Lifetime and Power Consumption Optimization for Distributed Passive Radar Systems

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***Abstract*—In this paper we address the power allocation problem for a system of distributed passive radar sensor network, where the location of the source is relatively constant, aiming at lifetime maximization and power consumption minimization. It is known that for a network in which the source location changes independently at each observation step, a nearly-optimal strategy can be obtained by minimizing the network power consumption at each iteration independently from other iterations. In this paper, we observe that this is not the case for a network with a constant source location. The reason is that for the latter case, the power of the nodes with good location will be expired very fast which leads to a significantly shorter network lifetime. In order to mitigate this effect, we propose a weighted sum-power minimization strategy which effectively reduces the gap with the optimal power allocation scenario, when the network resources are scarce. The numerical simulations compare the behavior of both strategies for various network conditions.**

1. Introduction

Power consumption and lifetime are essential features of sensor networks. On the one hand, the power consumption should be as low as possible to enable an energy-aware system, and provide an adequate lifetime to ensure for a comprehensive coverage. On the other hand, the performance of the network should satisfy the quality expectations, specially for the related applications to space and extreme environments. In particular, the goal of a distributed passive radar sensor network is to provide a reliable estimation from a source signal, by collecting and combining the individual passive observations from a network of sensor nodes (SN)s in a centralized node, i.e., fusion center (FC). However, these features, i.e., the extension of the network lifetime via energy aware operation and the resulting estimation quality, are contrary and they must be optimized simultaneously to achieve a desired performance.

In this paper, we consider a common sensor network, in the context of the passive distributed radar applications. Fig. 1 shows the studied setup, including a target emitter, the sensing channel, independent and distributed SNs, the communication channel, and a fusion center. This scenario is well-investigated in many publications and will also serve as our framework in the present paper. The authors in [1] have considered a sensor network composed of microsensors and described general architectural and algorithmic approaches to enhance the energy awareness. In [2] a cluster-based approach and a centralized routing protocol is used to improve the network lifetime. A

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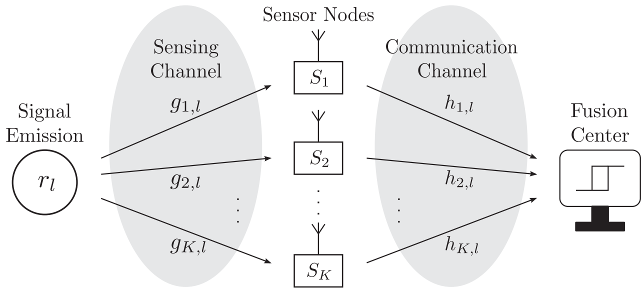

Fig. 1. A distributed sensor network.

theoretical upper bound for the network lifetime is investigated in [3], which is in practice not achievable. A further notable publication is [4] in which different heuristics are used for lifetime maximization. The corresponding optimization problems are subsequently solved by numerical methods. In contrast, an analytical solution in closed-form to the power allocation problem is presented for several power constraints in [5], which improves the work [6]. This investigation is later extended in various ways in [7]–[16] and [17]. In particular, the work in [17] studies a power minimization problem for a given network lifetime, such that a required estimation quality is satisfied. Interestingly, it is shown that for a network with independent source location, i.e., where the source location changes independently at each observation iteration, a near-optimal strategy can be obtained via minimizing the network power consumption at each iteration, independently from other iterations. Nevertheless, the available solutions fail to provide an acceptable performance for a scenario with a static source location.

In the present work, we extend the proposed solution in [17], for the scenario with a static source location. A detailed system description is hence provided in Section 2, following the prior studies in [5], [17]. The optimization strategy, and an overview of the available solutions are then provided in Section 3. Furthermore, an intuitive solution is proposed, in order to adopt the power allocation process to a setup with a static source location. In Section 4 the performance of the proposed solutions are studied under various network conditions.

Mathematical Notations:

Throughout this paper, we denote the sets of natural, real and complex numbers by $\mathbb{N}$, $\mathbb{R}$ and $\mathbb{C}$, respectively. Moreover,

$\mathbb{R}_+$ denotes the set of non-negative real numbers. We denote the absolute value of a number z by $|z|$. The expected value of a random variable v is denoted by $\mathcal{E}[v]$. Moreover, the notation $b^\star$ stands for the value of an optimization variable b where the optimum is attained.

2. Overview and Technical System Description

In this paper, we use a similar system model as to [17], as an extension of the model described in [5]. A network consisting of K SNs, a source and a fusion center (FC) is considered, see Fig. 2. The operation of the network is considered over its lifetime, i.e., $L \in \mathbb{N}$ number of observation iterations. The index set of all SNs in the network is represented by $\mathbb{F}_K := \{1, \ldots, K\}$ where the index set of all observation iterations are represented as $\mathbb{F}_L := \{1, \ldots, L\}$. The indices $l \in \mathbb{F}_L$ and $k \in \mathbb{F}_K$ respectively represent the intended observation iteration, and the SN. If a target signal $r_l \in \mathbb{C}$ with $R := \mathcal{E}[|r_l|^2]$ 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 $g_{k,l} \in \mathbb{C}$ and is disturbed by additive white Gaussian noise (AWGN) $m_{k,l} \in \mathbb{C}$ with $M_k := \mathcal{E}[|m_{k,l}|^2]$. All channels are wireless and follow a quasi-static flat fading channel[1].

All SNs continuously take samples from the disturbed received signal and amplify them by $u_{k,l} \in \mathbb{R}_+$. Thus, the output signal and the expected value of its transmission power are described by

$$x_{k,l} := (r_l g_{k,l} + m_{k,l}) u_{k,l}\,,\ k \in \mathbb{F}_K\,,\ l \in \mathbb{F}_L\,, \tag{1}$$

and

$$X_{k,l} := \mathcal{E}[|x_{k,l}|^2] = (R|g_{k,l}|^2 + M_k) u_{k,l}^2\,,\ k \in \mathbb{F}_K\,,\ l \in \mathbb{F}_L\,, \tag{2}$$

respectively. The local measurements are then transmitted to the FC 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-node interferences at the fusion center. The transmitted signal from each SN is weighted by the corresponding channel coefficient $h_{k,l} \in \mathbb{C}$ and is disturbed by additive white Gaussian noise $n_{k,l} \in \mathbb{C}$ with $N_k := \mathcal{E}[|n_{k,l}|^2]$ at the FC.

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

$$y_{k,l} := \big((r_l g_{k,l} + m_{k,l}) u_{k,l} h_{k,l} + n_{k,l}\big) v_{k,l}\,,\ k \in \mathbb{F}_K\,,\ l \in \mathbb{F}_L\,, \tag{3}$$

[1]It indicates that the channels are constant during each observation, but may vary from an observation to another.

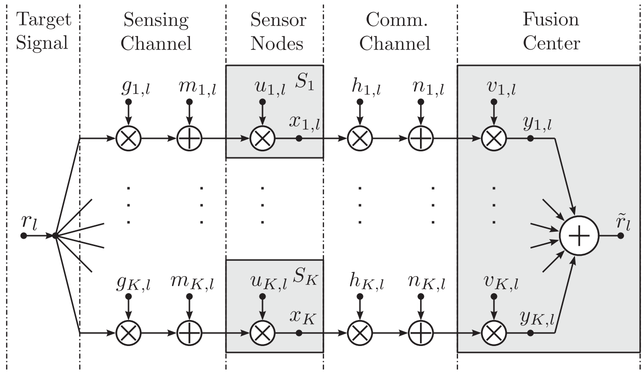

Fig. 2. System model of the distributed sensor network.

and hence,

$$\begin{aligned}\tilde{r}_l := \sum_{k=1}^{K} y_{k,l} = r_l \sum_{k=1}^{K} g_{k,l} u_{k,l} h_{k,l} v_{k,l} \\ + \sum_{k=1}^{K} (m_{k,l} u_{k,l} h_{k,l} + n_{k,l}) v_{k,l}\,.\end{aligned} \tag{4}$$

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 $\tilde{r}_l$ should be a good estimate of the present target signal r_l. Thus, the amplification factors $u_{k,l}$ and the weights $v_{k,l}$ should be chosen such as to minimize the average absolute deviation between $\tilde{r}_l$ and the true target signal r_l. The corresponding optimization program is elaborated in the next section.

3. Power and Lifetime Optimization

In this part we define our optimization strategy and review the available relevant solutions. This includes an optimal solution with the availability of the channel state information (CSI) for all observations, and an optimal solution with the consideration of the CSI, merely at the active observation iteration. Furthermore, we propose an intuitive algorithm which prevents the expiration of the available power at each SN, via individual pricing. In each case, the corresponding optimization problem is non-convex in its general form. Nevertheless it can be solved by subsequent applications of the Lagrangian multipliers method with equality constraints, Karush-Kuhn-Tucker (KKT) conditions, and straightforward usage of mathematical analysis, see [17, Section III] and [5].

A. The Optimization Problem

As mentioned in the last section, the quantity $\tilde{r}_l$ should be a good estimate for the present target signal r_l. In particular, we aim at finding estimators $\tilde{r}_l$ of minimum mean squared error in the class of unbiased estimators for each r_l. Similar to [5, Equation (5)] the unbiased estimation constraint is obtained as

$$\sum_{k=1}^{K} g_{k,l} u_{k,l} h_{k,l} v_{k,l} = 1\,,\ l \in \mathbb{F}_L\,. \tag{5}$$

Via the application of (5), the constraint on the tolerable estimation mean-square-error (MSE) is calculated for the corresponding observation iteration as

$$\mathcal{E}\left[|\tilde{r}_l - r_l|^2\right] = \sum_{k=1}^{K} \left(M_k u_{k,l}^2 |h_{k,l}|^2 + N_k\right) |v_{k,l}|^2 \leq V_{\text{max}} \, , l \in \mathbb{F}_L , \tag{6}$$

where V_{max} is the maximum tolerable estimation MSE for each iteration, and represents the required estimation quality. Moreover, via the utilization of (2), the network power constraints are formulated as

$$\begin{aligned} & P_{\text{min}} \leq X_{k,l} \leq P_{\text{max}} \\ \Leftrightarrow \; & P_{\text{min}} \leq (R|g_{k,l}|^2 + M_k) u_{k,l}^2 \leq P_{\text{max}} \, , \; k \in \mathbb{F}_K \, , \; l \in \mathbb{F}_L \, , \end{aligned} \tag{7}$$

and

$$\begin{aligned} & \sum_{l=1}^{L} X_{k,l} \leq P_{k,\text{bud}} \\ & \Leftrightarrow \; \sum_{l=1}^{L} (R|g_{k,l}|^2 + M_k) u_{k,l}^2 \leq P_{k,\text{bud}} \, , \; k \in \mathbb{F}_K \end{aligned} \tag{8}$$

where $P_{\text{min}}, P_{\text{max}}$ and $P_{k,\text{bud}}$ respectively represent the minimum required power for a SN to remain active, maximum allowed instantaneous power, and the available power of a SN which can be consumed over the L observations. Please note that for any feasible choice of the amplification coefficients, i.e., $u_{k,l}$, and consequently the choice of $X_{k,l}$, the optimal fusion strategy can be obtained similar to that of [5, Section III]. Furthermore, the choice of the fusion strategy has no impact on the defined power constraints (7) and (8). Via the utilization of the optimum fusion strategy at the FC the MSE constraint in (6) is obtained as

$$\sum_{k=1}^{K} \frac{X_{k,l} \alpha_{k,l}^2}{X_{k,l} + \beta_{k,l}^2} \geq V_{\text{max}}^{-1} \, , \quad l \in \mathbb{F}_L \, , \tag{9}$$

where

$$\alpha_{k,l} := \sqrt{\frac{|g_{k,l}|^2}{M_k}} \quad \text{and} \quad \beta_{k,l} := \sqrt{\frac{N_k (R|g_{k,l}|^2 + M_k)}{M_k |h_{k,l}|^2}} \, . \tag{10}$$

Consequently, the optimal power allocation strategy over all SNs and observation iterations can be obtained via

$$\begin{aligned} \underset{X_{k,l}, k \in \mathbb{F}_K, l \in \mathbb{F}_L}{\text{minimize}} \quad & \sum_{k=1}^{K} \sum_{l=1}^{L} X_{k,l} & \text{(11a)} \\ \text{subject to} \quad & P_{\text{min}} \leq X_{k,l} \leq P_{\text{max}} \, , \; k \in \mathbb{F}_K \, , \; l \in \mathbb{F}_L \, , & \text{(11b)} \\ & \sum_{l=1}^{L} X_{k,l} \leq P_{k,\text{bud}} \, , \; k \in \mathbb{F}_K \, , & \text{(11c)} \\ & \sum_{k=1}^{K} \frac{X_{k,l} \alpha_{k,l}^2}{X_{k,l} + \beta_{k,l}^2} \geq V_{\text{max}}^{-1} \, , \; l \in \mathbb{F}_L . & \text{(11d)} \end{aligned}$$

Note that the optimal designed strategy in (11) represents the situation where the CSI corresponding to all of the observation iterations are known a priori. As a result, the utilization of the each SN power is adjusted such that the overall, and not the instantaneous network power consumption is minimized. Nevertheless, in a practical situation where the CSI can not be estimated for the future observation iterations, the defined optimization strategy is not possible. Nevertheless, it represents an upper-bound of the achievable network lifetime, and will be used as a comparison benchmark.

B. Per-Observation Power Minimization Using Instantaneous CSI

In this part we reduce the proposed optimal design in (11), to a design where the network parameters are optimized in each observation iteration, similar to the proposed design in [17, Section III]

$$\begin{aligned} \underset{X_{k,l}, k \in \mathbb{F}_K,}{\text{minimize}} \quad & \sum_{k=1}^{K} X_{k,l} & \text{(12a)} \\ \text{subject to} \quad & P_{\text{min}} \leq X_{k,l} \leq P_{\text{max}} \, , \; k \in \mathbb{F}_K , & \text{(12b)} \\ & X_{k,l} - \sum_{i \in \{1, \ldots, l-1\}} X_{k,i}^{\star} \leq P_{k,\text{bud}} \, , \; k \in \mathbb{F}_K \, , & \text{(12c)} \\ & \sum_{k=1}^{K} \frac{X_{k,l} \alpha_{k,l}^2}{X_{k,l} + \beta_{k,l}^2} \geq V_{\text{max}}^{-1} \, , & \text{(12d)} \end{aligned}$$

where (12b) limits the power consumption of the each SN to the remaining power budget, and $X_{k,l}^{\star}$ represents the resulting power allocation via the application of (12), for the k-th SN and at the l-th iteration. The defined optimization strategy should be solved independently for each iteration index, i.e., l. As it is elaborated in [17], the per-observation design strategy, while does not depend on the CSI for all observation iterations, reaches very close to the optimal strategy (11) for a scenario where the source location is independent for each observation. Nevertheless, it does not consider the expected network performance at the future iterations, where the future channel conditions are dependent to the previous values. In particular, for a scenario that the location of the FC and the source are constant, the network tends to consume the power of the well-positioned SNs in the few iterations. Once the power of the well-positioned SNs are expired, the network reaches out to the SNs with worse channel conditions, and results in an increasingly higher power consumption. This effect reduces the efficiency and significantly reduces the network lifetime. In order to cope with this effect, in the following we propose an intuitive weighting strategy which prevents a rapid expiration of the power for the SNs with better channel quality.

C. Per-Observation Weighted-Sum Power Minimization

As we have observed from the last part, for a network with a correlated (or constant) position of the source, the network tends to consume the resources from the better positioned nodes in a greedy way, following (12). In order to alleviate this effect, in each iteration, we seek to minimize a weighted-sum of the network power consumption while satisfying a similar set of constraints as in (12). The problem is hence formulated as

$$\underset{X_{k,l}, k\in\mathbb{F}_K,}{\text{minimize}} \quad \sum_{k=1}^{K} \lambda_{k,l} X_{k,l} \tag{13a}$$

$$\text{subject to} \quad \text{(12b), (12c), (12d),} \tag{13b}$$

where $\lambda_{k,l} \in \mathbb{R}^+$ is the price corresponding to the k-th SN, and is calculated for each observation iteration as

$$\lambda_{k,l} = K \frac{\exp\left(\frac{P_{k,\text{bud}}}{P_{k,l,\text{remain}}+0.1P_{k,\text{bud}}}\right)}{\sum_{k\in\mathbb{F}_K} \exp\left(\frac{P_{k,\text{bud}}}{P_{k,l,\text{remain}}+0.1P_{k,\text{bud}}}\right)}, \tag{14}$$

where $\exp(\cdot)$ represents the exponential function. Moreover, $P_{k,l,\text{remain}} := P_{k,\text{bud}} - \sum_{i\in\{1,\ldots,l-1\}} X^{\star}_{k,i}$, represents the remaining power budget for each SN at the current observation, and $X^{\star}_{k,i}$ represents the optimal solution to (13) for $X_{k,i}$ at the i-th iteration. As it can be observed from (14), the average defined weight is equal to one, similar to that of (12). Nevertheless, the SNs with less remaining power budget obtain a higher price for the power consumption at the future observation iterations. In this way, the SNs with better position preserve their available power over longer observation iterations, which consequently, results in a higher network lifetime when the available resources is limited.

4. Visualization and Numerical Results

In this part, we evaluate the performance of the design strategies in Section 3 via numerical simulations. In order to realize a network with a fixed source location, the depicted setup in Fig. 3 is implemented. The distance of each SN from the source or to the FC, determines the path loss at the sensing and the communication channels, respectively. The channel coefficient between each two nodes are consequently realized as $h = \tilde{h}d^{-\zeta}$, where ζ represents the path loss exponent, d is the distance, and $\tilde{h}$ represents the complex-valued Rayleigh-distributed small-scale fading, with unit variance. The goal of our comparison is to observe how the proposed design strategies in (12) and (13) compare to the optimal power allocation strategy (11) in terms of the power consumption and network life time. Unless stated otherwise, the given values in Table I define the default network parameters. Furthermore, we define multiple simulation setups, see Figs. 4-10, where in each case one of the parameters is changed, see Table II.

In Figs. 4-10, the consumed power of the SNs at the beginning of the actual observation iteration l_{act} are depicted with the utilization of (11), labeled 'optimal' and in blue color, for all SNs. The x-axis represents the SN index, where SNs are sorted such that the index increases as the distance to the Source/FC decreases. Furthermore, for the scenarios where (12) or (13) are utilized as the design strategy, the difference of the power consumption value for each SN to the optimal case, i.e., where (11) is used, is depicted with red curves. In this case, a negative power value in red color represents the consumption of less power compared to the 'optimal' strategy, at the corresponding SN. The label 'independent' represents the utilization of the design strategy in (12), where label 'intuitive' represents the utilization of the proposed design strategy in (13).

For each plot, the network simulation is performed firstly with the utilization of (11), i.e., optimal design strategy, for $L = 100$ observation iterations. The resulting network power consumption over all observation iterations is named P_{overall} hereinafter, and used as a comparison benchmark to the other design strategies. In this regard, l_{act} represents the observation iteration where the total (cumulative) network power consumption exceeds P_{overall}, when (12) or (13) are utilized as the power allocation strategy. Please note that the closer l_{act} gets to 100, it shows the closeness of the applied power allocation strategy to the optimality for the corresponding scenario. The value ρ_{sum} represents the percentage of the P_{overall} which is consumed until the current observation iteration, i.e., l_{act}, via the utilization of (11). Furthermore, ρ_{diff} represent the difference of the power consumption, compared to the optimal case, at the current observation iteration.

In Fig. 4, the power consumption of each SN is depicted, where the default network parameters are used. As it can be observed from Fig. 4a the power of SNs with better location, i.e., the ones which are positioned at the center, are rapidly consumed in comparison with the optimal power allocation strategy. This results in a fast expiration of the affordable network life time. On the other hand, it can be observed from Fig. 4b that the network life time reaches closer to the optimal case via the utilization of (13).

In Fig. 5 and Fig. 6, the same study as in Fig. 4 is performed for the scenarios 'P_{bud}-down' and 'P_{bud}-up', respectively. It is observed that the collaboration of more (less) number of the nodes is required compared to the 'reference' scenario, in order to satisfy the network requirements, due to the less (more) available power budget for each SN. Furthermore, while the utilization of the (13) results in the improved network lifetime when the power budget of each SN is small, it reduces the overall performance when P_{bud} is high. This is expected, since when P_{bud} is relatively high, it prevents the proper utilization of the power of the nodes with good position, which results in a reduced performance.

In Fig. 7 and Fig. 8, the impact of the higher ($V_{\max}$-down) or lower ($V_{\max}$-up) required estimation quality is observed on the resulting network lifetime, via the utilization of (12), in Figs. 8a, 7a and via the utilization of (13), in Figs. 8b, 7b. As expected, the higher (lower) required estimation quality results in a higher (lower) consumption of the network resources, and engages the collaboration of more (less) nodes. Furthermore, while the utilization of (13) significantly enhances the network lifetime for '$V_{\max}$-down', it results in a lower performance for '$V_{\max}$-up'. This is expected as the utilization of (13) results in a better preservation of SNs power for higher number of the required observations when the required estimation quality is higher (and more network resources are required). On the other hand, for the scenario that the required estimation quality is relatively low (less network resources are needed), it prevents the proper utilization of the power of nodes with

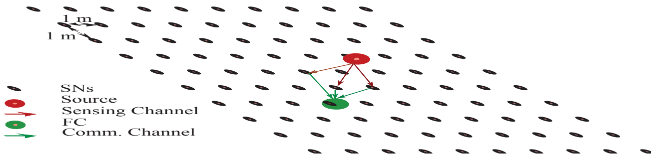

Fig. 3. The simulated SN setup, with 100 SNs on a surface. The source and FC nodes are positioned at the opposite sides, with 1 m distance from the surface. Each SN is positioned with 1 m distance to the adjacent node. A sub-set of SNs are active, at the depicted instance, to forward the sensed signal to the FC. The nodes at the center are better positioned compared to the nodes at the edge.

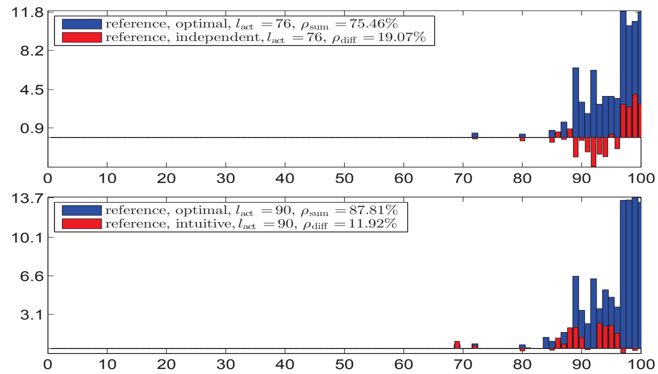

Fig. 4. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'reference' parameter set, see Table II. $P_{\text{overall}} = 109.4$. It is observed that the utilization of the intuitive pricing scheme in (13) enhances the network lifetime.

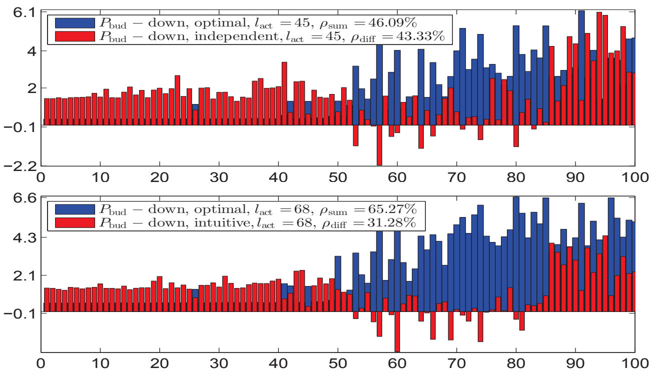

Fig. 5. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'P_{bud}-down' parameter set, see Table II. $P_{\text{overall}} = 370.9$. It is observed that the utilization of the intuitive pricing scheme in (13) enhances the network lifetime.

good positions, and leads to a lower performance.

In Fig. 9 and Fig. 10 the impact of the higher (P_{max}-up) or lower (P_{max}-down) maximum allowed individual SN power is observed on the resulting network lifetime. It is observed that the influence of P_{max} on the network lifetime is relatively less significant for the observed parameter set. Furthermore, as it is observed, the application of the intuitive pricing of the remaining power budget at each node results in a higher network performance for both scenarios.

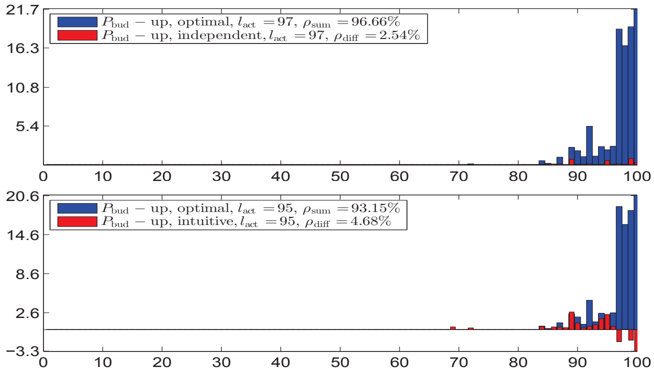

Fig. 6. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'P_{bud}-up' parameter set, see Table II. $P_{\text{overall}} = 101.8$. It is observed that the utilization of the intuitive pricing scheme in (13) reduces the network lifetime.

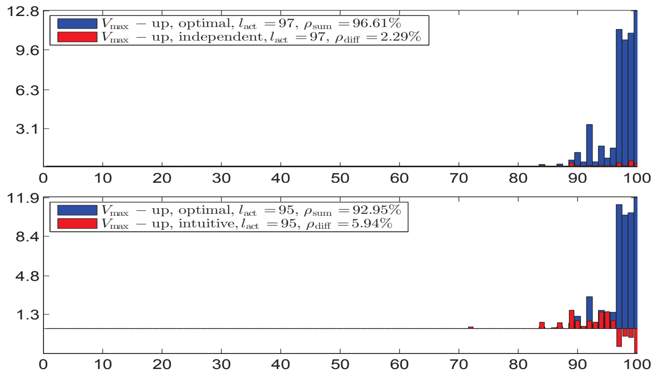

Fig. 7. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'V_{max}-up' parameter set, see Table II. $P_{\text{overall}} = 57.7$. It is observed that the utilization of the intuitive pricing scheme in (13) reduces the network lifetime.

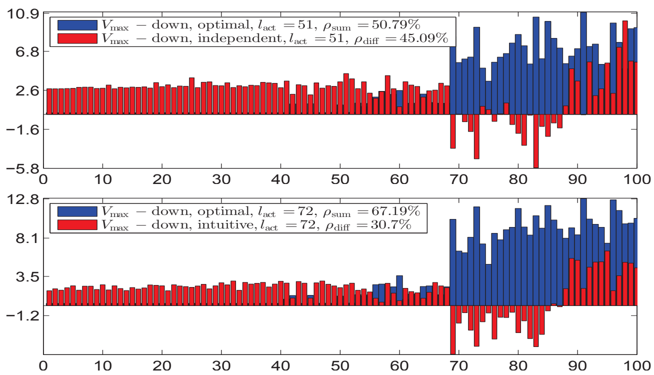

Fig. 8. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'V_{max}-down' parameter set, see Table II. $P_{\text{overall}} = 516.8$. It enhances the network lifetime.

TABLE I
DEFAULT (REFERENCE) PARAMETER VALUES FOR ALL PLOTS.

Param.	K	P_{max}	P_{bud}	V_{max}	M_k	N_k	R	P_{min}	ζ
Value	100	1	15	1	1	1	1	0	3

5. Conclusion

Power consumption and lifetime are pronounced features of sensor networks. In this paper we have studied theoretical and practical methods for minimizing the power consumption and enhancing the network lifetime, targeting at the passive distributed radar applications. In this regard, it is observed that a minimum power consumption design for each ob-

TABLE II
SIMULATED SCENARIOS

Scenario:	reference	P_{bud}-down	P_{bud}-up	V_{max}-down	V_{max}-up	P_{max}-down	V_{max}-up
Value:	See Table I	$P_{\text{bud}} = 7.5$	$P_{\text{bud}} = 30$	$V_{\text{max}} = 2/3$	$V_{\text{max}} = 3/2$	$P_{\text{max}} = 2/3$	$P_{\text{max}} = 3/2$

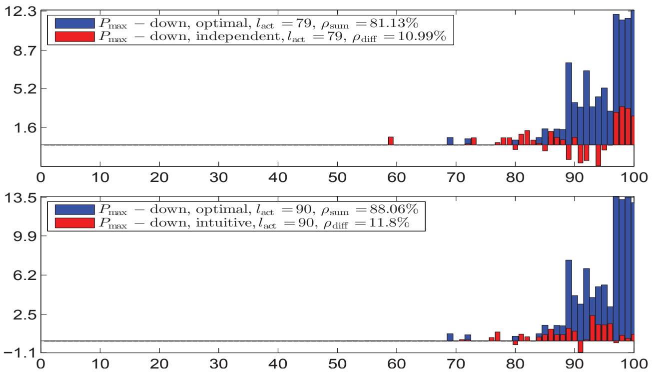

Fig. 9. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'P_{max}-down' parameter set, see Table II. $P_{\text{overall}} = 115.6$. It is observed that the utilization of the intuitive pricing scheme in (13) enhances the network lifetime.

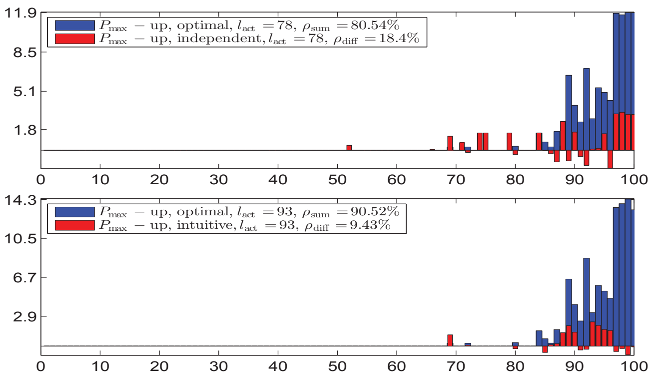

Fig. 10. Distribution of the SN power consumption is depicted for each SN index (x-axis) for 'P_{max}-up' parameter set, see Table II. $P_{\text{overall}} = 108.8$. It is observed that the utilization of the intuitive pricing scheme in (13) enhances the network lifetime.

servation results in a relatively large gap with the optimal performance for the networks with a static source location. An efficient power allocation scheme is hence proposed based on a weighted sum-power minimization for each observation. Numerical simulations show that the proposed method have effectively reduced the gap with the theoretical upper bound, when the network resources are scarce.

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