Sparse Signature Matrix Optimization for NOMA under Imperfect CSI

Kun Lu (✉ lukuncumt@126.com)

Beijing University of Posts and Telecommunications <https://orcid.org/0000-0001-6629-8004>

Hongwen Yang

Beijing University of Posts and Telecommunications

Research

Keywords: NOMA, LDSM, CSI, LMMSE, BBPSO

Posted Date: May 7th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-484566/v1>

License: This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

RESEARCH

Sparse signature matrix optimization for NOMA under imperfect CSI

Kun Lu* and Hongwen Yang

*Correspondence:
lukuncmt@126.com
School of Information and
Communication Engineering,
Beijing University of Posts and
Telecommunications, Xitucheng
Road 10, 100876 Beijing, China
Full list of author information is
available at the end of the article

Abstract

Non-orthogonal multiple access (NOMA) can support the rapid development of the Internet of Things (IoT) with its potential to support high spectral efficiency and massive connectivity. The low-density superposition modulation (LDSM) scheme is one of the NOMA schemes and uses the sparse signature matrix to reduce multiple access interferences (MAI). In order to improve the NOMA system performance in practice, this paper focuses on designing the sparse signature matrix with a large girth for LDSM under imperfect channel state information (CSI). Based on the orthogonal pilot and linear minimum mean square error (LMMSE) estimation, the LDSM optimized by bare-bone particle swarm optimization (BBPSO) algorithm has a larger girth and can gather more accurate information in the process of iterative decoding convergence. An extrinsic information transfer (EXIT) chart analysis is designed for the LDSM-OFDM system as a theoretical analysis tool. The simulation results show that the optimized LDSM outperforms the reference LDSM system, bringing about a 0.5 dB performance gain.

Keywords: NOMA; LDSM; CSI; LMMSE; BBPSO

1. Introduction

With the rapid development of the mobile Internet and mobile Internet of Things (IoT) [1–3], the Sixth generation (6G) mobile communication systems require a higher spectrum efficiency, connection number, and reliability [4]. The traditional Orthogonal Multiple Access (OMA) scheme can not satisfy the rapid demand of the mobile communication systems for the number of access users because of the limitation of time-frequency resources. Non-orthogonal multiple access (NOMA) is a potential technology that can improve users' access or devices in an IoT scenario. In the NOMA system, multiple users' signals are assigned to the same time-frequency resource for superimposed transmission. It can increase the number of access users or IoT devices through overload transmission. Interference is introduced in multi-user superimposed transmission, which requires an advanced detection algorithm to separate multi-user information.

To combat the multi-user superimposed interference, many NOMA schemes based sparse signature matrix have been proposed, such as low-density spreading (LDS) [5, 6], pattern division multiple access (PDMA) [7], sparse code multiple access (SCMA) [8], low density superposition modulation (LDSM) [9] and so on. The signals of users are mapped to the resource element (RE) by the sparse signature matrix. Sparse signature matrix reflects the collision of multiple users on the same resources. The signals superimposed on different resources are not uniform, relying on non-zero

entries in the sparse signature matrix. Due to the sparsity of the signature matrix, the message passing algorithm (MPA) is used to separate multi-user superimposed information. The MPA detection algorithm is an iterative decoding algorithm based on the factor graph between variable node (VND) and check node (CND) of the signature matrix. It is similar to the belief propagation (BP) decoding algorithm of low-density parity-check (LDPC) code. The sparse structure of the signature matrix affects the receiver's complexity and affects the performance of the NOMA system.

Various research works have been done to improve the performance of the NOMA system or reduce the computational complexity of the receiver for designed the sparse signature matrix. Most of the NOMA schemes are based on designing a low dimension signature matrix, such as LDS, SCMA, PDMA [10–12]. The NOMA sparse signature matrix dimension is low. The user's signals are mapped by the signature matrix and allocated to the closer resources, improving the transmission error rate. Moreover, there may be a short cycle in the low dimension NOMA sparse signature matrix, which affects the accuracy of iterative detection. [9] proposes a new LDSM scheme with a large dimension sparse signature matrix. The large dimension sparse signature matrix generally has a larger girth, so its iterative detection accuracy is higher than the low dimension matrix. The large dimension LDSM's user data symbols are more dispersed in time-frequency resources, so it has higher diversity gain. In [13], a method to optimize the degree distribution of the LDSM sparse signature matrix is proposed, which structures a larger girth for LDSM. Most of the research on NOMA technology is carried out in the perfect channel state information (CSI) scenario. To improve the practicability of NOMA technology, this paper studies the design of the NOMA sparse signature matrix under an imperfect CSI scenario.

Recently, some scholars have studied the NOMA system under realistic channel estimation. The least mean squares (LMS) algorithm is proposed to estimate the channel information of the power domain NOMA system [14]. In [15], the channel estimation error of linear minimum mean square error (LMMSE) algorithm is smaller than that of weighted least square (WLS) algorithm for uplink power domain NOMA systems. The error caused by imperfect CSI decreases the performance of the NOMA system. The sparse structure of the NOMA signature matrix also influences the performance of the NOMA system due to its dramatic impact on the multiple user interference.

This paper focuses on the optimization sparse signature matrix of NOMA under imperfect CSI conditions with bare-bone particle swarm optimization (BBPSO) algorithm [16]. The main contributions of this paper can be summarized as follows:

- We propose an uplink LDSM-OFDM system under imperfect CSI conditions, and the orthogonal pilot design of the NOMA system is given.
- We formulate the optimization problem for the sparse signature matrix of LDSM. Based on the EXIT chart, we utilize the BBPSO algorithm to optimize the degree distribution of the LDSM signature matrix. EXIT chart analysis is provided to illustrate the optimum solutions.
- Compare the performance of the optimized LDSM and reference LDSM [9]. The bit block error rate (BLER) simulations show that optimized LDSM outperforms the corresponding LDSM scheme. The reason is that the optimized matrix has a larger girth.

The rest of the paper is organized as follows. We present the proposed LDSM-OFDM system model and related optimization problems in Section 2. Simulation results and discussion are provided in Section 3. Finally, Section 4 includes the main conclusions of the paper.

2. Method

In this Section, the LDSM-OFDM system model under imperfect CSI conditions is firstly proposed. Then, the sparse signature matrix optimization method for LDSM is presented.

2.1 System model

Fig.1 describes an uplink LDSM-OFDM communication system with J users under imperfect CSI conditions. At the transmitter side, user j encodes the information sequence $\mathbf{b}_j$. The coded binary information data sequence for user j is modulated. The modulated symbols $\mathbf{c}_j$ are encoded by a $S \times l$ sparse signature matrix $\mathbf{F}_j$ which is part of LDSM sparse signature matrix $\mathbf{F} = [\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_J]_{S \times Jl}$. The encoding symbols vector for user j is $\mathbf{z}_j$, and the OFDM time-frequency resources are allocated to encoding data symbols. The transmitter generates a pilot signal, inserts a pilot sequence into the OFDM symbol. The symbols of each user are sent after OFDM modulation. In wireless communication, the signals sent by users arrive at the base station through different paths, including data symbols and pilot signals.

At the receiving, the received multi-user superimposed information is demodulated by OFDM first. The channel information of each user is estimated by the received signal at the pilot position. Then the data of each user is separated by the multi-user detection algorithm. The received symbol can be expressed as:

$$\mathbf{y} = \sum_{j=1}^J \text{diag}(\hat{\mathbf{h}}_j) \mathbf{z}_j + \mathbf{n}. \quad (1)$$

where $\text{diag}(\hat{\mathbf{h}}_j)$ is a diagonal matrix, $\hat{\mathbf{h}}_j$ represents the j -th user's channel coefficient, and $\mathbf{n}$ is the additive white Gaussian noise (AWGN) vector with zero mean and variance σ^2 .

2.1.1 LDSM coding

A LDSM coding process for user j is showed in Fig.2. $\mathbf{F}_j$ is the sparse signature matrix for user j . The column of the $\mathbf{F}_j$ is a sparse vector consisting of S REs which has many zero elements. Each modulated symbol is spread to S resources through sparse vector. The parallel data streams $\mathbf{c}_j = [c_1^j, c_2^j, \dots, c_l^j]^T$ are coding by $\mathbf{F}_j$. The superposition coding vector $\mathbf{z}_j$ can be expressed as:

$$\mathbf{z}_j = \mathbf{F}_j \mathbf{c}_j \quad (2)$$

The LDSM system's signature matrix $\mathbf{F}_{S \times Jl}$ has S rows and Jl columns. LDSM sparse signature matrix is constructed by progressive edge-growth (PEG) algorithm [17]. LDSM scheme can obtain the diversity gain in large dimensions. To improve the accuracy of the MPA decoding algorithm, we need to construct a larger girth for LDSM.

2.1.2 Pilot design

The pilot sequence position of the NOMA scheme is designed as shown in Fig. 3. It offers the pilot sequence design for six users. As shown in the figure, the pilot symbols for user j are separated by 6 REs on OFDM symbols, and the pilots of each user are distributed on the first and the seventh OFDM symbols. The remaining OFDM symbols are taken to send the signals to all users. The reference signal for user j denotes $\mathbf{R}_j$. The channel information of the data symbols can be obtained using the channel information estimated at the pilots. Suppose that the received signal at the pilot position of the user j is expressed as:

$$\mathbf{Y}_j = \mathbf{H}_j \mathbf{R}_j + \mathbf{N}_j \quad (3)$$

Where $\mathbf{N}_j$ is an AWGN with variance σ^2 and mean 0. $\mathbf{H}_j$ is the channel frequency response at pilot position for user j . LMMSE algorithm is used to estimate CSI. LMMSE algorithm is a modification of the least square (LS) channel estimation algorithm. The LS channel estimation algorithm calculates the channel response of the pilot position without considering the influence of Gaussian white noise. It then obtains the channel information of all users by interpolation. The $\tilde{\mathbf{H}}_{LS}$ channel estimation of each pilot symbol position obtained by the LS algorithm is expressed as:

$$\tilde{\mathbf{H}}_{LS} = \arg \min \left| \mathbf{Y}_j - \mathbf{R}_j \tilde{\mathbf{H}}_{LS} \right| \quad (4)$$

The $\tilde{\mathbf{H}}_{LMMSE}$ channel estimation by LMMSE algorithm is obtained by:

$$\tilde{\mathbf{H}}_{LMMSE} = \mathbf{R}_{\mathbf{H}\mathbf{H}_j} (\mathbf{R}_{\mathbf{H}_j \mathbf{H}_j} + \frac{\beta}{SNR} I)^{-1} \tilde{\mathbf{H}}_{LS} \quad (5)$$

where $\mathbf{R}_{\mathbf{H}\mathbf{H}_j} = E\{\mathbf{H}\mathbf{H}_j^H\}$, $\mathbf{R}_{\mathbf{H}\mathbf{H}_j}$ represents the covariance matrices. $\beta = E\{|\mathbf{X}_k|^2\}E\{|\mathbf{X}_k|^{-2}\}$ is a constellation factor depending on the signal constellation.

2.2 The sparse signature matrix optimization method

In this section, the sparse signature matrix optimization method is accomplished in two parts. First, the sparse signature matrix is represented as an optimization problem according to the extrinsic information transfer (EXIT) chart analysis. Second, the BBPSO search algorithm is used to solve the optimization problem.

2.2.1 Optimization problem based on EXIT Chart

The tool of EXIT chart is used for analyzing the iterative decoder process [18]. To get the EXIT charts for the LDSM system, the receiver of the LDSM system contains two parts. As shown in Fig. 4, EXIT function of decoder A and decoder B is $T_A(\cdot)$ and $T_B(\cdot)$. Decoder A includes the NOMA multi-user detector (MUD) demodulation, and Decoder B represents the FEC decoder. EXIT chart is obtained by EXIT curves of decoder A and decoder B. The information exchange between decoder A and decoder B with iterations is analyzed on multi-path fading channels. We divide the decoder's input information into two parts, which are defined as priority log-likelihood ratio (LLR) and extrinsic LLR. L_a denotes priori LLR and

L_e denotes its output extrinsic LLR. A priori LLR L_a is modeled as an independent Gaussian random variable. We can write a priori LLR L_a as follows:

$$L_a = u_A \cdot x + n_A, \quad (6)$$

where $u_A = \frac{\sigma_A^2}{2}$ and $x \in \pm 1$. n_A is a Gaussian random variable with variance σ_A^2 and mean 0. The probability density function is written as:

$$p(\varsigma | \mathbf{x} = x) = \frac{1}{\sqrt{2\pi}\sigma_A} \exp \left\{ - \left(\varsigma - \frac{\sigma_A^2}{2} x \right)^2 / 2\sigma_A^2 \right\}. \quad (7)$$

The mutual information $I_A = I(X; L_a)$ is calculated by [19]:

$$\begin{aligned} I_A(\sigma_A) &= \\ \frac{1}{2} \sum_{x=-1,1} \int_{-\infty}^{+\infty} p_A(\varsigma | X=x) \log_2 \frac{2p_A(\varsigma | X=x)}{p_A(\varsigma | X=-1) + p_A(\varsigma | X=1)} d\varsigma \\ &= 1 - \int_{-\infty}^{+\infty} \frac{e^{-((\varsigma - \sigma_A^2/2)^2 / 2\sigma_A^2)}}{\sqrt{2\pi}\sigma_A} \cdot \log_2(1 + e^{-\varsigma}) d\varsigma. \end{aligned} \quad (8)$$

We define

$$J(\sigma) := I_A(\sigma_A = \sigma). \quad (9)$$

with

$$\lim_{\sigma \rightarrow 0} J(\sigma) = 0, \quad \lim_{\sigma \rightarrow \infty} J(\sigma) = 1, \quad \sigma \geq 0.$$

The input information of MPA MUD include the information $\mathbf{y}$ from channel and a priori information I_A^A from the FEC decoder. The MPA MUD outputs mutual information I_E^A and I_E^A as a priori information is sent to FEC decoder. The extrinsic information I_E^B of the FEC decoder is passed to the MPA MUD as a priori information I_A^A . The EXIT curves for MPA MUD and FEC decoders reflect the performance of the iterative system. Therefore, it is useful to design an efficient algorithm to match decoder A chart and decoder B chart. The design of LDSM signature matrix has great influence on system performance. Therefore, it is very important to find an optimization method to design the signature matrix of LDSM. The degree distribution of LDSM VND detector denotes $\mathbf{m} = [m_1, m_2, \dots, m_{D_v}]$. The degree distribution of LDSM CND detector denotes $\mathbf{n} = [n_1, n_2, \dots, n_{D_c}]$. Therefore, the objective function problem is represented as:

$$f(\mathbf{m}, \mathbf{n}, \overline{SNR}, \tilde{\mathbf{H}}) = \min_{n=1,2,\dots,N_s} [T_A(I_A^A) - T_B^{-1}(I_E^B)]^2 \quad (10)$$

$$(\mathbf{m}, \mathbf{n}) = \arg \min_{\overline{SNR}} [f(\mathbf{m}, \mathbf{n}, \overline{SNR}, \tilde{\mathbf{H}}) > 0] \quad (11)$$

$$\begin{aligned}
s.t. \quad & f(\mathbf{m}, \mathbf{n}, \overline{SNR}, \tilde{\mathbf{H}}) > 0, \\
& \sum_i m_i = 1, \\
& \sum_j n_j = 1, \\
& 0 < m_i < 1, \\
& 0 < n_j < 1.
\end{aligned} \tag{12}$$

Where m_i is the VND degree distribution of degree i . n_j is the CND degree distribution of degree j . The minimum threshold channel is $SNR(dB)$.

2.2.2 BBPSO optimization method

The BBPSO algorithm is to search for the personal optimization solution and the global optimization solution through iterative updating. A feasible solution is regarded as a particle in a swarm. In BBPSO algorithm, the set of particles is represented by $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_W\}$, which each particle $\mathbf{x}_w = [x_{w,1}, x_{w,2}, \dots, x_{w,D}]^T$ denotes the potential solution, the total number of particles is W and the dimensions of problem is D . The fitness to evaluate a particle is equation (10). The position of particle i at iteration $(t+1)$ is updated as follows:

$$x_{i,j}(t+1) = u_{i,j}(t) + \sigma_{i,j}(t)N(0,1) \tag{13}$$

where

$$u_{i,j}(t) = 0.5(P_{i,j}(t) + G_{i,j}(t)) \tag{14}$$

$$\sigma_{i,j}(t) = |P_{i,j}(t) - G_{i,j}(t)| \tag{15}$$

Where x_{ij} denotes the j -th dimension for the particle i . $u_{i,j}$ is a mean of Gaussian distribution. $N(0,1)$ represents a standard Gaussian random variable with variance of 1 and mean of 0. $\mathbf{P}_i$ is the personal best position for the particle i . $\mathbf{G}_g$ denotes the global optimal position of particle in a particle swarm. The proposed BBPSO-EXIT algorithm can be summarized as follows:

According to Algorithm 1, The optimal solution is searched through iteration. The uplink LDSM-OFDM system is considered. LTE turbo code as channel coding and the degree distribution of LDSM signature matrix is optimized based on the BBPSO algorithm. The overload is 150%, QPSK modulation, the bit rate is 1/2, the number of users is 6, and the number of bits sent by each user is 144 bits. Therefore, the corresponding dimension of the LDSM matrix is $576 * 864$. The detailed simulation parameters are shown in Table 1. The optimal m_2 is 0.925 and the optimal m_3 is 0.075, respectively. The optimal n_3 is 0.887 and the optimal n_4 is 0.113, respectively. The girth of the large dimensional optimized matrix is 18. The girth of the reference LDSM in [9] is 10. The degree distribution of reference LDSM variable nodes is $m_2=m_4=0.5$. The degree distribution of reference LDSM check nodes is $n_4=n_5=0.5$. The corresponding EXITs analysis is shown in Fig.5. Observe from Fig.5a that the MPA MUD's mutual information I_E^A for optimized LDSM intersects with the decoder curve later than that for reference LDSM. The simulated SNR threshold for optimized LDSM is 5.0 dB. As shown in Fig.5b, The reference

Algorithm 1 :BBPSO-EXIT Algorithm.

```

1: Initialize: the dimensions  $S \times N_L$  of LDSM signature matrix  $F$ , overloading factor  $L = N_L/S$ , pilot
   design  $w$ , channel estimation algorithm  $\psi$ , the number of particle  $W$ , the number of iterations  $T$ ,
   the dimensions  $D$  of particle  $(\mathbf{m}, \mathbf{n})$ . Randomly initialize each particle  $(\mathbf{m}_i, \mathbf{n}_i)$ .
2: for  $t = 1 : T_{\max}$  do
3:   for  $j = 1 : W$  do
4:     for  $k = 1 : D$  do
5:       update the position of the particle by the formula(13), evaluate the objective function
       value  $\overline{SNR}$  by the formula (10).
6:     end for
7:   end for
8:
9:   for  $t = 1 : W$  do
10:     $\mathbf{P}_i(t+1) = \begin{cases} \mathbf{P}_i(t) & f(\mathbf{P}_i(t)) \leq f(\mathbf{x}_i(t+1)) \\ \mathbf{x}_i(t+1) & f(\mathbf{P}_i(t)) > f(\mathbf{x}_i(t+1)) \end{cases}$ 
11:     $\mathbf{G}_g(t+1) = \begin{cases} \mathbf{P}_i(t+1), & f(\mathbf{P}_i(t+1)) \leq f(\mathbf{G}_g(t)) \\ \mathbf{G}_g(t), & f(\mathbf{P}_i(t+1)) > f(\mathbf{G}_g(t)) \end{cases}$ 
12:     $(\mathbf{m}, \mathbf{n}) = \arg \min [f(\mathbf{G}_g(t+1))]$ 
13:   end for
14: end for
15: return the best degree distribution  $(\mathbf{m}, \mathbf{n})$  of LDSM

```

LDSM can achieve the same I_E^A at 5.5 dB. According to the predictions of the EXIT, the optimized LDSM scheme can obtain 0.5dB gains than the reference LDSM. The advantage of the optimized LDSM is that it has a larger girth. Consequently, it is possible to gather more accurate information in the process of iterative decoding convergence.

3. Results and discussion

In this section, uplink level simulation results are provided to evaluate the performance of the optimized LDSM scheme and the reference LDSM scheme. The average total received power and the spectrum efficiency (SE) per UE are kept the same. The signal to noise ratio (SNR) at the receiver is defined as the average total received power of the RE over noise power in the given bandwidth. Assuming 6 UEs with overloading factor of 150% on tapped delay line (TDL)-A-30 channel [20]. The total SE of LDSM system is 1.5 bps/Hz. BLER results for LDSM systems under imperfect CSI is shown in Fig. 6. The optimized LDSM achieves 0.5 dB SNR gain as compared with the reference LDSM [9] at target BLER 10^{-2} . Therefore, our EXIT chart predictions are consistent with the simulation results. The optimized LDSM has a smaller average row to reduce MUI and a larger girth to improve decoding accuracy.

4. Conclusion

In this paper, we investigated an uplink LDSM-OFDM system under imperfect CSI conditions. Based on the pilot design and LMMSE channel estimation, an optimal sparse signature matrix method for the LDSM scheme is proposed. The proposed method utilizes the BBPSO algorithm to obtain the optimized degree distribution of the sparse signature matrix. The optimized LDSM with a larger girth can improve the decoding performance of the system. Both EXIT analysis and simulation results proved that the proposed LDSM could achieve better BLER performance than the

reference LDSM. It is a suitable candidate for the high services demands of the IoT scenario.

Acknowledgements

Not applicable

Funding

None

Abbreviations

NOMA: Non-orthogonal multiple access; IoT: Internet of things; MAI: Multiple access interferences; LDSM: Low-density superposition modulation; CSI: Channel state information; LMMSE: Linear minimum mean square error; BBPSO: Bare-bone particle swarm optimization; EXIT: Extrinsic information transfer; 6G: Sixth generation; OMA: Orthogonal multiple access; LDS: Low-density spreading; PDMA: Pattern division multiple access; SCMA: Sparse code multiple access; RE: Resource element; MPA: Message passing algorithm; VND: Variable node; CND: Check node; BP: Belief propagation; LDPC: Low-density parity-check; LMS: Least mean squares; BLER: Bit block error rate; AWGN: Additive white Gaussian noise; PEG: Progressive edge-growth; MUD: multi-user detector; LLR: Log-likelihood ratio; SE: Spectrum efficiency; SNR: Signal to noise ratio;

Availability of data and materials

The paper is self-contained. Simulation description and parameters are provided in Section 3.

Ethics approval and consent to participate

Not applicable

Competing interests

The authors declare that they have no competing interests.

Consent for publication

Not applicable

Authors' contributions

KL proposed the designed algorithm and performed the experiments. HY gave some critical suggestions. All authors read and approved the final manuscript.

Authors' information

School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Xitucheng Road 10, Beijing 100876, China.

References

- Chettri, L., Bera, R.: A comprehensive survey on internet of things (iot) toward 5g wireless systems. *IEEE Internet of Things Journal* **7**(1), 16–32 (2020)
- Al-Falahy, N., Alani, O.Y.: Technologies for 5g networks: Challenges and opportunities. *IT Professional* **19**(1), 12–20 (2017)
- L. Dai, Y.Y.S.H.C.I.I. B. Wang, Wang, Z.: Non-orthogonal multiple access for 5g: solutions, challenges, opportunities, and future research trends. *IEEE Communications Magazine* **53**(9), 74–81 (2015)
- Y. L. Lee, L.-C.W. D. Qin, Sim, G.H.: 6g massive radio access networks: Key applications, requirements and challenges. *IEEE Open Journal of Vehicular Technology* **2**(0), 54–66 (2021)
- R. Hoshyar, F.P.W., Tafazolli, R.: Novel low-density signature for synchronous cdma systems over awgn channel. *IEEE Trans. Signal Process* **56**(4), 1616–1626 (2008)
- Beek, J.V.D., Popovic, B.M.: Multiple access with low-density signatures. *IEEE GLOBECOM*, 1–6 (2009)
- S. Chen, Q.G.S.K.S.S. B. Ren, Niu, K.: Pattern division multiple access a novel nonorthogonal multiple access for fifth generation radio networks. *IEEE Transactions on Vehicular Technology* **66**(4), 3185–3196 (2017)
- M. Taherzadeh, A.B. H. Nikopour, Ligh, H.B.: Scma codebook design. *IEEE 80th Veh. Technol. Conf.*, 1–5 (2014)
- Jiang, C., Wu, Z.: A novel uplink noma scheme based on low density superposition modulation. *IEEE 86th Vehicular Technology Conference*, 1–5 (2017)
- H. Wang, B.X. K. Xiao, Wang, J.: Performance analysis and optimization for the ldpc-coded multi-carrier lds system. *IEEE 89th Vehicular Technology Conference*, 1–5 (2019)
- B. Ren, X.D.K.N. Y. Wang, Tang, W.: Pattern matrix design of pdma for 5g ul applications. *China Communications* **13**(Supplement2), 159–173 (2016)
- Chen, Y., Chen, J.: On the design of near-optimal sparse code multiple access codebooks. *IEEE Transactions on Communications* **68**(5), 2950–2962 (2020)
- Lu, K., Jiang, C.: Optimized low density superposition modulation for 5g mobile multimedia wireless networks. *IEEE Access* **7**, 174227–174235 (2019)
- L. E. Sekokotoana, F.T., Oyerinde, O.O.: Least mean squares channel estimation for downlink non-orthogonal multiple access. *2019 IEEE AFRICON*, 1–5 (2019)
- M. B. Balogun, F.T., Oyerinde, O.O.: Weighted least square based iterative channel estimation for uplink noma-ofdm systems. *2019 13th International Conference on Signal Processing and Communication Systems (ICSPCS)*, 1–5 (2019)
- Kennedy, J.: Bare bones particle swarms. *2003 IEEE Swarm Intelligence Symposium*, 80–87 (2003)

17. X.-Y. Hu, E.E., D.-M. Arnold: Progressive edge-growth tanner graphs. IEEE Global Telecommunications Conference **2**, 995–1001 (2001)
18. El-Hajjar, M., Hanzo, L.: Exit charts for system design and analysis. IEEE Communications Surveys and Tutorials **16**(1), 127–153 (2014)
19. Li, K., Wang, X.: Exit chart analysis of turbo multiuser detection. IEEE Transactions on Wireless Communications **4**(1), 300–311 (2005)
20. 3rd generation partnership project; technical specification group radio access network; study on channel model for frequency spectrum above 6 ghz (release 14). 3GPP TS 38.900, version 14.2.0 (2016)

Figures

Figure 1: Uplink LDSM-OFDM system under imperfect CSI.

Figure 2: LDSM coding process for user j .

Figure 3: Pilot signals of the NOMA scheme.

Figure 4: Block diagram of the MPA MUD and FEC detector iteratively decoded system.

Figure 5: EXIT chart for turbo MUD with 150% at same SNR.

Figure 6: EXIT chart for turbo MUD with 150% at different SNR.

Figure 7: 6-user BLER performance comparison of LDSM schemes with load 150% under TDL-A-30 channel.

Tables

Table 1: Simulation parameters.

Parameter	Value
Carrier frequency	2GHz
System bandwidth	10MHz
Subcarrier spacing	15kHz
User velocity	3 km/h
Waveform	CP-OFDM
FFT length	1024
Code rate	1/2
Channel coding	LTE turbo
Antenna configuration	1Tx; 2Rx
Channel model	TDL-A-30
Channel estimation	Realistic
Length of information bits	144bits
Modulation	QPSK
Constellation factor β	1
The dimensions of LDSM	576x864
The number of particle W	30
The dimensions of particle D	4
The number of iterations $T_{\max}$	30
Users	6
Overloading factor	150%

$$\mathbf{F}_j = \begin{matrix} & c_1^j & c_2^j & & c_l^j \\ \begin{bmatrix} 1 & 0 & \cdots & 1 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & \cdots & 1 \end{bmatrix}_{S \times l} \end{matrix} \rightarrow \mathbf{z}_j = \mathbf{F}_j \begin{bmatrix} c_1^j \\ c_2^j \\ \vdots \\ c_l^j \end{bmatrix}$$

Uplink 1T2R 6 users 150% load TDL-A-30ns

Figures

Figure 1

Uplink LDSM-OFDM system under imperfect CSI.

$$\mathbf{F}_j = \begin{bmatrix} c_1^j & c_2^j & \dots & c_l^j \\ 1 & 0 & \dots & 1 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & \dots & 1 \end{bmatrix}_{S \times l} \rightarrow \mathbf{z}_j = \mathbf{F}_j \begin{bmatrix} c_1^j \\ c_2^j \\ \vdots \\ c_l^j \end{bmatrix}$$

Figure 2

LDSM coding process for user j

Figure 3

Pilot signals of the NOMA scheme.

Figure 4

Block diagram of the MPA MUD and FEC detector iteratively decoded system.

Figure 5

EXIT chart for turbo MUD with 150% at same SNR.

Figure 6

EXIT chart for turbo MUD with 150% at different SNR

Figure 7

6-user BLER performance comparison of LDSM schemes with load 150% under TDL-A-30 channel.