Computer Communications 176 (2021) 40–45

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

# Sparse Bayesian learning based channel estimation in FBMC/OQAM industrial IoT networks☆

Han Wang [a,b,c], Xingwang Li [d,*], Rutvij H. Jhaveri [e], Thippa Reddy Gadekallu [f], Mingfu Zhu [g], Tariq Ahamed Ahanger [h,*], Sunder Ali Khowaja [i]

[a] College of Physical Science & Engineering, Yichun University, Yichun 336000, China
[b] Institute of Data Science, City University of Macau, Macau 999078, China
[c] State Key Laboratory of Marine Resource Utilization in South China Sea, Hainan University, Hakou 570228, China
[d] School of Physics and Electronic Information Engineering, Henan Polytechnic University, Jiaozuo 454000, China
[e] Department of Computer Science & Engineering, Pandit Deendayal Petroleum University, Gandhinagar, India
[f] School of Information Technology and Engineering, Vellore Institute of Technology, India
[g] Henan Chuitian Technology Company Ltd., Hebei 458000, China
[h] Department of Information Systems, College of Computer Engineering and Science, Prince Sattam Bin Abdulaziz University, Saudi Arabia
[i] Department of Telecommunication Engineering, Faculty of Engineering and Technology, University of Sindh, Jamshoro, Pakistan

ARTICLE INFO

*Keywords:*
Industrial internet of things
Channel estimation
FBMC/OQAM
Sparse Bayesian learning

ABSTRACT

The next generation of communication technology is accelerating the transformation of industrial internet of things (IIoT). Filter bank multicarrier with offset quadrature amplitude modulation (FBMC/OQAM), as a candidate wireless transmission technology for beyond fifth generation (5G), has been widely concerned by researchers. However, effective channel estimation (CE) in IIoT communication should be solved. In practice, wireless channels have block–sparse structures. For the conventional sparse channel model, the general sparse channel estimation methods do not take the potential block–sparse structure information into account. In this paper, we have investigated the sparse Bayesian learning (SBL) framework for sparse multipath CE in FBMC/OQAM communications. Block SBL (BSBL) algorithm is proposed to estimate the channel performance by exploiting the block–sparse structure of sparse multipath channel model. The BSBL method can improve the estimation performance by using the block correlation of the training matrix. Computer simulation results demonstrate the robustness of the BSBL CE approach in FBMC/OQAM systems, which can achieve lower mean square error (MSE) and bit error rate (BER) than traditional least squares (LS) method and classical compressive sensing methods. The state of art compressive sampling matching pursuit (CoSaMP) greedy algorithm with a prior knowledge of sparse degree can provide slightly better CE performance than BSBL algorithm, but the proposed method maintains robustness in practical channel scenario without the prior knowledge of sparse degree.

## 1. Introduction

As a new generation of mobile communication technology, the rapid development of fifth generation (5G)–and–beyond technology is just in line with the application requirements of traditional manufacturing enterprises for the transformation of intelligent manufacturing to wireless network [1]. The three scenarios defined by 5G technology not only cover the traditional application scenarios such as high bandwidth and low delay, but also meet the requirements of equipment interconnection and remote interactive application in the industrial environment. Beyond 5G (B5G) technology can also use the three scenarios to connect the widely distributed and scattered people, machines and equipment to build a unified Internet. Due to the high real-time and reliability, B5G technology can not only be applied in industrial scenes, but also support personal mobile Internet applications. The development of B5G technology can help manufacturing enterprises get rid of the chaotic application state of wireless network technology, which has a positive significance to promote the implementation of industrial internet of things (IIoT).

5G is naturally suitable for the industrial internet of things (IIoT) [2]. Fig. 1 gives the IIOT framework with FBMC wireless communications. The wireless communication technology can provide low delay, high stability, large bandwidth, and can meet the demand of IIoT. Using

☆ This work was supported by the National Natural Science Foundation of China (No. 61901409), Jiangxi Provincial Natural Science Foundation (No. 20202BABL212001), Open Project of State Key Laboratory of Marine Resources Utilization in South China Sea (No. MRUKF2021034).
* Corresponding authors.
*E-mail addresses:* lixingwang@hpu.edu.cn (X. Li), t.ahanger@psau.edu.sa (T.A. Ahanger).

https://doi.org/10.1016/j.comcom.2021.05.020
Received 1 February 2021; Received in revised form 19 April 2021; Accepted 23 May 2021
Available online 29 May 2021

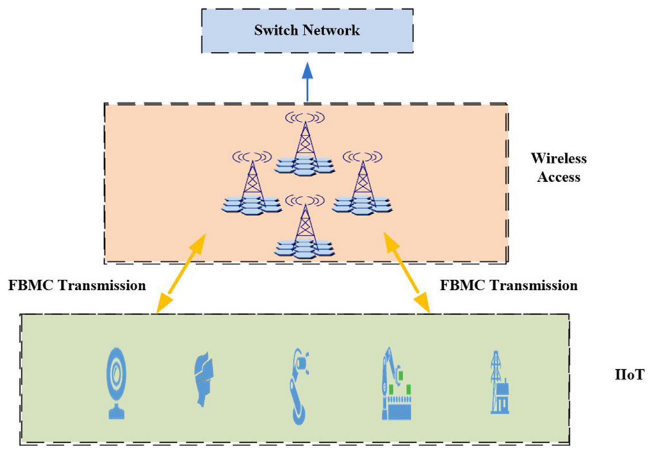


**Fig. 1.** The IIOT framework with FBMC wireless communications.

advanced wireless transmission technology, the data of IIoT can be transmitted in real time and accurately. However, it is not easy for the communication technology to successfully enable the IIoT. After all, the communication transmission performance requirements of IIoT are not comparable to the traditional demand scenarios. There is no doubt that the IIoT is a new field for the communication industry. How to meet the needs of IIoT users and realize the integration of 5G and IIoT is a difficult problem for the communication industry.

As a key technology in the communication process, wireless transmission technology has always been the research focus of scholars. Orthogonal frequency division multiplexing (OFDM) technology has been adopted by various communication standards because of its high spectrum efficiency, strong ability to resist inter symbol interference and high speed data transmission. However, there are two major drawbacks when traditional OFDM is applied to IIoT communication networks. The first is that it is difficult to achieve strict synchronization, and the other is that it has discontinuous band transmission, which is likely to cause serious spectrum leakage. Filter bank multicarrier with offset quadrature amplitude modulation (FBMC/OQAM) [3] technology, abbreviated as FBMC, can solve the above problems by using filter banks with good time–frequency feature. Firstly, FBMC system is not strictly orthogonal, when the channel is not highly selective, it does not need cyclic prefix (CP), and so that it has higher spectrum efficiency than OFDM. It should be noted that for highly selective channels, CP is also required in FBMC. Secondly, FBMC system can flexibly control the interference between adjacent subcarriers and make good use of scattered spectrum resources. Finally, the system processes channel estimation (CE) and synchronization separately on each subcarrier, which makes it more suitable for uplink communication. Although, the 3rd generation partnership project (3GPP) organization had pointed out that the 5G wireless communication system will adopt filtered-OFDM technology as the multicarrier transmission scheme. In view of the advantages of FBMC technology, scholars still maintain the research enthusiasm of FBMC, and would like to exploit it to future mobile communication systems [4,5].

However, due to the fact that FBMC system is strictly orthogonal only in real domain, there is inherent interference between filter basis functions [6]. Wireless channels have great randomness. In order to equalize the channel at the receiver, it is necessary to obtain more accurate channel state information. Nevertheless, this imaginary interference of FBMC will lead to the failure of traditional CE methods, which seriously affects the performance of CE. Therefore, how to achieve high accuracy CE in the presence of imaginary interference is a key problem in the practical application of FBMC wireless communication systems. The main contributions of this paper are shown below:

1. By exploiting the block structure characteristic of multipath channel, we propose the BSBL-based CE method for FBMC communication. To the best of our knowledge, no research has been found about CE based on Bayesian learning approach in FBMC communication systems yet.
2. Through computer simulations, we verify the effectiveness of BSBL approach for CE in FBMC systems. Compared with the traditional LS, SAMP, fast Bayesian matching pursuit (FBMP) and block CoSaMP (BCoSaMP), the simulation results show that the performance of BSBL method is better than traditional sparse CS methods.
3. By studying the CE of FBMC under sparse Bayesian framework, we come to the conclusion that BSBL approach in the practical channel environment is more robust than traditional CS methods which need sparse prior information.

## 2. Related work

A large number of channel measurement experiments [7] have confirmed that wireless channel presents sparse or block sparse structure. For example, underwater acoustic channel [8] and Ultra Wide Band (UWB) channel [9] often have sparse or nearly sparse impulse response. Therefore, various sparse CE methods have been proposed for sparse channel model based wireless communication systems. The famous compressive sensing (CS)-based CE approaches received great attention and has been widely studied. The classical CS methods include orthogonal matching pursuit (OMP) [10], compressive sampling matching pursuit (CoSaMP) [11], sparse adaptive matching pursuit (SAMP) [12] and variants improved algorithms based on these methods. In the early stage, most of the research on CS-based CE is focused on OFDM systems [13,14]. In recent years, researches have begun to study sparse CE methods in FBMC systems [15–17]. In [15], an OMP channel reconstruction scheme for FBMC systems was presented for the first time. The results showed that CS-based CE approach provides a significant performance improvement over conventional preamble based approach. A novel method was proposed in [16] to decrease the number of preamble. However, the above two studies assumed that the channel sparsity is priority known, but it is usually unknown. Then, an adaptive sparse CE algorithm for FBMC systems was proposed in [17]. Simulation results verified the validity of the adaptive CE methods.

In the above CS-based CE methods, channel is represented as sparse in the conventional sense, and the block sparse structure is not considered. As a matter of fact, wireless channel usually shows the characteristics of block sparse structure. In the reconstruction process, the block sparse reconstruction method can recover the original signal accurately without knowing the position coordinates of the non-zero coefficients in the original signal, and the reconstruction process is more simple and accurate. Some block CS methods [18–20] had been proposed for sparse CE, including group Lasso, block OMP (BOMP), and block CoSaMP (BCoSaMP). These kinds of methods also need the prior information of channel sparsity, and mainly focuses on the block sparse CE of OFDM systems [21–23]. Recently, CE methods based on block sparse Bayesian learning (BSBL) [24] for OFDM systems had been proposed. SBL algorithm [25] evaluates the posterior distribution of channel impulse response according to the received data, while the CS method estimates the non-zero point according the channel sparsity. By exploiting intra-block correlation of SBL, Gui et al. [26] studied the CE problem of OFDM system by utilizing BSBL approach, which has superior performance than traditional CS algorithms. Liu et al. [27] applied the clustering BSBL CE algorithm for millimeter wave systems, and in [28], the authors proposed an adaptive BSBL approach for CE in massive multiple input multiple output OFDM systems. Simulation results verified the superiority of the BSBL. The success of BSBL-based CE in past contexts prompted us to consider applying it to solve the sparse CE problem in FBMC systems and fill the gap.

Motivated by the above analysis, we utilize the intra-block correlation of block channel, to exploit the BSBL framework for sparse

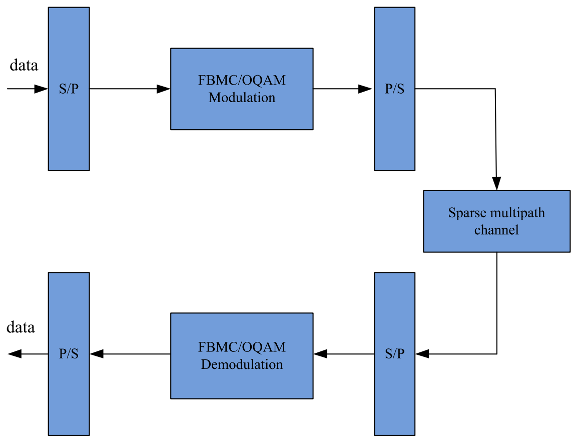


**Fig. 2.** The FBMC/OQAM communication system [6].

multipath CE in FBMC systems. The CE of OFDM systems based on SBL framework is realized by using preamble signal. The performance of CE can be improved by increasing the number of pilots. Different from OFDM systems, pilot exists in all subcarriers of FBMC systems. We propose joint BSBL algorithm that both the pilot and the data subcarriers are incorporated for CE.

This paper organizes as follows. Section 2 shows the related work. Section 3 presents the system model. The BSBL for FBMC channel estimation is investigated in Section 4. Channel estimation performance comparisons of LS, CoSaMP, SAMP, FBMP, BCoSaMP, and BSBL algorithms are given in Section 5. In Section 6, it gives the conclusions.

## 3. System model

For wideband wireless communication, the channel is usually assumed to be frequency selective fading [29,30]. The impulse response of time-varying wireless multipath channel can be expressed as

$$h(t,\tau)=\sum_{l=0}^{L-1} h_l(t)\delta(\tau-\tau_l(t)) \tag{1}$$

where $h_l(t)$ and $\tau_l(t)$ represent the gain and delay of the $l$ path at time $t$, respectively. $L$ denotes the length of channel. Let $\tau_{\max}$ be the maximum delay of the channel, $\tau_l(t)$satisfies $0\le\tau_l(t)\le\tau_{\max}$, and assuming that symbol period of FBMC is much smaller than the coherence time of the channel, the channel impulse response is considered time-invariant within a symbol period. The discrete channel vector can be expressed as $\boldsymbol{h}=[h_0,h_l,\ldots,h_{L-1}]$. Ref. [7] has shown that there exists block sparsity in wireless multipath channels. There are only a small number of non-zero elements in $\boldsymbol{h}$, and the block sparse form of $\boldsymbol{h}$ can be given as

$$\boldsymbol{h}=[\underbrace{h_0,\ldots h_{d_1-1}}_{h_1^T},\ldots,\underbrace{h_{d_{c-1}},\ldots,h_{d_c-1}}_{h_c^T}]^T \tag{2}$$

where $d_i$ is the length of each block, $c$ is the number of channel blocks, and satisfies $L=\sum_{i=1}^{c}d_i$. $h_{d_c-1}$ corresponds to $h_{L-1}$. It is generally assumed that the length of each block is equal, and only $K$ ($K\ll$ c) elements in the block are non-zero.

Assuming that the number of subcarriers in FBMC systems is $N$, the filter bank function in the system has good time–frequency characteristics, and the influence of imaginary interference is only affected by the first-order neighborhood. Fig. 2 gives the FBMC/OQAM communication system model.

The transmitted signal of FBMC system is given in Refs. [6], with

$$x(t)=\sum_{m=0}^{N-1}\sum_{n} d_{m,n}g_{m,n}(t) \tag{3}$$

where $d_{m,n}$ are real valued OQAM symbols, and $g_{m,n}(t)$ denotes the prototype function. $m$ denotes the sub-carrier index and $n$ denotes the OQAM symbol time index.

After channel transmission, the received signal of FBMC system can be expressed as

$$y(t)=x(t)H(t)+\eta(t) \tag{4}$$

where $x(t)$ is the transmitted signal of FBMC system, and $H(t)$ denotes a complex response of the channel at instant $t$. $\eta(t)$ represents the noise.

## 4. Implementation of CE algorithm based on BSBL

We usually set $P$ as the number of pilots, the received signal corresponding to the pilot can be written as

$$\boldsymbol{y}_P=\boldsymbol{x}_P\boldsymbol{H}_P+\boldsymbol{n}_P \tag{5}$$

where $\boldsymbol{y}_P$ is the received pilot signal, it can be obtained by LS method in this paper. $\boldsymbol{x}_P$ is the diagonal matrix of $P\times P$ dimension, the pilot is known along its diagonal. $\boldsymbol{H}$ denotes the multipath channel frequency response, with $\boldsymbol{H}_P=\boldsymbol{F}_P\boldsymbol{h}$. $\boldsymbol{F}_P$ is the discrete Fourier Transform (DFT) matrix of $P\times L$ dimension, and $\boldsymbol{n}_P$ is the noise at pilot signal.

As in fact, the pilots exist in all subcarriers in FBMC systems. The preamble sequence is superimposed on the data subcarriers. The received signal of FBMC system can be rewritten as

$$\boldsymbol{y}=\boldsymbol{x}\boldsymbol{H}+\boldsymbol{n} \tag{6}$$

where $\boldsymbol{x}=diag(x(0),x(1),\ldots,x(N-1))$, and $\boldsymbol{y}=[y(0),y(1),...,y(N-1)]^T$. $\boldsymbol{H}=\boldsymbol{F}_{NL}h$, and $\boldsymbol{F}_{NL}$ is a $N\times L$ row DFT matrix. $\boldsymbol{n}$ represents the noise matrix, with zero mean and variance of $\sigma^2$, and the matrix with $N\times N$. Here, we set $\boldsymbol{\Phi}=\boldsymbol{x}\boldsymbol{F}_{NL}$, and $\boldsymbol{y}=\boldsymbol{\Phi}\boldsymbol{h}+\boldsymbol{n}$.

In this section, CE based on BSBL framework for FBMC is studied. In BSBL framework, it is assumed that each channel block $\boldsymbol{h}_i$ satisfies the parameterized multivariate Gaussian distribution, with

$$p\left(\boldsymbol{h}_i;\gamma_i,\boldsymbol{B}_i\right)\sim CN(\boldsymbol{0},\gamma_i\boldsymbol{B}_i),\ i=1,\cdots,c \tag{7}$$

where parameters $\gamma_i$ and $\boldsymbol{B}_i$ are unknown. The non-negative parameter $\gamma_i$ is used to control the block sparsity of $\boldsymbol{h}_i$. For block sparse channel, most $\gamma_i$ is equal to or tends to zero in Bayesian learning channel estimation. $\boldsymbol{B}_i\in\mathbb{R}^{d_i\times d_i}$ is adopted to capture the correlation channel structure information of the $i$-th block, and it is positive definite matrix. It is assumed that the blocks of channel $\boldsymbol{h}$ are uncorrelated, the prior distribution of $\boldsymbol{h}$ is $p\left(\boldsymbol{h};\left\{\gamma_i,\boldsymbol{B}_i\right\}_{i=1}^{c}\right)\sim CN(\boldsymbol{0},\boldsymbol{\Sigma}_0)$, $\Sigma_0=\mathrm{diag}(\gamma_1\boldsymbol{B}_1,\cdots,\gamma_c\boldsymbol{B}_c)$. The noise vector satisfies $p(\boldsymbol{n};\lambda)\sim CN(\boldsymbol{0},\lambda\boldsymbol{I})$, with $\lambda$ be the noise variance, $\lambda\ge0$, $\boldsymbol{I}$ is the $N\times N$ dimension identity matrix. Thus, the posterior distribution of channel $\boldsymbol{h}$ is expressed as

$$p\left(\boldsymbol{h}\,|\boldsymbol{y}\ ;\lambda,\left\{\gamma_i,\boldsymbol{B}_i\right\}_{i=1}^{c}\right)\sim CN(\boldsymbol{\mu}_h,\boldsymbol{\Sigma}_h) \tag{8}$$

where $\boldsymbol{\mu}_h$ and $\boldsymbol{\Sigma}_h$ can be obtained by

$$\boldsymbol{\mu}_h=\boldsymbol{\Sigma}_0\boldsymbol{\Phi}^T(\lambda\boldsymbol{I}+\boldsymbol{\Phi}\boldsymbol{\Sigma}_0\boldsymbol{\Phi}^T)^{-1}y \tag{9}$$

$$\boldsymbol{\Sigma}_h=\left(\boldsymbol{\Sigma}_0^{-1}+\frac{1}{\lambda}\boldsymbol{\Phi}^T\boldsymbol{\Phi}\right)^{-1} \tag{10}$$

when we get the estimated values of parameters $\lambda,\left\{\gamma_i,\boldsymbol{B}_i\right\}_{i=1}^{c}$, the Maximum A Posteriori (MAP) estimate of $\boldsymbol{h}$, denoted by $\hat{\boldsymbol{h}}$, can be acquired from the mean of the posterior probability function, i.e., $\hat{\boldsymbol{h}}=\boldsymbol{\mu}_h$.

In BSBL framework, we assume that the length of each block in channel $\boldsymbol{h}$ is identical. According to the expectation maximization (EM) method [24], the parameters $\gamma_i$ and $\lambda$ can be obtained by the following two formulas

$$\gamma_i=\frac{1}{d_i}Tr\left[\boldsymbol{B}_i^{-1}(\boldsymbol{\Sigma}_h^i+\boldsymbol{\mu}_h^i(\boldsymbol{\mu}_h^i)^T)\right],\forall\boldsymbol{i} \tag{11}$$

$$\lambda=\frac{\|\boldsymbol{y}-\boldsymbol{\Phi}\boldsymbol{\mu}_h\|_2^2+Tr(\boldsymbol{\Sigma}_h\boldsymbol{\Phi}^T\boldsymbol{\Phi})}{N} \tag{12}$$

**Table 1**
Proposed CE-based BSBL Algorithm for FBMC.

Input: $\boldsymbol{y}$, $\boldsymbol{\Phi}$, $\boldsymbol{\Sigma}$
Output: $\hat{\boldsymbol{h}}$

Initialization: $\boldsymbol{\mu}_h \leftarrow 0$, $\boldsymbol{\Sigma}_h \leftarrow 0$
For $i = 1, 2, \ldots, c$

$$\boldsymbol{B} \leftarrow \frac{1}{c}\sum_{i=1}^{c}\frac{\boldsymbol{\Sigma}_h^i + \boldsymbol{\mu}_h^i(\boldsymbol{\mu}_h^i)^T}{\gamma_i}$$

$$\boldsymbol{B}_i \leftarrow \boldsymbol{B}(\forall \boldsymbol{i})$$

$$\gamma_i \leftarrow \frac{1}{d_i} Tr\left[\boldsymbol{B}_i^{-1}(\boldsymbol{\Sigma}_h^i + \boldsymbol{\mu}_h^i(\boldsymbol{\mu}_h^i)^T)\right], \forall \boldsymbol{i}$$

$$\boldsymbol{\mu}_h \leftarrow \boldsymbol{\Sigma}_0 \boldsymbol{\Phi}^T(\lambda \boldsymbol{I} + \boldsymbol{\Phi}^T \boldsymbol{\Sigma}_0 \boldsymbol{\Phi}^T)^{-1} y$$

$$\boldsymbol{\Sigma}_h \leftarrow \left(\boldsymbol{\Sigma}_0^{-1} + \frac{1}{\lambda}\boldsymbol{\Phi}^T\boldsymbol{\Phi}\right)^{-1}$$

$$\lambda \leftarrow \frac{|\boldsymbol{y} - \boldsymbol{\Phi}\boldsymbol{\mu}_h|_2^2 + Tr(\boldsymbol{\Sigma}_h \boldsymbol{\Phi}^T \boldsymbol{\Phi})}{N}$$

End

$$\hat{\boldsymbol{h}} \leftarrow \Sigma_0 \boldsymbol{\Phi}^T(\lambda \boldsymbol{I} + \boldsymbol{\Phi}\Sigma_0\boldsymbol{\Phi}^T)^{-1}\boldsymbol{y}$$

where $\boldsymbol{\mu}_h^i$ and $\boldsymbol{\Sigma}_h^i$ are the corresponding $i$-th block in $\boldsymbol{\mu}_h$ and corresponding $i$-th principal diagonal block in $\boldsymbol{\Sigma}_h$, respectively. By using EM method, we can also derive a learning rule for $\boldsymbol{B}_i$. However, each blocks in $\boldsymbol{h}$ has the same size, in order to avoid over-fitting problem, constraining $\boldsymbol{B}_i = \boldsymbol{B}$. Then, $\boldsymbol{B}$ can be given as

$$\boldsymbol{B} = \frac{1}{c}\sum_{i=1}^{c}\frac{\boldsymbol{\Sigma}_h^i + \boldsymbol{\mu}_h(\boldsymbol{\mu}_h)^T}{\gamma_i} \tag{13}$$

Table 1 summarizes the CE algorithm based on BSBL. By using the above mentioned BSBL method, we can obtain $\boldsymbol{B}$ and other parameters, the channel can be estimated by $\hat{\boldsymbol{h}} \leftarrow \Sigma_0\boldsymbol{\Phi}^T(\lambda\boldsymbol{I} + \boldsymbol{\Phi}\Sigma_0\boldsymbol{\Phi}^T)^{-1}y$.

## 5. Simulation results

In this section, bit error rate (BER) and mean square error (MSE) performance of different channel estimation methods of FBMC systems under two multipath channel environments are simulated. We select LS, CoSaMP, BCoSaMP, SAMP, and FBMP algorithms for analysis and comparison. Interference approximation method (IAM) preamble structure for the original LS CE is adopted. Fig. 3 gives the IAM preamble structure. The simulation channel parameters are as follows, and the detailed simulation parameters are shown in Table 2. The following two channel models are based on the modification of 3GPP extended pedestrian A (EPA) and pedestrian A (PA) channel models, which are used to evaluate channel estimation performance of different algorithms.

4-path channel model
Delay: [0 11 19 41] μs,
Relative power: [0 −9.7 −19.2 −22.8] dB;
7-path channel model
Delay: [0 3 7 9 11 19 41] μs,
Relative power: [0 −1 −2 −3 −8 −17.2 −20.8] dB.

We first study the BER performance of FBMC systems based on SBL approach in additive white Gaussian noise (AWGN) environment, as shown in Fig. 4. In the case of only Gaussian noise, the BER performance of SBL method is not as good as expected. However, by utilizing the block SBL framework, the BER performance is significantly improved. This shows that sparse Bayesian learning using the block structure information of the solution can improve the performance of the algorithm. The BER of BSBL method is also significantly better than that of traditional LS method. BSBL approach is more robust than traditional CS approach.

Through the above analysis, we find that the use of block structure information of the solution can improve the algorithm. Therefore, we think of comparing the greed block sparse reconstruction algorithm with BSBL to analyze its performance. The state of art CoSaMP algorithm is one of the classical greedy algorithms. We choose BCoSaMP method to compare with BSBL method. Fig. 5 shows the BER comparison of two block sparse methods with different block lengths. Three

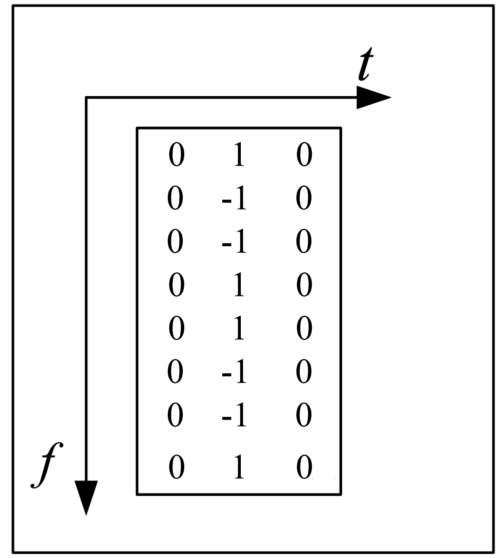


**Fig. 3.** IAM preamble structure for LS CE.

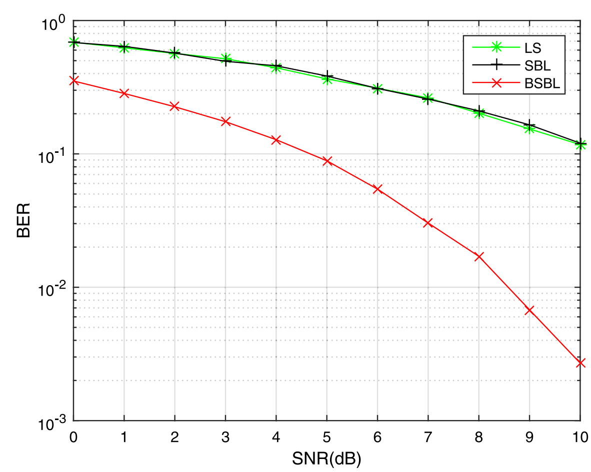


**Fig. 4.** The BER performance of SBL approach in Gaussian noise environment.

**Table 2**
The simulation parameters.

| Modulation | 4OQAM |
|---|---|
| Number of subcarriers | 256 |
| Filter bank | IOTA |
| Length of channel | 256 |
| Preamble structure | Interference approximation method (IAM) |

different block lengths are selected for analysis. In BCoSaMP method, when the block length is 2, the algorithm has the best BER values. Careful observation shows that the BSBL algorithm with a block length of 4, has similar BER performance with the best BCoSaMP algorithm. This may due to the fact that increasing the number of blocks will improve CE performance of Bayesian approach. In the following simulations, we select the BSBL method with a block length of 4 for discussion and analysis.

Figs. 6 and 7 show the BER and MSE performance curves obtained from different algorithms under 4-path channel model. It is worth pointed out that the initial channel estimates of all methods are based on IAM preamble-based approach. CS-based approach utilizes channel sparsity characteristics, and its CE performance is significantly better

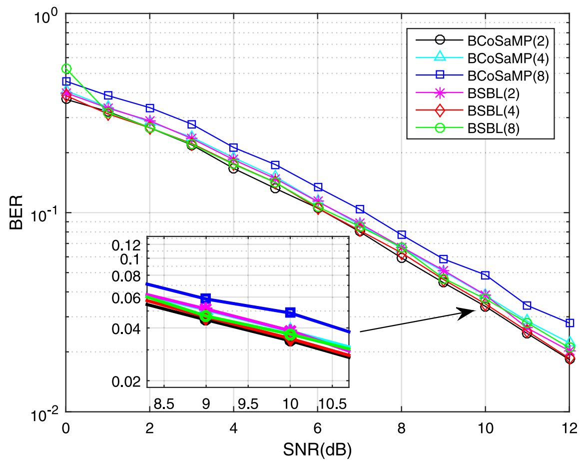


**Fig. 5.** BER comparison of two block sparse algorithms with different block lengths.

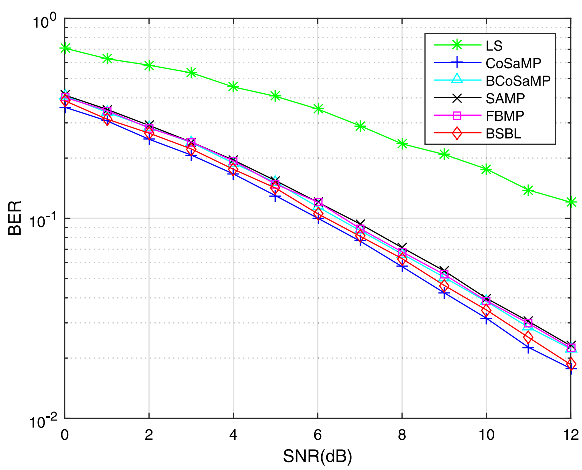


**Fig. 6.** BER comparison of different algorithms under 4-path channel model.

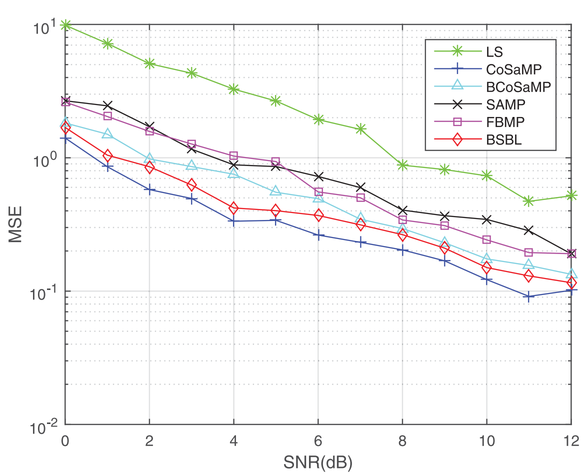


**Fig. 7.** MSE comparison of different algorithms under 4-path channel model.

than traditional LS method. The CoSaMP method with a prior knowledge of sparse channel degree can achieve the best CE performance among the six methods. The CE performance of the proposed BSBL algorithm is slightly worse than that of CoSaMP method, but better than the remaining BCoSaMP, SAMP, and FBMP methods. It is worth noting

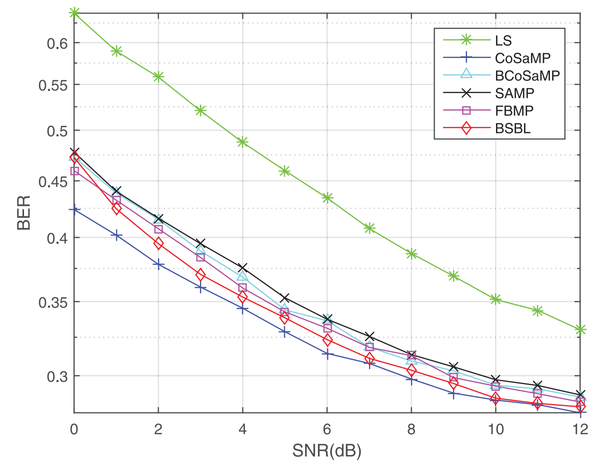


**Fig. 8.** BER comparison of different algorithms under 7-path channel model.

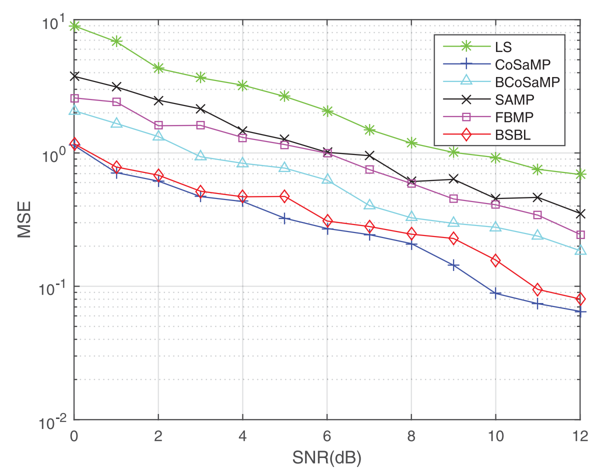


**Fig. 9.** MSE comparison of different algorithms under 7-path channel model.

that BSBL approach does not need to provide channel prior sparsity, which is more robust in practical channel environment.

In Fig. 6, the BER curves of the three CS methods of BCoSaMP, SAMP, and FBMP are very close. Under the same BER value, the BSBL method has performance improvement of about 1 dB compared with the three methods.

Fig. 7 shows the comparison chart of MSE performance curves. The overall curve trend is consistent with the BER performance. Compared with the BER curves of the algorithms, the difference between the MSE curves is more distinguishable. Block sparse CS approach is better than other traditional methods.

Figs. 8 and 9 depict the BER and MSE performance curves of different algorithms under 7-path channel model. The CE performance curve trend of all algorithms under 7-path channel is consistent with the algorithms in 4-path channel. BSBL algorithm is still the robustness CE method among the six methods under 7-path channel model.

From Fig. 8, we can find that the BER performance of all methods deteriorates with the increase of number of multipath channels. This is due to the increase of the number of multipath channels and the variation of the delay of each path. As shown in Fig. 9, FBMP and SAMP methods have similar MSE performance. The performance improvement of CoSaMP and BSBL methods are more obvious in Fig. 9. This shows that the two methods are more robust when the number of multi-paths increases.

Then, we study the computational complexity of the algorithms under 4-path channel model. We record the time spent on CE using

**Table 3**
The comparison of running time (Second).

| CoSaMP | BCoSaMP | SAMP | FBMP | BSBL |
|---|---|---|---|---|
| 2.7 | 2.66 | 2.65 | 3.18 | 4.92 |

the five CS methods. Table 3 gives the comparison of CE running times for CoSaMP, BCoSaMP, SAMP, FBMP and BSBL. These results are obtained using Matlab version R2014b on an Intel Core i7-8565U CPU with 8GB of RAM. Table 3 shows that the proposed BSBL algorithm for FBMC systems has the largest running time. However, other four algorithms are implemented in the case of a given sparsity, while the BSBL algorithm can obtain robustness result with a certain increase in computational complexity.

## 6. Conclusions

This paper explored the sparse CE problem of frequency selective multipath channel in FBMC IIoT communication systems from the perspective of SBL framework. In order to estimate the sparse block multipath fading channel, we proposed the BSBL algorithm and extended it to block sparse CE for FBMC communication systems. LS, CoSaMP, BCoS-aMP, SAMP, and FBMP algorithms were utilized for comparison. The simulation results showed that the proposed BSBL method took the advantage of the block sparsity of the channel, and made the CE accuracy better than traditional SBL method and most classical CS algorithms. Considering that the traditional CS approach required a priori known channel sparsity, BSBL algorithm without the prior knowledge of sparse degree could obtain robustness result with a certain increase in computational complexity.

## CRediT authorship contribution statement

**Han Wang:** Conceptualization, Software, Writing - original draft. **Xingwang Li:** Conceptualization, Software, Writing - original draft. **Rutvij H. Jhaveri:** Visualization, Validation, Proofread. **Thippa Reddy Gadekallu:** Visualization, Validation, Proofread, Supervision. **Mingfu Zhu:** Testing, Implementation. **Tariq Ahamed Ahanger:** Testing, Implementation, Supervision. **Sunder Ali Khowaja:** Visualization, Proofread, Editing.

## 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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