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Research on Computational Intelligence Algorithm in LTE Channel Estimation

Investigación sobre el algoritmo de inteligencia computacional en la estimación de canales LTE

Siraj Pathan[1], Sanjay Kumar Singh[1], Sunil Pathak[1], Mujib Tamboli[2]

[1]Amity School of Engineering & Technology, Amity University Rajasthan, Jaipur, India.
[2]Department of Electronics & Computer Science Engineering, Anjuman-I-Islam's Kalsekar Technical Campus, Mumbai University, India.
sirajpathan404@gmail.com, sksingh.eee@gmail.com, mujibtamboli@yahoo.co.in, sunilpath@gmail.com

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Abstract. Because data traffic is growing at a rapid pace thanks to advancements in the Internet of Things, precise modelling and precisely anticipating Long-Term Evolution (LTE) Channel is critical for a variety of applications like as video streaming, effective bandwidth consumption, and power management. In this research, we propose a model based on a Computational Intelligence (CI) Algorithm that may enhance Channel Estimation based on received signal. Two Algorithms are considered. In contrast to previous work that focused solely on designing models to estimate channel using traditional Minimum Mean Square Error (MMSE) and Least Square (LS) algorithms, we used 1) GA (Genetic Algorithm) and 2) PSO (Particle Swarm Optimization Algorithm) to work on Discrete and Continuous Long-Term Evolution (LTE) drive test data. We're looking at LTE in the 5.8 GHz band in particular. By lowering the mean square error of LS and the complexity of MMSE, the design model attempts to improve channel estimation. Pilots are put at random and sent with data to gather channel information, which aids the receiver in decoding and estimating the channel using LS, MMSE, Taguchi GA, and PSO. The Bit Error Rate (BER), Signal to Noise Ratio, and Mean Square Error of a CI-based model have all been estimated. In comparison to the MMSE and LS algorithms, the proposed model BER achieves the target gain of 2.4 dB and 5.4 dB.

Keywords: Genetic Algorithm, Particle swarm intelligence, Long Term Evolution, Minimum Mean Square Error, Least Square.

Resumen. Debido a que el tráfico de datos está creciendo a un ritmo rápido gracias a los avances en el Internet de las Cosas, el modelado preciso y la anticipación exacta del *Long-Term Evolution* (*LTE*) es fundamental para una variedad de aplicaciones como el *streaming* de vídeo, el consumo efectivo de ancho de banda, y la gestión de la energía. En esta investigación, proponemos un modelo basado en un Algoritmo de Inteligencia Computacional (IC) que puede mejorar la Estimación del Canal basado en la señal recibida. Se consideran dos algoritmos. A diferencia de los trabajos anteriores que se centraban únicamente en el diseño de modelos para estimar el canal utilizando los algoritmos tradicionales de Error Cuadrático Medio (*MMSE*) y de Mínimos Cuadrados (*LS*), nosotros utilizamos 1) *GA* (Algoritmo Genético) y 2) *PSO* (Algoritmo de Optimización de Enjambre de Partículas) para trabajar con datos de prueba de conducción discreta y continua de *Long-Term Evolution* (*LTE*). Nos fijamos en LTE en la banda de 5,8 GHz en particular. Al reducir el error cuadrático medio de *LS* y la complejidad de *MMSE*, el modelo de diseño intenta mejorar la estimación del canal. Los pilotos se colocan al azar y se envían con los datos para recopilar información sobre el canal, lo que ayuda al receptor a descodificar y estimar el canal mediante *LS*, *MMSE*, Taguchi *GA* y *PSO*. Se ha estimado la tasa de error de bits (*BER*), la relación señal/ruido y el error cuadrático medio de un modelo basado en IC. En comparación con los algoritmos *MMSE* y *LS*, el modelo *BER* propuesto alcanza la ganancia objetivo de 2,4 dB y 5,4 dB.

Palabras clave: Algoritmo Genético, Inteligencia de Enjambre de Partículas, Canal de Evolución a Largo Plazo, Error Cuadrático Medio Mínimo, Mínimos Cuadrados.

Paper Type: Research paper.

1 Introduction

Long Term Evolution (LTE) was first developed as a project by the Third Generation Partnership Project, a telecoms company, in early 2005. System Architecture Evolution (SAE) is the equivalent evolution of a 3G packet network. LTE combines the terms LTE and SAE (Paulraj et al., 2004; Muquet et al., 2002). The Universal Mobile Telecommunication System (UMTS) is a part of the Global System for Mobile Communications that evolved into the UMTS terrestrial radio network (E-UTRAN).

Figure 1 depicts the evolution of LTE and how various LTE versions included new technology to improve services. Because of the surge in mobile device data demand and the emergence of new applications arising from Internet of Things devices, the third Generation Partnership Project has been working on Long-Term Evolution (LTE) on the way to fourth-generation mobile. (Li et al., 1999; Wang et al., 2003).

LTE's main goal is to provide a packet-optimized wireless radio technology with high data rates and low error rates that can be scaled up and down. The LTE network architecture was designed to handle packet switching traffic while retaining good service quality and mobility. "Channel State Information" (CSI) is the most important parameter in wireless communication. This knowledge assists in comprehending signal propagation via the channel, as well as the signal's distortion and delay from transmitter to receiver.

The transmitting and receiving sides of the LTE network communicate current information, which is used to estimate the LTE channel. This method of signal reconstruction at the receiver end is aided by this channel estimation strategy. The LTE channel impulse response of the subcarriers between the pilots can be estimated at the receiver by using inserted pilot symbols, which are familiar to both the sending and receiving sides, and which apply various interpo1ation types to estimate the LTE channel response of the subcarriers between the pilots (3GPP, 2008; Van de Beek et al., 1995) (See Figure 1).

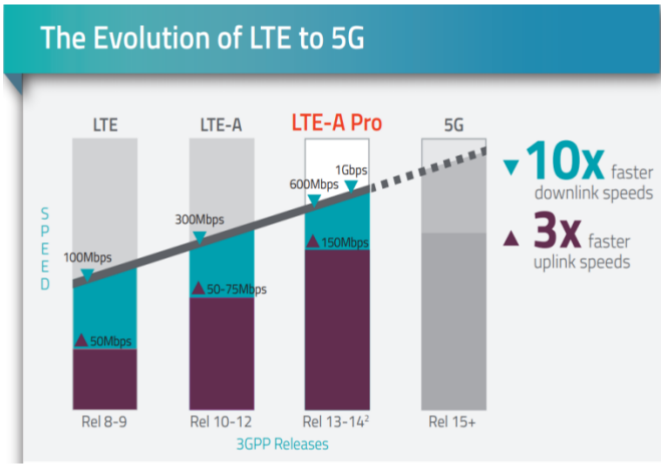

Figure 1. Evolution of LTE

Although blind channel estimation has a smaller overhead, it requires a large number of antenna signals to reconstruct the intended signal. The semi-blind channel estimating system, which employs pilot and data symbols, can increase the efficiency of channel estimation.

The signal recorded is used as a feedback mechanism to track channel performance, as well as a reference signal for data prediction in the future. Although symbol channel prediction provides the optimum performance, this is sent alongside data symbols, which affects transmission efficiency. When training symbols are used, LS and MMSE algorithms are used to estimate the channel, which enhances system performance by decreasing the BER (Edfors et al., 1996; Shaodan & Tung-Sang, 2007).

The process of designing a system with the purpose of decreasing manufacturing costs or enhancing production efficiency is referred to as optimization. The process for optimization algorithms is to run them indefinitely while evaluating alternate solutions until the best one is identified. The fittest particle is picked to build new generations of particles via a genetic algorithm.

Particle swarm optimization (PSO) is nothing more than the search for the optimum solution in space. It works on the objective function and is unaffected by the objective's differential form (Shaodan & Tung-Sang, 2006; Rana, 2010. The noised mixed, fading signal in the system is approximated at the receiver side in this study using pilot signals. The optimization methodology is adopted to random pilot signals, which are then compared to fixed pilot signals that are subjected to the LSE and MMSE algorithms (Simko et al., 2011; Khlifi & Bouallegue, 2011).

2 Related Work

Data-driven channel estimation is one of the applications that has attracted a lot of investigation. An approach for LTE channel prediction was proposed by Paulraj et al. (2004). This concept was used with hybrid LS techniques to improve the performance of a Millimeter wave-based LTE system that connects N multiple-input multiple-output (MIMO) users. Muquet et al. (2002) suggested a CI-Model in which orthogonal frequency division multiplexing (OFDM) is utilized as the receiver and the CI algorithm is used to collect (CSI) channel state information and figure out transmitted symbols.

Seshadri and Aryavisitakul (1999) looked at a massive LTE system based on MIMO that used an LS and MMSE to predict the channel matrix. However, using LS and MMSE for channel estimation has a significant disadvantage in that it requires a large quantity of training channel data, which may be prohibitive for time-changing channels. In a study made by Dongming et al. (2003), a bi-direction recurrent GA was used in combination with pilot samples to estimate the medium in a (FDD) frequency-division-duplex system. Furthermore, 3GPP (2008) proposed a CI-included channel evaluation notion for a MIMO antenna system that comprises of a MIMO base interacting with multiple single-antenna points. This research used computational intelligence to denoise the received signal rather of utilizing the least square (LS) technique to evaluate the medium coefficients.

To calculate MIMO wireless channel coefficients, van de Beek et al. (1995) developed a combined GA, LS-based channel estimation approach at the transmitter, which uses the receiver's (SNR) signal to noise ratio received from the output side. To solve the problems of anticipating a mixed selective wireless channel, Edfors et al. (1996) proposed adopting CI implementation. Using a CI to determine channel coefficients during the training phase was the focus of this investigation.

2.1 Contributions

The great majority of writers have largely focused on employing LS and MMSE to collect the CSI, according to the paper stated in the preceding section. On the other hand, Processing Intelligence algorithms have high computing requirements and require a large amount of data to train. This aspect inspired us to investigate the potential of implementing a low-complexity CI-based channel estimation approach.
The following are the contributions to the research paper:

We show how to use a sophisticated CI algorithm to estimate and monitor complex time-varying and frequency-selective multipath channels. This approach uses stochastic gradient descent to optimize the parameters and calculate the channel impulse response (CIR). The suggested CI algorithm is paired with an Orthogonal Frequency Division Multiplexing (OFDM) based transmission approach to compute the impulse response of a channel whose time is changing constantly. For a range of pilot sample counts, the performance of the suggested approach is compared to the well-known Least square and MMSE channel estimation techniques. The proposed technique outperforms the LS and MMSE algorithms even with a small number of pilot samples for each OFDM symbol, according to the results.

The complexity of the planned CI-Algorithm based wireless medium is measured using drifting numbers operations. According to the complexity evaluation, our method has a lower complexity than the traditional MMSE and LS. Finally, the convergence of the proposed algorithm is investigated by calculating the number of iterations necessary for the planned technique to satisfy the best possible estimation channel.

2.2 Organization of the paper

The paper is organized as follows: first, a detailed explanation of the system model using mathematical expressions; second, a detailed explanation of the transmitter as a designed channel model and its implementation using LS and MMSE techniques; third, a detailed explanation of the receiver; and finally, a detailed explanation of the results using all parameters.

2.3 System Model

As illustrated in Figure 2, we examine a simple LTE communication system in which many antennas are used for delivering and receiving data.

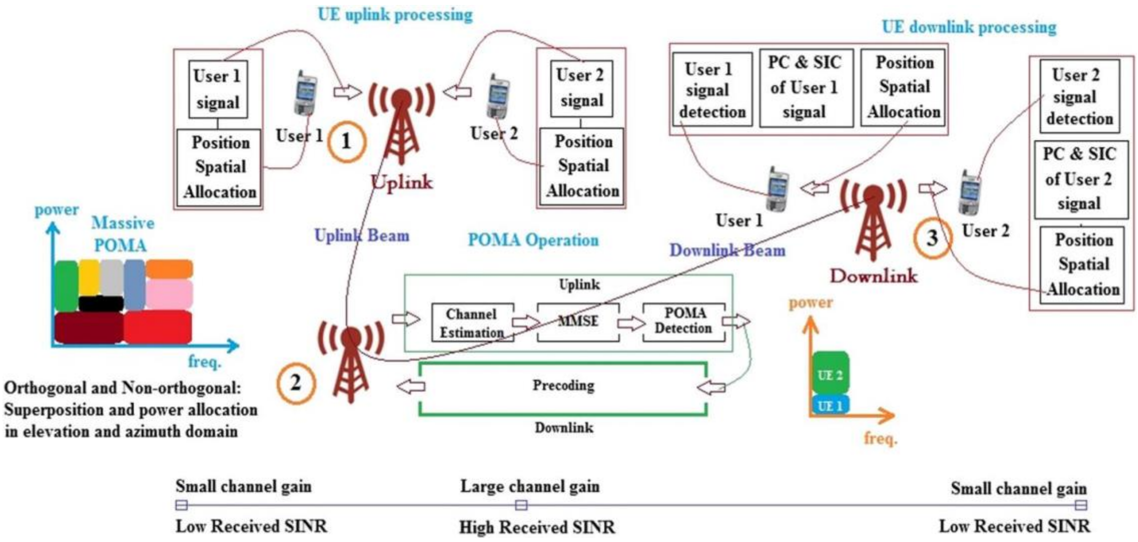

Figure 2. Overview of Computational Intelligence algorithm-based Channel Estimation for LTE.

Side communicates across a variable frequency channel with a variable time frequency. A multiplexing (OFDM) approach is employed to minimize ISI, and we apply the orthogonal frequency division multiplexing (OFDM) bock.

The data to be broadcast is first modulated using a K quadrature amplitude modulation (QAM) approach to generate an X frame comprising N-subcarrier symbols. After that, the OFDM model signal to be sent x(n) is computed using the (IDFT) inverse-Discrete-Fourier-transform technique on X.

$$x(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{T-1} X(k) e^{j2\pi} \quad k\frac{n}{N} \tag{1}$$

T is a power of two in practice, and IDFT is performed via the inverse-fast-Fourier transform (IFFT). In order to compute and track impulse response, as well as load, N_D data samples, we use OFDM data with N sub-carriers that are separated into N_P pilots.

On the transmitter side, using the Modulation block, the data was first coded and then mapped using QAM. We'll assume that the system delivers data in T-slots, with QAM symbols arriving at slot t.

$t = 1, \ldots., T$ this is combination of Data Vector and $x(t) \in C^N$, it defines as:

$$x(t) = x_1(t), x_2(t), x_3(t), \ldots\ldots., x_N(t) \tag{2}$$

N is symbol of modulation Following that, the encoded information is divided into N_T vectors that correspond to the Transmit antenna N_T as given below.

$$x_i(t) = [x_i(t), x_{i+N_T}(t), x_{i+2N_T}(t), \ldots\ldots] \quad i = 1,2,\ldots\ldots, N_T \tag{3}$$

Each antenna will send data in serial to parallel form, and pilot symbols are inserted to acquire knowledge of Transmitter and receiver side We define $x_a(t)$ and $a = 1, \ldots\ldots, N_T$ it is vector for signal with inserted in between pilot into the data $x_i(t)$ and after that block of inverse fast Fourier transform is applied to $x_a(t)$ transforming the signals from frequency domain to time domain defined by $\tilde{x}_a(t)$ as follows.

$$\tilde{x}_a(t) = IFFT\{x_a(t)\} \tag{4}$$

Then, using cyclic prefix insertion of length N_G as an interval of guard to remove the inter-symbol interference.

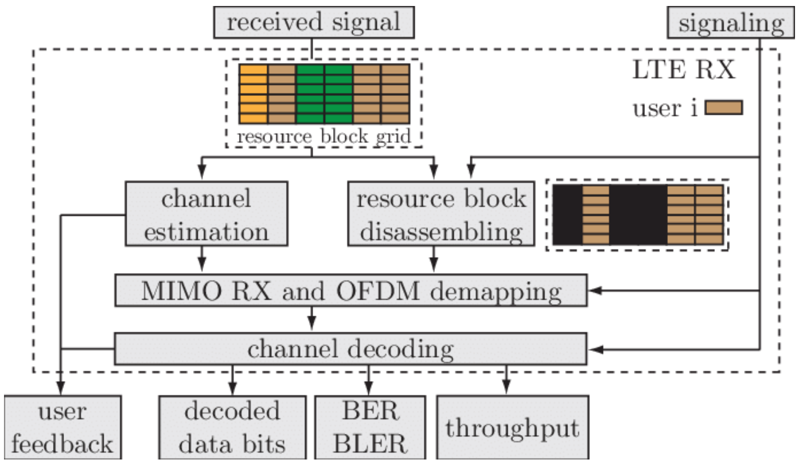

Figure 3. Illustration of Considered LTE Model with proposed CL Based Algorithm Module.

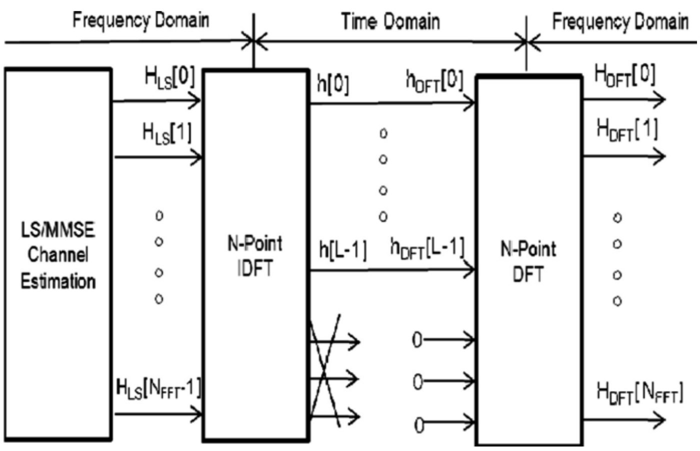

Figure 4. Block Diagram of Computational Intelligence Based LS and MMSE Channel estimation.

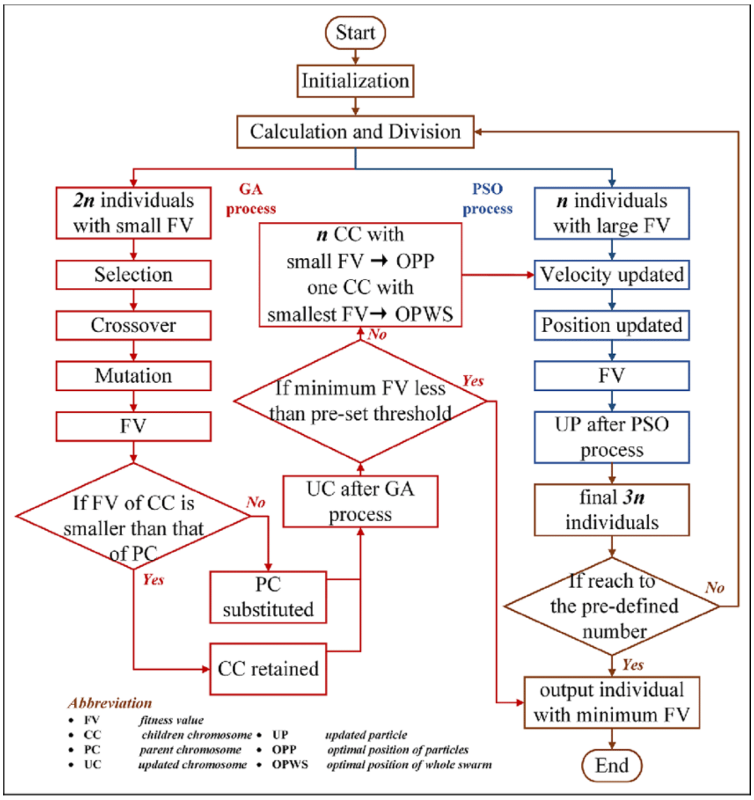

Figure 5. Flow chart of Computational Intelligence based GA and PSO Algorithm

The Genetic Strategy (GA) is a computer-aided search algorithm for discovering the lowest cost function while also maximizing fitness. Mutation, cross-over, and selection procedure are all parameters that determine this method. GA is the optimum option when a large number of variables are employed in a MIMO-OFDM-based LTE system. This approach, which is one of the best, gives the best solution to the problem and is used in a wide range of applications, including mobile communication systems. Reproduction, mutation, and crossover are the three elements of GA. These elements are needed to calculate the Fitness value, which is then used to choose the optimal channel. Following is the fitness formula:

$$fitness = \left(\frac{H - H_{GA}}{H}\right)^2 \tag{5}$$

In Particle Swarm Optimization (PSO), each particle is referred to as an agent, and it is kept in the search region in order to find the objective function from its current location. Each particle in the solution search space modifies its velocity in order to locate the best location search and optimization problem and identify the best answer.

$$fitness = \left(\frac{H - H_{PSO}}{H}\right)^2 \tag{6}$$

Designed Channel Model:

Received Output Signal defined as $y = x * h + n$ (7) Where n denotes the zero mean complex Gaussian noise with variance, x denotes the modulated N-length IFFT frame, h denotes the (CIR) channel impulse response, which is designed and considered as Length L vector, and * denotes the Convolution operation. Noise Power Spectral Density with its variance is given by

$$\sigma^2 = N_O/(2T_O) \tag{8}$$

Where T_o is Symbol Duration.
The time varying modelled using jakes's model is such that

$$h_{jake}(t) = \sum_{l} A_l e^{j[\theta_l + 2\pi f_{Dmax} \cos(\phi_l) t]} \tag{9}$$

Arrival angle, and phase of the lth path are represented by A_l, θ_l, and φ_l , respectively. It's worth noting that θ_l and φ_l are mutually independent and distributed uniformly between $[-\pi, \pi]$. Furthermore, f_{Dmax} specifies the highest possible Doppler frequency.

CI based channel estimation and Least Square Estimation:
The LS channel estimation technique assumes a block-type pilot configuration, with pilots located at all subcarriers of the OFDM signal. The received signal after FFT demodulation is:

$$Y_\rho = H_\rho X_\rho + W_\rho \tag{10}$$

When H_ρ denotes the Frequency Selective Channel's frequency response (FR) at pilot places, X_ρ and W_ρ defines pilot symbols of transmitter and samples of additive white Gaussian noise, respectively. To secure channel estimation after implementing LS, Cost function should be minimized.

$$J(\hat{H}_{LS}) = ||Y_P - X_P \hat{H}_{LS}|| \tag{11}$$

Furthermore, the equation in (11) should be calculated by considering $\hat{H}_{LS}$ and the output is set to zero to achieve the cost function's minimal value. This expression will be further simplified to give channel estimation because of LS.

$$\hat{H}_{LS} = \frac{Y_P(k)}{X_P(k)} \tag{12}$$

Minimum Mean Square Error (MMSE) Estimation:
Minimum Means square estimation is shown in Figure 6.

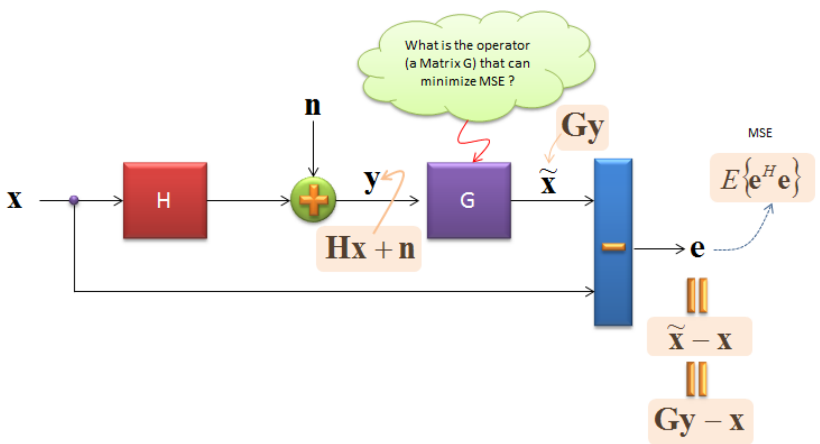

Figure 6. MMSE System

By close analysis of above figure the estimated channel obtained is $\hat{H}_{MMSE} = G\check{H}$ (13) At pilot position $\check{H}$ is given as $\check{H} = X_P^{-1} Y_P$ (14) by minimizing the below cost function MMSE estimate of the channel calculated $J(\check{H}_{MMSE}) = E\{||e||^2\} = E\{||H - \check{H}_{MMSE}||^2\}$ (15)

Receiver:

To acquire $\tilde{y}_b(t)$ vector of length N_{FFT} on side of receiver, the cyclic prefix is detached from the collected signal $\tilde{y}_{gb}(t)$ on every received antenna by the use of module for removing cyclic prefix. The FFT block then converts the signal to parallel form and transforms it into the frequency domain, yielding a frequency domain signal $\tilde{y}_b(t)$ of $y_b(t) = FFT\{\tilde{y}_b(t)\}$ (16)

For channel estimation, pilot signal is extracted from the domain of frequency signal. The layer demapping module equalizes and congregates the received signal $\tilde{y}_b(t)$ from all the reception antennas into a serial sequence after calculating the channel. Following that, the signal is demodulated using the same demodulation algorithm as the transmitter. At this phase, the LTE system model output is used to generate the final binary data sequence.

4 Results

This section includes both the results and a discussion of them. The simulation results in this section were generated using Spyder(anaconda3) and Google Colab on a 3 GHz CPU with 20 GB RAM and a 1053 GPU. The simulation results in this section were generated using Spyder(anaconda3) and Google Colab on a 3 GHz CPU with 20 GB RAM and a 1053 GPU.

Furthermore, we devised the proposed Computational Intelligence-based channel estimation approach to be implemented on a node that receives data via a time-varying frequency channel model utilizing Jakes model.

Table 1 and Table 2 represent the simulation and channel model settings, respectively, while Table 3 gives the algorithm parameters.

Table 1. Simulation settings.

Parameters	Values
FFT size	512
Number of symbols	100
No of Pilots	4
Carrier Frequency	3.7 GHZ
Mode of Modulation	16-QAM
Sub-carriers	2052
Max Velocity	85m/s
Doppler Shift	[33-973] Hz
Per user Bandwidth	20 MHz
Channel type	AWGN/Rayleigh/Rician

Table 2. CI network parameters.

Parameters	Values
Input Layer Size	2L
Output Layer Size	1
Number of Layers	2
Learning rate	0.001

Because the channel is thought to be twice selective and frequency selective, the frame period is τ_{f_p} adjusted to become shorter than the coherence time of channel τ_{C_h}.However, because channel response changes from frame to frame, the system must gather an accurate CIR for each frame. At the output side, we devised a CI-based estimation method to accurately estimate the channel impulse response and keep track of the CIR fluctuation.

We assume that there will be a period of training to receive the CIR before data transmission begins, and that once data transmission begins, the CI-based system will employ defined samples of pilot injected before each OFDM signal to keep track of the impulse response change over time. The mean square error (MSE) performance of the provided unique CI-based channel estimation was investigated for a various number of blocks of pilot in each block, as shown in Figure 7.

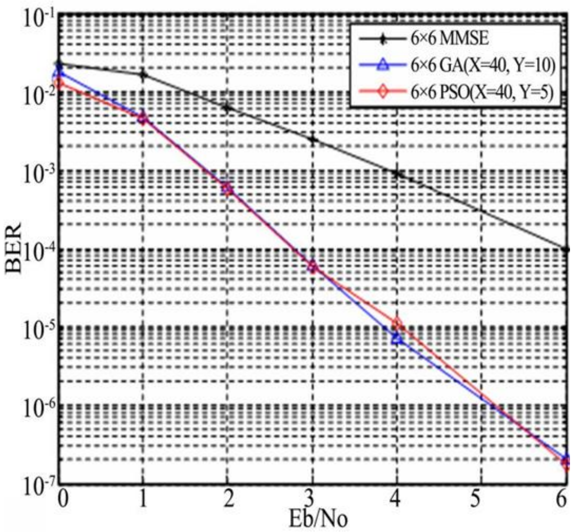

Figure 7. SNR vs BER performance Comparison

The pilots considered are $N_P = \frac{N}{8}, \frac{N}{4}, \frac{N}{2} and N$. The developed model's mean square error performance is compared to channel estimating algorithms such as LS and MMSE. The suggested approach outperforms the MMSE and LS algorithms even when the number of pilots is modest, according to a comprehensive examination of Figure 7. For $\frac{N}{8}$ data samples the designed model gives 3.6dB and 9.9dB over MMSE and LS Channel estimation algorithms. For $\frac{N}{4}$ samples of data the designed model has a gain of 8.1dB and 14.6dB over MMSE and LS. For $\frac{N}{2}$ samples model attained as 11.3dB and17.9dB compared with MMSE and LS.

We looked at how the MSE of a CI-based channel estimation technique is translated into BER at the receiving end for a variety of pilots. Figure 8 shows the Bit error rate performance for several four-channel state information (CSI) situations, including perfect or ideal CSI, CSI obtained using the LS technique, MMSE algorithm, and the proposed unique CI-based approach.

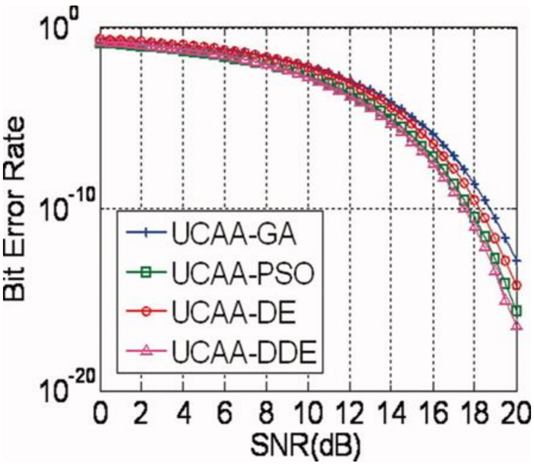

Figure 8. BER performance Comparison

Figure 8 hows that the developed model's BER performance is flawless and optimal. The efficiency of the planned model is demonstrated by this match. The performance of the developed model MSE is then evaluated in relation to the number of pilot samples. BER is compared to the number of pilot samples in a similar way. The BER performance is proportional to the number of blocks of pilots, as seen in the graphic above. The BER of the CI-dependent estimator has matched and reached the point where the BER of the ideal CSI has been evaluated, and no more changes are conceivable.

The graph depicts the CI-Based algorithm's convergence behavior. When SNR Value is 10dB, 15dB, and 20dB, respectively, we determined MSE performance for different iterations to reach the lowest MSE. Lowset MSEs of 17 and 19 are achieved using the Designed Model.

Table 3. Complexity analysis.

Estimator	Complexity
Estimator	Ô (Np)
LS	Ô (N^2p)
MMSE	Ô (L^2Np)
CI-Based estimator	Ô (Np)

Where Ô is Complexity constant and L is Floating point operations. Analysis of Table 3 shows that Complexity of CI-Model is less than LS and MMSE. If L is in between 3 to 10 times less than number of Samples NP. Because of this Proposed estimator converge the best Channel Impulse Response estimation. And finally, in Figure 9 Channel Quality Indicator for Designed Model is closely analyzed for different Longitude and Latitude for 1709 drive test data samples.

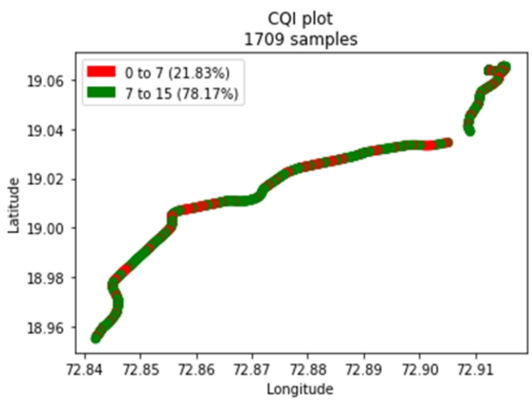

Figure 9. Complexity comparison

5 Conclusion

This research presented a simple yet effective channel evaluation technique that relies on Computational Intelligence. We looked into an unmarked OFDM-based LTE system that receives data across a time-varying frequency selective channel. The proposed method was then used to this OFDM-based system to analyze and track the changes in this time-varying channel from block to block. To begin, the performance of the proposed algorithm was compared to that of the LS and LMMSE channel estimation techniques in terms of MSE channel assessment performance. The results revealed that the provided technique outperformed the LS and LMMSE algorithms even with a small number of pilot samples utilized to estimate and track the CIR.

In terms of BER, the proposed CI-based approach outperforms MMSE and LS channel estimation algorithms by 2.4 and 5.4 decibels, respectively.

Furthermore, we examined the robustness of the suggested technique against a range of various maximum Doppler frequency values, and the results revealed that our system is successful in tracking the time-changing CIR, as a change in F only resulted in a little 0.19 dB drop in the outcome.

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Statement of conflict of interest

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ORCID iD

Siraj Pathan https://orcid.org/0000-0002-1728-3030
Sanjay Kumar Singh https://orcid.org/0000-0002-4426-3895
Mujib Tamboli https://orcid.org/0000-0002-5891-3713
Sunil Pathak https://orcid.org/0000-0001-7409-9814

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