Cooperative Closed-loop MIMO Transmissions in Bursty Interference

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***Abstract*—Inherent interfering signals generated by the underlying elements found in power substation have been known to span over consecutive noise samples, resulting in bursty interfering noise samples. Considering a Wireless Sensor Network (WSN) system, we adopt a two-state Markov-Gaussian noise model and explore closed-loop MIMO transmissions in Rayleigh channel corrupted by such noise. For uncoded transmissions, we show how sensor nodes transmission energy can be reduced by implementing a sub-optimum nodes selection technique for cooperative closed-loop MIMO and the corresponding Maximum Likelihood (ML) and Maximum a Posteriori (MAP) decoders linked to the noise parameters.**

***Index Terms*—Cooperative communications, Euclidean distance, impulsive noise model, Markov Gaussian, precoder, WSN.**

I. Introduction

The ubiquity of ad hoc wireless system such as the wireless sensor network (WSN) has found application in many fields, providing sensing, monitoring, and measurements to name but a few. In power substation environment, the inherent background Additive White Gaussian Noise (AWGN) is constantly present, but this classical observation is no longer relevant at an instant when the occurrence of an impulse becomes noticeable. Such impulse features an amplitude which supersedes the background AWGN. In such realistic environment, noise signals generated by the underlying elements span over several samples [1], giving rise to bursty appearances of impulses.

Due to autonomy of nodes in WSN, a WSN operating in power substation environment could permit nodes to cooperatively transmit by employing the Multiple-Input Multiple-Output (MIMO) technique. Linear closed-loop MIMO precoding [2], [3] is a technique involving multi-antenna transmissions, but with optimal distribution of resources on multiple transmit antennas, leading to a more improved system performance. Closed-loop cooperative transmission ensures that the source node cooperates with its idle neighbors to provide spatial diversity. Each cooperating node then precodes the data before it transmits over the diverse subchannels to the receiver where data is combined and detected. The advantages of the traditional precoded MIMO technique are inherited in this distributed system though with added overheads. This work aims to adapt the WSN transmissions to the bursty interferences found in the power substation environment.

In [4], performances of different diversity combining methods in impulsive interferers modeled by Class A have been studied, followed by the derivation of bounds for the bit error rate (BER). Cooperative diversity in the presence of Class A impulsive noise [5] have been investigated with the MAP detection derived for the Alamouti-based (open-loop) scheme. Neither of these work considered distributed closed-loop MIMO transmissions, moreover the channel considered is memoryless. Fertonani and Colavolpe [6] studied the performance/latency tradeoff of a low-density parity check (LDPC) coded Single-Input Single-Output (SISO) transmissions in a channel perturbed by bursty interferers modeled by two-state Markov-Gaussian noise model. The study established a relationship between the channel memory and the system information rate using a MAP symbol detection without exploiting the statistics of the interferers. The work in [7] exploits cooperative closed-loop MIMO transmissions in memoryless channel with the class A noise model using two closed-loop MIMO transmission techniques with nodes selection.

While being motivated by developing a wireless communication network that adapts to the power substation environments, the contribution of this paper follows:

(1) Reduce the complexity of nodes selection technique assuming full and limited channel information.
(2) Reduce the overall nodes transmission energy in bursty impulsive interferers.
(3) Extend the expression of ergodic capacity of a closed-loop MIMO system in bursty impulsive noise.

Section II considers the theory and the model of the implemented bursty impulsive noise model, while section III presents the considered MIMO precoding and cooperative system model. Presented in section IV are the MAP and ML optimal decoders. Section V highlights and discusses the obtained results while section VI concludes the paper.

II. Bursty Impulsive Noise Model

We adopt the two-state Markov-Gaussian impulsive noise model shown in figure 1 and described in [6], in which, the channel in good (G) state is the one impaired only by the background Gaussian noise. In the bad (B) state however, the noise is impaired by the impulsive interferers. In order to model the two-state Markov-Gaussian noise, the following parameters are assumed with ς quantifying the channel memory

$$\varsigma = \frac{1}{P_{GB} + P_{BG}} \tag{1}$$

The knowledge of the statistical parameter pair of P_{GB} and P_{BG} is enough to describe the system state process and are given as:

$$P_G = p(s_k = G) = \frac{P_{BG}}{P_{GB} + P_{BG}} \tag{2}$$

$$P_B = p(s_k = B) = \frac{P_{GB}}{P_{GB} + P_{BG}} \tag{3}$$

For our simulations, the we assumed $P_B = 0.1$ for the probability of bad state occurrence. Where the probability for the occurrence of good state $P_G = 1 - P_B$. Since we are interested in the channel with bursty impulsive noise, we consider the scenario where $\varsigma \geq 1$. The memoryless case encountered happens when $\varsigma = 1$, giving us the freedom of varying the burst of the noise process [6].

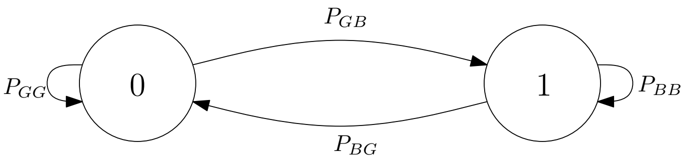

Fig. 1: The Two-state Markov Gaussian model.

III. System Model and Cooperative MIMO

A. System Model

We assume transmissions from a WSN system containing $\mathbb{N}$ set of nodes N_i (where $i = 1, 2, \dots a$). Two sets of nodes $\mathbb{N}_1$ and $\mathbb{N}_2$ are subsets of $\mathbb{N}$, such that $\{\mathbb{N}_1 \cup \mathbb{N}_2\} \subseteq \mathbb{N}$. Any node N_i in $\mathbb{N}_1$ is a single antenna node with the potential of being a cluster head (where $i = 1, 2, \dots n_c$) or a cooperating node. Node N_i could cooperate with $n_c - 1$ nodes located in the same cluster k, where n_c is the number of nodes in k. Node D_h in $\mathbb{N}_2$ is a multi antenna receiver, and a Data Gathering Node (DGN) equipped with relatively higher processing capability and without energy constraints (where $h = 1, 2, \dots c$, and $c < n_c$) .

B. MIMO Precoding

For a MIMO channel with no delay spread, the following linear system equation applies:

$$\mathbf{y} = \mathbf{HFs} + \mathbf{n} \tag{4}$$

where,

$$\mathbb{E}\{\mathbf{ss}^H\} = \mathbf{I}\ ,\ \mathbb{E}\{nn^H\} = N_0\mathbf{I}$$

and $\mathbf{y}$ is the received vector, $\mathbf{s}$ is the symbol vector of the constellation C, $\mathbf{n}$ is an $n_r \times 1$ additive noise vector, $\mathbf{H}$ is the $n_r \times n_t$ channel matrix, $\mathbf{F}$ is the precoder. The full Channel State Iinformation (CSI) permits the precoder to diagonalize the channel into b number of parallel SISO channels. If E_T is the total available power, the following power constraint is adhered to at the transmitter:

$$tr[\mathbf{FF}^H] = E_T \tag{5}$$

For a joint precoder and decoder design, the received symbol vector is

$$\mathbf{y} = \mathbf{GHFs} + \mathbf{Gn} = \mathbf{G}_d\mathbf{H}_v\mathbf{F}_d\mathbf{s} + \mathbf{G}_d\mathbf{n}_v \tag{6}$$

where $\mathbf{G}$ is the decoder matrix, and $\mathbf{H}_v = \mathbf{G}_v\mathbf{HF}_v = \mathrm{diag}(\sigma_1, \dots \sigma_b)$ is the virtual channel . The precoding and decoding matrix can be decomposed as $\mathbf{F} = \mathbf{F}_v\mathbf{F}_d$ and $\mathbf{G} = \mathbf{G}_v\mathbf{G}_d$ respectively.

The $\max - d_{\min}$ precoder maximizes the minimum Euclidean distance $d_{\min}$. Therefore its optimization problem entails finding the coefficient of the matrix $\mathbf{F}_d$ which, maximizes the $d_{\min}$ criterion of the received constellation between the signal points at the receiver:

$$\mathbf{F}_d = \arg\max_{\mathbf{F}_d} d_{\min}(\mathbf{F}_d), \quad d_{\min}(\mathbf{F}_d) = \min_{\mathbf{e}\in\mathcal{C}^b} \|\mathbf{H}_v\mathbf{F}_d\mathbf{e}\| \tag{7}$$

where $\mathbf{e} = (\mathbf{x}_k - \mathbf{x}_l)$, $k \neq l$. A promising solution of equation (7) is possible [8] for $b = 2$ and a 4-QAM. These solutions do not depend on the signal-to-noise ratio (SNR) but on the channel angle $\gamma = \arctan\frac{\sigma_2}{\sigma_1}$. The solutions for 16-QAM [9] and a suboptimal extension [10] are available. The solutions for the BPSK [8] and 4-QAM are given in (9), (10) and (11). The $d_{\min}$ expression for the BPSK solution is

$$d_{min}^{BPSK} = \sqrt{2\rho E_T}\cos\gamma \tag{8}$$

and its solution is

$$\mathbf{F}_d^{d_{min}} = \mathbf{F}_{BPSK} = \begin{pmatrix} 1 & 1i \\ 0 & 0 \end{pmatrix} \tag{9}$$

Parameter ρ acts as a scaling factor and does which does not influence $d_{\min}$ optimization. Notice the second row of (9) is null, indicating that the signal is entirely transmitted on the most favored subchannel. This solution could be compared to the $\max$-SNR that pours power only on the strongest eigenmode of the channel.

Solutions of $\mathbf{F}_d$ for 4-QAM are

$$\text{if } 0 \leq \gamma \leq \gamma_0,$$
$$\mathbf{F}_d^{d_{\min}} = \mathbf{F}_1 = \sqrt{E_T}\begin{pmatrix} \frac{\sqrt{3}+\sqrt{3}}{6} & \sqrt{3-\sqrt{3}}e^{i\frac{\pi}{12}} \\ 0 & 0 \end{pmatrix} \tag{10}$$
$$\text{if } \gamma_0 \leq \gamma \leq \pi/4,$$
$$\mathbf{F}_d^{d_{\min}} = \mathbf{F}_2 = \sqrt{\frac{E_T}{2}}\begin{pmatrix} \cos\psi & 0 \\ 0 & \sin\psi \end{pmatrix}\begin{pmatrix} 1 & e^{i\frac{\pi}{4}} \\ -1 & e^{i\frac{\pi}{4}} \end{pmatrix}, \tag{11}$$

and,

$$\begin{cases} \psi = \arctan\frac{\sqrt{2}-1}{\tan\gamma} \\ \gamma_0 = \arctan\sqrt{\frac{3\sqrt{3}-2\sqrt{6}+s\sqrt{2}-3}{3\sqrt{3}-2\sqrt{6}+1}} \approx 17.28^\circ \end{cases} \tag{12}$$

$$d_{\min} = \begin{cases} \sqrt{E_T}\rho\sqrt{1-\frac{1}{\sqrt{3}}}\cos\gamma & \text{if } 0 < \gamma \leq \gamma_0 \\ \sqrt{E_T}\rho\sqrt{\frac{(4-2\sqrt{2})\cos^2\gamma\sin^2\gamma}{1+(2-2\sqrt{2})\cos^\gamma}} & \text{if } \gamma_0 < \gamma \leq \frac{\pi}{4} \end{cases} \tag{13}$$

For the BPSK modulation and $b = 2$ data streams, the symbol vectors belong to set $\{1, -1\}$. The difference vectors is given by the possible transmitted vectors, $\mathbf{e} = \mathbf{x}_k - \mathbf{x}_l$ and $\mathbf{s}_k \neq \mathbf{s}_l$. Only the BPSK solution is considered in this paper.

C. Cooperative MIMO

In the case of the limited CSI, we implement finite codebook in which the receiver calculates the optimal matrix $\mathbf{F}_d$ that maximizes the optimization criterion $d_{\min}$. An empirical solution which involves the construction of codebook for $\mathbf{F}_d$ is considered, and performed for each $(n_r \times n_t)$ in conjunction with $\mathbf{F}_d$ dictionary. The two dictionaries are combined forming a single dictionary for the optimal precoding matrix $\mathbf{F} = \mathbf{F}_v\mathbf{F}_d$. Optimal $\mathbf{F}$ is selected by searching over all possible precoders in the codebook, this approach is intended to reduces the number of feedback bits on the feedback channel:

$$\mathscr{F}_v\mathscr{F}_d = (\mathbf{F}_{v_1}\mathbf{F}_{d_1}, \mathbf{F}_{v_2}\mathbf{F}_{d_2}, \dots, \mathbf{F}_{v_N}\mathbf{F}_{d_N}) = (\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_N) \tag{14}$$

where $N = 2^{B_1}$ is the dictionary size, with B_1 being the number of bits required to feedback the index of the precoding matrix to n_t nodes; B_1 of 3, 5 and 7 bits were determined to suffice for the quantization of the codebooks for 2, 3, and 4 transmit nodes respectively. The combined codebooks $\mathscr{F}_v\mathscr{F}_d$ are generated offline [11] and are made available to all nodes in the cluster and the destination node.

D. Nodes Selection

Our approach involves selecting a group of nodes belonging to a cluster of interest. The source node S which has data to send cooperates with $n_c - 1$ other nodes inside the cluster by declaring itself a clusterhead. All $n_c - 1$ nodes then send training frames to the destination. When the destination receives the training frame, F_{tra} it estimates the channel and sends back the index of the optimal precoder matrix $\mathbf{F}$ over the reverse link (i.e. the feedback channel) to the n_t selected nodes.

We propose nodes selection method by utilizing the max-$d_{\min}$ optimization criterion- $d_{\min}$. The destination searches and compute the best n_t nodes that would transmit in the next phase. Every possible set of nodes yields a different channel sub-matrix $\bar{H}[n_r \times n_t]$, hence the selection complexity is dictated by the cardinality $\binom{n_c}{n_t}$, and is given as $\Theta(n_c^{n_t})$.

We propose a sub-optimal selection approach based on the max-$d_{\min}$ optimization criterion. Rather than searching through L sub-matrices ($L = \frac{n_c!}{(n_t!(n_c - n_t)!)}$), our sub-optimal approach computes (maximizes) the $d_{\min}$ criterion for each cluster-destination link (columns of H) as opposed to each sub matrix in L, thereby reducing L to n_c:

$$q = \arg\max_{q} \; H_q \; (\min \|\mathbf{H}_v \mathbf{F}_d \mathbf{e}\|) \tag{15}$$

where H_q is the $q-th$ column of the cluster-destination channel matrix $H[n_c \times n_t]$ and n_t nodes are selected in descending order of their corresponding $d_{\min}$value. The BER

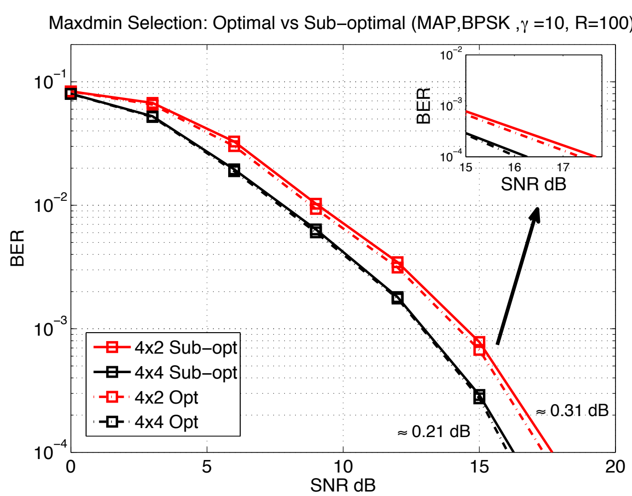

Fig. 2: BER: Sub-optimal and optimal nodes selection with MAP decoding

results in figure 2 shows the comparisons in performances of the sub-optimal and the optimal nodes selection for the MAP decoder. The performance penalties for the cases of 2 and 4 selected nodes from a cluster of 10 are about 0.31 dB and 0.21 dB respectively.

E. Closed-loop MIMO protocol

Consider a scenario where the substation elements and infrastructures are fitted with a number of wireless nodes such as temperature, pressure and electrical parameters sensors. Such sensors nodes are required to measure and cooperatively transmit measured data wirelessly to a DGN over a great distance d_{lh}. Assuming the cooperating nodes are separated by relatively shorter distances d_c, compared to d_{lh}, then transmissions between cooperating nodes are assumed to be error free hence AWGN channel is considered, and Rayleigh fading is considered over d_{lh}. The communication protocol depicted in figure 3 can be described as follows:

Declaration phase: We assume neighborhood discovery had been previously performed. Any source node having data to transmit forms a cluster and declares itself as the clusterhead using the *"first declaration wins"*[1] rule [12]. Every nodes that "hears" the source node sets their *status* to slave, ready to receive from the source. In an event that two or more nodes perform declaration, clusterhead with the least residual energy E_{res} wins, but nodes with data can still send to neighboring nodes.

Phase 1: The source node(s) multicast their data to n_{cl} neighbors over the average distance of d_{cl}; this is a SISO communication.

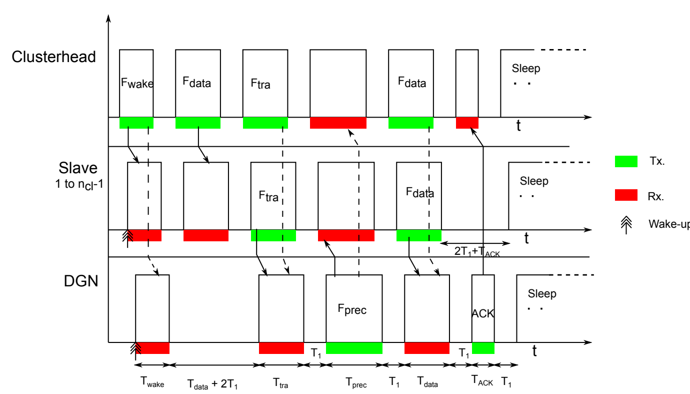

Fig. 3: Basic max-$d_{\min}$ cooperative MAC protocol.

Phase 2: Next the n_c neighbors, as potential relays, each sends the training frame F_{tra} to the DGN which uses this to estimate the multipath coefficients for each of its received antennas. It then constructs the channel matrix $\mathbf{H}$, computes and selects the best n_t nodes including the optimal precoding matrix index for the selected nodes.

Phase 3: The DGN selects n_t nodes that will transmit data in the next phase; n_t nodes will use the precoding matrix $\mathbf{F}_d$ whose index is found in the precoding frame F_{prec} sent by DGN to n_t nodes. The F_{prec} also includes the identification (ID) of the selected nodes.

Phase 4: The n_t selected nodes precode with optimal $\mathbf{F}_d$ and then transmit the data frames to the DGN using MIMO transmission over Rayleigh fading channel. Figure 3 shows the full diagrammatic description of the basic closed-loop cooperative MIMO protocol.

[1] A passive clustering algorithm

IV. Decoders

A. Maximum Likelihood (ML) and Maximum a Posteriori (MAP) Decoder

The ML and MAP decoders are implemented at the destination node. The ML decoding rule is extensively used and applied for different channel types [13],[14].

By implementing two-state Markov-Gaussian model [6] the correlation of the impulsive noise can be characterized. The state $s_k \in \{G, B\}$), where G and B represent the good (State 0) and bad state (State 1) of the channel respectively. Noise sample n_k at each time epoch is defined by the channel state s_k, assuming n_k to be a complex circularly Gaussian random variable whose variance is dependent on s_k such that its pdf is:

$$p(n_k|s_k = G) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{|\hat{\mathbf{n}}|^2}{2\sigma^2}\right) \tag{16}$$

$$p(n_k|s_k = B) = \frac{1}{2\pi R\sigma^2} \exp\left(-\frac{|\hat{\mathbf{n}}|^2}{2R\sigma^2}\right) \tag{17}$$

For the cluster-destination MIMO link, $\hat{\mathbf{n}} = \mathbf{y}_k - \sqrt{E_T}\mathbf{GHFs}$. Where $\mathbf{y}$ is given by equation (6) utilizing the $\max\text{-}d_{\min}$ precoding. The parameter $R(\geq 1)$ is the ratio between the average noise power in B and G channel state. The decoding complexity of the ML for $\max\text{-}d_{\min}$ precoding is M^b.

The statistical description of the state process s^K characterizes the channel. For the Markov-Gaussian channel, s^K is expressed as

$$p(s^K + 1 = p(s_0) \prod_{k=0}^{K-1} p(s_{k+1}|s_k) \tag{18}$$

Assuming the symbol vector $\mathbf{s} \in S^M$ are equiprobable, indicating that $p(\mathbf{s})$ is constant, then the optimal MAP detector rule can be written as

$$\hat{\mathbf{s}}_{MAP} = \arg\max_{\mathbf{s}\in S^M} p(\mathbf{y}|\mathbf{s}) \tag{19}$$

The decoding rule of the MAP detector, otherwise known as the log-likelihood ratio (LLR) is

$$L(x_s) = \ln\left(\frac{p(x_s = 1|y)}{p(x_s = -1|y)}\right) \tag{20}$$

If the expression in (20) is > 0 : the estimated symbol $\hat{x}_s$ is most likely to be 1. If (20) is < 0 : the estimated symbol $\hat{x}_s$ is most likely to be -1.

B. Optimal ML Decoding

By the approximation of the first two terms for the Middleton Class A model, i.e. $m = 0$ and 1, we have

$$f_M(\mathbf{n}) = \sum_{m=0}^{1} P_m g(\mathbf{n}, \mathbf{K}_m) = P_0 g(\mathbf{n}, \mathbf{K}_0) + (1-P_0) g(\mathbf{n}, \mathbf{K}_1) \tag{21}$$

where $P_0 = \frac{e^{-A}A^0}{0!} = e^{-A}$. Equation (21) is the extension of the general Middleton Class A noise for muti-antenna system. It is shown [15] that the stationary probabilities P_G and P_B can be expressed as

$$P_G = p(s_k = G) = \frac{1}{1 + A} \tag{22}$$

$$P_B = p(s_k = B) = \frac{A}{1 + A} \tag{23}$$

Thus, we obtain an expression for the multi-antenna extension for the theoretical ML decoding, with the knowledge of the bursty impulsive noise statistics thus:

$$\mathbf{L}(\mathbf{s}|\mathbf{y}) = \frac{e^{-\frac{P_B}{P_G}}}{(2\pi)^{\frac{n_r}{2}}|\mathbf{K}_G|^{\frac{1}{2}}} e^{\frac{-\hat{\mathbf{n}}^T\mathbf{K}_G^{-1}\hat{\mathbf{n}}}{2}} + \frac{1 - e^{-\frac{P_B}{P_G}}}{(2\pi)^{\frac{n_r}{2}}|\mathbf{K}_B|^{\frac{1}{2}}} e^{\frac{-\hat{\mathbf{n}}^T\mathbf{K}_B^{-1}\hat{\mathbf{n}}}{2}} \tag{24}$$

where $\mathbf{K}_m$ is the covariance matrix expressed for the G and B states, having the dimension $[n_r \times\ n_r]$.

C. Optimal MAP decoding

Similarly, the multivariate expression [16] considering the statistics of the multivariate noise on n_r antennas for the MAP decoding is:

$$p(n_k|s_k, \mathbf{K}_m) = \begin{cases} G, & \frac{1}{(2\pi)^{\frac{n_r}{2}}|\mathbf{K}_G|^{\frac{1}{2}}} e^{-\frac{\hat{\mathbf{n}}^T\mathbf{K}_G^{-1}\hat{\mathbf{n}}}{2}} \\ B, & \frac{1}{(2\pi)^{\frac{n_r}{2}}|\mathbf{K}_B|^{\frac{1}{2}}} e^{-\frac{\hat{\mathbf{n}}^T\mathbf{K}_B^{-1}\hat{\mathbf{n}}}{2}} \end{cases} \tag{25}$$

V. Results

Running Monte-Carlo simulations for 10^6 data bits, optimal and sub-optimal nodes selection are implemented to select 2, 3, and 4 transmit nodes from a cluster of 10. Data bits are modulated and precoded utilizing the BPSK modulation and $\max\text{-}d_{\min}$ precoder respectively. Assuming full channel knowledge, the system model described in section III is implemented, our simulation parameters for the two-state Markov-Gaussian noise model are $\varsigma = 10$, $R = 100$, and $P_B = 0.1$ for the probability of state B occurrence.

Here, the DGN at the receiver side decodes the received data using the ML and MAP decoder. We compare the BER results of the received bits over the perturbed channel for the case of random transmissions and selected transmissions of nodes based on $d_{\min}$ criterion.

Utilizing the optimal models in (24) and (25) for the ML and MAP decoders respectively, the receiver could exploit the knowledge of the bursty impulsive noise statistics, leading to further reductions in signal signal power to achieve the target BER as shown in figures 4 and 5 for ML and MAP decoders respectively We notice (cf. figure **??**fig:optimal-vs-Noptimal-MAP-Random) the performance of the MAP decoder is better without the knowledge of the impulsive noise statistics, being ≈20.68 dB (23.19 dB for ML), 19.10 dB (21.15 dB), and 18.16 dB (19.79 dB) when 2, 3, and 4 nodes are randomly transmitting. However, the optimal ML solution performance gains are 8.40 dB, 8.74 dB and 7.8 dB respectively for 2, 3, and nodes in random transmission scenario.

Moreover, a combined sub-optimal nodes selection and optimal ML and MAP decoding are implemented to further reduce the energy due to transmitted signal of nodes. Figures 6 and 7 show the performances of error rates of these implementations. In the case of optimum ML decoding, selection gains of about 1.62 dB, 1.30 dB, and 0.97 are recorded for 2, 3, and 4 selected nodes respectively. Conversely, selection gain of 1.58 dB, 1.10 dB, and 0.82 dB are recorded for the optimal MAP decoder. We concur that selection gains are fairly the same across these decoders.

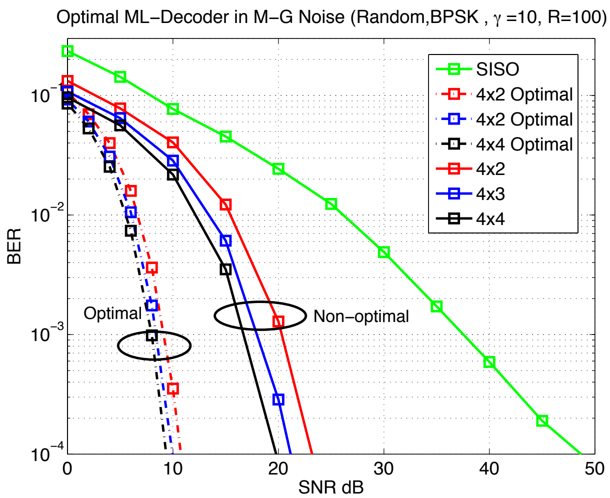

Fig. 4: Optimal ML decoding with random selection.

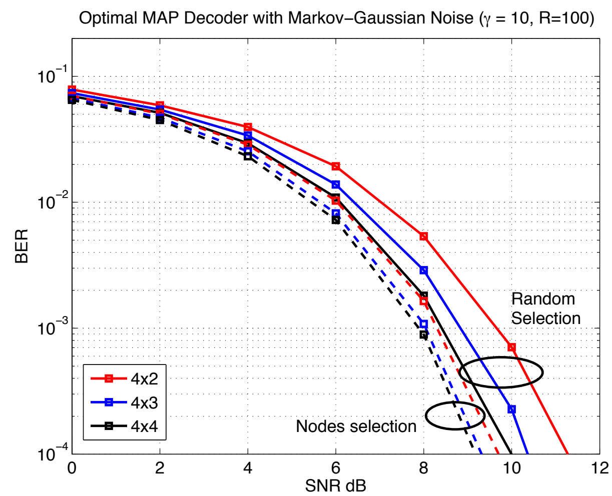

Fig. 7: Optimal MAP decoder with selected transmission.

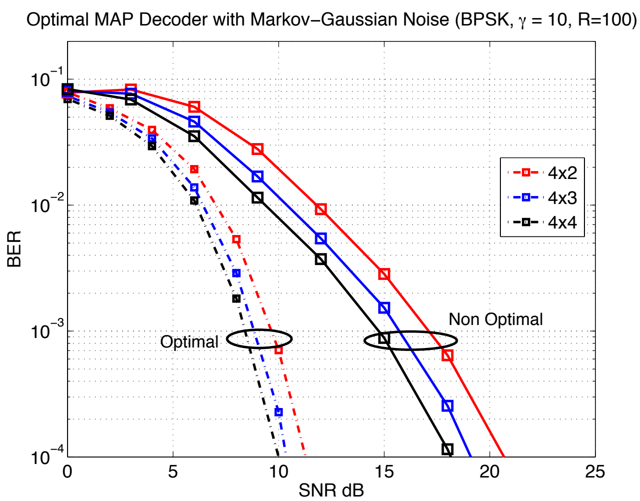

Fig. 5: Optimal MAP decoding with random selection.

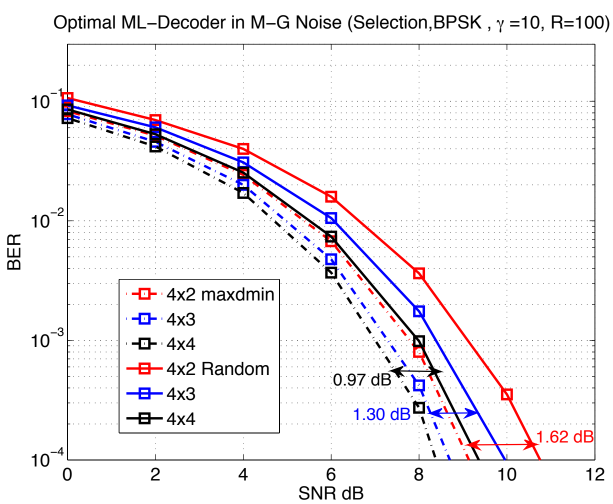

Fig. 6: Optimal ML decoding with selected transmission

A. Limited CSI

Thus far, we have assumed full knowledge of the CSI (FCSI). It is difficult to achieve full dynamic channel knowledge due to channel errors and communication latency among others. We now evaluate the system performance assuming limited or quantized CSI (QCSI). Codebook quantized using 3 bits, 5 bits and 7 bits for 2, 3 and 4 selected nodes are respectively respectively considered. The performances of MAP and ML decoders with quantized channel information are shown in figure 8. Figure 8 depicts a combination of scenarios ranging from random (R) or selected (S) transmissions assuming quantized (Q) channel information. Results are only shown for 2 and 4 transmit nodes. It is obvious that performance of ML and MAP decoders deteriorate with limited channel information (Q) for both random and selected cases. Notice the strange behavior of the MAP decoder at high SNR, when 2 (i.e. case 2—S+Q) and 4 nodes are selected to transmit. Similar behavior can be observed at low SNR when 2 and 4 nodes are allowed transmit randomly. A reasonable explanation is that the MAP decoder is more sensitive to quantization error.

Another performance indicator considered is the outage channel capacity. The analytic expression for max-$d_{\min}$ ergodic capacity of the AWGN channel in state m is given by

$$C(SNR)_m = E\left[log_2\left(\left|\mathbf{I}_b + \frac{SNR}{n_t}(\mathbf{GHF})^H\mathbf{GHF}\right|\right)\right] \tag{26}$$

We compute the ergodic capacity of the two state Markov-Gaussian (Markov-Middleton) channel model for (26) as [17]

$$C = \sum_{m=0}^{1} \pi(m)C(SNR)_m \tag{27}$$

where π is the steady-state probability distribution vector. We compute the cumulative distribution function(CDF) of the capacity in (27) and it is shown in figure 9, showing the averaged rate over many transmissions (10^4 Rayleigh fadings) at SNR = 10 dB. Figure 9 also indicates rates at 0.1 outage capacity, indicating our proposed nodes selection also improves the rate. We indicate the upper limit of the 0.1- outage capacity using the waterfilling (WF) capacity. The legend is interpreted as previously outlined except for newly added cases of full channel information (F), AWGN (G) and Impulsive (I) noises. We notice the two ranges of capacity distribution are formed by the lower group (random transmission) and upper group (selected transmission). In order to be fair with our analysis, we also limit the number of sub-channels to $b = 2$ for the WF scheme..

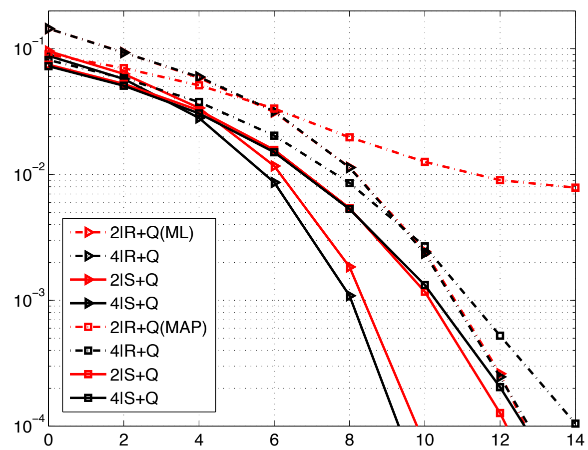

Fig. 8: Decoders performances using limited CSI.

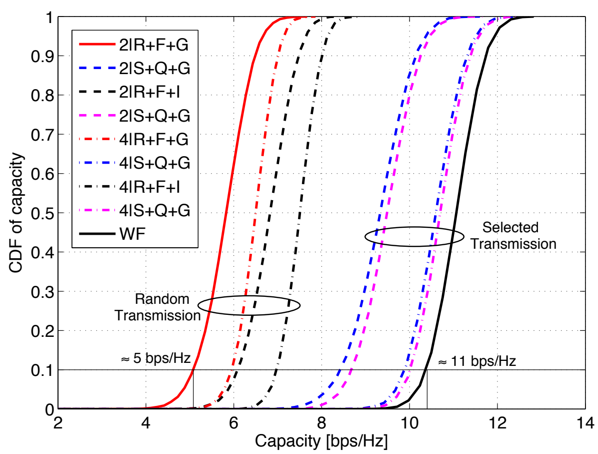

Fig. 9: Distribution of cooperative MIMO system channel capacity at SNR=10 dB in impulsive channel.

VI. Conclusion

At the receiver, the ML and MAP decoders have been implemented for cooperative MIMO transmissions in Rayleigh channel, perturbed by impulsive bursty interferers that is modeled by two-state Markov-Gaussian noise model. It is shown that the SNR of the signal can be reduced at the target BER of 10^{-4} when the channel statistics of the interferers are made available to the receiver. Sub optimal nodes selection technique has been proposed and its complexity reduced to the number of nodes in the cluster without sacrificing much on performance.

Comparisons of the BER results suggests the performances of both optimal decoders are quite similar for our $d_{\min}$based precoder under the assumption of full channel information. Under limited channel information, the two decoders suffer from quantization error which is more pronounced in the MAP. Another performance indicator, shows that ergodic capacity is improved with node selection in impulsive channel. This paper thus proposes a system approach to adapting decoders performances to power substation environment, whose channel is characterized by bursty impulsive interferers.

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