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A Systematic Review of Channel Estimation Methods and Proposing an Optimal Approach in MIMO-OFDM and NOMA-based Networks

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Abstract

One of the critical issues in broadband wireless access is the channel estimation problem. Efficient channel estimation leads to spectrally efficient wireless communications. The main parts of channel estimation are the features of the fast time change, the presence of noise, and the identification of network structure based on MIMO-OFDM or NOMA. Optimizing Quality of Service (QoS) criteria, including throughput, Bit Error Rate (BER), delay and NimaX, and Mean Square Error (MSE) during routing, as well as improving energy consumption, reducing interference and overlapping along with reducing noise and congestion are listed as the main targets of channel estimation. In this article, an attempt has been made to review and evaluate the latest methods and techniques of channel estimation in all types of wireless networks, including Wireless Sensor Networks (WSNs), wireless mesh networks, Internet of Things (IoT) networks, etc. based on MIMO-OFDM or NOMA. Finally, an optimal channel estimation for the TV broadcasting system is proposed. The results show that the proposed method has effectively improved the QoS criteria such as MSE, Signal to Noise Ratio (SNR), and Peak Signal to Noise Ratio (PSNR).

Keywords: Channel Estimation, MIMO-OFDM, NOMA, Wireless Networks, IoT, Adaptive Neuro-Fuzzy Inference System (ANFIS), SNR.

Introduction

Channel estimation is a particular case of the system identification problem with a long history in signal processing [1]. Channel estimation plays a vital role in the performance of wireless communication systems. The most common method for estimating a channel in a receiver is based on a training sequence [2]. Strategies explain the basic idea of channel estimation in single-carrier systems, which is still used by most advanced channel estimation techniques, such as system parameters, correlation, least squares, etc. [3]. Channel estimation can be carried out in different ways [4]: with or without the help of a parametric model, using frequency and time correlation properties in the wireless channel; blind methods or based on training pilots, adaptive methods, or non-adaptive nonparametric methods which they try to estimate desired values (for example, frequency response) without relying on a model of a specific channel.

On the contrary, parametric estimation assumes a model with a specific channel, determines the parameters of this model, and infers the desired values from it. Time-correlated and frequency-interval correlations are channel-specific features that can be included in the estimation method to improve the estimation quality [5]. Estimation methods based on pilot training are the most widely used [6]. They can be used in systems where the transmitter transmits a specific and known signal. On the other hand, blind estimation relies on some signal characteristics (for example, the cyclic stability of the signal). It is rarely used in practical Orthogonal frequency-division multiplexing (OFDM) systems [7]. Adaptive estimation methods are usually used for channels with fast time changes. Channel estimation based on training pilots can be obtained by inserting pilot rings in all carriers of OFDM symbols with a certain period or by inserting pilot rings in each OFDM symbol [8]. The first class, called channel estimation based on block pilots, is developed with the slow-fading channel hypothesis [9]. This type of pilot arrangement works well when the channel transmission performance does not change rapidly [10-11]. The second category, the comb pilot arrangement, can easily be used to monitor fast channels. In comb arrangements, each OFDM symbol has some pilot rings. For this, it works better in highly variable environments [12]. There are many ways for channel estimation, but fundamental concepts are similar. The process will carry out as follows [11]:

- Using the ' channel ' matrix, set a mathematical model to correlate the 'transmitted signal' and 'received signal'.
- Transmit a known signal (a 'reference signal' or 'pilot signal') and detect the received signal.

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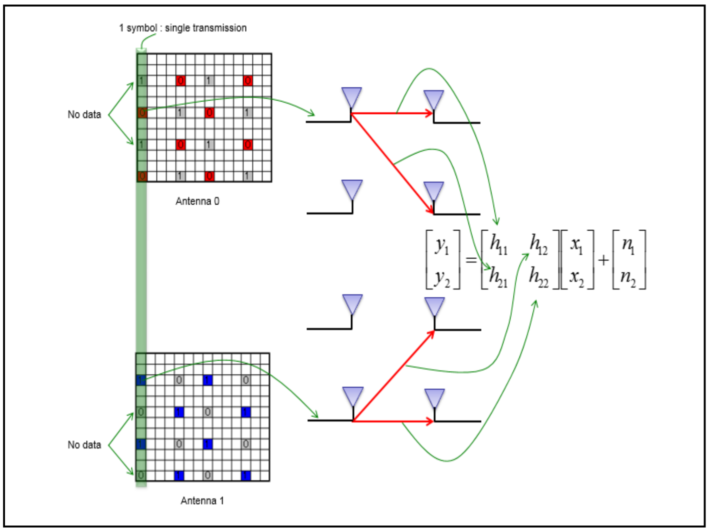
- By comparing the transmitted signal and the received signal, each element of the channel matrix can be figured out.

Fig. 1 shows the 2×2 MIMO communication system having two antennas at the transmitter and two antennas at the receiver end and the equations of the received signal at the antennas, where $h_{11}, h_{12}, h_{21}, h_{22}$ parameters denote channel information that must be estimated, x_1, x_2 denotes the transmitted signal and y_1, y_2 received signal and n_1, n_2 denotes the Additive White Gaussian Noise (AWGN) added to the signal.

Fig. 1. 2×2 MIMO communication system



Channel Estimation Methods

This section discusses recent trend methods and techniques in channel estimation of wireless networks. One of the newest papers which reviews channel estimation in the MIMO-OFDM system is mentioned in [13], which studied systematic based on performance analysis and future direction.
In [14], a nonlinear method based on the Hammerstein technique for robust and reliable channel estimation in WSN is proposed. This method guarantees evaluation criteria such as maximum correntropy, logarithmic hyperbolic cosine cost function, and Geman-McClure cost function.
Also, the reliable and robust method of using diffusion state for wireless sensor network channel estimation based on cost function optimization with logarithmic hyperbolic cosine is discussed in [15]. It is noticed that WSN under impulsive noise obtained good performance in terms of Mean Square Deviation (MSD) and Excess Mean Square Error (EMSE).
Federation learning technique for 5G networks channel estimation is proposed in [16]. This method was compared with classical Least Squares (LS), Linear Regression (LR), and MSE, which obtained better results.
Also, in [17], channel estimation in 5G networks based on convolutional neural networks is proposed. The suggested neural network-based method ran into Field Programmable Gate Array (FPGA) platform and obtained better BER.
Reference [18] proposed a channel and interference estimation method in 5G OFDM systems that used Co-Channel Interference (CCI).
In [19], a deep learning method for wireless MIMO networks, compared with LS and MMSE methods in terms of BER performance results, indicated a better output of the proposed Neural Network Machine Learning (NN-ML) method is presented.
Another deep learning method named Generative Adversarial Network (GAN) was used in [20] for wideband channel estimation, which compared with classical channel estimation networks and gained better SNR results.
In [21], user clustering optimization is performed along with power management and wireless channel allocation for NOMA-based IoT. In this paper, a QoS-aware resource manager is proposed as a resource for the NOMA algorithm to jointly optimize user clustering, power management, and wireless channel allocation. Therefore, the number of wireless channels is minimized, and user data need is satisfied. But the challenge of this research is in NOMA-based resource management to manage energy and wireless channel allocation to an acceptable level. Secure beam design on MIMO NOMA networks for the IoT with complete and incomplete Channel Status Information (CSI) is provided
in [22]. This research sends a controller of confidential messages to several stimuli, and a controller act as a blocker to prevent a potential listener of information. The aim is to expose the maximum confidential rate

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that can be successfully achieved by removing the interference, transmitting control, and blocking power limits. When the channel status information is completed, a safe beam shape is designed by creating an iterative optimization algorithm based on the MMSE method. When complete channel status information was unavailable, channel errors were modeled to a limited extent, and a robust and safe beam algorithm was designed based on weighted MMSE and beam adjustment methods. The challenge of this research is the existence of many errors in the channel structure.

Reference [23] presented the implementation of the MIMO-OFDM system using V-BLAST ZF and V-BLAST MMSE detection algorithms. In this paper, the MIMO-OFDM system is preferred over a network platform as it is much more practical due to the transmission of broadband data to reduce interference and increase system capacity. Zero Forcing (ZF) technique with MMSE has been used as a MIMO-OFDM detection scheme on the receiver side to estimate the transmitted data symbols. According to the simulation analysis, the MIMO-OFDM system uses the V-BLAST MMSE detection algorithm to provide better BER performance with high reliability and better quality of services. The challenge of this research is to identify any signal received at the receiver, and it may have any lexicon in the communication that leads to noise and specifically reduce the quality of services.

In [24], Improved low-complexity channel estimation algorithms are described based on discrete Fourier transform for LTE-based narrowband IoT systems. This paper proposes a low-amplitude channel estimation algorithm with the help of a Narrow Demodulation Reference Signal (NDMRS) called RS-LS and low-noise sorting. Another optimal estimator derived from the filtered channel estimation, Linear Minimum Means Squares Error Approximation (LMMSE-A), has also been studied. Using the conventional LS method, the authors first estimated the initial channel response at the pilot frequencies. Then they performed several additional operations to calculate the LS estimation error without exploiting the additional frequency band resources and increasing the computational complexity. Finally, the channel estimation for the remaining OFDM symbols in a narrowband IoT subset was obtained using subsequent linear interpolation. Through several simulation examples, the survival of the proposed estimators compared to conventional LS estimators, noise reduction, and LMMSE optimized in terms of MSE, block error rate, and SNR for LTE-based narrowband IoT systems.

In [25], pilot length and channel estimation for IoT systems were performed in MIMO format. The authors investigated the performance difference between simple channel estimation and the LMMSE channel estimation using
orthogonal and random pilot reuse schemes and the effect of pilot length. This paper developed simple algorithms for estimating the optimal pilot length that can support most IoT devices simultaneously.

In [26], estimating and evolving the link channel in the narrowband IoT system is proposed. It has been shown that the low complexity of MMSE-based methods in the narrowband IoT is possible using a small number of sub-carriers. In addition, noise variance estimation was proposed based on a combination of two consecutive pilot observations, assuming a slow channel change. The authors also demonstrated that the proposed estimator is efficient and simulates that both the LMMSE channel estimator and the MMSE equalizer can use the estimated noise variance instead of the exact value without performance loss.

In [27], link analysis and performance estimation of channel models are studied for wireless communication in the IoT. Wireless communication channels experience several channel defects, for example, attenuation due to loss of propagation, random fluctuations due to fading and shading on the channel, and Non-Line-of-Sight (NLOS) due to obstructions in the communication channel. Performance estimation approaches such as received signal strength, packet probability and Root Mean Square Error (RMS), RMS latency extension focusing on channel models, and three prominent IoT technologies are also included. This research may meet the demand for sufficient IoT channel modeling with channel models included and all analytical approaches presented.

In [28], a possible blind source isolation with a function for channel estimation and multi-node identification in green MIMO and multimedia communication systems is presented. This work demonstrated improved accuracy, robustness, and computational load of Blind Source Separation (BSS) and its application in estimating blind MIMO IoT interference channels, multi-node IoT data detection, separation, and identification in OFDM-based MIMO IoT networks. The superiority of possible corrections in blind source separation to the blind source separation model (AMUSE and SOBI as well-known second-rate techniques) was evaluated and clarified through experiments performed on MIMO IoT networks of various combinations. Also, comparative analysis of a combination of multimedia music, speech, and images represented the dominance of its performance.

Multiple non-OFDM access with channel estimation errors for linking IoT applications is provided in [29]. In this paper, the authors hypothesized that they use QPSK modulation and link NOMA schemes to channel estimation errors. The channels can be accurately tuned when pilot signals are mounted on

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shared sources, and a large number of devices made simultaneous random access to a single source station source, even in environments with a high SNR. In this paper, the authors proposed a high-link NOMA scheme that can reduce performance degradation due to channel estimation errors.

A channels tracker and estimation under the uncertain mode model for multi-user MIMOs in the IoT is proposed in [30]. In this paper, a Recursive Least Squares (RLS) detector and an Interacting Multiple-Mode (IMM) were developed to track these channels. In addition, by considering a model as an approximation of the channel model between the device and the central base antenna, the Auto-Regressive (AR) coefficients for all channels between the devices and the central base antennas are theoretically obtained. As a result, the optimal noise mode covariance of the channel mode is obtained using these adaptive coefficients online. In addition, the IMM detector's exponential stability and limiting error were derived, and the RLS detector's asymptotic stability. Finally, the performance of the introduced detectors was evaluated through simulations, and the amount of reduced total mass of MIMO systems was represented under the influence of time-varying channels.

In [31] the propagation of WiFi signal in IoT-edge computing is simulated. The authors of this paper proposed a new method based on the concept of information channels to develop with Convolutional Neural Networks (CNN) to reduce the time and resource cost of achieving real-time simulations with low-computing devices to determine RSSI based on completely new geometry (never used in training) that objects or obstacles (walls, cars, tables, etc.) and their respective location, size, and reflectance indicators along with antenna location were completely random.

The power allocation technique with guaranteed soft performance in OFDMA-NOMA hybrid radio systems with modeling and simulation is presented in [32]. This study suggested exploring the resource allocation technique for a combined OFDMA-NOMA system with a radiographic network to explain the potential capabilities of this system further. In this model, Sequential Convex Approximation (SCA) with a second-order conical approach is used to deal with non-convection problems of the developed optimization problem. Therefore it is evaluated the relevant optimization parameters. The simulation results showed that the proposed resource allocation technique for the OFDMA-NOMA CR hybrid system had a significant performance in terms of total network power and total transmission power required compared to conventional orthogonal resource allocation methods.

In [33], the issue of equitable power allocation in shared cognitive systems under NOMA transmission for IoT networks is addressed. The goal is to achieve fairness among secondary users (SUs) in NOMA-based cognitive radio transmission with the participation of the IoT. The paper's authors designed an energy allocation algorithm that considers an independent battery limit per node and applied a power gap between the transmissions of two NOMA users to eliminate consecutive interference. The simulation results indicated the proposed framework provided excellent performance and complete fairness for sufficient transmission power.

Reference [34] presented modulation of the OFDM-based dual-state index on NOMA networks. Index Modulation (IM) on the OFDM system created a new dimension for data transmission regarding subcarrier index selection bits to increase Spectral Efficiency (SE) by increasing selection variability. By combining conventional IM and OFDM with NOMA, multiple users benefit by changing the power allocation factors and the pattern of sub-carrier indicators. Inspired by OFDM-IM NOMA, a two-state OFDM-IM method presented in this paper. The proposed method increases the SE by using index selection bits and transmitting data through all OFDM carriers using different constellation sets. The error performance of the proposed method was evaluated using Maximum-Likelihood (ML) and Log-Likelihood Ratio (LLR) techniques. The simulation results for the proposed method modulated the improvement in SE compared to the conventional method for different degrees. Also, it presented the computational complexity for the proposed and existing OFDM-IM NOMA method using both ML and LLR detectors.

In [35], a comparative analysis of various NOMA schemes with code scope for future communication networks is presented. Future communication networks may face various issues to facilitate heavy heterogeneous data traffic and large numbers of users, so more advanced Multiple Access (MA) schemes are being developed to meet evolving needs. Under the NOMA scheme, an MA domain can be based on a signature code that is named the NOMA code domain.

In [36], IQI Imperaired NOMA Cooperative performance analysis for IoT with 5G connectivity is provided. This paper examined the common effects of in-phase and quadrature-phase imbalance (IQI) and the ImPerfect Successive Interference Cancellation (IPSIC) on the NOMA-based IoT network, whose channel type is the Nakagami erasure channel. The simulation results represented that compared to IQI, IPSIC had a more significant impact on the interrupt performance of the device near the intended IoT. In addition, with the documentation provided in this

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paper, it can be seen that the possibility of disconnecting IoT devices is minimized by choosing a specific energy allocation plan.

In [37], a performance analysis of the CR-NOMA smart model for IoT communications is proposed. This paper studied a simple Cognitive Radio NOMA (CR-NOMA) communication system intending to provide the low-latency wireless communication required in IoT applications is presented. The system consists of two secondary users (SUs) that interact dynamically with the primary user (PU), and the possibility of disconnection of the SU determines its performance. This cut-off probability is calculated under two conditions: a) PU transmission starts after obtaining the Channel State Information (CSI), so the base station is unaware of the interference, and b) PU interference when the base station is aware of it. NOMA transmission is consistent with more comprehensive knowledge of signal interference plus SNR. The results of this study indicated that when SUs are further away from the main transmitter or the PU signal is less powerful, the probability of power outages is reduced. The base station always performs better

when it is aware of interference. Therefore, the findings emphasize the importance of monitoring channel quality and real-time feedback to optimize CR-NOMA system performance.

In [38], NOMA-based IoT networks have been studied by the effects of impact noise and their reduction in network communications to increase system performance. This is a multi-step nonlinear processing approach explicitly designed for OFDM-based PDM-NOMA systems. A deep learning method for estimating the impact noise parameters received from the OFDM symbol is proposed to obtain the desired threshold for the corresponding users. As a result, this information can be used to assess the relevant optimal threshold using the ideal Siegert observer criterion. Finally, it highlighted the potential opportunities and challenges that are expected to arise when implementing NOMA in impact-noise environments.

In [39], the optimal allocation of resources in NOMA-based machine-to-machine communications is presented using a combined equestrian optimization algorithm with a Firefly Algorithm with the aim of IoT energy-saving strategy. As the number of users increases, Orthogonal Multiple Access (OMA) based approaches may not meet emerging stringent needs such as low latency, high spectral efficiencies, and massive device connectivity. In addition, due to the unique features of machine-to-machine-based applications, there are significant challenges in machine-to-machine communication with a mobile. To overcome these challenges, the NOMA principles emerge as a solution to increase spectral performance while allowing for some degree of multiple access interference at receivers. Hence, this paper intends to establish an optimal resource allocation mechanism for machine-to-machine communication. The main purpose of the proposed resource allocation model is to minimize the total network energy consumption. To achieve the lowest energy consumption, NOMA time allocation and transmission power are optimally adjusted by a hybrid optimization algorithm.

In [40], a channel estimation system for vehicle-to-everything (V2X) communication is presented. In recent years, automotive communication has been a hot topic worldwide. To avoid dangerous traffic accidents, traffic information is expected to be exchanged between vehicles and anything through wireless communication. The reliability of the received data and low latency is significant to ensure the safety of crash prevention systems. Also, high throughput is required to share sensor data with pedestrians and vehicles. Table 1 provides a comparison between different methods.

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Table 1. Channel Estimation Methods comparison

Reference Number	Improved QOS criteria																
	Throughput	BER	Latency	Energy & Power	Interference	Noise	Cost	Pocket losses	Complexity	SNR	Channel Allocation	Reliability	Capacity	Correntropy	RMSE	Spectral Efficiency	Eva. Criteria
14							*							*			
15						*											
16																	*
17		*															
18					*												
19										*							*
20										*							
21				*							*						
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33				*	*												
34		*							*							*	
35	*	*	*					*		*							
36				*	*												
37			*	*		*				*							
38						*											
39			*	*												*	
40	*		*									*					

A proposed approach for channel estimation

This paper proposes optimal channel estimation based on the least square-adaptive neuro-fuzzy inference system (LS-ANFIS). The proposed method uses nonlinear parametric models that make a mapping function in input and output data. Input data of channel estimation uses a TV band. TV band can be a TV broadcasting system with multi-antenna. The proposed method uses binary series of input and output. Binary series is defined as equation (1).

$$X_1^T = \{x_1, x_2, \dots \dots .., x_t, \dots \dots \dots ., x_T\} \quad (1)$$

$$T_c = T_{B1} + T_{B2} + NT_{ms} + 5T_{SIFS} \quad (2)$$

According to equation (1), for each channel with sensing status, a channel will be produced in each gap and in T time duration. Channel status in each gap is busy or not busy, which will be shown with 1 and -1 binary signs. Channel estimation learns by using binary series, and based on this learning, channel status in the next gap will be estimated by gap status records. Channel estimation allocates for each channel in a multi-channel system. N is the number of channels. T is the time range and T_c is the time duration of MAC message controlling is calculated as equation (2).

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According to equation (2), T_{B1} and T_{B2} are time duration of B_1 and B_2 nodes. NT_{ms} is the time duration of the report for N channel in the network, T_{SIFS} is (Short Inter Frame Spaces) SIFS unit for delay propagation and time for spectrum sensing of each channel that calculates as equation (3).

$$t_s = \left(\frac{\sqrt{2\lambda}+1Q^{-1}(P_d)-Q^{-1}(P_f)}{\lambda\sqrt{B}}\right)^2 \quad (3)$$

According to equation (3), $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} \exp\left(\frac{-t^2}{2}\right) dt$ and P_d and P_f are detection probability and false detection threshold defined by the channel estimator, B is channel bandwidth and λ is SNR sensitivity value to the detected spectrum. N channel detected slightly based on the number of channels try to sense spectrum to have an opportunity. It must be determined the number of users that do not have access to the channel for channel resource allocation to optimize the QoS. A channel considered that the primary user has an access certificate to it. A channel can be active or inactive at any moment. It is assumed that active or inactive time is exponential distribution. $S(n)$ used as channel status in n slot. If the channel is in inactive status, $S(\mathrm{n}) = 1$, and if the channel is in active or busy status, $S(n) = 0$. Therefore, the relations are as equation (4).

$$P(S(n+1) = 0|S(n) = 1) = q \quad (4)$$
$$P(S(n+1) = 0|S(n) = 0) = p$$

According to equation (4), $P(q)$ is the transition probability of the active (inactive) to inactive (active) state. $P|(p+q)$ is channel stability state probability for inactive status. A logical assumption is $(1-p-q>0)$ that implicates an adjacent slot that has the most similarity to the channel. Spectrum sensors report channel information of the network that tries to decide channel access. Now, criteria need for showing useful signals against noisy signals in the cognitive radio system. A value less than 12 dB shows a serious problem in channels. The value more than 20 dB is satisfying, and higher than 30 dB is so suitable. This index is better and shows a more useful signal. SNR is signal-to-noise ratio power and is calculated as equation (5).

$$SNR = \frac{P_{signal}}{P_{noise}} \quad (5)$$

According to equation (5), P is the average signal power value. Due to most signals having dynamic range, they are described as dB logarithmic, which will be equation (6) for power signal and noise.

$$P_{signal,dB} = 10log_{10}(P_{signal})$$
$$P_{noise,dB} = 10log_{10}(P_{noise}) \quad (6)$$

Also, the MSE criteria, that is average squared difference between the estimated values and the actual value calculated
as equation (7).

$$MSE = \sum_{i=1}^{n} \frac{(\widehat{y_i}-y_i)^2}{n} \quad (7)$$

Finally, PSNR criteria, the ratio between the maximum possible power of a signal and the power of corrupting noise calculates as equation (8). Like SNR, PSNR is usually expressed as a logarithmic quantity due to most signals having a wide dynamic range.

$$PSNR = 10\ Log\ \frac{{MAX_I}^2}{MSE} \quad (8)$$

Simulation & Results Discussion

In this paper, the MATLAB software has been used as a simulation platform environment. The target is channel estimation due to the quality of services optimization. Data are TV data that are generated as a mapping from input to output. The threshold value is defined as 0.181. The initial weight value is 0.5. Fig. 2 shows the normalized throughput ratio to average density per km^2. In Fig. 2, SS is the means of spectrum sensing for users on the main band in channel estimation.

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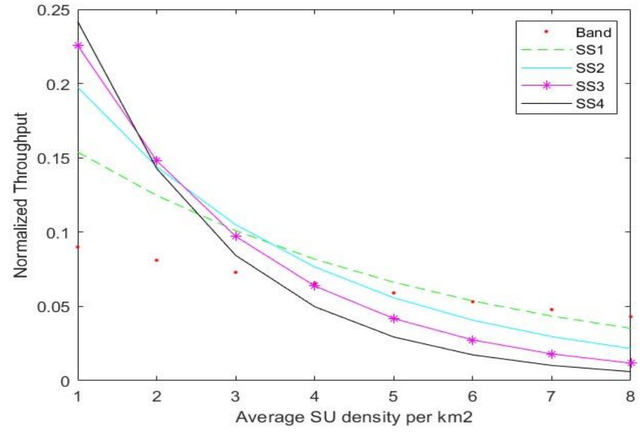

Fig. 2. Normalized throughput ratio to average density per km^2

ANFIS is used as a channel estimation approach. Fig. 3 shows the Evaluate of Root Mean Squared Error (RMSE) for training, validation, and test data (Error curves) versus Epochs in the ANFIS technique, which are acceptable values and confirm the accuracy of this training method.

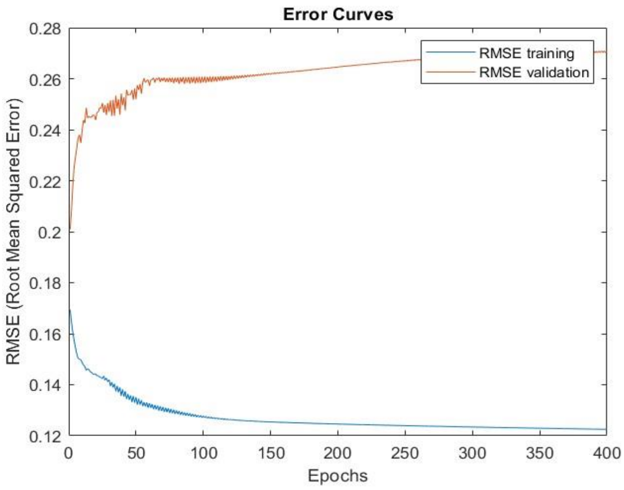

Fig. 3. RMSE for training, validation, and test data

The obtained results for MSE, PSNR, and SNR are represented in Table 2. Since MSE is the average squared difference between the estimated and actual values, it should be close to zero. On the other hand, an SNR value of more than 20 dB is satisfying, and higher than 30 dB is so suitable. Therefore, the results showed that the proposed approach has improved channel estimation & QoS such as MSE, PSNR, and SNR.

Table 2. Obtained Results of MSE, PSNR, and SNR

MSE	0.46
PSNR	21.4549
SNR	27.4231

Conclusions

This paper explains channel estimation methods and techniques in wireless networks. Also, MIMO-OFDM and NOMA-based systems in channel estimation are discussed. Also, methods such as MMSE, LS, LMMSE, and others are explained based on the pilot, comb pilot, and any noise condition. Then an optimal channel estimation method was proposed in nonlinear

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parametric models in TV band of broadcasting system with multi-antenna based on Least Square- Adaptive Neuro-Fuzzy Inference System (LS-ANFIS) to optimize the service quality criteria such as MSE, SNR, and PSNR. Since the MSE is the average squared difference between the estimated and actual values, it should be close to zero. On the other hand, the SNR value more than 20 dB is satisfying and higher than 30 dB is so suitable. The results showed that the proposed approach had improved MSE, PSNR, and SNR.

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