Joint Optimization of System Lifetime and Network Performance for Real-Time Wireless Sensor Networks

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Abstract. Maximizing the aggregate network utility and minimizing the network energy consumption are important but conflict goals in wireless sensor networks. Challenges arise due to the application-specific computing and communication resources constraints and end-to-end real-time constraints. This paper studies the tradeoff between energy consumption and network performance in Real-Time Wireless Sensor Networks (RTWSN) by investigating the interaction between the network performance optimization and network lifetime maximization problems. We address the tradeoff between these two conflict goals as a joint non-linear optimization problem. Based the solution of the optimization problem, we design an online distributed algorithm to achieve judicious tradeoff based on application-specific focus, while at the same time meeting real-time and resource constraints. Extensive simulation studies illustrate the efficiency and efficacy of the proposed algorithm.

Keywords: Real-Time, Wireless Sensor Networks, System Lifetime, Network Performance.

1 Introduction

Over the last few years, the design of wireless sensor networks has gained increasing importance due to their potential for many military and civil applications, such as fire monitoring, border surveillance, medical care, highway traffic coordination, etc. Many of those applications have real-time requirements. To satisfy the real-time requirements of many of these applications, Real-Time Wireless Sensor Networks (RTWSNs) have been developed in the literature [2] [9] [16][17][18][25].

To design an RTWSN, one has to consider the following issues: network performance, energy consumption, and real-time requirements. Network performance refers to the level of quality of service (QoS) provided by an RTWSN. For energy consumption, since sensor nodes are typically driven by batteries, they have to comply with limited battery budgets. Very often, battery recharging manually or replacement is impossible due to the deployment of sensor nodes in inaccessible or hostile environment. Such energy constraints bring about the notion of network

N. Bartolini et al. (Eds.): QShine/AAA-IDEA 2009, LNICST 22, pp. 317–333, 2009.

"lifetime". The network is considered to be alive while all the nodes still have some energy; the lifetime is the time from the initialization of the network to the time until the first node runs out of energy. For many applications mentioned above, the sensor data are only valid for a limited duration; hence need to be delivered within certain real-time constraints (e.g., deadlines). In this paper, we study problems in RTWSNs considering all of the above three metrics together.

For a specific application in RTWSNs, phenomena of interest will change with time. Instead of using worst-case sampling rates that will work for all the phenomena, dynamically finding the set of globally optimal sampling rates will provide better QoS. For most applications, higher sampling rates offer better QoS. We will exploit network aggregate utility over sampling rates and route selection to refer to the network performance.

In an RTWSN, we can increase the network lifetime or the network utility by using transmission schemes as dynamic routing selection and dynamically finding the set of optimal sampling rates under real-time constraints. We note that there is an inherent tradeoff between the network lifetime and the network utility. Maximizing network utility may require some nodes to lie on routes of many source destination pairs with higher sampling rates, which may cause them to run out of energy quickly. We can increase the network lifetime routing selection avoiding the creation of hot spots where some nodes die out quickly and cause the network to fail as well as decreasing the sampling rates at the expense of the network utility.

In this paper, we systematically study the joint optimization of system lifetime and network utility under schedulability and real-time constraints in an RTWSN. We first model and formulate the lifetime maximization and network utility maximization as two optimization problems separately. By introducing a designed parameter, we formulate the tradeoff between lifetime and network utility as a joint optimization problem. Due to the distributed nature of wireless sensor networks, we design a distributed algorithm for the joint optimization problem. We exploit the NUM framework as discussed in Shu et al.'s work [2]. In this paper, we propose a distributed algorithm for our optimization problem. We will illustrate the tradeoff between system lifetime and network utility by assigning different values to the designed parameter. The designed parameter is selected by domain experts. We will also show that the distributed algorithm is effective in both routes selection and sampling rates assignment.

In summary, the main contribution of this paper is twofold:

1) To the best of our knowledge, our study is the first to investigate the joint optimization of system lifetime and network utility under real-time constraints in a wireless sensor network. With different designed parameters for different applications, different routes selection and sampling rates are obtained to meet requirements from those applications.

2) We design a distributed algorithm that corresponds to the mathematical solution of our optimization problem, and show the efficiency of the algorithm through simulations.

The rest of this paper is organized as follows: Section 2 briefly introduces the relate work; Section 3 formulates and models the joint optimization between system lifetime and network utility; Section 4 solves the optimization problem using the primal-dual method and dual decomposition technique; Section 5 presents the distributed algorithm that matches the solution in Section 4; Section 6 evaluates the distributed algorithm and tradeoff problem; and Section 7 concludes the paper.

2 Related Work

Due to the wide deployment of wireless sensor networks, many researchers are now developing technologies such as localization, topology control, and power management for different kinds of applications. A comprehensive survey is referred to [10].

Energy efficiency routing algorithms for wireless sensor networks have attracted considerable attentions. Many of the works on this topic focus on minimizing the total energy consumption of the network [11][12][13][24][26][27][28]. Such optimization goal can lead to draining some nodes' energy very quickly. To remedy, [14] proposes the heuristics of selecting routes in a distributed manner to maximize the network lifetime. Distributed iterative algorithms for computing the maximum lifetime flow are described in [15], where each iteration involves a bisection search on the network lifetime and the solution of a max-flow problem to check the feasibility of the network lifetime.

Sha et al. [16] first study the problem of finding the optimal task execution rates subject to the schedulability constraints for digital controllers. To the best of our knowledge, works by Caccamo et al. [17] first deal with multi-hop RTWSN. Adopting their cellular base station backbone layout, Liu et al. design the Real-time Independent Channels (RICH) architecture [9]; model the real-time sampling rate assignment problem as a constrained optimization problem; and propose a distributed algorithm using Internet pricing schemes [18]. In contrast to Liu et al.'s work, Shu et al. [2] consider dynamic routing: in their model, each sensor source has one or more paths leading to its destination, and one path at a time is selected for data transmission. They show their proposed data transmission scheme outperforms the scheme in [9].

Although both network lifetime maximization and utility maximization have been extensively studied in recent years, few works consider them together and study the tradeoff between them in wireless sensor networks [19][20]. To the best of our knowledge, this paper is the first to study such tradeoff.

The problem of resource allocation for congestion control in computer networks is first studied by Kelly [4][5] and Low et al.[18], which lay the foundation of Network Utility Maximization (NUM). Recent researches model the overall communication network as a generalized NUM problem; each layer corresponds to a decomposed sub-problem; and the interfaces among layers are quantified as functions of optimization variables coordinating the sub-problems. The approaches of Chen [22], and Lin [23] show (from different aspects) how a joint optimization problem can be decoupled and separated into different network layers. Based on the primal-dual method and dual decomposition technique from the NUM framework, we solve the optimization problem is this paper, and find an effective distributed algorithm.

In terms of performance metric, we adopt the utility loss index to capture the performance loss. For more details, refer to [9]. RICH architecture is shown in Fig. 1

proposed by Liu et al. employs the mixed FDMA-CDMA scheme. Our work exploits the RICH architecture [9] to support real-time flows on wireless sensor networks. Schedulability analysis is similar to [2]. Due to space limit, interested readers are referred to [2] for details.

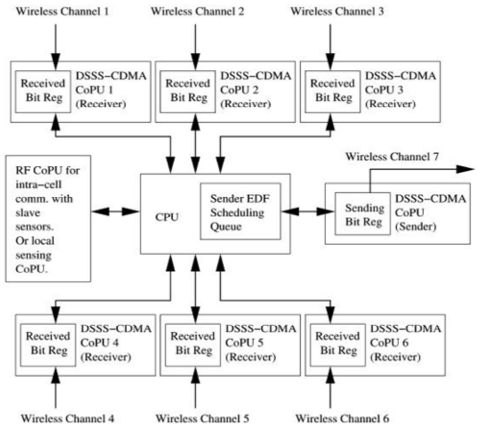

Fig. 1. The Internal Architecture of a RICH Base Station

3 Formulation and Modeling

In an RTWSN, a number of sensor nodes are deployed according to the RICH architecture [9]. We consider about non-rechargeable and irreplaceable sensor batteries. There are multiple source and destination pairs, and there is a set of paths for each source and destination pair, which can be chosen offline based on given routing algorithms for wireless sensor networks such as SPIN [4], GPSR [5], GEAR [6], SPEED [7] or RPAR [8]. The performance of the RTWSN is characterized by two metrics: the network lifetime and the network utility. The network utility is roughly proportional to the allocated sampling rate at each source node.

3.1 Supporting Multi-hop RTWSN

We assume that our wireless base stations (the so-called RICH base stations) have the internal architecture illustrated by Fig. 1. Each RICH base station has seven DSSS-CDMA modulation/demodulation co-processors. Each co-processor operates with a distinct *Direct Sequence Spread Spectrum* CDMA (DSSS-CDMA) *Pseudo Noise* sequence at a distinct FDMA RF band. Six of the DSSS-CDMA co-processors are receivers, and the other one is the only transmitter of the base station.

The broadcast of a RICH base station is overheard by its six neighbor base stations. The wireless medium to the six neighbors are usually. According to DSSS-CDMA theory, given RF band, the upper bound of data bit bandwidth is determined, which we call affordable bandwidth. Suppose for a base station X, due to the irregularity of wireless medium, the affordable bandwidths to its six neighboring RICH base stations are B_1, B_2, …, B_6. The transmission data bandwidth of X is $B = \min\{B_1, B_2, ..., B_6\}$. Therefore the broadcast of X is reliably received by all its six neighbors, i.e. B models factors such as the impact of radio irregularity on the wireless medium.

Consider an RTWSN with N nodes, among which there are S sources. Each source s has K^s available paths or routes from the source to its destination. Only one route is selected for transmitting the data for source s. Let f_s be the sampling rate of source s, and each node on the route of source s also forwards data at such rate.

Physical limitations of a sensor imply an upper bound on its sampling rate. On the other hand, an RTWSN application may require a minimum sampling rate to maintain a minimum performance. Hence we have:

$$f^{\min} \le f \le f^{\max}, \tag{1}$$

where f is the vector of sampling rates of all sources.

To meet the real-time requirement of an RTWSN, we explore non-preemptive EDF scheduling constraint as our schedulability constraint. For details, refer to [9]. We have:

$$Af \le b, \tag{2}$$

where matrix A corresponds to the routing topology and is obtained by node-wise analysis, column matrix b reflects the bandwidth of each node in the network.

3.2 Lifetime Maximization

To maximize RTWSN lifetime by joint rate assignment and dynamic route selection, we can formulate the problem as a nonlinear optimization problem with linear constraints.

For each node i, let d_{is} denote the ternary value which is decided by the network topology:

$$d_{is} = \begin{cases} 2, \text{if i both receives and transmits packets from s;} \\ 1, \ \text{if i only recieves or transmits packets from s;} \\ 0, \qquad\qquad \text{otherwise.} \end{cases}$$

Here we assume without loss of generality that the wireless transmission energy cost is the same as reception energy cost. Our analysis can be easily extended to the cases where these two costs are not equal.

Each node i is assumed to have initial battery energy E_i. The energy spent by node i to transmit or receive a unit of information is e_i. Then the lifetime of each node i is given by

$$T_i = \frac{E_i}{\sum_{s \in S} d_{is} e_i f_s}. \tag{3}$$

We define the network lifetime T_{net} to be the time until the first node runs out of energy, i.e.:

$$T_{net} = \min_{i \in N} T_i. \tag{4}$$

Our aim is to find an algorithm that maximized the network lifetime. Hence we introduce the network lifetime T_{net} as our objective function.

To find an algorithm that maximizes the network lifetime both under the constraints in (1) and (2), the following optimization problem should be solved:

$$\begin{aligned} &\max_{f,R} \quad T_{net} \\ &\text{subject to} \\ &\qquad f \le f^{\max}, \\ &\qquad f \ge f^{\min}, \\ &\qquad Af \le b. \end{aligned} \tag{5}$$

Here R refers to all available routes.

The problem in (5) can be re-written as:

$$\begin{aligned} &\max_{f,R} \quad T \\ &\text{subject to} \\ &\qquad f \le f^{\max}, \\ &\qquad f \ge f^{\min}, \\ &\qquad Af \le b, \\ &\qquad T\sum_{s\in S} d_{is} e_i f_s \le E_i, \forall i \in N, \end{aligned} \tag{6}$$

where the last set of constraints models the energy consumption at each node. Let $q = \frac{1}{T}$, and $P_{is} = d_{is} e_i$, we obtain an equivalent linear programming formulation:

$$\begin{aligned} &\min_{f,R} \quad q \\ &\text{subject to} \\ &\qquad f \le f^{\max}, \\ &\qquad f \ge f^{\min}, \\ &\qquad Af \le b, \\ &\qquad \sum_{s\in S} P_{is} f_s \le qE_i, \forall i \in N. \end{aligned} \tag{7}$$

3.3 Network Utility Maximization

The network utility maximization can be achieved by minimizing the network Utility Loss Index (ULI), which is used to capture the performance loss to the ideal case. According to [9], the ULI has the following general form:

$$U_s(f_s) = \omega_s \alpha_s e^{-\beta_s f_s},$$

where non-negative values ω_s, α_s and β_s are application-specific parameters, which can be determined through curve fitting using measured data.

By employing the ULI as our objective function, the optimization problem for network utility maximization based on joint dynamic routing selection and rate assignment under the constraints in (1) and (2) can be stated as follows:

$$\min_{f,R} \sum_s U_s(f_s)$$
subject to
$$f \le f^{\max}, \quad f \ge f^{\min}, \quad Af \le b. \tag{8}$$

3.4 Joint Network Lifetime Maximization and Utility Maximization

As stated above, we have two important but conflicting objectives when optimizing the network performance, i.e., achieving network lifetime maximization (5) and maximizing network utility among sensor nodes (8), both of which can be formulated as constrained minimization problem. Hence the tradeoff between them can be formulated as a joint programming problem by introducing the weighting method. In conclusion, we have the joint optimization problem for network lifetime maximization and utility maximization by introducing a designed parameter ω:

$$\min_{f,R} \omega q + (1-\omega)\sum_s U_s(f_s)$$
subject to
$$f \le f^{\max}, \quad f \ge f^{\min}, \quad Af \le b, \quad \sum_{s\in S} P_{is} f_s \le qE_i, \forall i \in N. \tag{9}$$

The designed parameter is based on the requirements from real applications. ω and $1-\omega$ demonstrate the weights of system lifetime and network utility separately. ω is selected by domain experts.

3.5 An Illustrating Example

To help the readers understand the algorithm better, we give a practical network topology as an example.

Consider the sensor network shown in Fig. 2, where nodes 1 and 3 are sources (numbered s_1, s_2 respectively) that send data to their corresponding destinations 9 and 10 (numbered d_1, d_2 respectively). Using a given routing algorithm, we can obtain the following candidate routes between the sources and the corresponding destinations:

$$(s_1 \to d_1) = \begin{cases} 1 \to 2 \to 4 \to 6 \to 9 \\ 1 \to 2 \to 4 \to 7 \to 9 \end{cases},$$

$$(s_2 \to d_2) = \begin{cases} 3 \to 4 \to 7 \to 10 \\ 3 \to 5 \to 7 \to 10 \\ 3 \to 5 \to 8 \to 10 \end{cases}.$$

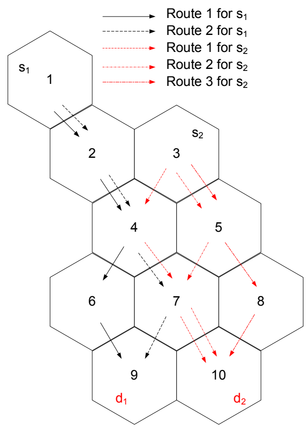

Fig. 2. The Network Topology

If every source s selects the first path as its route, then we can write the corresponding routing set as follows:

$$R = \begin{cases} 1 \to 2 \to 4 \to 6 \to 9 \\ 3 \to 4 \to 7 \to 10 \end{cases}.$$

We can define both an $N \times S$ traffic matrix T to specify the relationship between routers and sources, and an $N \times S$ energy matrix P to specify the relationship between nodes energy consumptions and sources. The corresponding traffic matrix and energy matrix for the above R are:

$$T = \begin{Bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 1 & 1 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{Bmatrix}, \quad P = \begin{Bmatrix} 1\times e_{1,1} & 0 \\ 2\times e_{2,1} & 0 \\ 0 & 1\times e_{3,2} \\ 2\times e_{4,1} & 2\times e_{4,2} \\ 0 & 0 \\ 2\times e_{6,1} & 0 \\ 0 & 2\times e_{7,2} \\ 0 & 0 \\ 1\times e_{9,1} & 0 \\ 0 & 1\times e_{10,2} \end{Bmatrix}.$$

The parameters of sources are defined in Table 1 and the parameters of nodes are defined in Table 2. The unit for packet size is Kb, the unit for sampling rate is Hz, and the unit for bandwidth is Mbps.

Table 1. Parameters of the data sources of the example

s	p_s	$f_s^{\max}$	$f_s^{\min}$	α_s	β_s	ω_s
1	10	11	30	0.33	0.3	4
2	15	2.5	25	0.22	0.2	3

Table 2. Parameters of the nodes of the example

n	**1**	**2**	**3**	**4**	**5**
B_n	0.25	0.6	0.4	0.7	0.3
n	6	7	8	9	10
B_n	0.3	0.8	0.15	0.3	0.4

Table 3. Parameters of the nodes energy consumptions of the example

n	**1**	**2**	**3**	**4**	**5**
e_n	0.001	0.001	0.001	0.005	0.001
n	6	7	8	9	10
e_n	0.001	0.001	0.005	0.001	0.001

The parameters of the nodes energy consumptions are defined in Table 3. We assume that each node in the network is charged with a 1000 A-hr battery. For sending or receiving a packet with fixed maximum packet length l once, the energy consumption for each sensor node is e_n A-hr. The fixed packet length is assumed to be 1 kb.

4 Joint System Lifetime and Network Utility Optimization

Due to the distributed nature of wireless sensor networks, the above optimization problem should be solved in a distributed manner, and can be interpreted as minimizing the maximum ratio of power consumption to energy supply as well as minimizing the utility loss index at a node. The recent research of Network Utility Maximization (NUM) formulates network system design problem as maximization of the aggregate utility of all the nodes subject to physical or economic constraints, and takes advantage of many advances in nonlinear optimization theory and distributed algorithm. In this section, we solve the optimization problem based on primal-dual method and dual decomposition techniques. We also modify the objective function of the joint optimization problem to meet the distributed computation requirement.

We first form the Lagrangian of the optimization problem as follows:

$$\begin{aligned} L(q,f,\lambda,\mu) &= \omega q + (1-\omega)\sum_{s\in S} U_s(f_s) \\ &+ \sum_{i\in N} \lambda_i \{\sum_s P_{is} f_s - qE_i\} \\ &+ \sum_{i\in N} \mu_i \{A_i f - b_i\} \\ &= \omega q + (1-\omega)\sum_{s\in S} U_s(f_s) \\ &+ \sum_{i\in N} \lambda_i \{\sum_s P_{is} f_s - qE_i\} \\ &+ \sum_{i\in N} \{f_s \sum_s A_{si}\mu_i - \mu_i b_i\}, \end{aligned} \tag{10}$$

where Lagrangian multipliers λ_i are introduced for the energy constraint while μ_i are introduced for the scheduling condition. Then the dual problem is

$$D(\lambda,\mu) = \inf_{f^{\min} \le f \le f^{\max}, q\ge 0} L(q,f,\lambda,u). \tag{11}$$

Since the objective function is not strictly convex in the primal variables, the dual function is non-differential. In this case, we change the primal objective function to $\omega\sum_{i\in N} q_i^2 + (1-\omega)\sum_{s\in S} U_s(f_s)$. For the detailed discussions, refer [3]. Define the two nodes sharing the same link in the wireless sensor network as neighbors to each other. Hence for a node i, we can define a set of nodes which are neighbors of i as its neighbor set N_i. Then we have the optimization problem as:

$$\begin{aligned} &\min_{f,R}\ \omega\sum_{i\in N} q_i^2 + (1-\omega)\sum_{s\in S} U_s(f_s) \\ &\text{subject to} \\ &\qquad f \le f^{\max}, \\ &\qquad f \ge f^{\min}, \\ &\qquad Af \le b, \\ &\qquad \sum_{s\in S} P_{is} f_s \le q_i E_i, \forall i \in N, \\ &\qquad q_i = q_j, \forall i \in N, j \in N_i. \end{aligned} \tag{12}$$

Hence the dual function is differentiable. Re-write the Lagrangian for the regularized objective function, we have:

$$\begin{aligned} L(q,f,\lambda,\mu,\gamma) &= -\sum_{i\in N} \mu_i b_i + (\omega\sum_{i\in N} q_i^2 - \sum_{i\in N} q_i \lambda_i E_i) \\ &+ \sum_s ((1-\omega)U_s(f_s) + f_s \sum_{i\in N} (\mu_i A_{si} - \lambda_i P_{is})) \\ &+ \sum_{i\in N} \sum_{j\in N_i} \gamma_{ij} (q_i - q_j)^2, \end{aligned} \tag{13}$$

from which it is clear that the dual function can be evaluated separately in each of the variables f_s and q_i. The dual decomposition results in each source s solving, for the given λ, μ and γ, at each iteration t :

$$f_s^{(t+1)} = \arg \min_{f^{\min} \le f_s \le f^{\max}} ((1-\omega)U_s(f_s) + f_s(\sum_{i\in N} \mu_i^{(t)} A_{si} - \lambda_i^{(t)} P_{is})), \tag{14}$$

$$R^s(t+1) = \arg \min_{R^s \in H^s} \sum_{i\in N} (\mu_i(t)A_{si} + \lambda_i(t)P_{is}), \tag{15}$$

and in each node i solving, for the given λ, μ and γ, at each iteration t:

$$q_i^{(t+1)} = \arg\min_{q_i}(\omega q_i^2 - q_i \sum_{i\in N} \lambda_i^{(t)} E_i + q_i^2 \sum_{j\in N_i} (\gamma_{ij} - \gamma_{ji})), \tag{16}$$

The master dual problem is given by

$$\begin{aligned} &\min_{\lambda,\mu,\gamma} \inf_{f^{\min} \le f \le f^{\max}, q\ge 0} L(q, f, \lambda, \mu, \gamma) \\ &\text{s.t.} \quad \lambda \ge 0, \quad \mu \ge 0, \quad \gamma \ge 0. \end{aligned} \tag{17}$$

Using sub-gradient method, the Lagrangian multipliers can be updated as following at each iteration t:

$$\lambda_i^{(t+1)} = [\lambda_i^{(t)} + \alpha_t(\sum_s P_{is} f_s^{(t)} - q^{(t)} E_i)]^+, \forall i \in N, \tag{18}$$

$$\mu_i^{(t+1)} = [\mu_i^{(t)} + \alpha_k (A_{si} f_s^{(t)} - b_i)]^+, \forall i \in N, \tag{19}$$

$$\gamma_{ij}(t+1) = [\gamma_{ij}(t) + \alpha_t (q_i - q_j)^2]^+, \forall i \in N, j \in N_i, \tag{20}$$

where α_t is a positive step-size and $[\bullet]^+$ is defined as $[x]^+ = \max\{x, 0\}$.

5 Distributed Algorithm

In this section, we present our design of the distributed algorithm for the optimization problem following the solution in Section 4 as follows:

1) Initialization of the distributed algorithm

a. Each node n sets all the energy constraints relevant prices and scheduling constraints relevant prices to 1.

b. Each node n adds all the neighbor nodes to its neighbor set and sets $q_n = \text{Inf}$.

c. Each source s sets the sampling rate f_s to $f_s^{\min}$.

d. Each source s selects the first candidate route as R.

2) Iteration of the distributed algorithm

In each iteration step t, the prices, sampling rates, lifetime and routes are updated.

Prices update

a. The latest rate proposal is sent by each source in a rate proposal packet to corresponding destination along the currently selected route.

b. On receiving rate proposals from all relevant sources, each node n computes new prices for the constraints with the price updating equations (18), (19) and (20).

Lifetime update

a. On receiving rate proposals from all relevant sources, each node n computes new local lifetime parameter q_n with the lifetime updating equation (16).

b. Each node n broadcasts both its new local lifetime and new price γ_n to all its neighbors and receives the update lifetime and price message from all its neighbors.

Sampling rates update

a. A sampling rate update packet with value 0 is sent by each destination along the reserved path of the current route to corresponding source.
b. Each node n adds $\mu_n A_{ns}$ and $\lambda_n P_{ns}$ to the value in the incoming sampling rate update packet, and forwards it along the reversed path.
c. On receiving all relevant sampling rate update packets, each source s updates its rate proposal according to local optimization with equation (14).

Routing update

a. A routing update packet with value 0 is sent by each destination along the reserved path of every possible route to the source.
b. Each node n adds $\mu_n A_{ns}$ and $\lambda_n P_{ns}$ to the value in the incoming routing update packet, and forwards it along the reversed path.
c. On receiving all relevant routing update packets, each source s updates routing according to local optimization with equation (15).

6 Performance Evaluations

In this section, we demonstrate the efficacy of our solutions with extensive MATLAB simulation results and some further analysis. The simulation is based on the parameters of the example in Section 4.

6.1 Convergence

First, we conduct a simulation experiment using the distributed algorithm proposed in Section 4 with the step size set to 0.2 and the designed parameter ω set to 0.0. Hence the optimization problem becomes an optimization problem for network utility maximization. The optimal network ULI is 0.0268, with very high q_n, which corresponds to very low network lifetime, $f^* = (15.6250, 19.0476)^T$, and $r^* = (2,1)$ where the sth element in r^* indicates the optimal route for source s. The convergence of the distributed algorithm is shown in Fig. 3. Fig. 3 shows the convergence of sampling rate of each source.

We also conduct a simulation experiment with $\omega = 1.0$, and the optimization problem becomes an optimization problem for network lifetime maximization. The optimal network ULI is 0.4490, with $q_n = 0.0270$, $f^* = (11.000, 2.500)^T$ and $r^* = (2,2)$.

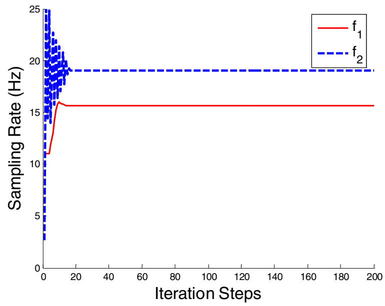

Fig. 3. The Convergence of Sampling rates with $\omega = 0.0$

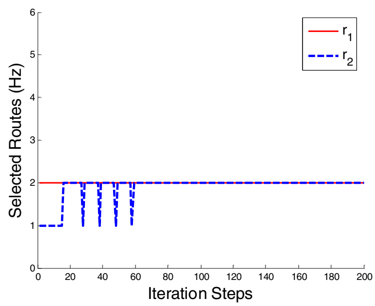

Fig. 4. The Convergence of Routing Selection with $\omega = 0.75$

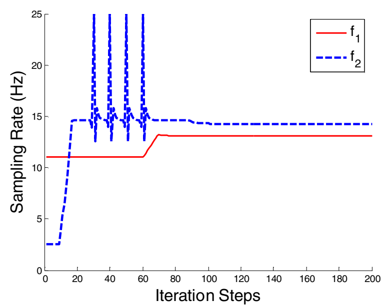

Fig. 5. The Convergence of Sampling Rates with $\omega = 0.75$

Again, with the designed parameter set to 0.75, the optimal network is 0.0641, with $q_n = 0.1307$, $r^* = (2,2)$ and $f^* = (13.0724, 14.2857)^T$. The convergence of sampling rate of each source is shown in Fig. 4 while the convergence of routing selection of each source is shown in Fig. 5.

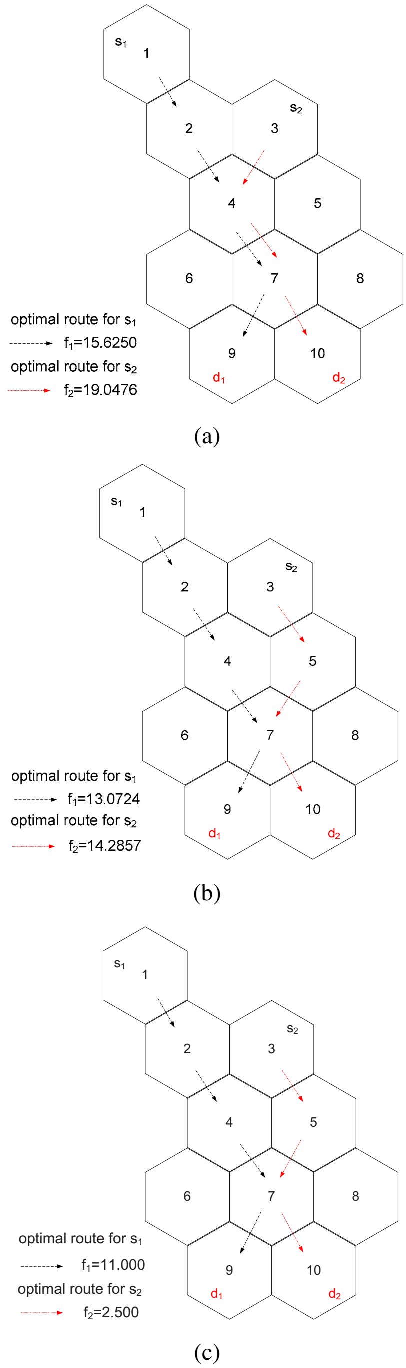

Fig. 6. (a) Sampling Rates and Routes Selection with $\omega = 0.0$ (b) Sampling Rates and Routes Selection with $\omega = 0.75$ (c) Sampling Rates and Routes Selection with $\omega = 1.0$

6.2 Illustrations of Tradeoff between System Lifetime and Network Utility

The optimal sampling rates and routes selection with different designed parameter ω are illustrated in Fig. 6 to demonstrate the necessity of calculating tradeoff between lifetime maximization and utility maximization. In Fig. 6 (a), the designed parameter ω is set to 0.0; hence only network utility maximization is taken into considerations; while in Fig. 6 (b), the designed parameter ω is set to 0.75; hence both network lifetime and utility maximization are taken into considerations. Comparing the results in Fig. 6 (b) against Fig. 6 (a), optimal sampling rates are decreased; hence network utility is decreased and the network ULI is increased from 0.0268 to 0.0641. It is clear that selected routes have changed to avoid the overload of sensor nodes (node 4 in this example) so as to improve the network lifetime. In Fig. 6 (c), the designed parameter ω is set to 1.0 and only network lifetime maximization is considered. Comparing the results in Fig. 6 (b) against Fig. 6 (c), optimal sampling rates are increased to improve the network utility. The above results show that depending on the given application, we can maneuver the designed parameters to adjust both sampling rates and selected routes to achieve the best combined network performance and lifetime.

7 Conclusion and Future Work

In this paper, we investigate the novel problem of the joint optimization of system lifetime and network utility in RTWSNs. We model the joint optimization as a holistic joint optimization problem by deriving the nonlinear objective function and linear constraints. We also introduce a designed parameter to capture the weight balance between network lifetime maximization problem and network utility maximization problem. An effective distributed algorithm is developed based on the primal-dual method and dual decomposition technique. We show the fast convergence and the efficacy of the distributed algorithm, via extensive simulation studies. We demonstrate the necessities of the joint optimization studies in RTWSNs by analyzing and comparing the numerical results with different values of the designed parameter.

As a next step work, we plan to carry out experiments in the real sensor test bed to evaluate our proposed method in this paper.

Acknowledgments. This work was supported in part by NSERC Discovery Grant 341823-07, NSERC Strategic Grant STPGP 364910-08, FQRNT Grant 2010-NC-131844 and Chinese National 863 project (No. 2007AA01Z223).

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