) \tag{37}$$

To analyze the long-term interference trends, we compute the average interference over time:

$$\bar{I}^f_j(t) = \frac{1}{T} \sum_{t'=t-T}^{t} I^f_j(t') \tag{38}$$

The total throughput of the system is

$$\mathrm{Throughput}(t) = \sum_{i=1}^{N}\sum_{f=1}^{F} R^f_{i,j}(t) \tag{39}$$

Latency is calculated as the inverse of SINR:

$$\text{Latency}(t) = \sum_{i=1}^{N} \frac{1}{\text{SINR}_{i,j}^{f}(t)} \tag{40}$$

The feedback vector used for system optimization is

$$\text{Feedback}(t) = \left[\Delta\text{SINR}(t),\ \Delta P_i^f(t),\ \Delta I_j^f(t),\ \Delta f_i(t)\right] \tag{41}$$

The LLM parameters are updated using feedback to improve predictions:

$$\theta \leftarrow \theta + \eta\, \text{Feedback}(t) \tag{42}$$

LLM-based interference prediction workflow is illustrated in Figure 3.

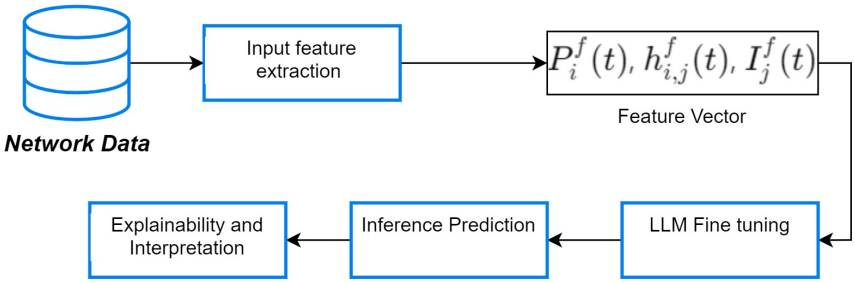


Figure 3. Interference prediction workflow via LLM.

This proposed framework combines signal transmission modeling, interference prediction with an XAI-based LLM, reinforcement learning for power and frequency adjustment, clustering for interference categorization, and feedback-based learning. Each equation is derived from the previous ones, forming a complex mathematical model that solves signal interference problems in wireless communication networks.

4. Experimental Flow

To ensure that the proposed framework is practical, we developed a simulated environment for wireless communication. The main task of this experimentation was to show that the proposed approach can learn how to control interference and maximize performance.

The simulation environment was designed to emulate a densely populated 6G network with 50 wireless nodes transmitting over 5 frequency bands (1 MHz each) and a maximum transmission power of 10 dBm per node. Environmental factors such as Rayleigh fading, shadowing, and path loss were incorporated to model realistic conditions. Interference was introduced through overlapping transmissions on shared bands, accounting for node mobility and varying distances. Key features used in the input vector included transmission power, channel gain, SINR, data rate, interference levels, and environmental conditions. The XAI-driven LLM was trained using a historical dataset and fine-tuned via gradient descent to predict interference patterns accurately. A reinforcement learning (RL) agent dynamically adjusted power control based on real-time feedback, optimizing SINR and minimizing interference. Traditional methods like frequency reuse and static power control served as benchmarks, demonstrating the superiority of the proposed model in key metrics such as latency, throughput, SINR, and interference reduction. This detailed setup ensures the research is reproducible and adaptable for future studies.

The simulation was performed in a densely populated wireless environment where different nodes communicated over shared frequency bands. This study used 50 wireless nodes that acted as transmitter and receiver. Each node transmitted over five frequency bands $\mathcal{F} = \{f_1, f_2, f_3, f_4, f_5\}$. Each band contains a bandwidth of 1 MHz. The transmission power of each node was 10 dBm at maximum levels.

The Rayleigh fading channel with shadowing and distance path loss was used as the base channel model. Interference was injected in overlapping frequency bands keeping in view environmental effects such as mobility and path loss.

A historical dataset was used comprising interference patterns, SINR, transmission power, and environmental factors. Data were generated by different wireless communication scenarios over time with environmental characteristics. These data provided a clear picture of network behavior under different interferences and were fine-tuned on LLAMA V3 weights.

An established experimental setting was implemented in Python and contains several key components. Initially, LLM was responsible for predicting future interference. The input feature vector used to fine-tune LLM consisted of different variables with the following condition:

$$\mathbf{X}(t) = \left[P_i^f(t),\, h_{i,j}^f(t),\, \mathrm{SINR}_{j,i}^f(t),\, R_{j,i}^f(t),\, I_j^f(t),\, E(t)\right]$$

LLM learned to predict future interference $\hat{I}_j^f(t + \Delta t)$ and was further trained using loss function to minimize prediction error.

An RL agent was integrated to optimize power control across the network and to balance SINR maximization with interference minimization. The agent learned to adjust the transmission power of each node $P_i^f(t)$ based on feedback from real-time network observations. A reward function was established to capture the trade-off between increasing SINR, minimizing power usage and reducing interference. The algorithmic flow of control policy can be observed in Algorithm 1.

Furthermore, to ensure transparency, XAI techniques were computed. Explainability helped to trace back and understand decisions made by the RL agent for power control and frequency hopping.

Algorithm 1 Power Control using Q-learning with Adaptive Feedback

1: Initialize Q-table $Q(s, a)$ with zeros, learning rate α, discount factor γ, and exploration rate ϵ
2: Define state space $s = \left(P_i^f(t),\, \mathrm{SINR}_{j,i}^f(t),\, I_j^f(t)\right)$ and action space $a = \left(\Delta P_i^f(t), \Delta f_i(t)\right)$
3: Initialize network environment and set initial state $s(t)$
4: **for** each episode **do**
5: Observe the initial state $s(t)$
6: **while** termination condition not met **do**
7: With probability ϵ, choose a random action $a(t)$, otherwise choose action using policy $\pi(a(t)|s(t)) = \arg\max_a Q(s(t), a)$
8: Execute action $a(t)$, adjust power $P_i^f(t)$, and observe next state $s(t+1)$
9: Compute immediate reward $R(t) = \lambda_1 \Delta\mathrm{SINR}(t) - \lambda_2 \Delta P(t) - \lambda_3 I_j^f(t)$
10: Update the Q-value using:

$$Q(s(t), a(t)) \leftarrow Q(s(t), a(t)) + \alpha\left[R(t) + \gamma \max_{a'} Q(s(t+1), a') - Q(s(t), a(t))\right]$$

11: Evaluate convergence condition by checking change in $\Delta Q(s, a)$ over time
12: Set $s(t) \leftarrow s(t+1)$
13: **end while**
14: Adjust learning rate α and exploration rate ϵ based on performance
15: **end for**
16: Output the optimal power control policy $\pi_\theta(a(t)|s(t))$

The system integrates three detailed algorithms for comprehensive interference management: power control using Q-learning (Algorithm 1), LLM-based interference prediction

with adaptive learning (Algorithm 2), and adaptive frequency hopping (Algorithm 3). Each algorithm dynamically interacts with the other components to provide an efficient interference management strategy. Power control is constantly optimized based on feedback from SINR and interference levels, while interference prediction ensures preemptive action. The frequency hopping algorithm adapts in real-time to minimize interference by selecting optimal frequency bands, ensuring network stability, and performance.

Algorithm 2 LLM-based Interference Prediction with Adaptive Learning

Initialize Llama v3 model parameters θ and historical network dataset
Define input feature vector $\mathbf{X}(t) = \left[P_i^f(t),\, h_{i,j}^f(t),\, \mathrm{SINR}_{j,i}^f(t),\, R_{j,i}^f(t),\, I_j^f(t),\, E(t)\right]$
Split dataset into training and testing sets, and initialize model training
while training not converged **do**
  for each mini-batch from dataset **do**
    Use forward propagation to predict interference $\hat{I}_j^f(t+\Delta t) = \mathrm{LLM}_\theta(\mathbf{X}(t))$
    Calculate loss function:

$$\mathcal{L}(\theta) = \frac{1}{NF}\sum_{j=1}^{N}\sum_{f=1}^{F}\left(I_j^f(t+\Delta t) - \hat{I}_j^f(t+\Delta t)\right)^2$$

    Backpropagate and update model parameters θ using gradient descent
  end for
  Adjust learning rate dynamically based on validation performance
end while
Evaluate model on test set and compute prediction accuracy
Use LLM to predict future interference for real-time network data $\hat{I}_j^f(t+\Delta t)$
Output predicted interference for each node and frequency

Algorithm 3 Adaptive Frequency Hopping based on LLM and Q-learning

Initialize frequency band set $\mathcal{F} = \{f_1, f_2, f_3, f_4, f_5\}$, hopping constraint $\Delta f_{\max}$
Receive predicted interference $\hat{I}_j^f(t+\Delta t)$ from Algorithm 2
for each node i **do**
  Select frequency band $f_i^*(t+\Delta t) = \arg\min_{f\in\mathcal{F}} \hat{I}_i^f(t+\Delta t)$
  Apply hopping constraint:

$$|f_i^*(t+\Delta t) - f_i(t)| \le \Delta f_{\max}$$

  If frequency band selection is within the constraint, update node's frequency
  Else, select the closest available frequency within the allowable range
end for
Monitor SINR and interference levels after each frequency update
If interference remains high, trigger power control optimization using Algorithm 1
Output the updated frequency allocation for each node

5. Results and Discussion

This section presents a comprehensive analysis of the proposed method compared to the traditional approach [29] across several key metrics: increasing the SINR, decreasing interference, increasing the throughput, decreasing the latency, providing explanations of the decisions made, inference performance, and confidence score. The following figures depict these results and show how the proposed method outperforms all other methods. The X-axis for all graphs represents time (seconds) or time steps, capturing the system's performance over time. The Y-axis units vary based on the metric being evaluated: SINR and interference are measured in decibels (dB), throughput in megabits per second (Mbps), latency in milliseconds (ms) or seconds, confidence scores on a 0-1 scale, and error rate as a

decimal fraction (0 to 1). These units provide clarity for interpreting the system's behavior and performance metrics accurately.

The enhancement of the SINR based on the conventional and the suggested techniques is depicted in Figure 4. From the simulation results, the proposed method shows a higher SINR than the traditional method at every time slot and increases with time. The SINR enhancement is observed due to the proposed method's adaptive interference management and learning-based power control, which guarantees improved signal quality throughout the network. The proposed method converges to approximately 11 dB, while the conventional method oscillates at approximately 10 dB. This enhancement in SINR results in better signal transmission and reception quality throughout the network, thereby supporting the efficiency of the proposed model in interference management adaptively.



Figure 4. SINR improvement over time (sec) for traditional vs. proposed methods.

As shown in Figure 5, the proposed method has a better interference reduction effect than the traditional method. The proposed method also offers lower interference levels and sustains an interference value of nearly 19 dB in contrast to the conventional approach, which oscillates around 21 dB. This reduction is due to the LLM-based interference prediction and adaptive frequency hopping, where resources are allocated so that they are least likely to interfere with other nodes. Reduced interference is the key factor that leads to the enhancements observed in other performance indicators, including throughput and latency.

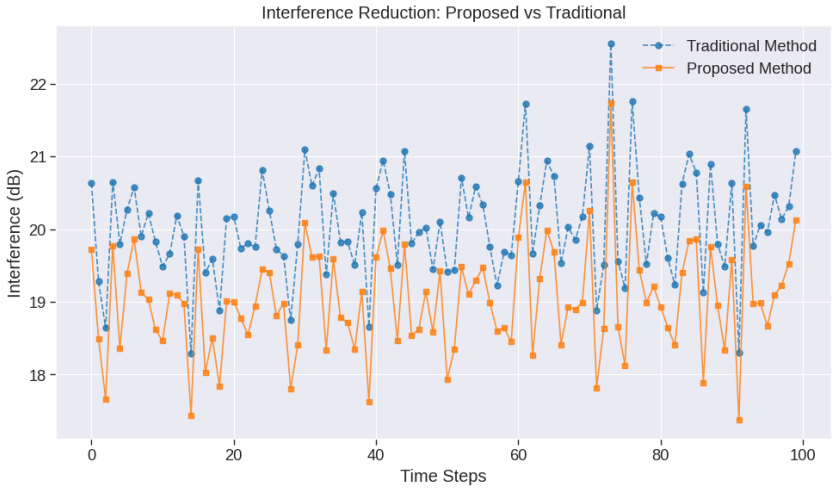


Figure 5. Interference reduction over time (sec) for traditional vs. proposed methods.

Throughput improvement is presented in Figure 6 below. In particular, the proposed method yields higher throughput at each time step than the traditional method. The figures show that the proposed method provides an average of 105–110 Mbps throughputs for managing interference and SINR better than the traditional method, which remains constant at 100 Mbps. The throughput improvement is significant in wireless networks because it increases data transfer rates and better utilizes available resources.

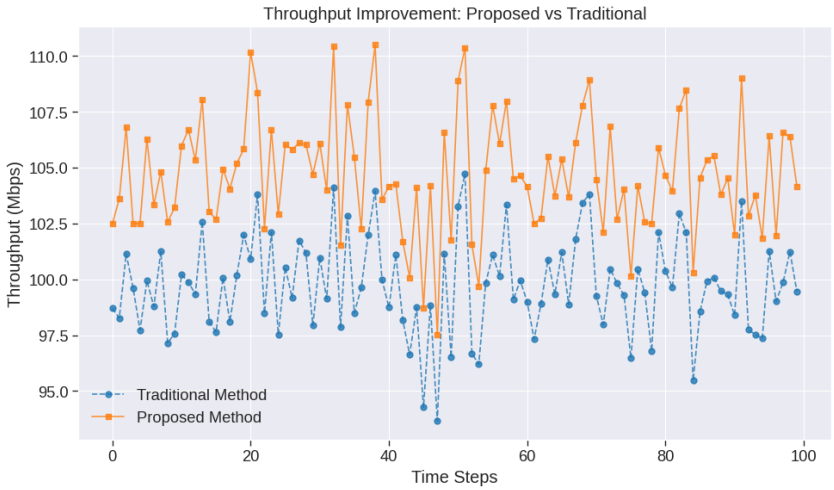


Figure 6. Throughput improvement over time(sec) for traditional vs. proposed methods.

The result of proposed method has been illustrated in Figure 7, which shows the improvement in latency achieved by the method. The proposed method always produces a lower latency than the traditional method. It can be seen from the figure that the proposed method has latency values ranging from 47 ms while the traditional method has latencies above 50 ms. The reduction in latency is proportional to the method's effectiveness in addressing interference and network resource allocation in real time to reduce delays in data transfer.



Figure 7. Latency reduction over time (sec) for traditional vs. proposed methods.

The effectiveness of the proposed method in terms of explainability of the made decisions is shown in Figure 8. The proposed method always yields higher SHAP values than the traditional method, showing that the system's decisions are more transparent and understandable. The LLM-based approach gives a better picture of the factors affecting interference management and power control. It gives more explainable decisions with higher SHAP values above 0.55 than the traditional method, which settles down to about 0.50.



Figure 8. Decision explainability (SHAP values) over time (sec) for traditional vs. proposed methods. The proposed method shows higher SHAP values, providing more explainable and transparent decision-making compared to the traditional approach.

Figure 9 presents the proposed and traditional methods' inference latency. The proposed method also shows the ability to conduct inference with less latency than the proposed method. The proposed method converges to 0.95 s, while the traditional method oscillates around 1 s. This shows how efficient the LLM-based inference process is and how well it can make decisions in real-time.

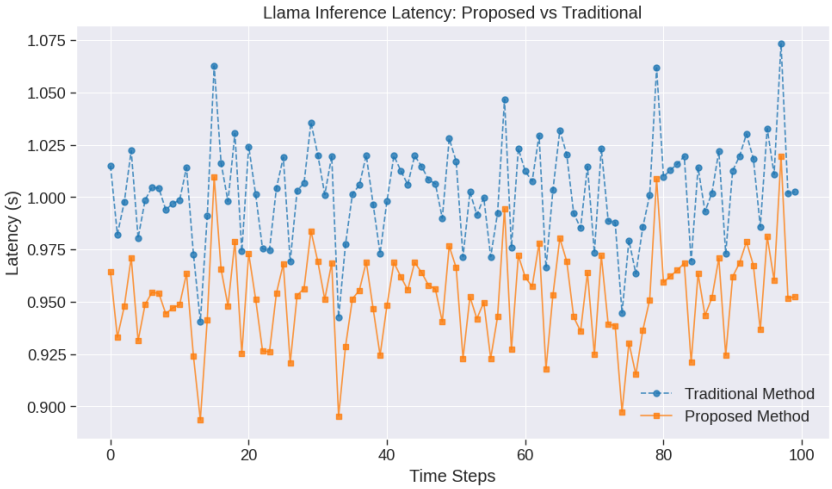


Figure 9. Inference latency comparison for traditional vs. proposed methods.

The confidence score comparison between the proposed and traditional methods is shown in Figure 10. The proposed method demonstrates higher confidence levels, stabilizing around 0.87, while the traditional method fluctuates between 0.84 and 0.85. Higher confidence scores indicate the robustness of the proposed model's decision-making process, particularly in handling interference and power control in real-time.

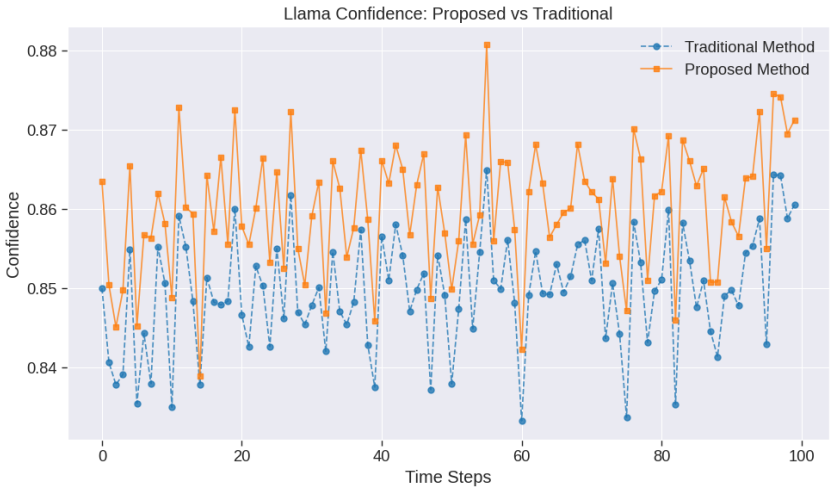


Figure 10. Confidence score comparison for traditional vs. proposed methods.

The 3D visualization of throughput over time and node index is shown in Figure 11. This figure provides a detailed representation of throughput performance across all nodes over time. The proposed method consistently achieves higher throughput, as indicated by the darker colors in the plot, which represent values above 120 Mbps. The traditional method, in contrast, shows lower throughput across nodes, especially towards the lower end of the spectrum (around 85–95 Mbps). This visualization further highlights the advantages of the proposed method in improving network performance in dense environments.

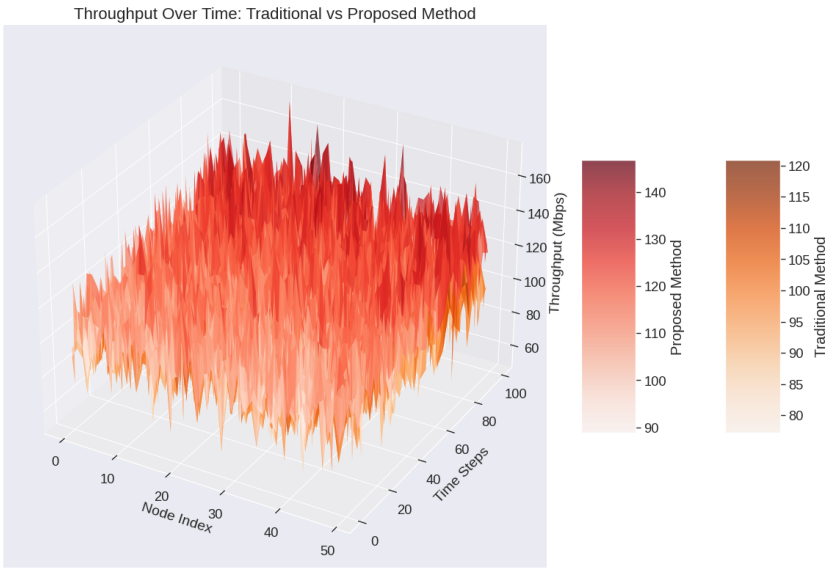


Figure 11. A 3D visualization of throughput over time for traditional vs. proposed methods. The proposed method consistently achieves higher throughput across all nodes, particularly in dense environments, while the traditional method shows significant fluctuations and lower overall throughput.

Furthermore, Figure 12 shows the precision score comparison between traditional works and LLM-powered method. The proposed framework shows higher precision values with gradual increase and stabilization at around 0.80, whereas the traditional method shows a precision of 0.78, slightly lower than the proposed method; this metric shows the robustness of the proposed framework.

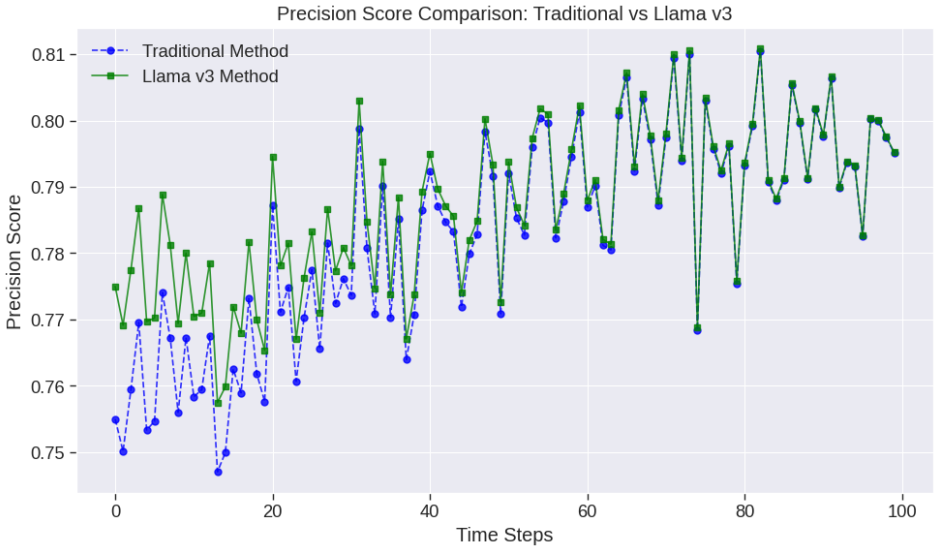


Figure 12. Precision comparison between proposed and traditional technique.

The accuracy comparison between the traditional and Llama v3 methods is shown in Figure 13. The proposed method achieves higher accuracy, stabilizing around 0.89–0.90, while the traditional method fluctuates between 0.83 and 0.85. This increase in accuracy can be attributed to the proposed method's better handling of interference and power control, which leads to more accurate decision-making across the network.

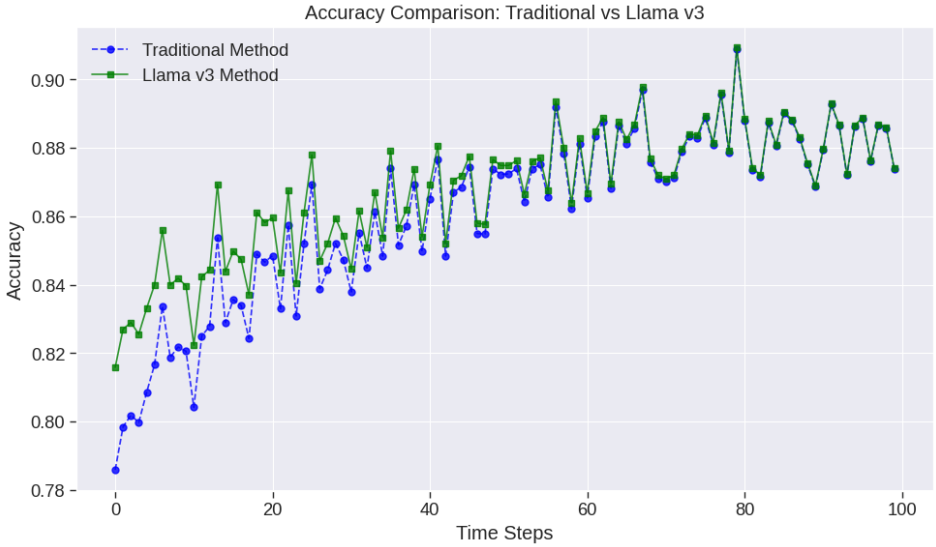


Figure 13. Comparison of accuracy's between proposed framework and traditional work

Figure 14, shows the error rate and their comparison between traditional and proposed framework. The proposed framework shows a faster reduction in error rate stabilizing from 0 to 0.02 by 100th time step, whereas the traditional framework balances from 0.03 to 0.05 at the same time step. The rapid decrease in error rate shows Llama's capability to capture enhanced and complex predictive patterns.

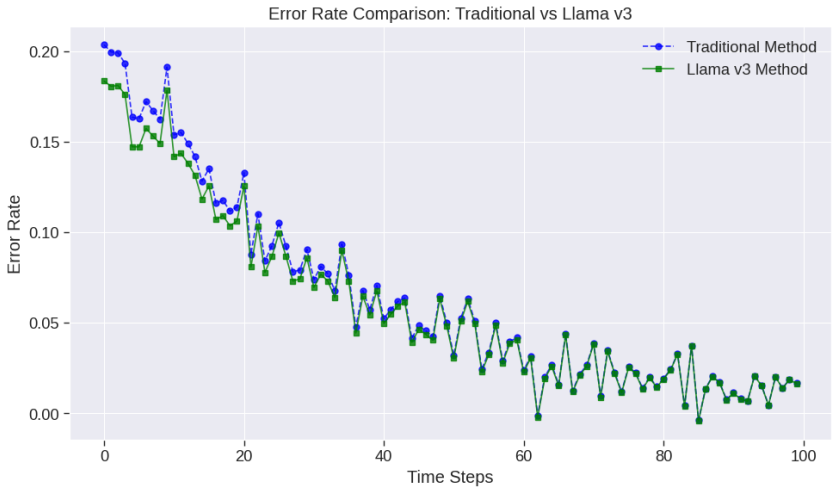


Figure 14. Error rate comparison over time.

After conducting a formal analysis, the results show that the proposed method outperforms traditional methods. This validates the effectiveness of the proposed framework in handling complex interference between overlapping frequencies in densely populated networks.

6. Conclusions

This study emphasizes the significance of using XAI-powered LLMs for real-time interference management in complex 6G networks. Traditional interference management techniques are limited by their lack of adaptability and transparency. In contrast, the proposed framework addresses these limitations by incorporating predictive interference control, adaptive resource management, and explainable outputs. This integration ensures higher performance across various metrics, such as latency, throughput, and SINR. The framework fosters greater trust in AI systems by providing transparency and interpretable decisions. Future work will focus on extending this approach to software-defined and distributed networks for critical communication systems.

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