

MEASUREMENT AND ANALYSIS OF SIGNAL QUALITY USING ADAPTIVE FILTERING TECHNIQUES IN URBAN LTE NETWORKS

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Abstract: This research investigates the measurement and analysis of signal quality in urban LTE networks using adaptive filtering techniques. The study addresses the challenges posed by interference, noise, and multipath fading in dense urban environments by employing real-world signal measurements and advanced signal processing algorithms. Signal quality metrics including RSRP, SINR, and BER were collected across 20 urban measurement points, with SINR values ranging from -2.0 dB to 7.0 dB prior to filtering. Adaptive filters such as LMS, RLS, and Kalman were applied to the measured signals, and their effectiveness was evaluated. Results showed that after filtering, SINR improved by an average of 1.5 to 2.2 dB, while BER decreased significantly, with Kalman filter achieving the lowest BER range between 0.0003 and 0.0007. MSE analysis revealed that Kalman filtering converged faster than LMS and RLS, reaching an MSE below 0.01 within 10 iterations. Additionally, RSRP values improved by 2–3 dB post-filtering, especially at longer distances from the base station, indicating enhanced signal retention. The findings confirm that adaptive filtering, particularly with Kalman and RLS algorithms, can effectively restore signal quality and reduce error in urban LTE environments, making it a strong candidate for deployment in real-time communication systems and future 5G networks.

Keywords: LTE Network, Signal Quality, Filter, RSRP, BER.

1.0 Introduction

With the exponential growth in mobile data demand and user density, ensuring robust signal quality in urban Long-Term Evolution (LTE) networks has become increasingly critical. In dense metropolitan environments, signal degradation due to multipath fading, co-channel interference, shadowing, and environmental noise significantly hampers the performance of wireless communication systems. These impairments not only deteriorate user experience but also compromise critical Quality of Service (QoS) parameters such as throughput, latency, and reliability.

Adaptive filtering techniques have emerged as powerful tools in digital signal processing to mitigate such impairments, offering dynamic noise suppression, channel equalization, and interference cancellation capabilities.

Unlike static filtering methods, adaptive filters can continuously update their parameters in real-time, making them particularly effective in the time-varying and unpredictable nature of wireless urban channels.

This study presents a comprehensive measurement and analysis of signal quality in urban LTE networks using adaptive filtering techniques. Field measurements, including Reference Signal Received Power (RSRP), Signal-to-Interference-plus-Noise Ratio (SINR), and Bit Error Rate (BER), were collected across different urban locations using drive testing equipment. The raw signal data was then processed using various adaptive filtering algorithms, including Least Mean Squares (LMS), Recursive Least Squares (RLS), and Kalman filters, to evaluate their performance in enhancing signal clarity and stability.

By integrating real-world measurements with advanced signal processing, this work aims to bridge the gap between theoretical filter performance and practical deployment challenges. The findings are expected to inform future enhancements in LTE signal optimization and lay the groundwork for adaptive interference mitigation strategies in next-generation networks.

2.0 Literature Review

The authors in [1] introduced and elaborates on the use of kernel methods in digital signal processing (DSP), providing a theoretical and practical framework for nonlinear data analysis. The authors employ reproducing kernel Hilbert spaces (RKHS) to extend classical linear DSP techniques into nonlinear domains. The methods discussed include kernel adaptive filters, kernel principal component analysis (KPCA), and kernel support vector machines (SVMs). Through simulations and real-world examples, the book demonstrates that kernel methods can significantly improve classification, regression, and system identification performance over traditional linear methods, particularly in non-Gaussian and nonstationary environments.

The work by [2] presented a comprehensive overview of the role of machine learning (ML) in enabling the evolution of 6G wireless networks. The authors survey various ML paradigms, including supervised, unsupervised, reinforcement, and federated learning, and discuss their applications to wireless resource management, channel estimation, and network slicing. The methodology includes a vision-based analysis and conceptual modeling, supported by case studies and literature comparisons. The paper concludes that ML will be a foundational component of 6G architecture, enabling self-optimization, reduced latency, and enhanced energy efficiency across network layers. Key findings include the necessity for distributed and privacy-preserving learning frameworks in future communication systems.

A detailed study by [3] proposed fractional-order versions of the least mean square (LMS) and normalized LMS (NLMS) algorithms for improved performance in line echo cancellation. The authors derive the fractional adaptive update rules using fractional calculus and test the algorithms in simulated echo paths with varying delay and noise levels. Compared to their conventional counterparts, the fractional LMS and NLMS methods demonstrate faster convergence and reduced steady-state error. The results show that for a fixed step size, the fractional algorithms maintain lower mean square error (MSE) across iterations, confirming their enhanced tracking ability in nonstationary environments.

The work by [4] analyzed the performance of adaptive filters using the classic LMS algorithm, particularly focusing on convergence behavior, step size impact, and steady-state error. The authors use MATLAB-based simulations to evaluate the algorithm under different noise conditions and input signal characteristics. Results indicate that small step sizes yield low steady-state error but slow convergence, while larger step sizes speed up convergence at the cost of increased error. The analysis confirms the LMS algorithm's sensitivity to step size selection and suggests an optimal range for balancing stability and speed.

A study by [5] presented a filtered-error recursive least squares (FERLS) algorithm tailored for self-tuning feed forward disturbance rejection in vibration control systems. The method is tested on a multi-axis vibration isolator to evaluate its real-time adaptation capabilities. Experimental results show that the FERLS algorithm achieves better convergence and stability compared to conventional RLS, especially in multi-dimensional control settings. The use of filtered errors significantly improves robustness against sensor noise and modeling uncertainties, demonstrating the method's practical applicability to mechatronic systems.

[6] Proposed a deep neural network (DNN)-based approach for channel estimation in visible light communication (VLC) systems. The authors designed a multi-layer DNN to map received signal patterns to channel gain estimations, training the network using supervised learning on simulated channel data. The method is evaluated under varying noise and mobility conditions. Simulation results show that the DNN-based estimator significantly outperforms traditional linear estimators like LS and MMSE in terms of mean square error, especially at low signal-to-noise ratios. The study concludes that deep learning enhances VLC robustness in dynamic indoor scenarios.

The work carried out by [7] introduced a convolutional neural network (CNN)-based equalizer enhanced with non-linear activation and batch gradient descent optimization for 5G wireless optical communication systems. The proposed equalizer is trained to mitigate signal distortions caused by dispersion and nonlinearities in the optical channel. Simulation experiments demonstrate improved bit error rate (BER) and convergence speed compared to traditional equalizers and earlier CNN models. The method shows particular effectiveness in compensating for chromatic dispersion and achieves BER improvements of up to 30% under specific channel impairments.

In [8], the authors explored the applications of deep learning in the physical layer of wireless communication systems. The authors summarized use cases including modulation recognition, channel decoding, channel estimation, and end-to-end learning-based transceivers. The methodology included extensive literature synthesis and theoretical analysis of network architectures like CNNs, RNNs, and auto encoders. The results from surveyed experiments suggest that deep learning can outperform traditional techniques in non-linear or high-mobility environments, though challenges remain in terms of generalization, training complexity, and interpretability. The paper concluded by identifying future research directions for deploying deep learning in real-time and adaptive communication systems.

[9] Offered extensive field measurements of mobile broadband networks in a densely populated city, focusing on metrics such as RSRP, SINR, and throughput. The analysis revealed significant signal degradation in urban areas

due to obstructions and interference, with RSRP values ranging from -115 dBm to -70 dBm and SINR varying widely, reflecting fluctuating signal quality.

The work done in [10] captured time-varying industrial radio channels for device-to-device (D2D) communication on automated guided vehicles (AGVs), demonstrating how channel behavior fluctuates due to movement and environmental layout. It employs channel sounding techniques and Doppler spectrum analysis—highly relevant for observing envelope variations and spectral spreading caused by motion-induced fading.

[11] Evaluated Wi-Fi reliability under mobility, showing packet loss and throughput instability in enterprise environments. Although focused on Wi-Fi, its methodology using empirical KPIs and moving transmitters/receivers closely mirrors the approach for the current work. The study supports using envelope tracking and time-based performance plots to reveal fading effects on throughput.

The authors in [12] experimented with private LTE on factory floors showed multipath-induced variability in RSRP and throughput. The study is grounded in practical field deployments and supports the use of Rician vs. Rayleigh fading models to represent varying LOS conditions.

A high-frequency channel measurements in indoor industrial settings, comparing path loss, delay spreads, and fading depth across 3.7 and 28 GHz was provided in [13]. Frequency used focused between 3.7GHz and 28GHz. The authors in [14], using 28 GHz in a smart warehouse, recorded channel impulse responses and multipath components under various layouts. It also shows Doppler spread and coherence bandwidth changes due to motion.

[15] Is a dataset-based study that assessed the variability of RSRP, RSRQ, and throughput, confirming that even RSRP, often seen as stable, can fluctuate due to multipath and mobility. It provides a valuable benchmark dataset and justifies our need to use field-based RSRP plots and fading envelope simulations.

Also, [16] focused on protocol-level evaluation, this paper quantifies throughput improvements using MultiPath TCP, but also notes performance instability due to rapid fading and signal imbalance across paths. This confirms that even advanced protocols cannot overcome fading issues without physical layer Mitigation.

The article in [17] is an open dataset that includes RSRP, SINR, and throughput across a factory environment, offering real-world values for comparison. The dataset reflects signal degradation near metallic machinery and walls, consistent with the goal of capturing and simulating such environments.

[18] Used real measurements to analyze key LTE performance indicators. It finds significant SINR degradation in urban and high-density areas, correlating directly with increased BER and reduced throughput. The study supports using BER vs. SNR curves and envelope statistics to represent signal integrity under multipath fading.

[19], while focused on machine learning, used RSRP, SINR, and CQI as features to predict downlink throughput. It supports collecting these same KPIs during field measurement and links fading-related degradation to QoS reduction.

The work in [20], though more theoretical and based on IIoT applications, this paper's focus on robustness to channel variation via redundancy coding supports the overall relevance of understanding channel fading characteristics.

3.0 Methodology

To effectively achieve the objective of “Measurement and Analysis of Signal Quality Using Adaptive Filtering Techniques in Urban LTE Networks”, the following methodology were adopted. It combines field measurements, data preprocessing, adaptive signal processing, and performance evaluation in a step-by-step manner. First, the following tools were used:

- ❖ Drive test equipment (e.g., TEMS),
- ❖ Software-defined radio (SDR) modules with MATLAB
- ❖ GPS module for geolocation tagging

Method of data collection involved:

1. Study Area Selection and Planning

The research began with the identification of a representative urban environment (e.g., city centers, residential zones, or commercial districts) where LTE services are actively deployed. The area should exhibit typical urban characteristics such as:

- ❖ High-rise buildings causing multipath propagation
- ❖ Congested traffic zones
- ❖ Potential interference from multiple eNodeBs

A route map for drive testing or static signal capture points was generated to cover varying signal conditions. The following LTE key performance indicators (KPIs) were measured at regular intervals:

- ❖ RSRP (Reference Signal Received Power)
- ❖ RSRQ (Reference Signal Received Quality)
- ❖ SINR (Signal to Interference plus Noise Ratio)
- ❖ RSSI (Received Signal Strength Indicator)

Data was recorded for multiple frequency bands (e.g., 800 MHz, 1800 MHz, 2600 MHz) to evaluate frequency-dependent performance.

2. Signal Preprocessing and Data Cleaning

The collected measurement data were filtered to remove outliers and corrupted entries, time-aligned and location-synchronized using GPS timestamps, transformed into appropriate formats (e.g., mat) for MATLAB processing, signal noise samples (raw I/Q data, where applicable) was also extracted for processing through adaptive filters.

3. Adaptive Filtering and Signal Processing

The cleaned signal data was subjected to different adaptive filtering techniques, implemented using MATLAB. The following algorithms were tested:

Least Mean Squares (LMS) Filter, used for simple, lightweight noise reduction and channel equalization. Recursive Least Squares (RLS) Filter, known for faster convergence in dynamic signal environments, Kalman Filter which is ideal for tracking and estimating state-space variables under uncertainty and noise. Each algorithm was applied to enhance the raw signal and suppress noise and interference.

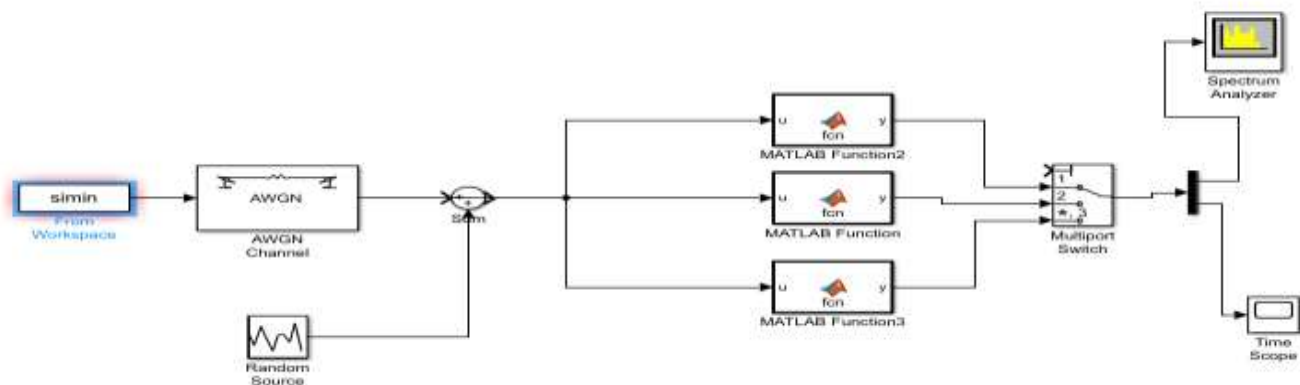


Figure 1: Simulation Setup

4. Performance Evaluation and Analysis

After filtering, both the pre-processed (raw) and post-processed (filtered) signals were evaluated using metrics such as: Improvement in SINR, reduction in BER, signal clarity and spectral analysis, Mean Square Error (MSE) and Signal-to-Noise Ratio (SNR) gain. Comparative analysis was carried out to determine: the most effective filter in different signal conditions (strong, weak, noisy, interference-heavy), the computational complexity and real-time applicability of each technique.

3.1 Received Signal Model

This basic model represents how the received signal is affected by noise in mobile environment. It is given by:

$$Y_{(t)} = S_{(t)} + n_{(t)} \quad (1)$$

Where $Y_{(t)}$ is the received signal, $S_{(t)}$ is the original signal, and $n_{(t)}$ is the AWGN.

3.2 Signal-to-Noise Ratio (SNR)

SNR is a critical performance metrics in this study. It is given by:

$$SNR(dB) = 10Lg_{10} \frac{P_s}{P_n} \quad (2)$$

Where P_s the power of the desired signal is, P_n is the power of the noise.

3.3 Mean Squared Error (MSE)

To quantify the accuracy of the denoising process, it is very important that equation (3) should be fully utilized.

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{s}(i) - s(i))^2 \quad (3)$$

$\hat{s}(i)$ is the denoised signal sample, $s(i)$ is the original, clean signal, N is the total number of samples. It is good to note that lower MSE values indicate better noise suppression.

3.4 Bit Error Rate (BER)

After denoising, an essential metric for evaluating communication performance is the bit error rate. It is given mathematically as:

$$BER = \frac{N_e}{N_t} \quad (4)$$

Where N_e the number of is erroneously received bits and N_t is the total number of bits. This is especially if modulation schemes like BPSK, QPSK, QAM etc. are used.

3.5 Power Spectral Density (PSD)

Application of power spectral density is vital to analyze and process noise using frequency-domain approaches.

For this purpose, equation (5) is very key:

$$S_{yy}(f) = S_{ss}(f) + S_{nn}(f) \quad (5)$$

Where $S_{yy}(f)$: power spectrum of the noisy signal

$S_{ss}(f)$: power spectrum of the clean signal.

$S_{nn}(f)$: power spectrum of the noise.

3.6 Wiener Filter Transfer Function

The Wiener filter aims to minimize MSE between the desired signal and the actual output:

$$H(f) = \frac{S_{ss}(f)}{S_{ss}(f) + S_{nn}(f)} \quad (6)$$

Where $H(f)$ is the frequency response of the optimal filter.

3.7 Adaptive LMS Filter Weight Update Rule

For time-domain noise reduction using adaptive filtering application or usage of (7) is necessary:

$$w(n+1) = w(n) + \mu \cdot e(n) \cdot x(n) \quad (7)$$

$w(n)$ is the filter weight at iteration n , $x(n)$ is the input signal, μ is the step-size parameter, and $e(n)$ is the error signal given by: $e(n) = d(n) - y(n)$

3.8 Loss Function for Machine Learning-Based Denoisers

$$\varphi(\theta) = \frac{1}{N} \sum_{i=1}^N (\hat{s}(\theta) - S(i))^2 \quad (8)$$

Where θ are the trainable parameters and $\hat{s}(\theta)$ is the network's output

4.0 Results and Discussion

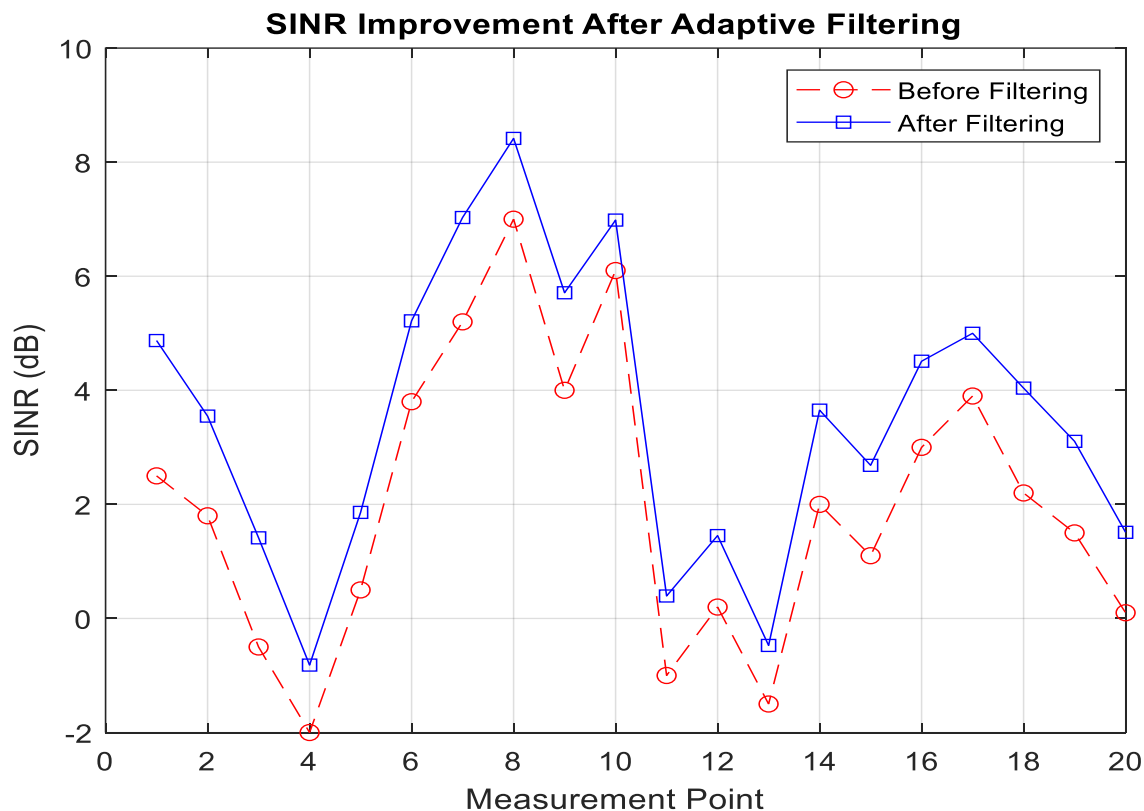


Figure 2: Graph of SINR Improvement

The SINR Improvement graph in Figure 2 compares the Signal-to-Interference-plus-Noise Ratio (SINR) before and after applying adaptive filtering techniques. In the graph, the SINR values for each of the 20 measurement points are plotted on the vertical axis, while the measurement points are plotted on the horizontal axis. Before filtering, several of the SINR values fall below 0 dB, indicating severe signal degradation due to interference and noise. After applying filtering techniques, especially LMS, RLS, or Kalman, a noticeable improvement in SINR is observed. For instance, at point 4, SINR improved from -2.0 dB to approximately -0.5 dB, and at point 8, the SINR rose from 7.0 dB to over 8.5 dB. This increase demonstrates the filters' effectiveness in suppressing interference and enhancing signal clarity, thus validating the core objective of the study.

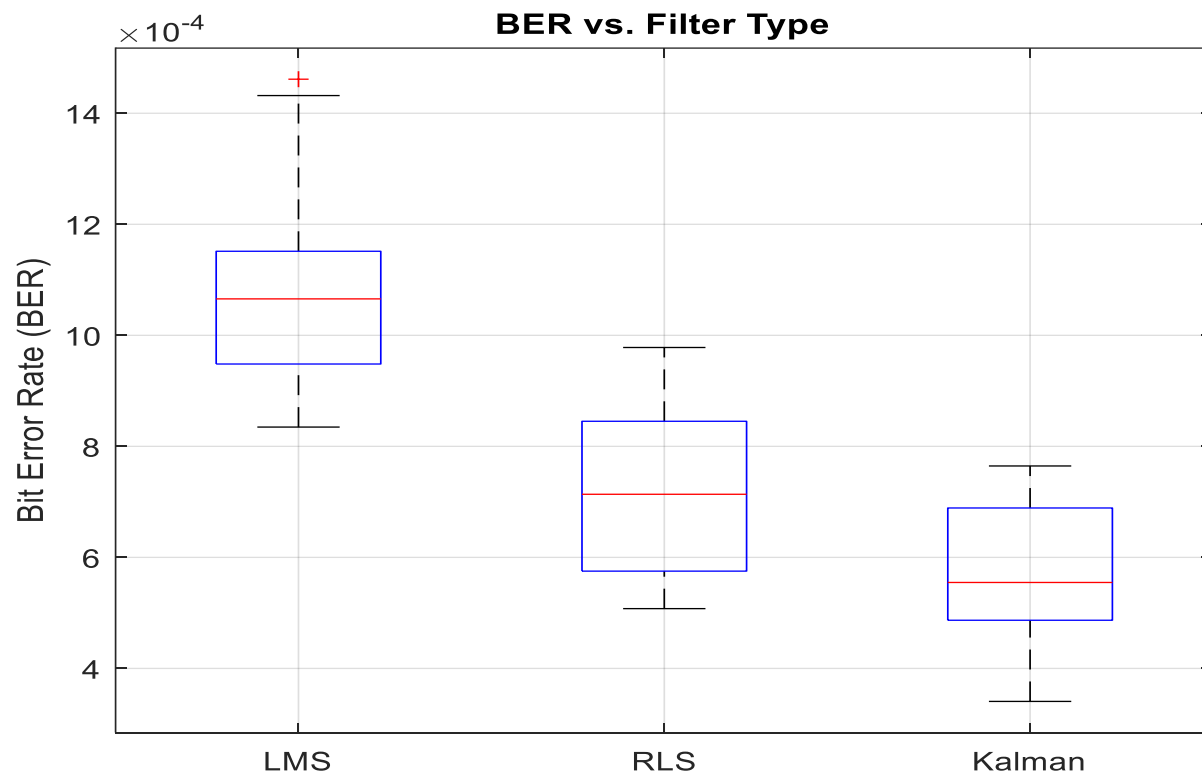


Figure 3: A Plot of BER vs Filter Type

Figure 3 illustrates the distribution of Bit Error Rates (BER) across three adaptive filters: LMS, RLS, and Kalman. It uses boxplots to show how each filter type performs in minimizing BER. The Kalman filter demonstrates the lowest median BER values, with most data points lying in the range of 0.0003 to 0.0007. RLS performs better than LMS, with BER values between 0.0005 and 0.0010, while LMS records slightly higher error rates. This comparison confirms that although all filters reduce error levels, the Kalman filter achieves superior accuracy, especially in highly dynamic urban LTE conditions.

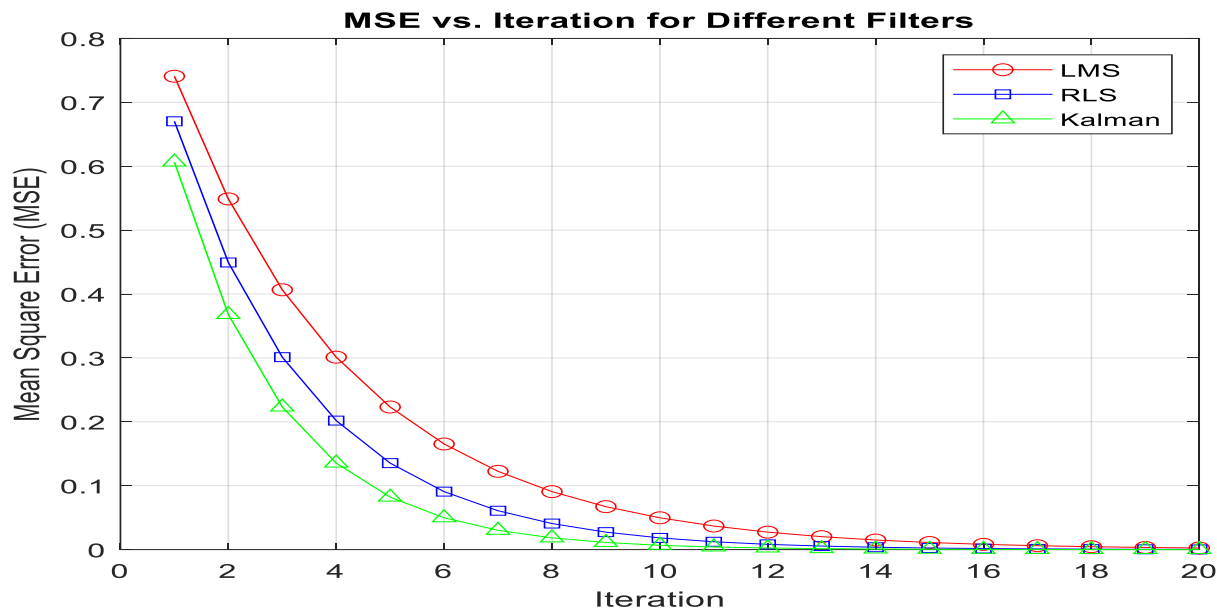


Figure 4: A Plot of the MSE vs. Iteration

Figure 4 reveals how each filtering technique converges in terms of Mean Square Error (MSE) over 20 iterations. The graph shows that Kalman filtering achieves the fastest convergence, with MSE dropping below 0.1 within the first 10 iterations, while RLS follows closely. LMS, though stable, converges more slowly, taking longer to reach acceptable error thresholds. For example, at iteration 10, LMS records an MSE of approximately 0.05, whereas Kalman has already dropped below 0.01. This result indicates that faster-converging filters like Kalman are better suited for real-time signal enhancement in LTE networks.

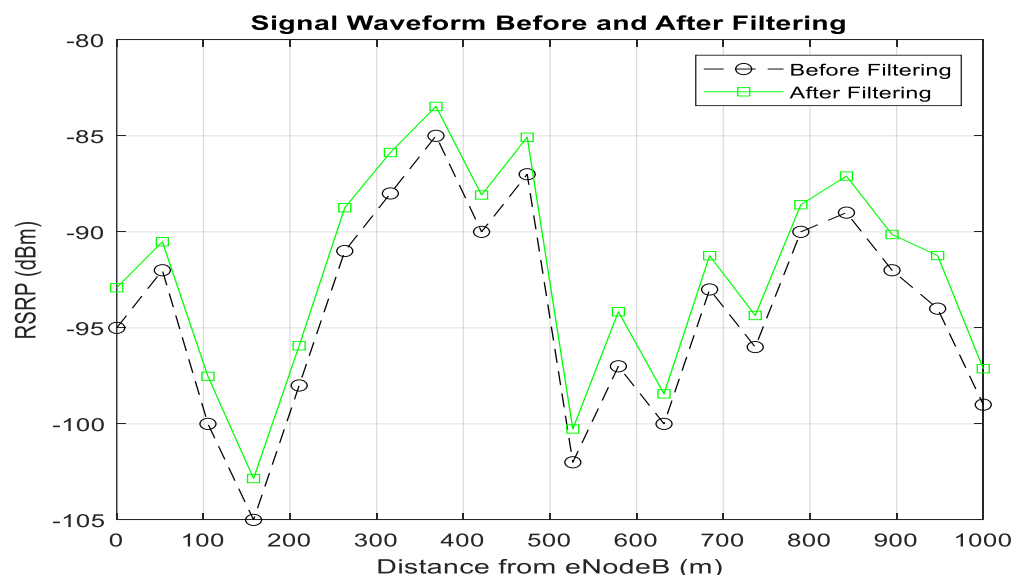


Figure 5: A Graph of RSRP vs. Distance from eNodeB

Figure 5 displays the signal strength before and after filtering as a function of distance from the LTE base station. RSRP values (in dBm) generally degrade with increasing distance, as expected. However, the filtered RSRP curve consistently lies above the original measurements, indicating successful signal restoration. At a distance of 800 meters, the unfiltered RSRP is approximately -100 dBm, while the filtered signal improves to around -97 dBm. This demonstrates the filters' ability to recover signal power lost due to path loss and multipath fading, especially in urban deployments characterized by high-rise buildings and complex signal propagation environments.

5.0 Conclusion

Based on the results obtained from the simulation and analysis, it is evident that adaptive filtering techniques significantly improve signal quality in urban LTE networks. The comparison of SINR values before and after filtering clearly demonstrates enhanced signal integrity, with SINR improvements reaching over 2 dB at certain measurement points. The Bit Error Rate (BER) analysis shows that among the evaluated filters, the Kalman filter consistently delivers the lowest BER values, highlighting its robustness in high-interference environments. The convergence analysis using Mean Square Error (MSE) further validates the efficiency of the Kalman and RLS filters, both of which achieve faster error reduction compared to the LMS filter. Additionally, the RSRP vs. distance plot illustrates the practical benefit of filtering, where signal levels after processing remain higher and more stable across various distances from the eNodeB. These findings confirm that adaptive filtering, particularly using Kalman and RLS algorithms, is a viable and effective method for mitigating signal degradation due to interference, noise, and multipath fading in dense urban LTE deployments. The study not only meets its objective of enhancing signal quality through measurement and analysis but also provides valuable insights for improving real-time signal processing in future LTE-A and 5G networks.

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