Towards Evolutionary-Pricing Framework for Mobile Sensor Network Self-organization

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***Abstract*—This paper reports on work in progress on developing a unified co-evolutionary/pricing framework for Mobile Sensor Networks (MSN) self-organization. MSN self-organization involves cooperative sensor positioning and formation of a multi-hop Mobile Ad-hoc NETwork (MANET) enabling sensor information acquisition and communication while prolonging MSN life-span. A number of inherent MSN traits such as lack of centralized control and variety of performance criteria suggest framing MSN self-organization as a sensor co-evolutionary optimization. The first issue to be addressed is aligning individual sensor utility/fitness landscapes with the overall MSN goals as "selfish" sensor behavior may result in suboptimal overall MSN performance. The paper proposes using "socially optimal pricing" to internalize the effect of each sensor relocation on the overall MSN performance. It is assumed that intermediate nodes in the MSN relay sensor information to a single fusion point without processing. The proposed framework is illustrated for the special case of a MSN tracking a single target.**

***Keywords*—mobile sensor network, socially optimal sensor fitness, pricing.**

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. Locations of sensors in a MSN affect both their ability to acquire information on the intended targets and events as well as their ability to communicate this information to the intended recipients. The information acquisition needs, which require proximity to the target(s), could potentially compete with communication needs, which require proximity to the recipient(s) of the sensor information. Inherent traits of MSN such as centralized control, variety of performance criteria, operational uncertainties, etc., make conventional approaches to MSN optimization inefficient. In continuation of our previous publications [1,2], this paper, suggests framing MSN self-organization as a co-evolutionary optimization problem, where sensors cooperate in finding their optimal locations while forming a multi-hop Mobile Ad-hoc NETwork (MANET).

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Here, some sensors may act as relay of other sensor's information in addition to transmitting their own data. The first step in developing a co-evolutionary framework for MSN self-organization is identifying "socially optimal" individual sensor fitness/utility landscapes in the inherently distributed environment of a MSN. "Social optimality" implies that each sensor maximization of its individual fitness results in overall performance optimization of the network. This is a challenging problem since MSN performance critically depends on sensors cooperation, and "selfish" sensors behavior typically results in drastic deterioration of the overall performance. For example, selfish sensor positioning can quickly deplete some sensor battery power; resulting in the network inability to carry out its mission. Note that performance loss due to selfish agent behavior, quantified by "price of anarchy", is currently an active are of research [3].

This paper builds on the proposed idea of extending pricing-based Network Utility Maximization (NUM) framework for MSN distributed optimization that includes sensor location [1,2,4-6]. Appeal of this unified MSN NUM (MSN-UM) framework is that while system utility maximization over sensor information flow rates in "fast" time scale yields the optimal cross-layer design of the MSN MANET, system utility maximization over sensor locations in "slow" time scale controls sensors motion. MSN-UM suitability for inherently distributed MSN environment is the result of using socially optimal pricing, which "internalizes" effect of sensor individual actions on the overall MSN performance. Major issues discussed in this paper are information asymmetry, cost of sensor relocation, simulated annealing type MSN optimization, and simulation results of some basic scenarios.

Information asymmetry is due to inherent distributed nature of MSN [2]. It can be assumed that the node which is the recipient of all sensors information is capable of estimating the aggregate utility of sensor information streams. On the other hand, each mobile sensor has direct knowledge of its remaining battery power and surrounding terrain which affect sensor ability to communicate and relocate. Here, we consider MSNs in which all sensors information is transmitted to a single destination (i.e. fusion) point, and the intermediate nodes only relay other sensor information without any processing. In this case, the fusion center guides individual sensor decisions by informing each sensor on the "willingness-to-pay" information.

A widely used approach to mobility control is based on *phenomenologically* defined potential fields and the corresponding virtual forces [7]-[9]. As opposed to this phenomenological approach, MSN-UM offers a consistent approach to aligning controlled sensor mobility with the overall MSN operational goals. Since sensor mobility often involves dissipation of non-renewable sensor battery power, dynamics of sensor repositioning is inherently non-potential, and thus cannot be completely characterized by sensor spatial fitness landscape. We overcome this shortcoming by assuming that sensor fitness depends on both initial and final sensor positions. This approach offers a tractable abstraction for expanding system phase space by including dissipation of sensor battery energy supply. This expansion significantly impacts the sensor relocation dynamics, e.g., making sensors more conservative in their "willingness" to relocate as compared to conventional schemes which do not account for the "cost" of relocation.

In the context of evolutionary robotics, this paper can be viewed as a framework for distributed on-line design of sensor fitness landscapes consistent with the overall MSN goals. The next step should be evaluation of performance of various sensor co-evolutionary algorithms where sensors attempt to increase their fitness by relocation. This paper discusses the possibility of simulated annealing type self-organization, where each sensor performs random walk with drift in the direction of the gradient of the socially optimal sensor utility/fitness along with random "mutations" to avoid trapping [9] in the local optima. This paper also reports simulation results for a simple scenario when six mobile sensors are tracking a single target on a flat terrain. The simulation reveals basic elements of self-organization i.e. sensors cooperate in forming a linear topology MANET from the target to the intended recipient of sensor information. This cooperation includes prolonging MSN life-span by ensuring that all sensors deplete their battery energies simultaneously.

The paper is organized as follows. Section II introduces utilities and penalties, which quantify MSN desired life-span with respect to MSN ability to acquire and transmit sensor information as well as extending MSN life-span by conserving battery energy. Section III quantifies energy requirements and constraints associated with performing basic MSN operations: sensor information acquisition, communication, and sensor relocation. Section IV frames sensor relocation as a co-evolutionary optimization by introducing "socially-optimal" individual sensor utility/fitness landscape and discussing simulated annealing type algorithm for the fitness/utility maximization. Section V discusses simulation results for a simple MSN that tracks a single target. Finally, Section VI briefly summarizes our results and discusses directions for future research.

II. UTILITIES AND COSTS

This Section introduces utility functions that drive MSN co-evolutionary self-organization. Subsection A quantifies value of sensor information based on the fusion point "willingness-to-pay" for this information. Subsection B quantifies the "cost" of sensor battery energy expenditure with respect to the corresponding reduction in the sensor network life-span.

A. *Utility of Sensor Information*

Consider a network formed by mobile sensors $s = 1,..,S$ transmitting to a single fixed destination point $s = 0 = D$, where all sensor information streams are fused. Sensor s, located at point x_s, transmits to the destination D at rate λ_s. Due to possible redundancy of information streams from different sensors, aggregate utility of sensor information $U(\lambda, x)$ is generally a function of all sensors rates $\lambda = (\lambda_1,..,\lambda_S)$ and locations $x = (x_1,..,x_S)$ [10]. While increasing sensor information rates is beneficial, their marginal benefit decreases; therefore, it is natural to assume that the function $U(\lambda, x)$ is monotonously increasing and concave in rates $\lambda = (\lambda_1,..,\lambda_S)$. The following representation for the aggregate utility of sensor information $U(\lambda, x)$ has been proposed in [2]:

$$U(x,\lambda) = \sum_{s\in S} w_s(x)\log\lambda_s \quad (1)$$

It can be assumed that given sensor locations $x = (x_s)$, the destination point D which fuses all sensor information streams into a coherent picture, approximates parameters $w_s(x)$ and notifies each sensor of its corresponding value. Parameters $w_s(x)$ $s = 1,..,S$ quantify the effects of the physical locations of all sensors $x = (x_1,..,x_S)$ on the value of information captured by each sensor. Dependence of $w_s(x)$ on the physical locations of all sensors $x = (x_1,..,x_S)$ can be explained as follows. While the value of the information collected by a single sensor s from the intended target(s) depends on the sensor physical location x_s relative to the target(s), this value can be reduced if other sensors are located close to sensor s due to redundancy of the acquired information. In the situation where all S sensors acquire information about a single target, the value of $w_s(x)$ also depends on the target location x_G i.e. $w_s(x) = w_s(x|x_G)$. The parameter $w_s(x)$ can be interpreted as the "willingness-to-pay" by the fusion point for marginal value of sensor s information stream.

We can characterize the overall network performance by the system social welfare $W(x,\lambda)$ as

$$W(x,\lambda) = \sum_{s\in S}\left[w_s(x)\log\lambda_s - f_s(x_s,\lambda_s)\right] \quad (2)$$

where $f_s(x_s,\lambda_s)$ is the penalty associated with resource expenditure of sensor s located at point x_s and transmitting at rate λ_s to the fusion point. Functions $f_s(x_s,\lambda_s)$ are assumed to be monotonously increasing and convex in rates $\lambda_s \ge 0$, $s=1,..,S$.

Due to our assumptions, given sensor locations $x=(x_s)$, system social welfare (2) is concave in rates $\lambda=(\lambda_s)$. Thus, optimal rates

$$\lambda^*(x)=\arg\max_{\lambda} W(x,\lambda) \tag{3}$$

are the unique solution of the following equations:

$$\lambda_s = w_s(x)/d_s(x_s,\lambda_s),\ s=1,..,S \tag{4}$$

where the marginal cost of sensor s transmission to the fusion point is:

$$d_s(x_s,\lambda_s) \overset{def}{=} \partial f_s(x_s,\lambda_s)/\partial\lambda_s \tag{5}$$

At the optimum (3), the "payment" each sensor $s\in S$ receives from the fusion point (i.e. $w_s(x)$) is equal to the "transmission cost" incurred by that sensor $d_s(x_s,\lambda_s)\lambda_s$.

B. Cost of Battery Energy

The sensor network life-span is limited by the sensors battery energy availability. We assume that the network life-span can be quantified by the penalty function $\varphi(T/\widetilde{T})$ where T is the time moment when the network becomes non-operational, and $\widetilde{T}$ is the target value for the desired network life-span [11]. Monotonously decreasing function $\varphi(y), y>0$ has an inverse S-shape and steeply decreases around $y\approx 1$.

A convenient two-parameter approximation for function $\varphi(y)$ is

$$\varphi(y) = -A\phi\left(\frac{y-1}{a}\right) \tag{6}$$

where sigmoid function

$$\phi(z)=\frac{1}{1+e^{-z}} \tag{7}$$

and parameters $a, A>0$ affect importance of enforcing network longevity until the desired moment $\widetilde{T}$ as compared to other considerations, e.g. high information rates. At time t when sensor s battery energy level and its corresponding draining rate are $E_s(t)$ and $p_s(t)$ respectively, the projected time of its battery energy depletion is $T_s \approx t + E_s(t)/p_s(t)$. Assuming that the MSN operation requires all sensors being operational, the aggregate penalty of draining sensor $s=1,..,S$ battery energies at rates $p=(p_s)$ is $V(t,p|E)$, where

$$V(t,p|E)=\sum_s v_s(t,p_s|E_s) \tag{8}$$

and

$$v_s(t,p_s|E_s)=\varphi\left(\frac{t+E_s/p_s}{\widetilde{T}}\right) \tag{9}$$

III. Penalties and Constraints

This Section quantifies energy requirements and constraints associated with MSN ability to perform its basic operations. Subsection A demonstrates that constraints on sensor ability to acquire relevant information can be formalized either in terms of feasible sensor locations relative to the target or energy expenditure. Subsections B and C quantify energy expenditure on sensor communication and relocation respectively.

A. Information Acquisition

Sensor ability to acquire relevant information can be modeled either as constraints on sensor locations or by introducing the corresponding penalties and prices. Area coverage constraints are often formulated as requirement for any point in the area to be within certain "sensing range" of at least one sensor. Constraints on MSN ability to track specific targets or events can be also formulated in terms of these targets or events being in the "sensing range" of at least one sensor. More elaborate location-dependent penalty function may encourage sensor(s) to stay in certain proximity to the locations/events/targets of interest.

Typically sensing involves battery energy expenditure, which generally depends on the relative target(s) and sensor(s) locations, terrain, and sensor information rate. One may approximate the power required for a sensor located at the position x_s acquiring information at rate λ from the target located at point x_G to be as follows:

$$p(\lambda;x_s,x_G)=\zeta(\lambda)/\xi(x_s,x_G) \tag{10}$$

where $\zeta(\lambda)$ is a non-decreasing and concave function of rate λ, and function $\xi(x_s,x_G)$ characterizes the attenuation of the corresponding tracked signal. For example, in the case of flat terrain $\xi(x_s,x_G)\sim\|x_s-x_G\|^{-\gamma}$, where γ is some positive constant and $\|.\|$ is the physical distance. This "sensing power" can be either used in constrains on the sensor location or incorporated into the penalty (6).

B. Communication

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:

$$c_{ij}=c_{ij}(SIR_{ij}) \tag{11}$$

where Signal-to-Interference Ratio on link $l=(i,j)$ is

$$SIR_{ij}(x,p)=\frac{p_{ij}\xi_{ij}}{\eta_j+\sum_{(n,k)\neq(i,j),n\neq i,j}p_{nk}\xi_{nj}} \quad (12)$$

In (12), path loss $\xi_{ij}=\xi_{ij}(x_i,x_j)$ corresponding to the link (i,j) depends on the locations of the communicating end-points x_i and x_j, and the noise power $\eta_j=\eta_j(x_j)$ only depends on the receiver location x_j. For example, in the case of free-space propagation:

$$\xi_{ij}=\zeta_{ij}\left\|x_i-x_j\right\|^{-\gamma} \quad (13)$$

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

Specific form of channel capacity (11) depends on the modulation and coding schemes. For example, Shannon capacity is given by

$$c_l=k_1\log(1+k_2SIR_l), \quad (14)$$

where k_1,k_2 are constant coefficients. A threshold-based channel model is given by

$$c_l(SIR_l)=\begin{cases}c & if \quad SIR_l>\chi\\ 0 & otherwise\end{cases} \quad (15)$$

where $c,\chi>0$ are some constants.

In the special case of an energy-limited network where interference from simultaneous transmissions by different sensors is negligible compared to the noise at the receiver i.e.

$$\sum_{(n,k)\neq(i,j),n\neq i,j}p_{nk}\xi(x_n,x_j)<<\eta(x_j), \quad (16)$$

Signal-to-Interference Ratio on the link (i,j) will become a function of the transmission power:

$$SIR_{ij}\approx p_{ij}\xi(x_i,x_j)/\eta(x_j) \quad (17)$$

Using a threshold-based channel model (15), the optimal transmission power for node s on an active link $l=(s,j)$ is:

$$p^*_{sj}(x_s,x_j)=\begin{cases}\chi_{sj}\,\eta(x_j)/\xi(x_s,x_j) & if \quad (s,j)\in L\\ 0 & otherwise\end{cases} \quad (18)$$

The total sensor s transmission power is

$$p^*_s(x)=\sum_{j:(s,j)\in L}p^*_{sj}(x_s,x_j) \quad (19)$$

where the set of active links L determines the network connectivity (i.e. topology).

C. *Sensor Relocation*

The rate of energy expenditure for sensor s located at point x_s and moving with speed $\dot{x}_s$ can be quantified by a monotonically increasing (and convex in $\dot{x}_s$) dissipative function $\varphi_s(x_s,\dot{x}_s)$, where $\varphi_s(x,\dot{x}_s)>0$ if $\dot{x}_s\neq 0$ and $\varphi_s(x_s,\dot{x}_s)=0$ if $\dot{x}_s=0$. However, as mentioned in [2], using dissipative function for "pricing" sensor relocation appears to be computationally intractable. However, as explained in the following, in some important practical situations significant simplification is possible.

Consider the case when the remaining network life-span is sufficiently long and thus sensors can relocate sufficiently slow in order to minimize the energy expenditure on relocation without regard for energy expenditure on communication and sensing during relocation. Under these assumptions energy expenditure for sensor s moving from point $x_s^{(0)}$ to point x_s can be expressed by

$$\Delta E_s(x_s^{(0)},x_s)=\inf_{t\geq 0}\ \inf_{(x_s(\tau),0\leq\tau\leq t)}\int_0^t\varphi[x_s(\tau),\dot{x}_s(\tau)]d\tau \quad (20)$$

where minimization over trajectory $(x_s(\tau),\ 0\leq\tau\leq t)$ is subject to fixed initial $x_s(0)=x_s^{(0)}$ and ending $x_s(t)=x_s$ trajectory points.

Reasonable approximations for the energy expenditure (20) can be used for special cases. For example, for a flat homogeneous terrain it can be assumed that

$$\Delta E_s(x_s^{(0)},x_s)=m_s\left\|x_s^{(0)}-x_s\right\| \quad (21)$$

where positive constant m_s characterizes resistance to sensor s movement, and $\left\|x_s^{(0)}-x_s\right\|$ is the physical distance between points $x_s^{(0)}$ and x_s.

IV. Evolutionary MSN Optimization

Given sensor locations, MSN utility maximized over sensor information acquisition and communication capabilities characterizes the MSN spatial fitness landscape. Subsection A demonstrates that NUM in "fast" time scale determines the "socially optimal" individual sensor utility/fitness landscapes, which are consistent with the overall MSN operational goals. While sophisticated versions of NUM for MANET have been developed which include optimization of transmission scheduling on different links [5,6], Subsection A only considers flow control and routing optimization for interference-limited MANET. The socially optimal sensor utility/fitness landscapes combine the result of NUM and at the same time, accounting for the "cost" of energy expenditure needed for sensor motion. Subsection B briefly discusses a simulated annealing type procedure [12,13] for co-evolutionary MSN optimization.

A. *Socially Optimal Sensor Fitness/Utility Landscapes*

In this paper we only consider a link-centric NUM formulation for the MSN; assuming that each sensor $s\in\{1,..,S\}$ transmits its acquired information to the fusion center at an end-to-end rate of λ_s by (possibly) splitting its flow among feasible routes $r \in R_s$: $\lambda_s = \sum_{r \in R_s} \lambda_r$. Thus, the aggregate load μ_l on link $l = (i, j)$ from node i to node j is the sum of the loads resulting from all flows traversing this link:

$$\mu_l = \sum_s \sum_{r:l \in r \subseteq R_s} \lambda_r . \qquad (22)$$

Now, the sensor s utility/fitness function can be defined as follows:

$$W_s(\lambda, x) = w_s(x) \log\left(\sum_{r \in R_s} \lambda_r\right) - v_s\left(\sum_i p_{si}(\lambda, x)\right) \qquad (23)$$

where p_{si} is power required for sensor s to communicate to i if i is another sensor or acquire sensor information from i if i is a target. The first component in the right-hand side of (23) is the utility of information stream from sensor s, and the second component, which includes the communication and sensing power, characterizes penalty associated with sensor s battery energy expenditure. Note that penalty $v_s(p_s)$ also explicitly depends on current time t and battery energy level $E_s(t)$. Sensor s location x_s affects not only sensor s utility but also affects utility of other sensors through (a) fusion point willingness-to-pay for other sensor $i \neq s$ information $w_i(x)$ and (b) energy cost of sensors $i \in \{1,.., S : i \neq s\}$ directly communicating to sensor s. This is because path losses $\xi_{is} = \xi_{is}(x_i, x_s)$ on links (i, s) affect transmission powers p_{is} on these links.

Due to these interdependencies maximization by each sensor s of its own utility (23) may result in poor overall network performance measured by the following utility/fitness function.

$$W(\lambda, x) = \sum_s W_s(\lambda, x) \qquad (24)$$

We assume that for a given vector of sensor locations $x = (x_s)$ and the current levels of remaining sensor battery power $E = (E_s)$, conventional NUM operates sufficiently fast to maximize the MSN fitness (24) over rates $\lambda = (\lambda_s)$. Take:

$$\lambda^*(x) = \arg\max_{(\lambda_r \geq 0)} W(\lambda, x) \qquad (25)$$

Then, the corresponding maximized fitness

$$W^*(x|E) = W[\lambda^*(x), x|E] \qquad (26)$$

is the MSN aggregate utility/fitness landscape in the space of joint sensor locations $x = (x_s)$ and conditioned on the remaining sensor battery power levels $E = (E_s)$. Due to the interdependencies between sensor utilities (23), sensor positioning by maximizing their individual fitness

$$W_s^*(x|E_s) = W_s[\lambda^*(x), x|E_s] \qquad (27)$$

could result in poor overall MSN performance measured by MSN fitness (24).

Now, Introduce function $u_s(.)$ as

$$u_s(x|E_s) = W_s^*(x|E_s) - x_s \bullet \sum_{i \neq s} g_{si} \qquad (28)$$

where $\bullet$ denotes scalar product, and

$$g_{si} = -\nabla_{x_s} W_i^*(x|E_i) \qquad (29)$$

characterizes the effect of sensor s location x_s on sensor i fitness $W_i^*(x|E)$. It is easy to see that if gradients (29) are fixed then $\nabla_{x_s} u_s(x_s|E_s) = \nabla_{x_s} W^*(x|E_s)$, and thus sensor s relocation from point $x_s^{(0)}$ to point x_s results in MSN fitness change

$$\Delta W(x_s|x^{(0)}, E^{(0)}) = u_s(x_s, x_{-s}^{(0)}|E^{(0)}) - u_s(x^{(0)}|E_s^{(0)}) \qquad (30)$$

up to the terms of order $o(\|x_s - x_s^{(0)}\|)$, where vector x_{-s} characterizes locations of all sensors except sensor s. Equation (30) demonstrates that sensor s relocation to increase its utility (28) also increases MSN utility (26).

Individual sensor utilities (28) however are not "socially optimal" because they do not take into account sensor s battery energy expenditure $\Delta E_s(x_s^{(0)}, x_s)$. To account for this energy, we define socially optimal sensor s utility/fitness as follows:

$$\begin{aligned} &U_s(x_s|x^{(0)}, E^{(0)}) = \\ &u_s\left[x_s, x_{-s}^{(0)}\middle|E_s^{(0)} - \Delta E_s(x_s^{(0)}, x_s), E_{-s}^{(0)}\right] - u_s(x^{(0)}|E_s^{(0)}) \end{aligned} \qquad (31)$$

Considering equations (28) and (30), the socially optimal sensor s utility/fitness landscape (31) can also be rewritten as follows:

$$\begin{aligned} U_s(x_s|x^{(0)}, E_s^{(0)}) &= W_s^*\left[x_s, x_{-s}^{(0)}\middle|E_s^{(0)} - \Delta E_s(x_s^{(0)}, x_s)\right] \\ &- W_s^*(x^{(0)}|E_s^{(0)}) - (x_s - x_s^{(0)}) \bullet \sum_{i \neq s} g_{si} \end{aligned} \qquad (32)$$

B. Sensor Relocation

Sensor s fitness equation (31)-(32) depends on the sensor s both initial $x_s^{(0)}$ and final x_s locations, and assumes that other sensors remain fixed at locations $x_{-s}^{(0)}$. Using this equation, various forms of "hill climbing" can be implemented. Deterministic hill climbing moves sensors to increase their fitness. It is known, however, that this strategy often traps sensors in one of numerous undesirable local maxima of the MSN fitness (26) [9].

Another important issue is sensor speed. On one hand the quicker sensors move to the optimal locations, the better overall MSN performance is going to be. On the other hand, faster sensor relocation typically requires more energy. Also, sensor s fitness (31)-(32) assumes that all other sensor locations $x_{-s}^{(0)}$ are fixed. Sensors speeds are also limited by MSN ability to update their individual fitness landscapes (31)-(32) as changes occur in the network e.g. sensors or target locations. Since these updates are associated with additional sensor battery energy expenditure, the corresponding trade-offs should be taken into account.

The rest of this subsection describes a "simulated annealing" type of hill climbing procedure [12]-[13], which attempts to take into account the above concerns. Assuming discrete time, let Δ_s be the maximum distance, sensor s is allowed to move in one time step. In practice, sensors relocate in continuous time and parameters Δ_s control the speed of sensors motion. By varying parameters Δ_s, one can control the additional sensor battery expenditure due to fast sensor mobility as well as MSN ability to update and propagate the changing information affecting individual sensor fitness $U_s(x_s | x^{(0)}, E^{(0)})$.

Now, consider the following scheme. Given vectors of sensor positions and battery energy levels $(x^{(k)}, E^{(k)})$ at time step k, sensor s selects its next position $x_s = x_s^{(k+1)}$ at time step $k+1$ with probability

$$\Pr(x_s) = Z_s^{-1} \exp\left[\beta_s U_s(x_s | x^{(k)}, E^{(k)})\right] \tag{33}$$

if $\left\| x_s - x_s^{(k)} \right\| \le \Delta_s$, and $\Pr(x_s) = 0$ if $\left\| x_s - x_s^{(k)} \right\| > \Delta_s$.

The normalization constant Z_s is

$$Z_s = \int_{\left\| x_s - x_s^{(k)} \right\| \le \Delta_s} \exp\left[\beta_s U_s(x_s | x^{(k)}, E^{(k)})\right] dx_s \tag{34}$$

and the "inverse temperature" β_s characterizes the level of "mutations". In the extreme case of only mutations without selection: $\beta_s \downarrow 0$, and sensor s performs a completely random walk without any drift. In the other extreme case of selection without mutations: $\beta_s \uparrow \infty$, sensor s performs a steepest fitness ascend.

Note that parameters β_s control the trade-off between MSN ability to operate in stationary or changing environments. It is known that in stationary environments, when MSN aggregate utility/fitness landscape does not change with time, e.g., due to moving target(s), the "temperatures" β_s^{-1} should be monotonously decreasing and approaching zero as time progresses [12]-[13]. This ensures convergence to the globally optimal sensor locations. Controlling parameters β_s in changing environment is still an open problem.

V. EXAMPLE: TRACKING A SINGLE TARGET

To demonstrate potential viability of the proposed framework, this Section reports simulation results for MSN tracking a single target on a flat terrain. The focus of MSN optimization is prolonging MSN life-span by ensuring that all sensors deplete their battery energy simultaneously. Subsection A briefly introduces the tracking model, and Subsection B reports the simulation results.

A. Model

Consider a MSN designed to track a single target G and communicate the desired information at a low rate to a fixed destination D. It can be shown that under some natural assumptions the optimal MSN topology is linear with only one sensor $s = S$ acquiring target information and the rest of the sensors $s = 1,..,S-1$ relaying this information to the destination D. In this linear topology, sensor information flows from the target to the destination: $G \to (s = S) \to \ldots \to (s = 1) \to D$, while the control information, e.g., destination "willingness-to-pay" for sensor information, flows in the opposite direction: $D \to (s = 1) \to \ldots \to (s = S)$.

We estimate the communication power using the threshold-based wireless channel model (15). We also estimate sensor $s = S$ power expenditure for tracking target G by function $\omega^{-1}(x_G, x_S)$, where $\omega(x_G, x_S)$ can be interpreted as the "path loss" with respect to the target G. Assumption of low information rate and thus low transmission powers allows us to neglect the interference and use formulas (18)-(19). Under these assumptions, the aggregate penalty associated with draining sensor battery energy is

$$\begin{aligned} V(x) = {} & v_S \left[\frac{\chi\eta}{\xi(x_S, x_{S-1})} + \frac{1}{\omega(x_G, x_S)} \right] + \\ & + \sum_{s=1}^{S-1} v_s \left[\chi\eta \left(\frac{1}{\xi(x_s, x_{s-1})} + \frac{1}{\xi(x_s, x_{s+1})} \right) \right] \end{aligned} \tag{35}$$

where for simplicity we assumed the same threshold for all sensors: $\chi_{s,s-1} = \chi_{s,s+1} = \chi$ and also location independent noise power: $\eta(x) = \eta$. We also formally identified destination D with sensor $s = 0$.

Minimization of its own penalty by each sensor may result in poor overall MSN performance. For example, each sensor $s = 2,..,S-1$ attempting to minimize its penalty while maintaining communication with neighboring sensors $s-1$ and $s+1$ typically has incentive to position itself at the "middle point" between the neighbors such that $\xi(x_s, x_{s-1}) = \xi(x_s, x_{s+1})$. This is done without any consideration for conserving the neighboring nodes' energy. This "selfish" sensor positioning may quickly deplete battery energy of some sensors disconnecting the network and destroying MSN ability to relay sensor information to the destination from sufficiently distant target.

B. *Simulation Results*

Consider a MSN with six mobile sensors tracking a single mobile target on a flat terrain where path losses are of the form (13). Assume that maximum sensing and communication distances are 6 and 12 meters respectively, and also sensor energy expenditure due to motion is negligible. It is also assumed that sensors have different initial battery energy levels (ranging between 5-50 KJ). Further details of sensor relocation algorithm for this particular scenario will appear in [14]. Figure 1 demonstrates inefficient "selfish" sensor relocations where sensors deplete their battery energy in the order of their initial energy levels. In the case of target being sufficiently distant from the destination, this selfish behavior makes the network non-operational in 60 minutes.

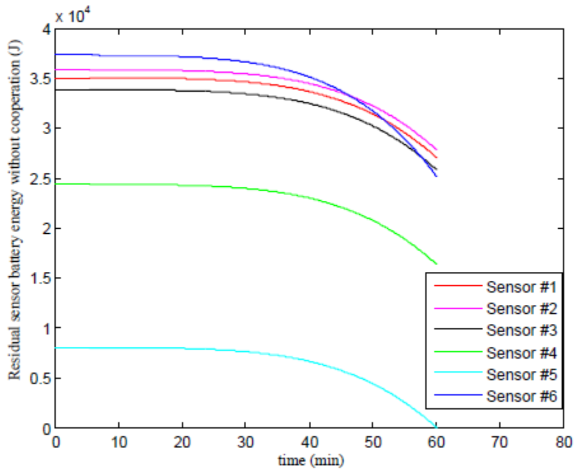

Figure 1: Residual sensor battery energy without cooperation

Figure 2 demonstrates that cooperative relocation which takes into account the residual battery energy levels can prolong the network life-span to 78.5 minutes. In this case, all sensors deplete their battery energy simultaneously.

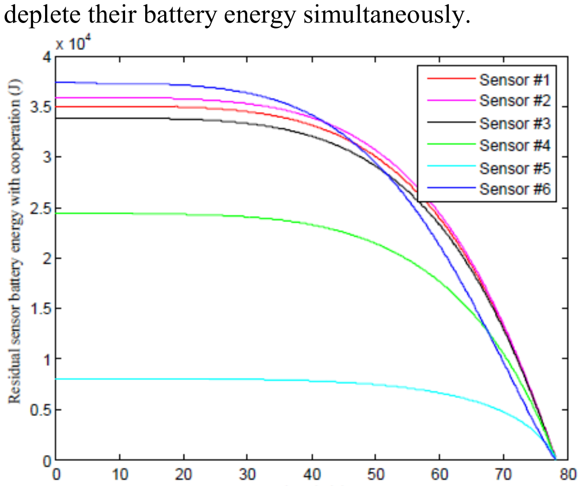

Figure 2: Residual sensor battery energy with cooperation

Figures 3-5 show sensor locations along with their communication regions and sensing region of sensor $s = S$ at time instants t=5, 50 and 72 minutes. Figure 6 shows the sensor battery energy levels at these moments for cooperatively moving sensors. First observe that all sensors position themselves on a straight line from the destination to the target. This is due to the flat terrain assumption.

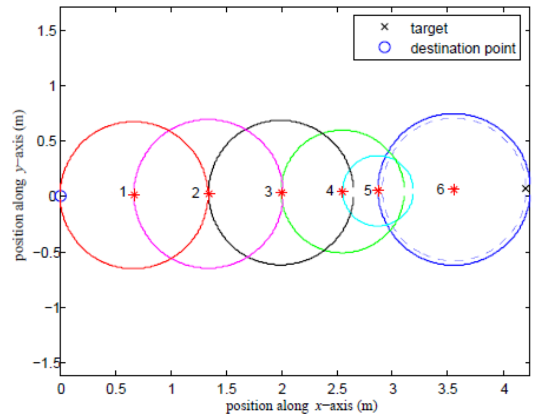

Figure 3: Target and sensor locations: $t = 5\,\text{min}$

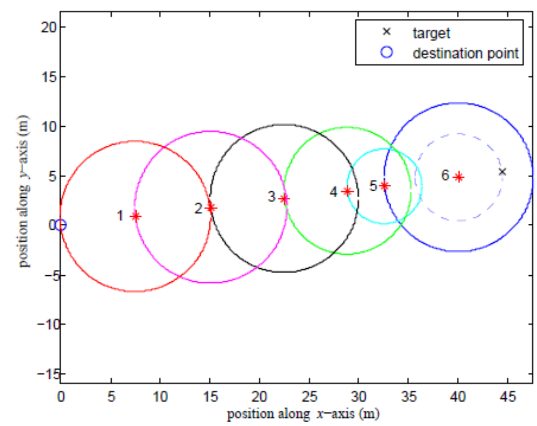

Figure 4: Target and sensor locations: $t = 50\,\text{min}$

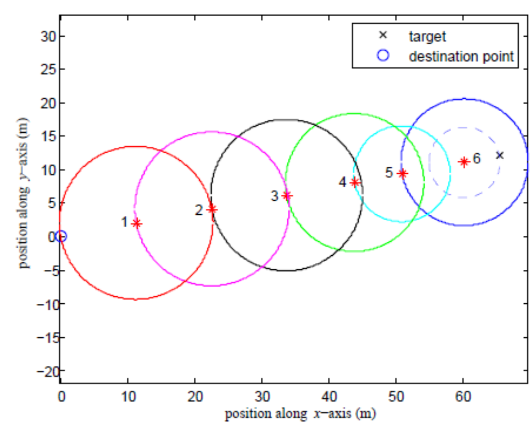

Figure 5: Target and sensor locations: $t = 72\,\text{min}$

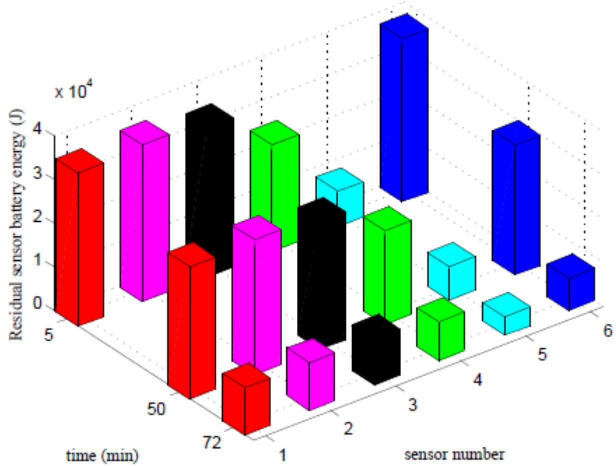

Figure 6: Sensor battery energy

Figures 3-6 exhibit some details of sensor cooperative repositioning for the purpose of preserving battery energy for sensors with lower residual battery energy. Since maximum sensing and communication distances are 6 and 12 meters respectively, the MSN is able to track a target within 78 meters from the destination point. In Figure 5, when the target is at the boundary of this "tracking range", sensors maintain the maximum communication and sensing ranges. By doing that MSN carries out its primary goal: tracking the target, at the cost of reducing the MSN life-span. Figures 3 and 4, when the target is located well within the "tracking range" and sensors have certain freedom in positioning themselves while MSN keeps tracking the target. Figures 3-6 demonstrate that sensors cooperatively position themselves to reduce communication range and thus reduce energy expenditure for sensors with low battery energy level.

VI. Conclusion and Future Research

The paper is proposing a unified pricing/evolutionary framework for MSN self-organization, which involves sensor cooperation in data acquisition and communication as well as sensor relocation. Socially optimal pricing, which internalizes the effect of each sensor action on the overall MSN performance, allows for decentralized MSN optimization. Presented results on a MSN, tracking a single target, suggest viability of the proposed framework for prolonging the MSN life-span at least in the case of a flat terrain.

Future research should address practicality of the proposed framework. Three major obstacles to overcome are (a) overhead associated with social pricing exchange, (b) multiple locally optimal sensor locations, and (c) numerous other uncertainties. While phenomenologically defined virtual forces are widely used for controlling mobility, the proposed unified framework leads to "socially optimal" virtual forces, which are consistent with the overall MSN goals. Evolutionary algorithms appear to be a natural approach to overcoming obstacles (a) and (b). To gain some insight, we plan to evaluate a simulated annealing type optimization of MSN tracking a single target in complex terrains.

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