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Original article

Deep learning-driven multi-user wavelet NOMA for user centric cell-free massive MIMO communications

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ABSTRACT

The evolution of Cell-Free Massive MIMO (CF-mMIMO) systems in the sixth-generation (6G) communications brings notable benefits including enhanced capacity, broader coverage, and greater reliability. However, these advanced systems may be subjected to critical challenges like, exponential growth in the user connectivity, precise channel estimation, and effective mitigation of the inter-user interference. This article addresses these challenges through Deep Learning (DL) for accurate channel estimation and a robust Wavelet Transform based Non-Orthogonal Multiple Access (NOMA) scheme to mitigate the inter-user interference in a user-centric CF-mMIMO system. By eliminating the reliance on pilot-assisted channel estimation, the DL-based approach achieves higher accuracy and lowers transmission overhead in a multi-user scenario. The results highlight the superiority of DL-based channel estimation for a CF-mMIMO system employing wavelet NOMA scheme over traditional methods, showing a 17% reduction in bit error rate (BER) and a 15% improvement in achievable sum-rate.

1. Introduction

Artificial intelligence (AI) has emerged as an effective approach for wireless communication systems from managing communications to optimizing the communication resources, especially under imperfect conditions [1]. Machine learning (ML) and deep learning (DL), two basic branches of AI, present tremendous potential to make profound technological advancements that may offer additional efficiency to the wireless communications systems' operations [2,3]. Furthermore, non-orthogonal multiple access (NOMA) and cell-free massive MIMO (CF-mMIMO) have emerged as the two promising technologies in order to meet the stringent requirements such as higher spectral efficiency (SE), greater coverage and capacity for future wireless communications [4,5]. Recent works in literature are evidence that the ML and DL techniques integrated with CF-mMIMO and NOMA may bring significant improvements in terms of signal detection, channel estimation (CE) and power allocation for future wireless communication systems [6,7].

For a CF-mMIMO system and NOMA scheme, it is extremely important to get the accurate channel state information (CSI) in order to reap their benefits. However, traditional CE methods such as minimum mean square error estimation (MMSE) and least square (LS) estimation methods may not provide satisfactory precision in the context of multiple users' channel links and their inaccurate estimation due to channel noise and user interference [8]. Moreover, where pilot tones are used for CE, this estimation problem is further aggravated due to the pilot contamination, which occurs due to multiple transmissions over the same frequency band in a CF-mMIMO NOMA system. [9]. Therefore, an innovative solution is required to address the pilot contamination and subsequently acquire an accurate CE of all multiple users links in a CF-mMIMO NOMA system. While, DL plays a significant role in wireless communication, it can also be applied to generate accurate versions of channel links.

Accurate CE can be implemented using DL techniques, which may reduce pilot contamination effect. In addition to accurate CE, waveform pulse-shaping is also an important consideration for a CF-mMIMO NOMA system, as some waveform patterns lead to user interference and degradation of the system performance [10]. Using appropriate waveform design techniques can help address this issue, among which the wavelet transform based pulse-shaping is regarded as one of the

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significant techniques [11]. Wavelet transform is used to analyse the time-varying and non-stationary signals in time and frequency domain [12]. Hence, due to these characteristics, wavelet transform based pulse-shaping methods are also considered suitable for CF-mMIMO NOMA systems to minimize user interference [13].

In literature, a CF-mMIMO system has been implemented with a conventional NOMA scheme, which uses orthogonal frequency division multiplexing (OFDM) pulse shaping method [14]. OFDM pulse shaping method uses guard band and cyclic prefix (CP), which helps in mitigating interference. However, insertion of guard band and CP results in lower bandwidth efficiency (BE) and SE [12,14]. This issue can be addressed using wavelet pulse-shaping for NOMA scheme, which achieves enhanced BE, SE and reduced computational complexity compared to the conventional NOMA scheme [13]. Hence, the performance of a CF-mMIMO system can be enhanced by accurate CE with DL technique and using wavelet pulse-shaping with NOMA scheme. A cellular mMIMO system employing a two-user wavelet NOMA scheme was investigated by authors in [11], which used DL for CE. Authors concluded that DL based CE outperforms traditional estimation methods in terms of symbol error rate (SER) of the system [11].

Moreover, for a CF-mMIMO NOMA system that may operate in 5G and beyond systems user pairing/ clustering is an essential part of its implementation. Therefore, user clustering for a CF-mMIMO NOMA system inevitably provides enhanced capacity, spectral efficiency (SE) and sum-rate. Unsupervised machine learning (ML) algorithms may be considered an effective solution for user clustering, as random clustering methods involve higher complexity [15,16]. Authors in [17], have proposed a CF-mMIMO NOMA system with learning-based user clustering for sum SE, which proved to be effective as compared to random clustering methods. In our previous work, we have analysed a 3-user NOMA scheme for a user centric (UC) CF-mMIMO system with three unsupervised ML algorithms k-means, k-means++ and improved k-means++ for user clustering. In this work, the ML based UC CF-mMIMO NOMA outperforms its conventional counterpart with traditional clustering methods [18]. The computational complexity of a multi-user CF-mMIMO system can be relatively reduced by adopting user centric (UC) approach, in which specific set of users may be served by a subset of access points (APs) [18,19].

To the best of authors' knowledge, majority of the research works for a CF-mMIMO system have been studied employing conventional NOMA scheme. Moreover, research work related to CF-mMIMO NOMA system used traditional user clustering methods and traditional CE methods, which may not provide satisfactory results under conditions of pilot contamination and user interference. In this article, a UC CF-mMIMO system is studied with multi-user wavelet NOMA scheme using ML for user clustering and DL method for CE. It is envisaged that the performance of the proposed system would improve in terms of reduced interference, pilot contamination and BER.

1.1. Related work

Majority of the literature related to CE for a CF-mMIMO NOMA system encompasses conventional estimation methods such as LS and MMSE, which uses pilot signals to get the estimates. This is not suitable for a scenario with multiple users as the pilot tones gets contaminated, which then further leads to greater interference. Due to this reason, DL based CE methods may provide a viable solution. In this subsection, a brief overview of the recent related works pertaining to the application of DL techniques for CE in communication systems is presented.

In [20], authors proposed a convolutional neural network (CNN) using predicted position information to solve low accuracy problems for CE in a mMIMO system. Authors concluded that the proposed DL model helps to improve the performance of the system in terms of BER [20]. Authors in [21] investigated a DL based method for joint CE and feedback implicitly and explicitly, which exhibits strong robustness to quantization errors. Another DL based method with the help of encoder network for CE was presented in [22], which aims to decrease feedback and pilot overhead.

Authors in [23] proposed a joint method for pilot design and CE based on deep residual learning, which helps to reduce the effects of pilot contamination considering hardware impairments. To mitigate the effect of pilot contamination, authors investigated linear MMSE method and then DL based pilot design is utilized to reduce the mean square error (MSE) of linear MMSE method [23], which proved to be effective as compared to the conventional approaches for CE. A DL based model for parametric CE along with pilot decontamination was presented by authors in [24]. The proposed framework combines the mMIMO parametric CE and DL for improved CE and pre-coding, which nullifies the pilot contamination with a high performance gain [24].

Authors in [25] investigated a CF-mMIMO system using two DL methods i.e., deep successive contamination cancellation and agnostic neural network to avoid pilot contamination in dense networks. Results achieved using the DL based methods showed the effectiveness of the proposed models for accurate CE [25]. A DL model for CE based on the fast and flexible denoising convolutional neural network (FFD-Net) was proposed by authors in [26], which proved to be fast and accurate compared to state-of-the-art channel estimators. Another DL based framework for joint CE and beam-forming was presented by authors in [27], which outperforms the benchmark approaches but with reduced complexity.

A learning based approach for CE was investigated in [28] to tackle the pilot contamination problem in a CF-mMIMO system by formulating an efficient pilot assignment strategy, which results in enhance SE of the system. To the best of authors' knowledge, DL based techniques for CE and pilot decontamination have not been applied for a CF-mMIMO system employing conventional/ wavelet NOMA scheme. However, a NOMA scheme implemented for a cellular mMIMO system has been explored with a DL method for CE in the literature, which is discussed in the following.

A DL based method for NOMA scheme was studied by authors in [29] to detect the channel characteristics. Authors employed long short term memory (LSTM) method for CE and concluded that the proposed DL method outperforms conventional method for CE [29]. Moreover, an effective DL based method for CE in a mMIMO NOMA system was proposed by authors in [30]. Authors analysed the SER and throughput of the system to prove the effectiveness of the proposed DL approach [30]. Another DL based joint CE and signal detection method for OFDM NOMA scheme was presented in [31]. Authors analysed the proposed system using two pilot insertions i.e., comb and block type and concluded that the proposed DL based CE method is robust against fading channel conditions. Hence, it is evident from the cited literature that DL based CE plays a significant role to enhance the performance of a communication system, whether cellular or cell-free system and also for NOMA scheme.

In addition to CE and pilot contamination, other important factors included in the proposed CF-mMIMO NOMA system are efficient user clustering and mitigation of user interference. Unsupervised ML algorithms can be implemented for user clustering in NOMA scheme for improved SE and sum-rate [17,18]. Authors in [17] investigated a CF-mIMO NOMA system using ML algorithms for user clustering. Authors concluded that the learning assisted CF-mMIMO NOMA system outperforms traditional pairing techniques in terms of SE [17]. Another CF-mMIMO NOMA system with UC approach and ML algorithms for user clustering was studied in [18], which is the authors' preceding work. Authors analysed that the achievable sum-rate of CF-mMIMO system is enhanced, if user grouping is implemented using ML algorithms [18]. Moreover, authors in [18] investigated a 3-user NOMA scheme for a UC CF-mMIMO system, which is considered complex in terms of increased user interference and can be mitigated using wavelet pulse-shaped NOMA scheme.

Wavelet pulse-shaping for NOMA scheme provides enhanced BE, SE and reduced computational complexity [35]. A performance comparison of the discrete wavelet transform (DWT) based NOMA and

Table 1
Existing studies for Wavelet NOMA and Cell-Free Massive MIMO system using DL.

Ref	Cell-Free mMIMO	User centric	NOMA	Wavelet pulse-shaping	Users per cluster	Learning based method
[32]	✓	✓	✓	×	2	×
[33]	✓	✓	×	×	×	×
[12–14,34–36]	×	×	✓	✓	2	×
[37]	×	×	✓	✓	3	×
[17]	✓	×	✓	×	2	ML for user clustering
[38]	✓	×	✓	×	2	DRL for user pairing
[11]	×	×	✓	✓	2	DL based CE
[39]	×	×	✓	×	2	DL based SIC
[18]	✓	✓	✓	×	3	ML based user clustering
Presented article	✓	✓	✓	✓	3	ML for user clustering and DL for CE

the conventional NOMA scheme has been proposed in [14], which demonstrates that the DWT based NOMA scheme provides relatively higher SE compared to the conventional NOMA scheme [14]. In [13], performance analysis of DWT based NOMA scheme for 5G networks has been presented, which shows that DWT based NOMA scheme provides reduced bit error rate (BER) by mitigating user interference. Moreover, authors in [11] investigated a cellular mMIMO system with wavelet NOMA scheme, which results in reduced symbol error rate (SER). To the best of authors' knowledge, literature work related to wavelet NOMA scheme comprises of two users, except for the work presented in [37].

Authors in [37] analysed a cellular mMIMO system with wavelet NOMA scheme with a 3-user case for reduced SER. A 3-user case for wavelet NOMA scheme is considered more complex in terms of user interference. Therefore, a CF-mMIMO system with UC approach needs to be investigated with a multi-user wavelet NOMA scheme adopting DL based CE to mitigate user interference and pilot contamination. Prior works for a UC CF-mMIMO system with wavelet NOMA scheme and DL based CE are summarized in Table 1. Thus, the information presented in Table 1 and Section 1.1 leads to the research gap presented in the following subsection.

1.2. Motivation and contributions

To the best of authors' knowledge majority of the research works studied a CF-mMIMO system with conventional NOMA scheme as mentioned in the Section 1.1. Moreover, in the existing literature, CF-mMIMO NOMA system has been analysed with a two-user case, except for the work presented in [18], which discussed a 3-user case and is the authors' preceding work. Moreover, CF-mMIMO NOMA system in literature has been investigated with traditional CE methods using pilot tones, which may result in degradation of the system performance due to pilot contamination. Furthermore, UC CF-mMIMO system with multi-user wavelet NOMA scheme and using DL based CE has not been explored in the literature yet. Therefore, a CF-mMIMO system with UC approach necessitates the exploration of multi-user wavelet NOMA scheme using DL based CE to mitigate user interference and pilot contamination, respectively.

In this article, a CF-mMIMO system with wavelet NOMA scheme for a 3-user case is proposed, which uses DL based CE to improve the BER and achievable sum-rate of the system. The presented article fills the research gap stated in this subsection and aims to develop a DL based CE for a UC CF-mMIMO system with multi-user wavelet NOMA scheme. Hence, the information presented in Table 1 indicates that the suggested solution works in an effective manner for a UC CF-mMIMO system with multi-user wavelet NOMA scheme and with reference to the application of DL based CE. Following are the main contributions of this research work:

- A multi-user wavelet NOMA scheme based CF-mMIMO system with UC approach is proposed, in which users are grouped with the help of unsupervised ML algorithm, namely as improved k-means++. Wavelet NOMA scheme helps to mitigate the user interference and thus leads to enhanced achievable sum-rate.
- To achieve better performance, DL approach has been implemented for CE of the proposed system, which can reduce the effect of pilot contamination. The proposed system is evaluated in terms of BER and achievable sum-rate with and without pilot contamination.
- Results for the proposed wavelet NOMA based CF-mMIMO system with DL based CE are compared with the traditional CE methods.
- Finally, the complexity of the proposed DL based CF-mMIMO system with a 3-user wavelet NOMA scheme is provided.

The organization of the article is given here. A detailed system model is provided in Section 2. Section 3 demonstrates the DL based CE for the proposed system. Expressions for user interference, BER and achievable sum-rate are given in Section 4. The results are presented and discussed in Section 5, while the conclusion is provided in the last section.

2. System model

In this paper, a UC CF-mMIMO system is implemented with A number of APs and K number of users, randomly distributed in a $D \times D$ Km^2 area. Each AP has L_A antennas and each user terminal has single antenna. User clustering is implemented using improved k-means++ algorithm, which gives reduced complexity compared to k-means and k-means++ [17,18]. It works by finding C number of clusters, which can be represented by C centroids [17], having L_c number of users. Improved k-means++ is well suited for user clustering with lower computational complexity, scalability and simpler interpretation. The complete algorithm for improved k-means++ is given in [18], which is the author's preceding work. In this article, power domain NOMA (P-NOMA) scheme will be implemented for the proposed CF-mMIMO system. In P-NOMA scheme, different power factors are allocated to users according to their channel conditions [40]. The lowest and highest power ratios are allocated to the best and the worst channel users respectively. In P-NOMA scheme, all the transmitted signals are combined at the transmitter side [40]. It is assumed that each user will perform successive interference cancellation (SIC) to detect its own signal. The user with greater transmit power recovers its signal considering other signals as noise. During SIC, each user detects the greater transmit power signals from other users and subtracts these from the received signal to detect its own data.

In this work, a 3-user NOMA scheme is implemented for a UC CF-mMIMO system. Continuous time signals acquired from three users are represented by $x_1(t)$, $x_2(t)$ and $x_3(t)$. Therefore, subsequent to signal conditioning and allocation of variable transmit power to each user, as per the concept of NOMA, the superimposed signal is, [37],

$$x[m] = \sqrt{(\alpha_1 p)} * x_1[m] + \sqrt{(\alpha_2 p)} * x_2[m] + \sqrt{(\alpha_3 p)} * x_3[m] \tag{1}$$

where α_1, α_2 and α_3 denote power factors for user 1, 2 and 3 respectively, x[m] is the discrete domain representation of signal x(t) and p is the total transmitted power. Users in the same cluster are allocated power factors according to channel conditions i.e., if $\left|h_1^2\right| > \left|h_2^2\right| > \left|h_3^2\right|$, then power allocation will be based on $\alpha_1 < \alpha_2 < \alpha_3$. Due to the adaptive power allocation, the power allocated to each user may vary according to channel statistics, however, the total power allocated is bound by the following condition,

$$\sum_{l=1}^{L_c} \alpha_l = 1 \tag{2}$$

where α_l is the power factor allocated to lth user and L_c denotes the total number of users in the cth cluster.

It is assumed for the given system, that time division duplex (TDD) mode is used for operation of APs. In uplink training phase, pilot sequences are transmitted by users to APs for CE. Users, in the same cluster use non-orthogonal pilot sequences that can be expressed as,

$$\varphi_{alc}^{H}\ \varphi_{al'c} \neq 0 \tag{3}$$

where, φ_{alc} is the pilot sequence to the lth user in the cth cluster from the ath AP. Channel vector between the ath APs and lth user in the cth cluster for downlink transmission is $\mathbf{h_{alc}}$, where $a \in \{1, 2, 3, \dots, A\}$ and $l \in \{1, 2, 3\}$ respectively, is expressed as [17],

$$\mathbf{h}_{\mathrm{alc}} = \sqrt{\beta_{alc}}\ \bar{\mathbf{h}}_{\mathrm{alc}} \tag{4}$$

where β_{alc} denotes large scale fading coefficient for path loss and shadowing, and $\bar{\mathbf{h}}_{\mathrm{alc}}$ is small scale fading vector respectively. Large scale coefficient $\beta_{alc} = 10^{(PL_{alc}/10)}\ 10^{(\sigma_{sh}/10)}$, where PL_{alc} is the path loss from lth user to ath AP and $10^{(\sigma_{sh}/10)}$ represents shadow fading having variance σ_{sh} [41]. Received training signal for uplink at ath AP is [17],

$$\mathbf{Y_{a_p}} = \sqrt{\alpha_p} \sum_{c=1}^{C} \sum_{l=1}^{L_c} \mathbf{h_{alc}}\ \varphi_{ac} + \mathbf{W_{a_p}} \tag{5}$$

where φ_{ac}, α_p and $\mathbf{W_{ap}}$ are pilot sequence allotted to cth cluster, transmit power of pilot and additive noise matrix for the ath AP, respectively. The aim of CE is to extract the channel vector from the received signal as accurate as possible. Traditional CE methods include LS and MMSE estimation for CE. Hence, LS and MMSE estimates of $\mathbf{h_{alc}}$ can be written as in Eqs. (7) and (6) respectively [18],

$$\hat{\mathbf{h}}_{\mathbf{alc}}^{\mathbf{LS}} = \mathbf{h_{alc}} + \sum_{l=1}^{L_c} \mathbf{h_{alc}} + \frac{\sqrt{\alpha_p}\ \beta_{alc} \cdot \hat{y}_{anp}}{1 + \tau_p\ \alpha_p\ \sum_{i=1}^{L_k}\ \beta_{aci}} \tag{6}$$

$$\hat{\mathbf{h}}_{\mathbf{alc}}^{\mathbf{MMSE}} = \frac{\sqrt{\alpha_p}}{1 + \tau_p\ \alpha_p\ \sum_{i=1}^{L_k}\ \beta_{aci}} \beta_{alc} \cdot \hat{y}_{anp} \tag{7}$$

In Eqs. (7) and (6), $\hat{y}_{anp}$ is the projection Y_{a_p} of onto φ_{ac}, τ_p is the length of pilot signal and β_{alc} is the large scale fading coefficient from ath AP to lth user in the cth cluster. In the proposed system, non-orthogonal pilot sequences are used for different users in a cluster. Hence, the pilot sequences are contaminated, thus it results in the intra-cluster interference due to which the performance of the system is degraded. This issue can be addressed using wavelet pulse shaping for NOMA scheme.

2.1. Wavelet NOMA scheme for the proposed system

For downlink transmission, it is assumed for UC CF-mMIMO system that a specific set of users is associated to specific APs. In this paper, it is assumed that ath AP can serve only N_a number of users, which can be represented by a set $N(a)$. The combined signal transmitted by ath AP to the cth cluster is expressed as,

$$x_{ac} = \sum_{L \in N(a)} \sum_{l=1}^{L_c} \sqrt{\alpha_{alc}\ p_a c}\ x_{alc} \quad \forall C \tag{8}$$

where x_{alc} is the transmitted data, p_{lc} is the transmit power for the cth cluster and α_{alc} is transmit power of lth user in cth cluster. After assigning the power to each user in a cluster, data symbols undergo modulation and source coding. Wavelet pulse-shaping is applied by using filter banks, named as synthesis filter bank (SFB) at the transmitter and analysis filter bank (AFB) at the receiver side. AFB and SFB are used to produce the discrete wavelet transform (DWT) and inverse DWT (IDWT) of the signal. The difference between wavelet NOMA and conventional NOMA lies in the manner in which signal waveform can be transformed, that are pulse-shaped using wavelet filter-banks (WFB) instead of discrete Fourier transform (DFT) filter-banks. A general structure for wavelet NOMA transceiver is presented in Fig. 1.

Each user bits are mapped to produce symbols into binary phase shift keying (BPSK). After this, each user in a NOMA cluster is allocated a power factor in accordance with its channel condition. The user with worst channel condition is allocated a highest power factor and so on. After this, a superimposed signal is formed by combining the signals of three users. Then a serial-to-parallel converter is used to convert this superimposed signal into a parallel stream of bits. For IDWT, this stream of bits is passed through the SFB, which then decomposes the input stream into high pass $h_s[m]$ and low pass components $g_s[m]$ through high pass filter (HPF) and low pass filter (LPF) respectively. After IDWT, the transmitted signal can be denoted as [36],

$$\begin{aligned} x_{a_{IDWT}}[m] &= \sqrt{2^{1-j}} \sum_{j \in I} a_j^0\ \gamma[2^{1-j}\ t - j] \\ &+ \sum_{m=1}^{J-1} \sqrt{2^{m-J}} \sum_{j \in I} a_j^m\ \psi[2^{m-j}\ t - j] \end{aligned} \tag{9}$$

where a_j^0 are complex valued symbol with $m = 0, 1, 2, \dots, j-1$, I is taken as integer for index set i.e., 0,1 and J represents level of decomposition for wavelet. γ and ψ are scaling and wavelet functions associated to HPF and LPF respectively. Scaling function and wavelet function are given as [13],

$$\gamma(m) = 2^{\frac{1}{2}}\ h_s[m]\ \gamma[2b - m] \tag{10}$$

$$\psi(m) = 2^{\frac{1}{2}}\ g_s[m]\ \gamma[2b - m] \tag{11}$$

This decomposed signal is then passed through the channel and after that from AFB, which also constitutes a LPF and HPF with $g_a[m]$ and $h_a[m]$ respectively. The signal after AFB is received by users at the receiver side. The user with the highest transmit power detects its signal, considering other signals as interference. The other two users need to perform SIC in order to detect their signals. For perfect reconstruction at the receiver side, wavelet and scaling filter coefficients are related as,

$$g_a[V - 1 - m] = (-1)^m\ h_s[m] \tag{12}$$

$$h_a[V - 1 - m] = (-1)^m\ g_s[m] \tag{13}$$

where V denotes the length of filter. The received signal in the cth cluster from the lth user is,

$$y_{alc} = \sum_{a \in A(n)} h_{alc}^H\ w_{alc} \sum_{l=1}^{L} \sqrt{p_{alc}}\ x_{a_{IDWT}} + w_{alc} \tag{14}$$

where, w_{alc} is the Additive White Gaussian Noise (AWGN). Although wavelet pulse shaping for CF-mMIMO NOMA system exhibits improved performance, however inaccurate CE poses significant challenges. MMSE and LS estimation methods may not provide satisfactory precision in scenarios with user interference. Therefore, a DL based CE is implemented for the proposed system in order to further improve the performance of the system.

3. Deep learning based channel estimation

In this article, DL model using DNN has been employed to perform CE by leveraging the effectiveness of neural networks (NN) [42,43]. The basic structure of DNN for the proposed system is presented in Fig. 2. The proposed DNN is organized into one input layer, one output layer and 4 hidden layers. The proposed DNN is trained for

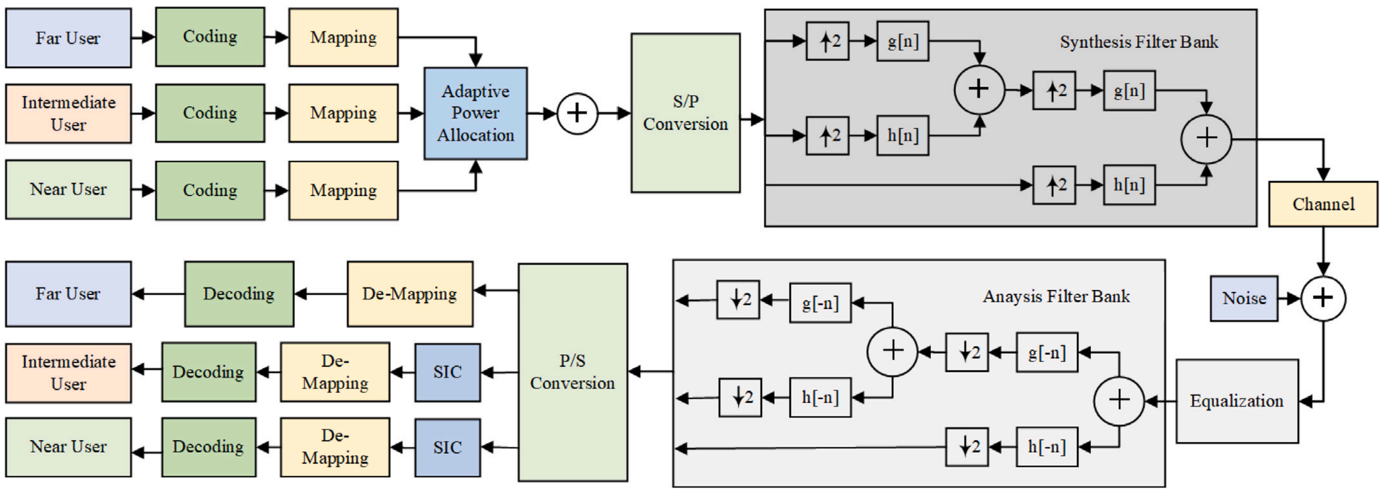

Fig. 1. Wavelet NOMA transceiver structure.

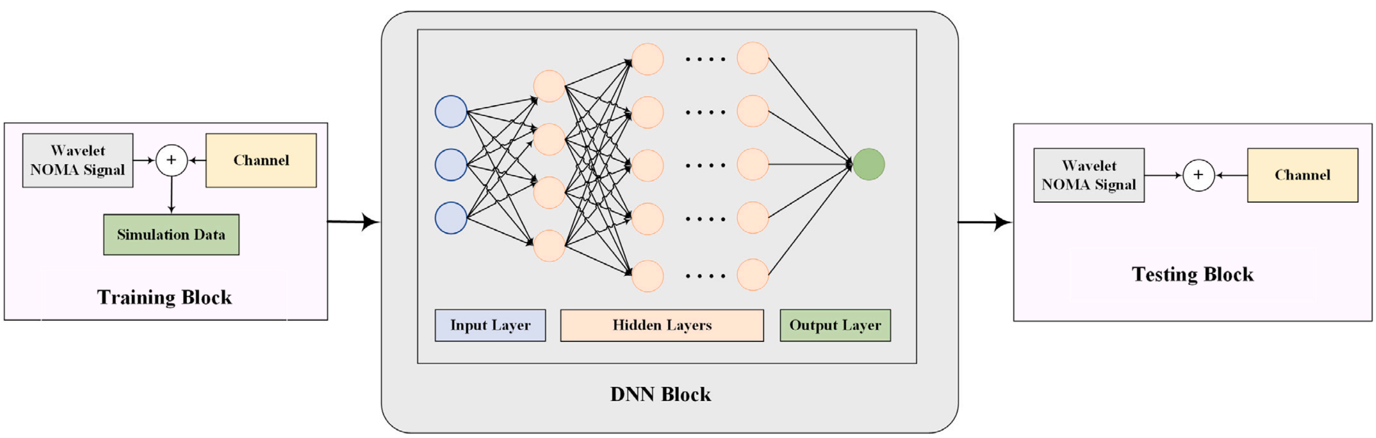

Fig. 2. DNN structure for wavelet NOMA scheme.

predicting channel estimates using received signals as inputs, which includes pilot contamination. After the training process, the DNN can learn to distinguish the contaminated pilots and desired channel, thus it improves the CE accuracy by reducing pilot contamination. *tanh* is used as an activation function for CE, which can be expressed as,

$$tanh(h) = \frac{e^h - e^{-h}}{e^h + e^{-h}} \tag{15}$$

For implementation of DNN, the system is adapted to an offline situation, while significant quantity of data is taken as input, which serves as the training set. The performance of DNN is evaluated using the trained networks.

3.1. Training and testing

The proposed DNN must be trained with a large number of iterations for channel impairments. The intention of DNN is to reduce the CE error. Therefore, the loss function can be written as mean square error (MSE),

$$MSE_{loss} = \frac{1}{M}\sum_{l=1}^{L_c}\left\|\mathbf{h}_{\mathbf{alc}} - \hat{\mathbf{h}}_{\mathbf{alc}}\right\|_2^2 \tag{16}$$

where M is total training samples. The gradient value of loss function is calculated with respect to model parameters [44]. This value indicates the magnitude and direction of change for minimizing the loss. The model parameters are updated using a gradient step using the learning rate of the optimizer.

In the testing phase of DNN, the system performance is evaluated based on a previous unseen data set [42,43]. In the testing phase, signals for the proposed system with wavelet NOMA scheme are generated. However, these signals do not require to be labelled because the purpose of testing phase is to evaluate the performance of DNN. It is expected that DL based CE would result in improved BER and achievable sum-rate of the proposed system. The expressions for achievable sum-rate and BER for the proposed wavelet NOMA based UC CF-mMIMO system are derived in the subsequent section.

4. Interference, BER and achievable sum-rate

Pilot contamination results in the intra-cluster and inter-cluster interference, for which closed-form expressions can be derived. A far user in the cluster will experience no interference from other user, because of highest power allocation. The other two users will experience interference from high power users. Therefore, using wavelet pulse-shaping scheme for the proposed system, intra-cluster interference between users can be expressed as,

$$W\_ICI_{alc} = \sum_{a\in A(n)}\sum_{l=1}^{L_c}\sum_{l'>1}^{L_c} x_{alc}x_{al'c} \tag{17}$$

where, x_{alc} and $x_{al'c}$ are given as,

$$x_{alc} = \sum_{i}\sum_{q=0}^{Q-1} S_{q,i}[r]\,\Phi_{q,i}[r] \tag{18}$$

where, Q denotes number of sub-carriers, i is the index of symbol for qth sub-carrier and $S_{q,i}$ is the ith symbol for the qth sub-carrier. $\Phi_{q,i}(t)$ represents the basis function that is used to modulate the incoming data symbols. It can be given as [14],

$$\Phi_{q,i}[r] = 2^{\frac{i}{2}}\ \Phi\ [2^{i} r - q] \tag{19}$$

Similarly, closed-form form expression for inter-cluster interference using wavelet pulse-shaping for the proposed system can be derived. Inter-cluster interference in the proposed system exists, if two far users of the adjacent clusters are located near to each other. Inter-cluster interference using wavelet pulse-shaping for the proposed system is given by,

$$W\_ICI_{inter_{alc}} = \sum_{a \in A(n)} \sum_{\substack{c=1 \\ c' \neq c}}^{C} x_{a2c} x_{a2c'} \tag{20}$$

where, x_{a2c} denotes the far user in cth cluster and $x_{a2c'}$ is the far user in adjacent cluster to cth cluster. Hence, in the cth cluster the achievable sum-rate can be expressed as,

$$R_{ac} = \emptyset_{alc} \sum_{l=1}^{L_c} \log_2(1 + SINR_{alc}) \tag{21}$$

where $\emptyset_{alc} = (1 - \frac{\tau_p}{\tau_{alc}})$ denotes the pre-log factor and $SINR_{alc}$ in the cth cluster is given by,

$$SINR_{alc} = \frac{Desired\ Signal}{Sum\ of\ all\ Interferences} = \frac{\left|DS_{alc}\right|^2}{IF_{alc}} \tag{22}$$

$$\begin{aligned} IF_{alc} &= \mathbb{E}\left[\left|W\_ICI_{inter_{alc}}\right|^2\right] \\ &\quad + \mathbb{E}\left[\left|W\_ICI_{intra_{alc}}\right|^2\right] + w_{alc} \end{aligned} \tag{23}$$

Using Eq. (21), the achievable sum-rate for wavelet NOMA based UC CF-mMIMO system is given as,

$$R_{sum} = \sum_{a \in A(n)} \sum_{c=1}^{C} R_{ac} \tag{24}$$

Furthermore, closed-form expression of BER for the proposed system is derived using Eq. (22), which is given as,

$$BER_{alc} = Q\ (SINR_{alc}) \tag{25}$$

where, BER_{alc} is the BER for lth user in the cth cluster. The wavelet pulse-shaping method for the NOMA scheme reduces the BER of the users, hence it implies that the achievable sum-rate of the users is also enhanced.

5. Results and discussions

In this article, a UC CF-mMIMO system is implemented with $A = 50$ having $L_A = 4$ and $K = 30$, randomly distributed over 1×1 km^2 area. For all K users, downlink transmit power is considered to be 200 mW. In this section, DNN based CE technique is implemented for a UC CF-mMIMO system with conventional and wavelet NOMA schemes. Non-orthogonal pilot sequences are used for LS and MMSE methods for CE as mentioned in Eq. (3) in Section 2. MMSE and LS are considered baseline methods for assessment and comparison of CE accuracy for the aforementioned techniques. The DNN proposed in this article is composed of one input layer, one output layer and 4 hidden layers, where number of neurons are 128, 2048, 1024, 512, 256, and 128. Tanh is used as an activation function for DNN, with 10^4 training samples and a batch size of 32. Adam optimizer is used for DNN with a learning rate of 0.01 and number of epochs is 50. This research work evaluates the effectiveness of DL based CE for CF-mMIMO system with wavelet NOMA scheme in comparison to conventional estimation methods. Simulations are done using MATLAB for achievable sum-rate and BER. Simulation parameters are described in Tables 2 and 3.

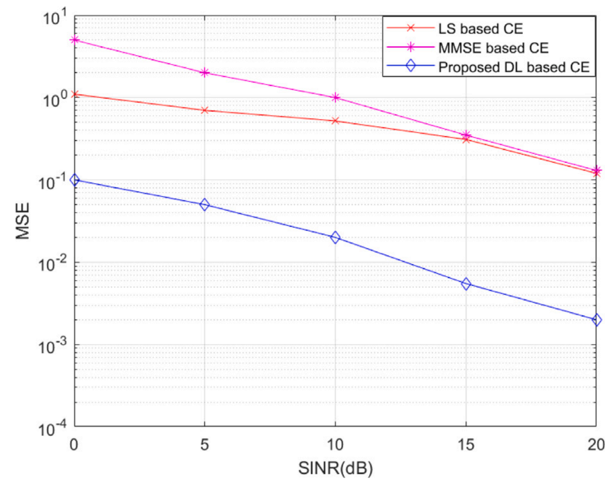

Fig. 3. MSE vs. SINR for CF-mMIMO system with wavelet NOMA scheme using LS, MMSE and DL based CE.

Table 2
Parameters setting.

Parameter	Value
Bandwidth	20 MHz
P_p	20 dBm
τ_p	20
σ_{sh}	8 dB
τ_{lc}	40
p_t	23 dBm
Wavelet level	2
Wavelet family	Daubechies

Table 3
Simulation parameters for DNN.

Parameter	Value
Learning rate	0.01
Total number of layers	6
Input layers	1
Hidden layers	4
Output layers	1
Epochs	50
Batch size	32
Training sample size	10^4

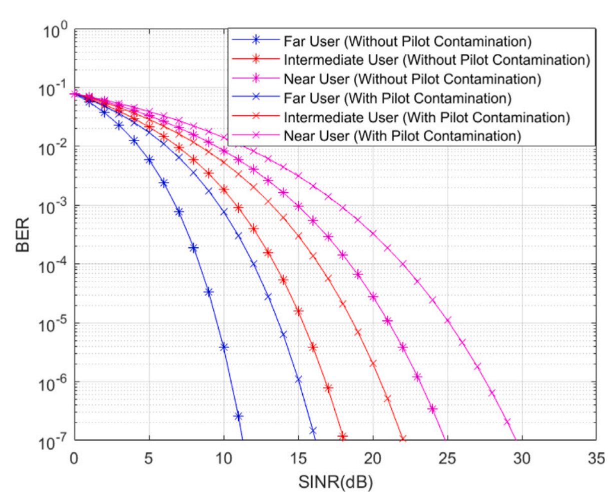

Fig. 4. BER vs. SINR in CF-mMIMO system with conventional NOMA using MMSE method for CE.

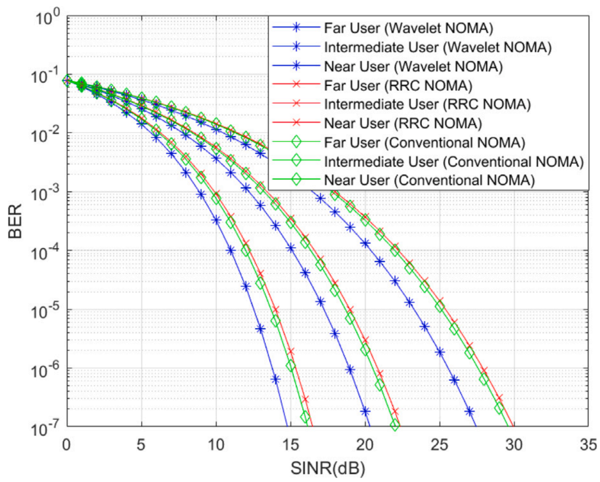

Fig. 5. BER vs. SINR in CF-mMIMO system using MMSE method for CE with pilot contamination.

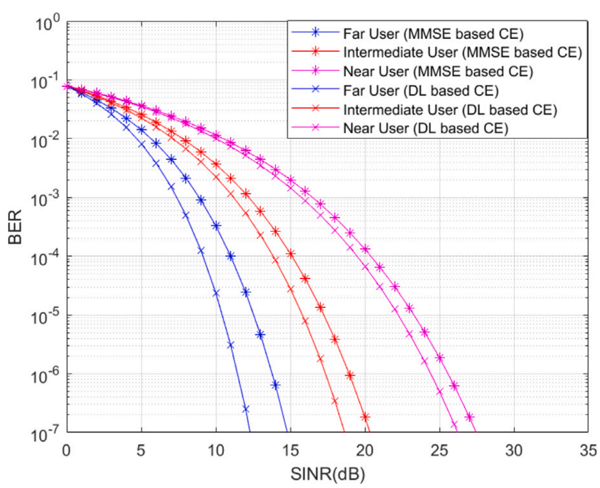

Fig. 6. BER vs. SINR for wavelet NOMA based CF-mMIMO system with pilot contamination.

Table 4
BER of users using MMSE and DL based CE with conventional and wavelet NOMA scheme.

BER with Conventional NOMA Scheme and MMSE			
SINR (dB)	8	10	12
Far user BER	0.0035	7×10^{-4}	1×10^{-4}
Near user BER	0.0116	0.0053	0.0020
Intermediate user BER	0.0222	0.0141	0.0082
BER with Wavelet NOMA Scheme and MMSE			
Far user BER	0.0021	3×10^{-4}	2.4×10^{-5}
Near user BER	0.0091	0.0036	0.0011
Intermediate user BER	0.0194	0.0115	0.0062
BER with Wavelet NOMA Scheme and DL based CE			
Far user BER	0.00049	2.3×10^{-5}	2.4×10^{-7}
Near user BER	0.0067	0.0022	0.0005
Intermediate user BER	0.0177	0.0101	0.0051

5.1. Analysis of BER of the system

Fig. 3 presents the MSE performance versus SINR of the proposed wavelet NOMA aided CF-mMIMO system for LS, MMSE and DL based CE. From this figure, it is observed that MSE for the proposed system is much reduced compared to both the LS and MMSE methods of estimations. At lower values of SINR the LS based CE shows improved performance compared to MMSE method, while for SINR values of 15 dB and above, both the LS and MMSE methods display similar values of MSE. The MSE for the CF-mMIMO with wavelet NOMA scheme using LS method of CE is $10^{-0.9}$ at 20 dB, which is almost equal to MMSE method of CE at 20 dB. Moreover, DL based CE for the proposed system provides MSE of $10^{-2.7}$ at 20 dB, which is much lower in value compared to the MSE produced by LS and MMSE methods for CE. Hence, DL based CE methods outperforms LS and MMSE for the proposed system with wavelet NOMA scheme, which also provides better performance in terms of reduced BER and increased achievable sum-rate.

In Fig. 4, BER of the users in a cluster is presented for the CF-mMIMO NOMA system with and without pilot contamination. From this figure, it is observed that the BER of all the users deteriorates in the presence of pilot contamination, whether they are near, intermediate or far user. The BER of the far user at 11 dB is about 2.6×10^{-7} when there is no pilot contamination, while it is 3×10^{-4} at 11 dB in the presence of pilot contamination. Similarly, near and intermediate users exhibit the same trend for BER for conventional NOMA CF-mMIMO system with pilot contamination.

Furthermore, Fig. 5 presents BER comparison of the users with root raised cosine (RRC) filtering, conventional NOMA and wavelet NOMA scheme using MMSE method for CE considering pilot contamination. From this figure, it is observed that the wavelet NOMA scheme for the CF-mMIMO system exhibits reduced BER, due to the inherent property of wavelet transform of reduced out-of-band radiations that helps mitigate inter-user interference caused by pilot contamination. Moreover, this figure shows that the with the application of wavelet NOMA scheme for the CF-mMIMO system in the presence of pilot contamination, the BER is reduced about 24% and 27% as compared to conventional NOMA scheme and RRC filtering respectively. Moreover, numeric values of BER for all the three users with conventional and wavelet NOMA scheme for the CF-mMIMO system using MMSE method for CE are shown in Table 4.

BER performance of wavelet NOMA based CF-mMIMO system is expected to improve with the application of DL for accurate CE compared to MMSE method for CE, as shown in Fig. 6. From this figure, it is observed that with pilot contamination, the BER of all three users is reduced using DL based CE. BER of the far user with wavelet NOMA scheme is about 2.4×10^{-5} at 12 dB SINR using MMSE method for CE. However, using DL based CE for the proposed CF-mMIMO system, the BER of the far user is 2.5×10^{-7} at 12 dB SINR. Similarly, BER of the near user is 6.2×10^{-3} at 12 dB using MMSE method for CE, while it is reduced to 5.1×10^{-3} with DL based CE. BER of the intermediate user is 5.4×10^{-4} and 1.1×10^{-3} at 12 dB with DL and MMSE method respectively. Moreover, from Fig. 6, it is observed that with wavelet NOMA scheme and DL based CE considering pilot contamination, the BER for each user in a cluster is almost 17% reduced. Furthermore, Fig. 7 shows the simulated and the analytical BER for three users in wavelet NOMA aided CF-mMIMO system with DL based CE, which validates the close agreement between two results. BER of three users with wavelet NOMA scheme using DL is also shown in Table 4. From this table, it is validated that DL based CE helps in reducing the BER of the system, which also results in an increased achievable sum-rate. Moreover, Table 5 shows the percentage improvement of BER for the CF-mMIMO system using different pulse-shaping methods and CE methods.

5.2. Analysis of achievable sum-rate of the system

The achievable sum-rate for the CF-mMIMO system using conventional NOMA scheme is shown in Fig. 8. From this figure, it is observed that the CF-mMIMO system with conventional NOMA scheme provides an achievable sum-rate of 51.5 bps/Hz at 40 dB SINR. However, the incorporation of wavelet pulse-shaping for the NOMA scheme in the CF-mMIMO system outperforms the conventional NOMA scheme.

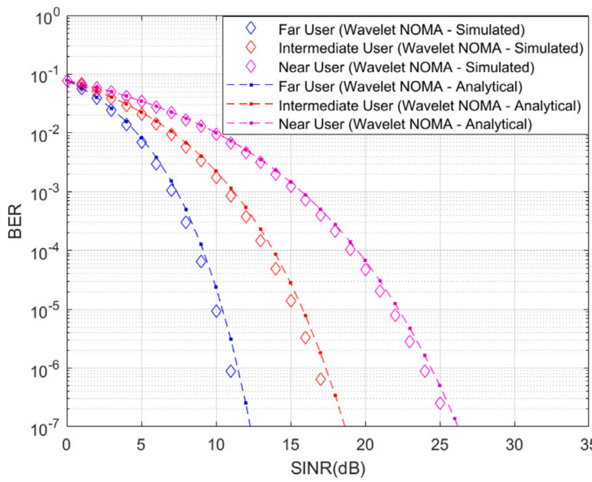

Fig. 7. Analytical and simulated BER vs. SINR of users in a CF-mMIMO system using DL based CE.

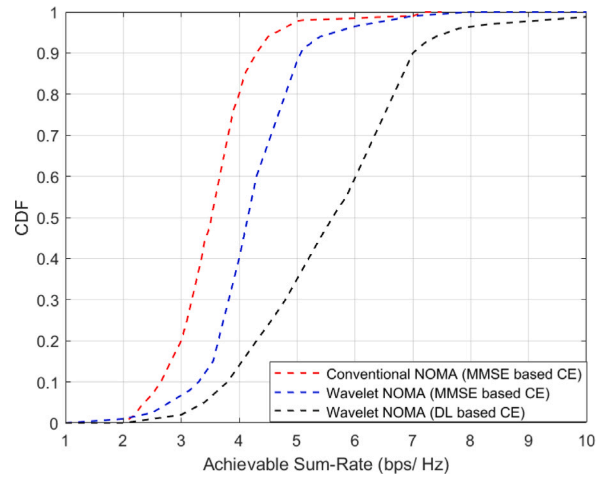

Fig. 10. Cumulative distribution of achievable sum-rate for CF-mMIMO system.

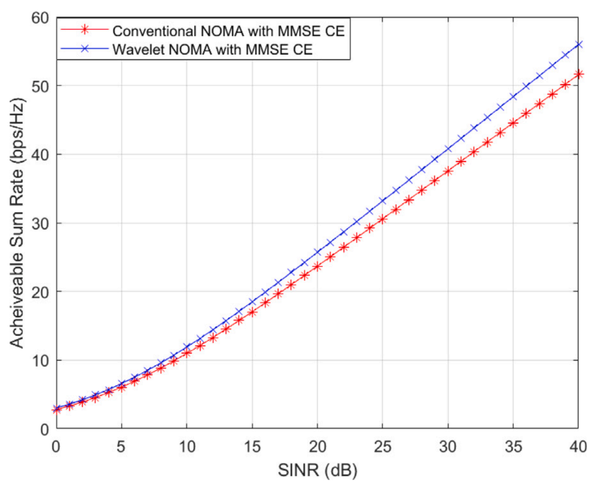

Fig. 8. Achievable sum-rate vs. SINR of CF-mMIMO system without pilot contamination.

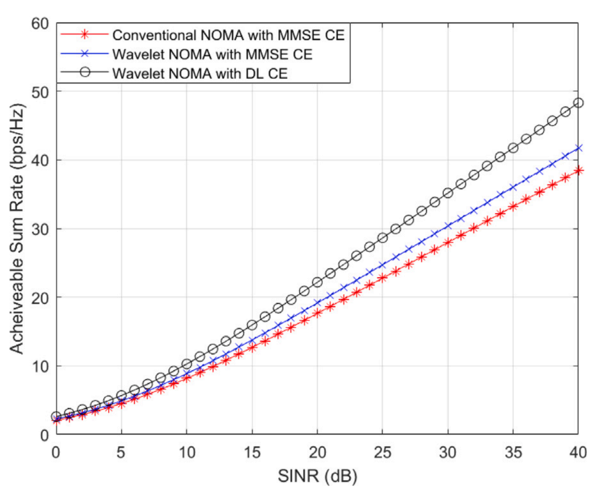

Fig. 9. Achievable sum-rate vs. SINR of CF-mMIMO system with pilot contamination.

This is because wavelet pulse-shaping does not utilize CP and due to its spectral confinement, it has greater immunity against inter-user interference. At a value of SINR equal to 40 dB, an achievable sum-rate attained by CF-mMIMO system with wavelet NOMA scheme is 54.5 bps/Hz, which is 5% higher than the conventional NOMA scheme at the same SINR.

Fig. 9 presents the achievable sum-rate of the proposed system for the conventional and wavelet NOMA scheme with pilot contamination using MMSE method and DL based CE. From this figure, it is observed that the achievable sum-rate at 40 dB SINR, for the wavelet based CF-mMIMO system with pilot contamination using MMSE method for CE, is 9% increased as compared to conventional NOMA scheme. Moreover, the proposed system with wavelet NOMA scheme considering pilot contamination and using DL based CE attains an achievable sum-rate of 49.2 bps/Hz at 40 dB SINR, which is 15% higher than wavelet NOMA scheme using MMSE method for CE. Since, MMSE method uses pilot tones for CE, the pilots get contaminated due to channel noise and thus leads to inaccurate CSI, thus inevitably produces reduced sum-rate. Furthermore, Fig. 10 presents the cumulative distribution function (CDF) of achievable sum-rate of the CF-mMIMO system. From this figure, it can also be observed that CF-mMIMO system, employing wavelet NOMA scheme and DL based CE, outperforms compared to conventional NOMA scheme and MMSE based CE. Hence, it is evident that DL based CE is more suited for a CF-mMIMO system with wavelet NOMA scheme as compared to the conventional estimation methods. Further, Table 5 shows the percentage improvement of achievable sum-rate offered by the proposed system in comparison to traditional estimation methods for CE.

Moreover, Fig. 11 shows the achievable sum-rate against number of APs in the CF-mMIMO system, employing conventional and wavelet NOMA scheme using MMSE method and DL based CE, when number of users are fixed, K=40. It can be observed that the achievable sum-rate for the CF-mMIMO system grows with an increase in the number of APs, which shows the scalability of the system. From this figure, it can be seen that using MMSE method for CE, CF-mMIMO system with wavelet NOMA scheme provides 6% higher achievable sum-rate compared to conventional NOMA scheme. Moreover, DL based CE for a CF-mMIMO system with wavelet NOMA scheme offers 22% higher achievable sum-rate compared to conventional and wavelet NOMA schemes with MMSE method.

Fig. 12 presents the achievable sum-rate with increasing number of users for the CF-mMIMO system with wavelet and conventional NOMA schemes, using MMSE and DL method for CE with 100 APs. This figure shows that when the number of users is less than the number of APs, the achievable sum-rate of the system shows an increasing trend. However, when number of users exceeds the number of APs in the system, it will results in achievable sum-rate with a decreasing trend.

Table 5
Percentage improvement of BER and achievable sum-rate.

	Percentage improvement of the proposed CF-mMIMO system employing Wavelet NOMA Scheme and DL based CE as compared to:		
	Conventional NOMA with MMSE	RRC Filtering NOMA with MMSE	Wavelet NOMA with MMSE
Improvement of BER at SINR = 12 dB	37%	40%	17%
Improvement of Achievable Sum-Rate at SINR = 40 dB	21%	23%	15%

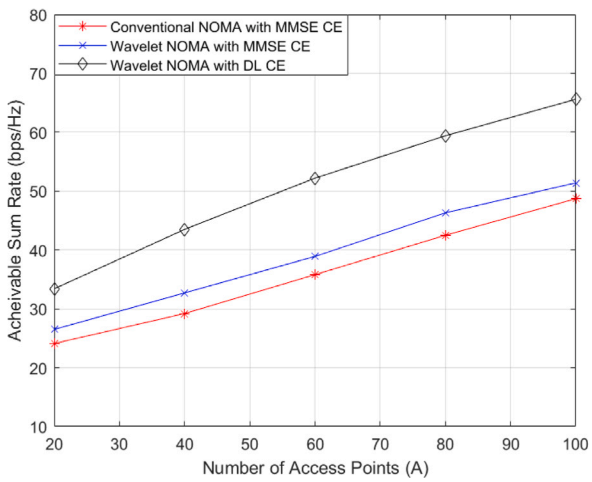

Fig. 11. Achievable sum-rate vs. Number of APs with $K = 40$ users.

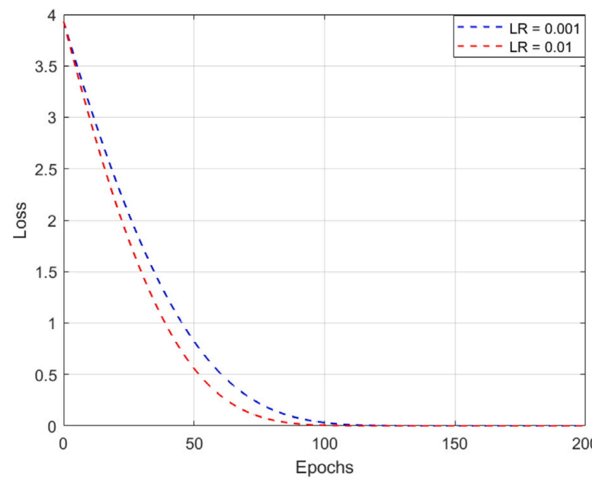

Fig. 13. Performance of DNN for different learning rates.

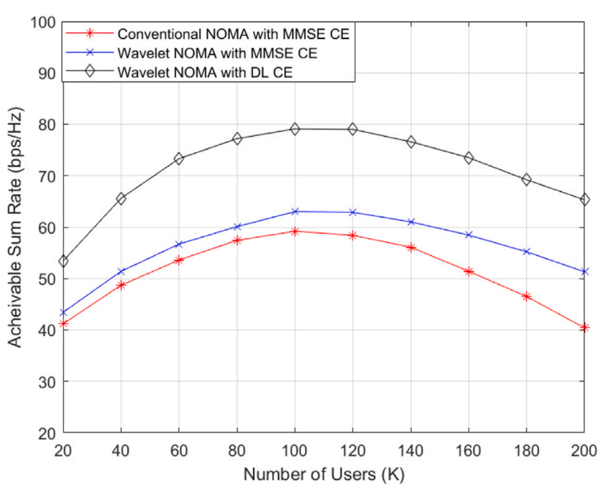

Fig. 12. Achievable sum-rate vs. Number of users with $A = 100$ APs.

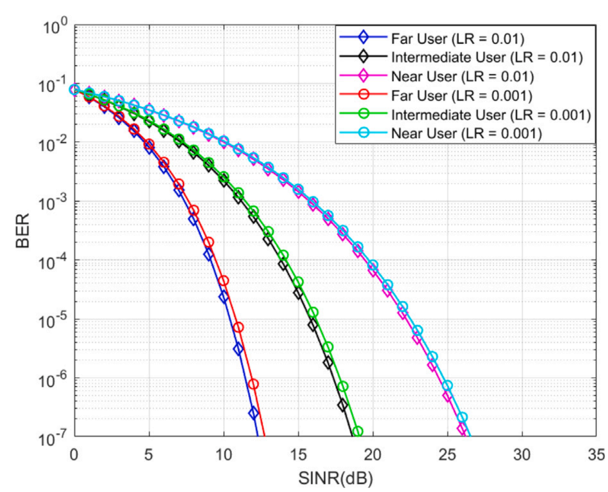

Fig. 14. BER vs. SINR of the proposed system with different LR.

This is because in a CF-mMIMO system all APs needs to coordinate with each other. When the number of users grows in the system, it will lead to signalling and computational overhead associated with this coordination and hence, the achievable sum-rate of CF-mMIMO system decreases.

The choice of adopting a suitable learning rate (LR) impacts the performance of the network by allowing a stable training process. For the proposed system, a LR of 0.01 has the greatest contribution in a stable training process and it achieves better performance as compared to LR = 0.001, as shown in Fig. 13. Moreover, Fig. 14 shows the BER of all three users for a particular cluster with 0.01 and 0.001 LR. From this figure, it is observed that the BER of each user is reduced with a LR = 0.01 as compared to LR = 0.001. Similarly, Fig. 15 shows that the proposed system attains a higher achievable sum-rate, when LR is set to 0.01. Furthermore, Fig. 16 shows the effect of number of nodes used in the proposed DNN. From this figure, it can be observed that MSE for CE is reduced with increasing number of nodes in the proposed DNN.

5.3. Complexity analysis

The results of the proposed technique present significant improvement over the conventional system, however, without considering the computational complexity of the proposed technique, this performance improvement cannot be completely justified. Initially, we discuss the complexity of user clustering for various k-means algorithms. In this article, user clustering is implemented with improved k-means++ algorithm, which leads to $O(2AK+CK)$ complexity. Here, A is the total APs, C is the total number of clusters and K is the number of users. However, its predecessor k-means and k-means++ algorithm have complexity of $O(AKIC)$ and $O(KCA)$, where I denotes the total number of iterations until convergence of the algorithm [17]. Improved k-means++ gives a lower computational complexity compared to k-means and k-means++.

The computational complexity of the UC CF-mMIMO NOMA system does not show linear growth as number of users are increased, as

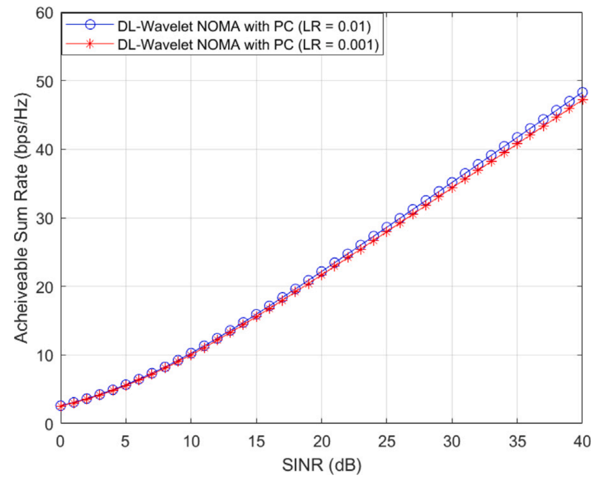

Fig. 15. Achievable sum-rate vs. SINR of the proposed system with different LR.

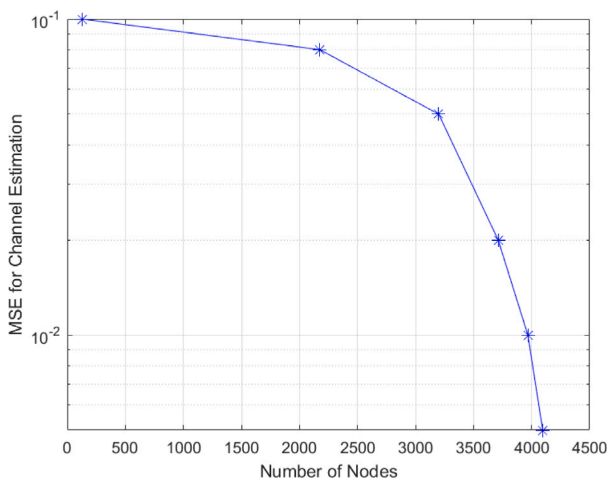

Fig. 16. MSE for CE vs. Number of nodes in DNN.

every ath AP can serve only N number of users associated to it. Thus, it is observed that the complexity of UC CF-mMIMO NOMA system is $O(\frac{AN+CN}{2})$, which is lower compared to conventional CF-mMIMO NOMA system. Hence, it is observed that UC CF-mMIMO NOMA system with ML approach may provide improved sum-rate and reduced complexity.

Moreover, the wavelet NOMA scheme is used for the proposed system with wavelet filter banks. DWT takes only $O(N)$ in certain cases when implemented with filter banks. If the length of $g[n]$ and $h[n]$, is independent of N (number of users associated with an AP), then $x * g$ and $x * h$ both take $O(N)$ operations. Filter banks do these convolutions with $O(N)$, then the signal is split into two branches of $N/2$ size. It will lead to the following recursive relation,

$$T(N) = 2N + T\left(\frac{N}{2}\right) \tag{26}$$

This relation given in Eq. (26) can be expanded into a tree to observe the value at each level,

$$T\left(\frac{N}{2}\right) = 2\left(\frac{N}{2}\right) + T\left(\frac{N}{4}\right) = N + T\left(\frac{N}{4}\right)$$

$$T\left(\frac{N}{4}\right) = 2\left(\frac{N}{4}\right) + T\left(\frac{N}{8}\right) = \frac{N}{2} + T\left(\frac{N}{8}\right)$$

At each level, the computational complexity of wavelet NOMA based CF-mMIMO system depends on the number of N users associated with an AP. The computational complexity increases as the number of users increases. At the ith level, the computational complexity is basically $2 \times N/2^i$.

Furthermore, complexity analysis for DL based model is basically to calculate the number of operations at fully connected layers. For the proposed CF-mMIMO system, the complexity of decoding for DNN is $O(L)$, where L is the number of users in the cth cluster. Thus, for the trained model of DNN, it is assumed that z_1, z_2, z_3, z_4 are the neurons in the DNN network. For t number of training samples with I_{DL} iterations required for DL process, complexity of DL based CF-mMIMO with wavelet NOMA scheme is given as,

$$O(t * I_{DL} * (z_1\ z_2 + z_1\ z_4 + z_3\ z_4)) \tag{27}$$

Computational complexity of DNN network differs for training and testing stages. For the proposed network, the output layer processes the decisions after the entire system has been given the inputs. Therefore, the complexity of the DNN network in Eq. (27) reduces to the following,

$$O(z_1\ z_2 + z_1\ z_4 + z_3\ z_4) \tag{28}$$

The computational complexity of LS method and MMSE method is $O(p^2)$ and $O(p^3)$ respectively, where I_{DL} is the number of iterations required for DL process. It is observed that the complexity of LS method and MMSE method is higher than the proposed DL based CF-mMIMO system with wavelet NOMA scheme. Hence, it is evident that the proposed DNN based model for CF-mMIMO system with wavelet NOMA scheme exhibits reduced computational complexity compared to traditional CE methods.

6. Conclusion

A CF-mMIMO system with multi-user wavelet NOMA scheme is proposed with UC approach, in which users are grouped in clusters with the help of improved k-means++, an unsupervised ML algorithm. Moreover, the proposed system's performance is enhanced with a DL based channel estimation technique, which subsequently reduces transmission overhead. The simulation results showed that in the presence of pilot contamination using conventional CE methods, the BER of wavelet NOMA scheme is improved by 24% compared to the conventional NOMA scheme. Moreover, the proposed CF-mMIMO system offers 17% reduced BER employing wavelet NOMA scheme and DL based CE as compared to MMSE with wavelet NOMA scheme. Furthermore, the achievable sum-rate for the proposed system with wavelet NOMA scheme is 9% higher compared to the conventional NOMA scheme using MMSE method for CE. Furthermore, in the presence of pilot contamination, the CF-mMIMO system with wavelet NOMA scheme and DL based CE outperforms the MMSE method with wavelet NOMA scheme by providing a 15% enhanced achievable sum-rate. Moreover, the proposed system also offers an overall reduced computational complexity compared to the conventional NOMA scheme and conventional CE technique. Hence, the proposed wavelet NOMA scheme-based UC CF-mMIMO system is well suited for the next-generation networks, which demand greater sum-rate and accuracy for multi-user communication in addition to reduced interference. Future works may consider CF-mMIMO system with wavelet NOMA scheme with a memory based recurrent model for further improvements in system performance.

CRediT authorship contribution statement

Rabia Arshad: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Sobia Baig:** Writing – original draft, Validation, Supervision, Formal analysis, Conceptualization. **Saad Aslam:** Writing – review & editing, Resources, Formal analysis. **Muneeb Ahmad:** Writing – review & editing. **Shahid Mumtaz:** Writing – review & editing, Supervision.

Declaration of competing interest

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.

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