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Performance Optimization for Anchor-Based Mobile Data Gathering in WSNs

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ABSTRACT: Most of the wireless sensor network consists of static sensors, which can be deployed in a wide environment for monitoring application. While transmitting the data from source to static link, the amount of energy consumption of the sensor mode is high. It results in reduced life time of the networks. Here a mobile collector roams over the sensing field and pauses at some anchor points on its moving tour such that it can traverse the transmission range of all the sensors in the field and directly collect data from each sensor. By an efficient and robust distributed algorithm we can increase the performance as well as the efficiency of such mobile data gathering scheme. The network cost minimization is achieved by the pricing-based algorithms, which results in 32% less network cost with respect to the existing algorithm.

KEYWORDS: Mobile data gathering, pricing mechanism, convex problem, decomposition, Karush-Kuhn-Tucker (KKT) conditions**.**

I.INTRODUCTION

Recent years have witnessed the proliferation of wireless sensor networks (WSNs) as a new information-gathering paradigm for a wide-range of applications, such as field exploration, environmental monitoring, and security surveillance. Besides the active (via in-situ observation) or passive (via remote-sensing technologies) sensing on the interested real word phenomena, the paramount task in a WSN is how to efficiently gather sensing data from scattered sensors. Traditional approaches, also referred to as static data gathering, typically inherit the basic idea of dynamic routing, where sensing data is routed to a static data sink via selected relay sensors.

In this paper, we will focus on anchor-based mobile data gathering and study how to achieve optimal performance in such a scheme. We characterize data gathering performance by introducing network cost, which is a function quantifying the aggregate cost on gathering data from sensors at different anchor points. The “cost” here physically implies the energy consumption or monetary expense on gathering a certain amount of data from a sensor at a particular anchor point. The relationship between the cost and gathered data amount may differ from sensor to sensor, one anchor point to another. In this way, optimizing data gathering performance is equivalent to solving the corresponding system-wide cost minimization problem. To find the optimal data gathering strategies, we consider regulating two unable system parameters. One parameter is the amount of data a sensor uploads to the mobile collector at a particular anchor point. Since it is expected to collect sufficient data from each sensor in a data gathering tour, we require that the aggregate data uploaded from a sensor to the mobile collector at all anchor points should be no less than a specified threshold. Another parameter is the sojourn time of the mobile collector at each anchor point

. We prove that the cost minimization problem can be solved by jointly solving the two sub problems. The negotiation between the two sub problems can be described as a pricing mechanism, where sensors independently adjust their payments to compete for the data uploading opportunity to the mobile collector based on the shadow prices of different anchor points set by the mobile collector. By iteratively updating the payment and the shadow price between each sensor and the mobile collector, an equilibrium that re-conciliates the two sub problems can be reached, where the overall network cost is minimized.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a sensor network which consists of a set of static sensors, denoted by N, and a set of anchor points, denoted by A. We study the anchor-based range traversing data gathering scheme, where the mobile collector gathers data directly from sensors by visiting each anchor point in a periodic data gathering tour. There are several ways to decide

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the locations of anchor points. One way is to consider the sensing field as a grid and anchor points can be uniformly distributed on grid intersections. An alternative way is to use the positions of a subset of sensors as the locations of anchor points. In this paper, we would follow the latter option based on following considerations. First, it simplifies the setting of anchor points since we do not need to separately locate specified positions for anchor points. Second, setting selected sensor locations as the anchor points can easily guarantee the coverage issue, i.e., all sensors need to be covered by visiting these anchor points. The locations of a subset of sensors, whose coverage area can cover all sensors, can be selected as the anchor points. It is clear that we can always find such subset of sensor locations as the anchor points. The worst case is just to visit the sensors one by one. However, this would not be easily achieved by grid setting pattern as the grid density should be carefully determined based on the sensor distribution and radio transmission range so as to ensure all sensors to get covered. Third, it makes the optimization on the moving trajectory easier. As the sensor locations form the pool of candidate locations for anchor points, the selected locations for anchor points can be naturally adaptive to the sensor distribution, which enables the mobile collector to shorten the moving tour by avoiding visiting the vacant areas with no sensors. Moreover, as the candidate locations are limited, it is possible for us to search for optimal anchor points so as to guarantee the coverage of all sensors as well as minimizing the moving trajectory. Fourth, such setting can facilitate the distributed implementation of our algorithm, where each sensor located at respective anchor point can play as a controller coordinating the local information exchange.

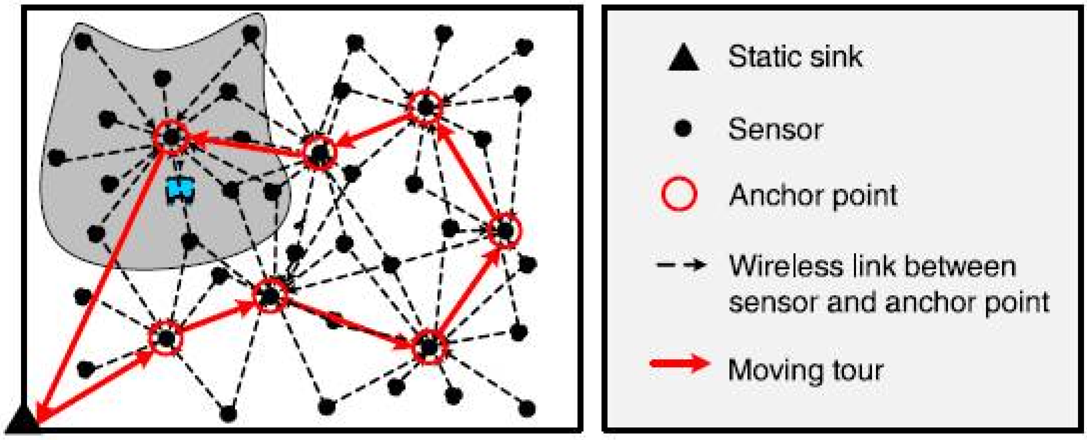

Fig. 1:Anchor based range traversing data gathering scheme

Since the SenCar moves over different anchor points, we now define two sets that depict the relationship between the SenCar and sensors in the movement. One set is Na (a ∈ A), which represents the sensors in the coverage area of anchor point a. These sensors can directly upload data to the SenCar when it arrives at anchor point a. Another set is Ai (i ∈ N), which contains the anchor points sensor i can reach in a single hop. To ensure that each sensor has the opportunity to upload data to the SenCar, we assume that Ai is always non-empty. This can be guaranteed by choosing the anchor points through finding a set of neighbour sets of sensors such that the selected sets contain all the sensors in the neighbour sets.

The SenCar would stay at anchor point a for a period of sojourn time ta to gather data from nearby sensors. In some time-sensitive applications, the data gathering task is expected to be completed in a bounded period, which is equivalent to constraining the total sojourn time at all anchor points within a limit. We denote such a limit by T and call it the bound of total sojourn time.
The network cost minimization problem can be formalized as follows:

Definition 1: (NCM: Network Cost Minimization Problem for Mobile Data Gathering in WSNs): Given a set of sensors, N, a set of anchor points, A, the minimum data amount of sensor i (i ∈ N), Mi, and the bound of total sojourn time at all anchor points, T, find: (1) the data amount xai uploaded from sensor I to the SenCar at anchor point a; the sojourn time ta of the SenCar at anchor point a, such that network cost is minimized.
Minimize:

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$$\sum_{a\in\mathcal{A}}\sum_{i\in\mathcal{N}^a} C_i^a\left(x_i^a\right) \quad (1)$$

Subjected to

$$\sum_{a\in\mathcal{A}_i} x_i^a \geq M_i, \quad \forall i \in \mathcal{N}$$

$$\sum_{i\in\mathcal{N}^a} \frac{x_i^a}{p_i^a} \leq B \cdot t^a, \quad \forall a \in \mathcal{A} \quad (2)$$

The constraints in the NCM problem can be explained as follows.

• Data constraint (2) shows that for each sensor, its aggregate uploaded data at all anchor points should be no less than the specified minimum amount.

• Link capacity constraint (3) enforces that when the SenCar is located at anchor point a, the total transmitted data amount from the sensors in the neighbourhood is restricted by the product of channel bandwidth B and sojourn time ta. As the SenCar locally schedules the data uploading from associated sensors one by one at each anchor point, we can consider the data uploading procedure to be collision-free among sensors. The retransmitted packets are mainly caused by the unreliable wireless links.

• Total sojourn time constraint (4) ensures that the total sojourn time of the SenCar at all anchor points is bounded by T.

III. PROBLEM DECOMPOSITION AND PRICING-BASED ALGORITHM

In the previous section, we provided the formulation of the NCM problem. Since the problem has a strictly convex function with respect to xai(a ∈ A, i ∈ Na) and is over a convex feasible region, the NCM problem is mathematically tractable. However, there exist some difficulties to directly solve it:(1) Cost functions, Cai (·), for all a ∈ A, are typically the knowledge of sensor i and are unlikely to be known by other sensors or a central network controller; (2) Due to the asymmetry of wireless channels, the successful delivery ratio pai that indicates the uplink channel quality from a sensor to the SenCar at an anchor point may not be easily obtained by sensors, which are the senders in the transmissions.

Suppose sensor i chooses to pay qai for the data uploading opportunity when the SenCar stops at anchor point a in a data gathering tour, and in return is permitted to upload xai amount of data proportional to qai, i.e., qai = λai xai, where λai can be considered as the price for uploading a unit amount of data over the link from sensor i to the SenCar at anchor point a. In the following, we simply call λai link price. Then, the local cost minimization problem for sensor i can be expressed as follows.

Sensor i:

Minimize:

$$\sum_{a\in\mathcal{A}_i} C_i^a\left(\frac{q_i^a}{\lambda_i^a}\right) + \sum_{a\in\mathcal{A}_i} q_i^a \quad (3)$$

Subjected to:

$$\sum_{a\in\mathcal{A}_i} \frac{q_i^a}{\lambda_i^a} \geq M_i, \quad (4)$$

In the above, we consider two parts of costs for sensor i: $\sum_{a\in\mathcal{A}_i} C_i^a\left(\frac{q_i^a}{\lambda_i^a}\right)$ represents the sum of data uploading cost to all the neighboring anchor points of sensor *i*, and is the total payment used in competing for the data uploading opportunity. In SENSOR−*i* problem, given link prices *λai*'s, sensor *I* independently minimizes its overall local cost by adjusting its payments (*qai* for all *a*) under the constraint that its aggregate uploaded data is no less than*Mi*. Note that to solve this problem, there is no need for sensor *i* to have the knowledge of link condition *pai* for all *a* ∈ *Ai*.

Sencar :

Mazimize

$$\sum_{a\in\mathcal{A}}\sum_{i\in\mathcal{N}^a} q_i^a \log\left(x_i^a\right) \quad (5)$$

Subjected to

$$\sum_{i\in\mathcal{N}^a} \frac{x_i^a}{p_i^a} \leq B\cdot t^a,\ \forall a\in\mathcal{A}$$

$$\sum_{a\in\mathcal{A}} t^a \leq T, \quad (6)$$

Clearly, the above maximization problem does not require the SenCar to know the cost functions $Cai\,(\cdot)$ for all $a \in A$ and $i \in Na$.

The following theorem shows that by solving SENSOR−*I* and SENCAR problems, optimal data control and sojourn time allocation can be achieved as the global cost minimization (i.e. NCM) problem.

Theorem 1: There exist non-negative matrices $x = \{xai|a \in A,\ i \in Na\}$, $q = \{qai\ |a \in A,\ i \in Na\}$ and $\lambda = \{\lambda ai\ |a \in A,\ i \in Na\}$, and non-negative vector $t = \{ta|a \in A\}$ with $qai = \lambda ai\ xai,\ \forall\ i \in N,\ a \in Ai$ such that

(a) For $i \in N$, with $\lambda ai > 0$ for all $a \in Ai$, $qi = \{qai\ |a \in Ai\}$ is the solution to the SENSOR−*i* problem;
(b) Given that each sensor is charged qai for uploading data to the SenCar when it is located at anchor point a, (x, t) is the solution to the SENCAR problem;

Proof: We first show the existence of x, q and λ that satisfy *(a)* and *(b)*, and then prove that the corresponding (x, t) is the solution to the NCM problem.

We assume that with proper settings of parameters Mi and T, there always exist feasible variable matrices x and q, and variable vector t that satisfy the constraints in NCM, SENSOR−*I* and SENCAR problems with strict inequality, which means that they are interior points in the feasible region of the respective problem. Thus, the Slater's condition for constraint qualification is satisfied. Since SENSOR−*i*, SENCAR and NCM problems are all convex problems, the solution to each problem that satisfies the corresponding Karush-Kuhn-Tucker (KKT) conditions is sufficient to be optimal for the respective problem.

Assuming $x* = \{xai*\ |a \in A,\ i \in Na\}$ and $t* = \{ta*\ |a \in A\}$ are the optimal solution to the NCM problem, we obtain the following KKT conditions.

By the KKT conditions, $q*\ i= \{qai*\ |a \in Ai\}$ is the optimal solution to SENSOR−*i* problem if and only if there exists $v*\ i$ that satisfies

$$\frac{\partial L_{\text{sen}-i}}{\partial q_i^a} = \frac{1}{\lambda_i^a}\cdot C_i^{a\prime}\left(\frac{q_i^{a*}}{\lambda_i^a}\right) + 1 - \frac{v_i^*}{\lambda_i^a} = 0,\ \forall a\in\mathcal{A}_i, \quad (7)$$

For a given q, by the KKT conditions, we have that matrix $x*$ and vector $t*$ are the optimal solutions to SENCAR problem if and only if there exist $\alpha* = \{\alpha a*\ |a \in A\}$ and $\beta*$ such that

Let $(x*,\ t*)$ be the optimal solution to the NCM problem and $\sigma*$, $\mu*$ and $\gamma*$ be the corresponding multipliers that satisfy the KKT conditions in (9)–(15). Let $xai= xai*$, $ta = ta*$, $\lambda ai= \sigma a*\ pai$ and $qai = \sigma a*\ pai\ xai*$. It is clear that xai, ta, λai

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and *qai* are all nonnegative. By defining *αa* = *σa*□ and *β* = *γ* □, we find that *x, t, α* and *β* satisfy the KKT conditions for SENCAR problem in (22)–(27). Thus, *(x, t)* solves SENCAR, which implies that the solution satisfying KKT conditions of NCM also identifies a solution to SENCAR. Defining *vi* = *μi* □ together with *λai* = *σa*□ *pai* , the KKT conditions of SENSOR−*i* problem are satisfied such that *qai* = *σa*□ *pai xai* □ is the solution to SENSOR−*i*. This analysis establishes the existence of *x*, *λ* .

The SENCAR problem requires the payment information from all sensors for all anchor points. It may incur high communication overhead if the SENCAR problem is solved in a centralized way.. The sub problems can be solved with the aid of these sensors. For clarity, we call them *help nodes* in the following. This way, to announce payment *qai* , sensor *i* only needs to locally inform the help node at anchor point *a*. In case that anchor points are not selected from sensor locations, we can also flexibly pick up one or more sensors close to each anchor point to serve as the help nodes.

Where *αa* is also referred to as *shadow price* of anchor point *a*. Given price *λ*, minimum of *L_ car* occurs when *xai* = *qai* /*λai* . Thus, the dual function is defined as

$$g(\alpha) = \inf_{t} \left\{ L'_{\text{car}}\left(\frac{q}{\lambda}, t, \alpha\right) \middle| \sum_{a\in A} t^a \leq T \right\}. \quad (8)$$

The dual problem is to find a shadow price vector *α* □ that maximizes dual function *g(α)*.
Moreover, based on Lagrangian *L*_car, we have

$$\frac{\partial L'_{\text{car}}}{\partial x_i^a} = -\frac{q_i^a}{x_i^a} + \frac{\alpha^a}{p_i^a} = -\lambda_i^a + \frac{\alpha^a}{p_i^a}. \quad (9)$$

Pricing-Based Algorithm: For each *a* ∈*A*, the help node independently initializes the shadow price *αa* for anchor point *a* to a positive value.

Repeat the following iteration until the shadow price vector*α* converges to *α*∗ .
At iteration *n*,

• For all *a* ∈*A*, the help node at anchor point *a* determines link price *λai (n)* for all *i* ∈*Na* by setting and then sends this information to sensors in its neighborhood.

• For all *i* ∈*N*, after learning link price *λai(n)* for all *a* ∈*Ai*, sensor *i* decides its payments *qai (n)*'s for its neighboring anchor points by solving SENSOR−*i* problem to minimize the local cost,and then announces these payments to the corresponding help nodes at neighboring anchor points.

In order to minimize *L*_car, each help node sets the sojourn time for its located anchor point by following rule

$$t^a(n) = \begin{cases} T, & \text{If } a = \arg\max_{a\in A} \alpha^a(n) \\ 0, & \text{Otherwise.} \end{cases} \quad (10)$$

It was proved in that when the diminishing step size is used, any accumulation point of sequence {ˆ*ta(n)*} generated by (35) is feasible to the primal problem and {ˆ*ta(n)*} can converge to a primal optimal solution.

$$\alpha^a(n+1) = \left[\alpha^a(n) + \theta(n)\left(\sum_{i\in\mathcal{N}^a} \frac{x_i^a(n)}{p_i^a} - Bt^a(n)\right)\right]^+, \quad (11)$$

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Where $[\cdot]+$ denotes the projection onto the positive orthant and $\theta(n)$ is a properly chosen scalar step size for iteration n. In our algorithm, we choose the diminishing step size, i.e., $\theta(n) = d/(b + cn)$, $\forall n, c, d > 0, b \geq 0$, where b, c and d are adjustable parameters that regulate the convergence speed. For example, if b and c are set with relatively large value and d is set with a very small value, for particular iteration n, $\theta(n)$ will result in a small step size. As iteration goes on, $\theta(n)$ will sharply decrease as n increases. Choosing a small step size will lead to high accuracy, however, slow speed of convergence. In contrast, if b, c and d are conversely set, though the step size is diminishing along with n, it results in relatively large step size in each iteration. Increasing the step size will improve the convergence speed, meanwhile reduce the accuracy. The diminishing step size can guarantee the convergence regardless of the initial value of αa .

Finally, as the results of the iterations, the converged value of matrix $x(n) = \{xai(n)|i \in N, a \in A\}$ and vector$(n) = \{\hat{}ta(n)|a \in A\}$ indicates the optimal data control for sensors and the optimal sojourn time allocation for the SenCar, i.e., $(x,\hat{}t)$ is the optimal solution to the NCM problem.

IV. LOCAL COST MINIMIZATION AT SENSORS

In this section, we consider the second step of the pricing based algorithm: how to solve SENSOR−i problem by each sensor under given link price vectoras aforementioned, $Cai(\cdot)$ is a monotonic increasing function. Thus, the minimum of the objective function in (6) should be achieved when considering this fact, the SENSOR−i problem can be rewritten as follows.

Sensor i

Minimize:

$$\sum_{a\in\mathcal{A}_i} C_i^a\left(\frac{q_i^a}{\lambda_i^a}\right) + \sum_{a\in\mathcal{A}_i} q_i^a \qquad (12)$$

Subjected to:

$$\sum_{a\in\mathcal{A}_i} \frac{q_i^a}{\lambda_i^a} = M_i, \qquad (13)$$

If there are multiple minimum-marginal-cost anchor points, we can randomly choose one. SenCar at those anchor points that incur the minimum marginal cost. This intuitively suggests that sensor i should gradually shift the payment to the minimum-marginal-cost anchor point from other neighboring anchor points and finally reach an equilibrium, where the aggregate marginal cost of anchor points selected for data uploading is less than or equal to that of unselected anchor points [40]. In the following, we present an adaptation algorithm that strikes for such equilibrium.

Adaptation Algorithm:

1) Case I: If $|Ai| = 1$, then $qai = \lambda ai\ Mi$;
2) Case II: If $|Ai| > 1$, sensor i first initializes its payment vector $qi(0) = \{qai(0) \geq 0|a \in Ai\}$ that satisfies
$\sum_{a\in\mathcal{A}_i} \frac{q_i^a(0)}{\lambda_i^a} = M_i.$ where $|Ai|$ represents the cardinality of set Ai.
Then, it iteratively updates vector $qi(k)$ according to following adaptation principle described by Eq. (41) and Eq. (42). Particularly, if anchor point a is not chosen as the minimum-marginal-cost anchor point by sensor I (i.e., $a = \hat{}ai$) and there still exists positive payment for it, this payment should be reduced. On the contrary, if a is chosen as the minimum-marginal-cost anchor point (i.e., $a = \hat{}ai$), the payment for it should be increased and the increased amount is proportional to the linear combination of the aggregate payment shifted from all other neighboring anchor points of sensor i .
Theorem 2: When step size $\delta(k)$ is small enough, the adaptation algorithm converges to a unique optimal solution $q*\ i$ to the SENSOR−i problem.

V. SIMULATION RESULTS

In this section, we provide simulation results to demonstrate the usage and efficiency of proposed algorithm and compare its performance with another data gathering strategy.Though the proposed algorithm may incur some

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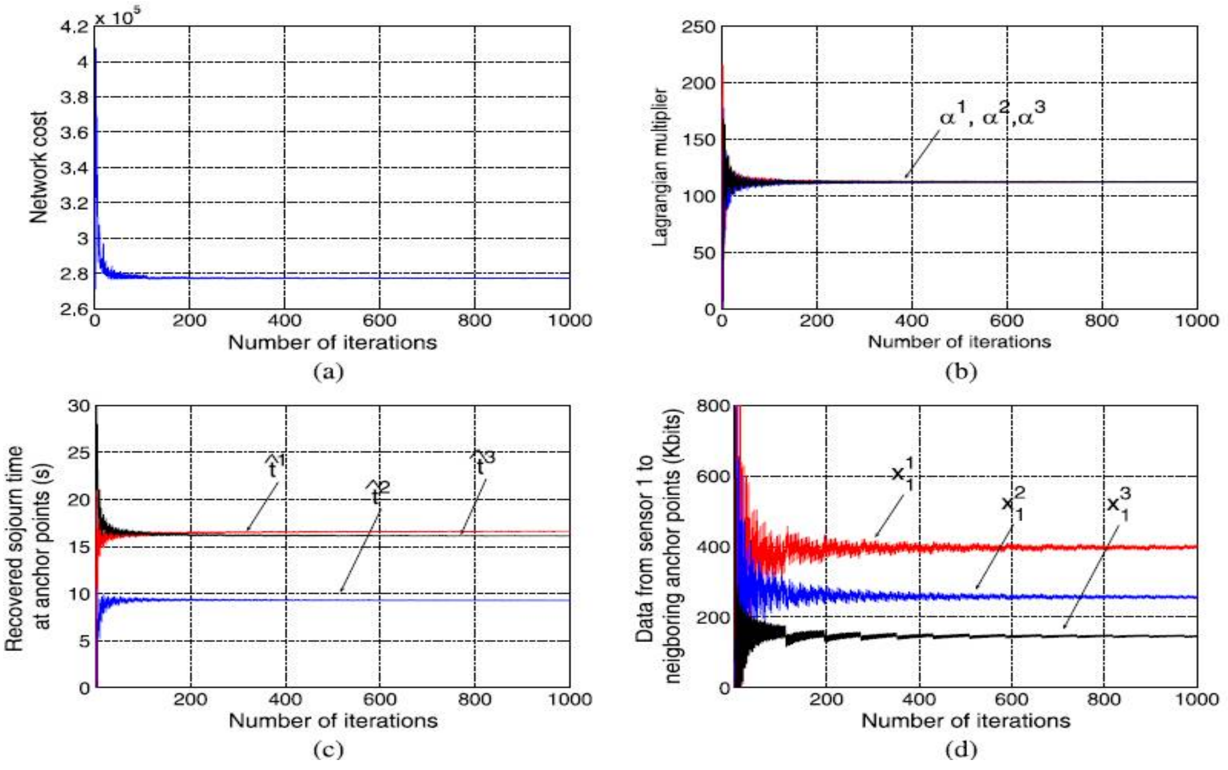
computation and communication overhead, it is worth pointing out that the algorithm is feasible in practice due to following reasons. First, the solution exploration procedure for the distributed algorithm is only a one-time operation. When the tunable parameters (i.e., the data amount of each sensor for different anchor points and the sojourn time of the SenCar at each anchor point) are set by the algorithm, the SenCar would always follow the determined rules and repeat same data gathering tours. Only if the network topology experience substantial changes, the algorithm will need to be executed again. Thus, the algorithm would not be frequently performed. Second, the solution exploration procedure can be executed in the initial setup phase of the network before mobile data gathering formally starts. The information exchange in iterations between the sensors and their corresponding anchor points can be performed along with data transmissions. That is, the payment information can be transmitted by piggybacking it with the sensing data. The help nodes at the anchor points can temporarily help buffer the sensing data and upload them to the SenCar once it comes. In this way, the communication overhead of the algorithm can be minimized by re-using the data transmissions. Third, there would not be many anchor points in the field such that the incurred overhead by the distributed algorithm can thus be greatly dampened.

A. Algorithm Convergence

In this subsection, we illustrate the convergence of the pricing-based algorithm via a numerical case study. We consider a WSN with a total of 12 sensors as shown in Fig. 3. The locations of sensors 3, 4 and 5 are chosen as anchor points and each of these sensors would act as the helping node in computing for the respective anchor point. In the figure, there is a link between an anchor point and each of its neighboring sensors. We define the cost function as $Ca\ i\ (xai) = \omega a\ i\ xai\ 2$, where $\omega a\ i$ is the weight of cost for sensor i to upload data to the SenCar at anchor point a. Clearly, a larger weight $\omega a\ i$ would have more impact on the entire network cost.

B. Network Cost

In this subsection, we conduct a suite of simulations to evaluate the network cost achieved by the pricing-based algorithm and compare the results with another data gathering strategy called cluster-based algorithm, where sensors are virtually clustered, i.e., each sensor is randomly associated with a neighboring anchor point and uploads all its data



Evolution of network cost, shadow prices of different anchor points, recovered sojourn time for SenCar stopping at different anchor points, and uploading data from sensors 1, 6 and 10 versus the number of iterations in the pricing-based algorithm. (a) Network cost vs. *n*. (b) *αa* vs. *n*. (c) ˆ*ta* vs. *n*. (d) *xa*1 vs. *n*. (e) *xa*6 vs. *n*. (f) *xa* 10 vs. *n*.

to the SenCar only when it arrives at this anchor point. This algorithm is commonly considered as a simple and effective strategy for the anchor based range traversing data gathering scheme in the existing literature [13]. We consider a generic sensor network with |*N*| sensors randomly distributed over the sensing field and |*A*| anchor points that can cover all sensors. The cost functions are defined as *Ca i (xai*) = *ωa i xai* 2 for all *a* ∈ *A*, *i* ∈ *Na* and the weights of the cost *ωa i* 's are generated as discrete uniform random numbers ranging from 0.01 to 0.10. We assume the minimum data amount *Mi* is equally set for all sensors and its value equals 800 Kb if not specified otherwise. The channel bandwidth *B* is set to 250 Kbps. Moreover, we introduce .*p* to denote the average successful delivery ratio of all links and use it to characterize the physical condition of the network. The successful delivery ratio *pai* of each link between a sensor and an anchor point would ranges from 2.*p* − 1 to 1. Considering the randomness of the network topology, each performance point in the figures below is the average of the results in 100 simulation experiments.

VI. CONCLUSION

In this paper, we have studied performance optimization for anchor-based mobile data gathering in WSNs. We formalized the problem as a cost minimization problem constrained by channel capacity, the required minimum data uploads from each sensor and the bound of total sojourn time at all anchor points. We characterized this problem as a pricing mechanism and decomposed it into two simpler sub problems, i.e., SENSOR−*I* and SENCAR sub problems. We have proved that network cost can be minimized by jointly solving the two sub problems. Correspondingly, we described a pricing-based algorithm that iteratively solves SENSOR−*i* and the dual problem of SENCAR. In each iteration, the help node sets the shadow price for its local anchor point and derives link prices between neighboring sensors and the anchor point. Each neighboring sensor then determines the payments to minimize its local cost. The minimum network cost can be achieved when reaching the equilibrium that re-conciliates the two sub problems. We also proposed an efficient adaptation algorithm for solving the SENSOR−*i* sub problem at each sensor. Finally, we gave extensive simulation results to validate the efficiency of the proposed algorithm and compare its performance with cluster based data algorithm.

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