

Error Rate Analysis of Sparse Vector Coding with Diversity Techniques in the Presence of Transceiver Hardware Impairments

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Abstract—Ultra-reliable and low-latency communication (URLLC) is essential for mission-critical applications in 6G, necessitating stringent reliability and latency requirements. Sparse vector coding (SVC) seems to be a suitable candidate for ultra-reliable short-packet communications in future wireless systems. In this paper, we propose an integration of SVC with receiver diversity schemes, namely maximal ratio combining (MRC), equal gain combining (EGC), and selection combining (SC), in the presence of non-ideal transceiver hardware impairments. The key idea is to weight the received signal with weighting coefficients such that the reliability of the SVC transmission is further enhanced. A step-by-step mathematical system model is developed considering imperfect channel state information (CSI) and hardware impairments (HWI) using a signal-dependent distortion model at both the transmitter and receiver. The packet error rate (PER) is assessed and compared with that of the conventional SVC scheme without diversity under the standard Extended Pedestrian A (EPA), Extended Vehicular A (EVA), and 5G Tapped Delay Line (TDL) vehicular-B model channel models. The findings demonstrate that all diversity schemes substantially outperform the conventional method, with MRC providing the highest performance due to its optimal combining strategy. The results illustrate that for the proposed scheme, a trade-off has been observed between improved reliability performance with the number of receiving antennas and the number of resources, against practical effects of the HWI and CSI estimation errors.

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Index Terms—ultra-reliability, sparse vector coding, diversity schemes, multipath matching pursuit, block error rate

I. INTRODUCTION

FIFTH-GENERATION (5G) has coined ultra-reliable and low-latency communication (URLLC) as one of the use cases due to the unprecedented wireless applications to meet the stringent requirement of achieving both reliability and low-latency simultaneously [1]. Sixth-generation (6G) seeks to enhance this capability further with extreme URLLC (xURLLC), facilitating transformative applications that were previously considered unattainable [2]. The primary challenge arises from

the incompatibility between two stringent quality of services (QoS) requirements: the demand for extremely low latency and the necessity for very high reliability. Industrial automation [3], extended reality (xR) for immersive experience, remote surgeries with robotic system assistance, and autonomous systems ranging from driverless vehicles to smart cities. One common feature among these applications is that the information to be communicated is small, demanding a shorter coding technique instead of long codewords [4].

In contrast to conventional error-control approaches, [5] proposed a novel short-packet transmission by combining compressed sensing (CS) and communication theory. The primary concept of sparse vector coding (SVC) is to convert information into a sparse vector with only a few non-zero entries. Subsequently, the sparse vector is transmitted following a process called random multi-code spreading. At the receiver, using greedy sparse recovery algorithm, the non-zero positions are identified, and thus the information bits can be decoded [5]. Research indicates that the packet error rate (PER) of SVC may be reduced compared to traditional channel coding schemes in a single-user scenario. To enhance the efficiency of traditional SVC, several variants of SVC have been introduced [6]–[10]. In [6], under slow channel variations, a pilot-less SVC transmission has been studied, where the input is represented as a combination of the sparse vector and fading channel, thereby reducing the pilot overhead. [7] introduces enhanced-SVC, where information is mapped into both the non-zero positions and modulated symbols in the form of phase shift keying (PSK) at the active indices. In order to improve the spectral efficiency, [11] proposed to transmit additional information using index modulation for codebooks of the conventional SVC scheme. To further improve the reliability of SVC, a constellation rotation-based approach was proposed in [8], where the goal is to optimize the selection of symbols from a multi-constellation set to keep the constellation points at maximum distance. As an extension, [9] introduced a multi-mode SVC scheme that retains the first two parts of the information as in [8], while mapping the third part of the information bits to permutations of the constellation alphabets. In contrast, since the column correlation coefficient of the codebook will directly impact the SVC performance, work in [10] focuses on minimizing the maximum correlation of the codebook columns using a convex optimization framework.

The demonstrated superiority of SVC for short-packet

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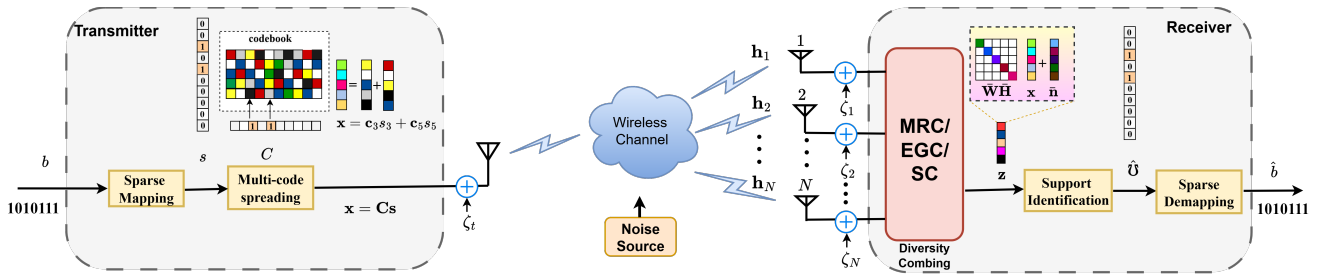


Fig. 1. SVC-aided receiver diversity combining.

communication has led to its adoption in various existing technologies, including multiple-input multiple-output [12], orthogonal time frequency space [13], integrated sensing and communication [14], industrial applications [15], rate-splitting [16], and intelligent reflecting surfaces (IRS) [17]. Specifically, a combination of SVC and transmitter diversity analysis has been carried out in [17], [18], where the maximal ratio transmission (MRT) scheme is employed. The main idea is that a composite of a sparse vector and an MRT-weighted coefficient is transmitted over a fading channel [18]. As expected, results demonstrate that the reliability of the SVC schemes can be improved by a multi-antenna system at the transmitter side [17]. SVC is a promising solution for URLLC because it offers low decoding latency and efficiently supports short-packet transmission. However, its reliability is highly sensitive to channel fading and noise. In contrast to the works carried out in [5]–[12], [17], [18], in this work, we carried out the integration of SVC with receiver diversity techniques, where multiple independently faded signal observations can be exploited via diversity combining to enhance detection robustness. Also, as noted in [5], an SVC in combination with a receiver diversity scheme can improve reliability by weighting the received signal, thereby affecting the overall signal-to-noise ratio (SNR). Motivated by these facts, in this work, we studied the receiver diversity techniques, such as maximal ratio combining (MRC), equal gain combining (EGC), and selection combining (SC), which aim to achieve ultra-high reliability within a single transmission opportunity.

On the other hand, hardware impairments (HWI) such as power amplifier nonlinearities, in-phase and quadrature (IQ) imbalance, and phase noise will individually impact, in general, the performance analysis of any communication system [19]. Hardware impairments impose an inherent ceiling on system performance that cannot be overcome by simply increasing transmit power [20]. Moreover, acquiring perfect channel state information (CSI) at the receiver is generally impractical in real-world wireless communication systems. Since the accuracy of channel estimation has a direct impact on the PER performance, it is essential to account for the effects of imperfect CSI when evaluating the system's performance [21]. However, these non-ideal impairments, such as HWI and imperfect CSI, where their impact is particularly pronounced in multi-antenna systems, are often overlooked in the development and performance evaluation of new transmission schemes, such as SVC [5]–[10], as well as in the design of corresponding receiver algorithms. To this end, in this work,

we also considered the effect of HWI and imperfect CSI on the SVC transmission along with the receiver diversity. The main contributions of the work carried out are mentioned below:

- We formulated a unified system model for the proposed work, including the transceiver HWI, imperfect CSI and various receiver diversity schemes, namely: MRC, EGC, and SC.
- The performance limitation under ideal transceiver impairments in [5] is resolved by studying the performance of the PER of the sparse vector coding with MRC, EGC, and SC techniques in the presence of practical hardware impairments.
- With the help of Monte Carlo simulations, we confirm that the proposed work outperforms conventional SVC in 3GPP-standardized Extended Pedestrian A (EPA), Extended Vehicular A (EVA), and 5G-TDL (Tapped Delay Line) Vehicular-B channels.
- Our analysis provides insights into the effect of the number of receiving antennas, HWI, imperfect CSI, resource allocation, and the number of non-zero positions in the sparse vector on PER performance.

Paper Organization: Section II presents the system model under consideration with a unified mathematical framework with both transmitter and receiver designs. Section III presents extensive simulation results. Section IV provides the concluding remarks for this work.

Notations: Bold lowercase symbols indicate vectors, and bold uppercase symbols indicate matrices. For a vector $\mathbf{a}$, $\text{diag}(\mathbf{a})$ refers to a diagonal matrix with diagonal elements given by $\mathbf{a}$. The identity matrix of size $M \times M$ is denoted as $\mathbf{I}_{M \times M}$. The notation $\mathcal{CN}(\mu, \sigma^2)$ represents a circularly symmetric complex Gaussian random variable with mean μ and variance σ^2 . The expectation operator is $\mathbb{E}(\cdot)$, $|\cdot|$ denotes the norm, and the transpose is indicated by $(\cdot)^T$.

II. SYSTEM MODEL

In this section, a detailed discussion on the transmitter and receiver design of the proposed system will be carried out.

A. Transmitter Design

As shown in Fig. 1, at the transmitter side, the SVC operation is divided into two blocks. Firstly, the information bits, b with each bit E_b energy, are encoded into a sparse vector s of length L with K non-zero entries (*a.k.a.* support positions) using a sparse mapping. In general, there are $\binom{L}{K}$ choices

to construct a K -sparse vector, facilitating the encoding of $\left\lceil \log_2 \binom{L}{K} \right\rceil \geq b$ bits of information, where $\lfloor \cdot \rfloor$ indicates the floor operation. As an example, if we choose $K = 2$ positions out of $L = 12$, then we have $\binom{12}{2} = 66$ choices and correspondingly we can encode $\left\lceil \log_2 \binom{66}{2} \right\rceil = 6$ bits of information. The sparse vector thus constructed using sparse mapping is spread across M resources using a spreading codebook $\mathbf{C} = [\mathbf{c}_1 \ \mathbf{c}_2 \ \dots \ \mathbf{c}_L]$, where $\mathbf{c}_l = [c_{l1} \ c_{l2} \ \dots \ c_{lM}]^T$ represents the spreading sequence. The transmitted signal vector $\mathbf{x}$ after resource mapping can be written as,

$$\mathbf{x} = \mathbf{C}\mathbf{s} = \sum_{l=1}^L \mathbf{c}_l s_l = \sum_{k=1}^K \mathbf{c}_{\mathcal{U}_k} s_{\mathcal{U}_k} \quad (1)$$

where $\mathcal{U}_k$ indicates the set of support positions, $\mathbf{c}_{\mathcal{U}_k}$ are the columns extracted from $\mathbf{C}$ indexed by the support position set. For example, if the third and fifth positions of the sparse vector $\mathbf{s}$ are non-zero (i.e., $\mathcal{U}_k = \{3, 5\}$), then the transmitted vector can be written as $\mathbf{x} = \mathbf{c}_3 s_3 + \mathbf{c}_5 s_5$. It is to be noted that, irrespective of how the non-zero elements are positioned, the codebook matrix $\mathbf{C}$ should be designed in such that the vector $\mathbf{C}\mathbf{s}$ retains enough information to enable accurate reconstruction of the sparse vector at the receiver. To this end, as long as $M \propto \mathcal{O}(K \log L)$, the signal recovery is possible [22].

B. Receiver Design

Let us consider the receiver equipped with N antennas. Let the channel vector between the transmitter and the r -th receiving antenna is denoted by $\mathbf{h}_r = [h_{r1}, h_{r2}, \dots, h_{rM}]^T$. In practical wireless transceivers, unavoidable radio frequency (RF) hardware imperfections result from power amplifier (PA) nonlinearities, IQ imbalance, oscillator phase noise, carrier frequency offset (CFO), and finite-resolution digital-to-analog/analog-to-digital converters (DAC/ADC). While calibration and compensation techniques can mitigate these impairments, residual distortions persist and cannot be entirely eliminated. The present study models these residual impairments using the widely adopted error vector magnitude (EVM)-based additive Gaussian distortion model, in which the aggregate transmitter and receiver impairments are represented as statistically independent zero-mean circularly symmetric complex Gaussian (CSCG) distortion noises [23]. In addition, perfect CSI is generally unattainable due to channel estimation errors, pilot contamination, feedback delay, and channel aging. To mitigate these challenges, in this work, an imperfect CSI model is adopted [21]. Taking transceiver hardware impairment and imperfect CSI into account, the received signal vector at the r -th receiving antenna can be written as,

$$\begin{aligned} \mathbf{y}_r &= \hat{\mathbf{H}}_r (\mathbf{x} + \boldsymbol{\zeta}_t) + \boldsymbol{\zeta}_r + \mathbf{n}_r \quad \forall \ r \in \{1, 2, \dots, N\} \quad (2) \\ &= \underbrace{\boldsymbol{\Theta}_r \mathbf{s}}_{\text{desired signal}} + \underbrace{\hat{\mathbf{H}}_r \boldsymbol{\zeta}_t + \boldsymbol{\zeta}_r + \mathbf{n}_r}_{\text{noise}} \quad (3) \end{aligned}$$

where $\hat{\mathbf{H}}_r = \mathbf{H}_r + \mathbf{E}_r$, $\mathbf{H}_r = \text{diag}(\mathbf{h}_r)$ denotes the true channel matrix, while $\mathbf{E}_r$ denotes the channel estimation error matrix. The entries of $\mathbf{E}_r$ are modeled as independent zero-mean CSCG random variables, $\mathbf{E}_r \sim \mathcal{CN}(0, \epsilon \mathbf{I})$. In this

context, ϵ denotes the error variance [21]. A value of zero for ϵ indicates perfect CSI, while higher values correspond to less accurate channel estimates. $\boldsymbol{\zeta}_t$, $\boldsymbol{\zeta}_r$ are the distortion noise characterizes the residual impairment at the transmitter side and r -th receiver antenna which follows $\boldsymbol{\zeta}_t \sim \mathcal{CN}(0, \kappa_t^2 \mathbf{P}_x)$, $\boldsymbol{\zeta}_r \sim \mathcal{CN}\left(0, \kappa_r^2 \mathbf{P}_x \mathbb{E}\left(\left|\hat{\mathbf{h}}_r\right|^2\right)\right)$ respectively [20] with $\hat{\mathbf{h}}_r = \text{diag}\left(\hat{\mathbf{H}}_r\right)$ being a vector whose elements are taken from the diagonal entries of $\hat{\mathbf{H}}_r$, $\mathbf{P}_x = \mathbb{E}\left(\left|\mathbf{x}\right|^2\right)$, κ_t and κ_r are the error vector magnitudes at the transmitter and r -th receiving antenna, $\mathbf{n}_r = [n_{r1}, n_{r2}, \dots, n_{rM}]^T$ with each element is a complex additive white Gaussian noise (AWGN) with zero mean and variance N_0 , and $\boldsymbol{\Theta}_r = \hat{\mathbf{H}}_r \mathbf{C}$ is the sensing matrix. For brevity, we use a generalized model with aggregate distortion level $\kappa = \sqrt{\kappa_t^2 + \kappa_r^2}$ [24]. Hence, the modified received signal accounts for HWI at both the transmitter and receiver can be written as,

$$\mathbf{y}_r = \hat{\mathbf{H}}_r \mathbf{x} + \mathbf{v}_r \quad (4)$$

where $\mathbf{v}_r = \hat{\mathbf{H}}_r \boldsymbol{\zeta}_t + \boldsymbol{\zeta}_r + \mathbf{n}_r$ is a complex Gaussian noise with zero mean and variance $\kappa^2 \mathbf{P}_x \mathbb{E}\left(\left|\hat{\mathbf{h}}_r\right|^2\right) + N_0$. The residual transmitter and receiver distortion noises are modeled as independent, zero-mean, CSCG random variables. These distortion noises are statistically independent of the transmitted signal, channel coefficients, and AWGN. The variances of these noises are proportional to the transmit and received signal powers, consistent with the EVM-based impairment model. Residual hardware impairments are considered independent across receive antennas. The channel is modeled as quasi-static block-fading, remaining constant during a single SVC packet and varying independently between packets.

In order to enhance the reliability, the received signal is then passed through a diversity combining block. All signals received in an MRC/EGC receiver are weighted and merged coherently to maximize overall SNR. To accomplish this, the amplitude and phase of the channel coefficients at each branch must be precisely predicted at all times. Specifically, the received signal at each receive antenna is multiplied by the weighting coefficient and given as,

$$\mathbf{z}_r = \mathbf{W}_r \mathbf{y}_r \quad (5)$$

where $\mathbf{W}_r$ is the weighting coefficient matrix given by,

$$\mathbf{W}_r = \begin{cases} \hat{\mathbf{H}}_r^* / \hat{\mathbf{H}}_{F,r}, & \text{for MRC} \\ e^{-j\angle \hat{\mathbf{H}}_r} / \hat{\mathbf{H}}_{F,r}, & \text{for EGC} \\ \mathbf{I}_{M \times M}, & \text{for SC} \end{cases} \quad (6)$$

where $(\cdot)^*$ indicates the complex conjugate, and $\hat{\mathbf{H}}_{F,r}$ denotes the Frobenius norm. Continuing the same example, if $\mathcal{U}_k = \{3, 5\}$, then the weighted received vector can be written as,

$$\begin{aligned} \mathbf{z}_r &= \mathbf{W}_r \hat{\mathbf{H}}_r \mathbf{x} + \mathbf{W}_r \mathbf{v}_r \\ &= [\mathbf{W}_r \hat{\mathbf{H}}_r \mathbf{c}_3 \quad \mathbf{W}_r \hat{\mathbf{H}}_r \mathbf{c}_5] \begin{bmatrix} s_3 \\ s_5 \end{bmatrix} + \mathbf{W}_r \mathbf{v}_r \end{aligned}$$

TABLE I
SIMULATION PARAMETERS

Description	Values
Sparse vector length, L	363
Sparsity level, K	2, 3, 4
Resource, M	24, 42, 63
Number of receive antenna, N	2, 3, 4
HWI parameter, κ	0, 0.4
Imperfect CSI error, ϵ	0, 0.2, 0.7

Now, the modified signal of all the weighted received signal vectors from each antenna after passing through an adder block is given by,

$$\mathbf{z} = \sum_{r=1}^N \mathbf{z}_r = \sum_{r=1}^N \mathbf{W}_r \mathbf{y}_r = \bar{\mathbf{W}} \bar{\mathbf{H}} \mathbf{x} + \bar{\mathbf{v}} \quad (7)$$

$$= \bar{\mathbf{W}} \bar{\mathbf{H}} \mathbf{C} \mathbf{s} + \bar{\mathbf{v}} \quad (8)$$

$$= \bar{\mathbf{\Theta}} \mathbf{s} + \bar{\mathbf{v}} \in \mathbb{C}^{NM \times 1} \quad (9)$$

where $\bar{\mathbf{W}} = \text{diag}(\mathbf{W}_1, \mathbf{W}_2, \dots, \mathbf{W}_N)$ denotes the block diagonal weighting coefficient matrix, $\bar{\mathbf{H}} = [\hat{\mathbf{H}}_1; \hat{\mathbf{H}}_2; \dots; \hat{\mathbf{H}}_N]$ is over all channel matrix with the vertical concatenation of the channel experienced at each antenna, $\bar{\mathbf{\Theta}} = \bar{\mathbf{W}} \bar{\mathbf{H}} \mathbf{C}$ is the modified sensing matrix and $\bar{\mathbf{v}} = \sum_{r=1}^N \mathbf{W}_r \mathbf{v}_r = \bar{\mathbf{W}} \tilde{\mathbf{v}}$ is the modified noise vector, with $\tilde{\mathbf{v}} = [\mathbf{v}_1; \mathbf{v}_2; \dots; \mathbf{v}_N]$ being the vertical concatenation of the noise experienced at each antenna. In the SC scheme, the received signal of the antenna that yields maximum SNR will be taken for further signal processing at the receiver. Mathematically, this can be written as,

$$\mathbf{z} = \mathbf{z}_i \quad \text{for } i = \max_r \text{SNR}_r \quad (10)$$

The output of the diversity block is passed through a support identification block, where a sparse recovery algorithm (multi-path matching pursuit (MMP) or orthogonal matching pursuit (OMP)) can be used to detect the support positions. Most of the recent studies employed the MMP algorithm due to its better decoding performance and moderate complexity [22]. Accordingly, the estimates of the non-zero positions can be given as,

$$\hat{\mathcal{U}}_k = \underset{a \in [1, a_{\max}]}{\text{MMP}}(\mathbf{z}, \bar{\mathbf{\Theta}}), \quad \forall k \in \{1, \dots, K\} \quad (11)$$

where $\hat{\mathcal{U}}_k$ is the estimate of the $\mathcal{U}_k$, a denote the searching path, and $a_{\max}$ denote the maximum number of searching paths. More details about the MMP search algorithm can be found in [5]. Depending on the $\hat{\mathcal{U}}_k$, the sparse demapping will be carried out to recover $\hat{b}$ bits of information.

III. RESULTS AND DISCUSSIONS

This section presents simulation results that evaluate the error rate performance of SVC using various receiver diversity techniques. The number of non-zero places is set at $K = 2$, and the total number of bits is selected at $b = 12$ bits. We looked at the Bernoulli codebook, with $c_{i,j} \in \{+1, -1\}$ that had been generated at random. The maximum correlation coefficient between any two codebook columns is 0.7, unless otherwise specified. However, one can employ an optimal

codebook studied in [10], [25]. Other simulation parameters are as per Table I. Channel coefficients are independent, complex Gaussian variables with specified tap durations and average powers. Table II, III present the channel delay profile for the 3GPP EPA and EVA TDL models, which represent low- and high-mobility multipath. These models investigate fast time-varying channels characterized by significant user velocities of 1.54 km/h and 21.60 km/h, corresponding to maximum Doppler frequencies of 70 Hz and 5 Hz, respectively. The associated coherence times are 16.04 ms and 84.60 ms for the EVA and EPA channel models, respectively. We have used the MMP method to identify the support location. We define a short packet transmission as successful when both support locations are successfully decoded; if not, we declare a block error. All modeling and methodological solutions were executed using MATLAB 2024a on a Nitro ANV15-51 system equipped with a 13th Gen Intel Core i7-13620H processor.

A. Impact of Number of Receiving Antennas under EPA Channel

Fig. 2 illustrates the PER performance of SVC for MRC, EGC, and SC under the EPA channel. For completeness, we have compared the diversity schemes with the conventional SVC. As expected, when $N = 1$ all three schemes results boils down to the conventional SVC [5]. We can observe from the figures that, as the number of receiving antennas increases, the PER values decrease drastically irrespective of the diversity combining technique. Quantitatively, at an SNR of 8 dB, the PER values for MRC are $\{6000, 200, 10, 1\} \times 10^{-5}$, and for EGC are $\{6000, 300, 60, 10\} \times 10^{-5}$, and for SC are $\{6000, 500, 100, 20\} \times 10^{-5}$ for $N = 1, 2, 3, 4$ respectively. We can also note that, MRC achieves the best PER performance compared to EGC and SC due to optimal weight adaptation. For example, at a PER point of 10^{-3} , as seen in Fig.2, the MRC attains 1, 1.2, 1.77, 2.13 dB and 0.9, 1.3, 2.18, 3 dB, gain over EGC and SC for $N = 1, 2, 3, 4$ respectively.

B. Effect of Number of Receiving Antennas under EVA Channel

Fig. 3 presents the PER performance of SVC with receiver diversity techniques for varying N under the EVA channel. Similar to Fig. 2, we can arrive at the same observation pattern. Firstly, when $N = 1$, the result matches the conventional SVC, validating the proposed system model [5]. Secondly, increasing the number of receiving antennas improves the detection of support positions using the MMP algorithm, thereby resulting in lower PER values. In other words, regardless of the diversity scheme, achieving the same PER requires a lower SNR for $N = 4$ than for $N = 1$. For example, the SNRs required to attain a PER value of 10^{-4} for $N = 4, 3, 2, 1$ are 4 dB, 6 dB, 8.5 dB, 17.5 dB for MRC, and 5 dB, 7 dB, 10.2 dB, 17.5 dB for EGC, and 8.5 dB, 10.1 dB, 12.5 dB, 17.5 dB for SC.

C. Implications on Number of Resources

Fig. 4 presents the performance of the SVC-aided receiver diversity combining technique for different values of the

TABLE II
CHANNEL DELAY PROFILE EPA

j -th sample	0	1	2	3	4	5	6
Excess Tap Delay (ns)	0	30	70	90	110	190	410
Relative Power (dB)	0	-1	-2	-3	-8	-17.2	-20.8

TABLE III
CHANNEL DELAY PROFILE EVA

j -th sample	0	1	2	3	4	5	6	7	8
Excess Tap Delay (ns)	0	30	150	310	370	710	1090	1730	2510
Relative Power (dB)	0	-1.5	-1.4	-3.6	-0.6	-9.1	-7	-12	-16.9

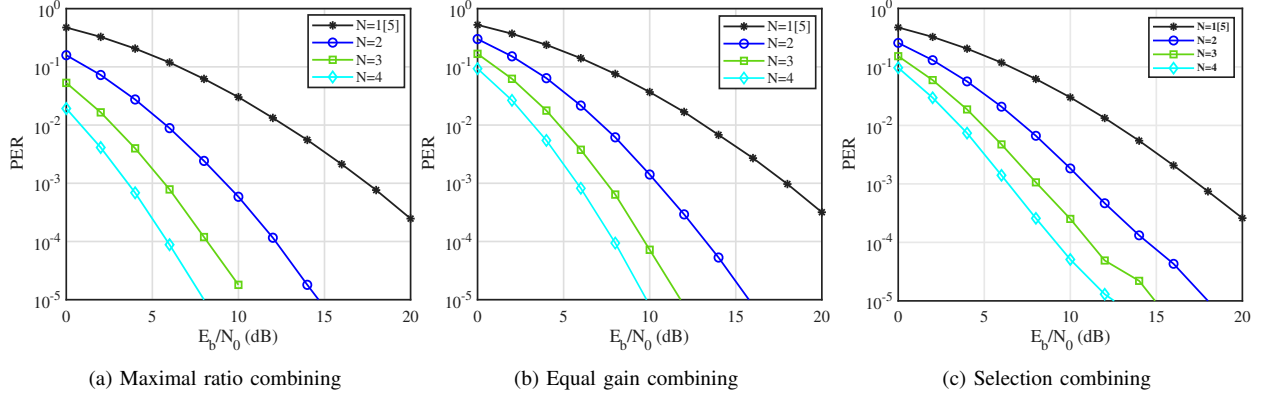


Fig. 2. PER performance under EPA channel for varying N , and $M = 42$

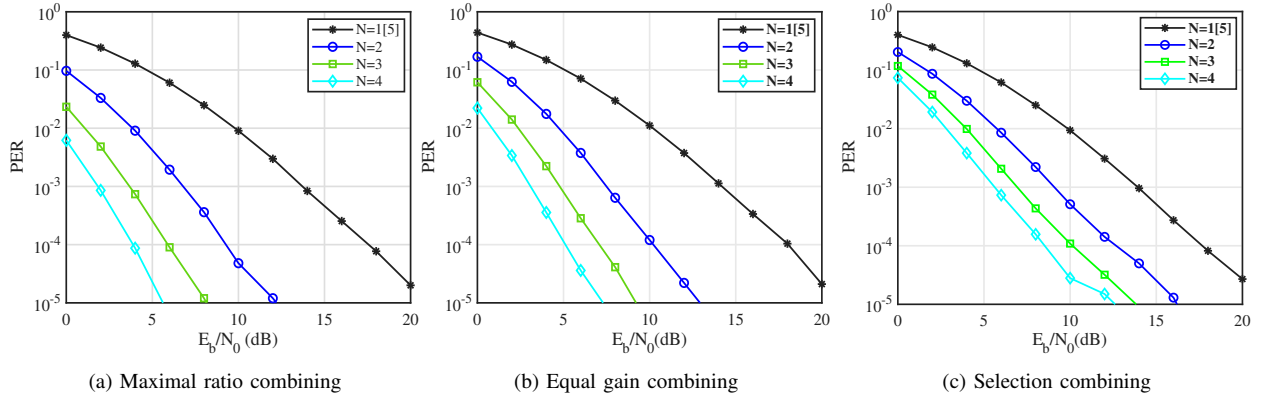


Fig. 3. PER performance under EVA channel for varying N , and $M = 42$

number of resources (M). An increase in M from 24 to 63 results in a higher probability of successful decoding of the short packet, demonstrating that PER is highly sensitive to variations in M . Also, we observed that MRC is the best among all the techniques, and as the resources increase from 24 to 63, the gain also increases. At 10^{-4} , MRC achieves a gain of around 2.4, 3.3 dB for $M = 63$, 1.8, 5.2 dB for $M = 42$, and 1.5, 5 dB for $M = 24$, compared to EGC and SC.

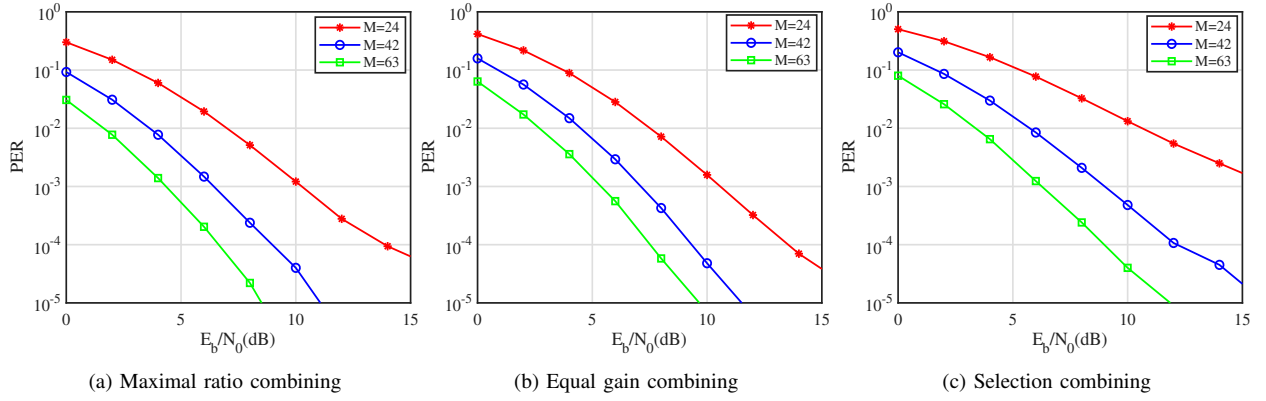
D. Insights on Varying Number of Non-zero Positions

The decoding success probability of the SVC-MRC scheme is evaluated across different sparsity levels, as illustrated

in the Fig. 5. As the sparsity parameter K increases, the curves shift toward higher SNR values, indicating that greater transmit power is required to maintain equivalent reliability. Quantitatively, the system achieves 50% decoding success probability for $K = 2$, $K = 3$, and $K = 4$ at SNR values of -6 dB, -3 dB, and 0 dB, respectively, demonstrating a consistent 3 dB power penalty per additional active element. This pattern highlights a fundamental trade-off: increasing K enhances spectral efficiency and data rate.

E. 3GPP 5G-TDL Vehicular-B

The PER performance of the SVC using MRC, EGC and SC over the standardized 3GPP 5G-TDL Vehicular-B (VB)

Fig. 4. PER performance comparison by varying the number of resource blocks with $N = 2$ under EVA channel.TABLE IV
CHANNEL DELAY PROFILE 3GPP 5G-TDL VEHICULAR-B

j -th sample	0	1	2	3	4	5
Excess Tap Delay (ns)	0	300	8900	12900	17100	20000
Relative Power (dB)	-2.5	0	-12.8	-10	-25.2	-16.0

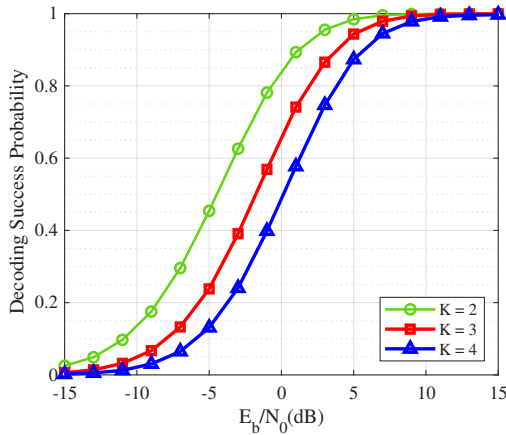


Fig. 5. Impact of decoding success probability of sparsity on SVC-MRC.

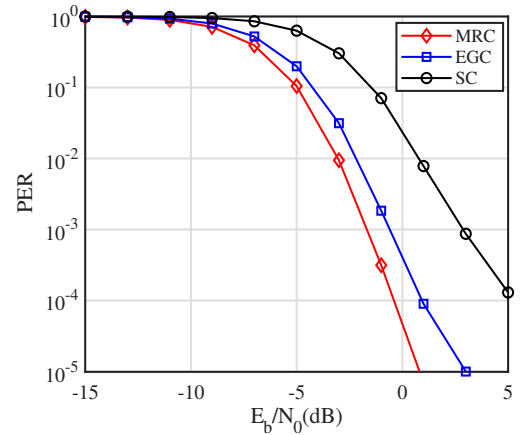


Fig. 6. PER performance comparison of SVC with MRC, EGC, and SC over the 3GPP Vehicular-B (VB) six-tap fading channel.

six-tap fading channel is shown in Fig. 6. The simulation uses a user velocity of 120 km/h, a maximum Doppler frequency of 389 Hz, and a coherence time of 1.09 ms. The channel delay profile is provided in Table IV. It is observed that SVC-MRC provides the best error performance. At the target PER of 10^{-4} SVC-MRC requires ≈ 0 dB SNR, SVC-EGC requires 1 dB, and SVC-SC requires 5 dB. MRC achieves an SNR gain of approximately 1.5 dB compared to EGC and 5 dB compared to SC. These gains are particularly evident in the low PER region, highlighting the superior diversity combining capability of MRC under the 3GPP Vehicular-B six-tap fading channel.

F. Effect of HWI

Fig. 7a and Fig. 7b illustrate PER performance of the SVC scheme employing MRC under both ideal and non-ideal conditions in EVA and EPA channel models, respectively. At low SNR, noise predominates in both; however, at high

SNR, HWI results in significant degradation. Quantitatively, we can observe that the HWI scenario has a baseline of roughly 10^{-4} , suggesting a reduction of 7 dB SNR, whereas the ideal situation shows a PER of less than 10^{-5} . The signal-dependent distortion limits performance and worsens as the received power increases. However, SVC performs well under HWI, suggesting a trade-off between hardware realism and performance, demonstrating its adaptability for real-world applications.

G. Impact of imperfect CSI

Fig. 8 illustrates the error rate performance of the SVC scheme employing MRC under both perfect and imperfect CSI for $K = 2$ and $N = 2$. In the case $\epsilon = 0$, which corresponds to perfect CSI, the system achieves optimal performance, requiring approximately 10.8 dB to attain a PER of 10^{-5} . Under imperfect CSI conditions, the required SNR increases to 11 dB for $\epsilon = 0.2$ and 12 dB for $\epsilon = 0.7$. As channel

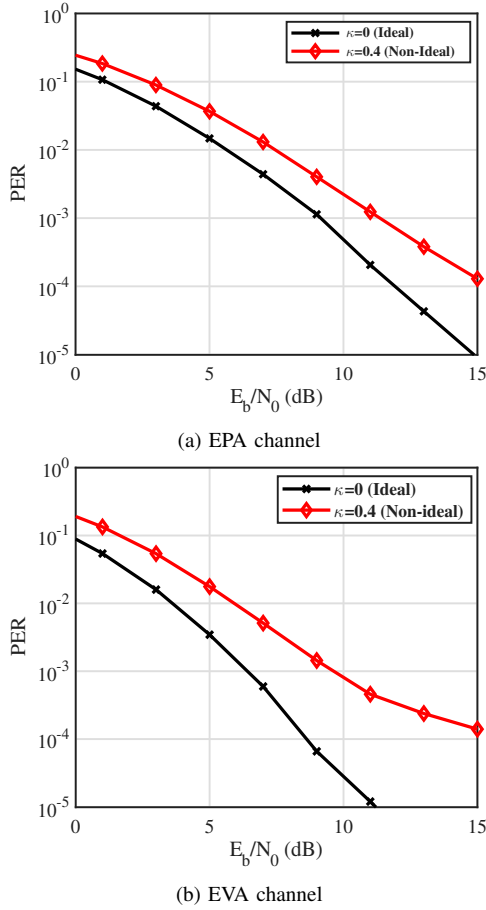


Fig. 7. PER performance comparison of SVC-MRC under ideal hardware and HWI scenarios for $N = 2$.

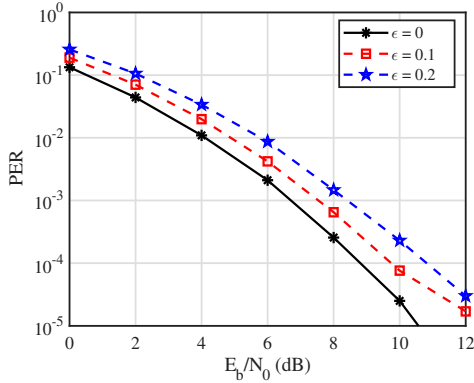


Fig. 8. PER performance comparison for perfect CSI and imperfect CSI on SVC-MRC by considering $K = 2$ and $N = 2$.

estimation error increases, PER performance deteriorates due to reduced accuracy in channel state information, resulting in diminished detection reliability. Nevertheless, the proposed scheme demonstrates only minor performance gaps of approximately 0.2 dB and 1.2 dB relative to the perfect CSI scenario, which indicates strong robustness to CSI imperfections. It can be noted that, in this work, we explored a Gaussian error model to study the imperfect CSI case; however, conventional channel estimation methods for SVC can be found in [26].

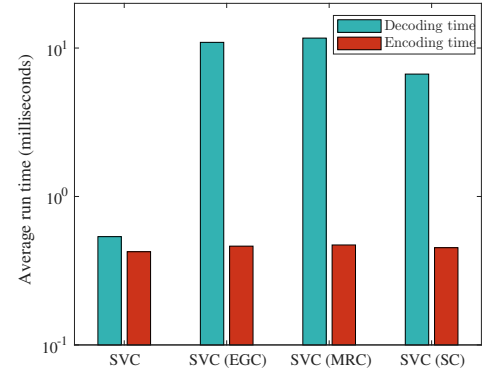


Fig. 9. Comparison of encoding and decoding time of different schemes with $K = 2$ and $N = 2$.

TABLE V
COMPUTATIONAL COMPLEXITY OF CONVENTIONAL SVC AND SVC-MRC, EGC, SC USING MMP ALGORITHM

Method	Computational Complexity
SVC [15]	$\mathcal{O}(2LMK + 2L^2M^2 + i^3 + 2i^2LM)$
SVC-MRC	$\mathcal{O}(2LMK + 2L^2M^2 + i^3 + 2i^2LM + MN)$
SVC-EGC	$\mathcal{O}(2LMK + 2L^2M^2 + i^3 + 2i^2LM + MN)$
SVC-SC	$\mathcal{O}(2LMK + 2L^2M^2 + i^3 + 2i^2LM + N)$

H. Latency Analysis

The processing latency performance of the evaluated coding framework is assessed by averaging the encoding and decoding run times for SVC, SVC-EGC, SVC-MRC, and SVC-SC, as illustrated in Fig. 9. Since encoding and decoding operations account for most of the total processing delay in SVC-based schemes, we evaluate overall processing latency by considering their times. All encoding variants achieve significant reliability, with average times below 1 ms, ranging from 0.45 ms for SVC-SC, SVC-EGC, and SVC-MRC to 0.4244 ms for standard SVC. Standard SVC and SVC-SC demonstrate minimal decoding overhead at 0.536 ms and 6.676 ms, respectively. In contrast, integrating logic into SVC-EGC and SVC-MRC increases latency to 10.922 ms and 11.667 ms, respectively, reflecting the computational cost of weighting multiple channel branches to enhance signal reliability. Despite this increased overhead, SVC-MRC emerges as the most effective strategy, as it maximizes the output SNR by proportionally weighting branches according to instantaneous signal quality. In 3GPP-standardized EPA and EVA channels and fading environments, this approach provides robust protection against deep fades. For URLLC applications, where reliability is paramount, the marginal increase in latency represents a necessary trade-off for successful packet recovery. Consequently, SVC-MRC is established as the benchmark for high-performance diversity systems in mission-critical scenarios.

I. Complexity Analysis

Table V summarises the computational complexity of the conventional SVC and the proposed SVC-aided diversity schemes. Since the proposed receiver uses the same MMP-based support recovery algorithm as the conventional SVC receiver, the support detection complexity remains unchanged.

In this context, i is the number of support positions in each iteration. Therefore, any increase in computational complexity arises solely from the diversity-combining stage. Specifically, SC requires channel gain computation and antenna selection; EGC involves phase extraction, phase normalization, complex multiplication, and summation; and MRC requires channel conjugation, complex weighting, and summation. Although EGC and MRC exhibit the same asymptotic complexity $\mathcal{O}(MN)$, MRC requires a greater number of complex arithmetic operations, resulting in a slightly higher implementation cost. For the URLLC configuration considered, this additional complexity is negligible and is compensated by improved PER performance.

IV. CONCLUSION

This paper investigates the error rate performance of receiver diversity combining-aided sparse vector coding for short packet communications. The analysis indicates that the integration of diversity-combining techniques (MRC, EGC, SC) with SVC markedly improves error rate performance, with MRC providing greater benefits than EGC and SC, attributable to its optimal SNR-maximization capability. Additionally, the impact of hardware impairments and imperfect CSI is then characterized by asymptotically analyzing the system's behaviour in terms of PER. Although non-ideal impairments degrade PER compared to ideal hardware, the findings highlight a significant performance trade-off and should be carefully considered in future communication systems. The proposed SVC-MRC demonstrates superior resilience, maintaining a lower PER floor even with increased transceiver distortion. As diversity gain increases, error floors decrease exponentially, with decreasing benefits beyond 2 – 4 antennas in fading channels. While the proposed scheme demonstrates significant performance gains under practical hardware impairments and imperfect CSI, the present study assumes independent fading across receive antennas, no delay cost for pilot processing, and synchronization. Some of the possible future research directions could be to consider more advanced imperfect CSI models, incorporate spatially correlated fading channels, explore hybrid combining techniques on other SVC variants, consider delay penalties due to synchronization, and experimental validation using software-defined radio (SDR) platforms to provide a more comprehensive evaluation of the scheme's practical feasibility.

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