Comparing Several Power Allocation Strategies for Sensor Networks

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***Abstract*—The power consumption of sensors is a crucial point for developing large-scale sensor networks nowadays. Many methods are proposed in the literature in order to optimize the power allocation to the sensor nodes under several constraints and different system aspects. In the present publication, we present a uniform framework to enable the comparison of different power allocation methods within the same scenario. Furthermore, we compare the most significant methods with each other via numerical simulations and show their performance with respect to service lifetime, power consumption and system reliability as well as computation complexity and implementation effort.**

***Index Terms*—Non-convex optimization; lifetime maximization; passive radar; distributed sensing;**

I. Introduction

The fast rise of 5$^{\text{th}}$ generation wireless systems (5G) pushes massively the development of sensor networks for various applications. In most of these applications, the sensor nodes (SNs) are used for sensing the environment and monitoring of targets. These tasks are performed independently and in a distributed fashion by the SNs, which are rather weak in their abilities, e.g., poor signal processing units, low signal-to-noise ratio (SNR) regions for data transmission, and limited power supplies or non-renewable energy sources. The bottleneck of such networks, especially when the number of SNs is huge and the size of each SN is tiny, is the limited service lifetime. In order to prolong the lifetime, two different strategies are pursued by the scientists. The first strategy is to minimize the power consumption of each SN by smart hardware implementations while the second one is to minimize the power consumption or to maximize the lifetime of the whole network by performing intelligent power optimization techniques. In general, both strategies benefit from each other and are thus conclusively justified for common applications. Since the first strategy is specific for a single SN, a comparison of different hardware implementations is less difficult compared to the second strategy in which all SNs with many system parameters are involved. These system parameters are usually scenario dependent and hence can influence the system performance massively. In addition, a comparison in real scenarios is further exacerbated, since the important parameters are often random, e.g., the position of the distributed SNs, the distances between the SNs and the moving targets, the fluctuation of noise and channel realizations, and so on. Hence, reliable frameworks for comparing different methods of power minimization or lifetime maximization techniques are rarely developed and seldom proposed by scientists. We aim to close this gap by establishing a solid framework in the present work, in order to enable a fair assessment of different optimization techniques.

In practice, the mostly engaged power allocation technique is the uniform scheme such that all SNs are allocated with equal power. As an example, we can mention the neutrino telescope '*IceCube Neutrino Observatory*' at the Amundsen-Scott South Pole Station [1] in Antarctica, where a network with over 5000 nodes is implemented. The uniform allocation of power is the simplest method, since neither a channel state information nor a complicated optimization procedure is needed for the power distribution. For a smart optimization technique usually an objective along with few system constraints as well as a centralized unit or a decentralized approach for regulation and controlling of the sensor network are needed. Furthermore, the optimization procedure will be successful when additional information is available such as the channel state information or the statistical properties of involved random variables. In the literature, the most well-known objectives are the minimization of the mean squared error [2], [3] (MSE) and the maximization of the data rate or system capacity [4]–[8]. The latter one is a challenging approach, since a closed-form formula describing the capacity of general sensor networks is missing in the literature. Hence, the former approach receives more attention for investigation. For example, in [9]–[15] the MSE approach is applied to achieve optimal solutions in closed-form to the power allocation problem. The optimization problems there are subject to individual power and sum power constraints. Furthermore, a fusion center is considered in order to combine the independent observations of the SNs into a single reliable estimate of the target. Apart from these techniques, several powerful optimization strategies are proposed, which however have a minor importance for the present work. Nevertheless, we want to mention the work [16], where a cluster-based approach and a centralized routing protocol is used to improve the performance. Moreover, a theoretical upper bound is investigated in [17], which is in practice not achievable. Finally, a further notable publication is [18] in which different heuristics are proposed.

In the present work, our goal is the comparison of five state-of-the-art optimization techniques for allocation of power in sensor networks. We start with the uniform power allocation and end with an optimal power allocation which even considers occasional node failures. We show the performance of each optimization technique via numerical simulations and discuss their advantages and disadvantages. Furthermore, the computational complexity, the implementation effort and the system reliability are our next focus.

We start our investigations with the description of the underlying system model and scenarios in the next section. Subsequently, all optimization strategies are explained and presented. Then, simulation results are shown and discussed. Afterwards, we summarize our contributions in the conclusion.

Mathematical Notations:

Throughout this paper, we denote the sets of natural, real and complex numbers by $\mathbb{N}$, $\mathbb{R}$ and $\mathbb{C}$, respectively. Note that the set of natural numbers does not include the element zero. Moreover, $\mathbb{R}_+$ denotes the set of non-negative real numbers. Furthermore, we use the subset $\mathbb{F}_N \subseteq \mathbb{N}$, which is defined as $\mathbb{F}_N \coloneqq \{1, \ldots, N\}$ for any given natural number N. We denote the absolute value of a real or complex-valued number z by $|z|$. The expected value of a random variable v is denoted by $\mathcal{E}[v]$ while the probability that an event A is occurred is described by $\mathrm{Prob}(A)$. Moreover, the notation $V^\star$ stands for the value of an optimization variable V where the optimum is attained.

II. The System Model

In this section, we use the same system model that is elaborated in [11] for the most optimization strategies. This system model is depicted in Figure 1 and is briefly presented in the following. For a system in which occasional node failures are allowed, we use an extended system model, which is described in the next subsection. An overview of all system parameters is given in Table I.

We assume a discrete time system with perfect time, phase and frequency synchronization. A sensor network consisting of $K \in \mathbb{N}$ independent and spatially distributed SNs is considered, where each SN receives random observations from a jointly observed target in each observation process. If a target signal $r \in \mathbb{C}$ with $R \coloneqq \mathcal{E}[|r|^2]$ and $0 < R < \infty$ is present, then the received power at the SN S_k is a part of the emitted power from the actual target. Each received signal is weighted by the corresponding channel coefficient $g_k \in \mathbb{C}$ and is disturbed by additive white Gaussian noise (AWGN) $m_k \in \mathbb{C}$ with $M_k \coloneqq \mathcal{E}[|m_k|^2] < \infty$. In this paper, we assume that the sensing channel is constant, i.e., $\mathcal{E}[g_k] = g_k$ and $\mathcal{E}[|g_k|^2] = |g_k|^2$. The sensing channel is obviously wireless.

All SNs continuously take samples from the disturbed received signal and amplify them by the amplification factors $u_k \in \mathbb{R}_+$ without any additional data processing. Thus, the output signal and the expected value of its transmission power are described by

$$x_k \coloneqq (rg_k + m_k)u_k\,,\ k \in \mathbb{F}_K\,, \tag{1}$$

and

$$X_k \coloneqq \mathcal{E}[|x_k|^2] = (R|g_k|^2 + M_k)u_k^2\,,\ k \in \mathbb{F}_K\,, \tag{2}$$

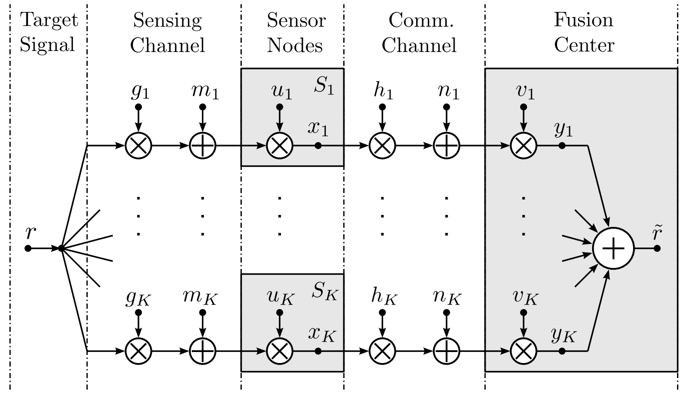

Fig. 1. The system model of the distributed sensor network, which shows the signal flow from a target signal over the sensor nodes to a fusion center.

respectively. The local measurements are then transmitted to a fusion center which is placed at a remote location. The data communication between each SN and the fusion center can be either wired or wireless. In the latter case, a distinct waveform for each SN is used to distinguish the communication of different SNs and to suppress inter-user (inter-node) interferences at the fusion center. Hence, all K received signals at the fusion center are pairwise uncorrelated and are assumed to be conditionally independent. Each received signal at the fusion center is also weighted by the corresponding channel coefficient $h_k \in \mathbb{C}$ and is disturbed by additive white Gaussian noise $n_k \in \mathbb{C}$ with $N_k \coloneqq \mathcal{E}[|n_k|^2] < \infty$, as well. We assume that the communication channel is also constant, i.e., $\mathcal{E}[h_k] = h_k$ and $\mathcal{E}[|h_k|^2] = |h_k|^2$.

The noisy received signals at the fusion center are weighted by the fusion weights $v_k \in \mathbb{C}$ and combined together in order to obtain a single reliable observation $\tilde{r}$ of the actual target signal r. In this way, we obtain

$$y_k \coloneqq \big((rg_k + m_k)u_k h_k + n_k\big)v_k\,,\ k \in \mathbb{F}_K\,, \tag{3}$$

and hence,

$$\tilde{r} \coloneqq \sum_{k=1}^{K} y_k = r \underbrace{\sum_{k=1}^{K} g_k u_k h_k v_k}_{\text{signal gain}} + \underbrace{\sum_{k=1}^{K} (m_k u_k h_k + n_k) v_k}_{\text{noise}}\ . \tag{4}$$

Note that the fusion center can separate the input streams because the data communication is either wired or performed by distinct waveforms for each SN.

In order to obtain a single reliable observation at the fusion center, the value $\tilde{r}$ should be a good estimate of the present target signal r. Thus, the amplification factors u_k and the weights v_k should be chosen such as to minimize the average absolute deviation between $\tilde{r}$ and the true target signal r. Hence, the amplification factors and the fusion weights are the only optimization parameters to accomplish a given optimization strategy.

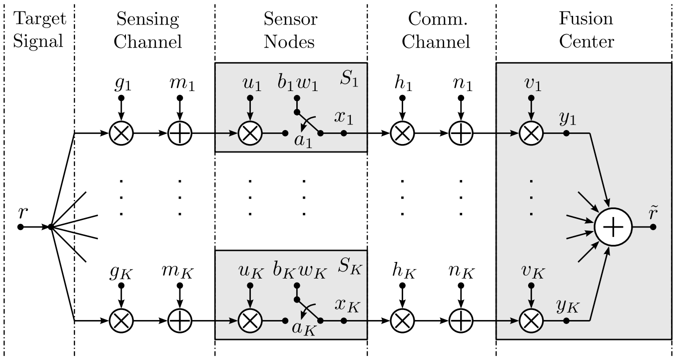

Fig. 2. The extended system model with presentation of occasional node failure.

A. The Extended System Model

In the above system model, it is assumed that each SN perfectly works and can be configured by a controlling unit, e.g., the fusion center, at any time. This assumption is often not valid in practice, since the SNs are usually too weak and sensitive, and thus easily damaged. Hence, we update the previous system model by an extended one, which is depicted in Figure 2 and explained in the following.

We incorporate the binary random variables $a_k \in \{0,1\}$ and $b_k \in \{0,1\}$ with the corresponding probabilities $\mathrm{Prob}(a_k = 1) = \zeta_k$ and $\mathrm{Prob}(b_k = 1) = \gamma_k$ into the previous system model, respectively. If a_k of the k^{th} SN is equal to one, then this SN is sound and accurate, and will work normal. In contrast, if a_k is equal to zero, then the k^{th} SN is brocken or faulty and can act in two different ways. The first way is described with $b_k = 0$, when the SN is completely brocken and cannot send any information. The second way is described with $b_k = 1$, when the SN is defect and faulty, and will send useless information w_k to the fusion center. The signal $w_k \in \mathbb{C}$ with the power $W_k := \mathcal{E}[|w_k|^2] < \infty$ is assumed to be zero-mean and can be interpreted as interference, which cannot be suppressed at the fusion center. In summary, we can distinguish between three operating modes ***i)*** The k^{th} SN is healthy with probability ζ_k, i.e., $a_k = 1$ and $b_k \in \{0,1\}$, ***ii)*** it is brocken and silent with probability $(1-\zeta_k)(1-\gamma_k)$, i.e., $a_k = 0$ and $b_k = 0$, ***iii)*** it is defect and acts as interference with probability $(1-\zeta_k)\gamma_k$, i.e., $a_k = 0$ and $b_k = 1$.

With this new setup, the output signal and the expected value of its transmission power are described by

$$x_k := (rg_k + m_k)u_k a_k + b_k w_k (1-a_k)\,,\ k \in \mathbb{F}_K\,, \quad (5)$$

and

$$X_k = (R|g_k|^2 + M_k)u_k^2 \zeta_k + \gamma_k W_k (1-\zeta_k)\,,\ k \in \mathbb{F}_K\,, \quad (6)$$

respectively. This leads to the estimate

$$\begin{aligned}\tilde{r} &= r\sum_{k=1}^{K} g_k u_k h_k v_k a_k \\ &\quad + \sum_{k=1}^{K}\big(m_k u_k h_k a_k + b_k w_k (1-a_k) h_k + n_k\big) v_k\,. \end{aligned} \quad (7)$$

B. Power Limitations of the System

As mentioned in the introduction, a smart hardware implementation of the SNs is highly necessary in order to prolong the lifetime and enable an energy-aware operation of the SNs. Following this trend, the average power consumption of each SN is approximately equal to its average output power X_k, if the input signal is negligible in comparison to the output signal and if the nodes have smart power components with low-power dissipation loss. We assume that equality between X_k and the average power consumption of each node is ensured. In the present work, we assume that the output power-range of each SN is in average limited by $P_{\text{min}} \in \mathbb{R}_+$ and $P_{\text{max}} \in \mathbb{R}_+$ with $0 \le P_{\text{min}} < P_{\text{max}}$. The lower limit P_{min} denotes the minimum power which is needed to guarantee the awareness and presence of the SN while the upper limit P_{max} denotes the maximum allowed transmission power per SN due to power regulation standards or due to the functional range of the integrated circuit elements.

In addition, each SN is usually powered by weak energy supplies, e.g., batteries, such that the operation time of the entire sensor network is limited. Hence, it is wise to incorporate and consider a sum power constraint $P_{\text{tot}} \in \mathbb{R}_+$ with $KP_{\text{min}} \le P_{\text{tot}} \le KP_{\text{max}}$. In this way, the sensor network shall operate under the constraints

$$P_{\text{min}} \le X_k \le P_{\text{max}}\,,\ k \in \mathbb{F}_K\,, \quad (8)$$

and

$$\sum_{k=1}^{K} X_k \le P_{\text{tot}}\,. \quad (9)$$

Note that the output power X_k is a function of the amplification factor u_k and thus we can adjust X_k in order to satisfy given optimization strategies.

III. Optimization Strategies

In this section, we present five state-of-the-art optimization strategies in order to enable a fair comparison and a fruitful discussion.

A. Optimal Power Allocation

In order to obtain an accurate estimate $\tilde{r}$ of the target signal r, we aim at finding estimators $\tilde{r}$ of minimum mean squared error in the class of unbiased estimators. With the aid of (4), we hence minimize the deviation

$$V := \mathcal{E}\big[|\tilde{r} - r|^2\big] = \sum_{k=1}^{K} |v_k|^2 \big(u_k^2 |h_k|^2 M_k + N_k\big) \quad (10)$$

with respect to u_k and v_k under the unbiasedness

$$\mathcal{E}[\tilde{r} - r] = 0 \quad \Leftrightarrow \quad \sum_{k=1}^{K} g_k u_k h_k v_k = 1\,. \quad (11)$$

In addition, the optimization problem shall be subject to both power constraints (8) and (9).

It is simple to show that this optimization problem is non-convex and very hard to solve. Nevertheless, its optimal solution in closed-form is worked out in [11] and later extended

TABLE I

NOTATION OF SYMBOLS THAT ARE NEEDED FOR THE DESCRIPTION OF EACH OBSERVATION PROCESS.

Notation	Description
K	number of sensor nodes;
k	the k^{th} sensor node;
$\mathbb{F}_K$	the index-set of K nodes;
r, R	the present target signal and its quadratic absolute mean;
$\tilde{r}$	the estimate of r;
g_k, h_k	complex-valued channel coefficients;
m_k, n_k	complex-valued zero-mean AWGN;
M_k, N_k	variances of m_k and n_k;
u_k, v_k	non-negative amplification factors and complex-valued weights;
ϑ_k	phase of v_k;
ϕ_k	phase of the product $g_k h_k$;
a_k, ζ_k	binary random variable and its expected mean to distinguish between healthy and brocken sensor nodes;
b_k, γ_k	binary random variable and its expected mean to distinguish the grade of defectiveness;
w_k, W_k	faulty signal and its power of k^{th} sensor node;
x_k, X_k	output signal and output power of k^{th} sensor node;
y_k	input signals of the combiner;
P_{min}, P_{max}	lower and upper output power limitations of each sensor node;
P_{tot}	the total power consumption of the network.

in [19]. This solution yields the optimal amplification factors $u_k^\star$ and fusion weights $v_k^\star$ which in turn specify the optimal transmission powers $X_k^\star$. The ratio $\frac{R}{V^\star}$ is then equivalent to the SNR of the entire sensor network and describes the quality of the estimate $\tilde{r}$ at the output of the fusion center. This ratio will help us to fairly compare different optimization strategies by variation of different system parameters. To avoid confusion, we hereinafter denote this ratio by SNR_{O}.

B. Optimal Power Allocation with Occasional Node Failure

Now, we consider the more realistic system model in which occasional node failure are allowed, cf. Subsection II-A. We again are interested in finding estimators of minimum mean squared error in the class of unbiased estimators. By using (7), the objective for minimization is given by

$$\begin{aligned} V &:= \mathcal{E}\big[|\tilde{r}-r|^2\big] \\ &= \sum_{k=1}^{K} |v_k|^2 \big(u_k^2 |h_k|^2 M_k \zeta_k + N_k\big) \\ &\quad + \sum_{k=1}^{K} |v_k|^2 (1-\zeta_k) |h_k|^2 \big(R u_k^2 |g_k|^2 \zeta_k + W_k \gamma_k\big) \end{aligned} \tag{12}$$

with respect to u_k and v_k under the unbiasedness

$$\mathcal{E}[\tilde{r}-r] = 0 \quad \Leftrightarrow \quad \sum_{k=1}^{K} g_k u_k h_k v_k \zeta_k = 1\,. \tag{13}$$

In addition, the optimization problem shall be subject to both power constraints (8) and (9). Note that in contrast to the objective in (10) the deviation in (10) is a function of the parameters ζ_k and γ_k and has thus more degree of freedom.

Also this optimization problem is non-convex and even harder to solve than the previous one. Its optimal solution is characterized in our paper [20]. The optimal values $u_k^\star$, $v_k^\star$, $X_k^\star$ and $V^\star$ are obviously functions over $\zeta_k \in (0,1)$ and $\gamma_k \in (0,1)$. The SNR of the entire sensor network is again described by the ratio $\frac{R}{V^\star}$. We hereinafter denote this ratio by SNR_{OwF}.

Note that both SNR_{O} and SNR_{OwF} are functions over P_{min}, P_{max} and P_{tot} as well as M_k, N_k, g_k and h_k. This means that for the optimal allocation strategy all these parameters must be known beforehand. However, this knowledge is often not available so that such optimization strategies are rather used for theoretical considerations. We will discuss in detail the advantages and disadvantages later in Section V.

C. Uniform Power Allocation with Optimal Fusion Rule

The simplest power allocation strategy is the uniformly distributed one. That means that the total power P_{tot} is equally divided and shared between all SNs such that the output power of each SN becomes

$$X_k^\star = \max\big\{P_{\text{min}}, \min\{P_{\text{max}}, \frac{P_{\text{tot}}}{K}\}\big\} \tag{14}$$

From this we can calculate the optimal amplification factors $u_k^\star$ by the relation (2). It remains to optimize the fusion weights. If the goal is again to find estimators of minimum mean squared error in the class of unbiased estimators, then we can minimize the objective

$$V := \mathcal{E}\big[|\tilde{r}-r|^2\big] = \sum_{k=1}^{K} |v_k|^2 \big(u_k^2 |h_k|^2 M_k + N_k\big) \tag{15}$$

for fixed amplification factors $u_k = u_k^\star$ and with respect to v_k under the unbiasedness

$$\mathcal{E}[\tilde{r}-r] = 0 \quad \Leftrightarrow \quad \sum_{k=1}^{K} g_k u_k^\star h_k v_k = 1\,. \tag{16}$$

As is easily to see, this optimization problem is a convex program and can again be solved in closed-form. The optimization of (15) will lead to the optimal fusion weights $v_k^\star$ and the deviation $V^\star$. However, this result is a particular solution of the problem (10). To see this relation, we only need to pretend $P_{\text{min}} = \frac{P_{\text{tot}}}{K}$ or $P_{\text{max}} = \frac{P_{\text{tot}}}{K}$, due to equation (14), and solve (10) with respect to both u_k and v_k which will then lead to the same solution.

We hereinafter denote the ratio $\frac{R}{V^\star}$ by SNR_{U}.

D. Uniform Power Allocation with Optimal Fusion Rule and Occasional Node Failure

Analog to the previous case, the total power P_{tot} is uniformly allocated to the SNs, which will result in $X_k^\star$ as given in (14). By pretending $P_{\text{min}} = \frac{P_{\text{tot}}}{K}$ or $P_{\text{max}} = \frac{P_{\text{tot}}}{K}$ we can use the results for the problem in (12) in order to obtain the optimal values $u_k^\star$, $v_k^\star$ and $V^\star$. We hereinafter denote the ratio $\frac{R}{V^\star}$ by SNR_{UwF}.

Note that any defect SN will have the output power $X_k^\star = b_k W_k$, which can totaly differ from the adjusted one, i.e., $X_k^\star = \frac{P_{\text{tot}}}{K}$.

TABLE II
STANDARD VALUE OF SYSTEM PARAMETERS.

Parameter:	K	R	M_k	N_k	$P_{\min}$	$P_{\max}$	P_{tot}
Value:	100	1	2	2	0.1	2	30

E. Best Single Node Selection

Another important system is the single node strategy, in which only one powerful SN will consume the entire power P_{tot}, while all other SNs are inactive. This system is important, because it enables the comparison between a large-scale sensor network with many weak SNs and a powerful single node system which is established at the position of the most reliable SN. The main question is which of the SNs is the most reliable one? In [21], it is shown that the SN with the smallest c_k is the most reliable SN, where c_k is defined by

$$c_k := \sqrt{\frac{N_k(R|g_k|^2 + M_k)}{|g_k h_k|^2}}\,. \tag{17}$$

In this way, we can re-index all SNs, such that $c_k \le c_{k+1}$ for all $k \in \mathbb{F}_{K-1}$ holds and select the first SN which should be virtually replaced by a powerful node. This node obtains the power $X_1^\star = P_{\text{tot}}$ and in turn $u_1^\star$ by the aid of (2). Keeping $u_1 = u_1^\star$ and $u_k = u_k^\star = 0$ fixed for all $k > 1$, we can use the same objective and constraint as in (10) and (11), respectively, in order to obtain the weight $v_1^\star$ and the deviation $V^\star$. The entire SNR of this system is hereinafter denoted by SNR_B.

IV. Preliminary Simulation Results

In this section, we set out to compare the solution of the different optimization strategies from Section III via numerical simulations. We consider different scenarios with randomly distributed SNs to demonstrate the performance of all optimization strategies.

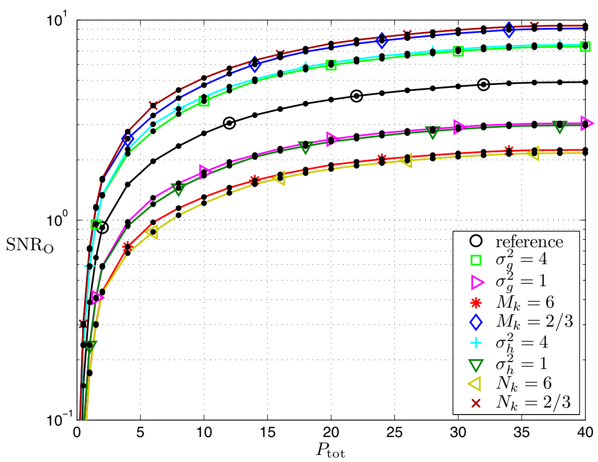

Fig. 3. The behavior of SNR_O with respect to P_{tot} is visualized. All curves show an increasing property in P_{tot}. In order to show a wide range of different cases, we have simulated a *reference* curve with the default parameters $\sigma_g^2 := \mathcal{E}[|g_k|^2] = \sigma_h^2 := \mathcal{E}[|h_k|^2] = 2$ with expectation over k. We usually create a new curve by changing only the value of a single parameter which is given in the legend.

A. Simulation Setup

In order to fairly evaluate the performance of all optimization strategies with each other, we perform five simulations in the same scenario and for the same sensor network. For all five simulations all channel and noise realizations remain the same to simplify subsequent comparisons. These realizations are drown randomly from independent Gaussian distributions. The target signal r is randomly generated with a uniform distribution on $\{z \in \mathbb{C} \mid |z| \le 1\}$ in each simulation step. The number of iterations per simulation point is always 100000 to guaranty the convergence of the simulations and to obtain smooth curves. Table II shows the standard values of parameters, which will remain fixed for particular curves.

V. Discussion of Results

VI. Conclusion

VII. For the Anonymes Reviewer

Dear reviewer, thank you very much for reviewing our paper. Because of heavy simulation frameworks and very high number of parameters, we cannot present our results at the moment. Hence, the last four sections and subsections (marked in red color) are left empty. We apologize for this problem, but hope that the first sections are satisfactory for presenting the importance of the current work. In the finale version, we will include all simulation results and discuss the different issues.

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