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Improved channel quality indicator estimation using extended Kalman filter in LTE networks under diverse mobility models

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ABSTRACT

Accurate channel quality indicator (CQI) estimation is crucial for optimizing resource allocation, improving link adaptation, and sustaining high performance in long term evolution (LTE) networks. In real-world scenarios, where channel conditions fluctuate rapidly due to user mobility, inaccurate CQI estimation can lead to suboptimal scheduling, degraded throughput, and reduced quality of service (QoS) for both users and network operators. Traditional Kalman filter (KF) approaches often struggle with the non-linear and time-varying nature of wireless channels, especially under unpredictable mobility patterns. This paper proposes an improved CQI estimation method based on the extended Kalman filter (EKF), which models non-linear system dynamics more effectively. The method is implemented in LTE-Sim, analyzed using MATLAB, and evaluated under random and Manhattan mobility models. Results show that across mobility regimes, KF outperforms EKF in the structured Manhattan model, while in the non-linear random-direction model, EKF yields markedly higher signal-to-interference-plus-noise ratio (SINR) stability and robustness to channel variation with SINR values above 10 dB between 300-450 s and a peak of approximately 60 dB. These results underscore the importance of mobility-aware estimation strategies in enhancing LTE network adaptability and throughput.

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1. INTRODUCTION

In long term evolution (LTE) networks and other wireless mobile communication networks, accurate knowledge of channel conditions is fundamental to ensuring efficient spectrum utilization, optimal scheduling, and consistent service quality [1]. In modeling wireless communication systems, understanding the inherent characteristics of the channel helps in capturing the dynamism associated with channel state variation. The channel characteristics could be quantified as channel quality indicator (CQI) or channel state information (CSI). While the CSI provides detailed information about the channel conditions and is used for link adaptation, beamforming, and other transmission techniques, the CQI provides a quantized measure of channel quality and is used to determine the modulation and coding scheme (MCS) most suitable for signal transmission [2]. In LTE systems, CQI estimation plays a pivotal role in dynamic resource allocation, enabling the eNodeB to assign appropriate MCS based on real-time channel conditions. Accurate CQI reporting is crucial for maintaining quality of service (QoS), reducing retransmissions, and ensuring spectral efficiency, particularly in heterogeneous networks and for users located in regions with poor signal coverage, such as cell edges. In other words, CQI accuracy directly impacts throughput and reliability [3]. Estimating the CSI accurately in a wireless fast-fading channel is highly challenging due to its complexity and the associated level of uncertainties, unlike the CQI, which is relatively straightforward. However, CQI estimation in mobile environments poses a significant challenge due to the highly dynamic nature of wireless channels, which are influenced by factors such as fading, interference, and varying user mobility patterns [4]. These factors are more pronounced in high mobility scenarios, as it becomes more challenging to estimate the channels accurately [5]. As users move, channel conditions can change unpredictably, resulting in outdated or inaccurate CQI reports that degrade link adaptation and overall network performance [5], [6].

In determining channel conditions as a function of time, it is necessary to put into perspective the reality of value depreciation or ageing arising from the effect of the difference between the time of measurement and the time of usage of the measured values. If substantial time elapses between the submission of the CQI report and its use in decision-making (such as scheduling decisions), the report’s relevance may be significantly degraded, potentially leading to reduced network spectral efficiency [7]. Consequently, it is recommended that the estimation bias is very close to zero, such that the estimated value does not deviate much from the actual condition of the channel. The traditional Kalman filter (KF) is a model-based iterative technique that utilizes a series of observations to obtain a more accurate estimate of the state parameters [8]. Although the KF techniques are effective for linear systems, they often exhibit reduced accuracy in the presence of non-linear channel variations, commonly observed in random or irregular mobility scenarios [9].

Several techniques have been adopted in wireless networks for estimating the CQI. Rao and Naidu [10] proposed a signal-to-noise ratio (SNR) estimation algorithm for orthogonal frequency division multiple access (OFDMA) systems in which the orthogonal frequency division multiplexing (OFDM) training symbols are employed in evaluating the noise variance, while second-order moments of the received symbols are used in estimating the signal plus noise power. Simulation results demonstrate comparable performance with theoretical analysis, complemented by its outstanding performance when benchmarked against selected estimation methods. Similarly, to improve SNR estimation in OFDM networks, Ling [11] adopted an approach that aligned with the network’s non-linearity features by employing the extended Kalman filtering technique. Comparative analysis revealed that the extended Kalman filter (EKF) estimator outperforms the least squares (LS) and minimum mean square error (MMSE) techniques. In pursuit of even lower bit error rate (BER), Kapil *et al*. [12] proposed a modified extended Kalman filter (MEKF) to jointly estimate the channel response and auto-regressive (AR) model coefficients, combining the fast convergence rate of EKF and the correlation feature of 2D interpolation using least squares (2DILS). Although it achieved lower BER than EKF and 2DILS, MEKF is prone to estimation errors and comes with higher computational complexity.

In another study, Tang *et al*. [13] proposed a KF-based channel estimation method for 2×2 and 4×4 space-time block coding multiple-input and multiple-output orthogonal frequency division multiplexing (STBC MIMO-OFDM) systems in dynamic environments, using orthogonal space-time codewords and pilot sequences to suppress antenna interference before applying the KF’s prediction–update process with noise suppression. This approach achieved strong BER and normalized mean square error (NMSE) performance, but at the cost of increased computational load due to iterative KF processing and pilot design. Kumar and Malleswari [14] integrated the EKF with a sliced multi-modulus algorithm (SMMA) for improving OFDM-MIMO systems, outperforming traditional multi-modulus algorithms in terms of BER and inter-symbol interference metrics. Rajender *et al*. [6] provides a comprehensive review of Kalman filter-based channel estimation capabilities across OFDM and MIMO-STBC systems, highlighting both accuracy and computational demands. Similarly, Drakshayini and Kounte [8] classified techniques into model-based and deep learning-based categories, noting that while KF yields highly accurate estimates through iterative observation, it comes with substantial computational complexity.

Building on the strengths of KF approaches, several works have adapted them specifically for CQI prediction and dynamic resource optimization. For instance, Sulthana and Nakkeeran [15] addressed the unrealistic assumption of perfect CQI in earlier research by predicting SNR from imperfect CQI using Kalman filtering. The predicted SNR was then used to estimate transmission rates and design priority utilities for scheduling decisions. Teixeira and Timoteo [16], LTE resource allocation was enhanced by using a KF-based prediction method for determining the data rate. However, parameter fine-tuning was not considered. In a related study Biswas *et al*. [17], multiple linear regression was used to estimate future throughput, followed by KF correction to mitigate prediction and measurement errors. This approach delivered timely and accurate throughput predictions without overfitting, making it suitable for energy-constrained LTE devices, though with limited performance in highly dynamic channels. Extending the predictive framework to spectrum management, Timóteo *et al*. [18] applied the Kalman-Takens filter (KTF) for real-time 5G spectrum allocation. By minimizing root mean square error (RMSE), the method effectively captured traffic dynamics, optimized throughput and latency, and adapted well to high-demand scenarios. Nonetheless, its performance depends heavily on dataset-specific parameter tuning and understanding inter-parameter dependencies.

With the rise of machine learning, deep learning-based approaches for CQI and channel estimation have been extensively investigated, offering new opportunities for pattern extraction and long-term prediction. A comparative analysis in Jiang and Schotten [19] showed that while recurrent neural network (RNN)-based predictors exhibit higher computational complexity than KF-based predictors, both achieve comparable single-step accuracy, though RNNs demonstrate superior performance in multi-step prediction. In vehicular systems, Kim and Han [4] proposed an received signal strength indicator (RSSI)-driven long short-term memory (LSTM)-based CQI predictor that outperformed conventional time-series models, while Qu *et al*. [20] proposed a temporal-spatial collaborative framework combining binary particle swarm optimization (BPSO), max-relevance and min-redundancy (MRMR) feature selection, deep neural network (DNN), and attention mechanisms, yielding proactive long term evolution-railway (LTE-R) base station maintenance, though with significant computational demands. For unmanned aerial vehicle (UAV) ultra-reliable low-latency communications, Bartoli and Marabissi [21] applied deep recurrent neural networks (DRNNs) with LSTM, which reduces decode error probability and improves throughput. However, this approach is limited to temporal CQI data and neglects spatial/frequency correlations.

Furthermore, Cwalina *et al*. [22] modeled a non-linear relationship between channel parameters and block error rate (BLER), achieving a gain of up to 40% over linear models with low computational complexity. Similarly, Diouf *et al*. [23] applied DNN and LSTM to real 4G datasets, achieving low RMSE and strong prediction accuracy, but requiring large, high-quality datasets for training. Advanced wireless scenarios, such as vehicle-to-vehicle (V2V), industrial IoT (IIoT), RIS-based systems, and mmWave MIMO, have motivated the development of specialized and hybrid schemes. In V2V and IIoT networks, Liao *et al*. [24] designed two Bayesian filter-based channel estimation techniques-basis extended model-unscented Kalman filter (BEM-UKF), offering strong robustness at high complexity, and Basis Extended Model-extended Kalman filter (BEM-EKF), with moderate robustness at lower complexity. For industrial subnetworks, Gautam *et al*. [25] introduced a variational deep state space model (vDSSM) with sparse student-t process regression and modified unscented KF, ensuring ultra-reliable BLER control despite the need for real-time validation. In 5G/6G CSI prediction, Soszka [26] highlighted the potential of LSTM RNNs across sub-6 GHz and mmWave, optimizing features and hidden layers but stressing the need for more measurement-driven studies. In mmWave MIMO systems, Huang *et al*. [27] combined least square estimation (LSE) and sparse message passing (SMP) to exploit channel sparsity, reaching near-cramer-rao lower bound accuracy within five iterations, though adjacent-entry correlation remains unaddressed. Reconfigurable intelligent surfaces (RIS)-assisted systems were targeted in Wei *et al*. [28], which proposed parallel factor analysis (PARAFAC) decomposition using alternating least squares (ALS) and vector approximate message passing (VAMP) algorithms, both of which outperformed benchmark schemes and achieved near-perfect sum rate performance. Constraints on RIS element numbers and training symbol lengths, as well as estimation ambiguity, were noted as limitations. Finally, Serunin *et al*. [29] developed a CSI-RS-based CQI evaluation method involving noise estimation, SNR transformation, and MCS selection, achieving accurate CQI reporting under additive white gaussian noise (AWGN) conditions, but requiring further evaluation in complex fading environments.

The KF's limitation, exemplified by reduced accuracy in modeling non-linear channel behavior, motivates exploring the EKF, which uses first-order linearization to accommodate non-linear system dynamics and has been shown to improve estimation in time-varying channels. This study proposes an EKF-based CQI estimation approach for LTE networks and evaluates its performance against the classical KF under two distinct mobility models: the structured Manhattan model and the unstructured random direction model. Using LTE-Sim for signal-to-interference-plus-noise ratio (SINR) extraction and MATLAB for analysis, the work demonstrates how the EKF technique enhances CQI estimation accuracy, particularly under non-linear mobility conditions. The results are relevant for improving LTE network adaptability, throughput, and QoS in real-world deployments.

The rest of the paper is structured as follows: section 2 presents the system model, providing a detailed explanation of CQI estimation using KF and EKF; section 3 discusses the simulation results; and section 4 concludes the paper.

2. METHODS

2.1. System model

In LTE networks, the channel quality can be a function of several time-varying factors, including SINR, fading effects, interference, noise, and others. These factors assume a time-varying process, and as such, channel quality is seen as a continuous variable that evolves in accordance with the dynamics defining the wireless environment. This study models the channel estimation process using a linear state-space framework, where the state and observation vectors describe the system's underlying dynamics and measurement processes, respectively [30]:

$$\begin{cases} x_{t+1} = A_t x_t + B_t u_t + \psi_t \chi_{\_t} \\ w_t = C_t x_t + D_t u_t + \eta_{\_t} \end{cases} \quad (1)$$

Where: A_t, B_t, ψ_t, C_t, and D_t are respectively, $n \times n, n \times m, n \times p, q \times n,$ and $q \times m$ constant matrices in which $1 \le m, p, q \le n$; $\{u_t\}$ is a deterministic input sequence of m-vectors, i.e., $u(t) \in \mathcal{R}^m$; $\{\chi_{\_t}\}$ is the system noise sequence (zero-mean Gaussian white noise process); $\{\eta_{\_t}\}$ is the observation noise sequence (zero-mean Gaussian white noise process).

The system shown in (1) could be decomposed into the state dynamics of a linear system to give a sum of a linear deterministic system and the purely stochastic system shown in (2) and (3), respectively [30]:

$$\begin{cases} z_{t+1} = A_t z_t + B_t u_t \\ s_t = C_t z_t + D_t u_t \end{cases} \quad (2)$$

$$\begin{cases} y_{t+1} = A_t y_t + \psi_t \chi_{\_t} \\ v_t = C_t y_t + \eta_{\_t} \end{cases} \quad (3)$$

Therefore,

$$w_t = s_t + v_t \quad (4)$$

$$x_t = z_t + y_t \quad (5)$$

While x_t represents the system state vector which is a function of the system's dynamics, the w_t is the observation vector which is a function of measurements.

2.2. Estimation methods

To estimate the CQI effectively, two filtering approaches were employed: the KF for linear systems, and the EKF for systems with non-linear dynamics. These filtering techniques were selected because of their effectiveness in handling noisy measurements and their suitability for channel state estimation in wireless communication systems. The following subsections detail their underlying principles, mathematical formulations, and application to LTE CQI estimation.

2.2.1. Kalman filter

The KF is a computational method that uses a state-space model to estimate the state of a system or process in the time domain. It leverages the relationship between the system's state and measurement equations to recursively estimate the state with minimal mean squared error [31], [32]. For dynamic systems with inherent randomness and nonlinearity, the evolution of their state probability distribution over time can be modeled using a set of non-linear differential equations [33]. KF are used for estimation in systems that can be modeled with linear differential equations, where the state and measurements equations are presented as linear functions within a state-space framework [34]. The estimation process involves a prediction-correction cycle, guided by rules that refine the estimate [6]. The estimation accuracy of KF technique is high due to the fact that it involves a series of measurements conducted over a period of time, which provides statistically sufficient information for effective predictions of the current state [35].

In estimating the CQI using the KF, the prediction stage involves calculating the current CQI perceived by the user based on the user's CQI value from the previous transmission time interval (TTI). Therefore, the correction stage involves minimization of the error between the observed value and the current value [15]:

$$X_{t|t-1} = A_t X_{t-1} + v_t \quad (6)$$

$$Z_t = H_t X_t + w_t \quad (7)$$

The (6) shows that the KF predicts the unknown state X_t based on preceding state at time $(t-1)$ using the measurement vector, Z_t. The v_t is a zero-mean system or process noise while A_t is the state transition matrix [18]. Similarly, the H_t in (7) represents the measurement matrix, while w_t is a zero-mean observation noise.

The Kalman gain is meant to minimize estimation error and is given in (8) as [18]:

$$K_t = P_{t|t-1} H_t^T \left(H_t P_{t|t-1} H_t^T + w_t \right)^{-1} \quad (8)$$

where $P_{t|t-1}$ is the covariance matrix at time t based on the estimate $X_{t|t-1}$ at time $(t-1)$.
For the Update phase, the optimal estimate at time t is given in (9), thus:

$$X_t^{\%} = X_{t|t-1} + K_t \left(Z_t - H_t X_{t|t-1} \right) \quad (9)$$

The (10) gives the updated covariance matrix for the optimal estimate as:

$$P_t = P_{t|t-1} (I - K_t H_t) \quad (10)$$

Where, K_t is the Kalman gain and I is the identity matrix.

2.2.2. Extended Kalman filter

The KF assumes an accurate mathematical model, but this assumption is often compromised due to truncation errors when approximating non-linear systems with linear models [32]. Although the KF is effective for many estimation problems, its limitation to finite-dimensional state representations makes it unsuitable for systems with non-linear dynamics. To address this limitation, the EKF, which provides a first-order linearization of non-linear systems, was developed. The enhancement achieved by EKF is a result of its capability to approximate non-linear filtering problems using Taylor polynomial expansion [36]. This linearization enables the EKF to apply the iterative and correction processes of the KF to systems that are non-linear, such as the time-varying channels [37]. EKF comprises two stages, which include the prediction stage and the correction stage [38].

In the prediction stage, an estimated current state of the channel and the error covariance estimate are used to calculate the estimates for the next state [12].

$$X_{t|t-1} = f(X_{t-1}, u_t, 0) \quad (11)$$

The (11) implies that the state transition model is a differentiable function, unlike the case of KF, where it is defined as a linear function. Similarly, the (12) shows that the measurement model could be defined as a non-linear function.

$$Z_t = h(X_t) + w_t \quad (12)$$

$$P_{t|t-1} = A_t P_{t-1} {A_t}^T + W_t Q_{t-1} {W_t}^T \quad (13)$$

The (13) provides the error covariance estimate, where A_t is the state transition matrix, ${A_t}^T$ is the transpose of the state transition matrix and $\left(W_t Q_{t-1} {W_t}^T \right)$ represents the covariance of the noise.

In the correction stage, the predicted estimate is subjected to a correctional process using the observation model to minimize the error covariance of the estimator, resulting in an improved estimate, as shown in (14). The (15) gives an updated error covariance estimate.

$$X_t^{\%} = X_{t|t-1} + K_t \left(Z_t - h(X_{t|t-1}, 0) \right) \quad (14)$$

$$P_t = P_{t|t-1} (I - K_t H_t) \quad (15)$$

Where K_t is the KF given by:

$$K_t = P_{t|t-1} H_t^T \left(H_t P_{t|t-1} H_t^T + w_t \right)^{-1} \quad (16)$$

Where $H_t P_{t|t-1} H_t^T + w_t$ is the innovation covariance. The matrix inversion in (15) increases complexity, and there is always a trade-off between computational complexity and the EKF estimation accuracy [36].

2.2.3. Determination of the key parameters in the filtering process

The performance of KF and EKF depends on the appropriate selection of parameters such as initial state, covariance matrices, and process/measurement noise covariances. In implementing KF and EKF for

CQI estimation in this study, key parameters were chosen through a combination of empirical analysis, simulation-based tuning, and reference to LTE specifications. The selection process is detailed as follows:

a. Initial state (x_0): for both the KF and EKF implementations, the initial state was set to the first CQI value obtained from the LTE-Sim simulation output, with the assumption that the initial measured CQI is a reasonable approximation of the true channel quality.
b. Initial covariance matrix (P_0): the initial error covariance matrix was chosen to be a diagonal matrix with relatively large values, reflecting the initial uncertainty. For both estimation techniques, the same initial covariance matrix value was used to allow for a fair comparison between KF and EKF. However, differences in their underlying assumptions and algorithmic structures led to distinct performance characteristics, especially in non-linear systems.
c. Process noise covariance (Q): the Q matrix was tuned experimentally by running LTE-Sim scenarios with varying Q values and comparing the estimated CQI against reference values. The optimal value, minimized mean squared error (MSE), was selected to balance responsiveness to channel variations and the smoothing of random fluctuations.
d. Measurement noise covariance (R): this was derived from the variance of CQI measurement errors in the simulation, calculated as the variance between the simulator's instantaneous CQI output and a moving-average reference CQI over the same period. This derivation ensured that R accurately reflected the inherent noise level of the CQI reporting process in the simulated LTE environment.
e. Kalman gain: in both KF and EKF, the Kalman gain was computed dynamically at each step from the chosen Q, R, and updated covariance values. No fixed gain was imposed, allowing the filter to adjust weighting between prediction and measurement adaptively.
f. State transition and observation matrices: in KF implementation, both matrices were set to unity to model a direct relationship between the previous and current states, as well as between the state and observation. In contrast, in EKF implementation, the state transition Jacobian (F_k) and measurement Jacobian (H_k) were recalculated at each iteration based on the non-linear state and measurement models derived from the channel mapping. These matrices ensured correct linearization for prediction-update cycles.

2.3. Simulation setup

Simulations were conducted using LTE-Sim, which provided a robust platform for modeling LTE system behavior under various scenarios. MATLAB was subsequently employed for post-simulation data processing, statistical analysis, and visualization of the obtained results. The simulation environment was configured to emulate realistic LTE downlink conditions.

2.3.1. Simulation parameters

The LTE-Sim simulation software was used to extract the SINR from the estimated CQI, and the plots were carried out using MATLAB. To estimate the channel quality, the adaptive modulation and coding (AMC) module in LTE-Sim was modified, and the estimated channel quality was used to determine the SINR. Details of the simulation parameters are presented in Table 1.

Table 1. Simulation parameters

Parameter	Value used
Cell scenario	Single-cell
Cell radius	1 km
Number of RBs	50
Bandwidth	10 MHz
Frame structure	FDD
UE speed	3 km/hr
Propagation model	PED-A, Typical Urban
Mobility models	Manhattan, random
Scheduling type	Downlink scheduling algorithm with imperfect CQI (DSA)
Simulation duration	500 s

2.3.2. Mobility models

The mobility models considered in this work are the Manhattan mobility model and the random mobility model. In the context of LTE network simulations, the Manhattan mobility and random direction mobility models are commonly used to simulate user movement, with the Manhattan model representing movement along a grid-like path, with temporal dependencies, geographic restrictions but with no spatial dependencies and the random direction model representing random movement between points, with no temporal dependency, nor spatial dependency, nor geographic restrictions [39]. Mobility models significantly affect SINR in LTE networks, since user mobility can lead to changes in signal strength as mobile user moves away from the eNodeB, interference levels, and channel conditions such as path loss or fading [40].

3. RESULTS AND DISCUSSION

The SINR plots for the KF and the EKF estimations are shown in Figures 1 and 2, respectively. In Figure 1, the SINR for the random mobility model drops below 10 dB for approximately 85% of the observation period. In contrast, for the Manhattan mobility model, the SINR remains above 10 dB for over 50% of the observation period. This indicates that the KF is better at estimating the SINR for users following the Manhattan mobility model than for those with random direction mobility. Figure 2 further illustrate that, for users with random direction mobility, the SINR exceeds 10 dB for around 45% of the observation period, with a peak value reaching 60 dB. Conversely, users with the Manhattan mobility model experience SINR values dropping below 10 dB for about 70% of the observation period.

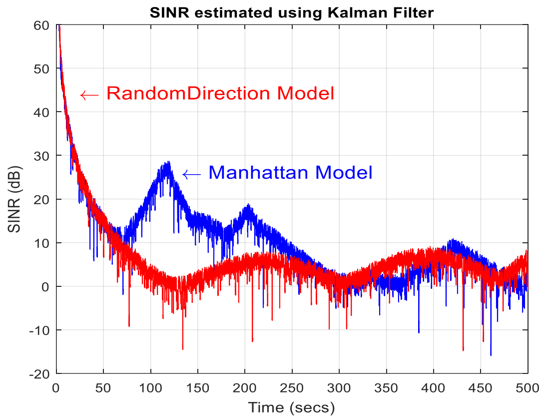

Figure 1. SINR Estimations using KF

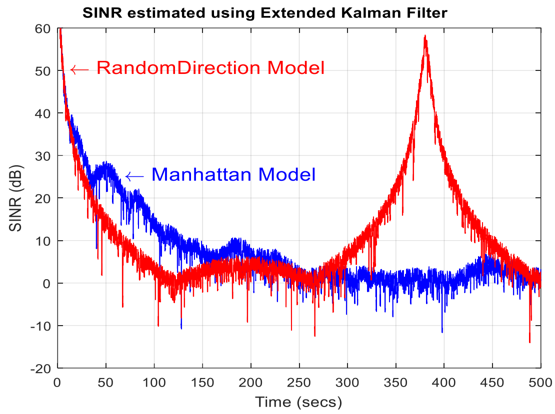

Figure 2. SINR Estimation using EKF

For the Manhattan mobility model, the SINR estimated using the EKF are higher than those estimated with the KF at the early stages of estimation. However, this trend reverses in the later stages. This observation may be due to non-linear start-up transients and greater initial uncertainty at the early stage, which the EKF manages to capture more effectively. As the estimation progresses, the channel statistics becomes more linear, making the KF more suitable for later stages. In contrast, in a random mobility model, the movement of users are unpredictable and non-linear. In these situations, the EKF, which, is specifically designed to handle non-linear systems, provides a more accurate estimate of the SINR. In summary, while both KF and EKF techniques are valid options for SINR estimation, the EKF demonstrates superior performance in LTE networks characterized by non-linear dynamics.

To contextualize the performance of the improved CQI estimation method, a comparative analysis of the simulation results obtained was carried out using recent literature findings. Figure 1 shows that KF estimates SINR more accurately in structured mobility patterns, aligning with the findings in [13], where KF demonstrated strong BER and NMSE performance under structured channel conditions. However, it requires iterative processing and pilot design. In a similar manner, [16] reported improvements in throughput and a reduction in packet loss with LTE-Sim when using KF-based predictions, particularly in controlled or less variable mobility scenarios, which aligns with our results from the Manhattan mobility model. On the other hand, Figure 2 supports the findings of [11], which indicated that the EKF outperformed both LS and MMSE methods in non-linear OFDM channels. Also, the results are consistent with [14], highlighting the EKF's superior ability to manage inter-symbol interference and non-linearities compared to traditional algorithms. Our findings also align with [24], where the authors demonstrated that EKF-based estimators maintain robustness in dynamic and unpredictable mobility environments, such as V2V and IIoT networks. In comparison to the LSTM-based CQI predictors in [4], our approach provides a more straightforward implementation with competitive performance, though less adaptive. Furthermore, the MEKF approach described in [12] achieved a lower BER, but this came at the cost of significantly increased computational overhead. In contrast, our results indicate that the KF and EKF strike a practical balance between estimation accuracy and computational feasibility, particularly under the Manhattan and random mobility models.

In summary, our finding contributes to the existing literature by comparing KF and EKF within a single cell LTE-Sim framework, assessed under structured and unstructured mobility model. The result obtained confirm previous research indicating that KF remains efficient for structured mobility due to its lower computational cost. Conversely, EKF effectively manages non-linear systems with unpredictable mobility, providing greater stability and robustness regarding SINR in such scenarios. These comparisons underscore that while advanced machine learning or hybrid techniques may achieve better accuracy, EKF remains a practical and lightweight solution for real-time CQI estimation in LTE network environments with varying mobility dynamics.

4. CONCLUSION

This study demonstrates that while both KF and EKF can effectively estimate CQI in LTE networks, EKF offers superior robustness in scenarios with unpredictable, non-linear user mobility. Simulation results show that the EKF achieves higher SINR stability in random direction mobility, whereas the KF is more effective in structured mobility patterns, such as the Manhattan model. These findings suggest that EKF is particularly beneficial for LTE networks with significant variations in user movement, as it can better adapt to dynamic channel conditions, improving throughput and overall network performance.

For network operators, adopting mobility-aware estimation strategies such as EKF can lead to more efficient resource allocation and enhanced quality of experience (QoE) on the part of users. Future research will focus on optimizing EKF estimation parameters through artificial intelligence techniques and extending the analysis to additional mobility models (Gauss-Markov mobility model and random waypoint mobility model) to further validate its applicability in diverse wireless environments, including vehicle-to-everything (V2X) networks and LTE-vehicular ad hoc network (VANET) hybrid networks.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
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So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Authors also state that there is no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, Ezea, H. U. He can be contacted via email: hilary.ezea@fuoye.edu.ng.

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