IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 21, 2020, accepted February 12, 2020, date of publication February 24, 2020, date of current version March 4, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2975834

Collaborative Data Transmission in Wireless Sensor Networks

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The research of Lazar Berbakov was funded by grant TR32043 of the Ministry of Education, Science and Technological Development of the Republic of Serbia. The research of Goran Dimić was supported by grant III44003 of the Ministry of Education, Science and Technological Development of the Republic of Serbia. The research of Marko Beko was supported in part by Fundação para a Ciência e a Tecnologia under Projects IF/00325/2015, foRESTER PCIF/SSI/0102/2017, and UIDB/04111/2020, and by Universidade Lusófona/ILIND internal project DECODY. The research of Jelena Vasiljević and Željko Stojković was funded by grant III43002 of the Ministry of Education, Science and Technological Development of the Republic of Serbia.

ABSTRACT Collaborative beamforming (CBF) is a promising technique aimed at improving energy efficiency of communication in wireless sensor networks (WSNs) which has attracted considerable attention in the research community recently. It is based on a fact that beampattern with stable mainlobe can be formed, if multiple sensors synchronize their oscillators and jointly transmit a common message signal. In this paper, we consider application of CBF with one bit of feedback in different communication scenarios and analyze the impact of constraints imposed by simple sensor node hardware, on the resulting signal strength. First, we present a CBF scheme capable of reducing interference levels in the nearby WSN clusters by employing joint feedback from multiple base stations that surround the WSN of interest. Then, we present a collaborative power allocation and sensor selection algorithm, capable of achieving beamforming gains with transmitters that are not able to adjust their oscillators' signal phase. The performance of the algorithms is assessed by means of achieved beamforming gain which is given as a function of algorithm iterations. The presented results, which are based on numerical simulations and mathematical analysis, are compared with the ideal case without constraints and with negligible noise at the Base Station (BS).

INDEX TERMS Collaborative beamforming, collaborative communication, wireless sensor network.

I. INTRODUCTION

Recently, wireless sensor networks (WSN), which are seen as one of the main pillars of the future Internet of Things (IoT), have attracted considerable interest in the research community. WSNs, which are formed by multiple sensor nodes, are capable of measuring different phenomena in their surroundings and sending their observations to a remote Base Station (BS), where the measurements are analyzed. Typical applications of WSNs include: smart homes [1], health care [2], environment monitoring [3], battlefield control [4], and many others. With potentially large WSNs consisting of many sensor nodes, which are often deployed across large remote areas, energy consumption becomes one of the main barriers in their wider usage. This constraint becomes even more severe, since often, frequent battery replacement is very costly and in some cases even not feasible. For simple low-cost sensor nodes, which have constrained computational capabilities, wireless data transmission to the remote BS consumes most of the available energy. One approach to the optimal usage of the available energy for the wireless communication link would be to use a transmitter with multiple antennas and direct most of the irradiated energy towards the BS. This, however would require more costly sensor nodes with more processing power and complex RF chain, which often is not feasible.

Another possibility is to harness a large number of deployed sensor nodes and resort to a so-called virtual antenna array. This approach, known as collaborative beamforming (CBF), has drawn significant interest among the

The associate editor coordinating the review of this manuscript and approving it for publication was Hongwei Du.

researchers over the past decade. In this setting, sensor nodes share a common message[1] which is then collaboratively transmitted to a distant BS. CBF is capable of improving the network lifetime by consuming available energy in a more efficient manner. In addition, it also ensures stable communication link in scenarios where multi-hop communication schemes are not feasible due to terrain and network topology constraints.

Similarly to centralized antenna arrays, collaborative beamforming results in an increase of the received Signal to Noise Ratio (SNR). If transmit power is fixed at each distributed antenna, CBF with a WSN consisting of N sensor nodes provides the gain in received power of N^2. In other words, reduction of transmitted power can be achieved on the order of $1/N^2$, if the received power level is fixed.

Because of distributed and random nature of wireless sensor networks, the initial work in this area focused on beampattern properties for different sensor node location probability density functions. Ochiai *et al.* [5] have analyzed the distribution of the average beampattern, for uniform distribution of sensor nodes. Similarly, in [6], the authors assume a Gaussian distribution of sensor nodes in a circle, and derive a closed-form solution for an average beampattern in such scenario. Both papers assume that the sensor nodes can be perfectly synchronized. Also, a method to evaluate average far-field beampattern properties for arbitrary distribution of sensor nodes is presented in [7]. In the aforementioned works, the authors concluded that for large number of sensor nodes N, the mainlobe of the beampattern becomes narrower by increasing the normalized (by wavelength λ) WSN radius R. Besides, it was shown that the WSN with sensor nodes distributed according to Uniform distribution have narrower mainlobe compared to nodes distributed with Gaussian distribution. Nevertheless, uniform distribution leads to sidelobes which follow Bessel function, whereas the Gaussian distributed network on average leads to beampattern where sidelobes slowly decreases, as it was shown in [6].

CBF approach, however requires a number of challenges to be solved. Namely, sensor nodes do not share a common oscillator, meaning that their frequencies and phases need to be well synchronized so that their signals form a coherent sum at the BS, which is not a trivial task. In particular, energy consumption of any synchronization scheme shall be as low as possible, in order not to diminish gains achieved by CBF transmission. Besides, limited computing capabilities and RF chain complexity pose additional constraints on the feasibility of distributed carrier synchronization schemes.

Existing research, which focused on carrier synchronization in WSNs can be divided into two groups: closed-loop and open-loop schemes. In this paper, we focus on closed-loop methods where the synchronization is achieved by periodic feedback from the distant BS. A distributed algorithm, which forms the basis of the schemes presented in this paper is described in [8], where the authors proposed a carrier phase synchronization technique that requires a feedback of only one bit per algorithm iteration. The one-bit-of-feedback phase synchronization algorithm requires that the sensor nodes add randomly chosen phase perturbation to the carrier signals during each iteration. The remote BS then estimates the received signal strength (RSS) and compares it with the RSS which was estimated during the previous algorithm iteration. Once the comparison is made, the result is transmitted to all the sensor nodes in the WSN, which based on the received feedback either keep or reject the last perturbation of their carrier phase. The aforementioned scheme is repeated until the measured RSS at the BS hits the previously configured level.

The performance of the algorithm proposed in [8] is further enhanced in [9] by considering an additional bit of feedback in the scheme called random 2 bits feedback. With that scheme, sensor nodes get an enriched feedback regarding the RSS increments, which allows them to better adapt the distribution range of their perturbations according to the received feedback. In the work of Mudumbai *et al.* [8], the assumption is that the measurement noise is negligible, which results in the perfect estimation of received signal strength at the remote BS. Having this assumption in mind, in [8] it was proven that the distributed one-bit-of-feedback scheme converges to full synchronization of carrier phases at the BS, where the convergence time grows linearly with the network size N. The phase synchronization scheme presented in [8] is improved in [10], to enable simultaneous synchronization of carrier phase and frequency. Moreover, the one bit feedback algorithm is enhanced in [11] by including the optimization of the size of phase perturbation, and in [12] where the proposed scheme employs the negative feedback from the BS rather than directly rejecting the phase perturbation. Besides, a possibility to perform simultaneous phase synchronization and data transmission was investigated in [13].

Further improvement of the algorithm can be achieved by considering signed perturbation, as has been shown in [14] and [15]. This approach is further enhanced in [16], where the authors propose an algorithm with perturbation at all nodes continuing in the same direction until the destination BS sends a negative feedback. The authors in [17], propose an algorithm capable of improving the convergence speed of the phase alignment, by employing directional search and perturbation theory. Their work is further extended in [18] where the authors improve the aforementioned approach and obtain the optimal step size so that an appropriate trade-off between maximum speed of convergence and minimum convergence error can be achieved.

In [19], the authors consider a scenario where sensor nodes are divided into two groups where one group forms a beam towards the BS of interest, while the other group forms interference aimed at obfuscating the eavesdropping BS. The algorithm they propose is based on the algorithm of [8] and employ two bits of feedback per algorithm iteration with the assumption of no knowledge regarding

[1] A common message can be simply broadcasted by a given sensor node to neighboring nodes in the WSN cluster.

the positions of potential eavesdropping BS. In work of Navarro-Camba *et al.* [20], the authors present one possible implementation of CBF. In their work, they propose an algorithm that assumes random retransmissions of the sensor node by introducing synchronization errors coming from the non perfect real sensor nodes available commercially. After a number of transmission repetitions, they show that the algorithm results in a coherent sum of the signals at the direction of main BS.

A deterministic phase perturbation algorithm is proposed in [9], where all nodes have a previously defined set of K phase perturbations and try all possible combinations with the aim of improving the RSS level over iterations. Based on the previous algorithm, in [21], the authors propose a closed-loop phase synchronization algorithm which employs quantized feedback from the BS. This scheme assumes that each node transmits independently only once during the phase synchronization interval. The destination BS receiver estimates the phase offsets for each received signal and provides the feedback to that particular node, indicating it to retain the previously defined set of phases for CBF. Practical considerations in implementation of CBF schemes on commercially available sensor nodes with related constraints have been analyzed in [22]. A method for collaborative beamforming, which is based on the observation that collaborative transmission with carriers not perfectly aligned at the BS can still provide notable beamforming gain, is presented in [23]. This observation enables the authors to design a beamforming scheme which selects a subset of all available sensor nodes in a WSN whose transmitted carrier signals align only partially at the remote BS.

A. CONTRIBUTIONS

In this paper, we present two extensions of CBF with one bit of feedback algorithm proposed by Mudumbai *et al.* [8] in different communication scenarios, with constraints imposed by simple sensor node hardware, and analyze their impact on the resulting signal strength:

1) Collaborative beamforming with sidelobe control (CBF-SC) in a scenario where multiple BSs are surrounding the WSN of interest, which was originally presented in [24]. This work is further extended here, by developing the proof of optimality of the proposed distributed synchronization scheme. The algorithm is designed so that the level of RSS at the main BS is maximized while simultaneously the interference to the remaining BSs is kept below some threshold.
2) CBF with distributed power allocation, suitable for simpler sensor nodes that employ amplitude modulation (AM) schemes, which was originally proposed in [25]. Furthermore, in this paper, we extend the analysis and present the algorithm's behavior when noise cannot be neglected and investigate the impact of perturbation size on the algorithm's performance.

B. ORGANIZATION

The paper is organized as follows. In Section II, we present the general system model and problem statement for CBF in WSN. Then, in Section III, we revisit the one-bit of feedback algorithm for distributed carrier synchronization and introduce the problem of CBF with sidelobe control. Next, in Section IV, we propose collaborative beamforming scheme with distributed power allocation for sensors nodes not capable of changing the oscillator signal phase. Numerical simulation results for the aforementioned schemes are presented in Section V. Finally, Section VI concludes the paper by summarizing the main results and conclusions.

II. SYSTEM MODEL AND PROBLEM STATEMENT

In this paper, we focus on the scenario with a WSN which consists of N sensor nodes, deployed in a random manner over a disk of radius R in the XY plane, according to a uniform distribution, as it is shown in Figure 1. The WSN is surrounded by K BSs, which are placed in directions $\mathcal{A} = \{\alpha_1, \alpha_2, \ldots, \alpha_K\}$ and at distances $\mathcal{D} = \{D_1, D_2, \ldots, D_K\}$. In addition, it is assumed that BSs are located far away and outside the coverage of each sensor node. The aim is to send a common message signal $m(t)$ to the BS1 (denoted as *main* BS) in a collaborative manner, and possibly keep the interference level at the remaining unintended $K-1$ BSs below the previously assigned threshold.

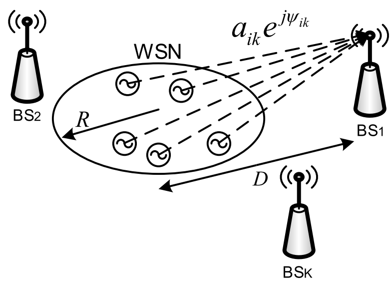

FIGURE 1. WSN cluster surrounded by multiple base stations.

To be able to optimally use the energy stored in a battery, the wireless sensor nodes remain for longer periods of time in the sleep mode, with negligible energy consumption. When new data needs to be collected, the BS1 transmits an RF signal that activates the carrier detectors at the sensor nodes and wakes them up from the sleep mode (see [26]). For simplicity, in this paper, we assume that the sensor nodes have previously shared the common message $m(t)$ where $\mathbb{E}\left[|m(t)|^2\right] = 1$. Consequently, the baseband signal which is generated by sensor node i equals:

$$s_i(t) = g_i^* m(t)\, e^{j(2\pi f_c t + \gamma_i)}, \tag{1}$$

where $g_i = b_i e^{j\theta_i}$ stands for the corresponding transmit weight, which will be designed during the training stage of the algorithm. Furthermore, we assume that the frequency drift of the oscillators is very low, so that after they are waked from the sleep mode, carrier frequency f_c is not changed.[2] The oscillator phase offset at sensor node γ_i is not known, and the assumption is that it is uniform ($\gamma_i \sim \mathcal{U}(-\pi, \pi)$) independent identically distributed (i.i.d.) random variable. The channel from each sensor to the remote BS is denoted by $h_{i,k} = a_{i,k}e^{j\psi_{i,k}}$, where $a_{i,k}$ stand for the channel magnitude and $\psi_{i,k}$ account for the phase shift due to the distance between the given i-th sensor and k-th BS. In the sequel, we assume that $h_{i,k}$ is unknown to BSs and sensor nodes. Therefore, the received signal at the k-th BS is given by:

$$r_k(t) = m(t)e^{j2\pi f_c t}\sum_{i=1}^{N} a_{i,k}b_i e^{j(\gamma_i+\psi_{i,k}-\theta_i)} + w(t), \quad (2)$$

where $w(t) \sim \mathcal{CN}(0, \sigma_w^2)$ stands for additive white Gaussian noise (AWGN), that is assumed to be negligible. Besides, the distance between each sensor node i and the k-th BS is larger than distances among the sensor nodes. This along with the assumption of line-of-sight communication, results in $a_{i,k} = 1$ across all the sensor nodes. Finally, the RSS at the k-th BS during n-th iteration equals:

$$\mathrm{RSS}_k\,[n] = R_k[n] = \left|\sum_{i=1}^{N} a_{i,k}b_i[n]e^{j\Phi_{i,k}}\right|, \quad (3)$$

with $\Phi_{i,k} = \gamma_i + \psi_{i,k} - \theta_i$ standing for the total phase rotation of the received signal at k-th BS coming from the sensor node i, whereas $b_i[n]$ denotes the magnitude of the beamforming weight, calculated with the algorithms that we propose in this paper.

III. ONE BIT OF FEEDBACK ALGORITHM FOR DISTRIBUTED CARRIER SYNCHRONIZATION

By observing (3), it is clear that the RSS at the BS1 (main BS) reaches maximum when the signals from individual sensor nodes are combined in a coherent manner, i.e. when $\gamma_i + \psi_{i,1} - \theta_i = C; \forall i$ (where C is a constant) that results in beamforming gain[3] $Y_1[n] = Y_{\max} = |\sum_{i=1}^{N} a_{i,1}b_i[n]|$. In order to achieve this, sensors nodes need to pre-compensate the unknown sum of oscillator and channel phase offsets by changing the θ_i during the so-called training period. In [8], the authors propose a collaborative carrier synchronization algorithm, that achieves this task in an iterative manner.

In initial iteration, the phases of the signals received from the sensor nodes at the base station[4] $\Phi_{i,1}[0] = \gamma_i + \psi_{i,1} - \theta_i[0] = \gamma_i + \psi_{i,1}$, are distributed uniformly in $[-\pi, \pi]$. This comes from the observation that the oscillators run independently and $R \ll D$. During the algorithm's runtime, each sensor node tracks the best value of $\theta_{\mathrm{best},i}[n]$. During a given iteration, $\theta_{\mathrm{best},i}[n]$ is modified by adding a random phase perturbation $\delta_i[n]$ taken from a given probability distribution $f_\delta(\delta_i)$. Then, all sensor nodes send training signals with the phase rotations that increment, i.e. $\theta_i[n+1] = \theta_{\mathrm{best},i}[n] + \delta_i[n]$ and the RSS at the BS is measured again. Next, the BS compares $R_1[n+1]$ with $R_{\mathrm{best},1}[n] = \max_{m\le n} R_1[m]$, that is the largest RSS at the BS up to time instant n. In other words, the BS finds out whether the last set of perturbations $\Delta[n] = [\delta_1[n], \ldots, \delta_N[n]]$ should be accepted (when RSS has increased) or rejected (when RSS has decreased). Then, the BS informs the sensor nodes about the resulting decision by transmitting one bit of feedback over a signaling channel, that we assume to be error-free. In other words, the sensor nodes will update their carrier phases and adjust them with the following recursion:

$$\theta_{\mathrm{best},i}[n+1] = \begin{cases} \theta_{\mathrm{best},i}[n] + \delta_i[n] & \text{if } R_1[n+1] \ge R_{\mathrm{best},1}[n] \\ \theta_{\mathrm{best},i}[n] & \text{otherwise} \end{cases} \quad (4)$$

Consequently, the beamforming gain at the main BS $Y_1[n]$ is adjusted as follows:

$$Y_{\mathrm{best},1}[n+1] = \begin{cases} Y_1[n+1] & \text{if } R_1[n+1] \ge R_{\mathrm{best},1}[n] \\ Y_{\mathrm{best},1}[n] & \text{otherwise,} \end{cases} \quad (5)$$

with a similar recursion applying to $R_{\mathrm{best},1}[n]$.

A. COLLABORATIVE BEAMFORMING WITH SIDELOBE CONTROL

In the sequel, we consider a more complex scenario where, in contrast to [8], we assume that there exists one main BS and multiple *unintended* BSs, which possibly serve other sensor networks located nearby. Moreover, we assume that the sensor nodes transmit with equal power and can only change their oscillator phase offsets. Consequently, and without loss of generality, we can assume that $b_i = 1$ for $i = 1, \ldots, N$. Our goal is to maximize the RSS at the main BS, while simultaneously keeping the RSS at k-th unintended BS below some prescribed thresholds Γ_k, for $k = 2 \ldots K$.

1) OPTIMIZATION PROBLEM

The optimization problem of collaborative beamforming with sidelobe control constraints is given by:

$$\begin{aligned} &\max\ Y_1 \\ &\text{subject to } Y_k \le \Gamma_k, \quad k = 2, \ldots, K, \end{aligned} \quad (6)$$

where Y_1 denotes the beamforming gain at the main BS, Y_k for $k = 2, \ldots, K$ denote the beamforming gain at the unintended BSs, and the Γ_k thresholds are assumed to be system parameters, configured to keep the interference level at unintended BSs at acceptable levels. By moving to vector notation, and defining vectors $\mathbf{g}_k = [a_{1,k}e^{j(\gamma_1+\psi_{1,k})}, \ldots, a_{N,k}e^{j(\gamma_N+\psi_{N,k})}]^T$, $\mathbf{w} = [e^{j\theta_1}, \ldots, e^{j\theta_N}]^T$, the problem (6) can be rewritten as follows:

$$\begin{aligned} &\max_{w}\ \left|w^H g_1\right| \\ &\text{subject to } \left|w^H g_k\right| \le \Gamma_k, \quad k = 2, \ldots, K. \\ &\qquad \mathrm{diag}\left[ww^H\right] \le 1, \end{aligned} \quad (7)$$

[2]The case considering simultaneous phase and frequency synchronization with one-bit of feedback algorithm in the scenario where frequency drift cannot be neglected has been analyzed in [10].

[3]Authors in [8] assume that the impact of additive noise is negligible, which leads to: $Y_1[n] = R_1[n]$

[4]In [8], only one - the main base station is considered.

with 1 denoting $N \times 1$ vector with all elements equal to 1. In such a way, vector $\mathbf{w}$ contains the beamforming weights, which will be optimized, whereas $\mathbf{g}$ stands for the channel propagation and phase offset. The definition of optimization problem in (7) is particularly useful when the problem is solved numerically. Finally, it is worth noting that the optimal solution can only be achieved when the second constraint holds with equality since, otherwise, the objective function could always be increased by simply multiplying the vector of weights by a scalar factor. This is consistent with our definition of vector $\mathbf{w}$.

The optimization problem (7) is clearly not convex because the aim is to maximize a convex objective function subject to a number of convex inequality constraints. In addition, it can be observed that the objective function is invariant to an arbitrary rotation of phase applied to all elements of vector w. In order to transform the optimization problem given in (7) into a convex optimization problem, the vector w can be forced to fulfill[5] $\Im\left(w^H g_1\right) = 0$, where $\Im(\cdot)$ represents the imaginary part of the complex product. This change leads to the following expression equivalent to (7):

$$\begin{aligned} &\max_{w} \Re\left(w^H g_1\right) \\ &\text{subject to } \Im\left(w^H g_1\right) = 0 \\ &\qquad \Re^2\left(w^H g_k\right) + \Im^2\left(w^H g_k\right) \le \Gamma_k^2, \quad k = 2, \ldots, K \\ &\qquad \text{diag}\left[w w^H\right] \le 1, \end{aligned} \tag{8}$$

with the last constraint in (8) becoming active for large number of sensors N in the WSN (see the Appendix) and $\Re(\cdot)$ representing the real part of the complex product. Then, the following change of variables is applied:

$$\hat{w} = \begin{bmatrix} \Re(w) \\ \Im(w) \end{bmatrix}; \; \hat{g}_k = \begin{bmatrix} \Re(g_k) \\ \Im(g_k) \end{bmatrix}; \; g_k = \begin{bmatrix} \Im(g_k) \\ -\Re(g_k) \end{bmatrix}; \tag{9}$$

consequently, the optimization problem is finally given by:

$$\begin{aligned} &\max_{\hat{\mathbf{w}}} \hat{\mathbf{w}}^T \hat{g}_1 \\ &\text{subject to } \hat{\mathbf{w}}^T g_1 = 0 \\ &\qquad \left(\hat{\mathbf{w}}^T \hat{g}_k\right)^2 + \left(\hat{\mathbf{w}}^T g_k\right)^2 \le \Gamma_k^2, \; k = 2, \ldots, K. \\ &\qquad \text{diag}\left[(M\hat{\mathbf{w}})(M\hat{\mathbf{w}})^H\right] \le 1, \end{aligned} \tag{10}$$

where $\mathbf{M} = [I_N, jI_N]$ with I_N standing for an $N \times N$ identity matrix. It is now clear that the problem (10) is convex, since the aim is to maximize[6] a linear objective function (which is both concave and convex, by definition), the inequality constraint functions are convex (actually quadratic), and the equality constraint is affine. Therefore, the optimization problem in (10) can be numerically solved by using convex optimization tools. Nevertheless, to be able to solve it numerically, the BS needs to have *full* Channel State Information (CSI), which is not practical in wireless sensor networks with large number of sensor nodes. This is the reason why we propose an iterative algorithm, which is presented in the sequel.

[5] This can be enforced by adjusting the phase rotation of the carrier signal.

[6] By choosing one of the two phase rotations for which $w^H g_1 = \Re(w^H g_1)$, the formulation leads to the one that results in $\Re(w^H g_1) > 0$.

2) ONE BIT OF FEEDBACK ALGORITHM FOR COLLABORATIVE BEAMFORMING WITH SIDELOBE CONTROL (CBF-SC)

To be able to find a solution of the problem defined in (10) in a decentralized manner, we propose an iterative algorithm which only requires partial CSI knowledge. In particular, it requires Signal to Noise Ratio (SNR) measurements at all BSs along with one bit of feedback per algorithm iteration from all of them, based on the technique proposed in [8].

The original distributed beamforming algorithm, which is presented therein, aims to maximize the RSS at the main BS in an iterative manner and does not consider the interference created in the directions of the unintended BSs (i.e. the optimization problem without constraints in (6)). As discussed previously, the BS sends its decision to the sensor nodes on whether phase perturbation should be kept or not. Correspondingly, the feedback from the BS1 (main BS) is set to:

$$z_{\text{FB},1}[n+1] = \begin{cases} 1 \text{ if } R_1[n+1] \ge R_{\text{best},1}[n] \\ 0 \text{ otherwise,} \end{cases} \tag{11}$$

where the sensor nodes adjust their transmitter oscillator phases as follows:

$$\theta_{\text{best},i}[n+1] = \begin{cases} \theta_{\text{best},i}[n] + \delta_i[n] & \text{if } z_{\text{FB},1}[n+1] = 1 \\ \theta_{\text{best},i}[n] & \text{otherwise.} \end{cases} \tag{12}$$

The CBF-SC algorithm is inspired by the observation that there exists a subset of the perturbations sequence $\{\Delta[n]\}$ that is able to *simultaneously* increase $R_1[n]$ at the main BS and decrease $R_k[n]$ for $k = 2 \ldots K$ unintended BSs.

In order to accomplish this, in addition to the main BS, the unintended BSs also need to estimate the RSS level and inform the sensors about this measurement with the following message, i.e.

$$z_{\text{FB},k}[n+1] = \begin{cases} 1 \text{ if } R_k[n+1] < R_{\text{best},k}[n] \\ 0 \text{ otherwise,} \end{cases} \tag{13}$$

for $k = 2 \ldots K$. Finally, the sensor nodes will retain the oscillator phase perturbations only if both main and unintended BSs send the positive feedback messages:

$$\theta_{\text{best},i}[n+1] = \begin{cases} \theta_{\text{best},i}[n] + \delta_i[n] & \text{if } z_{\text{FB},k}[n+1] = 1 \\ \theta_{\text{best},i}[n] & \text{otherwise} \end{cases} \tag{14}$$

for $k = 1, \ldots, K$. The aforementioned scheme is run until the RSS level at the main BS saturates whereas the RSS levels at the unintended BS remain below the previously defined Γ_k thresholds, or until the algorithm reaches the allowed number of iterations L_{final}. As can be seen, introduction of the constraints on maximum interference levels into the optimization problem results in a slower rate of convergence. Based on our simulations, we can conjecture that the convergence time of the CBF-SC is of the same order as the simpler, original CBF algorithm proposed and analyzed in [8], which is linear in the number of nodes, N. The analysis of algorithm complexity in terms of required number of iterations is left for the future work. As we will discuss in Section V, the introduction of constraints is very destructive in a scenario where the direction of main α_1 and unintended BSs α_k; $k = 2, \dots, K$ are located nearby each other, or with a large number of unintended BSs $(K - 1)$. The proof of optimality of the proposed algorithm is provided in the Appendix.

IV. COLLABORATIVE BEAMFORMING WITH DISTRIBUTED POWER ALLOCATION

Unlike in algorithm presented in [8], in the sequel, the assumption is that each sensor node can change the transmitter power between 0 and $P_{\max}$, while it cannot change the phase of the oscillator because of the simple sensor node transmitter hardware [25]. This hardware constraint prevents us from resorting to synchronization techniques that change the oscillator phase, allowing us to only use the schemes with sensor selection.

However, we cannot employ the sensor selection algorithm that is presented in [23], since it requires the knowledge of full CSI, which is not the case in this scenario. To that aim, in the sequel, we propose an algorithm for simultaneous selection of sensor nodes and power allocation for collaborative beamforming.

A. OPTIMIZATION PROBLEM FOR COLLABORATIVE BEAMFORMING WITH DISTRIBUTED POWER ALLOCATION

The optimization problem where the RSS at the remote BS is maximized by using power allocation is given by:

$$\begin{aligned} &\max R \\ &\text{subject to } P_i \le P_{\max},\ i = 1, \dots, N, \\ &\qquad \sum_{i=1}^{N} P_i \le P_{\mathrm{T}}, \end{aligned} \tag{15}$$

with R standing for the RSS, P_{T} accounting for the total power which is used by all the sensor nodes in WSN and $P_{\max} = 2\frac{P_{\mathrm{T}}}{N}$ denoting the maximum output power of the sensor node.

When we move to vector notation, and define $\mathbf{g} = [a_1 e^{j(\gamma_1+\psi_1)}, \dots, a_N e^{j(\gamma_N+\psi_N)}]^T$ $\mathbf{w} = [b_1\, e^{j\theta_1}, \dots, b_N e^{j\theta_N}]^T$, the optimization problem from (15) is now given by:

$$\begin{aligned} &\max_{w} \left| w^H g \right| \\ &\text{subject to } \mathrm{diag}\left[w w^H \right] \le 2\frac{P_{\mathrm{T}}}{N} 1. \\ &\qquad w^H w \le P_{\mathrm{T}} \end{aligned} \tag{16}$$

As we can see, vector $\mathbf{w}$ now contains the beamforming weights, and as defined previously, $\mathbf{g}$ stands for the starting phase offset of the sensor node oscillator and the effects of channel propagation. This definition can be used to solve the optimization problem with numerical optimization tool. However, to be able to perform numerical optimization, it is necessary to have full CSI, which is not available in the present scenario. In order to find the optimal power allocation, a power allocation and sensor selection algorithm is proposed.

B. POWER ALLOCATION AND SENSOR SELECTION ALGORITHM FOR COLLABORATIVE BEAMFORMING

In the sequel, we assume that the sensor nodes' transmitter oscillators have initial phase offsets distributed uniformly $\gamma_i \sim [-\pi, \pi]$. In addition, the phase shifts of the channel are also assumed to be distributed uniformly $\psi_i \sim [-\pi, \pi]$. Besides, as stated previously, the sensor nodes cannot change carrier phases due to simple transmitter hardware. The beamforming weight arguments at all the sensor nodes can be fixed to a given constant[7] $\theta_i = \theta_c$, without loss of generality. As a consequence, the total signal phase offset from i-th sensor to the main BS remains to be distributed uniformly $\Phi_i \sim [-\pi, \pi]$. If transmit power at each sensor node is set to P_T/N, the resulting RSS at the main BS equals[8] $\sqrt{P_T}$. In order to increase the level of RSS at the main BS, we propose a scheme which calculates the sensor nodes' power allocation in an iterative manner, as explained in the sequel:

- All sensor nodes transmit carrier signal, which is unmodulated, with transmit powers set to equal values $P_i = P_T/N = P_{\max}/2$.
- Main BS measures the RSS level and stores the current RSS value in the memory.
- All the sensor nodes transmit carrier signals which now have changed transmit power which is configured as follows: Sensor nodes adjust the values of transmit power in pairs. The first sensor of a pair sets the new transmit power by adding random power perturbation δ_i, while the second sensor sets its transmit power by subtracting it for the same amount, therefore keeping constant the total transmit power in the WSN.[9] If newly calculated power in any of the sensor pairs goes below 0 or above $P_{\max}$, the previously selected power is taken in the current algorithm iteration.
- Main BS compares newly obtained RSS value with the old RSS value memorized in the previous iteration and transmits one bit of feedback to the sensor nodes in a WSN, informing them either to keep new power value (when RSS level increases), or to reject it and set the previously chosen power (when RSS level decreases).

[7] There is no change in the RSS level at the BS if equal change of phase is added to all the sensor nodes' oscillators.

[8] $\sqrt{P_T}$ is calculated as the expected value of the sum of complex random variables whose arguments are uniformly distributed with magnitude that equals $\sqrt{P_T/N}$.

[9] The pair of sensors is pre-configured to employ the same pseudo-random number generator seed.

- The proposed algorithm runs until the RSS level at the main BS does not change significantly (RSS change is smaller than the preconfigured threshold).

For the CBF with distributed power allocation, the convergence time may also be linear in the number of nodes, N, but we do not have sufficient analytical results to claim so. The analysis of algorithm complexity in terms of required number of iterations is left for the future work.

V. NUMERICAL RESULTS AND DISCUSSION

In this section, we present the results of computer simulations with the aim of illustrating the behavior of the aforementioned CBF schemes. Here, the focus is on the analysis of the performance loss due to communication scenario and simple sensor node hardware constraints. Where applicable, the numerical solutions will be employed as a benchmark.

A. COLLABORATIVE BEAMFORMING WITH SIDELOBE CONTROL

The WSN consists of $N = 100$ sensor nodes uniformly deployed across a disk of radius R. The BSs are located at the same distances with $D_k = D \gg R$ far away from the WSN cluster. Without loss of generality, it can be assumed that the main BS is placed at direction $\alpha_1 = \alpha_{\text{main}} = 0°$. The random oscillator phase perturbations used in algorithms are selected independently for each sensor node from a uniform distribution: $\delta_i \sim \mathcal{U}(-\frac{\pi}{50}, \frac{\pi}{50})$. The allowed number of algorithm iterations is $L_{\text{final}} = 5 \cdot 10^4$.

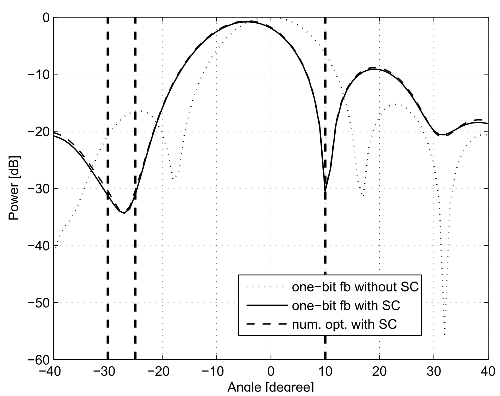

FIGURE 2. **Beampattern of collaborative beamforming algorithms with and without sidelobe control mechanisms ($R = 2$, $K = 4$, $\alpha_1 = 0°$, $\alpha_2 = -30°$, $\alpha_3 = -25°$, $\alpha_4 = 10°$, $\Gamma_{dB} = -30$ dB).**

In Figure 2, we present the effect of sidelobe control techniques on the collaborative beamforming beampattern. As can be seen, the CBF-SC is able to reduce the RSS levels in the directions of the unintended BSs, which are marked with vertical dashed lines in the figure, to the levels of $\Gamma_2 = \ldots = \Gamma_K = -30$ dB or even less. On the other hand, in the original beampattern without sidelobe control, the levels of RSS in those directions are substantially above. Nevertheless, it can also be observed that the beampattern maximum does not point to the direction of the main BS, i.e. $\alpha_{\text{main}} = 0°$. This can be explained by the fact that one of the unintended BSs lays inside the mainlobe region of the beampattern without sidelobe control ($\alpha_2 = 10°$). In addition, Figure 2 also shows that the beampatterns resulting from the proposed CBF-SC scheme and numerical optimization method are identical. This observation confirms the validity of the proposed CBF technique. Finally, from Figure 2 we can see that the observation from [8], that algorithm almost surely achieves full beamforming gain at the main BS (RSS normalized by the number of sensors nodes N is equal to 1), does not hold anymore. Namely, due to constraints imposed by RSS levels at the unintended BSs, the algorithm cannot achieve full coherence of the individual signals at the main BS.

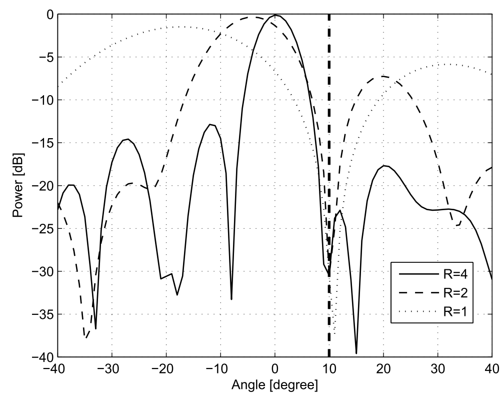

FIGURE 3. **Mean beampattern of collaborative beamforming algorithm with sidelobe control mechanisms ($K = 2$, $\alpha_1 = 0°$, $\alpha_2 = 10°$, $\Gamma_{dB} = -30$ dB).**

Figure 3 presents the mean beampattern for different radii R of WSN in the scenario where only one unintended BS is located at direction $\alpha_2 = 10°$. As one can expect, the large WSN radius results in the narrow mainlobe. For $R = 4$, the maximum of the mainlobe still points to the direction of main BS. On the other hand, in the case of small WSN radius, the beampattern maximum is moved away. Consequently, lower RSS is achieved in the direction of the main BS. We can observe this behavior in Figure 4 (top) where we present the change of the average normalized RSS at the main BS as a function of algorithm iterations. When the convergence of the algorithm is reached, the loss of normalized RSS for the WSN radius $R = 1$ equals approximately 7 dB.

It can also be observed that the speed of convergence at which the CBF-SC attains the optimal solution is dependent on the network diameter. Although for larger radius the reduction is smaller when compared to the case without sidelobe constraint (dotted curve in Figure 4 (top)), for small network radius the slope of the convergence curves is significantly less steep. This can be explained by the observation that for wider mainlobe it is indeed more difficult task to select those perturbations that can simultaneously improve the RSS at the main BSS while keeping the RSS level at the unintended ones below the prescribed threshold. This impact can be seen in Figure 4 (bottom) where the change of the normalized RSS at the unintended BSs is presented. From that figure, it is clear

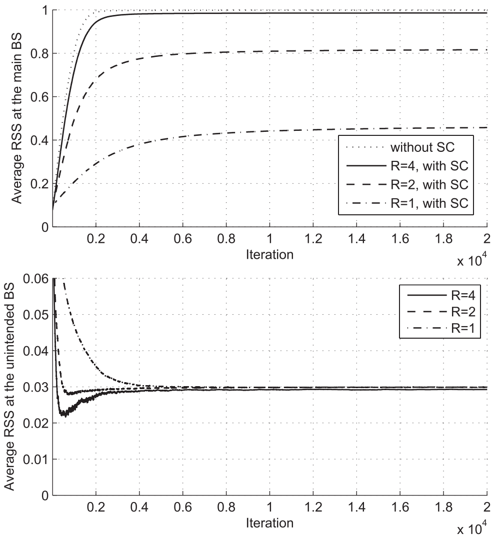

FIGURE 4. Mean normalized RSS level for the main (top) and unintended BS (bottom) as a function of the number of iterations ($K = 2$, $\alpha_1 = 0°$, $\alpha_2 = 10°$, $\Gamma_{dB} = -30$ dB).

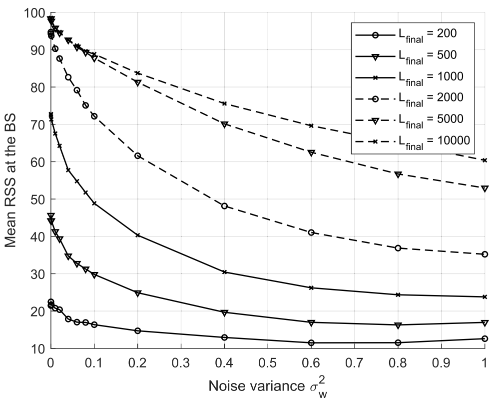

FIGURE 5. Mean RSS at the main BS as a function of noise variance σ_w^2, for different algorithm duration L_{final} ($K = 2$, $N = 100$, $\alpha_1 = 0°$, $\alpha_2 = 10°$, $\Gamma_{dB} = -30$ dB).

that the interference at the unintended BS decreases more slowly for smaller WSN radius.

In Figure 5, we present mean RSS at the main BS as a function of noise variance for a collection of different values of maximum number of algorithm iterations L_{final}. As it is expected, the observation noise at the BS may lead to incorrect decision on whether to keep or discard the phase perturbation, since now the measured RSS represents the sum of beamforming gain and observation noise. Consequently, the increase of RSS at the BS is slower, which results in lower RSS level once the algorithm reaches last iteration L_{final}. This behavior is in line with our previous work presented in [27], where we analyzed the impact of observation noise on behavior of the original one-bit of feedback algorithm without sidelobe constraint in a scenario with simultaneous phase synchronization and data transmission.

B. COLLABORATIVE BEAMFORMING WITH DISTRIBUTED POWER ALLOCATION

In this section, we provide computer simulation results which aim to present the performance of the communication scheme that employs distributed power allocation and sensor selection. It is assumed that the number of sensors N in WSN belongs to set 10, 100, 1000, where the sensors are located according to uniform distribution across a disk of radius $R = 4$ (where R is normalized to the wavelength). The chosen transmit power value at each sensor is calculated in an iterative manner by adding a random power perturbation that follows the uniform distribution $\delta_i \sim \mathcal{U}(-0.05, 0.05)$.

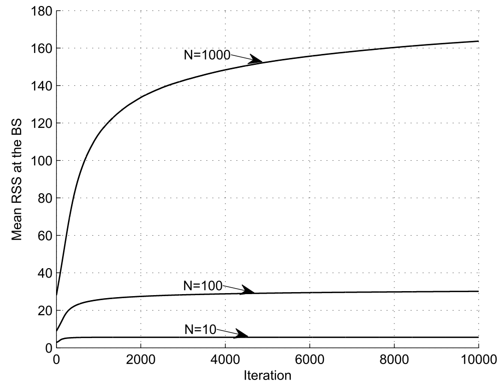

FIGURE 6. Mean RSS as a function of algorithm's iteration ($\delta_i \sim \mathcal{U}(-0.05, 0.05)$, $P_T = N$).

Figure 6 depicts the change of the mean RSS level at the main BS (for different number of sensor nodes N), which is given as a function of distributed power allocation algorithm's iteration. As we can expect, increased number of sensor nodes results in a higher level of RSS at the main BS. In addition, it can be noted that the RSS level saturates much faster for smaller WSN size. This can be explained by the observation that for small network size it turns out to be much easier to identify the converging solution, due to the fact that there exist small number of variables that perturb their values across algorithm iterations.

In Figure 7, we present the mean RSS (normalized by the number of sensors N) at the main BS which is given as a function of algorithm's iteration. RSS normalization is performed in order to provide a deeper look into energy efficiency of the collaborative beamforming as a function of different size of a WSN cluster. As we see, the smaller WSN size leads to higher normalized RSS level of 0.56, which results in a more energy efficient transmission. In this case, the achieved RSS level is a function of smaller number of variables. Therefore, it is much easier to maximize the RSS, since the probability that the perturbation is good is higher. Conversely, if a larger number of sensors is involved in collaborative transmission, the RSS in the final iteration is lower, resulting in a less energy efficient operation. It has to be noted that in the case of completely coherent transmission considered in [8], where

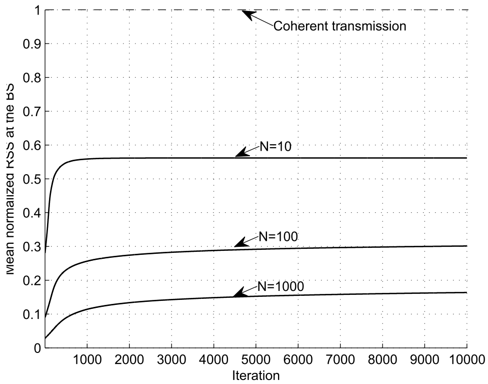

FIGURE 7. Mean normalized RSS as a function of algorithm's iteration ($\delta_i \sim \mathcal{U}(-0.05, 0.05)$, $P_T = N$).

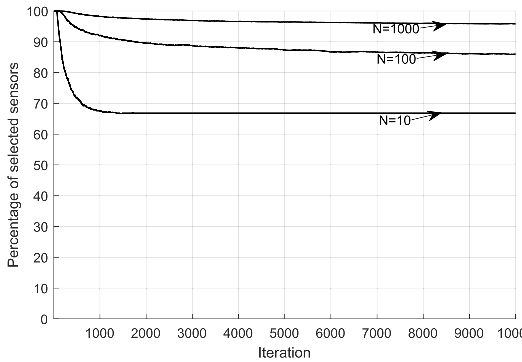

FIGURE 8. Percentage of selected sensors as a function of algorithm's iteration ($\delta_i \sim \mathcal{U}(-0.05, 0.05)$, $P_T = N$).

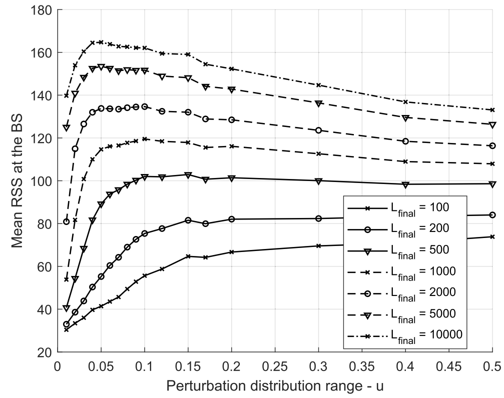

FIGURE 9. Mean RSS at the BS as a function of perturbation distribution range - u $\delta_i \sim \mathcal{U}(-u, u)$, for different algorithm duration L_{final} ($\sigma_w^2 = 0$, $P_T = N$).

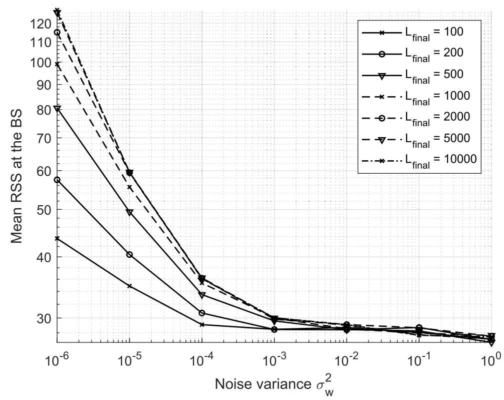

FIGURE 10. Mean RSS at the BS as a function of noise variance σ_w^2, for different algorithm duration L_{final}, ($N = 1000$, $u = 0.1$, $P_T = N$).

the same transmit power is applied to all sensor nodes that have their phases ideally aligned, the resulting mean RSS (normalized to the number of sensors) equals 1.

Figure 8 presents the percentage of the nodes selected by the algorithm (those having $P_i > 0$), given as a function of algorithm's iteration. As we can see, in scenario with small WSN networks (small N), the algorithm selects (allocate nonzero power level) only the sensors (68% of all of them) that have their signals combined in close-to-coherent way at the location of the main BS. Conversely, for larger WSN networks, the algorithm turns out to select larger subset of sensors (96%). This behavior results in a sum at the main BS, which is less coherent, leading to a lower achieved normalized RSS, as it has been shown previously in Figure 7).

In Figure 9, we present the RSS (averaged over multiple algorithm runs) at the main BS which is given as a function of perturbation distribution range u, where perturbations are distributed according to uniform distribution $\delta_i \sim \mathcal{U}(-u, u)$, for a collection of different algorithm durations, denoted by ending iteration index L_{final}. In the case where the algorithm has less time to calculate the power allocation ($L_{\mathrm{final}} = 100$), we can see that it is more advisable to use larger perturbation distribution range, which would enable the algorithm to reach higher RSS levels at the end. On the other hand, when the total number of iterations is large ($L_{\mathrm{final}} = 10000$), it is better to use smaller perturbations ($u \in [0.04, 0.1]$), which would allow finer adjustments in the calculation of transmit power, leading to higher RSS levels.

Figure 10 depicts the mean RSS at the main BS which is given as a function of noise variance, in the case where the effect of noise cannot be neglected. As expected, the noise causes erroneous decisions whether to reject or retain the power perturbation, since it may happen that the resulting RSS increase due to additive noise and not due to good power perturbation. These erroneous decisions result in decrease of the achievable RSS level, where as expected, larger noise results in lower final RSS levels. This behavior is in line with the one presented in [27], where the authors considered the effect of additive noise on the algorithm of Mudumbai *et al.* [8].

Finally, in Figure 11, we present the mean beampattern of collaborative beamforming transmission with aforementioned distributed power allocation algorithm. As we see, the proposed communication scheme provides main lobe which points towards the main BS, whereas at the same

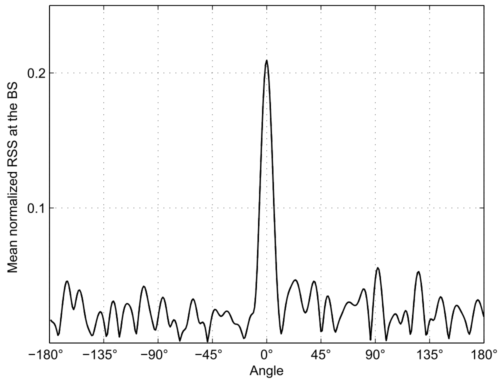

FIGURE 11. Mean normalized RSS beampattern. ($N = 1000$, $\delta_i \sim \mathcal{U}(-0.05, 0.05)$, $P_T = N$, BS located at 0° direction).

time it wastes less power to other directions. As a consequence, it causes less interference to other WSN located nearby. It must be noted, that in the considered scenario, the transmitters are not capable of changing their oscillator phases (which requires transmitter to be more complex). Consequently, the achieved RSS at the main BS turns out not to be the maximum possible.

VI. CONCLUSION

In this work, we have proposed two different collaborative beamforming algorithms, where each of them aims at solving particular communication problem, and analyzed the corresponding performance loss with respect to the ideal case. First, we proposed a collaborative beamforming scheme with sidelobe control, which reduces interference level in nearby clusters of sensor nodes, while simultaneously maximizing the signal level at the BS of interest. As has been shown, the algorithm performs oscillator phase synchronization in a distributed manner and does not require full CSI, which makes it particularly suitable for large WSN with simple sensor nodes. Next, we presented a distributed power allocation and node selection algorithm aimed at simple sensor node transmitters. It was shown that with such scheme, the notable beamforming gain is achievable. In addition, when the total number of iteration is large, it is advisable to use smaller power perturbations. Finally, the achieved RSS levels are smaller when the additive noise cannot be neglected, since the noise causes the wrong decision whether to keep or reject the power perturbations.

As a possible future work, we plan to consider the case where number of unintended BSs grows large, where it is unlikely that positive feedback will be received by each of them, leading to slower convergence speed. In such scenario, it is necessary to consider different rules for accepting the phase perturbations. Besides, additional constraints imposed by sensor nodes that may harvest available energy for data transmission will be considered, as well. Finally, we aim to perform the complexity analysis, i.e. evaluation of the algorithm convergence time.

APPENDIX: PROOF OF THE CBF-SC ALGORITHM SOLUTION OPTIMALITY

The original optimization problem, considered in [8], without sidelobe constraint can be posed as:

$$\begin{aligned} &\max_{\hat{\mathbf{w}}} \hat{\mathbf{w}}^T \hat{g}_I \\ &\text{subject to } \hat{\mathbf{w}}^T g_I = 0 \\ &\qquad \text{diag}\left[(M\hat{\mathbf{w}})(M\hat{\mathbf{w}})^H\right] \leq 1, \end{aligned} \tag{17}$$

For the given problem, we write the following Karush Kuhn Tucker (K.K.T.) conditions:

$$\begin{aligned} \nabla f_0(\mathbf{w}^*) + \sum_{i=1}^{m} \lambda_i^* \nabla f_i(\mathbf{w}^*) + \sum_{i=1}^{p} \nu_i^* \nabla h_i(\mathbf{w}^*) & \\ = \mathbf{0} & \\ f_i(\mathbf{w}^*) \leq 0 \text{ for } i = 1, \ldots, m & \\ h_i(\mathbf{w}^*) = 0 \text{ for } i = 1, \ldots, p & \\ \lambda_i^* \geq \mathbf{0} \text{ for } i = 1, \ldots, m & \\ \lambda_i^* f_i(\mathbf{w}^*) = 0 \text{ for } i = 1, \ldots, m & \end{aligned} \tag{18}$$

For the convex optimization problem (17), these K.K.T. conditions are given by:

$$\hat{g}_I + 2\Lambda\hat{\mathbf{w}} + \nu\mathbf{g}_I = 0 \tag{19}$$

$$\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \ddots & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \lambda_N & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \lambda_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda_2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_N \end{bmatrix} \tag{20}$$

From (19), we can obtain the optimal beamforming vector:

$$\hat{\mathbf{w}} = \frac{\Lambda^{-1}}{2}(-\nu\mathbf{g}_I - \hat{g}_I) \tag{21}$$

In order to calculate the beamforming vector $\hat{\mathbf{w}}$, we have to invert the matrix Λ, which is diagonal. The inverse of this matrix can be found only when all the diagonal terms $\Lambda_{ii} \neq 0$, which means that all the λ_i are strictly positive. In order to fulfill the last KKT condition (18) all the inequality constraints must be satisfied with an equality, meaning that all the sensors have to transmit with full power.

The optimization problem with sidelobe constraint can be posed as:

$$\begin{aligned} &\min_{\hat{\mathbf{w}}} \hat{\mathbf{w}}^T \hat{g}_I \\ &\text{subject to } \hat{\mathbf{w}}^T g_I = 0 \\ &\qquad \left(\hat{\mathbf{w}}^T \hat{g}_k\right)^2 + \left(\hat{\mathbf{w}}^T g_k\right)^2 \leq \Gamma_k^2, \; k = 2, \ldots, K. \\ &\qquad \text{diag}\left[(M\hat{\mathbf{w}})(M\hat{\mathbf{w}})^H\right] \leq 1, \end{aligned} \tag{22}$$

The K.K.T. conditions for this convex optimization problem are given by:

$$\hat{g}_I + 2\mu \mathbf{G}_k \hat{\mathbf{w}} + 2\Lambda \hat{\mathbf{w}} + \nu \mathbf{g}_I = 0 \tag{23}$$

$$(\hat{\mathbf{w}}^T \mathbf{G}_k \hat{\mathbf{w}}) - \Gamma_k^2 \leq 0 \; k = 2, \ldots, K \tag{24}$$

$$\text{diag}\left[(M\hat{\mathbf{w}})(M\hat{\mathbf{w}})^H\right] - 1 \leq 0 \tag{25}$$

$$\hat{\mathbf{w}}^T g_I = 0 \tag{26}$$

$$\mathbf{G}_k = \hat{g}_k \hat{g}_k^T + g_k g_k^T \tag{27}$$

From (23) we obtain the following beamforming vector:

$$\hat{\mathbf{w}} = \frac{(\mu \mathbf{G}_k + \Lambda)^{-1}}{2}(-\nu \mathbf{g}_I - \hat{g}_I) \tag{28}$$

In order to invert the matrix $\mathbf{B} = \mu \mathbf{G}_k + \Lambda$ it is necessary that it has full rank, namely $2N$.
Using the property $\text{rank}(A + B) \leq \text{rank}(A) + \text{rank}(B)$ we conclude that, since $\text{rank}(\mu \mathbf{G}_k) = 2$, the matrix Λ could have at most 2 zero diagonal elements, meaning that at most one λ_i could be zero. In the case when two or more λ_i are equal to zero, for sure the matrix B is not full rank, meaning that it can not be inverted. Consequently, the optimal solution allow at most one sensor to have the power less than maximum. As a result, for WSN with large number of sensors, the solution obtained with CBF-SC scheme converges to the optimal solution of the problem (22) which is given by (28).

REFERENCES

[1] S. Shin and T. Kwon, "A lightweight three-factor authentication and key agreement scheme in wireless sensor networks for smart homes," *Sensors*, vol. 19, no. 9, pp. 1–24, Apr. 2019.

[2] H. Ghayvat, J. Liu, S. C. Mukhopadhyay, and X. Gui, "Wellness sensor networks: A proposal and implementation for smart home for assisted living," *IEEE Sensors J.*, vol. 15, no. 12, pp. 7341–7348, Dec. 2015.

[3] S. Chatterjea and P. Havinga, "Improving temporal coverage of an energy-efficient data extraction algorithm for environmental monitoring using wireless sensor networks," *Sensors*, vol. 9, no. 6, pp. 4941–4954, Jun. 2009.

[4] R. C. Jisha, M. V. Ramesh, and G. S. Lekshmi, "Intruder tracking using wireless sensor network," in *Proc. IEEE Int. Conf. Comput. Intell. Comput. Res.*, Dec. 2010, pp. 1–5.

[5] H. Ochiai, P. Mitran, H. V. Poor, and V. Tarokh, "Collaborative beamforming for distributed wireless ad hoc sensor networks," *IEEE Trans. Signal Process.*, vol. 53, no. 11, pp. 4110–4124, Nov. 2005.

[6] M. F. A. Ahmed and S. A. Vorobyov, "Collaborative beamforming for wireless sensor networks with Gaussian distributed sensor nodes," *IEEE Trans. Wireless Commun.*, vol. 8, no. 2, pp. 638–643, Feb. 2009.

[7] J. Huang, P. Wang, and Q. Wan, "Collaborative beamforming for wireless sensor networks with arbitrary distributed sensors," *IEEE Commun. Lett.*, vol. 16, no. 7, pp. 1118–1120, Jul. 2012.

[8] R. Mudumbai, J. Hespanha, U. Madhow, and G. Barriac, "Distributed transmit beamforming using feedback control," *IEEE Trans. Inf. Theory*, vol. 56, no. 1, pp. 411–426, Jan. 2010.

[9] I. Thibault, G. E. Corazza, and L. Deambrogio, "Random, deterministic, and hybrid algorithms for distributed beamforming," in *Proc. 5th Adv. Satell. Multimedia Syst. Conf. 11th Signal Process. for Space Commun. Workshop*, Sep. 2010, pp. 221–225.

[10] M. Seo, M. Rodwell, and U. Madhow, "A feedback-based distributed phased array technique and its application to 60-GHz wireless sensor network," in *IEEE MTT-S Int. Microw. Symp. Dig.*, Jun. 2008, pp. 683–686.

[11] C. H. Wong, Z. W. Siew, R. K. Y. Chin, A. Kiring, and K. T. K. Teo, "Adaptive phase synchronisation algorithm for collaborative beamforming in wireless sensor networks," in *Proc. 7th Asia Model. Symp. (AMS)*, Jul. 2013, pp. 289–294.

[12] S. Song, J. S. Thompson, P.-J. Chung, and P. M. Grant, "Exploiting negative feedback information for one-bit feedback beamforming algorithm," *IEEE Trans. Wireless Commun.*, vol. 11, no. 2, pp. 516–525, Feb. 2012.

[13] L. Berbakov and M. Beko, "Simultaneous distributed carrier synchronization and data transmission in wireless sensor networks," in *Proc. 22nd Telecommun. Forum Telfor (TELFOR)*, Nov. 2014, pp. 280–283.

[14] J. A. Bucklew and W. A. Sethares, "Convergence of a class of decentralized beamforming algorithms," *IEEE Trans. Signal Process.*, vol. 56, no. 6, pp. 2280–2288, Jun. 2008.

[15] S. Song, J. S. Thompson, P.-J. Chung, and P. M. Grant, "Improving the one-bit feedback algorithm for distributed beamforming," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Apr. 2010, pp. 1–6.

[16] C.-S. Tseng, C.-C. Chen, and C. Lin, "A bio-inspired robust adaptive random search algorithm for distributed beamforming," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2011, pp. 1–6.

[17] H. Yang, N. Ding, Z. Zheng, S. Lin, Z. Zhang, and G. Li, "Collaborative beamforming based on directional perturbation using one bit feedback," *J. Syst. Eng. Electron.*, vol. 27, no. 3, pp. 549–554, Jun. 2016.

[18] J. Guo, "Improved directional perturbation algorithm for collaborative beamforming," *Amer. J. Netw. Commun.*, vol. 6, no. 4, pp. 62–66, 2017.

[19] J. Kong, F. T. Dagefu, and B. M. Sadler, "Distributed adaptive beamforming and nullforming for covert wireless communications," in *Proc. IEEE 90th Veh. Technol. Conf. (VTC-Fall)*, Sep. 2019, pp. 1–6.

[20] E. Navarro-Camba, S. Felici-Castell, J. Segura-García, M. García-Pineda, and J. Pérez-Solano, "Feasibility of a stochastic collaborative beamforming for long range communications in wireless sensor networks," *Electronics*, vol. 7, no. 12, p. 417, Dec. 2018, doi: 10.3390/electronics7120417.

[21] I. Thibault, A. Faridi, G. E. Corazza, A. V. Coralli, and A. Lozano, "Design and analysis of deterministic distributed beamforming algorithms in the presence of noise," *IEEE Trans. Commun.*, vol. 61, no. 4, pp. 1595–1607, Apr. 2013.

[22] S. Felici-Castell, E. Navarro, J. Pérez-Solano, J. Segura-García, and M. García-Pineda, "Practical considerations in the implementation of collaborative beamforming on wireless sensor networks," *Sensors*, vol. 17, no. 2, p. 237, Jan. 2017.

[23] M.-O. Pun, D. Brown, and H. Vincent Poor, "Opportunistic collaborative beamforming with one-bit feedback," in *Proc. IEEE 9th Workshop SPAWC 2008.*, Jul. 2008, pp. 246–250.

[24] L. Berbakov, C. Anton-Haro, and J. Matamoros, "Distributed beamforming with sidelobe control using one bit of feedback," in *Proc. IEEE 73rd Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.

[25] L. Berbakov and M. Beko, "One bit of feedback power allocation algorithm for collaborative beamforming in wireless sensor networks," in *Proc. 23rd Telecommun. Forum Telfor (TELFOR)*, Nov. 2015, pp. 188–191.

[26] G. Mergen, Q. Zhao, and L. Tong, "Sensor networks with mobile access: Energy and capacity considerations," *IEEE Trans. Commun.*, vol. 54, no. 10, p. 1896, Oct. 2006.

[27] L. Berbakov and M. Beko, "Collaborative beamforming techniques for data transmission in wireless sensor networks," *Telfor J.*, vol. 7, no. 2, pp. 62–67, 2015.

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