Impulsive noise suppressing method in power line communication system using sparse iterative covariance estimation

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RESEARCH

Impulsive noise suppressing method in power line communication system using sparse iterative covariance estimation

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Abstract

Power line communication is severely affected by impulsive noise, especially asynchronous impulsive noise with high power spectral density and short duration. This paper presents an asynchronous impulsive noise suppression method in power line communication system. Based on the component of the asynchronous impulsive noise and the background noise extracted from the received signal by using a null subcarrier matrix, a sparse iterative covariance estimation method is proposed. A optimization problem for estimating impulsive noise power is formed based on a minimum covariance matrix fitting criterion, and the impulsive noise power is then obtained by an iterative algorithm. After that, the impulsive noise is estimated by using the linear minimum mean square estimate method and subtracted from the received signal. Finally, simulation results show that the proposed method can achieve better performance in terms of bit error rate, and has lower computational complexity.

Keywords: power line communication; impulsive noise; sparse iterative covariance estimation

1 Introduction

Power line communication (PLC) is a communication technique which uses electrical lines to carry both data and electric energy simultaneously [1].Typical applications of PLC range from automatic meter reading, real-time pricing, and smart energy management [2]. However, since PLC is not designed for signal transmission initially, a number of challenges need to be addressed including channel frequency attenuation, multipath transmission effects, and noise. Among these challenges, noise is the major concern. In general, noise in PLC can be classified into three categories, generalized background noise, periodic impulsive noise, and asynchronous impulsive noise [3]. Among these, asynchronous impulsive noise has the most serious affect on the performance of PLC. This is due to the fact that asynchronous impulsive noise is of short-time duration and has high amplitude, causing wide bandwidth occupation up to 11MHz in frequency domain [4].

A number of methods have been proposed to mitigate asynchronous impulsive noise. In [5], Zhidkov employs nonlinear methods, including clipping, blanking, and combined clipping and blanking at the receiver to process received signals. Nevertheless, the performance of these methods is sensitive to the selection of threshold values which may result in poor performance due to inaccurate threshold. Then an improved blanking/clipping based impulsive noise mitigation method is proposed

in [6]. This method can minimize the possibility of impulsive noise detection errors compared with traditional nonlinear pre-processor technology. However, the main challenge for this method is that the characteristics of impulsive noise must be a-priori known at the receiver.

Recently, there has been growing interest in developing compressed sensing (CS) based impulsive noise mitigation methods that exploit the time-domain sparsity of impulsive noise. The methods proposed in [7]- [10] applied CS techniques to estimate the impulsive noise from null subcarriers of the received signal. Due to the sparsity property of impulsive noise, it can also be recovered by the Sparse Bayesian Learning (SBL) algorithm [11]. SBL algorithm is applied to estimate impulsive noise from both null subcarriers and all subcarriers to improve performance and robustness. However, the computational complexity of the SBL algorithm is very high.

In this paper, we propose a sparse iterative covariance estimation (SPICE) algorithm for estimating the impulsive noise in PLC. This idea comes from [12] with its initial purpose for spectrum analysis. Here, we apply this idea for impulsive noise estimation. In this algorithm, first, based on a minimum covariance matrix fitting criterion, a weighted l_1-norm type convex optimization problem for impulsive noise power is constructed, then an iterative algorithm for estimating the impulsive noise power is developed, and finally the impulsive noise is estimated. The complexity of the proposed method with other discussed methods are also analyzed. Simulation results show that the proposed method provides better estimation accuracy and lower complexity.

The rest of the paper is organized as follows. In Section II we introduce the system and impulsive noise models. Section III formulate the problem and discuss the proposed impulsive noise estimation algorithm. In Section IV we analyze the computational complexity of the discussed algorithms. Section V verify the performance of the proposed algorithms. Finally, we draw conclusions in Section VI.

2 System model

In this section, we describe a complex baseband equivalent discrete time model for an OFDM based PLC system. At the transmitter, a binary data stream is encoded into a codeword and mapped into an OFDM symbol by Quadrature Amplitude Modulation (QAM). The mapped data vector $X = [X_1, X_2, ..., X_N]^T$ is then converted to the time domain by inverse discrete Fourier transform (IDFT) and can be written as $x = [x_1, x_2, ..., x_N]^T = F^H X$, where F is a $N \times N$ unitary DFT matrix and F^H is the Hermitian transpose of F. It is assumed that the time domain signal x is only transmitted in $N - M$ data subcarriers and the remaining M are null subcarriers. When x is transmitted to the PLC channel and appended by the impulsive noise i and background noise n, the received signal can be written as

$$y = Hx + i + n \tag{1}$$

where H is a $N \times N$ circulant matrix whose first column equals to the impulse response of the normalized discrete time channel. The AWGN n is zero mean with variance σ_n^2. Thus the signal to background noise ratio can be written as $SNR = 1/\sigma_n^2$ when the OFDM signal power is normalized. The impulsive noise is typically

described as three models: Bernoulli-Gaussian (BG), Gaussian-mixture (GM), and Middleton class A (MCA). Since the two models BG and MCA can be represented by the GM model, the GM model is used to simulate impulsive noise in this paper. In this model, the probability density function (PDF) of a noise sample x is a weighted summation of different Gaussian variables given by

$$f(x) = \sum_{k=0}^{K-1} p_k g_k(x) \tag{2}$$

where $g_k(x)$ is the PDF of the complex Gaussian variable with zero-mean and variance γ_k, and p_k is the mixing probability of the kth component such that $\sum_{k=0}^{K-1} p_k = 1$.

In order to extract the components of asynchronous impulsive noise and background noise from the received signal, we firstly construct a $M \times N$ null subcarrier matrix Φ with M rows obtained from the original DFT matrix F. Then according to the orthogonality of each tone in OFDM, we can obtain the following equation by multiplying the null subcarrier matrix Φ on each side of equation (1) as

$$\begin{aligned} r &= \Phi y \\ &= \Phi H x + \Phi i + \Phi n \\ &= \Phi i + \Phi n \end{aligned} \tag{3}$$

After the noise estimation and mitigation block, the processed signal is then passed to the DFT block, demapping block and decoding block successively and finally decodes the transmitted message at the receiver.

3 Proposed Method

We rewrite equation (3) as

$$r = \Phi i + v \tag{4}$$

where Φn has the same mean and variance as n due to the unitary property of Φ, so $v \sim \mathcal{CN}(0, \sigma^2 I_M)$.

The null subcarrier matrix Φ with dimension $M \times N$ formed from DFT can be regard as a steering matrix

$$\Phi = [a(\omega_1), \ldots, a(\omega_N)] \tag{5}$$

where $a(\omega_s) = \frac{1}{\sqrt{N}}[1, e^{-j\omega_s}, \ldots, e^{-j(M-1)\omega_s}]^T, s = 1, 2, \ldots, N$.

For the convenience of analysis, let $a_n = a(\omega_n), n = 1, 2, \ldots, N$. Then the formula (4) can be rewritten as

$$r = \sum_{n=1}^{N} a_n i_n + v \tag{6}$$

A rough estimate of i_n by using the least squares method from (6) yields

$$\hat{i}_n = \frac{a_n^H r}{\|a_n\|^2} \tag{7}$$

Such a estimator ignores background noise, causing inaccurate estimation. However, (7) can be used as an initial value in the next proposed iteration method.

Based on the observation that variables i and v are uncorrelated, the impulsive noise i can be estimated by using linear minimum mean square estimate (LMMSE) from linear model (6) as follows [13]

$$\hat{i} = R_{ii}\Phi^H(\Phi R_{ii}\Phi^H + R_{vv})^{-1} r \tag{8}$$

where

$$R_{ii} = E(ii^H) = diag(|i_1|^2, ..., |i_N|^2) \tag{9}$$

$$R_{vv} = E(vv^H) = diag(\sigma_1^2, ..., \sigma_M^2) \tag{10}$$

Through the above analysis, the estimation contains the covariance matrices of impulsive noise and background noise, both are diagonal matrices with diagonal elements correspond to the power of impulsive noise and background noise respectively. Therefore both the background noise and impulsive noise estimation is transformed to the noise power estimation. We propose the following SPICE algorithm for noise power estimation.

3.1 The basic framework of SPICE algorithm

The covariance matrix corresponding to the observed signal vector r is

$$R = E(rr^H) = \sum_{n=1}^{N} |i_n|^2 a_n a_n^H + diag(\sigma_1^2, ..., \sigma_M^2) \triangleq APA^H \tag{11}$$

where

$$A = [a_1, \ldots, a_N \quad I] \triangleq [a_1, \ldots, a_N, a_{N+1}, \ldots, a_{N+M}] \tag{12}$$

$$\begin{aligned} P &= diag(|i_1|^2, \ldots, |i_N|^2, \sigma_1^2, \ldots, \sigma_M^2) \\ &\triangleq (p_1, \ldots, p_N, p_{N+1}, \ldots, p_{N+M}) \end{aligned} \tag{13}$$

Each p_n can be estimated by minimizing the following weighted covariance fitting criterion [14]:

$$f = \|R^{-1/2}(\hat{R} - R)\|_F^2 \tag{14}$$

where $\hat{R} = rr^H$.

Expansion (14) yields

$$f = -2\|r\|^2 + \|r\|^2 r^H R^{-1} r + tr(R) \tag{15}$$

where

$$tr(R) = \sum_{n=1}^{N+M} \|a_n\|^2 p_n \tag{16}$$

Then minimization of f with respect to p_n is equivalent to minimization of the following function

$$\min_{\{p_n \geq 0\}} r^H R^{-1} r + \sum_{n=1}^{N+M} \omega_n p_n \tag{17}$$

where

$$\omega_n = \frac{\|a_n\|^2}{\|r\|^2} \tag{18}$$

Problem (17) is a SDP (semidefinite programming) optimization problem which can be solved by many software packages. However, the following proposed iteration method can obtain the noise power in lower complexity.

3.2 Noise power estimation

Let $\varphi \in \mathbb{C}^{(N+M)\times 1}$ be an auxiliary variable such that $A\varphi = r$. Then problem (17) can be converted to the following constraint minimization problem (the proof of (19) is given in the Appendix A)

$$\min_{\{p_n \geq 0\}} \varphi^H P^{-1} \varphi + \sum_{n=1}^{N+M} \omega_n p_n \qquad s.t. \quad A\varphi = r \tag{19}$$

First fixed P, then the optimal solution φ has the following form (the detailed proof is provided in Appendix B)

$$\varphi = P A^H R^{-1} r \tag{20}$$

By using the diagonal property of matrix P, problem (19) can be easily transformed into the following equivalent problem

$$\min_{\{p_n \geq 0\}} \sum_{n=1}^{N+M} \frac{|\varphi_n|^2}{p_n} + \omega_n p_n \tag{21}$$

where φ_n is the nth element of the vector φ.

Applying the mean inequality yields

$$\frac{|\varphi_n|^2}{p_n} + \omega_n p_n \geq 2\sqrt{\omega_n}|\varphi_n| \tag{22}$$

The optimal solution in (21) is achieved only when

$$\frac{|\varphi_n|^2}{p_n} + \omega_n p_n = 2\sqrt{\omega_n}|\varphi_n| \tag{23}$$

which provides the following solution

$$p_n = \frac{|\varphi_n|}{\sqrt{\omega_n}} \tag{24}$$

Giving the initialization of power estimation from (7)

$$p_n(0) = \frac{|a_n^H r|^2}{\|a_n\|^4} \tag{25}$$

Combining (20) and (24), we provide the following updated formula for noise power estimation

$$\hat{p}_n(j+1) = \hat{p}_n(j)\frac{|a_n^H \hat{R}^{-1}(j) r|}{\sqrt{\omega_n}} \tag{26}$$

where the index j denotes the iteration number, and $\hat{R}(j)$ is the matrix $\hat{R}$ made from $\hat{p}_n(j)$.

Therefore, based on the requirement of impulsive noise power in (8) and the iteration of impulsive noise power completed in (26), we can obtain an estimate of impulsive noise

$$\hat{i}_n = \hat{p}_n a_n^H \hat{R}^{-1} r \tag{27}$$

where $n = 1, ..., N$ and $\hat{R} = A\hat{P}A^H$.

The above method is summarized as follows

Algorithm 1 Sparse Iterative Covariance Estimation (SPICE)

Initiate $p_n(0) = \frac{|a_n^H r|^2}{\|a_n\|^4}$,and set $j = 1$
while the stopping criterion is not meet **do**
    Let $\hat{R}(j) = A\hat{P}(j)A^H$
    Update $\{p_n(j)\}$ from (26), for each $n = 1, \ldots, N + M$
    Set $j = j + 1$
end while
Output $\hat{i}_n$ from (27), for each $n = 1, \ldots, N$

Remark: In each iteration of the proposed algorithm, the main complexity is from $\hat{R}^{-1}(j)r$. Denote $x = \hat{R}^{-1}(j)r$, and take $\hat{R}(j) = A\hat{P}(j)A^H$, we obtain

$$A\hat{P}(j)A^H x = r \tag{28}$$

by using the Fourier structure of matrix A, x can be obtained by using IFFT and FFT. Therefore, the main complexity in each step is $O(N \log_2 N)$.

4 Complexity analysis

The complexities of the proposed method with other discussed methods are compared in this section. Based on the above analysis, the complexity of the proposed method is $O(N \log_2 N)$, while the complexities of the 'SBL null subcarrier' and 'SBL all subcarrier' based on the null subcarriers and all subcarriers in [11] are respectively as $O(N^2M + M^3)$ and $O(N^3)$. These results show that the proposed method has the lowest complexity among the three methods.

5 Results and Discussion

Computer simulation results are provided in this section to compare the performance among 'SPICE' proposed in this paper, 'LS' based on equation (7), 'SBL null subcarrier' and 'SBL all subcarrier' proposed in [11], the last two methods based on the sparse Bayesian learning use the null subcarrier and the all subcarrier cases respectively.

The 15-path multipath channel model is used as the PLC system, and parameters are the same as those listed in Table IV in [15]. The frequency range is $35 \sim 91kHz$, which is adopted as the narrowband power line communication standard. The total noise (impulsive noise and background noise) of the system uses a 3-ary GM model, which represents 90% of background noise and 10% of impulsive noise (which is 7% higher than the background noise power of 20dB and 3% higher than the 30dB), this noise model is also commonly used in power line communication. The system bit error rate (BER) is defined as $BER = \frac{P_e}{P_t}$, where P_e represents the number of erroneous bits and P_t represents the total number of bits. The detailed simulation parameters are shown in Table 1.

Figures 1-4 compare the BER performances of all the above mitigation methods for uncoded and coded systems using 4-QAM and 16-QAM, respectively.

We first analyze the results for the uncoded 4-QAM system in Figure 1. Obviously, our proposed 'SPICE' outperforms all the other methods. At the same time, as SNR increases, our method becomes the most advantageous in moderate to high SNR region.

Then, we analyze the results presented in Figure 2 for the coded system using 4-QAM. Again, our proposed method demonstrates a favorable capability of outperforming most of other algorithms in a similar tendency to that for the uncoded systems in Figure 1. And compared with Figure 1, the performance of each method in Figure 2 has been improved, which shows that the performance of the system can be effectively improved by using convolutional coding.

Figures 3 and 4 respective provides the simulation results for uncoded and coded 16-QAM case. It is observed that the BER performances of all the mitigation methods are degraded in both uncoded and coded cases. This is due to the fact that the constellation points for high order modulation become much tighter for the given transmit power, and, hence, the detection of OFDM data symbols are more susceptible to the impulsive noise residual. It is promising to observe that, in the 16-QAM systems, our method can obtain substantial performance gains over all other methods for moderate to high SNR values.

Figures 5 and 6 compare the BER performance of all the above mitigation methods for uncoded and coded systems using 4-QAM with different numbers of null subcarriers, respectively.

It can be seen from Figure 5 that the BER of the four algorithms decreases with the increase the number of null subcarriers. This is because more number of null subcarriers allows the system to obtain more observations, and therefore provide better estimate of the impulsive noise. In addition, it is clearly seen that our method is better than all the other methods under different numbers of null subcarriers.

By analyzing the results presented in Figure 6 for the coded 4-QAM system, we obtain the similar conclusion. Again, our proposed 'SPICE' demonstrates a favorable capability of outperforming most of other algorithms in a similar tendency to that for the uncoded systems in Figure 5.

6 Conclusions

In this paper, we proposed an asynchronous impulsive noise mitigation method in an OFDM based PLC system. The proposed method uses SPICE to estimate the asynchronous impulsive noise and then subtracts the estimation noise from the received signal for mitigation. It is shown via simulation results that the proposed method is superior to the other methods by comparing the BER performances in different simulation environments. Moreover, compared with the existing methods, our proposed method can obtain computational saving to some extent.

Appendix A

To prove (19) we make the following equivalent transformation

$$r^H R^{-1} r = r^H R^{-1} R R^{-1} r \tag{29}$$

Since $R = APA^H$, formula (29) can be further written as

$$r^H R^{-1} r = r^H (APA^H)^{-1} APP^{-1} PA^H (APA^H)^{-1} r \tag{30}$$

Let

$$r^H (APA^H)^{-1} AP = U \tag{31}$$

$$PA^H (APA^H)^{-1} r = V \tag{32}$$

We can get

$$UA^H = r^H \tag{33}$$

$$AV = r \tag{34}$$

Because $A\varphi = r$ and $\varphi^H A^H = r^H$, we have $U = \varphi^H, V = \varphi$. Therefore, $r^H R^{-1} r$ can be converted as $\varphi^H P^{-1} \varphi$.

Appendix B

The optimization problem in (15) is convex, based on Lagrange multiplier, the optimal solution can be obtained by solving the partial derivative and setting the derivative to zero

$$\frac{\partial}{\partial \varphi}[\varphi^H P^{-1}\varphi + \lambda^H(A\varphi - r)] = 0 \tag{35}$$

which can be simplified as

$$2P^{-1}\varphi + A^H\lambda = 0 \tag{36}$$

By using $A\varphi = r$, λ and φ can be solved from (36)

$$\lambda = -2(APA^H)^{-1}r \tag{37}$$

$$\varphi = PA^H R^{-1}r \tag{38}$$

Abbreviations

PLC: Power line communication; CS: Compressed sensing; SPICE: Sparse iterative covariance estimation; QAM: Quadrature amplitude modulation; IDFT: Inverse discrete fourier transform; BG: Bernoulli-gaussian; GM: Gaussian-mixture; MCA: Middleton class A; PDF: Probability density function; LMMSE: Linear minimum mean square estimate; SDP: Semidefinite programming; SBL: Sparse bayesian learning; BER: Bit error rate; SNR: Signal to noise ratio

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Author's contributions

YW conceived and designed the study. YW performed the simulation experiments. YW wrote the paper. YL reviewed and edited the manuscript. QQ, YY, WH, and XT provided support in the simulation work. All authors read and approved the final manuscript.

Availability of data and materials

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Figures

Figure 1 BER performance comparison in uncoded 4-QAM system. Figure 1 shows the variation of the system BER with different SNR when the 4-QAM modulation mode is adopted in the uncoded system by four different methods.

Figure 2 BER performance comparison in coded 4-QAM system. Figure 2 shows the variation of the system BER with different SNR when the 4-QAM modulation mode is adopted in the coded system by four different methods.

Figure 3 BER performance comparison in uncoded 16-QAM system. Figure 3 shows the variation of the system BER with different SNR when the 16-QAM modulation mode is adopted in the uncoded system by four different methods.

Figure 4 BER performance comparison in coded 16-QAM system. Figure 4 shows the variation of the system BER with different SNR when the 16-QAM modulation mode is adopted in the coded system by four different methods.

Figure 5 BER performance comparison in uncoded 4-QAM system under different numbers of null subcarriers. Figure 5 shows the variation of the system BER with the number of different null subcarriers when the 4-QAM modulation mode is adopted in the uncoded system by four different methods.

Figure 6 BER performance comparison in coded 4-QAM system under different numbers of null subcarriers. Figure 6 shows the variation of the system BER with the number of different null subcarriers when the 4-QAM modulation mode is adopted in the coded system by four different methods.

Tables

Table 1 Simulation parameter table

Parameter name	**Parameter value**
Number of Subcarriers	128
Number of Data Subcarriers	72
Number of Null Subcarriers	56
Modulation	4-QAM,16-QAM
FEC Code	Rate-1/2 convolutional code
GM Model	$K = 3, p_k = \{0.9, 0.07, 0.03\}, \gamma_k = \{1, 100, 1000\}$

Figures

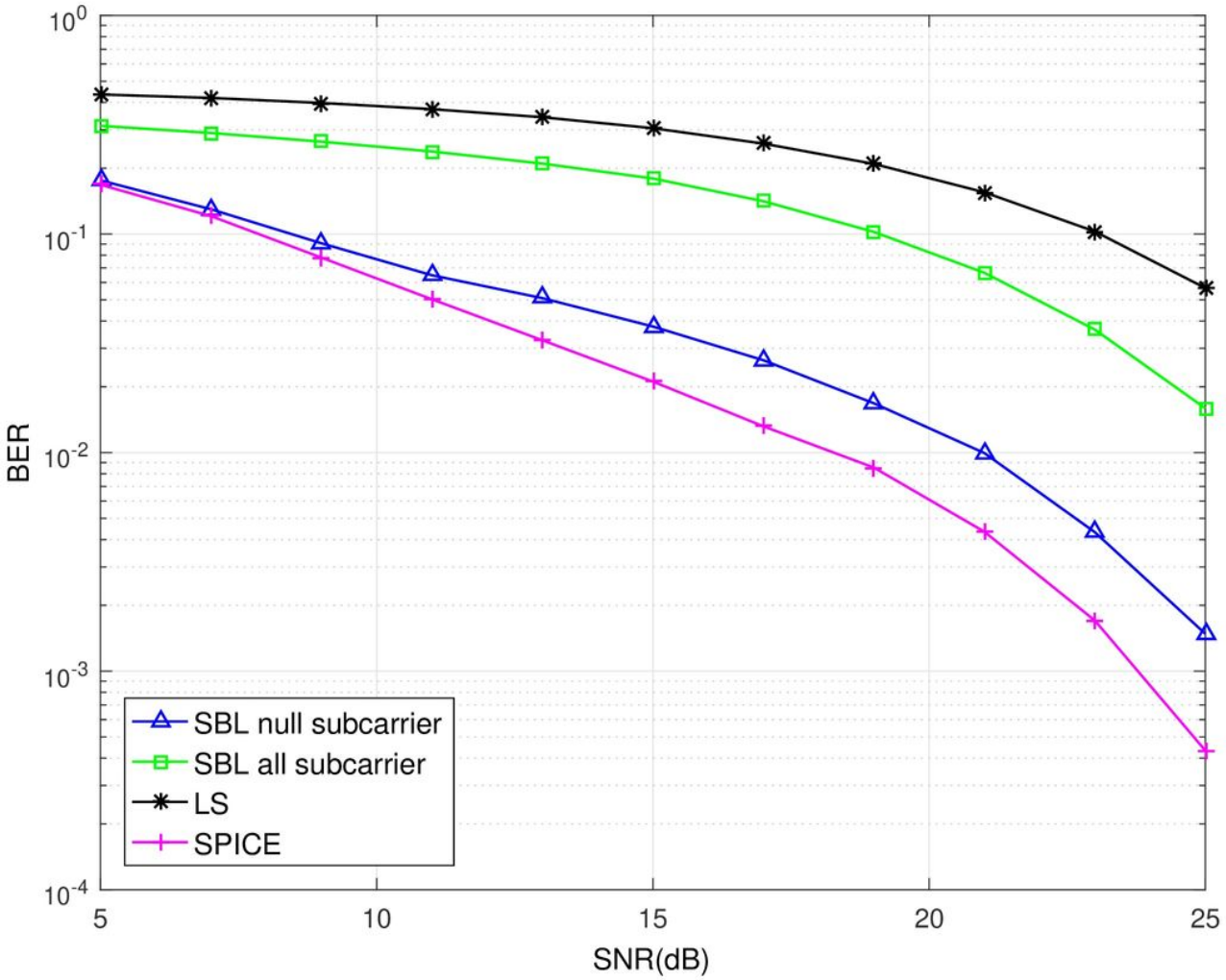

Figure 1

BER performance comparison in uncoded 4-QAM system. Figure 1 shows the variation of the system BER with different SNR when the 4-QAM modulation mode is adopted in the uncoded system by four different methods.

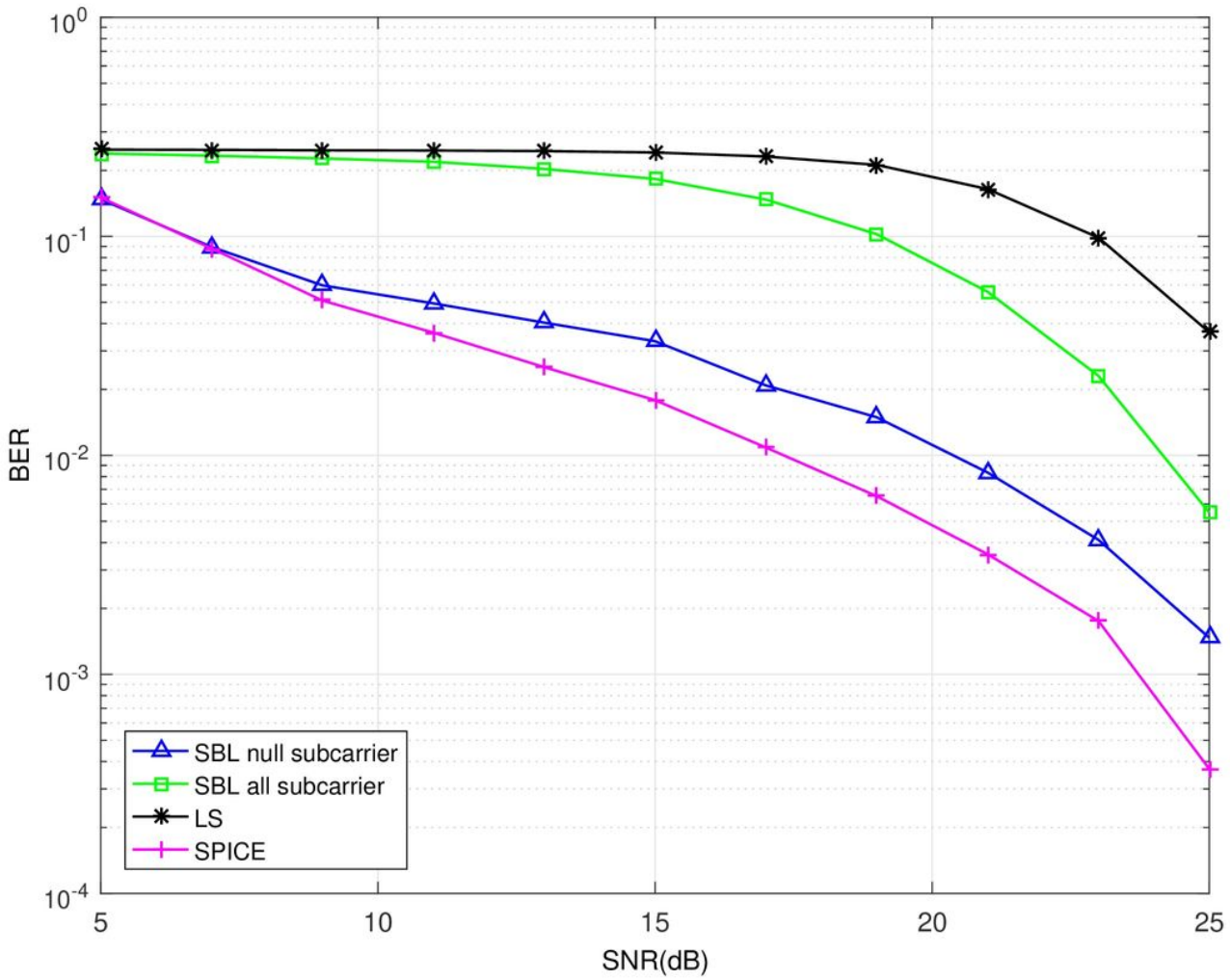

Figure 2

BER performance comparison in coded 4-QAM system. Figure 2 shows the variation of the system BER with different SNR when the 4-QAM modulation mode is adopted in the coded system by four different methods.

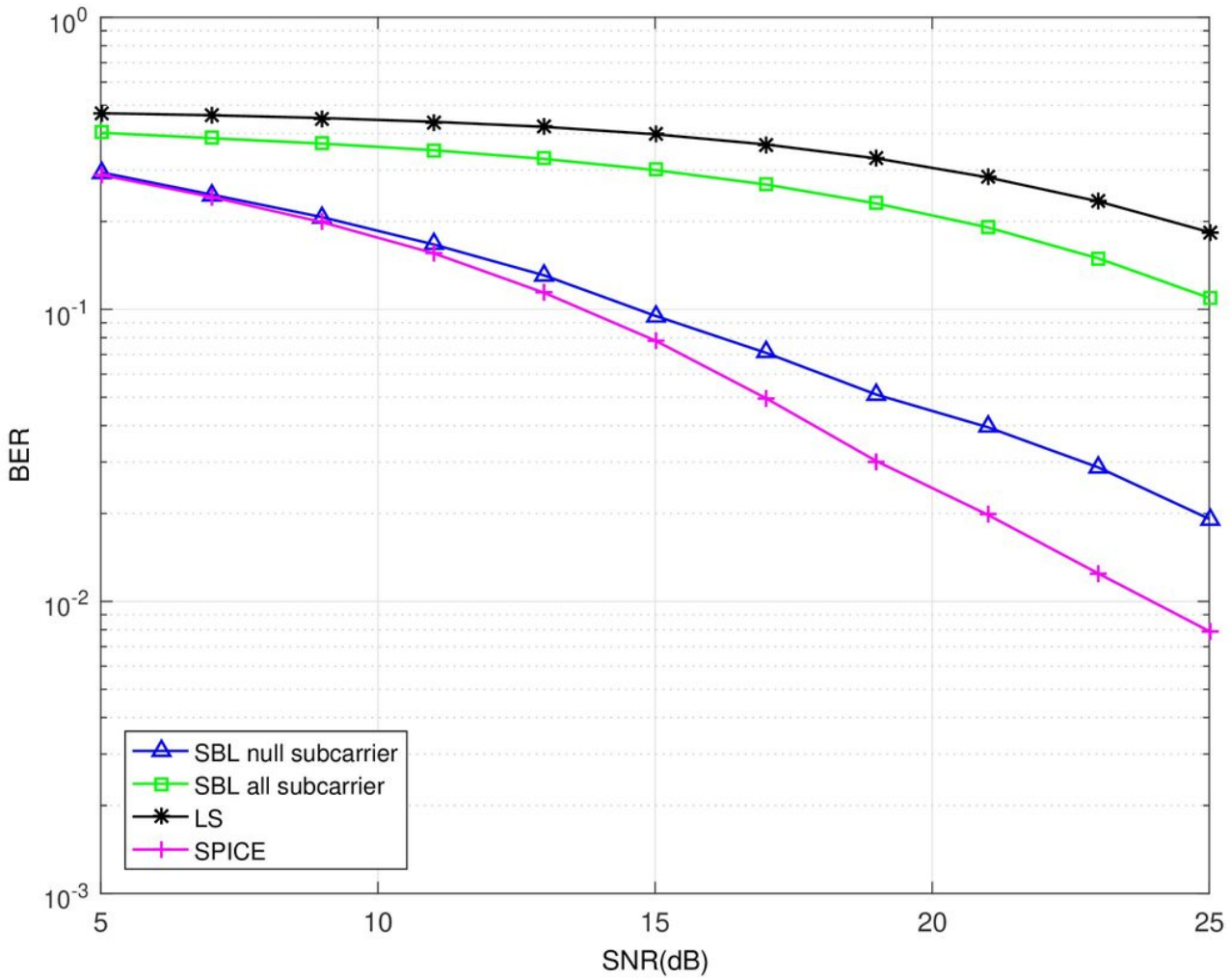

Figure 3

BER performance comparison in uncoded 16-QAM system. Figure 3 shows the variation of the system BER with different SNR when the 16-QAM modulation mode is adopted in the uncoded system by four different methods.

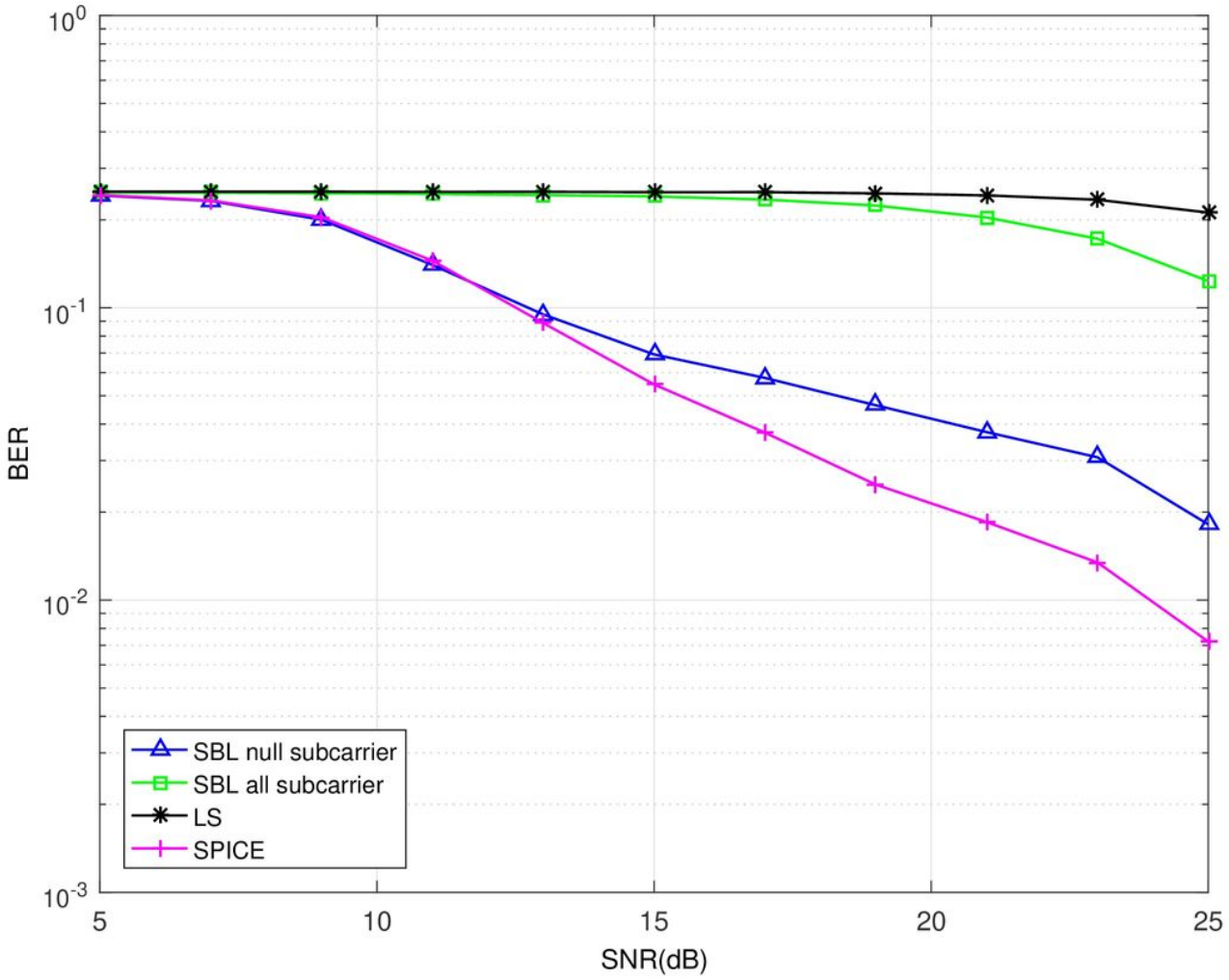

Figure 4

BER performance comparison in coded 16-QAM system. Figure 4 shows the variation of the system BER with different SNR when the 16-QAM modulation mode is adopted in the coded system by four different methods.

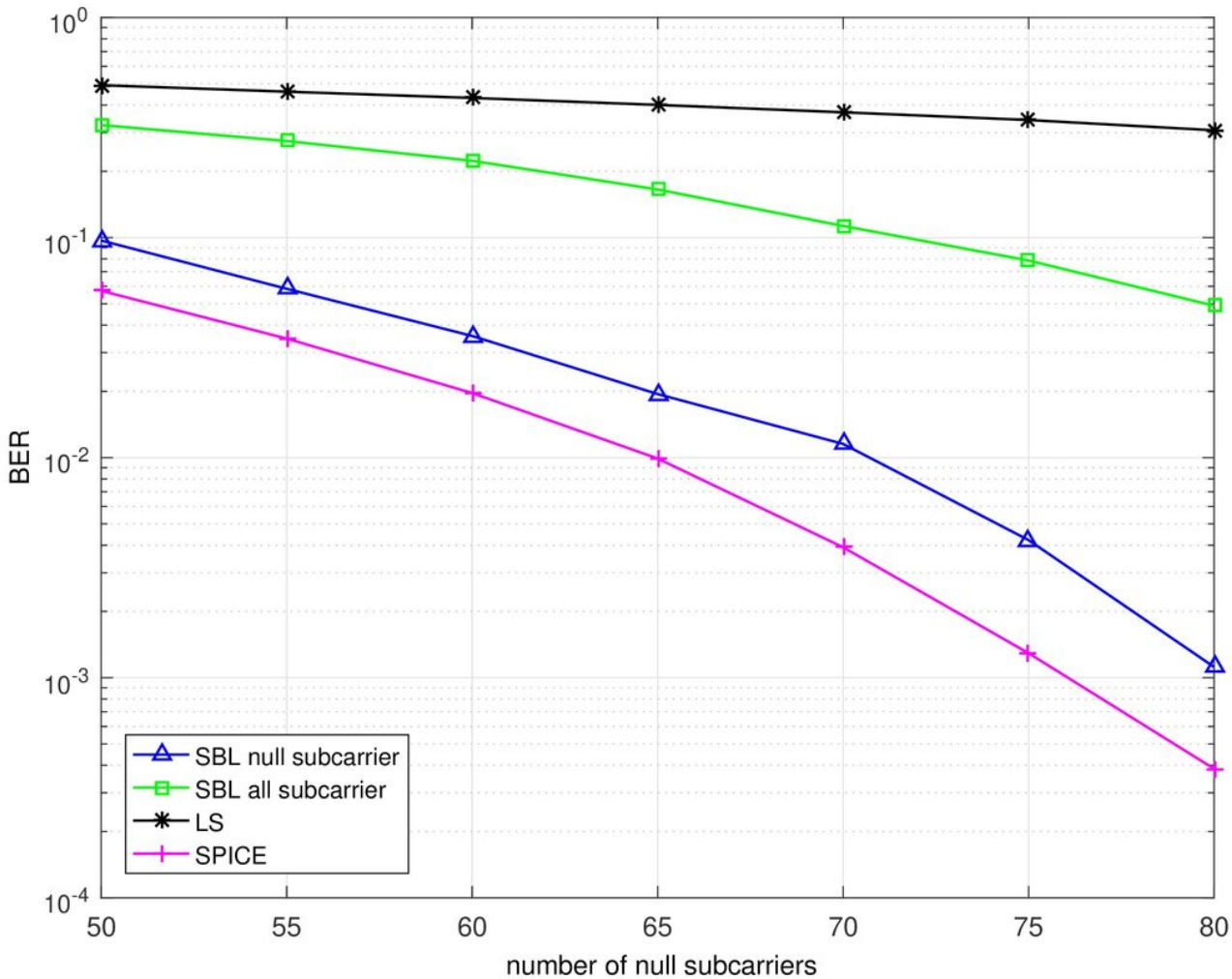

Figure 5

BER performance comparison in uncoded 4-QAM system under different numbers of null subcarriers.
Figure 5 shows the variation of the system BER with the number of different null subcarriers when the 4-QAM modulation mode is adopted in the uncoded system by four different methods.

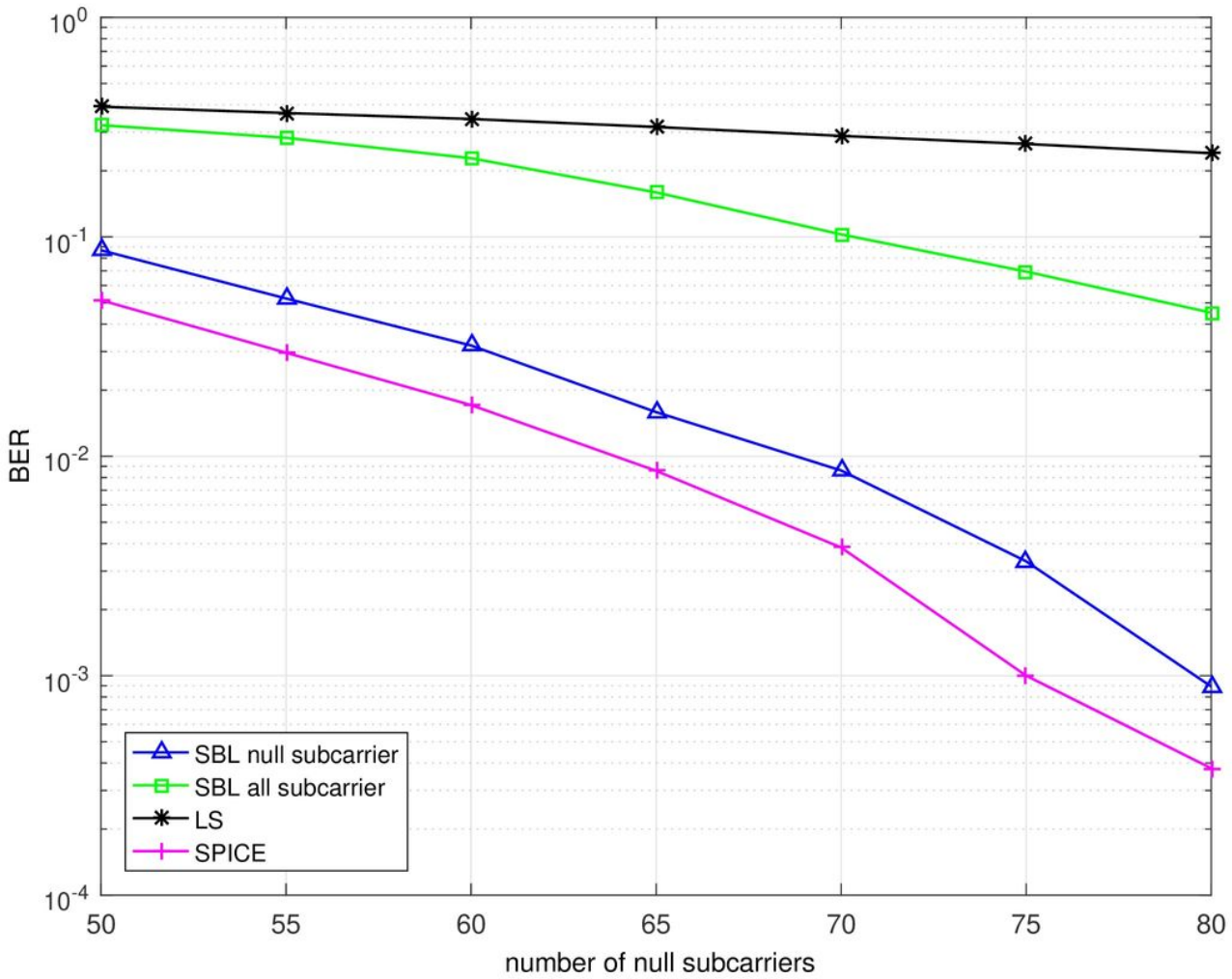

Figure 6

BER performance comparison in coded 4-QAM system under different numbers of null subcarriers. Figure 6 shows the variation of the system BER with the number of different null subcarriers when the 4-QAM modulation mode is adopted in the coded system by four different methods.