Optimizing Path Loss Prediction: Advancements in Signal Parameter Estimation through Wavelet Neural Networks

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This study assesses the effectiveness of Neural Net- works (NN) and Wavelet Neural Networks (WNN) in predicting signal strength in wireless communication systems. WNNs, which integrate wavelet theory with NN architecture, demonstrate supe- rior performance. Significant reductions in Mean Squared Error (MSE) from 32.93 (NN) to 11.94 indicate improved precision for WNNs. Root Mean Squared Error (RMSE) decreases from
5.73 (NN) to 3.45 with WNNs, highlighting more consistent predictions. Mean Absolute Error (MAE) decreases from 4.62 (NN) to 2.75, showcasing enhanced accuracy in WNNs.
For predicting Average Distance, WNNs outperform NNs with lower MSE (59.4 vs. 106.65), RMSE (7.7 vs. 10.32), and MAE (5.73 vs. 7.878). The study, conducted on the Colab platform using Python, emphasizes that incorporating wavelet transforms enhances the model's ability to recognize complex signal propagation patterns.

Keywords: Wavelet, Neural Network, Prediction, signal, parameters.

1. Introduction

In the evolving landscape of wireless communication tech- nologies, intelligent planning is crucial for delivering a broad spectrum of wireless services. Central to this planning are channel propagation models, which are pivotal for predict- ing signal levels from a network of transmitters in various environments. These models play a vital role in optimizing the placement of network access points, assessing interference with neighboring systems, and evaluating overall network performance [1].

To develop these propagation models, several physics-based methodologies are commonly employed. These include ray- tracing [2]–[4], the vector parabolic equation (VPE) [5]– [7], and various comprehensive electromagnetic analysis tech- niques [7]. For specific applications like tunnel radio propaga- tion, initial models were formulated based on waveguide mode theory [8]. These have evolved to incorporate more advanced methods such as the finite difference time domain technique [9], [10], along with ray-tracing [11], [12] and VPE-based models [13]. Furthermore, there's been a growing interest in hybrid techniques that integrate these various methods for more robust modeling [14], [15]. Despite their effectiveness, the development of physics-based models can be demanding Identify applicable funding agency here. If none, delete this in terms of the required expertise and computational resources, making them less feasible for real-time applications [16], [17]. Another strategy for channel characterization involves ex- perimental measurements. While this approach can provide valuable insights, it tends to be costly and only partially effective, particularly in the face of uncertainties associated with measurements. These challenges are heightened in the complex environment of contemporary wireless services. Empirical path-loss models offer a more accessible alternative in the field of wireless communication. These models can be calibrated using actual measurement data or estimated from pre-established tables [16], [18]–[20], providing a simpler approach, though with certain drawbacks. Neural Networks often fail to reflect complex indoor and outdoor propagation effects, making parameter extraction ambiguous. Generalized, non-site-specific character causes this shortcoming [1].

Recent research have shown that artificial neural networks (ANNs) are effective propagation modelers in diverse contexts. These include urban [21], suburban [23], rural [24], and interior settings like mines [25]. These investigations used real-world measurements and simulator-generated synthetic data for ANNs [26], [27]. By learning from real data, ANNs have increased empirical model correctness [23] and fixed systemic faults [28], [29]. These tests show ANNs' regression ability, but their full potential in predicting propagation properties in particular spatial configurations is untapped.

A cutting-edge wavelet neural network (WNN) model accurately predicts wireless communication properties in this article. This method improves wireless signal frequency and temporal detection using wavelet analysis and neural networks. This is necessary for assessing signal strength, interference, and route loss in varied conditions. Model can be used in cities and rural areas. Environmental characteristics and transmitter-receiver spatial dynamics are among its inputs. Its versatility is crucial for network optimization. This model's unique architecture improves network design and efficiency by combining wavelets' detailed analysis with neural networks' adaptive learning. Learning from real-world and simulated data enhances forecast precision, setting a new wireless communication network planning and assessment benchmark.

This study explores complicated communication networks, focusing on nowcasting and forecasting signal properties. Artificial intelligence, especially neural networks, improves signal parameter prediction methods.

The research begins with a detailed signal transmission factor examination. Factors include weather, physical obstacles, interference, and communication equipment. A thorough assessment of these elements will prepare the research for further study.

The paper then evaluates contemporary nowcasting and signal parameter forecasting approaches. The study critically analyses these methodologies' strengths and flaws to discover field gaps and areas for improvement. Improved predictive models will result from this evaluation.

At the core of the research is the creation of an advanced neural network-based solution. This model is designed to adapt to the ever-changing dynamics of communication systems, providing precise and consistent predictions. The model will undergo extensive phases of training, testing, and validation to ensure its effectiveness and reliability.

Moreover, a key aspect of this research is to ensure the practical application of the developed model. The goal extends beyond conceptual development; the intention is to produce a tool that can be effectively integrated into current commu- nication infrastructures, thereby improving their operational efficiency and dependability.

2. RELATED WORKS

This paper examines the rapid evolution of 5G networks, which are projected to experience a substantial increase in traffic, potentially quintupling compared to present levels, necessitating advanced management techniques [30]. Central- ized processing units, particularly in Cloud Radio Access Networks (C-RAN), emerge as crucial for effective resource management. C-RAN facilitates dynamic resource allocation and adaptability, optimizing radio and hardware resources by recognizing demand patterns and enhancing the efficiency of Baseband Unit (BBU) pools, addressing traffic variability often influenced by the tidal effect [31], [32].

A 2015 study [33] highlighted the growing global data traf- fic and its impact on existing network structures, advocating for C-RAN as a solution due to its high processing power and intelligent UE mapping capabilities. Using a Key Performance Indicator (KPI) to minimize blocked UEs, the research applied a Discrete Particle Swarm Optimization (DPSO) algorithm, demonstrating the potential to significantly reduce Base Sta- tion (BS) activity during low traffic periods.

Further advancements in 2016 included research [34] that utilized C-RAN architecture to propose a resource provision- ing strategy aimed at lowering power consumption at cell sites and in the cloud, addressing fluctuations in per-user capacity demand. In another study [35], the focus was on addressing interference and energy efficiency issues in small cell deployments using C-RAN virtualization technologies, introducing an adaptive mechanism within a Software-Defined Wireless Network (SDWN) paradigm. The same year, research [36] delved into resource virtualization within C-RAN, ex- amining wireless interface virtualization, traffic-aware joint scheduling, and collective programming for spectral efficiency enhancement.

In 2017, a study [37] discussed a two-level energy effi- ciency optimization problem in H-CRAN networks, involving a dynamic shutdown algorithm for picocells and algorithms to reduce BBU servers, effectively maintaining User Equip- ment (UE) Quality of Service (QoS) while reducing energy consumption.

By 2018, research [38] explored network sizing through dynamic adaptation to fluctuating demands using a self- organizing C-RAN framework, incorporating Cell Differentia- tion and Integration (CDI) for semi-static scaling of the BBU pool and Remote Radio Heads

(RRHs).

In 2019, a study [39] highlighted the importance of 5G tech- nologies like HetNets for load balancing in LTE-A networks, proposing a hardware utilization model to address spectrum shortages.

Moving to 2020, research [40] focused on strategies in Het- erogeneous Centralized Radio Access Networks (H-CRAN), utilizing handover indicators and a genetic algorithm to man- age active cells and reduce operational costs. The same year, studies [41], [42] addressed hardware resource provisioning in RRH-BBU combinations for 5G networks, focusing on QoS and physical resource block allocation. Additionally, research [43] introduced a DES for predicting influenza-like illness death counts, with Dias and Windeatt [44] presenting a variant, Dynamic Ensemble Selection with Instantaneous Pruning (DESIP), for signal calibration applications.

In 2021, a study [45] shifted focus to the PRRH-BBU assignment problem in 5G networks, formulating an optimiza- tion model for efficient resource allocation at multiple levels. Related to ensemble methods, Moraitis et al.'s research [46] explored various models like MLP, SVR, RF, and KNN regressors using bagging in rural environments, finding KNN regressors with bagging to be highly accurate. Further studies [47]–[49] showed the consistency of Random Forest in outperforming other algorithms in path loss predictions, with Sotiroudis et al. [50]finding XGBoost to be superior in this regard.

This study amalgamates four datasets to develop a more universally applicable model, addressing challenges in uni- fied modeling using Dynamic Regressor Selection (DRS) or Dynamic Ensemble Selection (DES). Techniques like oversampling, undersampling, and synthetic data generation (SMOTER, SMOGN, GAN) are considered to address data imbalances [51]–[57]. The paper emphasizes the potential of DRS and DES in enhancing predictive accuracy across various datasets, noting their variable performance based on dataset characteristics [43], [58]–[61]. This comprehensive approach to model selection and data handling aims to optimize pre- dictive accuracy in the rapidly evolving field of 5G network management.

In previous research, [62] introduced an approach for de- termining the optimal operational configuration of a Wireless Sensor Network (WSN) through the application of exact mathematical programming techniques, notably Mixed Integer Programming (MIP). However, it is acknowledged that these techniques entail high computational complexities. As an alter- native, recent efforts have explored the integration of learning algorithms, such as Neural Networks (NNs), to predict WSN settings with heightened accuracy and significantly reduced computational costs compared to MIP solutions.

Researchers have directed their attention towards forecasting crucial WSN parameters, namely network lifetime, transmission power level, and internode distance. These parameters exhibit interdependence and play pivotal roles in achieving optimal WSN functionality. Building upon the foundation laid by [1], The focus has shifted towards utilizing machine learning algorithms that concentrate on employing data and algorithms to mimic human learning processes. [63], particularly NNs, to efficiently predict and optimize the WSN operational parameters. This approach not only streamlines computational costs but also contributes to enhancing the overall efficiency of WSNs.

In a related study, the authors in [64] aimed to enhance the prediction accuracy of respiratory signals by adapting the multi-layer perceptron neural network (MLP-NN) model, It is a branch of deep learning [65] to accommodate dynamic changes in respiratory patterns. The foundation of their work involved the development of an initial MLP-NN designed to predict respiratory signals sourced from a real-time position management (RPM) device. However, early testing outcomes revealed diminished prediction accu- racy, particularly for irregular breathing patterns, attributable to the use of a fixed dataset in a one-time training scenario.

To address this limitation and bolster accuracy, the authors introduced a novel continuous learning technique. This method involved updating the training data continuously, thereby re- placing the conventional one-time learning process based on fixed training data. Notably, a dual MLP-NN configuration was employed in their adaptation approach, where one MLP-NN performed real-time prediction of respiratory signals, while the other underwent training using updated data, and vice versa. The predictive performance was quantitatively assessed using the root-mean-square-error (RMSE) metric, employing respiratory patterns from 202 patients, each with a recording length of 1 minute.

The investigation delved into the impact of various factors on the new predictor's performance, including the addition of an extra network, training parameters, and irregularity in respiratory signals. The authors explored four distinct network configurations: a single MLP-NN, high-computation dual MLP-NNs (U1), and two combinations of high- and low-computation dual MLP-NNs (U2 and U3). Results indicated that the RMSEs using the U1 method were notably reduced by 34%, 19%, and 10% in comparison to MLP-NN, U2, and U3 methods, respectively. The continuous training approach with a dual-network configuration demonstrated improved prediction accuracy compared to the conventional one-time training of an MLP-NN using fixed signals.

In this paper, the significance lies in the pioneering intro- duction of a cutting-edge Wavelet Neural Network (WNN) based model, meticulously engineered to predict crucial pa- rameters influencing wireless communication. By seamlessly integrating wavelet analysis with neural network frameworks, this model achieves an advanced capability to discern both the frequency and temporal aspects of wireless signals. This unique fusion enables a more comprehensive assessment of signal strength, interference patterns, and path loss in diverse settings, spanning densely populated urban areas to open rural spaces. The WNN model optimizes networks by responding to environmental factors and transmitter-receiver spatial dynamics.

Wavelets' thorough analysis and neural networks' adaptive learning increase network design and efficiency. This improves forecast accuracy by analyzing various inputs and learning from real-world and simulated data. This study forecasts and predicts communication signal parameters and proposes a cutting-edge wireless communication network planning and assessment method to enhance academic research. This sophisticated neural network-based approach could improve communication infrastructure operational efficiency and reliability as AI becomes more important in signal prediction.

3. METHODOLOGY

This section presents a structured strategy for evaluating Neural Networks (NNs) and Wavelet Neural Networks (WNNs) for signal parameter prediction. After data gathering, critical preprocessing activities prepare the data for analysis.

Table I. Comparison Of Related Works In 5g Network Management And Respiratory Signal Prediction

Year	**5G Network Management**	**Respiratory Signal Prediction**
2015 [33]	Advocated for C-RAN to handle growing global data traffic; applied DPSO algorithm for UE minimization	-
2016 [34]	Proposed C-RAN strategy to lower power consump- tion; addressed fluctuations in per-user capacity de-mand	Addressed poor prediction accuracy in MLP-NN for irregular respiratory patterns; introduced continuouslearning with dual MLP-NNs [2]
2017 [37]	Discussed energy efficiency optimization in H- CRAN networks; dynamic shutdown algorithm forpicocells	-
2018 [38]	Explored network sizing through dynamic adaptation using self-organizing C-RAN framework	-
2019 [39]	Emphasized HetNets for load balancing in LTE-A networks	-
2020 [40]	Focused on strategies in H-CRAN using handover indicators and genetic algorithm	Addressed poor prediction accuracy in MLP-NN for irregular respiratory patterns; introduced continuouslearning with dual MLP-NNs [2]
2021 [45]	Formulated an optimization model for efficient re- source allocation in 5G networks	-
	Ensemble Methods and Data Handling	
-	-	Explored DRS and DES in enhancing predictive accuracy; addressed data imbalances using oversam- pling, undersampling, and synthetic data generation [51]–[57]; emphasized the potential of DRS and DES across various datasets [43], [58]–[61]

Regular NNs and advanced WNNs are used in further research. All paths train and test their models on the dataset.

The evaluation phase extensively tests each model's prediction ability, measuring performance. The procedure closes with a detailed comparison of traditional NN and WNN results. The benefits and cons of each strategy are compared.

The core hypothesis driving this comparative study is that WNNs may offer superior performance over conventional NNs in specific signal-processing tasks. By clearly outlining the differences between these two approaches, the study aims to highlight the potential improvements in accuracy and reliability that WNNs might offer.

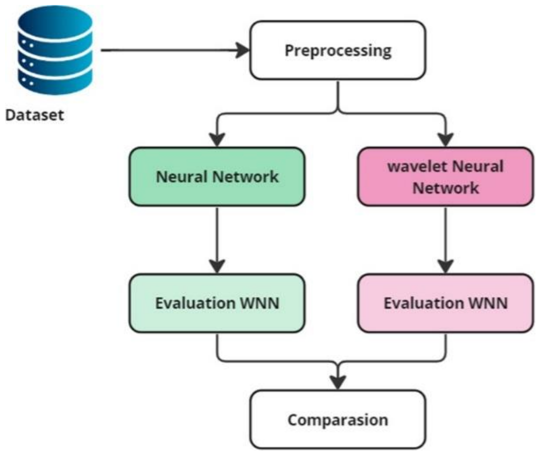

Fig. 1. General Flowchart

This methodology will be explained in the next subsections. These sections include data pretreatment, neural network architecture and training protocols, evaluation metrics, and comparative analysis statistics. This detailed explanation explains the study's process and findings.

A. Dataset

Smart devices with sensors and Wi-Fi and cellular networks are changing university operations in the digital age. University campuses rely heavily on Information and Communication Technologies (ICTs), laying the framework for many smart campus applications. Effective radio network planning and optimization are essential for these applications' QoS. Signal path loss models, which predict radio wave signal strength at different transmitter-receiver distances, are crucial to this procedure. Transmission of electromagnetic waves might vary depending on the channel's physical qualities. Existing path loss models may need to be adjusted or recalibrated using data particular to smart campuses to appropriately reflect their features.

Path loss, the attenuation of signal power from the transmitter to the receiving antenna over varying distances, is important in this study. The study measured three routes at Covenant University in Ota, Ogun State, Nigeria. In order to acquire path loss statistics and campus terrain details. From the area's Digital Terrain Map (DTM), the terrain profile data comprised longitude, latitude, elevation, altitude, clutter height, and transmitter-receiver distance. Use this dataset to construct empirical radio wave propagation models for smart campuses.

Analysis of Survey Routes X, Y, and Z data showed path loss statistics and terrain profile differences. In the following table, first-order descriptive statistics summarize wireless signal characteristics throughout the three survey routes in a smart campus:

Table 2. Consolidated Overview Of Wireless Signal Characteristics Across Three Survey Routes In A Smart Campus Environment

Statistical Measure	**Route X**	**Route Y**	**Route Z**
Mean Longitude	3.1651	3.1669	3.1600
Mean Latitude	6.6777	6.6742	6.6727
Mean Elevation (m)	54.22	61.03	48.61
Mean Altitude (m)	59.68	54.00	52.21
Mean Clutter Height (m)	4.97	5.03	6.93
Mean Distance (m)	399.81	460.49	447.42
Mean Path Loss (dB)	142.42	139.72	146.34
Standard Deviation (Path Loss dB)	9.42	9.52	7.30
Sample Size	937	1229	1450

A rigorous analytical process is used in this study to obtain detailed insights into wireless signal characteristics in a smart campus setting. We carefully measured path loss and terrain profile parameters along Covenant University Survey Routes X, Y, and Z. Our technique is distinguished by data analyses, comparisons, and findings displays. Table II shows mean values and standard deviations of path loss, longitude, latitude, elevation, altitude, clutter height, and distance. This detailed overview demonstrates our commitment to acquire data and study its complexities, contributing to the understanding of radio wave propagation in a smart campus. To place our findings in the perspective of wireless communication research, we cite [30]–[32]. We apply a deliberate and analytical approach to enhance the discussion on optimal Quality of Service in smart campus applications.

B. Preprocessing

Combining survey data from X, Y, and Z into a single dataset is crucial during preprocessing. This procedure integrates longitude, latitude, elevation, altitude, clutter height, distance, and path loss measurements into a single dataset. The study mixes different datasets to capture each route's unique traits and variances in a single data structure. Normalization follows merging all route data. Data values must be standardized using this procedure. The study normalizes data within a range, usually 0 to 1, using min-max scaling. Scaling neural network inputs improves learning by ensuring consistency and impartiality. Normalization divides data into training and testing. The training subset teaches neural networks signal strength and route loss prediction. This subset tests the model's projected performance. Data partitioning is essential for validating models' generalization to fresh data, demonstrating robustness and effectiveness.

The study's success hinges on sophisticated preprocessing. Next, we'll describe how each preprocessing step affects the study approach. This detailed examination describes neural network training and evaluation's meticulous data preparation.

C. Neural Network

This research estimates Neural Network (NN) signal intensity using a computer model inspired by human brain neural pathways. Many layers of the NN process and transmit input data. Longitude, latitude, elevation, and others are sent to the input layer. The layer's vast connections connect every neuron to every input. This design analyzes input signals to simplify pattern recognition.

Hidden layers follow the input layer. These layers improve data processing. They transfer inputs from previous layers to subsequent layers. An important feature of these hidden layers is the incorporation of activation functions, which introduce non-linearities into the model. This non-linearity is essential for the NN's ability to learn and represent more complex relationships within the data.

Architecture concludes with output layers. Unlike the previous layers, the output layer outputs the projected signal strength continuously. The regression research purpose is met. The model's intrinsic NN parameters are adjusted iteratively throughout training. Trainings aim to bridge model prediction-observation gaps. A statistical analysis evaluates NN performance. These measures compare model prediction accuracy to measurements. They demonstrate NN prediction capacity and inform model training.

This section highlights the NN's learning progression visually. These visuals provide significant information regarding the model's prediction skills during training and generalization to fresh data. They help uncover issues like overfitting, where the model overlearns from the training data, or underfitting, indicating a model too simple to catch data patterns.

Finally, the NN component stresses signal strength prediction model creation. The NN's smart campus signal strength prediction strengths and weaknesses are revealed by final analysis utilizing established criteria.

D. Wavelet Neural Network

Novel computer model Wavelet Neural Network (WNN) blends wavelet techniques with neural network design. Before feeding neural network input data for prediction, wavelet analysis is done. Mathematical wavelet analysis shows input data frequency and time. Both perspectives are essential to uncover data patterns that may be hidden in time or space. The WNN design begins with wavelet-modified input data.

Approximation coefficients reflect the data's trend, while detail coefficients show its shorter-term features. The original data is numerically represented by these coefficients.

After the wavelet transformation, the WNN's structure mirrors that of a traditional neural network, with an input layer specifically designed to accept the wavelet-transformed coefficients. Following this, the network comprises multiple layers of nonlinear processing units, each contributing to the model's ability to discern complex relationships within the data.

The WNN output layer predicts signal strength in this study. A variety of statistical measures evaluate the WNN's expected accuracy. Loss curves show model learning throughout training iterations. Model convergence and generalization to fresh data are shown visually.

Wavelet transformation preprocessing distinguishes WNNs from neural networks. This feature may improve model data interpretation and prediction.

The wavelet transform of a function is mathematically represented as

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \cdot \psi \left(\frac{t-b}{a} \right) dt \quad (1)$$

where

- Wf (a, b) (a, b) represents f's wavelet transform at scale a and location b.
- ψ(t) is mother wavelet function,
- a is scale factor,
- b is translation factor.

4. COMPARISON

This mathematical foundation lets the WNN find patterns in data of various sizes and places. We methodically compare the standard Neural Network (NN) and Wavelet Neural Network (WNN). Comparisons of wavelet analysis' neural network signal strength prediction are needed. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are key performance measures in this study. These measurements will be compared across both models to determine their practicality, precision, and reliability.

Critically analyzing models' learning curves and numerical data. Graphs show training and validation loss over time, determining model learning efficiency. These signals suggest overfitting (model performs well on training data but badly on unseen data) or underfitting (model fails to recognize data complexity). The practical implications of each model are also examined in this comparison.

This includes training and inference computation efficiency, model implementation complexity, and dataset and context scalability. Comparison is used to assess model strengths and drawbacks. Evidence-based conclusions and suggestions for NN and WNN implementation in real-world signal strength prediction scenarios are planned. This comparison study should show how advanced neural network architectures might benefit wireless communications.

5. EXPERIMENT RESULTS

A. Neural Network Results

Neural Network (NN) performance on the test set has shown insights, particularly in prediction accuracy. Mean Squared Error (MSE) is 32.934, suggesting a moderate average of the squares of the errors, which are the differences between expected and actual signal strength. The NN can predict, but its predictions and observations diverge. The MSE-derived Root Mean Squared Error (RMSE) is 5.738, indicating the forecast error. RMSE is in signal strength units, hence the model's predictions are 5.738 units off. This error level may be acceptable or excessive depending on the application.

The Mean Absolute Error (MAE) of 4.621 measures the average absolute difference between model predictions and data. With an average error size of 4.621 units, the MAE's insensitivity to outliers supports consistent test set performance. These measurements quantify the NN's prediction abilities, however domain-specific criteria must be considered. Signal strength forecasts may require even small RMSE or MAE errors for connection or safety. In applications with higher error tolerance, these figures may work.

The results also suggest model improvements. Should the error metrics exceed acceptable thresholds, adjustments in the model's architecture, like modifying the number of layers or neurons, trying various activation func- tions, or integrating regularization techniques, could be explored to improve performance. Enhancing the training dataset or employing more sophisticated preprocessing methods might also contribute to better generalization and reduced error rates. In conclusion, the promising results of the NN need to be con- textualized within the specific application and benchmarked against other models such as the WNN to determine the most effective approach for predicting signal strength.

Table 3. Neural Network Performance Metrics

Metric	Value
MSE	32.934
RMSE	5.738
MAE	4.621

In Figure 2, the loss curve of the NN depicts the model's learning progression throughout its training over 100 epochs. The graph features two distinct curves: one for training loss and another for validation loss, each providing valuable in- sights into the model's learning dynamics.

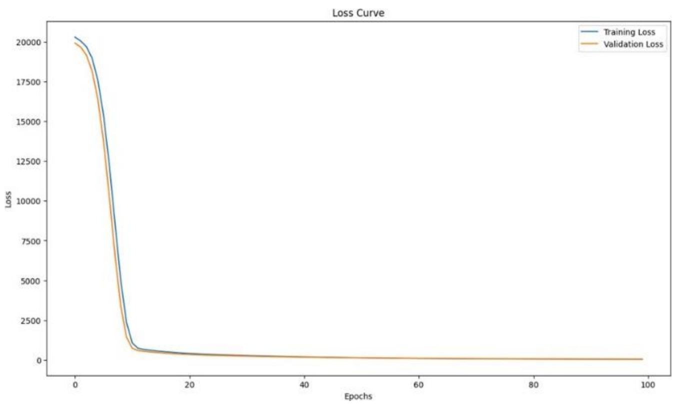

Fig. 2. Loss curve NN

The training loss curve reflects the model's ability to fit the training data over time. At the outset, there is a notable steep decline in loss, indicative of rapid learning and substantial gains in the model's predictive accuracy. This steep decrease is a common occurrence in the initial phase of training, where the model begins to assimilate knowledge from a relatively uninformed state.

Conversely, the validation loss curve illustrates the model's performance on unseen data, separate from the training dataset. This curve is crucial as it indicates the model's capacity to generalize its learning to new data. In the depicted scenario, the validation loss mirrors the downward trend of the training loss, suggesting that the model is effectively capturing generalizable patterns instead of merely memorizing specifics from the training dataset.

As training progresses, both curves tend to plateau, sig- naling that the model has reached a saturation point where additional learning, with the existing architecture and hyper-parameters, leads to minimal further reductions in loss. This plateau often marks the convergence of the model, implying that extending the training with more epochs is unlikely to enhance performance significantly.

An important observation is the close alignment and similar trajectory of the training and validation loss curves. This closeness is a positive indication of the model’s generalization capabilities, as it implies a low likelihood of overfitting to the training data.

The initial high loss value at the start of training might be attributed to several factors, such as the scale of the data, the initialization of the model’s weights, or the inherent complexity of the task. However, the model's rapid loss drop shows its ability to overcome initial hurdles and adapt to the data format.

B. Wavelet Neural Network Results

WNN results show powerful prediction skills, as seen by lower error metrics than classical NN.

A significant improvement over the NN's MSE is the WNN's 11.942. The WNN's predictions are on average closer to the actual values, indicating a superior data fit. MSE decreases significantly when wavelet processing is integrated into the WNN architecture, allowing it to capture more signal patterns and dynamics.

WNN RMSE is 3.455, significantly lower than NN. Since RMSE uses the same units as signal strength, it is useful in practical applications. A reduced RMSE suggests WNN forecasts are closer to real signal intensities in critical situations. The WNN's MAE is 2.755, better than the NN. MAE, a simple metric of average error size, shows that the WNN has less absolute disparities between forecasts and actual values.

These improved WNN measurements offer various insights. First, wavelet analysis may help the WNN capture local and global data patterns better than regular NNs, resulting in more accurate predictions. This helps with non-linear or noisy signal strength data. Second, the WNN's reduced MSE, RMSE, and MAE indicate better prediction ability and greater robustness to outliers and noise. Real-world applications with data inconsistencies require such robustness.

However, this improved accuracy of the WNN must be weighed against potential increases in computational com- plexity. While the WNN has showcased enhanced accuracy, considerations around training duration, implementation com- plexity, and model interpretability are also crucial.

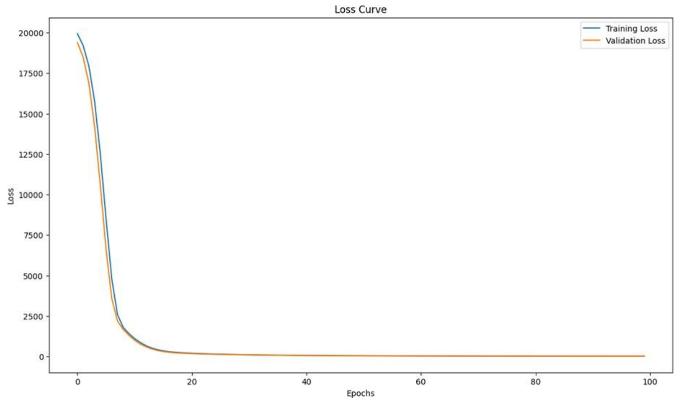

Fig. 3. Loss curve WNN

In conclusion, the WNN results indicate a more advanced ability in accurately predicting signal strength compared to the NN. This positions the WNN as a highly effective option for applications where precise and reliable prediction of signal strength is a key requirement.

Table 4. Wavelet Neural Network Performance Metrics

Metric	**Value**
MSE	11.942
RMSE	3.455
MAE	2.755

Figure 3 in the study presents the loss curve for WNN, showcasing how the model's error evolves throughout its training over 100 epochs. This graph, like that of the NN, plots both the training and validation loss, providing insight into the WNN's learning efficiency and its capability to generalize. The training loss curve shows how well the WNN fits training data. Models that learn data patterns usually reduce initial loss significantly. For excellent prediction, the WNN must detect and learn from training dataset patterns and characteristics, as shown by this significant loss curve reduction.

The validation loss curve compares the WNN's performance to a dataset not used for training to measure generalization. The WNN is learning to generalize its predictions to new data when the validation loss matches the training loss and settles without divergence. The model predicts reduced error because these curves converge at a lower plateau. The model has learned its maximum given the architecture and hyperparameters, therefore more training epochs are unlikely to improve results.

Additionally, the WNN effectively avoids overfitting by closely tracking training and validation loss curves during training. This shows that the model is robust and accurate.

Wavelet-transformed data gives the WNN better performance than the NN in training and validation, according to loss values. The previously lower error measurements support this.

In summary, the loss curves in Figure 3 validate the effective training of the WNN and its proficiency in generalizing from the training data to unseen data. This ability is crucial for prac- tical applications where dependable predictions on new inputs are required. The demonstrated results of the WNN highlight its potential as an effective tool for accurately predicting signal strength, offering clear advantages over traditional neural network models.

C. Comparison Results

The WNN outperforms the NN in performance metrics, as seen in the table. The WNN outperformed the regular NN in MSE, RMSE, and MAE, as seen in the table.

WNN (11.94) has a substantially lower MSE than NN (32.93). The WNN's substantial MSE decrease signals a more accurate prediction model due to fewer errors between projected and actual values. RMSE, which measures average error in the same units as the predicted variable, is lower in WNN (3.45) than NN (5.73). The WNN's lower RMSE makes its predictions closer to signal strength values, making it better for precision-critical scenarios.

The MAE, which averages absolute differences between forecasts and actual data, shows that the WNN (2.75) surpasses the NN (4.62). WNNs perform better due to their reduced MAE and more consistent prediction accuracy across the dataset.

This shows that the Wavelet Neural Network estimates signal strength more precisely and reliably. Wavelet analysis in the neural network architecture helps the WNN capture more complex data patterns that the normal NN may miss. on applications that need precise signal strength prediction, the WNN excels on all three criteria.

Table 5. Comparison Of Nn And Wavelet Nn Performance Metrics

Metric	**NN**	**Wavelet NN**
MSE	32.93	11.94
RMSE	5.73	3.45
MAE	4.62	2.75

6. CONCLUSION

This study indicates that Wavelet Neural Networks (WNNs) identify complex signal propagation properties better than Neural Networks (NNs). WNNs increase prediction accuracy with wavelets' dual time-frequency localization. WNNs' quality benefits wireless communication. WNNs' lower Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) error rates show they can make accurate predictions, which is useful in network planning and optimization.

7. FUTURE WORK

This study prepares for future research. Future research could examine how wavelet families affect model performance in WNN architecture. More research is needed on WNNs' scalability for larger datasets and signal data adaption. WNNs in real time in dynamic situations with changing signal properties are another option. Edge computing devices using WNNs for instantaneous signal strength prediction could change mobile networks.

Domain knowledge like urban or rural signal propagation characteristics can improve the WNN model for more accurate real-world applications. WNNs with cutting-edge technologies like 5G and Internet of Things (IoT) make intriguing research areas. Finally, making the WNN model easier to utilize for industry professionals by building a user-friendly software solution. This platform would bring WNN technology to practitioners by connecting sophisticated research to real-world application. Finally, WNNs' promising results in this study are just the beginning. These techniques could transform wireless network architecture and signal strength prediction with future refinement.

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