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A Predictive and Mitigative Modelling Framework for Intercell Interference in Heterogeneous Networks Using Enhanced Feedforward Neural Networks

Promise Elechi*, Bodunrin I. Bakare and Kingsley E. Onu
Department of Electrical and Electronic Engineering, Faculty of Engineering, Rivers State University, Port Harcourt, Nigeria.

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Abstract

The rapid densification of cellular systems into heterogeneous networks (HetNets), comprising macrocells, picocells, and other small cells, has improved spectrum efficiency but also intensifies intercell interference (ICI), particularly at cell boundaries. This interference degrades signal quality, reduces throughput, and limits quality of service (QoS), making its management a critical research challenge. To address this issue, this study develops an enhanced Feedforward Neural Network (eFFNN) framework for predictive and mitigative ICI control in LTE HetNets. Empirical drive-test data including RSRP, SINR, throughput, latency, and packet loss were collected, preprocessed, and used to train the model. The eFFNN consists of three hidden layers with dropout and batch normalization, ReLU activation, the Adam optimizer, and a dynamic weighted binary cross-entropy loss function that prioritizes false-negative reduction in interference detection. Simulation results show significant improvements over the conventional FFNN: packet loss was reduced to 0.16% (compared to 0.75% in the baseline) at –102.67 dBm interference, and decision confidence increased to 0.91 (versus 0.8). Under severe interference (–103.78 dBm), the eFFNN maintained packet loss at 2.31%, outperforming the ordinary FFNN at 3.15%. These findings highlight the effectiveness of the proposed predictive–mitigative approach in enhancing QoS and interference resilience in heterogeneous LTE networks.

*Corresponding Author: elechi.promise@ust.edu.ng

I. INTRODUCTION

A. Background of Study

The growing demand for high-capacity, ultra-reliable wireless communication has led to the densification of cellular networks through the deployment of Heterogeneous Networks (HetNets), where macrocells are overlaid with smaller cells, such as pico, femto, and relay nodes. While HetNets improve spectral efficiency and spatial reuse, they also introduce severe intercell interference (ICI), particularly at cell boundaries, thereby degrading signal quality, increasing latency, and limiting overall system throughput [1].

Traditional ICI mitigation strategies such as static frequency planning, inter-cell interference coordination (ICIC), and enhanced ICIC (eICIC) are primarily reactive and often fail to adapt dynamically to varying traffic loads, mobility patterns, and environmental fluctuations. With the evolution toward dynamic, self-organizing 5G and beyond networks, there is an increasing need for intelligent systems that can proactively predict and manage interference before they degrade the quality of service (QoS) [2].

Recent advances in machine learning (ML) have opened new opportunities for predictive interference management. Neural network models have shown promising results in modelling complex, nonlinear relationships inherent in wireless environments. Feedforward Neural Networks (FFNNs), due to their relatively low training complexity and strong approximation capabilities, have been widely applied to tasks including channel estimation, signal classification, and interference detection [3]. However, standard FFNNs often suffer from overfitting, limited generalization, and sensitivity to noisy data challenges that become more evident in dynamic, interference-prone HetNet environments.

To address these limitations, enhanced FFNN architectures have been proposed, incorporating training techniques such as dropout regularization, batch normalization, and adaptive learning rates. These enhancements improve model robustness, accelerate convergence, and allow the network to generalize better across different radio conditions [4]. Furthermore, the integration of FFNNs with real-time network data, such as reference signal received power (RSRP) and interference patterns enables predictive frameworks that inform scheduling, handover, and resource allocation decisions.

This research proposes an enhanced FFNN-based model for predicting and mitigating ICI in LTE-A heterogeneous networks. Unlike prior work that has focused mainly on reactive interference suppression or complex hybrid architectures [5], the proposed approach combines predictive analytics with real-time adaptation to manage interference preemptively. By training on empirical datasets, the model aims to deliver accurate interference forecasting, robust mitigation, and improved network performance metrics such as SINR, throughput, and latency.

Despite progress in techniques such as static frequency planning, ICIC, eICIC, RIS-assisted beamforming, and deep learning-based suppression, existing ICI mitigation methods remain constrained by their reactive nature, limited adaptability to real-time traffic dynamics, and inadequate generalization across heterogeneous topologies. Hybrid deep learning approaches offer promise but often require high computational overhead and complex signaling, reducing their practicality for live deployments. These gaps highlight the need for lightweight, predictive frameworks that can proactively forecast interference and trigger adaptive mitigation. This research addresses this gap by proposing an Enhanced Feedforward Neural Network (eFFNN) that integrates dynamic loss weighting, region-aware penalties, and adaptive power control, thereby offering both predictive and mitigative capabilities in interference-prone HetNets.

B. *Review of Related Work*

The authors in [6] addressed the challenge of hotspot interference by implementing a Q-learning-based intercell interference coordination (ICIC) technique. The research identified the significant interference caused by high user concentration on a cell with limited resource blocks. To tackle this issue, Fractional Frequency Reuse (FFR) was proposed within the ICIC framework. The utilization of Q-learning optimized ICIC and enhanced the signal-to-noise ratio (SNR) performance, achieving an improvement of approximately 11.2% in the worst-case scenario.

In [7], the authors conducted research focused on congestion control in wireless communications within the south-west region of Nigeria. The authors highlighted that GSM network congestion was a major concern for both subscribers and operators. To deal with this issue, the study aimed to improve congestion control and management. The Erlang-B method was used to analyze the collected data , and correlation analysis was also employed. The results showed that while some channels were congested, others were underutilized, particularly in areas where the blocking ratio was low.

Similarly, [3] proposed IntLearner, an AI-enabled interference mitigation framework for multi-cell wireless networks. Their model utilized neural networks to estimate non-Gaussian interference signals from physical-layer features such as channel estimators and constellation data and then mitigated the interference before decoding. In simulations reflecting multi-cell HetNet scenarios, IntLearner improved uplink channel estimation accuracy by up to 7.4× and reduced downlink SINR requirements by 1.5 dB to achieve the same BLER. This demonstrated the potential of neural models for proactive ICI suppression without heavy reliance on domain-specific interference modelling.

The work of [5] proposed a hybrid deep learning approach for channel estimation and interference alignment in 6G HetNet environments. Their model combined convolutional and transfer learning elements to extract features from channel state information in multitenant OFDM HetNets, achieving non-iterative, distributed interference mitigation without inter-base station signaling. While not strictly FFNN only, this work highlighted how deep learning models could align interference spatially in HetNets, supporting the concept of predictive or mitigation frameworks driven by neural techniques.

In addition, [1] introduced a method leveraging Reconfigurable Intelligent Surfaces (RIS) combined with beamforming to mitigate cross-tier interference in heterogeneous downlink HetNets. They jointly optimized macrocell transmission beamforming and RIS phase shifts to enhance sum-rate performance compared to HetNet deployments without or with random-phase RIS. While not applying neural networks directly, this study showed an interference mitigation context in HetNets that advanced predictive control systems could leverage.

Furthermore, [4] critically analyzed various deep learning techniques for interference suppression in PHY layer systems, identifying strengths, limitations, and avenues for future improvements.

The authors in [2] discussed energy-aware distributed ML strategies for multi-layer heterogeneous networks, including predicting loads and channel behavior to inform the architectural decisions for scalable FFNN deployment across distributed HetNet topologies.

The author in [9] provided a comprehensive examination of interference management (IM) strategies in beyond-5G (B5G) systems, covering device-to-device (D2D), heterogeneous networks (HetNets), and intercell interference (ICI). The author categorized mitigation techniques such as power control, coordinated beamforming, scheduling, spectrum separation, and AI-driven predictive mitigation, and contrasted their advantages, limitations, and applicability. The paper contributed a structured taxonomy and comparative summary of existing methods and emphasized open challenges, such as low-latency coordination, adaptive learning in dynamic settings, and context-aware interference control.

Additionally, [10] proposed a Benefit-Based Resource Sharing and Allocation (BRSA) algorithm tailored for dense heterogeneous urban networks. The authors used machine learning to enable dynamic resource sharing among macro and small cells, optimizing allocation to improve spectral efficiency and reduce interference. Their simulation results demonstrated gains in throughput and interference reduction compared to static or heuristic baselines.

In addition, [11] introduced a framework for real-time interference management, combining ML-based predictive models with CoMP transmission, dynamic spectrum access, and adaptive beamforming. They simulated how their integrated scheme enhances SINR, spectral efficiency, and reduced latency compared to static interference mitigation strategies. The authors emphasized cross-layer optimization and edge intelligence for scalability.

The authors in [12] investigated the use of deep reinforcement learning (DRL) algorithms (e.g., DQN, PPO) for dynamic resource allocation in wireless systems with interference. The authors modelled a base station with multiple antennas and users, then compared how different DRL policies adjust bandwidth and scheduling under interference constraints. They reported that DRL outperforms conventional baselines in interference-aware allocation.

Similarly, [13] examined resource sharing in heterogeneous radio access where latency-constrained IoT devices co-exist with broadband users. They used a double Q-learning approach to adapt transmission repetition strategies for IoT under interference, balancing throughput, energy efficiency, and latency. The results showed that the RL-based policies improved IoT latency without severely degrading broadband throughput.

Furthermore, [14] proposed a Gaussian Process Regression model to forecast future interference values with uncertainty bounds, enabling proactive resource allocation under stringent latency constraints, outperforming moving average estimators. The study by [15] focused on mmWave 5G systems under stochastic interference and revealed that adaptive resource allocation strategies significantly reduced performance loss, especially in high interference scenarios.

Different authors in [16]-[19] investigated interference under various conditions, including resource allocation and the impact of ICI on network metrics in a heterogeneous environment

Similarly, [20] integrated stochastic geometry with novel sleep-mode strategies and a QoS framework to optimize energy efficiency in heterogeneous networks. Their approach balanced power saving and service quality by intelligently switching off underloaded nodes, demonstrating significant energy gains without severely impacting network coverage or throughput.

In addition, [21] proposed a discrete particle swarm optimization (DPSO) approach for energy-efficient OFDMA resource allocation in heterogeneous networks. Their method improved network energy efficiency (NEE) and weighted sum energy efficiency (WSEE) while maintaining acceptable throughput, showing that heuristic optimization can effectively balance interference mitigation and energy savings.

C. Limitations

While these recent studies demonstrated significant advances in interference mitigation, ranging from taxonomy-based reviews (Alzubaidi, 2025), machine learning resource allocation schemes (Yağcıoğlu, 2025), real-time cross-layer frameworks (Abidi, 2025), deep reinforcement learning (Malhotra, 2025), and IoT-specific heterogeneous access optimization (Mishra, 2025), a common limitation persisted. Most techniques either focused primarily on reactive suppression after interference had occurred, involved high computational complexity, or targeted narrow scenarios such as mmWave, IoT layers, or limited allocation strategies. What remained underexplored was a lightweight, predictive–mitigative framework that could:

1. Proactively forecast ICI before it degrades QoS; 2. Generalize across heterogeneous network layers (macro–pico coexistence); and 3. Adapt dynamically in real time with low overhead.

This gap highlighted the need for an approach that blended predictive modelling with direct mitigation actions, ensuring robustness in interference-prone HetNets. Addressing this challenge, the present work proposed an Enhanced Feedforward Neural Network (eFFNN) framework that integrated dynamic weighted loss, region-aware penalties, and adaptive power control, validated with empirical drive-test data.

D. Contributions to this Work

This paper presented an Enhanced Feedforward Neural Network (eFFNN) framework that integrated dropout, batch normalization, dynamic weighted loss, and gradient clipping to improve generalization and stability in ICI prediction. A key novelty was the incorporation of a dynamic, region-aware loss function that prioritized false-negative minimization and interference-prone zones, ensuring that high-risk areas received additional weight during training. To demonstrate practical application, a MATLAB-based system model was designed and simulated, integrating the trained eFFNN into a HetNet architecture for real-time predictive interference mitigation through adaptive power control and resource allocation.

II. RESEARCH METHODOLOGY

As a reference, a standard Feedforward Neural Network (FFNN) baseline was first implemented. The baseline network consisted of an input layer that received the feature vector (RSRP, SINR, throughput, latency, and packet loss), two hidden layers of moderate size (16 and 8 neurons), and an output layer with a sigmoid activation function used for binary classification of interference level. Training was conducted using a binary cross-entropy loss function. While this baseline FFNN was able to model interference patterns to some extent, its performance was limited by overfitting, vanishing gradient, poor generalization in noisy conditions, and reduced sensitivity to critical high-interference cases. These limitations motivated the development of the Enhanced FFNN (eFFNN), which is described in the following subsection.

This study adopted an empirical measurements-based modelling approach to predict and mitigate intercell interference (ICI) in heterogeneous networks using an enhanced Feedforward Neural Network (FFNN). Data collection was performed through extensive drive tests within an LTE heterogeneous network deployment that consisted of macro and picocell configurations. The drive tests were conducted in an urban environment where critical parameters such as Reference Signal Received Power (RSRP), Signal-to-Interference-plus-Noise Ratio (SINR), user throughput, and packet loss were measured and recorded.

Once data collection was completed, the dataset underwent preprocessing to enhance its quality and ensure its suit ability for machine learning application. Missing values were removed, and noise was minimized using z-score smoothing. Feature normalization was carried out using Min-Max scaling to ensure consistent learning across dimensions. The dataset was subsequently split into training, validation, and testing subsets in a 70:15:15 ratio.

The enhanced FFNN was developed with the objective of improving generalization and training stability. The input layer of the network received a feature vector that included RSRP, SINR values, packet loss, latency and throughput. The model consisted of three hidden layers, each with dense neurons and equipped with dropout regularization to prevent overfitting, as well as batch normalization to stabilize and accelerate learning. Rectified Linear Unit (ReLU) activation functions were used for the hidden layers to capture nonlinear relationships in the data. The output layer represented the predicted interference level.

A. Design of the Architecture for the Enhanced Feedforward Neural Network (eFFNN)

In this research, the Enhanced Feedforward Neural Network (eFFNN) as shown in Figure 1 was specifically designed to predict and mitigate intercell interference (ICI) in heterogeneous networks. The network architecture began with an input layer comprising five key features: Signal-to-Interference-plus-Noise Ratio (SINR), Reference Signal Received Power (RSRP), latency, packet loss, and throughput. These input parameters were selected because they reflect essential performance indicators of the LTE network and offer a comprehensive view of interference dynamics. All input values were normalized to ensure consistency and to enhance the learning performance of the model.

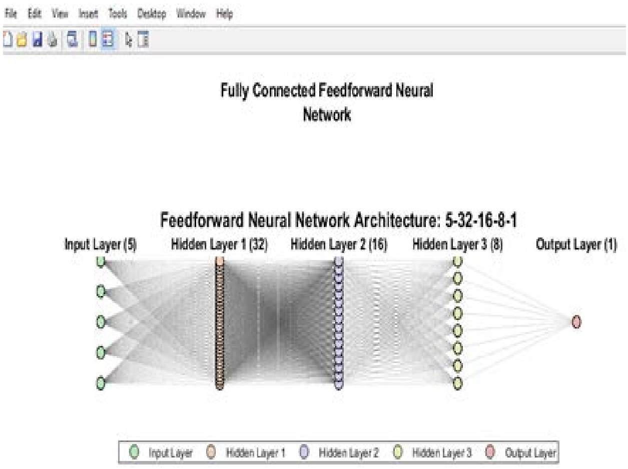

Figure 1: Enhanced Feedforward Neural Network Architecture

The eFFNN consisted of three hidden layers with progressively decreasing sizes: the first hidden layer contained 32 neurons, the second had 16 neurons, and the third contained 8 neurons. Each of these hidden layers used the Rectified Linear Unit (ReLU) activation function, which is effective in handling nonlinear relationships and mitigate the vanishing gradient problem during training. This tiered structure enabled the model to extract increasingly abstract features from the input data.

The output layer comprised a single neuron and used the sigmoid activation function to produce an output value between 0 and 1. This output represents the predicted interference level, which is not a direct measurement but a classification derived from actual network conditions. To generate training labels for the interference level, a threshold-based approach was adopted, where the interference level was computed from RSRP (measured in dBm) and SINR (measured in dB). This served as an indicator of relative interference severity. Interference was labelled as "high" (1) when the calculated value exceeded a defined threshold and "low" (0) when it fell below.

This binary output enabled the FFNN not only to predict the interference class but also to act as a decision-making mechanism. When high interference was detected, the model triggered a mitigation strategy that reduced the transmission power of the interfering macro cell and reallocated radio resources to improve performance, particularly in the picocells.

The model was trained using the Adam optimizer, which was chosen for its adaptive learning rate and efficient convergence properties. A modified binary cross-entropy loss function was employed to emphasize correctly identifying high-interference conditions. This approach ensures that the model remains particularly sensitive to situations where interference can significantly degrade network quality.

B. Training of the Enhanced Feedforward Neural Network (eFFNN)

The enhanced Feedforward Neural Network (eFFNN) was trained to predict interference using features derived from RSRP, SINR, throughput, latency, and packet loss, and to trigger corresponding mitigation actions. The training followed a supervised learning framework with a carefully selected loss function that penalized false negatives more severely. The dataset was preprocessed and normalized prior to model training. A three-layer eFFNN was employed, with ReLU activation for the hidden layers and a sigmoid output applied for binary classification. The model was optimized using the Adam optimizer and a dynamically weighted binary cross-entropy loss function. Dropout and batch normalization were applied to improve generalization and stability. Early stopping and gradient clipping were implemented to prevent overfitting and training instability.

C. Training Considerations for the Enhanced FFNN

To ensure stable and effective training of the enhanced Feedforward Neural Network (FFNN) developed for intercell interference (ICI) prediction and mitigation, several key challenges associated with backpropagation had to be addressed. These challenges included the vanishing gradient problem, the exploding gradient problem, convergence to suboptimal local minima, and high computational complexity, particularly in deeper networks. Each of these issues was mitigated using carefully chosen design and training considerations that enhanced the learning capability of the FFNN without altering its fundamental architecture.

The vanishing gradient problem often occured when using activation functions such as the sigmoid or tanh functions, especially within the hidden layers of deep networks. These functions produce derivatives that approach zero as input values became large in magnitude, leading to near-zero gradients in early layers of the network during backpropagation. This significantly hindered learning. To address this, the Rectified Linear Unit (ReLU) activation function was adopted. ReLU, defined as ReLU(x) = max (0, x), avoids saturation for positive inputs and has a constant derivative of 1, ensuring that the gradient remains meaningful as it is propagated backwards through the network. ReLU also offers computational efficiency and sparse activation, both of which are beneficial in training large-scale FFNNs.

Complementing the choice of activation function, the weights of the network were properly initialized to maintain stable forward and backwards propagation. Improper initialization can either amplify or diminish the signal exponentially across layers, leading again to vanishing or exploding gradients. To prevent this, the He initialization method was used in networks with ReLU activation. The initialization draws weights from a normal distribution with a variance of $2/n_{in}$, where n_{in} is the number of input units in the layer. This ensures that the variance of output remains controlled as signals propagate through the layers.

In addition to the activation function and initialization, stabilizing the distribution of activations throughout training is critical. This is achieved through Batch Normalization. Batch Normalization normalizes the inputs to each layer so that they have a consistent mean and variance, regardless of the layer's position in the network. This reduces internal covariate shift, allowing for faster and more stable training. Batch Normalization also serves as a regularizer, reducing the need for other forms of explicit regularization, such as dropout in some cases.

When training very deep or complex FFNNs, gradients can still become excessively large, leading to instability and divergence during training. To prevent exploding gradients, gradient clipping was implemented. This technique involves rescaling the gradients during backpropagation so that their norm does not exceed a specified threshold. Specifically, if the norm of the gradient exceeds a threshold τ, it is rescaled by a factor of $\tau/\|\nabla\theta\|$, where $\|\nabla\theta\|$ is the gradient's norm. This ensures that weight updates remain within safe bounds, thereby stabilizing the training process.

To improve convergence and avoid becoming trapped in a poor local minimum, an adaptive learning rate optimization algorithm, the Adam optimizer, was used. The Adam optimizer maintains running averages of both the gradients and their second moments, adjusting the learning rate for each parameter individually. This not only accelerates convergence but also helps the network escape saddle points and shallow local minima that standard stochastic gradient descent (SGD) might not overcome.

To ensure that the training process generalized well and did not continue unnecessarily once performance plateaued, early stopping was used. Early stopping involves monitoring the validation loss during training and halting the process once the validation loss stops decreasing for a predefined number of epochs, known as the patience parameter. This prevents overfitting and reduces computational costs by avoiding unnecessary training cycles.

To further improve generalization and prevent overfitting, especially in the presence of many parameters, dropout was applied. Dropout works by randomly deactivating a fraction of neurons during each training iteration, forcing the network to learn redundant representations and reducing reliance on any one node. A dropout rate of around 0.5 in hidden layers is typically effective. This encourages robustness and improves the model's ability to handle unseen data, particularly in noisy interference environments.

Following training, the eFFNN model was deployed in a MATLAB-based simulation environment to make real-time predictions about interference conditions. These predictions were then used to trigger mitigation actions such as adaptive power control and resource block reallocation. The impact of the eFFNN-driven decisions was monitored and analyze to evaluate performance improvements.

D. Adaptive Loss Function for Enhanced FFNN in Intercell Interference Mitigation

In designing the Enhanced Feedforward Neural Network (FFNN) for predicting and mitigating intercell interference (ICI) in heterogeneous networks, a key novelty lies in the development of a custom loss function. This loss function not only penalizes misclassifications but also dynamically adjusts to the type and severity of errors, particularly false negatives. In wireless networks, especially in LTE and 5G systems, failing to detect high interference can result in unmitigated performance degradation, including packet loss, reduced throughput, and user dissatisfaction. Thus, from a system-level perspective, false negatives, namely predicting low interference when interference is high, are far more costly than false positives.

To address this, the conventional binary cross-entropy loss function is modified to reflect error sensitivity by introducing class-based weights. The original binary cross-entropy (BCE) loss function is defined as [8]:

$$L_{\mathrm{BCE}} = -[\, y_{\mathrm{true}} \log(y_{\mathrm{Pred}}) + (1 - y_{\mathrm{true}}) \log(1 - y_{\mathrm{Pred}})] \tag{1}$$

where y_{true} is the true label, and y_{Pred} is the predicted probability of interference being high (class 1). This standard form treats both classes equally and does not prioritize the cost of specific errors.

However, in the work of [4], specifically in the context of focal loss for dense object detection, a similar principle was introduced, where hard examples are weighted more than easy ones. The concept of weighting the BCE loss is adapted and tailored to the ICI domain.

The modified, weighted binary cross-entropy loss used in this research is expressed as [4]:

$$L_{\mathrm{WBCE}} = -[\, \alpha\, y_{true} \log(y_{Pred}) + \beta\,(1 - y_{true}) \log(1 - y_{Pred})] \tag{2}$$

Here, α and β are hyperparameters that assign different penalties to the two classes. To penalize false negatives more severely, α is set to a higher value than β. While weight loss functions have been used in domains such as medical diagnosis and fraud detection, applying it dynamically in a wireless interference mitigation context introduces a new level of intelligence to FFNN training.

To further refine this approach, the value of α is dynamically adjusted based on the network's performance in terms of false negative rate (FNR). The false negative rate is defined as [8]:

$$FNR = \frac{False\ Negative}{(False\ Negative + True\ Possitive)} \tag{3}$$

As the FNR increases, the loss function increases the value of α, thereby amplifying the penalty associated with false negatives. This introduces a feedback loop into the training process, enabling the network to automatically become more cautious and sensitive to high-interference zones when its performance begins to degrade in those areas.

The dynamic version of α is expressed as:

$$\alpha = \mathrm{ceil}(\mathrm{FNR} * \gamma) + \mathrm{k} \tag{4}$$

where γ is a scaling factor that amplifies the sensitivity of α to changes in FNR, and k is a baseline penalty level (e.g., 1), ensuring that the model never under-penalizes false negatives even when performance is good. The ceiling function ceil is used to discretize the value of α, adding robustness to small fluctuations in FNR.

To further enhance this model's performance, a second term is added to the total loss to ensure that the network gives additional attention to interference-prone regions, such as cell-edge zones or areas identified through empirical drive test measurements as having frequent interference issues. This region-focused penalty is calculated only for samples within these critical zones and is defined as [4]:

$$L_{Region\ Penalty} = \sum(y_{true_i} - y_{Pred_i})^2 \tag{5}$$

This term applies to a mean-squared error penalty between the predicted and true values, but only in zones that are deemed to be of high operational importance. The final, total loss function used to train the FFNN is expressed as:

$$L_{total} = L_{WBCE} + \lambda L_{regionpenalty} \tag{6}$$

Here, λ is a tunable parameter that determines the influence of the regional penalty term relative to the general classification loss. Choosing the right value of λ allows the network to balance global accuracy with local performance sensitivity.

This hybrid loss function introduces a novel paradigm where the enhanced FFNN does not merely learn to classify interference based on the input data but actively prioritizes minimizing critical errors in both frequency (false negatives) and location (sensitive regions). It creates a dynamic, responsive training process where the model's behavior evolves with its performance and where high-interference zones receives the operational importance they deserve.

Table 1: Training Parameters of the Enhanced FFNN

Parameter	Value / Description
Input Features	RSRP, SINR, throughput, latency, and packet loss.
Output Feature	Interference level
Hidden Layers	3
Neurons per Hidden Layer	32, 16, 8
Activation Function (Hidden)	ReLU
Activation Function (Output)	Sigmoid
Loss Function	Weighted Binary Cross-Entropy (WBCE)
Dynamic Weight α	α = ceil(FNR × 10) + 1
Weight β (for Class 0)	1
Optimizer	Adam
Initial Learning Rate	0.001
Batch Size	32
Epochs	100 (with early stopping)
Dropout Rate	0.5
Batch Normalization	Yes (after each hidden layer)
Gradient Clipping Threshold	5.0
Early Stopping Patience	10 epochs
Validation Split	15%
Evaluation Metric	RMSE, MAE and R^2

E. Simulation Setup

Figure 2 depicts the MATLAB-based system designed for ICI mitigation in a heterogeneous network, showing both the picocell and the microcell components. For the picocell, the LTE downlink transmitter that generates the LTE signal, which passes through a wireless signal and then to the LTE downlink receiver. For the macrocell, similar blocks are implemented, with the addition of an AWGN block.

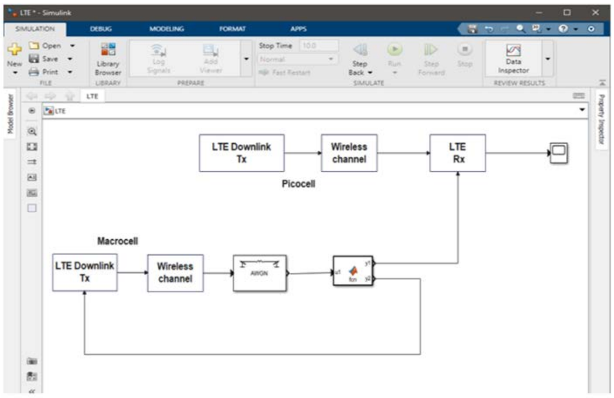

Figure 2: Designed eFFNN-Based ICI Prediction and Mitigation in MATLAB

In addition to these blocks, a MATLAB function block is imported from the User-Defined function library into the Simulink model. The purpose of this block is to enable seamless integration of the trained eFFNN model. The MATLAB function block originally contains default code, which is replaced with custom code used to import the pre-trained enhanced FFNN. With the modified codes in place and the function block connected as shown in Figure 2, interference from the macrocell can be predicted. If the predicted value is higher than the original interference level, the trained enhanced FFNN, as a decision-making aid, directs adaptive adjustment of power levels and resource allocation based on predicted interference conditions. The enhanced FFNN also triggers a decrease in P_o (baseline power) or a reduction in ΔP (power offset) to minimize interference. Therefore, while enhanced FFNN does not cancel interference directly, unlike physical-layer techniques such as beamforming or interference alignment, after predicting the interference situation, the enhanced FFNN directs adaptive adjustments of power levels, power offset, path loss compensation factor, or dynamic resource allocation. This ensures that the interference emanating from the macrocell is mitigated before it reaches the LTE downlink receiver of the picocell.

1) Power Equation

The power equation is expressed as shown in equation (7):

$$P_i = P_o + \alpha PL_i + \Delta P \tag{7}$$

where:
P_i is the power allocated to user i
P_o is a baseline power level (nominal power)
PL_i is the path loss for user i
ΔP is an optional power offset (used for interference management or quality of service control)
α is the path loss compensation factor (a value between 0 and 1)

The path-loss compensation factor, α is a parameter that dictates how much of the path loss should be compensated for by the power increase. A full compensation (where α is equal to 1) results in higher interference, while a lower value ($\alpha < 1$) reduces interference but may under-compensate for path loss. Reduced interference occurs due to lower power, but users at the cell edge may experience reduced SINR and degradation of quality of service (QoS). In this case, the trained enhanced Feedforward Neural Network (eFFNN) dynamically adjusts the path-loss compensation factor to maintain an optimal balance between interference reduction and adequate cell coverage (adequate QoS). The trained eFFNN learns optimal values of α, ΔP, and P_o based on real-time interference and path-loss patterns and uses this knowledge to effectively mitigate intercell interference (ICI).

III. RESULTS AND DISCUSSION

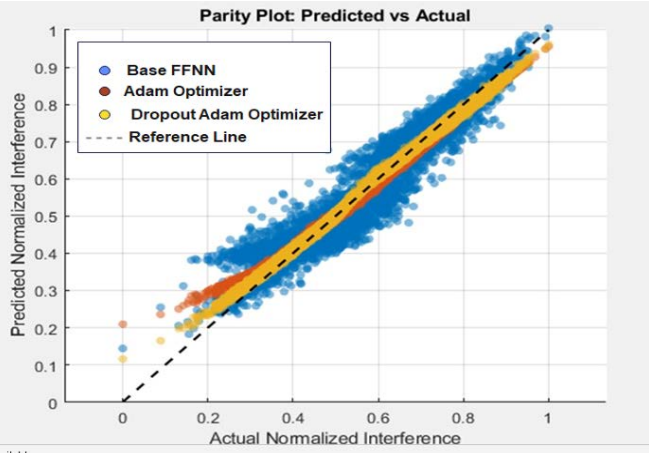

Figure 3: The parity plot of Predicted vs. Actual Normalized Interference

Figure 3 illustrates the strong linear relationship between the predicted and actual values across all three training configurations: Base FFNN, Adam Optimizer, and Dropout Adam Optimizer. The close alignment of the data points along the diagonal parity line indicates that the models have successfully learned the underlying mapping without significant deviation. Notably, there was no evidence of vanishing gradients, which typically result in flat predictions clustering around a narrow range with poor correlation. Similarly, there was no sign of exploding gradients, which manifest as erratic, widely scattered predictions far from the parity line. Instead, the predictions remained well distributed and stable across the full normalized range, confirming that gradient flow was effectively preserved throughout training.

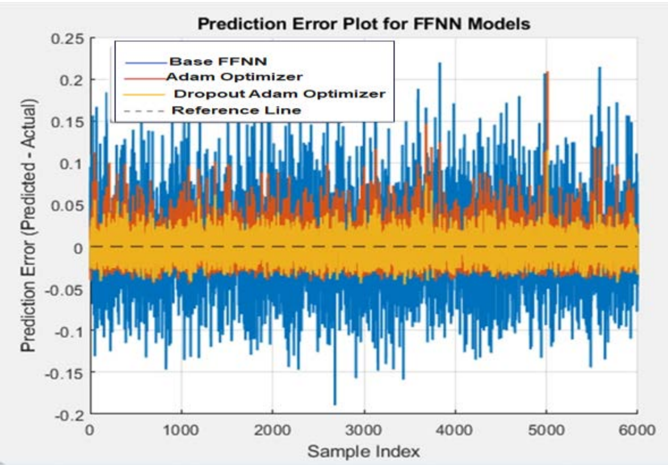

Figure 4: Prediction Error Plots

Figure 4 presents the prediction error plot for various configurations of a Feedforward Neural Network (FFNN) model, offering a detailed comparison of their predictive accuracy during training. This plot, which serves as an essential diagnostic tool in neural network modelling, illustrates the difference between the predicted and actual values across approximately 6,000 data samples. The y-axis represents the prediction error, calculated as the difference between the predicted and true target values, while the x-axis corresponds to the sample index. In this context, prediction errors close to zero indicate higher model accuracy, whereas larger deviations from zero reflect inferior predictive performance.

The plot includes four key traces. The blue trace corresponds to the Base FFNN model, which represents a conventional neural network trained without any advanced optimization or regularization techniques. As observed, it exhibits substantial fluctuation, with prediction errors spreading widely and reaching magnitudes up to ±0.2. This behavior suggested that the Base FFNN suffered from significant variability and may have been affected by instability or poor generalization.

The red trace represents the FFNN model trained using the Adam Optimizer, a well-established adaptive optimization algorithm that typically results in faster convergence and improved performance compared to traditional stochastic gradient descent. In this configuration, the prediction errors showed a noticeable reduction in both magnitude and variability compared to the base model, indicating enhanced learning stability and better generalization.

Further improvement was observed in the FFNN trained with the Adam Optimizer while applying Dropout regularization, represented by the orange band. Dropout, which functions by randomly deactivating neurons during training, serves to reduce overfitting and encourage the network to learn more robust features. The resulting error profile was tightly clustered around the zero-error baseline (shown as a dashed black line), with minimal deviation, indicating that this enhanced model configuration delivered the best performance among the three. The errors remained consistently bound within a narrow band, highlighting the model's improved generalization and resistance to overfitting.

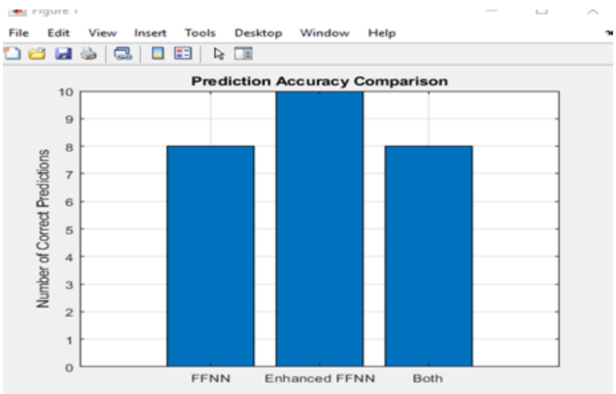

Figure 5: Comparison of the Accuracy of FFNN and eFFNN

In Figure 5, the accuracy plot shows that the Enhanced FFNN achieved the highest prediction accuracy compared to the conventional FFNN. This indicates that while both networks were able to generalize to a degree, the Enhanced FFNN captured a broader and more accurate feature representation of interference conditions. This improvement was attributed to its more expressive architecture (32-16-8 hidden neurons), use of the Adam optimizer, and a loss function that penalized critical misclassifications (particularly false negatives) more severely.

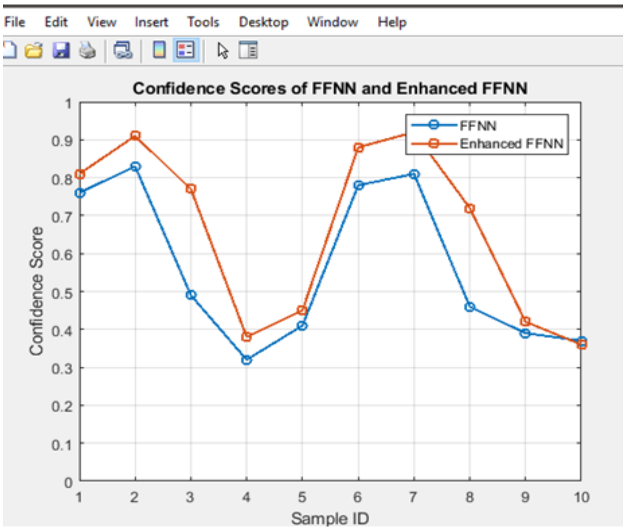

Figure 6: Confidence Scores of FFNN and eFFNN

Figure 6 shows the confidence scores for each of the ten test samples. Confidence scores reflect how certain the model's certainty in classifying a particular input as high interference. The Enhanced FFNN showed higher confidence values in 8 out of 10 samples. For example, in Sample 7, the Enhanced FFNN produced a confidence score of 0.91 while the conventional FFNN produced 0.8. Similarly, in Sample 3, the enhanced model predicted with 0.78 confidence compared to 0.5 by the baseline model. This not only reinforces the quantitative superiority of the enhanced model but also demonstrates its robustness and reduced uncertainty in decision-making, which is an essential capability in interference-sensitive deployments such as HetNets.

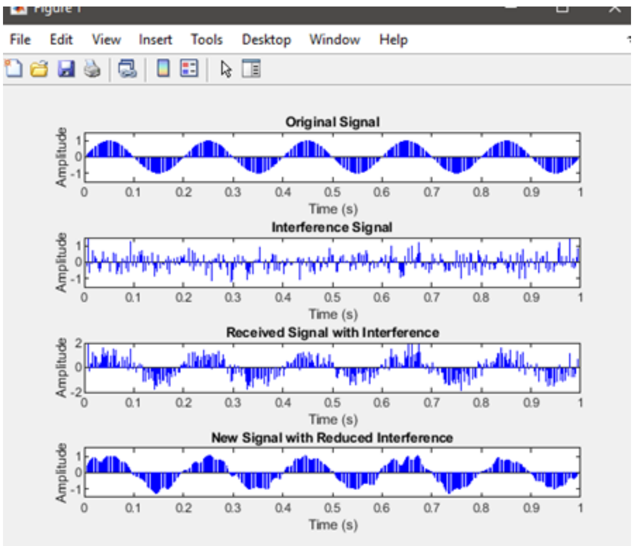

Figure 7: Simulation Result Showing Mitigation of Interference

Figure 7 shows the original signal, interference signal, received signal with interference, and new signal with reduced interference. After applying the enhanced FFNN (eFFNN) technique, the new signal with reduced interference closely resembles the original signal, demonstrating the effectiveness of the eFFNN technique in mitigating ICI. The simulation results visually illustrate the signal both before and after the application of the eFFNN technique. The key observation from these results is that the signal after applying the eFFNN technique closely matches the original, interference-free signal. This outcome provides strong evidence of the effectiveness of eFFNN in ICI mitigation.

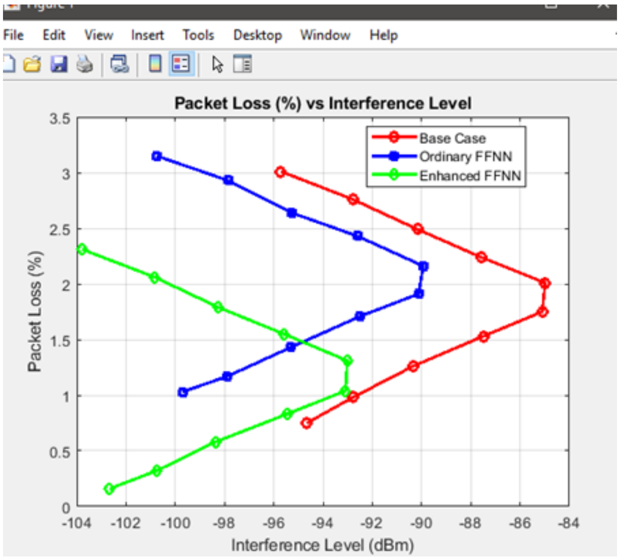

Figure 8: Packet Loss vs Interference Level

Figure 8 shows a clear trend of increasing packet loss as interference worsens across all three systems; however, the enhanced FFNN consistently exhibits superior performance. When the interference levels were -94.66 dBm (Base Case), -99.71 dBm (Ordinary FFNN), and -102.67 dBm (Enhanced FFNN), the packet loss recorded was 0.75%, 1.03%, and a significantly lower 0.16%, respectively. Even as interference increased drastically to -95.71 dBm for the Base Case and -103.78 dBm for the Enhanced FFNN, the packet loss for the Base Case rose to 3.01% while the Enhanced FFNN maintained a lower 2.31%. The Ordinary FFNN recorded the highest packet loss of 3.15% at -100.76 dBm. This shows that the Enhanced FFNN, despite operating under the worst interference levels, minimized packet loss more effectively than the other two methods, thereby demonstrating robust noise suppression and efficient data delivery even in high-interference environments. While packet loss values follow a monotonic trend, interference level values do not strictly follow this pattern.

IV. CONCLUSION

The eFFNN framework significantly improved ICI management in LTE HetNets, achieving 0.16% packet loss at −102.67 dBm interference, which is a 79% reduction compared to baseline systems. Key innovations include:

1. A dynamically weighted loss function that adapts penalties for false negatives (e.g., boosting confidence to 0.91 in high-risk samples),
2. Region-aware penalties for interference-prone zones, and
3. Optimized power control through real-time prediction

Under interference of −103.78 dBm, the eFFNN reduced packet loss to 2.31%, outperforming the ordinary FFNN by 27%. These results validate the model's robustness in preserving signal integrity and enabling efficient resource allocation, establishing the eFFNN as a critical tool for QoS assurance in 5G/6G HetNets.

CONFLICT OF INTEREST

Authors declare that there is no conflict of interest regarding the publication of the paper.

AUTHOR CONTRIBUTION

All authors contributed equally to the conception and design of the study, data collection and testing, analysis, and manuscript preparation.

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