Performance Analysis of Distributed Wireless Sensor Networks for Gaussian Source Estimation in the Presence of Impulsive Noise

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***Abstract*—We address the distributed estimation of a scalar Gaussian source in wireless sensor networks (WSNs). The sensor nodes transmit their noisy observations, using the amplify-and-forward relaying strategy through coherent multiple access channel to the fusion center (FC) that reconstructs the source parameter. In this letter, we assume that the received signal at the FC is corrupted by impulsive noise and channel fading, as encountered for instance within power substations. Over Rayleigh fading channel and in presence of Middleton class-A impulsive noise, we derive the minimum mean square error (MMSE) optimal Bayesian estimator along with its mean square error (MSE) performance bounds. From the obtained results, we conclude that the proposed optimal MMSE estimator outperforms the linear MMSE estimator developed for Gaussian noise scenario.**

***Index Terms*—Distributed WSN, MMSE optimal Bayesian estimation, Middleton class-A impulsive noise, Rayleigh fading.**

I. Introduction

The difficulty of estimating a Gaussian source from its available noisy measurements is prevalent in numerous signal processing contexts. In this aspect, over the past few years, researches on the implementation of distributed WSN has been evolving very rapidly. For example, the authors in [1] considered the distributed estimation of scalar source parameters using a collaborative WSN. It is shown that depending on the available information about the source statistics and the noise behaviour, different estimators can be used to achieve the MSE criterion. Similar performance analyses are carried out in [2]–[4] to show the optimality of the maximum likelihood estimator (MLE) [2], best linear unbiased estimator (BLUE) [3], and the MMSE estimator [4] based on the available information about the source statistics.

However, all of the above performance analyses for distributed estimation schemes have been carried out over the Gaussian noise scenario. On the other hand, the noise characteristics, usually observed in many environments, such as the power transmission lines areas, the power substations, and in some mobile radio scenarios, are inherently impulsive in nature [5]. For example, in power substations, the noise emitted from various power equipment are impulsive [6]. In this context, the impacts of impulsive noise have been widely investigated on the detection of finite alphabets in point-to-point and collaborative WSN communications [7], [8]. However, the performance of estimation techniques in the presence of impulsive noise is not widely acknowledged.

Recently, the authors in [9] considered the MMSE optimal Bayesian estimation (OBE) for a Gaussian source impaired by Middleton class-A impulsive noise. It is shown that the performance of the proposed MMSE OBE strictly depends on the statistical characteristics of the received signal. The authors in [10] derived the MMSE OBE and its MSE performance bounds in closed form assuming that the noise and the source signals are Gaussian mixture (GM) distributed. The obtained results showed that the performance improvement of the optimal MMSE estimator over the linear MMSE (LMMSE) estimator under this condition is substantial. However, the analyses in [9], [10] are restricted to the point-to-point scenario and the effect of channel fading is not considered. To the best of authors knowledge, no result exists for the distributed estimation of Gaussian sources in the presence of impulsive noise under Rayleigh fading. Here, we provide a mathematical framework for the performance analysis of distributed estimation of a scalar Gaussian source impaired by Middleton class-A noise. A Middleton class-A process is a simple and effective way to model an impulsive noise channel [5], [9]. Our work is an extension of [9] to the distributed WSN scenario. It is assumed that each sensor node transmits its observations to the FC through a coherent multiple access channel (MAC) using AF strategy. It is widely acknowledged that AF schemes significantly outperform the traditional source-channel coding for Gaussian signal estimation while preserving the sensor's radios low complexity [11]. The FC uses the received signal to estimate the source parameter with minimum MSE.

The contributions of this work are as follows. First, we derive the MMSE OBE for a scalar Gaussian source estimation using distributed WSN in the presence of impulsive noise under Rayleigh fading. It is seen that the presence of impulsive noise makes the input-output characteristics of MMSE OBE non-linear especially when the environment is more impulsive, as indicated by the rare impulsive events. This leads to a non-linear MMSE estimator. Then, we provide upper and lower bounds for its MSE performance. Finally, the derived bounds are validated through the Monte Carlo simulation. Interestingly, from the obtained results, it is seen that the proposed optimal MMSE estimator attains the lower bound for highly impulsive noise environment and performs significantly better than the LMMSE estimator developed for AWGN scenario.

II. System model

As shown in Fig. 1, we consider a WSN of M sensor nodes from S_1 to S_M and a FC. The sensor nodes observe a scalar

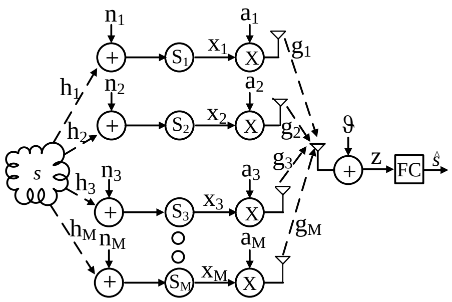

Fig. 1. Distributed WSN for Gaussian source estimation.

parameter s, which is modeled by a Gaussian random variable (rv) with mean μ_s and variance σ_s^2. Let the signals measured by the ith sensor node, $i = 1, 2, \ldots, M$, can be expressed as

$$x_i = h_i s + n_i, \tag{1}$$

where h_i and n_i denote the channel coefficient and the measurement noise at the ith sensor node, respectively. In this work, as usual, the measurement noise variables $\{n_i\}_{i=1}^M$ are assumed to be Gaussian with mean μ_n and variance σ_n^2. Now, the sensor nodes follow two-hop collaborative communications to send the data from the source to the destination using AF strategy. In the first hop, the sensor nodes measure the data of the source to be estimated and in the second hop, each sensor node amplifies its measured signal x_i by a factor of a_i and transmits it to the FC through a coherent MAC channel [1]. The received signal, z, at the FC is then given by

$$z = \sum_{i=1}^{M} g_i a_i x_i + \vartheta, \tag{2}$$

where g_i is the channel coefficient between the ith sensor node and the FC, and ϑ is the communication noise. We assume that the channel coefficients follow the Rayleigh distribution and for each link, they are considered to be static for one symbol duration, while they vary from one symbol to another. Therefore, both h_i and g_i are modeled by a zero-mean independent, circularly symmetric complex Gaussian random variable with variances σ_h^2 and σ_g^2, respectively. It is assumed that the channel coefficients are known at both the transmitters and receiver side. Since the sensor transmitters are assumed to have their channel phase information, they can individually cancel this phase at the transmitter and hence signals can be added coherently at the FC [1]. It is also assumed that ϑ follows Middleton class-A distribution to account for impulsive communication disturbance. Hence, the probability density function (PDF) of ϑ is given by [5]

$$f(\vartheta) = \sum_{m=0}^{\infty} \frac{p_m}{\sqrt{2\pi}\sigma_m} \exp\left(-\frac{\vartheta^2}{2\sigma_m^2}\right), \tag{3}$$

where $p_m = \frac{e^{-A}A^m}{m!}$ is the steady state probability of the m^{th} impulsive source and $\sigma_m^2 = \sigma_\vartheta^2 \frac{m/A+\Gamma}{1+\Gamma}$ is the variance of that impulsive source. For $m = 0$, the model generates the traditional AWGN component. Also, the parameters A, Γ, and σ^2 are called the global parameters as they characterize the PDF [5]. The physical significance of these parameters are: A denotes the impulsive index, Γ indicates the Gaussian to impulsive noise power ratio, and σ^2 represents the total power of the noise ϑ.

III. MMSE Optimal Bayesian Estimation

In this section, we consider the MMSE optimal Bayesian estimation of a scalar Gaussian source s impaired by Middleton class-A noise under Rayleigh fading. The MMSE optimal Bayesian estimation corresponds to the posteriori mean [12] and is given by

$$\hat{s} = \varepsilon\left(s|z\right) == \int s f\left(s|z\right) ds, \tag{4}$$

where $\hat{s}$ indicates the MMSE estimation of s and ε is the expectation operator. From equation (4), we can deduce that the posteriori probability $f(s|z)$ is required to derive the MMSE estimator. Although the distribution of $f(s|z)$ already exists for AWGN channel [1], here, we derive the distribution for impulsive noise scenario. Now, equation (2) can be rearranged as

$$z = \mathbf{g}^T\mathbf{W}\mathbf{h}s + \mathbf{g}^T\mathbf{W}\mathbf{n} + \vartheta = \alpha s + \beta, \tag{5}$$

where $\mathbf{g}$=$[g_1, \ldots, g_M]^T$, $\mathbf{h}$=$[h_1, \ldots, h_M]^T$, $\mathbf{W}$=diag($\mathbf{a}$) with $\mathbf{a} = [a_1, \ldots, a_M]^T$, and $\mathbf{n} = [n_1, \ldots, n_M]^T$. Here, the amplification factor for each node is $a_i = \sqrt{(P_T/M(\sigma_h^2\sigma_s^2 + \sigma_n^2))}$, where P_T is the total transmission power of all the sensor nodes. Also, $\alpha = \mathbf{g}^T\mathbf{W}\mathbf{h}$ and $\beta = \mathbf{g}^T\mathbf{W}\mathbf{n} + \vartheta$. It is assumed that $N = \mathbf{g}^T\mathbf{W}\mathbf{n}$ and ϑ are mutually independent with each other. Then, from the convolution property, the distribution of β is represented by

$$\begin{aligned} f(\beta) &= \sum_{m=0}^{\infty} p_m \mathcal{N}(\beta, 0, \sigma_m^2) * \mathcal{N}(\beta, \mu_N, \sigma_N^2), \\ &= \sum_{m=0}^{\infty} p_m \mathcal{N}(\beta, \mu_\beta, \sigma_{\beta,m}^2), \end{aligned} \tag{6}$$

where $\mathcal{N}(\beta, \mu_\beta, \sigma_{\beta,m}^2)$ is a Gaussian rv with mean $\mu_\beta = \mathbf{g}^T\mathbf{W}\mu_\mathbf{n}$ and variance $\sigma_{\beta,m}^2 = \mathbf{g}^T\mathbf{W}\mathbf{\Sigma_N}\mathbf{W}^T\mathbf{g} + \sigma_m^2$, $\mathbf{\Sigma_N} = \varepsilon\left\{\mathbf{n}\mathbf{n}^T\right\}$. Moreover, s and β are mutually independent. Then, the joint distribution of s and β is given by

$$f(s,\beta) = f(s) \times f(\beta) = \sum_{m=0}^{\infty} p_m \mathcal{N}(s, \beta, \mu_m, \mathbf{\Sigma}_m), \tag{7}$$

where $\mu_m = [\mu_s \quad \mu_\beta]$ and $\mathbf{\Sigma}_m = \left[\sigma_s^2 \quad 0; 0 \quad \sigma_{\beta,m}^2\right]$. Now, from equation (5) we have,

$$\begin{bmatrix} z \\ s \end{bmatrix} = \begin{bmatrix} \alpha s + \beta \\ s \end{bmatrix} = \begin{bmatrix} \alpha & I \\ I & 0 \end{bmatrix} \begin{bmatrix} s \\ \beta \end{bmatrix} = \mathbf{C} \begin{bmatrix} s \\ \beta \end{bmatrix}, \tag{8}$$

It is well known that if s and β are jointly Gaussian, then z and s will also be jointly Gaussian, since the linear transformation of a Gaussian vector is Gaussian too [12, pg. 325]. However, it holds for GM also and hence $[z, s]^T = \mathbf{C}[s, \beta]^T$ is also jointly GM with [10]

$$f(z,s) = \sum_{m=0}^{\infty} p_m \mathcal{N}(z, s, \mathbf{C}\mu_\mathbf{m}, \mathbf{C}\mathbf{\Sigma_m}\mathbf{C}^T), \tag{9}$$

where,

$$\mathbf{C}\mu_\mathbf{m} = \begin{bmatrix} \alpha & I \\ I & 0 \end{bmatrix} \begin{bmatrix} \mu_s \\ \mu_\beta \end{bmatrix} = \begin{bmatrix} \alpha\mu_s + \mu_\beta \\ \mu_s \end{bmatrix} = \begin{bmatrix} \mu_z^m \\ \mu_s \end{bmatrix}, \tag{10}$$

and

$$\mathbf{C}\mathbf{\Sigma_m}\mathbf{C}^T = \begin{bmatrix} \alpha\sigma_s^2\alpha^T + \sigma_{\beta,m}^2 & \alpha\sigma_s^2 \\ \sigma_s^2\alpha^T & \sigma_s^2 \end{bmatrix} = \begin{bmatrix} \sigma_{z,m}^2 & \sigma_{zs}^2 \\ \sigma_{sz}^2 & \sigma_s^2 \end{bmatrix}. \tag{11}$$

Now, from the joint distribution of (9), the conditional PDF of s given z can be evaluated as

$$f(s|z) = \frac{f(s,z)}{f(z)} = \frac{\sum_{m=0}^{\infty} p_m \mathcal{N}(z, s, \mathbf{C}\mu_\mathbf{m}, \mathbf{C}\mathbf{\Sigma_m}\mathbf{C}^T)}{\sum_{m=0}^{\infty} p_m \mathcal{N}(z, \mu_z^m, \sigma_{z,m}^2)},$$

$$= \sum_{m=0}^{\infty} \chi_m(z)\mathcal{N}(s, \mu_{s|z}^m(z), \Sigma_{s|z}^m(z)). \tag{12}$$

Where the third equality comes from [12, Theorem 10.3] and considering

$$\chi_m(z) = \frac{p_m \mathcal{N}(z, \mu_z^m, \sigma_{z,m}^2)}{\sum_{m=0}^{\infty} p_m \mathcal{N}(z, \mu_z^m, \sigma_{z,m}^2)}. \tag{13}$$

Using [12, Theorem 10.3], we can write

$$\mu_{s|z}^m(z) = \mu_s + \sigma_{sz}^2 \left(\sigma_{z,m}^2\right)^{-1}(z - \mu_z^m), \tag{14}$$

$$= \mu_s + \frac{\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g}}{\mathbf{g}^T \mathbf{W}\mathbf{h}\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g} + \mathbf{g}^T \mathbf{W}\mathbf{\Sigma_N}\mathbf{W}^T \mathbf{g} + \sigma_m^2}(z - \mu_z^m) \tag{15}$$

and,

$$\Sigma_{s|z}^m(z) = \sigma_s^2 - \sigma_{sz}^2 \left(\sigma_{z,m}^2\right)^{-1} \sigma_{zs}^2, \tag{16}$$

$$= \sigma_s^2 - \frac{\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g}\mathbf{g}^T \mathbf{W}\mathbf{h}\sigma_s^2}{\mathbf{g}^T \mathbf{W}\mathbf{h}\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g} + \mathbf{g}^T \mathbf{W}\mathbf{\Sigma_N}\mathbf{W}^T \mathbf{g} + \sigma_m^2}. \tag{17}$$

Hence, using equation (4) and (12), the MMSE estimation of s given z is obtained by

$$\begin{aligned} \hat{s} &= \int s \sum_{m=0}^{\infty} \chi_m(z)\mathcal{N}(s, \mu_{s|z}^m(z), \Sigma_{s|z}^m(z))ds, \\ &= \sum_{m=0}^{\infty} \chi_m(z) \int s\mathcal{N}(s, \mu_{s|z}^m(z), \Sigma_{s|z}^m(z))ds, \\ &= \sum_{m=0}^{\infty} \chi_m(z)\mu_{s|z}^m(z). \end{aligned} \tag{18}$$

Where $\chi_m(z)$ and $\mu_{s|z}^m(z)$ are defined in (13) and (15), respectively. Equation (18) highlights how the MMSE OBE depends on the signal, noise, and channel parameters for the proposed scenario. In the special case of when both n_i and ϑ are Gaussian as in [1], the corresponding MMSE estimation of s given z is given by

$$\hat{s} = \frac{\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g}}{\mathbf{g}^T \mathbf{W}\mathbf{h}\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g} + \mathbf{g}^T \mathbf{W}\mathbf{\Sigma_N}\mathbf{W}^T \mathbf{g} + \sigma_\vartheta^2} z. \tag{19}$$

Which is equivalent to the expression in [1, pp. 760]. It should also be noted that (18) is equivalent to the expression of the OBE in [9, eqn. (8)] in the special case of when $\mu_s = 0$ and z is the measurement, for a point-to-point scenario.

A. Distortion Analysis

The distortion of this scheme is evaluated in terms of MSE and it can be obtained by

$$D \equiv \varepsilon\left\{(s - \hat{s})^2\right\} = \int_s \int_z \left(s - \mu_{s|z}\right)^2 f(s,z)dsdz, \tag{20}$$

$$= \int_s \int_z \left(s - \mu_{s|z}\right)^2 f(s|z)f(z)dsdz = \int_z \Sigma_{s|z} f(z)dz, \tag{21}$$

where the posteriori covariance $\Sigma_{s|z}$ can be obtained as derived in [10]

$$\Sigma_{s|z} = \sum_{m=0}^{\infty} \chi_m(z)\left(\Sigma_{s|z}^m + \left(\mu_{s|z}^m\right)^2\right) - \left(\mu_{s|z}\right)^2. \tag{22}$$

Hence, from equation (21) we have

$$D = \int_z \sum_{m=0}^{\infty} \chi_m(z)\left(\Sigma_{s|z}^m + \left(\mu_{s|z}^m\right)^2 - \left(\mu_{s|z}\right)^2\right) f(z)dz,$$

$$= \sum_{m=0}^{\infty} p_m \int_z \left(\Sigma_{s|z}^m + \left(\mu_{s|z}^m\right)^2 - \left(\mu_{s|z}\right)^2\right) f_m(z)dz, \tag{23}$$

where $f_m(z) = \mathcal{N}(z, \mu_z^m, \sigma_{z,m}^2)$. However, equation (23) is similar to the expression in [10, eqn. (21)] and can not be solved analytically. Hence, we may derive its bounds. In this vein, a lower bound (LB) is obtained under the hypothetical assumption that there is no uncertainty about the impulsive component m and the Rayleigh channel state information, i.e., the genie condition. Following the same procedure as in [10], the LB (D_{LB}) under this consideration can be obtained as

$$D_{LB} = \sum_{m=0}^{\infty} p_m \Sigma_{s|z}^m(z). \tag{24}$$

Where $\Sigma_{s|z}^m(z)$ is defined in (17). To derive the upper bound (D_{UB}), as in [10], we invoke the LMMSE estimator since the LMMSE obtains the smallest MSE among all the estimators which are linear in the observations [10]. The MSE of the LMMSE estimator for this scheme is

$$D_{UB} = D_{LMMSE}, \tag{25}$$

$$= \sigma_s^2 - \frac{\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g}\mathbf{g}^T \mathbf{W}\mathbf{h}\sigma_s^2}{\mathbf{g}^T \mathbf{W}\mathbf{h}\sigma_s^2 \mathbf{h}^T \mathbf{W}^T \mathbf{g} + \mathbf{g}^T \mathbf{W}\mathbf{\Sigma_N}\mathbf{W}^T \mathbf{g} + \sigma_\vartheta^2}. \tag{26}$$

IV. Numerical Results

In this section, the performance of MMSE optimal Bayesian estimator and distortion parameter bounds are evaluated under AWGN, and Middleton class-A noise over Rayleigh quasi-static flat fading channel with respect to the communication signal-to-noise ratio (SNR). Here, the communication SNR is defined as $\sigma_h^2\sigma_s^2 + \sigma_n^2/\sigma_\vartheta^2$ and the measurement SNR as $\sigma_s^2/\sigma_n^2 = 0$ dB, where $\sigma_s^2 = 1$. In this model, a total number of 10 sensor nodes transmit with equal power their observations to the FC using AF strategy. The total transmission power of all the sensor nodes is $P_T = 1$ dB. Moreover, the channel fading have variances $\sigma_h^2 = \sigma_g^2 = 1$. The Middleton class-A model has the total number of impulsive sources which is equal to 30 and $\Gamma = 0.01$. As in [9], it is assumed that the impulsive noise parameters are known at the receiver side.

Fig. 2 shows the input-output characteristics of MMSE OBE using equation (18) for different values of the impulsive index A. As observed in Fig. 2, when the value of A increases, the impulsive noise becomes closer to the Gaussian noise and the input-output characteristics of MMSE OBE tend to the well-known LMMSE estimation which is optimal in the case of Gaussian noise. On the other hand, when the value of A decreases, the environment becomes more impulsive as indicated by rare impulsive events and the input-output

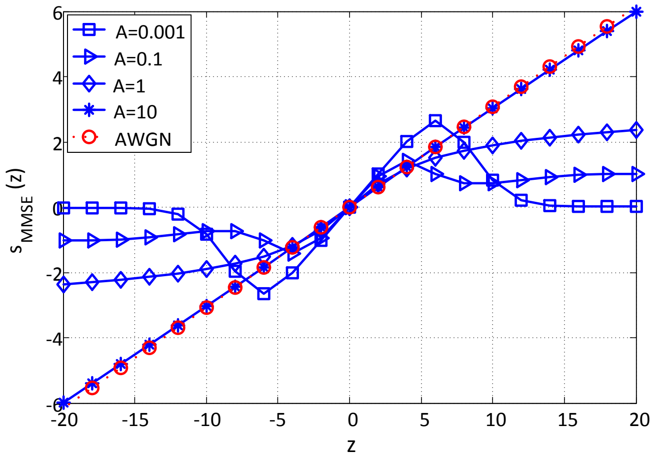

Fig. 2. Impact of the impulsive index A on the input-output characteristics of MMSE optimal Bayesian estimation. It is assumed that both the measurement SNR and the communication SNR are equal to 0 dB.

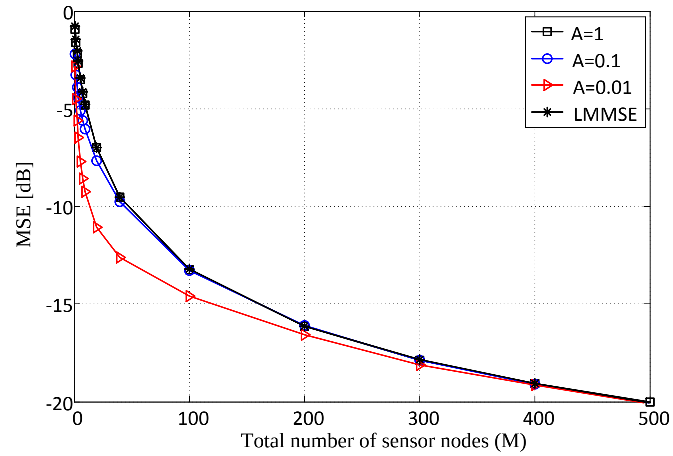

Fig. 4. Plot of distortion versus the total number of sensor nodes under different values of impulsive index A. It is assumed that both the measurement SNR and the communication SNR are equal to 0 dB.

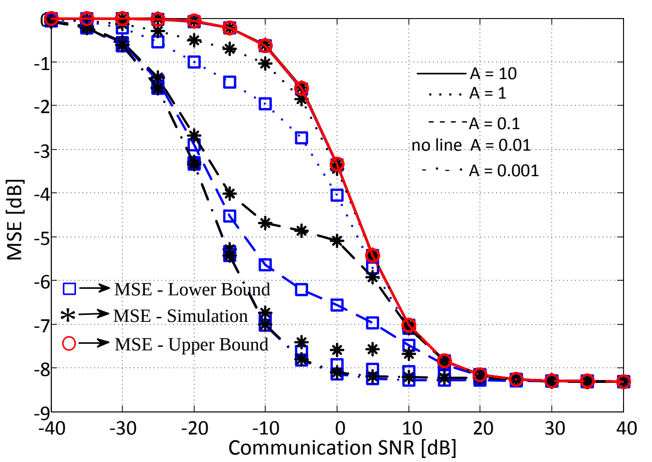

Fig. 3. Impact of the impulsive index A on the distortion performance. It is assumed that the measurement SNR is equal to 0 dB.

characteristic becomes more non-linear. Thus, similar to point-to-point scenario, the presence of impulsive noise introduce non-linearity in the measurement z. Hence, the MMSE optimal Bayesian estimator becomes non-linear under that scenario. Therefore, the nature of the impulsive noise should be taken into consideration for designing distributed estimation schemes because the presence of very rare impulsive events deteriorates its performance from linearity.

To visualize the effect of the non-linearity, we also have plotted the distortion performance for the proposed scenario. Fig. 3 shows the simulated MSE performances of the optimal MMSE estimation along with its derived analytical upper and lower bounds for different values of the impulsive index A. The simulated MSE performance is obtained by calculating the sample-mean of $(s - \mu_{s|z})^2$. From Fig. 3, it is seen that at both low and high SNR values the MMSE performs as the LMMSE (upper bound) estimator. However, at intermediate SNR levels, the MMSE estimator performs significantly better than the LMMSE estimator by using the impulsive noise characteristics in the estimation process and the amount of improvement depends on the impulsive nature as indicated by different values of A. From Fig. 3, it is further confirmed that as the value of A increases, the nature of impulsive noise becomes more Gaussian and the MSE performance of MMSE estimator approaches to the LMMSE estimator for all SNR values. Under this situation, the performance gap between the lower and the upper bounds decreases and approaches to zero for sufficiently larger values of A. On the other hand, for small values of A, the impulses are less dominant (more impulsive) and the performance gap between the upper and lower bounds becomes larger. The MMSE estimator approaches the lower bound under this scenario. Interestingly, when the impulsive events are very rare, the MMSE converges to the lower bound. Hence, the derived lower bound is very tight for highly impulsive noise environments.

Lastly, Fig. 4 shows the simulated MSE performances of the proposed system as a function of the total number of sensor nodes under different values of the impulsive index A. From Fig. 4, it is seen that similar to Gaussian case, the distortion performance decreases exponentially as the value of M increases while keeping the total transmission power constant. Also, for sufficiently large value of M the performance of the proposed non-linear MMSE estimator converges with the LMMSE estimator irrespective of the value of A.

V. Conclusion

WSN consists of spatially distributed sensors, identified as a promising technology for unknown parameters estimations. In this letter, the distributed estimation of a scalar Gaussian source in WSNs in the presence of Middleton class-A noise is considered. For this scheme, a closed-form expression for the MMSE optimal Bayesian estimation and the upper and lower bounds for the MSE are derived to show the effect of impulsive noise. It is shown that the performance improvement of the derived optimal MMSE estimator over the LMMSE estimator depends on the impulsive nature of the noise and on the operating SNR regions.

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