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SPECIAL ISSUE ON Energy efficiency management for distributed computation and applications in sensor networks

Energy efficiency management for distributed computation and applications in sensor networks

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Distributed signal processing, learning, inference and computation has been applied to sensor networks in a broad range of applications like distributed localization, target tracking, environmental monitoring, and surveillance. Sensors are typically equipped with wireless interfaces to allow sensor-to-sensor communications in order to perform collaborative and distributed inference. The sensors can operate in either static networks or dynamic networks like vehicular ad hoc networks. However, energy efficiency of such sensor networks is a critical issue. The carbon footprint of a network can be large if the sensors are operated inefficiently.

This special issue of E-Letter focuses on the recent progresses of energy efficiency management in sensor networks. It is the great honor of the editorial team to have four leading research groups to report their solutions for meeting these challenges and share their latest results.

In the first article titled, "*Joint Design of Optimal Sensor Selection and Collaboration Strategies for Distributed Estimation",* Liu, Kar, Fardad and Varshney from Syracuse University and Intel Corporation considered sensor collaboration for distributed estimation. Collaboration cost and unknown collaboration topologies are incorporated into an optimization framework in order to determine the optimal subset of sensors that should communicate with the fusion center of the network. A joint sensor selection and collaboration convex optimization problem is formulated and solved via the alternating direction method of multipliers (ADMM). The trade-off between sensor selection and sensor collaboration for a given estimation performance is studied. The proposed approach can be applied to addressing communication problems such as cooperative spectrum sensing in cognitive radio networks.

In the second article titled "*A Sensor Scheduling Protocol for Energy-efficiency and Robustness to Failures*", Du, Fischione and Xiao from KTH Royal Institute of Technology, Sweden devise a sensor scheduling protocol that is both energy-efficient and robust to failures. A compressed data gathering (CDG) approach is utilized to improve the energy efficiency of the data gathering process. In this approach, all senor nodes combine their local measurement with data received from their children nodes in the routing tree to transmit a vector of fixed size. The sensors' measurements are then recovered at the sink nodes. A sink node coordinates the activation of sensors in each timeslot in order to take into account sensor failures and energy balancing. An optimization problem is formulated and evaluated through simulations, which show that by scheduling only a small subset of sensors to sense and transmit, monitoring accuracy can be maintained while lengthening network lifetime.

The third article is contributed by Lanza-Gutierrez and Gomez-Pulido from the University of Extremadura, Spain, and the title is *"Multiobjective Metaheuristics for Solving Two Approaches to the Relay Node Placement Problem in Outdoor Wireless Sensor Networks"*. In a sensor network, information captured by the sensor nodes are sent to a collector node using a multi-hop topology. This may lead to unbalanced energy distribution in the network with sensors using more energy than others called the bottlenecks. To avoid these, relay nodes with higher energy capacity are used. Placement of energy-harvesting relay nodes is studied and the paper proposed two multiobjective approaches that considers average energy cost, average sensitivity area, and network reliability. The approaches are studied using a synthetic sensor network dataset, which demonstrates that using a swarm intelligence algorithm gives the best average result.

The fourth paper, titled "*How to Efficiently Deploy Applications in WSNs Using Distributed Approaches*", is a contribution of Pilloni and Atzori from the University of Cagliary, towards distributed WSN applications with the purpose of extending the network lifetime. The authors highlight the benefits of distributed approaches in comparison with centralized solutions when these can be split into smaller tasks and assigned to different nodes. After characterizing the network and application models, the paper describes two different algorithms to maximize the network lifetime: The Decentralized Lifetime Maximisation Algorithm (DLMA), which executes a local optimization between neighboring nodes to locally reassign the tasks to the nodes and The Task Allocation Negotiation Algorithm (TAN), which is a multi-objective algorithm, reducing both network energy consumption and application execution time. Overall the paper shows that distributed algorithms can be used not only to improve lifetime, but also to reduce task completion time.

The final paper is "*Optimization of Information Neighbors for Energy-constrained Diffusion*", by Hu and Tay from Nanyang Technological University, Singapore. This paper proposes a multi-hop diffusion strategy for distributed estimation in a WSN, in which parameter estimates at each sensor is based on information a set of information neighbors instead of the physical neighbors. The information neighbors can be more than one hop away from the sensor. They showed that it is possible to optimize the information neighborhood of each sensor so that the local energy budget and network-wide energy budgets are satisfied. A mixed integer linear program is formulated, and a distributed and adaptive algorithm can be used to select the information neighbors and combination weights for each node.

Energy management in sensor networks is nowadays a critical issue that still limits widespread adoption of related technologies in different fields of application. Therefore, increasingly efficient solutions will be under research and development in the years to come. While this special issue is far from delivering a complete coverage on this exciting research area, we hope that the four invited letters give the audiences a taste of the main activities in this area, and provide them an opportunity to explore and collaborate in the related fields. Finally, we would like to thank all the authors for their great contribution and the E-Letter Board for making this special issue possible.

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Joint Design of Optimal Sensor Selection and Collaboration Strategies for Distributed Estimation

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1. Introduction

Wireless sensor networks consist of a large number of spatially distributed sensors that often cooperate to perform parameter estimation; example applications include environment monitoring, source localization and target tracking [1-2]. Under limited resources, such as limited communication bandwidth and sensor battery power, it is important to design an energy-efficient architecture for distributed estimation.

Recently, the problem of distributed estimation with sensor collaboration has attracted significant attention [3-5], where collaboration refers to the act of sharing measurements with neighboring sensors prior to transmission to a fusion center (FC). In [3], the problem of sensor collaboration was studied by assuming an orthogonal multiple access channel (MAC) setting with a fully connected network, where all of the sensors are allowed to collaborate. It was shown that the presence of sensor collaboration smooths out the observation noise, thereby improving the quality of the signal and the eventual estimation performance. In [4], optimal power allocation schemes were proposed given star, branch and linear network topologies. The problem of sensor collaboration over a coherent MAC was studied in [5], where it was observed that even a partially connected network can yield performance close to that of a fully connected network. The works [3-5] assumed that there is no cost associated with collaboration, that the collaboration topologies are fixed and given in advance, and that the only unknowns are the collaboration weights used to combine sensor observations.

In this letter, we present a tractable optimization framework to solve the collaboration problem with non-zero collaboration cost and unknown collaboration topologies. We incorporate energy costs associated with selected sensors while determining the optimal subset of sensors that communicate with the FC. For the joint design of optimal sensor collaboration and selection schemes, we describe collaboration through a collaboration matrix, and associate (a) the cost of sensor collaboration with the number of nonzero entries of a collaboration matrix (i.e., its overall sparsity), and b) the cost of sensor selection with the number of nonzero rows of the collaboration matrix (i.e., its row-sparsity). We show that there exists a trade-off between sensor selection and sensor collaboration for a given estimation performance.

This letter highlights our recent work [6] on joint design of optimal sensor collaboration and selection strategies. More of our contributions to problems of resource management in sensor networks, such as sensor scheduling, energy-aware field reconstruction, and sensor selection with correlated noise, can be found in [7-9].

2. Sparsity-Aware Sensor Collaboration

In this letter, the task of the sensor network is to estimate a random parameter θ which follows a Gaussian distribution with zero mean and variance η^2. In the collaborative estimation system, sensors first acquire their raw measurements via a linear sensing model. Individual sensors can then update their observations through spatial collaboration, which refers to (linearly) combining observations from other sensors. The updated measurements are transmitted through a coherent MAC. Finally, the FC determines a global estimate of θ by using a linear estimator. We show the collaborative estimation system in Fig. 1.

This work was supported by U.S. Air Force Office of Scientific Research (AFOSR) under grant FA9550-10-1-0458, and National Science Foundation (NSF) under awards EAGER ECCS-1545270 and CNS-1329885.

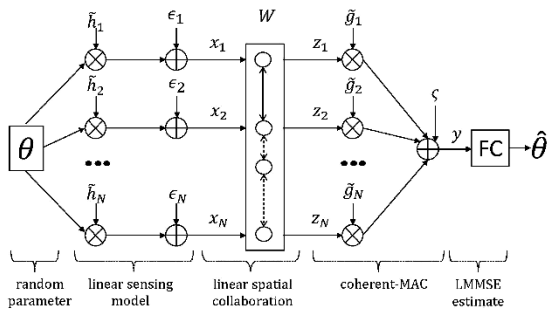

Figure 1: Collaborative estimation architecture.

As shown in Fig.1, the sensor collaboration process is described by

$$\mathbf{z} = \mathbf{W}\mathbf{x}, \quad \mathbf{W} \in \Re^{N\times N},$$

where **z** denotes the message after collaboration, **W** is the collaboration matrix that contains weights used to combine sensor measurements, and **x** is the vector of raw sensor measurements. We note that the nonzero entries of **W** correspond to the active collaboration links among sensors. For example, $W_{mn} = 0$ indicates the absence of a collaboration link from the *n*th sensor to the *m*th sensor. Conversely, $W_{mn} \neq 0$ signifies that the *n*th sensor shares its observation with the *m*th sensor. Thus, the sparsity structure of W characterizes the collaboration topology.

The *sensor collaboration cost* is given by

$$Q_{\mathbf{W}} = \sum_{m=1}^{N}\sum_{n=1}^{N} C_{mn}\|W_{mn}\|_0,$$

where C_{mn} is the cost of sharing an observation from the nth sensor with the *m*th sensor, and $\|\cdot\|_0$ denotes the l_0 norm of a vector (or scalar) which returns 1 if $W_{mn} \neq 0$ and 0 otherwise.

Next, we define the sensor selection cost. Partitioning the matrix **W** rowwise, the non-zero rows of **W** characterize the selected sensors that communicate with the FC. The *sensor selection cost* is then given by

$$S_{\mathbf{W}} = \sum_{n=1}^{N} b_n \left\| \|\mathbf{w}_n\|_2 \right\|_0,$$

where b_n is the cost of selecting the *n*th sensor, $\mathbf{w}_n$ denotes the *n*th row of **W**, and $\|\cdot\|_2$ is the Euclidean norm of a vector.

After sensor collaboration, the resulting signal is transmitted to the FC through a coherent MAC, which leads to the *transmission cost* $T_{\mathbf{W}}$. At the FC, the linear minimum mean squared-error estimator is used to estimate the random parameter θ. The resulting estimation performance is evaluated in terms of *Fisher information* $J_{\mathbf{W}}$. Both the transmission cost $T_{\mathbf{W}}$ and Fisher information $J_{\mathbf{W}}$ can be expressed as explicit functions of the collaboration weights,

$$T_{\mathbf{W}} = \mathbf{w}^T\mathbf{\Omega}_{\mathrm{T}}\mathbf{w} \qquad J_{\mathbf{W}} = \frac{\mathbf{w}^T\mathbf{\Omega}_{\mathrm{JN}}\mathbf{w}}{\mathbf{w}^T\mathbf{\Omega}_{\mathrm{JD}}\mathbf{w} + \sigma^2},$$

where $\mathbf{w}=[\mathbf{w}_1, \ldots, \mathbf{w}_N]^T$ is a vector that consists of the entries of **W** in a rowwise manner, the coefficient matrices are positive semidefinite which were defined in [6, Appendix A], and σ^2 is the variance of channel noise.

Motivated by scenarios where saving energy is our primary goal in resource management, we design optimal sensor collaboration and selection schemes by minimizing the energy consumption subject to an information constraint,

$$\underset{\mathbf{W}}{\text{minimize}} \;\; Q_{\mathbf{W}} + S_{\mathbf{W}} + T_{\mathbf{W}} \quad \text{subject to} \;\; J_{\mathbf{W}} \geq J_0, \qquad \text{(P0)}$$

where $J_0 > 0$ is a given information threshold. In the above problem, the l_0 norm that appears in the sensor collaboration cost $Q_{\mathbf{W}}$ and the selection cost $S_{\mathbf{W}}$ promotes the sparsity of the collaboration matrix **W**. Therefore, we refer to (P0) as a sparsity-aware sensor collaboration problem for distributed estimation.

3. Joint Sensor Collaboration and Selection via Convex Optimization

In this section, we present an efficient optimization approach for the joint design of sensor collaboration and selection schemes. First, we convexify (P0) by using an iterative reweighted l_1 minimization method and a linearization method. The resulting convex problem is then solved via the alternating direction method of multipliers (ADMM).

Convexification.

Due to the presence of the l_0 norm, (P0) is combinatorial in nature. A method for solving it is to relax the l_0 norm to a weighted l_1 norm [10]. This leads to the following optimization problem

$$\underset{\mathbf{w}}{\text{minimize}} \quad \mathbf{w}^T\mathbf{\Omega}_{\mathrm{T}}\mathbf{w} + \|\mathbf{\Omega}_{\mathrm{C}}\mathbf{w}\|_1 + \sum_{n=1}^{N} d_n \|\mathbf{w}_n\|_2$$

$$\text{subject to} \quad \mathbf{w}^T(J_0\mathbf{\Omega}_{\mathrm{JD}} - \mathbf{\Omega}_{\mathrm{JN}})\mathbf{w} + J_0\sigma^2 \le 0,$$

where $\mathbf{\Omega}_{\mathrm{C}}$ is a diagonal vector given by diag($\alpha_1 c_1, \ldots, \alpha_L c_L$), $L=N^2$, $\mathbf{c} = [c_1, \ldots, c_L]^{\mathrm{T}}$ is the rowwise vector of the collaboration cost matrix C formed by $\{C_{mn}\}$, $d_n=\beta_n b_n$ for $n = 1, \ldots, N$, $\{\alpha_i\}$ and $\{\beta_n\}$ denote the weights that are iteratively updated in order to ensure that the last two terms in the objective function are good proxies for the l_0 norms they replace, namely,

$$\alpha_i \leftarrow 1/(w_i + \varepsilon), \quad \beta_n \leftarrow 1/\|\mathbf{w}_n\|_2 + \varepsilon.$$

Here ε is a small positive number which ensures that the denominator is always nonzero.

The resulting l_1 optimization problem involves a convex objective function and a nonconvex quadratic constraint. This nonconvex constraint can be recast as a difference of convex functions [11]

$$J_0\mathbf{w}^T\mathbf{\Omega}_{\mathrm{JD}}\mathbf{w} + J_0\sigma^2 - \mathbf{w}^T\mathbf{\Omega}_{\mathrm{JN}}\mathbf{w} \le 0.$$

We linearize the convex function $\mathbf{w}^T\mathbf{\Omega}_{\mathrm{JN}}\mathbf{w}$ around a feasible point $\boldsymbol{\gamma}$, and obtain

$$J_0\mathbf{w}^T\mathbf{\Omega}_{\mathrm{JD}}\mathbf{w} + J_0\sigma^2 \le \boldsymbol{\gamma}^T\mathbf{\Omega}_{\mathrm{JN}}\boldsymbol{\gamma} + 2\boldsymbol{\gamma}^T\mathbf{\Omega}_{\mathrm{JN}}(\mathbf{w} - \boldsymbol{\gamma}), \quad (1)$$

whose left hand side is an affine lower bound on the convex function $\mathbf{w}^T\mathbf{\Omega}_{\mathrm{JN}}\mathbf{w}$. This implies that the set of $\mathbf{w}$ that satisfy the linearized constraint is a strict subset of the set of w that satisfy the original constraint.

After linearization, we obtain a convex problem

$$\underset{\mathbf{w}}{\text{minimize}} \quad \mathbf{w}^T\Omega_{\mathrm{T}}\mathbf{w} + \|\mathbf{\Omega}_{\mathrm{C}}\mathbf{w}\|_1 + \sum_{n=1}^{N} d_n \|\mathbf{w}_n\|_2 \qquad \text{(P1)}$$

$$\text{subject to} \quad \text{convex quadratic constraint (1)},$$

where non-smooth norms appear in the objective function. In what follows, we will employ ADMM to find the optimal solution of (P1).

Solution via ADMM.

The major advantage of ADMM is that it allows us to split (P1) into a convex quadratic program with only one quadratic constraint and a proximal operator [12] of a sum of l_1 and l_2 norms, where the former can be efficiently solved by exploring its KKT conditions, and the latter admits an analytical solution. ADMM is performed based on the augmented Lagrangian function [13] of (P1), where we alternatively solve the resulting two subproblems. We refer the readers to [6, Sec.VI] for details on the proposed ADMM algorithm.

3. Performance evaluation

In this section, we illustrate the performance of our proposed sparsity-aware sensor collaboration methods through numerical examples.

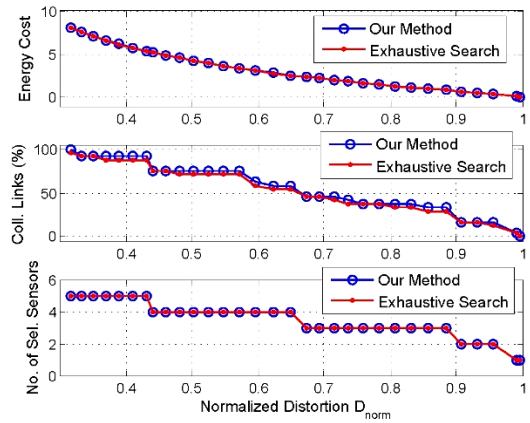

Figure 2: Performance evaluation of sensor selection and collaboration

In Fig.2, we show the energy consumption, number of collaboration links and selected sensors as functions of the normalized estimation distortion D_{norm} that provides the information threshold. For comparison, we also present the optimal results obtained from an exhaustive search, where $N = 5$ sensors are assumed in this example. We observe that the proposed approach assures near optimal performance for all values of estimation distortion. Moreover, the energy cost, number of collaboration links and selected sensors increases as D_{norm} decreases, since a smaller estimation distortion enforces more collaboration links and activated sensors.

In Fig.3, we present specific sensor collaboration and selection schemes by increasing the sensor selection cost under a given estimation distortion $D_{\text{norm}} = 0.7$. In the figure, the solid line with an arrow represents the collaboration link between two sensors, and the dashed line from one sensor to the FC signifies that this sensor is selected to communicate with the FC. As we can see, in the left plot in which sensor selection cost is lower, three sensors are selected to communicate with the FC, and three collaboration links are established. While in the right plot in which sensor selection cost is higher, fewer sensors are selected and more collaboration links are established. This exhibits a trade-off between sensor collaboration and sensor selection.

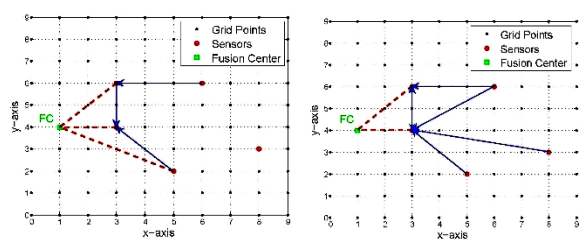

Figure 3: Trade-off between collaboration & selection

4. Conclusion

In this letter, which is based on our recent work [6], we described a novel framework for the joint design of optimal sensor collaboration and selection schemes in the distributed estimation context. We showed that optimal sensor collaboration and selection schemes can be designed by promoting the elementwise and rowwise sparsity of the collaboration matrix. The formulated sparsity-aware optimization problem is nonconvex in nature, and we convexified the problem by using a reweighted l_1 norm and the convex restriction method, and solved the resulting convex program via ADMM. It was empirically shown that there exists a trade-off between sensor collaboration and sensor selection for a given estimation performance. The methodology of sparsity-aware sensor collaboration could provide valuable insights into addressing communication problems such as cooperative spectrum sensing in cognitive radio networks.

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A Sensor Scheduling Protocol for Energy-efficiency and Robustness to Failures

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1. Introduction

The recent advances in sensing and wireless communication technologies facilitate automated environment monitoring by wireless sensor networks (WSNs) [1]. Typical WSN setups, such as underground pipelines, tunnels and bridges, are not easily accessible, and hence it is necessary to minimize the required human intervention. Since sensor nodes are battery-powered devices, and battery replacement or recharging is difficult, maximizing WSN lifetime is of utmost importance [2]. Towards an automated WSN monitoring system, we devise a sensor scheduling protocol that is both energy-efficient and robust to failures.

Sensors are deployed in an area of interest to monitor a physical process and then transmit the collected data to a sink node for further analysis and to drive decision making. Data transmission is typically the most energy consuming function of a sensor node, much higher than sensing and computing [3]. Short-range multi-hop data relaying is a traditional method to reduce energy consumption in wireless networks [3,4]. A sensor node, acting as a relay, collects the data from its children nodes in the routing tree, combines its measurements and sends them to its next-hop node. Thus, sensors closer to the sink node have higher loads to transmit and their battery will deplete much earlier causing the disconnection of the whole network. The lifetime of such nodes closer to the sink becomes the bottleneck.

The idea of compressed sensing (CS) has been proposed to improve energy efficiency of the data gathering process in WSNs [5]. In the compressed data gathering (CDG) approach [6], all sensor nodes transmit a vector of the same size, which is based on their local measurement and the received data from their children nodes in the routing tree. Their measurements are recovered at the sink nodes. Thus, all the sensor nodes consume approximately the same energy, and the energy consumption of the WSN is more balanced. Furthermore, CS exploits the correlation of measurements to reduce the number of required measurements and consequently transmissions (much smaller than the number of nodes in the network). In dense sensor network, strong spatial correlations [6] on measurements enable us to turn off some sensor nodes for further energy saving [7], i.e. reducing the nodes that transmit data. The data of the turned-off sensor nodes can be accurately estimated later [8].

In this paper, we focus on tandem multi-hop WSNs (Fig.1), monitoring an area with a long strip shape, such as pipelines, tunnels, towers, and bridges. We present a protocol for CS-based data gathering and scheduling of the sleep/awake of sensor nodes to prolong network lifetime. The proposed protocol ensures that the residual energy of the sensor nodes is balanced and the overall consumption of the network per timeslot is minimized by CS.

2. Sensor scheduling protocol

In this section, we first present the CS data gathering scheme for energy efficiency. Then we describe the protocol to coordinate transmission scheduling in a line network.

Compressive sensing for data gathering

Since the monitored area has a long strip shape, it could be modeled as a 1-dimensional line. Given a WSN of N sensor nodes: $\mathcal{V} = \{v_1, \ldots, v_N\}$, where v_N is the furthest sensor node from the sink node v_0, and a virtual node v_{N+1} is placed on the other end of the line. The CDG approach is shown in Figure 1 (a). Every sensor node v_i makes a measurement d_i in a timeslot, then it multiplies it with a random vector of size $m \ll N$, $\boldsymbol{\phi}_i$. The first node v_N transmits the result $\mathbf{y}_N = \boldsymbol{\phi}_N d_N$ to its next hop node v_{N-1}. Every node v_i receives the packet y_{i+1} from its previous node. Then, it sums the received vector with $\boldsymbol{\phi}_i d_i$ i.e., $\mathbf{y}_i = \mathbf{y}_{i+1} + \boldsymbol{\phi}_i d_i$, and sends it to its next hop node. In so doing, the sink node receives $\mathbf{y}_1 = \sum_{i=1}^{N} \boldsymbol{\phi}_i d_i$, and it recovers $d_1, \ldots, d_N$ based on y_1 and $\phi_1, \ldots, \phi_N$ by solving a l_0-norm minimization problem [6]. In so doing, the payloads of the sensor nodes are the same.

Inspired by this approach, we propose the scheduling scheme depicted in Figure 1 (b), where only a subset of the sensor nodes are activated for sensing. Due to strong spatial correlation of the sensor nodes, the measurements of the

inactivated sensor nodes could be accurately estimated based on the measurement of the active sensor nodes. To handle the sleep/awake activation of the sensor nodes, a protocol is described in the next subsection.

A protocol to coordinate transmission scheduling.
The sink node coordinates the activation of the sensor nodes in each timeslot. As sensor nodes may fail, the sink node has to modify the activation schedule. Thus,

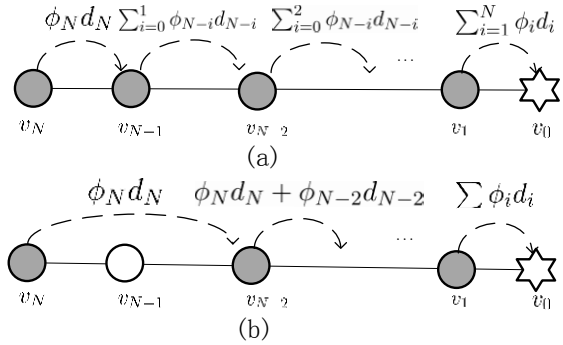

Figure 4 Data gathering based on compressive sensing. In grey we depict the active sensor nodes, and the white star is the sink node. (a) Compressed data gathering approach; (b) Our approach where the white nodes are turned off for energy saving.

once the sink detects a failure, it calculates the new schedule and updates the sensor nodes with the new activation schedules. The exact steps of the protocol are shown in Figure 2. Initially, the sink node estimates the residual energy of the sensor nodes. It determines the activation schedules for the upcoming K timeslots, and broadcasts the schedules to the sensor nodes. In each timeslot, the corresponding sensor nodes are activated to measure and relay data along with their id according to the CDG approach. On receiving the data, the sink node checks whether the ids of activated nodes coincide with the announced schedule, e.g. by checking the sum of the ids of the active sensor nodes. If they are different, some of the sensor nodes have failed, and re-scheduling is needed. In this case, the sink node identifies and removes the failed sensor nodes from the network. It re-collects the residual energy of the sensor nodes, then determines the new schedules and broadcasts them to the sensor nodes. Otherwise, the sensor nodes follow the schedule to activate in the next timeslot. Every K timeslots, the sink node re-calculates the schedule for the next period of K timeslots, until the network becomes disconnected.
In short, the sink node updates the activation schedule every K timeslots or whenever it detects failure. In the next section, we describe an efficient algorithm to determine which sensor nodes should be activated.

3. Sensor node activation based on energy balancing.
As mentioned before, in each timeslot, part of the sensor nodes are selected to be active, to sense and transmit their measurements within the timeslot to the sink node in a CDG manner. Notice that the power consumptions of a node can be considered as proportional to d^{α}, where d is the transmission distance and $\alpha \geq 2$ is the system parameter depends on the wireless channel, the power consumption grows rapidly with the distance. To save energy, it is

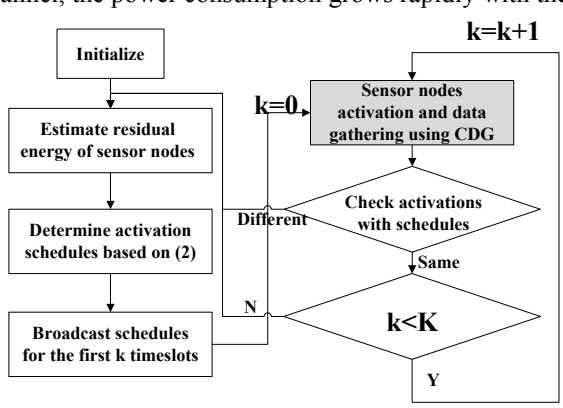

Figure 5 Flow chart of the WSN protocol, where the boxes in white represent the operations on sink node, the box in grey represent the operation on sensor nodes

desired to set the transmission power of the sensor nodes to be minimum Recall that the payloads of the active sensor nodes are the same; hence, we may normalize their energy consumptions to 1. Let $x_i(t) = 1$ represent that sensor node v_i is activated in timeslot t. Otherwise, $x_i(t) = 0$. Thus, by denoting E_i the battery of a node v_i, the residual energy of v_i at timeslot t is $E_i(t) = E_i - \sum_{k=1}^{t} x_i(k)$. Then, the normalized residual energy of v_i is defined by $p_i(t) = E_i(t)/E_i$.

In a timeslot, the activated sensor nodes should be connected to the sink node, such that the data can reach the sink node. Furthermore, the activated nodes should span the line to monitor the whole area. Thus, it is desired that the active nodes are also connected with a virtual node v_{N+1}. Thus, a connectivity constraint has to be introduced: $G(x(t))$ has to be connected, where $G(x(t))$ is the sub-graph of the activated nodes in timeslot t, together with v_0 and v_{N+1}. Besides, for a good monitoring accuracy, the number of activated sensor nodes should always exceed a threshold M_a. This gives us the cardinality constraint: $\sum_{i=1}^{N} x_i(t) \geq M_a$.

To prolong the network lifetime, we need to determine the activations of the sensor nodes: $x_1(t), \ldots, x_N(t)$, so that both the connectivity constraint and the cardinality constraint are satisfied for as long as possible. Denote M_c the minimum number of sensor nodes to be activated such that there exists a route from v_0 to v_{N+1}. Then, the node activation problem for timeslot t is formulated as follows

$$\begin{aligned} \max_{x_1(t),\ldots,x_N(t)} \quad & \sum_{i\in\mathcal{V}} x_i(t)p_i(t) \\ \text{subject to} \quad & G(x(t)) \text{ is connected,} \\ & \sum_{i\in\mathcal{V}} x_i(t) = \max\{M_a, M_c\}, \\ & x_i(t) \in \{0,1\}, \forall v_i \in \mathcal{V}, \end{aligned} \quad (1)$$

where the first constraint represents the connectivity constraint, the second constraint represents the cardinality constraint. After the activation, the residual energy of the sensor nodes are updated as $E_i(t+1) = E_i(t) - x_i(t)$. The idea of the optimization problem is that, in each timeslot, the number of the activated sensor nodes should be as small as possible, whereas among the subsets of sensor nodes of the same size, the one of highest total residual energy is preferred.

The energy balancing problem can be considered as finding the maximum weighted connected subset of nodes, which rooted at v_0 and v_{N+1}, with exact $M = \max\{M_a, M_c\}$ nodes, which is generally NP-Hard. Our solution approach consists of two steps: (1) Determine M; (2) Finding the maximum weighted connected subset with exact M nodes.

In the first step, recall that $M = \max\{M_a, M_c\}$, where M_a is determined by the cardinality constraint and is known, the major task here is to calculate M_c, the minimum number of sensor nodes to be activated such that there exists a route from v_0 to v_{N+1}. Thus, a shortest path searching could be used to find M_c by setting the length of all the edges in the network to be 1. Notice that if the route does not exist, $M_c = +\infty$ which indicates that the network is disconnected.

In the second step, we need to find the maximum weighted connected sub-graph that connects both v_0 and v_{N+1} including at least M additional nodes. Suppose that one wants to find the maximum weighted connected sub-graph that connects a node v_i and v_{N+1} with additionally k nodes. The connectivity requirement gives us that the sub-graph must contain the maximum weighted sub-graph that connects a neighbor node of v_i, say v_j, and v_{N+1} with additionally $k-1$ nodes. This observation provides us a dynamic programming based algorithm. Denote $g(v_i, k)$ the maximum weight of the connected sub-graph that connects v_i and v_{N+1} with additional k nodes, then a recursive function can be derived as

$$g(v_i, k) = \max_{v_j \in \mathcal{N}(v_i)} \{g(v_j, k-1) + p_j(t)\}, \quad (2)$$

where $g(v_i, 0)$ are set to 0 for all i, if v_i is the neighbor of v_{N+1}, otherwise they are $-\infty$. The corresponding nodes that lead to $g(v_0, M)$ are the nodes to be activated in the timeslot. More details can be found in [9].

4. Performance evaluation

In this section, we first show the monitoring performance on estimation error of the CDG data gathering. Then, we will show the network performance in terms of lifetime.

First, we show the achievable recovery error for different numbers of activated sensor nodes. WE consider a scenario in which $N = 50$ sensor nodes deployed in the monitored area. In each timeslot, only M of the sensor nodes are activated. We simulate scenarios where the activation ratio N/M ranges from 0.1 to 0.4, i.e., 10%-40% of the sensor

nodes are activated. The recovery error against the activation ratio is shown in Figure 3, where the blue, green, and red lines represent different monitoring scenarios, where the measurements of the sensor nodes have a Gaussian white nose with covariance 0, 0.01, and 0.05 multiplied with the maximum measurement, respectively. The result shows that when the activation ratio is above 0.25, the estimation accuracy does not improve a lot with the increment of activation nodes. Therefore, by activating about one-fourth of the sensor nodes in every timeslot, we can achieve a good monitoring performance.

Then, we show the approximation ratio of the proposed algorithm, i.e. the ratio of the lifetime achieved by the algorithm and the lifetime upper bound of the network, with different activation ratio and nodal transmission ranges in Figure 4. In the simulation, M out of 100 sensor nodes need to be activated in a timeslot by the cardinality constraint. The normalized transmission range is the ratio of the nodal transmission range to the length of the monitored area. It shows that, the approximation ratio increases with the increment of the transmission range. Besides, the approximation ratio is close to 1 when the transmission range of the sensor nodes is large enough, which means that the energy balancing is a good approach to prolong network lifetime.

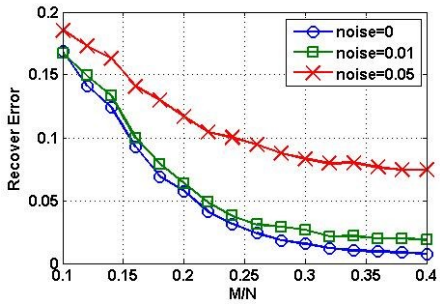

Figure 6 Recover error of the sensor nodes with different activation ratio

4. Conclusion

In this paper, we proposed a sensor scheduling protocol that exploits compressive sensing to prolong network lifetime. In order to ensure robustness to sensor failures, the proposed protocol pursues to balance sensor's residual energy. The simulation results reveal that by scheduling only a small subset of the sensors to sense and transmit, we can effectively increase network lifetime, without minimal loss in monitoring accuracy.

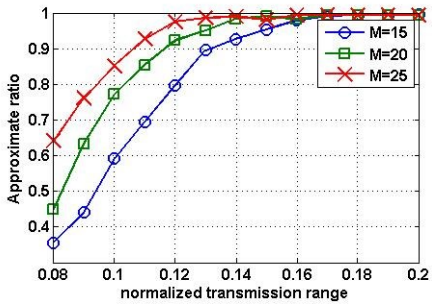

Figure 7 Ratio of lifetime achieved by the proposed algorithm to the lifetime upper bound with different activation ratios and transmission ranges

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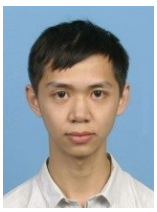

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Multiobjective Metaheuristics for Solving Two Approaches to the Relay Node Placement Problem in Outdoor Wireless Sensor Networks

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1.Introduction

Nowadays, wireless sensor networks (WSNs) are deployed in many different fields of application, such as industrial control, robotics, smart cities, and intensive agriculture, among many other cases [1].

Traditionally, a WSN is composed of a set of sensor nodes (SNs) capturing information about the environment and a single collector node (CN) getting all these data. The SNs have some interesting features, which encourage the use of this technology, *e.g.* they are wireless, cheap, power-autonomous, and scalable. These features allow deploying WSNs in environments where other technologies would be very expensive or even impossible to be applied. In fact, this is one of the great contributions of this technology [2].

WSNs also present shortcomings, affecting critical features for the industry, such as energy consumption and quality of service. Traditionally, the SNs are powered by batteries to reduce deployment costs. Thus, WSNs are particularly sensitive to energy cost, affecting the network behaviour. All the information captured by the SNs is sent to the CN, involving an energy cost. If the WSN considers a star topology, all the SNs follow a similar energy cost distribution. However, if we assume a habitual multi-hop topology, the energy distribution could be unbalanced, implying the existence of bottlenecks, *i.e.* SNs subject to significantly higher energy costs than others.

With the purpose of avoiding these bottlenecks, a new type of device called relay node (RN) is added to traditional WSNs [3]. This new device only forwards all the received information to the CN, reducing the workload of the SNs in its environment. The RNs have higher energy capacity than the SNs. They can be plugged into the grid, have greater batteries, or be energy-harvesting devices (*e.g.* powered by solar energy). Thus, they are not limited to be deployed close to a plug, instead, they can be placed on difficult terrains, such as war zones, farmland, and forests.

The efficient deployment of traditional WNS depends on many factors, even more if RNs are included. In fact, this is an NP-hard optimization problem in the literature [4,5]. This type of problems cannot be solved through exact techniques, but approximate ones, such as evolutionary algorithms (EAs) [6].

We have studied how to deploy energy-harvesting RNs in previously-stablished traditional static outdoor WSNs. This is the so-called relay node placement problem (RNPP). We consider two multiobjective (MO) approaches to this problem, where different objectives are optimised. One the one hand, a bi-objective approach considers average energy cost (AEC) and average sensitivity area (ASA). On the other hand, a three-objective approach deals with AEC, ASA, and network reliability (NR).

A wide range of MO metaheuristics are assumed for solving both approaches to the RNPP:

Three EAs: non-dominated sorting genetic algorithm II (NSGA-II), strength Pareto evolutionary algorithm 2 (SPEA2), and multiobjective evolutionary algorithm based on decomposition (MOEA/D) [7-9].

Three swarm intelligence algorithms adapted to the MO field by ourselves: multiobjective artificial bee colony (MO-ABC), multiobjective firefly algorithm (MO-FA), and multiobjective gravitational search algorithm (MO-GSA) [10-12].

Two approaches to the trajectory algorithm multiobjective variable neighbourhood algorithm (MO-VNS) [13].

2. Definition of the wireless sensor network model

In this section, we provide a brief description of the WSN model considered in this work. A complete description is found in [14].

Assumptions

The network is composed of three types of static devices: a CN, $\tilde{s_s}$ SNs, and $\tilde{s_r}$ RNs placed on the same 2D-surface without prohibited areas of size $d_x x d_y$.

The SNs are powered by batteries. The RNs and the CN are energy-harvesting devices.

The multi-hop routing protocol is provided by Dijkstra's algorithm for minimum path length, following a single-tiered approach.

Any two devices can be linked if the distance between them is lower than the communication radius r_c and they have enough energy capacity.

All the SNs start with a same initial energy charge. If an SN is exhausted, it cannot be linked again nor capture more data.
The SNs capture information about the environment on a regular basis and with a sensitivity radius r_s.This information is immediately sent to the CN, which is the only connection point of the WSN to the outside.
We suppose a perfect synchronization between devices and the use of an efficient medium access control (MAC) protocol.

Energy expenditure
The energy consumed by the SNs follows the approach proposed by A. Konstantinidis *et al.* in [15], where the energy expenditure is only due to the sending task. This model includes packet loss and relaying.

Sensitivity area
SNs cover circumferences of radius r_s. The sensitivity area at a given time is calculated as the union of all areas, whose sensors are alive, *i.e.* they have enough energy capacity and it exists a path to the CN.

Network lifetime
It is the number of time periods over which a WSN is useful. We assume a coverage threshold method, *i.e.* if the sensitivity area is lower than co_{th}, we consider that the information provided is not enough.

3. Optimization problem formulation
Let f_1 be the AEC of the sensors over the network lifetime, which is given by

$$f_1 = \frac{\sum_{t=1}^{t_n}\left(\sum_{i\in S_s(t)}\frac{Ee_i(t)}{s_s(t)}\right)}{t_n}, \qquad f_1 \in \mathbb{R}^+, \qquad (1)$$

where t_n is the network lifetime, $S_s(t)$is the set of alive sensors at t, $s_s(t)$ is the cardinality of $S_s(t)$, and $Ee_i(t)$ is the energy cost of the sensor $i \in S_s(t)$.
Let $f_2$be the ASAprovided by the WSN given by

$$f_2 = \frac{\sum_{t=1}^{t_n} A(t)}{t_n}, \qquad f_2 \in [0,1], \qquad (2)$$

where $A(t)$is the sensitivity area at time t.
Let $f_3$be the NR, showing the probability that the SNs send information successfully to the CN. That is,

$$f_3 = \sum_{i\in\widetilde{S_s}}\frac{re_i}{\widetilde{s_s}}, \qquad f_3 \in [0,1], \qquad (3)$$

where $\widetilde{S_s}$ is the set of initial SNs (before capturing any data), $\widetilde{s_s}$ is the cardinality of $\widetilde{S_s}$, and re_i is the reliability of the sensor $i \in \widetilde{S_s}$ as defined by B. Deb *et al.* in [16].
We define the bi-objective approach to the RNPP as given a previously-stablished traditional WSN, *i.e.* a CN and $\widetilde{s_s}$ SNs, the objective is to place $\widetilde{s_r}$ RNs to

$$\min(f_1)\ and\ \max(f_2), \qquad (4)$$

subject to

$$\forall r \in \widetilde{S_r}, r = (x,y) : x \in [0,d_x], y \in [0,d_y], \qquad (5)$$

where $\widetilde{S_r}$ is the set of RNs and $\widetilde{s_r}$ is its cardinality.
Similarly, the purpose of the three-objective approach to the RNPP is given by

$$\min(f_1), \max(f_2), and\ \max(f_3), \qquad (6)$$

subject to the constraint in Equation (5).

4. Experimental methodology
The dataset described in Table 1 [17] allows to study the behaviour of the metaheuristics, and is composed of four scenarios where a traditional WSN is deployed, with sizes 50x50, 100x100, 200x200, and 300x300. The CN is placed in the middle of the scenario and the coordinates of the SNs are provided by the dataset. Table 1 includes the tests cases considered for each instance, i.e. the number of RNs studied to optimise the WSN. This value was defined assuming that deploying RNs involves an economic cost.
Two different r_c values are considered to simulate networks with different capabilities, 30 and 60 meters. The values taken by the remainder parameters of the model are described in [14]. We only consider an r_c value of 30 for the three-objective RNPP, because NR does not need to be optimised for a value of 60.

Specific details for implementing and configuring the metaheuristics are included by ourselves in [14,18-23].
The metaheuristics are applied for solving the dataset assuming several stop criteria based on the number of evaluations: 50 000, 100 000, 200 000, 300 000, and 400 000. We perform 31 independent runs for each stop condition, test case, metaheuristic, and optimization problem. The results obtained are analysed by assuming a statistical methodology based on two MO metrics: hypervolume and set coverage.

Table 1. Description of the dataset.

Instance name ($d_x x\ d_y$)	Reference points (f_1, f_2, f_3)		Test cases ($\tilde{s}_r$)
	ideal	nadir	
50x50	(0.02,1.00,1.00)	(0.04,0.60,0.50)	1
100x100	(0.02,1.00,1.00)	(0.10,0.60,0.50)	2,3
200x200	(0.10,1.00,1.00)	(0.30,0.60,0.50)	2,4,6,9
300x300	(0.04,1.00,1.00)	(0.50,0.60,0.50)	6,12,18,24

5. Discussion of the results obtained

Starting with the bi-objective RNPP, Table 2 shows the percentage of test cases, where the metaheuristics are significantly better and worse than others for all the stop conditions and instances.
The first step is to analyse if data follow a normal distribution through Kolmogorov-Smirnov-Lilliefor's and Shapiro-Wilk's tests, assuming the null hypothesis H_0 if data follow a normal distribution. P-values lower than 0.05 were obtained for all the cases. Hence, we cannot assume H_0.
Next, we study if there are significant differences among the algorithms.

Table 2: According to the hypervolume metric and for the bi-objective RNPP, percentage of test cases where the metaheuristics are significantly better and worse for all the test cases and stop conditions.

	A is worse than B								
A \B	NSGA-II	SPEA2	MO-VNS	MO-VNS*	MO-ABC	MO-FA	MO-GSA	MOEA/D	Percentage
A is better than B: NSGA-II	0.00%	0.79%	0.37%	0.10%	0.12%	0.00%	0.14%	0.66%	2.17%
SPEA2	0.74%	0.00%	0.43%	0.19%	0.27%	0.00%	0.31%	0.58%	2.52%
MO-VNS	1.59%	1.43%	0.00%	0.62%	0.68%	0.37%	1.28%	1.20%	7.16%
MO-VNS*	1.82%	1.68%	1.01%	0.00%	0.72%	0.39%	1.37%	1.41%	8.40%
MO-ABC	1.84%	1.82%	1.12%	0.93%	0.00%	0.45%	1.28%	1.45%	8.88%
MO-FA	2.11%	2.07%	1.24%	1.30%	1.12%	0.00%	1.76%	1.90%	11.49%
MO-GSA	1.59%	1.51%	0.68%	0.48%	0.31%	0.00%	0.00%	1.01%	5.57%
MOEA/D	1.20%	1.04%	0.58%	0.39%	0.23%	0.00%	0.37%	0.00%	3.81%
Percentage	10.87%	10.35%	5.42%	4.01%	3.44%	1.20%	6.50%	8.20%	100.00%

Table 3: According to the hypervolume metric and for the three-objective RNPP, percentage of test cases where the metaheuristics are significantly better and worse for all the test cases and stop conditions.

A \B	MOEA/D	MO-FA	MO-VNS*	MO-ABC	NSGA-II	SPEA2	MO-VNS	MO-GSA	Percentage
A is better than B: MOEA/D	0.00%	0.76%	1.20%	1.48%	1.40%	1.52%	1.36%	2.00%	9.74%
MO-FA	0.92%	0.00%	1.56%	1.36%	1.96%	1.72%	1.56%	2.52%	11.62%
MO-VNS*	0.48%	0.28%	0.00%	1.12%	1.12%	0.88%	0.40%	1.12%	5.41%
MO-ABC	0.28%	0.40%	0.76%	0.00%	1.20%	1.20%	0.80%	1.00%	5.65%
NSGA-II	0.24%	0.00%	0.36%	0.76%	0.00%	0.16%	0.04%	1.12%	2.68%
SPEA2	0.32%	0.00%	0.80%	0.92%	1.28%	0.00%	0.40%	1.16%	4.89%
MO-VNS	0.48%	0.32%	0.76%	1.16%	1.40%	0.92%	0.00%	1.32%	6.37%
MO-GSA	0.00%	0.28%	0.60%	0.84%	0.80%	0.64%	0.48%	0.00%	3.65%
Percentage	2.72%	2.04%	6.05%	7.65%	9.17%	7.05%	5.05%	10.26%	100.00%

To this end, as data do not follow a normal distribution and samples are independent, we consider Wilcoxon-Mann-Whitney's test with null hypothesis $H_0 \overline{Hyp_i} \leq \overline{Hyp_j}$, assuming i=1, 2, ..., 8, j=2, 3, ..., 8, i<j, 1=MO-FA, 2=MO-ABC, 3=MO-VNS, 4=MO-VNS*, 5=SPEA2, 6=NSGA-II, 7=MOEA/D, and 8=MO-GSA, where $\overline{Hyp_i}$ is the median hypervolume of the algorithm i for a given test case and stop condition.
We see in Table 2 that the swarm intelligence algorithm MO-FA provides the best significant behaviour, followed by MO-ABC and MO-VNS.
Table 3 shows the same study for the three-objective approach to the RNPP. In this case, we note that MO-FA is again the algorithm providing the best average behaviour, followed by MOEA/D and MO-VNS.
As stated before, we also consider the set coverage metric as a checking procedure. We analysed the results by considering this MO metric, getting the same conclusions as for hypervolume.

6. Conclusions

In this work we studied how to deploy RNs in traditional static WSNs by assuming a wide range of MO metaheuristics, while considering two approaches to the RNPP: two objectives *vs.* three objectives. All the metaheuristics were applied for solving the same data set, reaching that the swarm intelligence algorithm MO-FA provides the best average behaviour for the two approaches. This means that MO-FA is a robust algorithm for solving this optimisation problem.

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How to Efficiently Deploy Applications in WSNs Using Distributed Approaches

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1. Introduction

The increase in computation and sensing capabilities of commercially available Wireless Sensors Network (WSN) nodes has evolved them into complex systems that can gather information about the monitored environment and make prompt and intelligent decisions, becoming important components of the Internet of Things (IoT) [1]. However, the deployment of WSNs is still limited by their scarce resources, in particular node lifetime. In fact, WSN nodes are typically battery powered, and this severely restricts their lifetime to the duration of their battery, which replacement might be even impossible (e.g. underground or underwater nodes). Many efforts have been made so as to extend network lifetime, one of which is the development of algorithms that effectively assign execution tasks to network nodes with an eye to energy consumption.

One method to perform task assignment is the use of a *central controller* that divides large application programs into smaller and easily executable tasks and then distributes these tasks to nodes. For instance, in [2] a centralized solution for the maximization of the WSN lifetime is proposed. In [3][4][5], centralized algorithms for both reducing network energy consumption and application execution time are proposed. The main issues related to centralized algorithms are: scalability, frequent collection of updates from nodes, limit adaptability.

Due to these drawbacks, *distributed* solutions have recently been proposed to perform task allocation in WSNs [6][7][8]. Distributed algorithms reduce the problem complexity, as only local areas are considered rather than the whole network. They also reduce the communication overhead caused by data exchanges between network nodes and central controller.

In this letter we discuss how two distributed algorithms cope with the problem of extending network lifetime in WSNs: the former, called DLMA, is based on gossip; the latter, called TAN, is based on game theory. TAN also introduces a multi-objective approach that allows to enhance other constraints, e.g. task completion time.

2. Problem formulation

Before proceeding with the description of the algorithms, the scenario and the parameters and variables that intervene in the network dynamics need to be defined. In this section we introduce a model that characterizes the network nodes, the tasks in which the application assigned to the WSN is subdivided, and the energy consumption dynamics.

Network model.

The WSN is modeled as a Directed Acyclic Graph (DAG) $\mathcal{G}_X = (X, \boldsymbol{E}_X)$, where the vertices represent the nodes $X = \{i\}^N$, while the links are described by the set of edges $\boldsymbol{E}_X = \left(e_{ij}^X\right)$, where each edge represents a connection from node i to node j. Node i can be a sensing node, a router or an actuator (or a node with a combination of these roles). The network is considered to have only one sink, referred to as node 1.

The neighborhood of node i is defined as the set of nodes that share a communication channel with node i. We define the set of out-neighbors, i.e. nodes that receive information from node i, as $\mathcal{N}_i^{out} = \{j \in X: (i,j) \in E_X\}$. We further define the set of in-neighbors, i.e. nodes that send information to node i to reach the sink, as $\mathcal{N}_i^{in} = \{j \in X: (j,i) \in E_X\}$. These two sets are defined with respect to the flowing of data from the sensors toward the sink.

Application model.

The application to be deployed in the network can be decomposed into a sequence of distributed tasks. This application could represent diverse operations, such as: computing the average of the temperature in a given geographical area, measuring the light intensity in a room, video-surveillance of a specific geographical area, or a combination of these.

In an application, the relations among tasks are described by a Directed Graph (DG) $\mathcal{G}_T = \{T, \boldsymbol{E}_T\}$, where $T = \{t\}$ is the sequence of tasks in which the application can be subdivided, while $\boldsymbol{E}_T = (e_{uv}^T)$ is the set of edges e_{uv} representing a unidirectional data transfer from task u to task v.

Tasks can be either sensing or processing tasks. If a processing task is performed directly on a sensor node before being transmitted, the number of bits to be sent, and thus the related transmission energy consumption, decreases; however, processing energy consumption could increase. It is then necessary to understand which combination of

assignment of tasks to network nodes is more efficient in terms of reduction of node battery consumption, i.e. increment in network lifetime.
We define a binary state vector $\boldsymbol{s}_i = \{s_{ik}\}$, representing the tasks currently assigned to node i. To each configuration of the node setting corresponds different energy consumption. The algorithms described further take a high-level request as input, evaluate which matrix of statuses $\boldsymbol{S} = \{\boldsymbol{s}_1, \dots, \boldsymbol{s}_i, \dots, \boldsymbol{s}_N\}$ permits the application to be performed with the highest possible lifetime τ, and finally assigns to the nodes the most appropriate tasks to be performed. Hence, it is evident that τ will vary depending on the status of each node, that is, how the tasks are assigned to network nodes. The problem addressed is then defined as the set of statuses $\boldsymbol{S}$ that minimizes the impact of the application on the network lifetime τ.

Network lifetime model.
The problem addressed in this letter is that of extending the *network lifetime* τ, intended as the time until at least one node has exhausted its residual energy [9]. The lifetime $\tau_i(t)$ of node i at time t is then defined as the ratio between its residual battery charge E_i^{res} and the sum of all the power consumption contributions related to its activities:

$$\tau_i(t) = E_i^{res} / \sum_k \left(E_{ik} f_{ik}(t) s_{ik}(t)\right)$$

where E_{ik} is the energy consumed by task k, and $f_{ik}(t)$ is the frequency at which node i performs task k at time t. We distinguish three main energy consumption contributions: the energy e_{ik}^{sens}spent by node $i$to perform sensing task k, the energy e_{ik}^{proc} spent by node i to perform a processing task k, and the energy per bit e_{ik}^{tx} spent to send data from node i to the adjacent nodes due to task k. We can then define E_{ik} as

$$E_{ik} = e_{ik}^{sens} + e_{ik}^{proc} + e_{ik}^{tx}$$

More details about the network lifetime model can be found in [7].

3. The distributed task assignment algorithms.
In next two subsections we present two alternative methods, based on ether gossiping or game theory.

Gossip-based distributed task assignment.
In this distributed task assignment algorithm, a communication scheme based on gossip [10] is adopted. The aim of the proposed solution is to find the matrix of statuses $\boldsymbol{S}$ that maximizes the lifetime τ, by iteratively and asynchronously solving an equivalent local optimization problem that involves at each iteration only node *i* and its in-neighbors $\mathcal{N}_i^{in}$. While network lifetime is locally minimized, attention has to be paid so that the traffic flow coming from node i to its out-neighbors $\mathcal{N}_i^{out}$does not increase after the optimization. In fact, this would entail that data to be processed by the following nodes increases, and thus their lifetime might decrease. We define the traffic flow received by node *i* as $\boldsymbol{\Theta}_i^{in}$, over which it performs the tasks corresponding to its assigned status $\boldsymbol{s}_i$. The effect of this task is the generation of the output traffic $\boldsymbol{\Theta}_i^{out} = (\theta_{ih}^{out})$, where $\theta_{ih}^{out} = \{k_{ih}^{out}, f_{ih}^{out}\}$ corresponds to a traffic flow where each sample of k_{ih}^{out} bits is transmitted at the frequency f_{ih}^{out}. The output traffic flow is computed by function *p* as follows

$$\boldsymbol{\Theta}_i^{out} = p\left(\boldsymbol{\Theta}_i^{in}, s_i\right)$$

The output traffic is then sent to the next node towards the sink, according to adjacency matrix $\boldsymbol{E}_X$.
The proposed method involves two decentralized algorithms. First, Algorithm 1, called **Mininum Lifetime Estimation** (MLE) algorithm, is used to spread information about the current minimum node lifetime in the network. It consists in a broadcast message that is updated every time it is retransmitted by the nodes, until all the nodes in the network receive at least one of these messages. Whenever a node i receives an estimation update $x_j(t_k)$ by an out-neighbor $j \in \mathcal{N}_i^{out}$, it updates its own minimum lifetime estimation $x_i(t_k + 1)$ according to $x_i(t_k + 1) = min\{\tau_i, x_j(t_k)\}$. By the execution of this algorithm, each node estimates what the minimum node lifetime is in the set of nodes included in all the paths between itself and the sink.
Second, Algorithm 2, called **Decentralised Lifetime Maximisation Algorithm** (DLMA), executes an iterative local optimization between neighboring nodes exploiting information only locally available, to locally reassign the tasks to the nodes. The DLMA consists in a local state update rule applied by nodes whenever they are triggered by the system. It is based on the local maximization of network lifetime,
The algorithm can be summarized as follows:
Node *i*, with a current processing state $\bar{\boldsymbol{s}}_i$ and current output traffic flow $\bar{\boldsymbol{\Theta}}_i^{out}$, enquires the state $\bar{\boldsymbol{s}}_j$ and current input traffic $\bar{\boldsymbol{\Theta}}_j^{in}$ to all its in-neighbors $j \in \mathcal{N}_i^{in}$;

If $\tau_i > \min_{j \in \mathcal{N}_i^{in}} \tau_j$, then node i finds the matrix of the statuses $\{\boldsymbol{s}_i, \boldsymbol{s}_j \ \forall j \in \mathcal{N}_i^{in}\}$ that maximizes the lifetime of itself and its neighbors, provided that this does not affect the following nodes in the path to the sink, i.e. $\boldsymbol{\Theta}_i^{out} \leq \overline{\boldsymbol{\Theta}}_i^{out}$;
If $\tau_i > x_i$, i.e. if node i's lifetime is higher than that of the following nodes, then node i finds the matrix of the statuses $\{\boldsymbol{s}_i, \boldsymbol{s}_j \ \forall j \in \mathcal{N}_i^{in}\}$that minimizes the output data flow, provided that the lifetime of its in-neighbors is not affected.
As proven in [7], this algorithm monotonically increases network lifetime, thus maximizing its value.

Game theory-based distributed task assignment.
The algorithm proposed in this Section, named **Task Allocation Negotiation** (TAN) algorithm, aims not only to improve the existing algorithms performance reducing computational complexity, but it is also a multi-objective algorithm, reducing both network energy consumption and application execution time. The major contribution is the adoption of the rules of non-cooperative game theory. Sensor nodes negotiate among each other while setting the application configuration. In doing so, each node aims at maximizing its own utility in a rational way. Therefore, a status $\boldsymbol{s}_i^*$, is preferred to a status $\boldsymbol{s}_i$ if and only if its utility $u_i(\boldsymbol{s}_i^*)$ is higher than utility $u_i(\boldsymbol{s}_i)$. The vector of status of a node $\boldsymbol{s}_i$ is called its strategy.
We define the *task utility function* associated to task k

$$u_k(\boldsymbol{S}) = \max_i \left\{ \left[\Omega_t(i,k) + \frac{\alpha}{NF(k)} \cdot \Omega_\tau(i,k,\boldsymbol{S}) \right] \cdot s_{ik} \right\}$$

where:
$\Omega_t(i,k) = \frac{t_d(k) - t_c(i,k)}{t_d(k)}$ is the *task completion time component* of task k when it is performed by node i, with $t_d(k)$ deadline for successfully completing task k and $t_c(i,k)$ completion time if task k is performed by node i;
$\Omega_\tau(i,k,\boldsymbol{S}) = F_p\left(e_{ik}^{proc}\right) + F_{tx}(e_{ik}^{tx}, \boldsymbol{S})$is the *network lifetime component* when task k is performed by node i according to strategy $\boldsymbol{S}$, with $F_p\left(e_{ik}^{proc}\right)$ component related to the change in network lifetime due to the processing cost needed to perform task k in node i, and $F_{tx}(e_{ik}^{tx}, \boldsymbol{S})$ component related to the change in network lifetime due to the transmission of the necessary data for task k to node i (for more details refer to [8]);
$NF(k)$ is a normalization factor that eliminates the difference in magnitude between Ω_t and Ω_τ;
$\alpha > 0$ is a weighting factor.
The maximum operation ensures that the task can only be assigned to the node that maximizes the utility function $u_k(\boldsymbol{S})$: since the goal of the game is to maximize $u_k(\boldsymbol{S})$, only the node that ensures the best outcome will be chosen for task k.
Therefore, we can define the *node utility function* $u_i(\boldsymbol{s}_i)$ as an aggregation of the *marginal* contributions $u_k^{mar}(\boldsymbol{s}_i)$ of node i to each task k

$$u_i(\boldsymbol{s}_i) = \sum_k u_k^{mar}(\boldsymbol{s}_i)$$

where $u_k^{mar}(\boldsymbol{s}_i)$ is the difference between the task utility for a given node strategy $\boldsymbol{s}_i$ and the task utility for the null strategy $\boldsymbol{s}_i^0$, in which the node is not contributing to any task $u_k^{mar}(\boldsymbol{s}_i) = u_k(\boldsymbol{s}_i) - u_k(\boldsymbol{s}_i^0)$.
Since the global utility for the whole network, i.e. the *network utility*, is expressed as

$$u_g(\boldsymbol{S}) = \sum_k u_k(\boldsymbol{S})$$

it is possible to infer that a change in node i's strategy $\boldsymbol{s}_i$ that increases its utility, entails the same increment in the network utility. This property is particularly desirable because it implies that the game under consideration is a *potential game*, where the potential function is given by the network utility function. Potential games have the *Finite Improvement Property*: every sequence of changes in the strategy that improves the network utility converges to a Nash equilibrium in finite time. This property ensures that many simple adaptive processes, such as the Distributed Stochastic Algorithm (DSA) [11], converge to Nash equilibria.

4. Performance evaluation.
In this Section, we show the effectiveness of the two distributed algorithms presented, by applying them to a realistic smart city scenario where nodes have been positioned along the streets as shown in Figure 1.

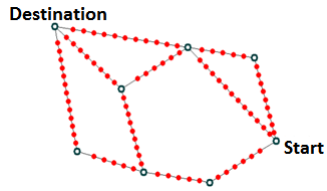

Figure 1. Test network topology

All solid markers represent nodes equipped with sensors for speed measurement of the vehicles passing through. Empty markers are more capable nodes which do not perform any sensing task, but can perform more complex processing operations. The assigned application consists in a driver, placed in the Start point, which would like to know which is the fastest way to reach Destination, based on the speed information collected by sensor nodes. The detailed parameters are shown in [7][8].

The described scenario has been simulated, and the performance of the proposed algorithms in terms of energy consumption and completion time have been compared with two alternative approaches:

all the data sent to the sink and processed only by the sink, that is the Start node (mechanism S);

data processed according to the centralized algorithm described in [2] (mechanism CO).

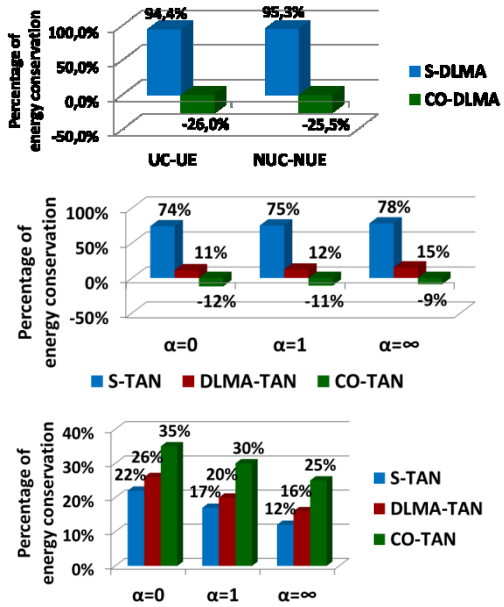

Figure 2. Percentage values of mean energy conservation and completion time gain

Figure 2 shows the percentage of energy conservation and completion time gained when using TAN and DLMA with respect to the alternative approaches. These comparisons are referred to as S-DLMA, CO-DLMA, S-TAN, CO-TAN and DLMA-TAN.

Simulations have been run for: $\alpha = 0$ (null network lifetime component); $\alpha = 1$ (comparable Ω_t and Ω_τ); $\alpha = \infty$ (null task completion time component).

A marked improvement of energy conservation and a good improvement in completion time gain is observed with respect to the static S mechanism. TAN outperforms DLMA both for energy conservation and completion time gain. Of course, good results could not be expected for energy conservation in comparisons CO-DLMA and CO-TAN, but a marked improvement in completion time gain is observed, mainly due to the fact that centralized algorithm is more complex and needs more time to be accomplished.

As expected, when α increases, which means that the utility function is more and more over-balanced in favor of its network lifetime component, the energy conservation percentage increases, while the completion time gain decreases; on the contrary, when α decreases, the utility function is over-balanced in favor of its task completion time component: the energy conservation percentage decreases, while the completion time gain increases.

5. Conclusion

In this paper we presented the benefits of using distributed algorithms to maximize network lifetime in WSNs, with respect to using static mechanisms (in particular sending all data to a sink which processes them) and centralized

algorithms. We proved through simulations that distributed algorithms can be used not only to improve lifetime, but also to enhance other performance, such as reducing task completion time.

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Optimization of Information Neighbors for Energy-constrained Diffusion

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1. Introduction

Distributed estimation is of increaisng interest to a broad range of applications. Several distributed solutions have been developed for this purpose, such as consensus strategies, incremental strategies, and diffusion strategies [1]. The diffusion strategies are particularly attractive because they are scalable, robust, fully-distributed, and endow networks with real-time adaptation and learning abilities. They have superior stability ranges and transient performance compared to the consensus strategies when continuous adaptation is required under varying network conditions [2].

In each iteration of a diffusion strategy, each node obtains intermediate parameter estimates from its neighbors, which are those nodes within communication range of itself [1, 3]. We call these neighboring nodes the *physical neighbors* of the node. The communication cost per iteration of each node in a static network is thus fixed, and the total communication cost can be large if the diffusion algorithm converges slowly. On the other hand, when designing or upgrading a cooperative sensor network, the existing diffusion strategies are unable to account for predefined node energy budgets even though they are more energy-efficient overall. This prevents energy efficiency planning even if we have knowledge about the network operating environment. Moreover, as the available strategies only allow a node to exchange information with its physical neighbors, this limits the estimation performance that a network can achieve.

In this letter, we consider diffusion estimation with local and network-wide energy budgets per iteration. We generalize the concept of single-hop diffusion from physical neighbors to multi-hop diffusion from a set of *information neighbors*. We propose a multi-hop version of the adpat-then-combine (ATC) diffusion algorithm, which we call mATC. We apply mATC to handle the distributed estimation problem with communication energy budget constraints. We provide a rule to select the combination weights for mATC that optimizes an approximate trade-off between the convergence rate of the algorithm and the steady-state network MSD. We also show how to select information neighbors to approximately minimize an upper bound of the steady-state network MSD in two network classes: simple networks with a unique transmission path from one node to another, and arbitrary networks utilizing diffusion consultations over at most two hops.

This letter highlights our recent work [4, 5] on multi-hop and energy-constrained diffusion adaptation over networks. We have also made additional contributions to other problems of distributed estimation in [6, 7].

2. Multi-hop Diffusion LMS

Consider a network represented by a directed graph $\mathrm{G}=(\mathrm{N},\mathrm{E})$, where $\mathrm{N}=\{1,2,...,N\}$ is the set of nodes, and E is the set of communication links between nodes. Node l is a *physical neighbor* of node k if either $(l,k)\in\mathrm{E}$ or $l=k$, and is within the *multi-hop neighborhood* of node k if there is a path in G from node l to node k. Let the physical neighborhood of node k be $\mathrm{N}_{k\leftarrow}$, and its multi-hop neighborhood be $\overline{\mathrm{N}}_{k\leftarrow}$. Node l is within the *reachable neighborhood* of node $k\neq l$ if there is a path in G from node k to node l. Node l is directly reachable from node k if $(k,l)\in\mathrm{E}$. Let $\mathrm{N}_{k\rightarrow}$ be the set of directly reachable neighbors of node k, and $\overline{\mathrm{N}}_{k\rightarrow}$ be the reachable neighborhood of node k. We have $\mathrm{N}_{k\rightarrow}\subseteq\overline{\mathrm{N}}_{k\rightarrow}$. The various types of neighbors are illustrated in Figure 8.

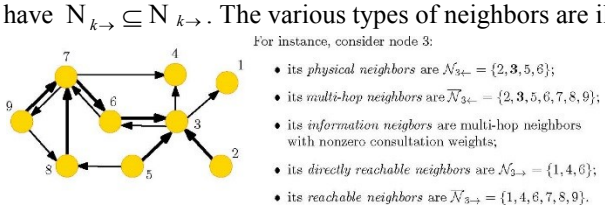


Figure 8. The different types of neighbors of a node.

At every iteration i, each node k is able to observe realizations $\{d_k(i), u_{k,i}\}$ of a scalar random process $\mathbf{d}_k(i)$ and a $1\times M$ vector random process $\mathbf{u}_{k,i}$ with a positive definite covariance matrix, $R_{u,k} = \mathrm{E}\mathbf{u}_{k,i}^*\mathbf{u}_{k,i} \succ$. The random processes $\{d_k(i), u_{k,i}\}$ are related via the linear regression model:

$$\mathbf{d}_k(i) = \mathbf{u}_{k,i}\omega^o + \mathbf{v}_k(i),$$

where ω^o is an $M\times 1$ parameter to be estimated, and $\mathbf{v}_k(i)$ is measurement noise with variance $\sigma_{v,k}^2$, and assumed to be temporally white and spatially independent, i.e.,

$$\mathrm{E}\mathbf{v}_k^*(i)\mathbf{v}_l(j) = \sigma_{v,k}^2\delta_{kl}\delta_{ij},$$

where δ_{kl} is the Kronecker delta function. The regression data $\mathbf{u}_{k,i}$ are likewise assumed to be temporally white and spatially independent. The noise $\mathbf{v}_k(i)$ and the regressors $\mathbf{u}_{l,j}$ are assumed to be independent of each other for all $\{k,l,i,j\}$. All random processes are assumed to be zero mean.

The network aims to estimate ω^o in a distributed and iterative way subject to certain energy constraints. During the estimation process, the energy cost of node k per iteration consists of sensing cost, computing cost and communication cost. The communication cost depends on the information that is disseminated or relayed by a node in every iteration and forms the major cost incurred. For simplicity, we ignore the sensing and computing costs and use the terms "energy cost" and "communication cost" interchangeably. Denote the communication cost per iteration of a node k as c_k^{cm}. The nodes estimate ω^o by solving a constrained least mean-squares (LMS) problem:

$$\begin{aligned} &\text{(P0)} \qquad \min_{\omega} \sum_{k\in\mathrm{N}} \mathrm{E}\,|\mathbf{d}_k(i) - \mathbf{u}_{k,i}\omega|^2 \\ &\text{s.t.,} \qquad c_k^{cm} \le c_k, \forall k \in \mathrm{N}, \text{ and } \sum_{k\in\mathrm{N}} c_k^{cm} \le c, \end{aligned} \qquad (1)$$

where c_k and c are the node- and network-wide energy budgets imposed in each iteration, respectively.

To solve (P0) in a distirubted manner, we extend the one-hop ATC diffusion strategy [3] by allowing a node to consult nodes in its multi-hop neighborhood. The resulting mATC strategy uses the following update equations,

$$\begin{aligned} \mathrm{y}_{k,i} &= \omega_{k,i-1} + \mu_k\mathbf{u}_{k,i}^*[\mathbf{d}_k(i) - \mathbf{u}_{k,i}\mathrm{w}_{k,i-1}], \\ \mathrm{w}_{k,i} &= \sum_{l\in\overline{\mathrm{N}}_{k\leftarrow}} a_{lk}\mathrm{y}_{l,i}, \end{aligned} \qquad (2)$$

where the combination weights satisfy

$$a_{lk} \ge 0, A^T\mathbf{1}_N = \mathbf{1}_N, \text{and } a_{lk} = 0 \text{ if } l \notin \overline{\mathrm{N}}_{k\leftarrow}. \qquad (3)$$

The only difference between mATC and ATC is in the combination step: the node k consults its multi-hop neighbors $\overline{\mathrm{N}}_{k\leftarrow}$, which include the physical neighbors $\mathrm{N}_{k\leftarrow}$ as a subset. If $a_{lk} > 0$, we say that node l is an *information neighbor* of node k (cf. Figure 8).

Define the following matrices:

$$\mathrm{A} \triangleq A \otimes I_M,\ \mathrm{M} \triangleq \mathrm{diag}\{\mu_1 I_M, \mu_2 I_M, \ldots, \mu_N I_M\},$$

$$\mathrm{R} \triangleq \mathrm{E}\,\mathrm{diag}\{\mathbf{u}_{1,i}^*\mathbf{u}_{1,i}, \mathbf{u}_{2,i}^*\mathbf{u}_{2,i}, \ldots, \mathbf{u}_{N,i}^*\mathbf{u}_{N,i}\},$$

$$\mathrm{B} \triangleq \mathrm{A}^T(I_{NM} - \mathrm{M}\,\mathrm{R}),\ \mathrm{Y} \triangleq \mathrm{A}^T\mathrm{M}\,\mathrm{SM}\,\mathrm{A},$$

$$\mathrm{S} \triangleq \mathrm{diag}\{\sigma_{v,1}^2 R_{u,1}, \sigma_{v,2}^2 R_{u,2}, \ldots, \sigma_{v,N}^2 R_{u,N}\}.$$

The steady-state network MSD can then be derived to the first order of the step size $\{\mu_k\}$, as

$$\mathrm{MSD}_\infty = \frac{1}{N}\sum_{j=0}^{\infty}\mathrm{Tr}\left(\mathrm{B}^j\mathrm{Y}\mathrm{B}^{*j}\right). \qquad (4)$$

It is essentially dependent on the combination matrix A.

3. Selecting the Combination Weights

Let $\overline{\mathrm{N}}'_{k\leftarrow}$ be an arbitrary set of information neighbors selected for node k. We seek for an analytical solution of the combination weight matrix A that *approximately* minimizes an *upper bound* of the steady-state network MSD. The approximate optimization is derived as:

$$\min_{A} \quad \alpha \mathrm{Tr}(\mathrm{Y}) + (1-\alpha)\mathrm{Tr}(\mathrm{BB}^*)$$

$$\text{s.t.} \quad a_{lk} \geq 0, A^T \mathbf{1}_N = \mathbf{1}_N, \text{and } a_{lk} = 0 \text{ if } l \notin \overline{\mathrm{N}}'_{k\leftarrow}, \qquad (5)$$

where $\alpha \in [0,1]$ is a tunable scalar. This yields the following solution for the combination weights:

$$a_{lk} = \begin{cases} \gamma_l^{-2} \Big/ \sum_{j \in \overline{\mathrm{N}}'_{k\leftarrow}} \gamma_j^{-2}, & \text{if } l \in \overline{\mathrm{N}}'_{k\leftarrow}, \\ 0, & \text{otherwise}, \end{cases} \qquad (6)$$

where the composite variance γ_l^2 is defined by

$$\gamma_l^2 @ \alpha \mu_l^2 \cdot \sigma_{v,l}^2 \cdot \mathrm{Tr}(R_{u,l}) + (1-\alpha)\mathrm{Tr}\left((I_M - \mu_l R_{u,l})^2\right). \qquad (7)$$

We call the closed-form solution of the combination weights given in (6) as the "balancing rule", since it optimizes a trade-off between the diffusion convergence rate (measured through $\mathrm{Tr}(\mathrm{BB}^*)$), and the steady-state network MSD (measured through $\mathrm{Tr}(\mathrm{Y})$). The trade-off can be tuned by varying the coefficient α within the range of [0,1].

4. Selecting the Information Neighbors

With the combination weights given in (6), the cost function in (5) simplifies and problem (P0) is approximated by using this simpler cost function:

$$\text{(P1)} \quad \min_{\{\overline{\mathrm{N}}'_{k\leftarrow} : \overline{\mathrm{N}}'_{k\leftarrow} \subseteq \overline{\mathrm{N}}_{k\leftarrow}\}_{k\in\mathrm{N}}} \sum_{k\in\mathrm{N}} \frac{1}{\sum_{l\in\overline{\mathrm{N}}'_{k\leftarrow}} \gamma_l^{-2}}$$

$$\text{s.t., } c_k^{cm} \leq c_k, \forall k \in \mathrm{N}, \text{ and } \sum_{k\in\mathrm{N}} c_k^{cm} \leq c.$$

The communication cost per iteration of node k (c_k^{cm}) depends on its multi-hop neighbors and reachable neighbors since it may be required to relay estimates from its multi-hop neighbors to its reachable neighbors.

Problem (P1) is tractable under two assumptions in the next two cases, which are treated separately later on:

- Case 1 (Simple topology): For any pair of nodes, there is at most one directed simple path connecting them.
- Case 2 (Two-hop consultations): The network has an arbitrary topology but the information neighbors of every node are restricted to be within two hops away.

Assumption 1. *Every broadcast conveys information from a single node, and incurs a communication cost (which may be different for different nodes). All nodes having the broadcast node as a physical neighbor receives the information being broadcast.*

Assumption 2. *At every iteration, each node relays the same piece of information at most once.*

We introduce selection variables $\delta_{lk} \in \{0,1\}$, for all $l \in \overline{\mathrm{N}}_{k\leftarrow}$ and $k \in \mathrm{N}$, where $\delta_{lk} = 1$ if and only if node l is selected to be an information neighbor of node k. We also introduce relay variables $\pi_{lk} \in \{0,1\}$, for all $l \in \overline{\mathrm{N}}_{k\leftarrow}$ and $k \in \mathrm{N}$, where $\pi_{lk} = 1$ if and only if node k relays the information originating from node l.

In Case 1, (P1) can be reformulated into and hence solved from the following MILP:

$$\text{(P2)} \quad \min \sum_{k\in\mathrm{N}} z_k \qquad \text{s.t.} \sum_{l\in\overline{\mathrm{N}}_{k\leftarrow}} \gamma_l^{-2} p_{lk} = 1, \forall k \in \mathrm{N} \qquad (8)$$

$$p_{lk} \leq \overline{z}_k \delta_{lk} \text{ and } p_{lk} \geq \underline{z}_k \delta_{lk}, \forall l \in \overline{\mathrm{N}}_{k\leftarrow}, k \in \mathrm{N} \quad (9)$$

$$p_{lk} \geq z_k + \overline{z}_k(\delta_{lk} - 1), \forall l \in \overline{\mathrm{N}}_{k\leftarrow}, k \in \mathrm{N} \qquad (10)$$

$$p_{lk} \le z_k + \underline{z}_k(\delta_{lk} - 1), \forall l \in \overline{\mathrm{N}}_{k\leftarrow}, k \in \mathrm{N} \qquad (11)$$

$$\pi_{lk} \le \sum_{j \in \overline{\mathrm{N}}_{l\rightarrow} \setminus \{k\}} \eta_{lj,k}\delta_{lj} \le |\overline{\mathrm{N}}_{l\rightarrow}| \pi_{lk}, \forall l \in \overline{\mathrm{N}}_{k\leftarrow}, k \in \mathrm{N} \qquad (12)$$

$$\sum_{l \in \overline{\mathrm{N}}_{k\leftarrow}} c_k^{cm,0}\pi_{lk} \le c_k, \forall k \in \mathrm{N}, \text{ and } \sum_{k \in \mathrm{N}} \sum_{l \in \overline{\mathrm{N}}_{k\leftarrow}} c_k^{cm,0}\pi_{lk} \le c, \qquad (13)$$

$$\delta_{lk}, \pi_{lk} \in \{0,1\} \text{ and } z_k, p_{lk} \in \mathrm{R}_{\ge 0}, \ \forall l \in \overline{\mathrm{N}}_{k\leftarrow}, k \in \mathrm{N} \qquad (14)$$

Constraints (8)-(11) arise from the linearization of the nonlinear objective of (P1). Constraint (12) describes the relation between the relay and the selection variables. Constraint (13) characterizes the energy costs and their budgets for each single iteration.

In Case 2, we denote the set of neighbors of node k within two hops away as $\overline{\mathrm{N}}^2_{k\leftarrow}$. We use P_k to denote the set of physical neighbors of node k that have reachable neighbors who may need node k to relay information to. They are called the *relay customers* of node k. On the other hand, suppose that $k \to l \to m$ is a directed path so that node m is reachable but not directly reachable from node k. Then, node l is called a *relay server* of node k. Let P^k denote the set of relay servers of node k. We have

$$\mathrm{P}_k = \{k\} \cup \{l \in \mathrm{N}_{k\leftarrow} : \mathrm{N}_{k\rightarrow} \text{Ú} \mathrm{N}_{l\rightarrow}\} \subseteq \mathrm{N}_{k\leftarrow},$$

$$\mathrm{P}^k = \{l \in \mathrm{N}_{k\rightarrow} : \mathrm{N}_{l\rightarrow} \text{Ú} \mathrm{N}_{k\rightarrow}\} \subseteq \mathrm{N}_{k\rightarrow}.$$

The solution for (P1) is then obtained from (P3), which is a modification of (P2): The constraints (12) are replaced with the following ones

$$\delta_{lk} \le \pi_{ll}, \forall l \in \overline{\mathrm{N}}^2_{k\leftarrow} \setminus \{k\}, k \in \mathrm{N}, \qquad (15)$$

$$\delta_{lk} \le \sum_{j \in \mathrm{P}^l \cap \mathrm{N}_{k\leftarrow} \setminus \{k\}} \pi_{lj}, \forall l \in \overline{\mathrm{N}}^2_{k\leftarrow} \setminus \mathrm{N}_{k\leftarrow}, k \in \mathrm{N}, \qquad (16)$$

and the information neighbor set $\overline{\mathrm{N}}_{k\leftarrow}$ is replaced with $\overline{\mathrm{N}}^2_{k\leftarrow}$ everywhere, and furthermore, the relay variables π_{lk} are defined only for all $l \in \mathrm{P}_k, k \in \mathrm{N}$.

Problems (P3) and (P2) have the following useful property, from which a distributed and adaptive algorithm can be developed to select information neighbors and determine the associated combination weights for each node. Refer to [4] for details.

Lemma 1 *Given a feasible solution of (P2) or (P3), a better solution can be obtained if more information neighbors can be included without violating the energy budgets specified in (13).*

5. Simulation Results

We randomly generated an undirected network with 20 nodes within a 10×10 square area. The data power $\mathrm{Tr}(R_{u,k})$ is equally distributed over the parameter components of each node k. The communication cost incurred is assumed to be equal to the square distance of a node to its farthest directly reachable neighbor. The numerical results are averaged over 1000 instances.

Figure 9 shows the energy-performance trade-off when the mATC diffusion strategy adopts the balancing rule given in (17). We observe that the steady-sate network MSD decreases almost monotonically with the energy budget, while the convergence rate of the network MSD first increases as cooperation is enabled, and then fluctuates and becomes steady as more energy budget is available. The corresponding changes in the information neighbor configuration are illustrated in Figure 10.(a)-(d). We observe that the performance gain becomes very small if the energy budget is large enough, and that the mATC diffusion strategy outperforms the ATC strategy because of the ability to optimize the selection of information neigbhors within the two-hop instead of single-hop neighborhoods.

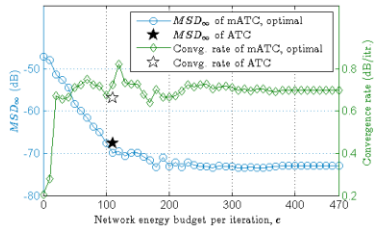
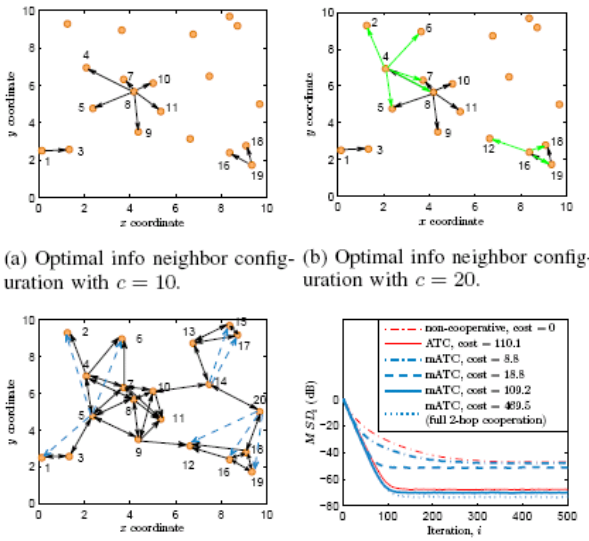


Figure 9. The energy-performance trade-offs and convergence rates of mATC and ATC strategies.



(a) Optimal info neighbor configuration with $c = 10$.

(b) Optimal info neighbor configuration with $c = 20$.

(c) Optimal info neighbor configuration with $c = 110$.

(d) Network MSD curves for different energy costs.

Figure 10. Three optimal configurations of information neighbors and related network MSD curves obtained from simulations. The arrows in (a)–(c) indicate the diffusion directions. The thicker green arrows in (b) indicate new diffusions relative to those in (a), and the light blue dashed arrows in (c) represent two-hop diffusions.

6. Conclusion

We have considered the use of multi-hop diffusion that allows nodes to exchange intermediate parameter estimates with their selected information neighbors instead of just the physical neighbors. For two classes of networks, we propose an MILP to select the information neighbors together with the relay nodes for each node, which approximately optimizes a trade-off between the available energy budgets for each iteration, and the steady-state network MSD performance. For arbitrary networks in which there are only local energy budget constraints, and consultations constrained to within a fixed number of hops, a distributed and adaptive algorithm can also be developed to select the information neighbors [4]. Simulation results suggest that our proposed methods achieve better MSD performance than the traditional diffusion strategy, while having the same or lower communication cost.

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