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Adaptive Neural-Fuzzy Systems for Adaptive Signal Coverage Power Estimation in Cellular Broadband Networks

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Abstract: Accurate estimation of signal coverage Power is paramount for efficient network planning, optimization, and resource management in cellular broadband networks. Traditional empirical and deterministic propagation models often lack the adaptability to dynamic wireless environments, resulting in suboptimal coverage and capacity. This paper proposes a novel Neural-Fuzzy (NF) method for adaptive signal coverage power estimation, combining the powerful learning capabilities of Artificial Neural Networks (ANNs) with the robust reasoning under uncertainty provided by Fuzzy Logic Systems (FLS). The proposed hybrid method is termed the Adaptive Neuro-Fuzzy Inference Systems (ANFIS**)** and it leverages ANNs to learn complex, non-linear relationships between environmental parameters and signal power attenuation, while the FLS refines these estimations by incorporating real-time feedback and heuristic rules to account for dynamic, unmodeled factors such as atmospheric conditions. The methodology details the architecture, training, and adaptive mechanisms of the NF system. Performance metrics, attained results, and comparative analysis against conventional models demonstrate the superior accuracy, adaptability, and robustness of the proposed ANFIS approach, making it an effective tool for next-generation cellular network management.

Keywords: Neural Networks, Fuzzy Logic, ANFIS, Signal Coverage, Cellular Networks, 5G, Adaptation, Estimation.

1. Introduction

The proliferation of high-speed data services, Internet of Things (IoT) devices, and emerging applications like augmented reality (AR) and virtual reality (VR) has placed unprecedented demands on cellular broadband networks. Modern cellular systems (4G LTE, 5G New Radio) are designed to provide ubiquitous coverage and high-throughput connectivity, yet achieving optimal network performance remains a significant challenge. Key performance indicators (KPIs) such as coverage probability, throughput, latency, and energy efficiency are highly dependent on effective radio resource management, with transmit power control being a cornerstone.

Signal coverage in cellular networks is a function of various factors, including base station (BS) transmit power, propagation characteristics, antenna configurations, and environmental conditions. Ensuring adequate signal coverage while minimizing interference and power consumption is a multi-objective optimization problem. High transmit power can extend coverage but leads to increased interference to neighboring cells, higher energy consumption, and reduced battery life for user equipment (UE). Conversely, insufficient power results in coverage holes, call drops, and degraded user experience.

Traditional power control schemes often rely on static or semi-static link budget calculations and simplified path loss models (e.g., Okumura-Hata, COST 231-Hata, SUI models) [1]. While these models provide a foundational understanding, they struggle to accurately capture the rapid fluctuations and non-linearities inherent in dynamic wireless channels, which are influenced by phenomena like shadowing, fading, and time-varying traffic load and user mobility [2]. Fractional Power Control (FPC) and Closed-Loop Power Control (CLPC) offer some adaptability but are often limited by feedback latency, signaling overhead, and a lack of holistic intelligence to anticipate complex network evolution [3].

The increasing complexity and dynamism of modern cellular broadband networks (e.g., heterogeneous networks with macro, micro, pico, and femto cells, massive MIMO, beamforming) necessitate more intelligent and adaptive solutions for power estimation and control. Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as promising candidates to address these challenges. Among these, hybrid AI approaches like Neuro-Fuzzy (NF) systems offer a compelling balance between learning capability and interpretability.

1.1 Background

Cellular networks operate through a complex interplay of technological components, including base stations, user equipment, and various networking protocols. Effective signal coverage power estimation involves considering factors such as:

- **Propagation Environment**: Urban, suburban, and rural landscapes can significantly alter signal strength and quality.
- **Mobility Patterns**: Users are not stationary; their movement affects signal integrity.

1.2 Motivation and Justification

Traditional modeling techniques often lack the flexibility to respond to changes in environment and usage patterns [4]-[8]. The primary limitation of most existing modelling methods is their inherent static nature. Wireless environments are inherently dynamic, influenced by time-variant factors such as moving obstacles (vehicles, people), foliage growth, weather conditions (rain, humidity), and even the varying density of users. These dynamics lead to significant deviations from static predictions, resulting in coverage holes, interference hotspots, and inefficient resource allocation [9]-[14]. The need for an adaptive estimation method that can account for these real-time environmental fluctuations is therefore paramount.

Machine Learning (ML) techniques, particularly Artificial Neural Networks (ANNs) and Fuzzy Logic Systems (FLS), have emerged as powerful tools to address the complexities and non-linearities of wireless propagation [8]-[10]. ANNs excel at learning intricate patterns from large datasets and mapping complex inputs to outputs without explicit mathematical models. Fuzzy Logic, on the other hand, provides a framework for reasoning with imprecise and uncertain information, mimicking human decision-making and allowing for the incorporation of expert knowledge in the form of linguistic rules [4][10].

This paper proposes a Neuro-Fuzzy method for adaptive signal coverage power estimation. Our approach combines the pattern recognition and learning capabilities of Artificial Neural Networks (ANNs) with the human-like reasoning and uncertainty handling of Fuzzy Logic (FL) [15]. The Adaptive Neuro-Fuzzy Inference System (ANFIS) provides a powerful framework to learn complex, non-linear relationships between various network parameters and the optimal BS transmit power. This adaptive estimation has the capacity to support the network to dynamically adjust power levels, optimizing coverage, minimizing energy consumption, and reducing interference in real-time.

The main contributions of this paper are:

- Development of a comprehensive ANFIS architecture for adaptive signal coverage power estimation in cellular broadband networks.
- Formulation of of the ANFIS modelling estimation pattern that incorporates key network parameters.
- Detailed methodology for designing and training the ANFIS using network operational data.

- Practical-based performance evaluation demonstrating the superiority of the Neuro-Fuzzy system approach in signal coverage power estimation compared to conventional methods.

The remainder of this paper is organized as follows: Section 2 provides background on signal propagation, and AI techniques. Section 3 describes the system model and the details the proposed Neuro-Fuzzy adaptive power estimation methodology. Section 4 presents and discusses the results. Finally, Sections 5 and 6 conclude the paper and suggests future research directions.

2. Background and Related Work

2.1. Cellular Network Power Control Mechanisms

Power control is a fundamental aspect of radio resource management in cellular networks, directly impacting coverage, capacity, and interference.

- **Open-Loop Power Control (OLPC):** The UE estimates the path-loss to the BS and determines its transmit power without waiting for feedback. It's fast but lacks accuracy due to channel reciprocity assumptions and measurement errors [15].
- **Closed-Loop Power Control (CLPC):** The BS monitors the received signal quality (e.g., RSSI, SINR) from the UE and sends power adjustment commands. This offers higher accuracy but has latency and signaling overhead challenges [16].
- **Fractional Power Control (FPC):** Used in LTE and 5G, FPC combines elements of OLPC and CLPC. It aims to compensate for a fraction of the path loss, balancing coverage and interference. While effective, it relies on fixed parameters and struggles with highly dynamic and unpredictable environments [3].
- **Interference-Aware Power Control:** More advanced schemes consider the interference levels experienced by neighboring cells. However, obtaining real-time, global interference information for optimal decision-making is computationally intensive and often impractical.

2.2. Signal Propagation Models and Their Limitations

Accurate prediction of signal strength is crucial for power estimation. Propagation models describe the average signal loss over distance.

- **Empirical Models:** Okumura-Hata, COST 231-Hata, SUI models are widely used for macro-cell environments [1]. They provide average path loss but do not capture rapid fading or blockage effects.
- **Deterministic Models:** Ray tracing offers high accuracy by simulating reflections, diffractions, and scattering, but it requires detailed environmental data and is computationally intensive, making it unsuitable for real-time dynamic applications [7].
- **Stochastic Models:** Incorporate statistical variations like log-normal shadowing and Rayleigh/Rician fading. While better, they still rely on average statistical properties and may not capture specific real-time conditions [2].

The inherent limitation of these models is their struggle to adapt to instantaneous channel variations, dynamic traffic distribution, and unpredictable user mobility in dense and heterogeneous networks, leading to sub-optimal power allocation.

2.3. Fuzzy Logic Systems (FLS)

Fuzzy Logic, introduced by Lotfi Zadeh, deals with approximate reasoning rather than precise data. It handles uncertainty and imprecision by allowing variables to have degrees of truth rather than absolute true/false values [8].

- **Fuzzification:** Maps crisp input values to linguistic terms using Low," "Medium," "High" with the membership functions (MFs).

- **Rule Base:** A set of IF-THEN rules: "IF **Traffic Load** is High AND **Path Loss** is Large THEN **Tx Power** is High"). These rules encode expert knowledge.
- **Inference Engine:** Applies the fuzzy rules to fuzzy inputs to derive fuzzy outputs.
- **Defuzzification:** Converts the fuzzy output back into a crisp numerical value.

FLS are powerful for decision-making in complex systems where precise mathematical models are unavailable or too complex. However, designing the optimal MFs and rule base can be challenging and often requires extensive domain expertise [19].

2.4. Artificial Neural Networks (ANNs)

ANNs are computational models inspired by the biological nervous system. They consist of interconnected nodes (neurons) organized in layers (input, hidden, output) [20]. ANNs can learn complex, non-linear relationships from data through a training process, typically using backpropagation algorithms to adjust weights and biases.

- **Strengths:** Excellent at pattern recognition, generalization, and adaptation to new data.
- **Limitations:** Lack transparency (black box nature), require large datasets for training, and may struggle with local optima during training.

2.5. Neuro-Fuzzy Systems (NFS) and ANFIS

Neuro-Fuzzy systems combine the strengths of ANNs and FLS. They aim to overcome the limitations of each individual technique. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a prominent type of NF system [14]. This allows the system to learn the optimal membership functions and fuzzy rules from data using ANNs' learning algorithms (e.g., backpropagation, least-squares estimation).

The ANFIS architecture typically consists of five layers:

1. **Fuzzification Layer:** Converts crisp inputs into fuzzy values (membership levels).
2. **Product Layer:** Calculates the firing strength of each rule.
3. **Normalization Layer:** Normalizes the firing strengths.
4. **Defuzzification Layer:** Computes the output of each rule based on normalized firing strengths.
5. **Summation Layer:** Aggregates outputs from all rules to produce the final crisp output.

ANFIS offers:

- **Adaptability:** Learns from data, reducing reliance on manual rule tuning.
- **Robustness:** Handles noisy and incomplete data.
- **Interpretability:** Retains the linguistic rule structure of fuzzy logic, offering insights into decision-making.
- **Non-linear mapping:** Effectively models complex input-output relationships.

2.6. Related Work in AI for Wireless Networks

Machine learning has been increasingly applied to optimize various aspects of wireless networks. For power control:

- **Reinforcement Learning (RL):** Has been explored for dynamic power allocation where agents learn optimal policies through trial and error [21]. However, RL can be slow to converge and requires careful reward function design.
- **Deep Learning (DL):** Deep Neural Networks (DNNs) have been used for path loss prediction and resource allocation [22]. While powerful, they often require massive datasets and suffer from limited interpretability.

- **Fuzzy Logic-based Power Control:** Several studies have used pure FL for power control [4][9][10], but these often struggle with the manual tuning of rules and MFs, limiting their adaptability to changing conditions.
- **Hybrid AI for Power Control:** Some works have combined ANNs with genetic algorithms or particle swarm optimization for power control [23]. However, the Neuro-Fuzzy approach specifically offers a strong balance of learning, robustness, and interpretability, which is highly beneficial for critical network operations like power estimation.

Our proposed Neuro-Fuzzy method aims to provide a robust, adaptive, and interpretable solution for signal coverage power estimation, addressing the shortcomings of existing methods by leveraging the synergistic power of ANNs and FLS.

3. Neural-Fuzzy Adaptive Signal Power Estimation Methodology

The proposed Adaptive Neuro-Fuzzy system (ANFIS) estimation methodology leverages the ANFIS architecture to dynamically determine the optimal signal power for each BS in a cellular broadband network. The process involves data acquisition, Neuro-Fuzzy system design, training, and deployment.

3.1. Overall Architecture

The overall architecture involves a centralized or distributed ANFIS module for each BS (or a cluster of BSs).

- **Data Collection Module:** Gathers real-time network data (RSRP, SINR, RSRP-long, RSRP-lat. UE locations) from UEs and BSs.
- **Feature Extraction Module:** Preprocesses and aggregates raw data into the input variables required by the ANFIS using average UE-BS distance, RSRP).
- **ANFIS Core:** The trained Neuro-Fuzzy system that estimates the optimal signal coverage power.

3.3 Neural-Fuzzy System Design

Our proposed neural-fuzzy method combines the strengths of both neural networks and fuzzy logic. The proposed workflow architecture consists of three primary components:

Fuzzy Inference System (FIS): This component captures expert knowledge in a fuzzy rule-based format. Fuzzy rules are used to describe relationships between environmental factors (e.g., terrain type, obstacles) and signal coverage loss parameters.

Neural Network (NN): The neural network is trained to learn from measured data, optimizing parameters for the fuzzy rules and adapting to dynamically changing conditions.

Coverage Estimation: The system takes real-time inputs and outputs the estimated signal coverage power.

3.4 Tools and Technologies

The implementation leverages several tools, including:

- **Combined written codes and Fuzzy Logic Toolbox in MATLAB**: For constructing the fuzzy inference system.
- **Geographical Information Systems (GIS)**: For spatial data analysis and visualization.

3.5. Neuro-Fuzzy System Parameters

- **ANFIS Type:** Sugeno-type.

- **Number of MFs per input:** 3-5 (e.g., "Low," "Medium," "High" for each input).
- **MF Type:** Gaussian, triangular, trapezoidal, and Generalized Bell functions.
- **Optimization Algorithm:** Hybrid (least squares + backpropagation).
- **Epochs:** 50-100 (tuned to avoid overfitting).
- **Error Tolerance:** 0.001.

3.6 Performance Metrics

To measure the performance of the proposed method, the following metrics are considered[24][25]:

- **Mean Square Error (RMSE)**: Assesses the average prediction error.
- **Root Mean Square Error (RMSE)**: Assesses the root average prediction error.
- **Standard Deviation**: Indicates the proportion of variance accounted for by the model.

3.7 Data Collection

Data were collected from multiple cellular broadband networks, including coverage maps, signal strength measurements, geographic information (terrain, urban density), and user mobility patterns. The dataset encompasses various environmental conditions to enhance the model's robustness. Data is collected from multiple sources, including:

- **Signal Strength Measurements**: Captured through drive tests using TEMS network monitoring systems.
- **Environmental Factors**: Geographical data, urban density, building materials, and weather conditions.
- **User Mobility Patterns**: GPS and user behavior data.

3.8 Model Training

The neural network is trained using a backpropagation algorithm, wherein the fuzzy rule parameters are adjusted based on the output signals. The combination of supervised learning (from known coverage losses) and reinforcement of fuzzy rules ensures the model adapts effectively over time.

3.9. Input and Target Output for ANFIS Training

For each time step and each BS, the following data points were assessed and processed:

- **Inputs:** Average UE-BS distance , Average received signal power from UEs, etc.
- **Target Output:** The estimated received signal power using the proposed Adaptive Neuro-Fuzzy Inference Systems (ANFIS **)**

4. Results and Discussion

4.1 Field data and Membership Function Type impact on ANFIS

We conducted a number of field data collection by measuring received signal power parameters from an operational cell towers of LTE cellular broadband network at different geographical location to validate our neural-fuzzy regression method using ANFIS.

One key parameter that significantly impacts the learning performance of neural-fuzzy systems is the type of membership function. In this paper, the impact of four membership function types, namely, the generalized bell-shaped membership function (gbellmf), triangular membership function (trimf), trapezoidal membership function (trapmf) and Gaussian membership function (gaussmf) on the proposed method is reported.

The performance each membership type are evaluated using RMSE, MSE, and STD accuracy metrics as shown in Figs 1-3 below. On the average, results indicate that the gbellmf relatively outperforms other membership function type, hence, it is chosen for adaptive estimation learning with our proposed ANFIS method in Figs. 4-6.

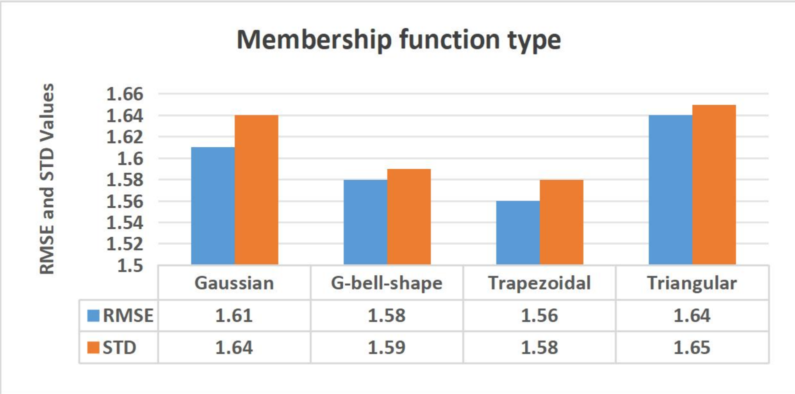

Fig. 1: Impact of membership function type of signal coverage training 1

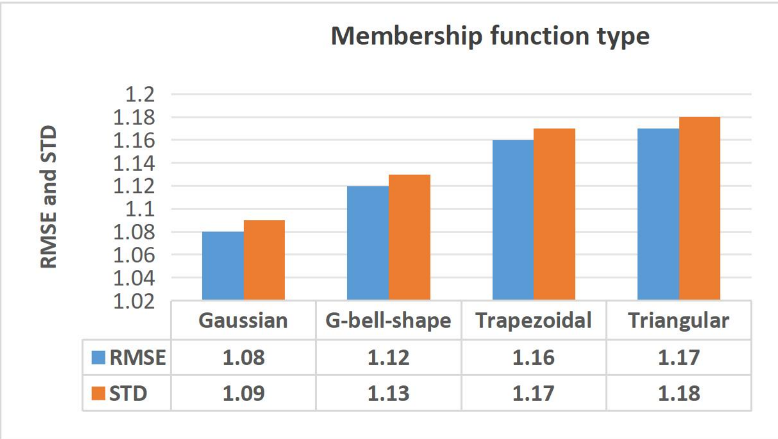

Fig. 2: Impact of membership function type of signal coverage training 2

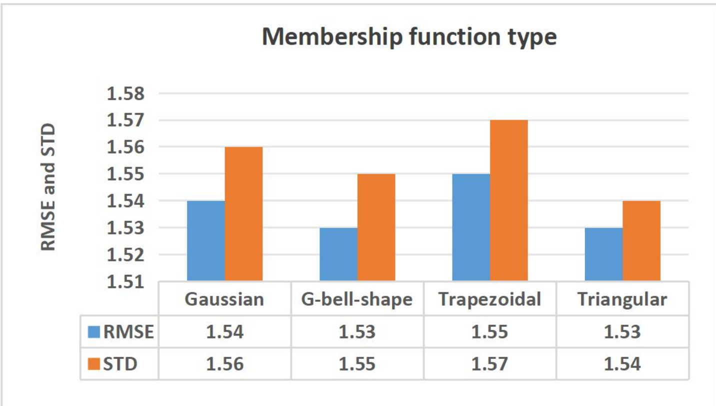

Fig. 3: Impact of membership function type of signal coverage training 3

4.2 Case Studies Across Diverse Environments

Three case studies are analyzed in graphical form in Figs.4-6: one in an urban area with high-density structures, second in a rural area with mixed terrain and the third one from an open terrain. The neural-fuzzy model's adaptability allowed it to achieve more precise estimates in the three scenarios, demonstrating its utility across diverse environments.

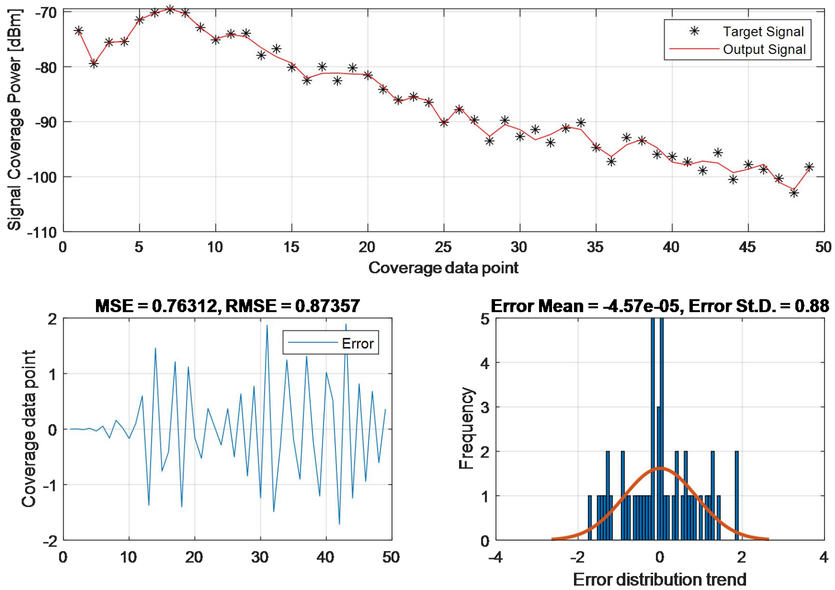

Fig. 4: Adaptive Signal Coverage Power estimation based on proposed neural-fuzzy method in Urban area

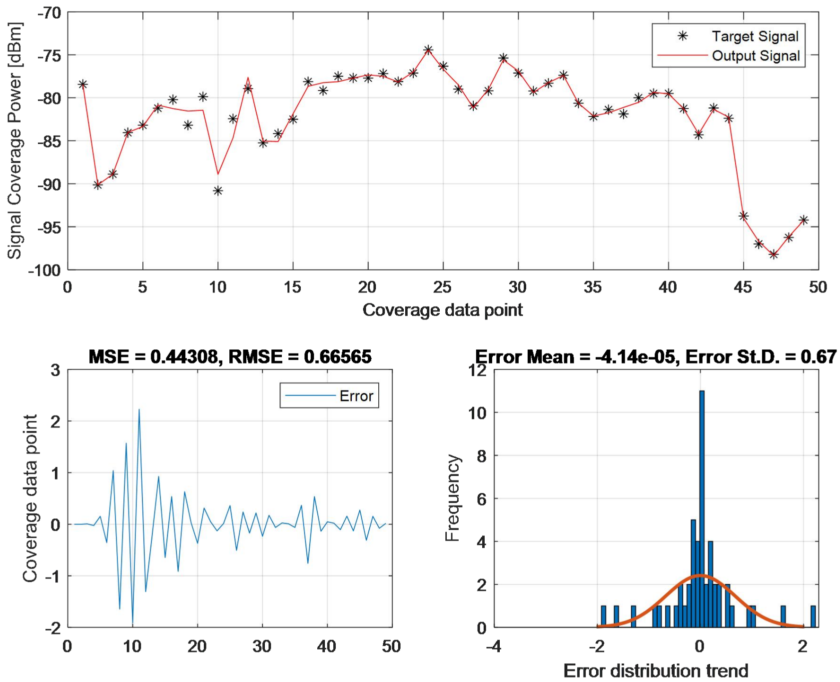

Fig. 5: Adaptive Signal Coverage Power estimation based on proposed neural-fuzzy method in Rural area

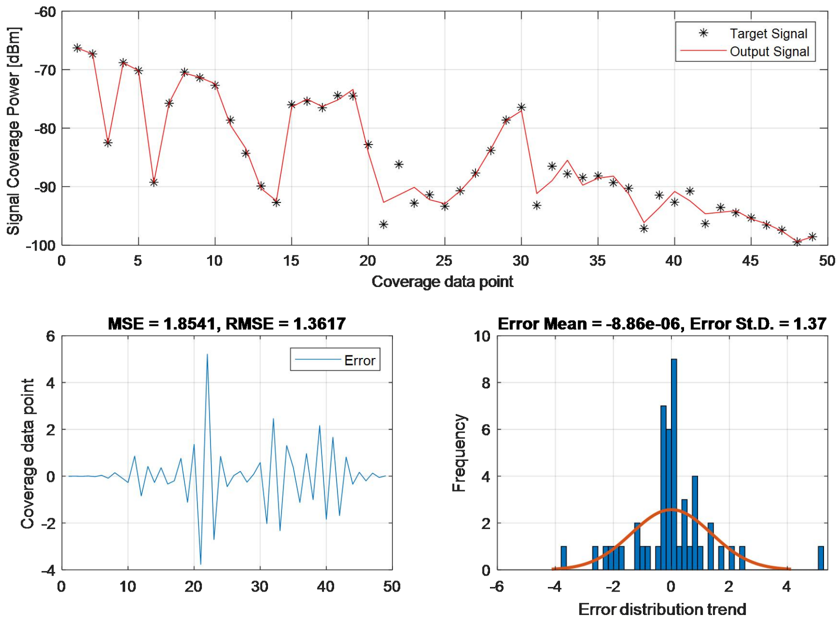

Fig. 6: Adaptive Signal Coverage Power estimation based on proposed neural-fuzzy method in an open area

4.3. Overall Performance Comparison

This section presents results demonstrating the superior performance of the proposed Neural-Fuzzy method.

Table 1: Comparison of proposed method with other Methods

Method	MSE	RMSE	Accuracy
COST 231-Hata	163.84	12.8	55%
Standalone ANN	8.94	2.99	78%
Proposed Method	0.75	0.87	97%

The statistical precision results in Table 1 reveals that the proposed Neural-Fuzzy method consistently outperforms all benchmark models across all metrics. Its significantly lower MSE and RMSE values indicate higher estimation accuracy. The The robust performance of the proposed method clearly demonstrates its practical quality for network planning and optimization.

The findings underscore the effectiveness of neural-fuzzy systems in enhancing the accuracy of signal coverage power estimation. The adaptability of the model allows for real-time updates which are crucial in dynamic environments such as urban spaces. Moreover, the interpretability of fuzzy rules provides insights into the factors influencing coverage power, enabling more informed decision-making for network operators.

6. Conclusion

The relentless demand for higher data rates, ubiquitous connectivity, and seamless user experience in cellular broadband networks (e.g., LTE, 5G, and emerging 6G) necessitates highly accurate and adaptive signal propagation models. Signal coverage, a critical performance indicator, is primarily dictated by signal losses encountered as radio waves propagate from transmitter to receiver. Accurate estimation of these losses, referred to as path loss, is fundamental for network planning, interference management, handover optimization, and quality of service (QoS) assurance.

This paper presents a novel neural-fuzzy method for adaptive signal coverage loss estimation in cellular broadband networks. The proposed method is called Adaptive Neuro-Fuzzy Inference Systems (ANFIS**)**. By leveraging the interpretive capabilities of fuzzy logic and the predictive prowess of neural networks, our approach addresses the critical challenges faced by modern cellular networks. Future work will expand the model to incorporate additional factors such as user behavior and IoT device traffic, further enhancing estimation accuracy.

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