Cooperative Sensor Relocation in a Mobile Sensor Network by Distributed Subgradient Algorithm

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***Abstract*—Collaborative sensor relocation has potential to improve Mobile Sensor Network (MSN) performance while prolonging its life span by conserving sensor battery energy. However, lack of centralized control, variety of performance criteria, numerous uncertainties, and a possibility of sensor trapping in sub-optimal positions make collaborative sensor relocation an exceedingly challenging problem. Assuming that the sensing and communication operations are optimized much faster than sensors relocate, this paper proposes a sensor relocation strategy based on iterations of a Distributed Subgradient Projection Algorithm (DSPA). While maintaining inherently distributed nature of the computations, DSPA-based sensor relocation is capable of aligning sensor mobility with the overall MSN goals. This approach also accounts for a possibility of abrupt topology changes as sensors relocate.**

Keywords—mobile sensor network, controlled mobility, distributed subgradient algorithm.

I. INTRODUCTION

Mobile Sensor Networks (MSN) are envisioned to offer a novel set of applications in detecting, monitoring and tracking people, targets or events in pervasive computing environments [1]. Locations of sensors in a MSN affect both their ability to acquire information on the intended target(s) and event(s) as well as their ability to communicate this information to the intended recipient(s). The information acquisition needs, which require proximity to the target(s), often compete with the communication needs, which require proximity to the recipient(s) of the sensor information. Inherent traits of MSN such as lack of centralized control, variety of performance criteria, operational uncertainties, and possibilities of MSN topology change and sensor trapping in suboptimal locations make MSN optimization an exceedingly challenging problem.

Our previous publications [2]-[4] proposed aligning sensor mobility with the overall MSN goals by assuming that (a) sensing and communication are optimized much faster than sensors relocation and (b) sensor relocations are governed by cost/benefit analysis where "cost" of sensor battery energy expenditure for sensor relocation is weighted against projected performance gains due to new sensor locations. This approach is vastly superior to sensor mobility control based on *phenomenologically* defined potential fields and the corresponding virtual forces [5]. This is because dissipation of the non-renewable sensor battery energy, asymmetric virtual forces due to asymmetric wireless channels, and abrupt changes in the optimal MSN topology with sensor relocation are inconsistent with the existence of global potential field.

Practicality of the framework proposed in [2]-[3] depends on overcoming numerous challenges with (inherently) distributed nature of MSN being the most critical. An intelligent sensor may have direct knowledge of its current life expectancy determined by its battery energy level and depletion rate affected by the surrounding terrain as well as sensor information acquisition and transmission capabilities. However, a sensor typically has no direct knowledge of the effect of its relocation on the rest of the MSN.

This paper suggests that the class of Distributed Subgradient Projection Algorithms (DSPA) [6]-[7] has potential for addressing major challenges of controlled sensor mobility in MSN. Subgradient-based iterations allows for dynamic network topology optimization. Projection of the algorithm iterations onto the set of feasible sensor locations ensures sensor information acquisition and communication needs. Most importantly communication overhead reducing techniques allow for addressing the inherently distributed nature of MSN. While more conventional pricing-based algorithms effectively reduce the communication overhead in some particular situations, recently emerged consensus-based algorithms have low communication overhead in a more general setting.

Consensus-based algorithms differ in their approach to achieving consensus. In the first type [6] each agent maintains and iterates its own sequence, and consensus is achieved by communicating this sequence to the neighboring nodes, who incorporate neighbors' sequences into their own sequences through averaging. In the second type [7] all agents update a single sequence and consensus is achieved by passing the sequence instances to each other. In this paper, we concentrate on the first type since updating and passing instances of a single sequence by agents to each other exposes algorithm to the risk of manipulation by malicious agents while averaging with judiciously chosen weights can mitigate this risk. Comparison and suitability of a particular consensus-based algorithm for controlling sensor mobility is left for a future study.

A major difficulty with controlling sensor relocation is the possibility of sensor trapping in suboptimal locations (e.g. in non-flat terrain) due to typical non-convexity of the performance criterion [8]. A possible approach to overcoming

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this difficulty is allowing occasional random sensor relocations to escape the potential traps in the spirit of simulated annealing optimization algorithm [9]-[10]. One of the advantages of the proposed approach in this paper is in its ability to incorporate such random moves in a distributed way.

The rest of this paper is organized as follows. Section II quantifies the effect of sensors positions on MSN performance; while the effect of sensors relocation in discussed in section III. Section IV describes sensor relocation algorithms based on maximization of the corresponding performance gain. Section V discusses initial simulation results showing benefits of cooperative sensor relocation for the case of a MSN tracking a single target on a flat terrain. Finally, section VI briefly summarizes the proposed approach to controlled sensor mobility and outlines directions for future research.

II. MSN Performance

We consider a Mobile Sensor Network (MSN) comprised of sensors/nodes $s \in \mathbf{S} = \{1,..,S\}$, which acquire and communicate information to a single destination formally identified as node $s = 0$. The MSN topology is $\Gamma = (N, L)$ with set of nodes N and set of links L. Here, we assume that our goal is to maximize the MSN life span, given the constraints on sensors ability to acquire and communicate sensor information at some low fixed rate and sensor battery energy availability. Subsection A describes requirements on MSN ability to acquire and communicate information to the destination. Subsection B quantifies effect of sensor locations on MSN performance.

A. Sensing and Communication Requirements

Requirements on sensor ability to acquire and communicate information can be incorporated into performance optimization either through penalty for the corresponding energy expenditure or directly in terms of feasible sensor locations. In a wireless interference-limited network, capacity c_l of a link $l = (i, j)$ from node i to node j depends on the transmission power, channel condition, and node locations through the Signal-to-Interference Ratio:

$$SIR_{ij} = p_{ij}\xi_{ij} \Big/ [\eta_j + \sum\nolimits_{(n,k)\neq(i,j),n\neq i,j} p_{nk}\xi_{nj}], \qquad (1)$$

where path gain $\xi_{ij} = \xi_{ij}(x_i, x_j)$ depends on the locations of the link (i, j)'s end-points x_i and x_j, and the noise power $\eta_j = \eta_j(x_j)$ at the receiver located at x_j.

Specific form of channel capacity $c_{ij} = c_{ij}(SIR_{ij})$ as a function of SIR_{ij} depends on the modulation and coding schemes. We assume a threshold-based channel model: $c_l(SIR_l) = c$ if $SIR_l > \chi$ and $c_l(SIR_l) = c$ otherwise, where $c, \chi > 0$ are some constants. We also assume that the interference from simultaneous transmissions by different sensors is negligible as compared to the noise at the receiver:

$$\sum\nolimits_{(n,k)\neq(i,j),n\neq i,j} p_{nk}\xi(x_n, x_j) << \eta(x_j), \qquad (2)$$

Thus, Signal-to-Interference Ratio on the link (i, j) is a function of the transmission power on this link:

$$SIR_{ij} \approx p_{ij}\xi(x_i, x_j) \big/ \eta(x_j). \qquad (3)$$

For a threshold-based channel model the minimal transmission power for node s on an active link $l = (s, j) \in L$ is:

$$\breve{p}_{sj}(x_s, x_j) = \chi_{sj}\, \eta(x_j) \big/ \xi(x_s, x_j). \qquad (4)$$

The minimal total transmission power required for sensor s to send information at low rate to nodes $i : (s,i) \in L$ is

$$\breve{p}_s = \sum_{i:(s,i)\in L} \chi_{sj}\, \eta(x_j) \big/ \xi(x_s, x_j) \qquad (5)$$

where the set of nodes active links L determines the network topology. In the case of free-space propagation:

$$\xi_{ij} = \zeta_{ij} \left\| x_i - x_j \right\|^{-\gamma} \qquad (6)$$

where ζ_{ij} and γ are positive constants, and $\left\| x_i - x_j \right\|$ is the Euclidian distance between sensors i and j with coordinates x_i and x_j respectively.

B. MSN Utility

Following [8] we assume that sensor $s \in \mathbf{S}$ utility of preserving battery energy until moment T can be quantified by utility function $u_s(T/T_s^*)$ where T_s^* is the corresponding target. Monotonously increasing functions $u_s(z), z > 0$ have an S-shape and steeply increases around $z \approx 1$. A convenient approximation for functions $u_s(z)$ is

$$u_s(z) = A_s \big/ [1 + e^{-(z-1)/a_s}], \qquad (7)$$

where parameters $a_s, A_s > 0$ affect importance of conserving sensor battery energy as compared to other considerations, e.g. high information rates. At moment t, sensor s remaining battery energy level is $E_s = E_s(t)$ and the battery energy draining rate is $p_s = p_s(t)$. Then, the projected battery energy depletion time is $T_s \approx t + E_s / p_s$, and thus the corresponding utility is

$$u_s(T_s / T_s^*) = u_s[(t + E_s / p_s) / T_s^*]. \qquad (8)$$

Given sensor locations $\mathbf{x} = (x_s, s \in \mathbf{S})$ and sensor battery energy levels $\mathbf{E} = (E_s, s \in \mathbf{S})$, we quantify MSN performance by the aggregate utility:

$$W(t, \mathbf{x}|\mathbf{E}) = \sum_s w_s(t, \mathbf{x}|E_s) \qquad (9)$$

where

$$w_s(t, \mathbf{x}|E_s) = u_s\left(\frac{t + E_s / \breve{p}_s(\mathbf{x})}{T_s^*} \right) \qquad (10)$$

For simplicity we further assume that power draining rates $\breve{p}_s = \breve{p}_s(\mathbf{x})$ are only due to communication and thus are given by (5). We also assume that requirements on sensor ability to acquire information are formalized directly in terms of sensor locations, e.g., with respect to the tracked target(s) or with respect to their ability to cover the area of interest.

III. RELOCATION GAIN

Subsection A quantifies cost/benefits of sensor relocations, where cost is associated with the energy expenditure on sensor relocations; and, potential benefits are associated with better information gathering (or transmission) due to the new sensor positions. Subsection B introduces subgradients of MSN utility and describes the effect of sensor relocations on the MSN performance. It also discusses communication overhead required for estimation of these subgradients.

A. MSN Utility Gain

Sensor $s \in \mathbf{S}$ relocation from point x_s to point $x_s + \Delta x_s$ during time interval $[t, t+\theta)$ results in the following gain in this sensor utility:

$$v_s(\mathbf{x}, \Delta x_s) = w_s(t+\theta, \mathbf{x}'_s | E_s - \Delta E_s) - w_s(t, \mathbf{x} | E_s) \quad (11)$$

where function $w_s(.)$ is given by (10), ΔE_s is the energy expenditure on communication and sensor relocation, $\mathbf{x}'_s = (x_i + \delta_{is}\Delta x_i, i \in \mathbf{S})$ is the vector of sensor positions after sensor s relocation, and δ_{is} is the Kroneker symbol (i.e. $\delta_{is} = 1$ if $i = s$ and $\delta_{is} = 0$ otherwise).

Assuming a small θ, the communication energy can be approximated by $\breve{p}_s(\mathbf{x})\theta$, where communication power $\breve{p}_s(\mathbf{x})$ is given by (5). Estimation of relocation energy E_s is more complicated since this energy depends not only on the initial and final positions of sensor s , but also on the entire relocation process. Here, we assume that given sensor s initial (x_s) and final positions ($x_s + \Delta x_s$) respectively, the relocation process will take place in such a way that minimizes the relocation energy. Therefore, making E_s a function of the initial and final locations only (i.e. $\mathsf{E}_s = \mathsf{E}_s(x_s, \Delta x_s)$). In practice, this minimization is possible for sufficiently small step size θ when one may assume that the sensor motion occurs on a straight line connecting points x_s and $x_s + \Delta x_s$.

Our assumptions above lead to the following approximation:

$$\Delta E_s(\mathbf{x}, \Delta x_s) = p_s(\mathbf{x})\theta + \mathsf{E}_s(x_s, \Delta x_s) \quad (12)$$

Small sensor relocation from points $\mathbf{x} = (x_s, s \in \mathbf{S})$ to point $\mathbf{x} + \Delta\mathbf{x} = (x_s + \Delta x_s, s \in \mathbf{S})$ results in the following gain in the aggregate utility (9):

$$V(\mathbf{x}, \Delta\mathbf{x}) \approx \sum_s v_s(\mathbf{x}, \Delta x_s) \quad (13)$$

A natural sensor relocation algorithm maximizes this gain (13) over $\Delta\mathbf{x}$ subject to feasibility of the new sensor locations:

$$\Delta\mathbf{x}^* = \arg \max_{\Delta\mathbf{x}: \mathbf{x}+\Delta\mathbf{x} \in X} V(\mathbf{x}, \Delta\mathbf{x}) \quad (14)$$

B. Subgradients of MSN Utility

Assuming a fixed network topology $\Gamma = (N, L)$, gradient $g_{ss}(\mathbf{x}) = \nabla_{\Delta x_s} v_s(\mathbf{x}, \Delta x_s)\big|_{\Delta x_s = 0}$ characterizes the gain in sensor s utility (10) resulting from small sensor s relocation from point x_s to point $x_s + \Delta x_s$:

$$g_{ss} = -\frac{u'_s}{T^*_s \breve{p}_s}\left(\frac{E_s}{\breve{p}_s}\nabla_{x_s}\breve{p}_s(\mathbf{x}) + \nabla_{\Delta x_s}\mathsf{E}_s(x_s, \Delta x_s)\big|_{\Delta x_s = 0}\right) \quad (15)$$

Expression (15) accounts for change in sensor s communication power $\breve{p}_s(\mathbf{x})$ and the energy expenditure of the relocation. Gradient $g_{si}(\mathbf{x}) = \nabla_{x_i} w_s(\mathbf{x})$ characterizes the gain in sensor s utility (10) resulting from small sensor $i \neq s$ relocation from point x_i to point $x_i + \Delta x_i$:

$$g_{si} = -\frac{u'_s}{T^*_s}\frac{E_s}{\breve{p}^2_s}\nabla^T_{x_i}\breve{p}_{si}(x_s, x_i) \quad (16)$$

The change in sensor $s = i$ utility is due to change in sensor s communication power $\breve{p}_{si}(x_s, x_i)$.

Sensor $s \in \mathbf{S}$ relocation only affects neighboring sensors $\mathbf{S}^-_s = \{i : (i, s) \in L, i \in \mathbf{S}\}$, that directly send information to s . Sensor $s \in \mathbf{S}$, on the other hand, is only affected by relocation of neighboring sensors $\mathbf{S}^+_s = \{i : (i, s) \in L, i \in \mathbf{S}\}$, that receive information directly from s . For brevity, we further assume that all links are un-directional, i.e., $(i, s) \in L \Leftrightarrow (s, i) \in L$; and thus, sensor s relocation directly affects only sensors $i \in \mathbf{S}_s \overset{def}{=} \mathbf{S}^+_s = \mathbf{S}^-_s$: $g_{is}(\mathbf{x}) \equiv 0$ if $i \notin \mathbf{S}_s$.

Pricing-based cooperative sensor relocation algorithm, described in Subsection B, assumes that each sensor s can estimate the subgradient

$$g_s(\mathbf{x}) = \sum_{i \in \mathbf{S}_s} g_{is}(\mathbf{x}) \quad (17)$$

which quantifies the effect of this sensor relocation on the rest of the MSN. However, except for some particular situations, estimation of the subgradient (17) by sensor s is associated with high communication overhead. Subsection C demonstrates how this communication overhead can be reduced with consensus-based algorithm, which requires sensor $s \in \mathbf{S}$ to estimate $g_{si}(\mathbf{x})$ rather than $g_{is}(\mathbf{x})$ for $i \in \mathbf{S}_s$. This is a much easier task since an intelligent

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sensor s can estimate $g_{si}(\mathbf{x})$ by (a) measuring its remaining battery energy level E_s and communication powers $p_{si}(\mathbf{x})$ to the neighbors $i \in \mathbf{S}_s$, (b) estimating its relocation energy $\mathsf{E}_s(x_s, \Delta x_s)$, and (c) estimating the positions of the neighboring nodes $(x_i, i \in \mathbf{S}_s)$.

IV. Cooperative Sensor Relocation

Subsection A proposes cooperative sensor relocation following iterations of subgradient projection algorithm for solving the optimization problem (13)-(14). Subsection B proposes consensus-based cooperative sensor relocation, which mitigates high communication overhead. This is achieved by following iterations of the *decentralized* subgradient projection algorithm. Subsection C suggests that combining *decentralized* subgradient projection algorithm with simulated annealing may result in avoiding traps on non-flat terrains.

A. Relocation by Performance Gain Maximization

In the case when sensor $s \in \mathbf{S}$ is aware of the effect of its relocation on the entire MSN (as measured by (17)), the following relocation algorithm greedily maximizes the MSN performance gain. At step k, given sensor positions $\mathbf{x}^{(k)} = (x_s^{(k)}, s \in \mathbf{S})$ and remaining sensor battery energy levels $\mathbf{E}^{(k)} = (E_s^{(k)}, s \in \mathbf{S})$, cross-layer network optimization produces the optimal network topology $\Gamma^{(k)} = (N, L^{(k)})$. At the next step $k+1$, each sensor $s \in \mathbf{S}$ is relocated following the subgradient (17):

$$x_s^{(k+1)} = P_X[x_s^{(k)} + \alpha^{(k)} g_s(\mathbf{x}^{(k)})] \tag{18}$$

where scalar $\alpha^{(k)}$ is the step size, and P_X denotes the Euclidean projection onto the set of feasible sensor locations X. Then, given new sensor locations $\mathbf{x}^{(k+1)} = (x_s^{(k+1)}, s \in \mathbf{S})$ and remaining sensor battery energy levels $\mathbf{E}^{(k+1)} = (E_s^{(k+1)}, s \in \mathbf{S})$:

$$E_s^{(k+1)} = E_s^{(k)} - \mathsf{E}_s(x_s^{(k)}, x_s^{(k+1)} - x_s^{(k)}) - \breve{p}_s(\mathbf{x}^{(k)})\theta\,, \tag{19}$$

cross-layer network optimization produces new optimal network topology $\Gamma^{(k+1)} = (N, L^{(k+1)})$ ..

The main assumption that sensors $s \in \mathbf{S}$ are aware of the gradients (17) can be justified for the case of symmetric propagation matrix: $\xi_{ij} = \xi_{ji}; \forall i, j \in \mathbf{S}; i \neq j$, where $\breve{p}_{ji}(x_j, x_i) \equiv \breve{p}_{ij}(x_i, x_j)$. In this case, if each sensor $i \in \mathbf{S}$ estimates the "pricing" for its battery energy $\pi_i = (u_i' E_i) / (T_i^* \breve{p}_i^2)$ and propagates this price to its neighbors, then each sensor $s \in \mathbf{S}$ can directly estimate the effect of its relocation on the rest of the MSN as follows:

$$g_{is}(\mathbf{x}) = (\pi_i / \pi_j) g_{si}(\mathbf{x})\,. \tag{20}$$

B. Relocation by Building Consensus

Assume that each sensor $s \in \mathbf{S}$ is aware of the impact of its own and neighbors $i \in \mathbf{S}_s$ relocation on its performance as measured by $g_{si}(\mathbf{x})$. We consider cooperative sensor relocation by iterations of Distributed Subgradient Projection Algorithm (DSPA) for solving optimization problem (13)-(14). DSPA achieves cooperation by building consensus on optimal sensor locations through information exchange between each sensor and its neighbors. In effect, DSPA offers a consistent approach to overall performance optimization while minimizing the communication overhead. Again for brevity, we only describe DSPA-based cooperative sensor relocation and refer to [6] for elaborate details of DSPA.

The algorithm proceeds in steps. At step k, each sensor $s \in \mathbf{S}$ updates its own position $x_s^{(k)}$ and vector of estimates of the positions of its neighboring sensors $i \in \mathbf{S}_{s,k}$, (i.e., sensors directly communicating with sensor s at step k, $\tilde{\mathbf{x}}_s^{(k)} = (\tilde{x}_{si}^{(k)}, i \in \mathbf{S}_{s,k})$) as follows:

$$x_s^{(k+1)} = P_X[x_s^{(k)} + \alpha^{(k+1)} g_{ss}(\tilde{\mathbf{x}}_s^{(k)})] \tag{21}$$

$$\tilde{\mathbf{x}}_s^{(k+1)} = P_X[\mathbf{z}_s^{(k)} + \alpha^{(k+1)} \mathbf{g}_s(\tilde{\mathbf{x}}_s^{(k)})] \tag{22}$$

where X is the set of feasible sensor location, $\alpha^{(k+1)} > 0$ is the step size, and P_X denotes the Euclidian projection onto the set of feasible sensor locations X.

The vector $\mathbf{z}_s^{(k)}$ is the weighted average of $\tilde{\mathbf{x}}_s^{(k)}$ which is computed by sensor s as follows:

$$\mathbf{z}_s^{(k)} = \sum_{j \in \mathbf{S}_{s,k+1}} a_{s,j}^{(k+1)} \tilde{\mathbf{x}}_j^{(k)} \tag{23}$$

Scalars $a_{s,j}^{(k+1)}$ are the non-negative weights that sensor s assigns to sensor j's iteration at step $k+1$. Equation (23) represents a "consensus"-based step that ensures under conditions specified in [6], sensor $s \in \mathbf{S}$ estimates of other sensor positions converge to their actual positions (i.e. $\tilde{x}_{si}^{(k)} \to x_i$ as $k \to \infty$).

C. Escaping Traps with Random Moves

Using local information for controlled sensor relocation on non-flat terrain is prone to sensor trapping in suboptimal positions due to typical non-convexity of the performance criterion [8]. A combination of controlled sensor mobility with simulated annealing to avoid sensor trapping has been proposed in [9] and further discussed in [10]. This subsection discusses a possibility of combining DSPA-based sensor relocation and simulated annealing algorithms.

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Conventional simulated annealing algorithm [9] suggests sensor relocations from points $\mathbf{x} = (x_s, s \in \mathbf{S})$ to points $\mathbf{x} + \Delta\mathbf{x} = (x_s + \Delta x_s, s \in \mathbf{S})$ with probability

$$\Pr ob(\Delta\mathbf{x}) = Z^{-1} \exp[\beta V(\mathbf{x}, \Delta\mathbf{x})] \qquad (24)$$

where function $V(\mathbf{x}, \Delta\mathbf{x})$ is given by (13), Z is the normalization constant, and β is the inverse "temperature". In the case of "high temperature": $\beta \to 0$, sensors perform random walk, while in the case of "low temperature": $\beta \to \infty$, sensors perform optimization (13)-(14). The main advantage of simulated annealing algorithm is that it allows for obtaining guidelines on the "cooling schedule" in order to ensure convergence to the global solution of optimization problem (13)-(14). Therefore, with a proper cooling schedule sensors can avoid traps.

The problem with random relocations following (24) is that this algorithm is centralized. In the spirit of a distributed subgradient algorithm, it is natural to relocate sensor s from point x_s to point $x_s + \Delta x_s$ with probability

$$\Pr ob(\Delta x_s) = Z_s^{-1} \exp[\beta v_s(\mathbf{x}, \Delta x_s)] \qquad (25)$$

where function $v_s(\mathbf{x}, \Delta x_s)$ is given by (11), Z_s is the normalization constant, and β is the inverse "temperature". In a simulated annealing version of algorithm (21)-(23) sensor s relocates from point x_s to point $x_s + \Delta x_s$ with probability (25) while updating estimates of locations of its neighboring sensors following (22)-(23).

In the case of "low temperature": $\beta \to \infty$, sensors will perform optimization (21)-(23). The similarity with conventional simulated annealing suggests the possibility of existence of a cooling schedule that allows sensors to avoid traps with a distributed version of simulated annealing.

V. EXAMPLE: TRACKING A SINGLE TARGET

Consider a MSN designed to track a single target G and communicate the desired information at a low rate to a fixed destination D. For brevity, here we only discuss simulation results for a scenario with $S = 6$ sensors on a flat terrain where signal attenuation depends only on the distance (6). To simplify further, we assume that energy required for relocation is proportional to the travelled distance. It can be shown that under some natural conditions and for sufficiently high initial sensor battery energy levels, the optimal MSN topology is linear with only one sensor tracking the target and the rest of the sensors relaying this information to the destination, formally identified as sensor $s = 0$.

Figure 1 shows this linear topology with six sensor, where information flows from the target to the destination: $G \to (s = 6) \to \ldots \to (s = 1) \to (s = 0)$, while the control information flows in the opposite direction: $(s = 6) \leftarrow \ldots \leftarrow (s = 1) \leftarrow (s = 0)$.

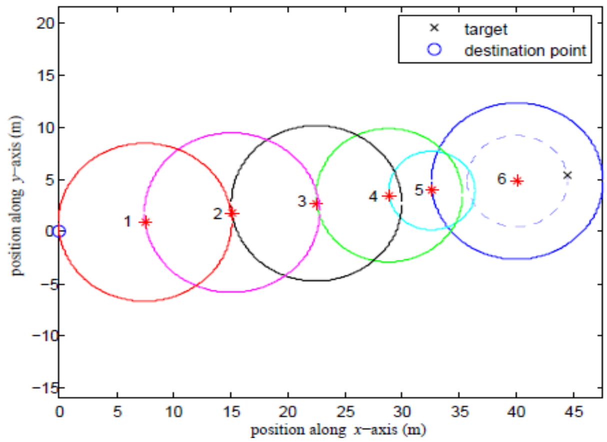

Figure 1. Linear topology with six sensors

We also assume that sensors have the maximal communication and sensing range indicated by the corresponding circles in Figure 1. Sensor relocation algorithm accounts for existence of these maximal ranges by projecting the iterations of the relocation algorithm onto properly designed set of feasible sensor positions.

In a case of stationary sensors, Figure 2 shows that sensor battery energy draining rate is completely determined by the initial sensor positions with respect to the stationary destination and the target (which may or may not be stationary).

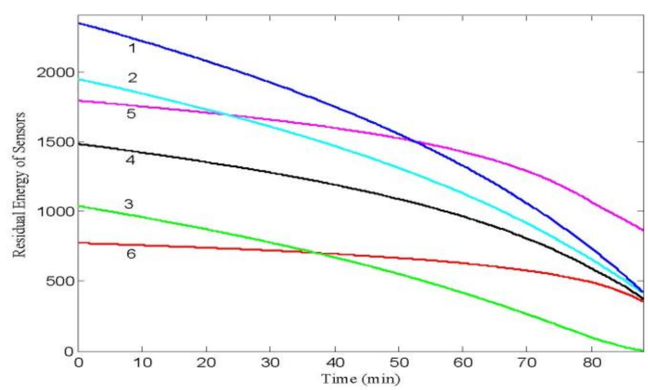

Figure 2. Residual sensor energy: stationary sensors

Figure 2 demonstrates imbalances in sensor battery energy draining rates due to initial sensor positions. Since in our model sensors use minimal communication power required for MSN operation, the network becomes non-operational in approximately 90 minutes. This is the time when sensor $s = 3$ spends all of its energy.

In the case of non-cooperative sensor relocation, shown in Figure 3, the MSN becomes non-operational in approximately 140 minutes when sensors $s = 1$, $s = 3$ and $s = 6$ deplete their battery energy.

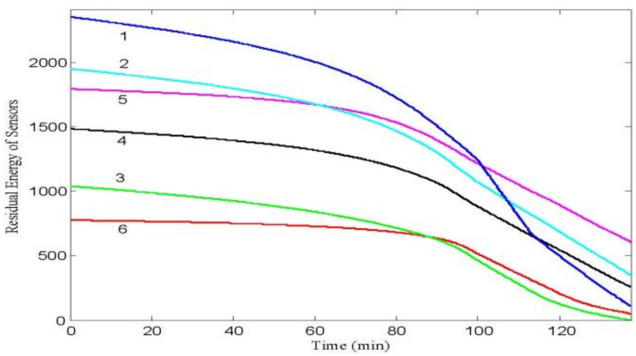

Figure 3. Residual sensor energy: selfish relocation

The inverse S-shape of the residual sensor energy evolution, shown in Figure 3, is indicative of selfish sensor relocation when each sensor attempts to prolong its own life-span. In this case, each sensor is attempting to minimize its transmission power by positioning itself at the "middle point" of the neighboring sensors without any consideration for conserving the neighbors' battery energy. This "selfish" sensor positioning is responsible for lack of coordination shown in Figure 3.

In a case of cooperative sensor relocation, shown in Figure 4, all sensors deplete their battery simultaneously prolonging MSN life span to approximately 300 minutes. This is achieved through cooperation, when sensors with longer life expectancy are "willing" to relocate longer distances in order to save energy for sensors with shorter life expectancy.

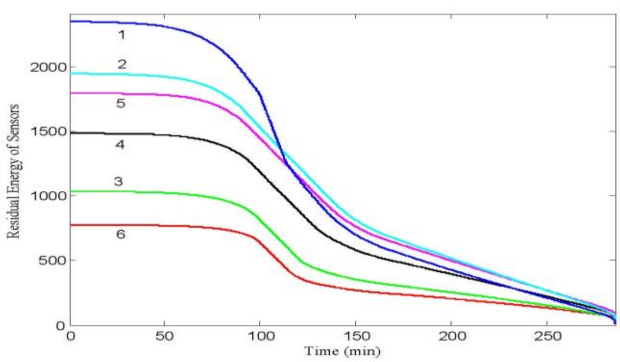

Figure 4. Residual sensor energy: cooperative relocation

VI. CONCLUSION AND FUTURE RESEARCH

This paper has proposed an approach to controlled cooperative sensor relocation in a Mobile Sensor Network (MSN) by following iterations of a Distributed Subgradient Projection Algorithm (DSPA) for aggregate performance optimization. The main advantage of this approach is in its ability to accommodate locally available information on battery energy availability, sensing, communication and relocation "costs" with respect to the energy expenditure in an inherently decentralized environment. Initial simulation results indicate viability of this approach for prolonging the MSN life-span.

Future research should evaluate pros and cons of different versions of distributed subgradient algorithms with respect to controlled sensor relocation, and provide guidelines for selection of the algorithm step size and free parameters involved in the "consensus" step. These selections affect the trade-off between the algorithm convergence rate and communication overhead. The ability to avoid traps on non-flat terrains is critical for practical implementation of controlled sensor relocation. This paper has suggested the possibility of achieving this by combining a distributed subgradient projection and simulated annealing algorithms. More studies need to be done to realize this possibility, including developing distributed cooling scheduling.

Finally, note that the important issue of initial network formation has not been discussed. Distributed subgradient optimization algorithms assume agent connectivity. However, at the initial stage mobile sensors may be organized in several disconnected clusters. In that case, controlled sensor mobility should simultaneously pursue two goals: collaboration within clusters and establishing connectivity between clusters. This problem, which can be broadly framed as controlled mobility in Disruption Tolerant Networks (DTN), would require new ideas and approaches.

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