Utility-Based Asynchronous Flow Control Algorithm for Wireless Sensor Networks

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***Abstract*—In this paper, we formulate a flow control optimization problem for wireless sensor networks with lifetime constraint and link interference in an asynchronous setting. Our formulation is based on the network utility maximization framework, in which a general utility function is used to characterize the network performance such as throughput. To solve the problem, we propose a fully asynchronous distributed algorithm based on dual decomposition, and theoretically prove its convergence. The proposed algorithm can achieve the maximum utility. Extensive simulations are conducted to demonstrate the efficiency of our algorithm and validate the analytical results.**

***Index Terms*—flow control, sensor networks, asynchronous setting, dual decomposition.**

I. Introduction

Wireless Sensor Networks (WSNs) are composed of a large number of low-power, multi-functioning sensor nodes, operating in an unattended environment with limited computation and sensing capabilities. The flexibility, fault tolerance, high sensing fidelity, low-cost and rapid deployment characteristics of WSNs have made them widely used in military, disaster relief, environment monitoring and healthcare, etc [1] [2] [3]. Despite their rapid development, there is an increasing demand on designing more efficient WSNs, due to the inherent limitations in the available resources, such as energy, computational capability and storage [4] [5].

A flow control algorithm is a practical method to successfully deal with congestion control and resource allocation (particularly in proportional fairness) by regulating source transmission rates in response to changes in network conditions. It has been extensively studied in typical wired networks [6] [7], cellular wireless networks [8] and ad hoc networks [9] [10] to maximize the sum of utility, where a utility function is generally used to characterize the network performance (e.g., throughput) [11]. In order to design an efficient flow control algorithm for WSNs, there are three main factors to be considered, which limit their applications: 1) network lifetime, which is caused by the limited energy each sensor node has. WSNs are often powered with energy-limited batteries and scattered in a large region. The sensor nodes can not be recharged because it may be expensive or the region is inaccessible, which poses a performance limitation on the achievable network lifetime. As a consequence, network lifetime has become a significant metric for evaluating the effectiveness of applications in WSNs [5] [12]. Many protocols have been designed to show tradeoff between the application performance and the network lifetime [13]. It is shown in [14] that without any load balancing mechanism, the sensor nodes near sink nodes will die quickly, leading to the partition of the network; 2) link interference, which is caused by the spatial contention between concurrent transmission over a shared wireless medium [15] [16]. Due to the broadcast nature of the wireless medium, the flows contend in the spatial domain for the shared wireless medium if they are within the interference ranges of each other. The interference greatly limits the network throughput; and 3) asynchronous setting, which is caused by the large-scale inherent and different, variable communication delays in WSNs. Most of the current works on the flow control problem assume that the updates for the links/sources are synchronous. Therefore, all of the links/sources will exchange congestion price simultaneously and execute an iteration of the algorithm at every time instance. However, in realistic WSNs applications, sensor nodes may be scattered in a large region. Such network-wide synchronization is very difficult and highly costly to be achieved due to the large amount of messages exchanged and variable propagation delays in a real WSN. Therefore, it is challenging to design a distributed flow control algorithm for WSNs by taking all three factors into consideration.

In this paper, we formulate a utility-based flow control optimization problem to maximize the whole utility, by considering the lifetime constraint and link interference. Based on the framework of network utility maximization (NUM) [17], we adopt Lagrange Dual method to decompose this optimization problem into several subproblems. Through the coordination of Lagrange multipliers, maximizing the utility function of each flow can achieve the global optimal solution. Specifically, a Utility-based Asynchronous Flow Control (UAFC) algorithm, is proposed to solve the optimization problem. To the best of our knowledge, this is the first asynchronous flow control algorithm for WSNs by considering the lifetime constraint and link interference. Because of the asynchronous setting, each link has to estimate the link prices from its interference set and congestion prices from the network, and each flow has to estimate the link prices and energy prices from the network. We show that the errors of these estimations eventually decrease to zero. Furthermore, we prove

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theoretically the convergence of UAFC. We introduce an asynchronous parameter B, which is defined as the time bound between the consecutive updates of link price/source rate. We show that given an asynchronous parameter B, we can always choose a sufficient small stepsize, γ, to make the sequence generated by UAFC convergent. UAFC is a very general asynchronous algorithm, which can be reduced to different partial asynchronous cases by setting the parameters properly. The UAFC is amenable to fully distributed implementations, which corresponds to the decentralized nature of WSNs. Extensive simulations are conducted to further validate our analysis results, which show the convergence of UAFC, as well as the relationships between the convergent rate of UAFC and the asynchronous parameter B.

The remainder of this paper is organized as follows. Section II presents some related works. After introducing the system model and formulating the flow control optimization problem in Section III, we propose the asynchronous flow control algorithm, UAFC, to solve this problem in Section IV. The convergence proof is given in Section V. Section V presents simulation results. We conclude our work in Section VII.

II. Related Work

Recently, there are increasing numbers of network applications where their performance is highly dependent on the high data rate. This indicates that higher link capacity is desirable. However, the link capacity is limited in the wireless networks. Thus, many researchers focus on flow control designs to achieve efficient and fair rate allocation [7] [18]. NUM framework is first applied to flow control design of the wireline context by Kelly *et al.* [6]. Surveys on the NUM problem over the past decade are carried out in [17] [19]. A set of mathematical tools for solving the NUM problem are given in [20] [21]. With these fundamental works, NUM framework finds its applications in many fields [22] [23] [24]. Chiang *et al.* focus on a cross-layer design and present algorithms to balance congestion control and power control to enhance the overall performance [22]. Wang *et al.* propose algorithms for joint congestion control and MAC layer design [23]. Xu *et al.* study the congestion control problem in ad hoc networks [25]. Considering that the objective of maximizing rate allocation can lead to unfairness in rate allocation among the sensor nodes, Hou *et al.* advocate the use of lexicographical max-min (LMM) rate allocation, and propose a polynomial-time algorithm-serial LP with Parametric Analysis (SLP-PA) to calculate the LMM rate allocation problem [26]. All the works mentioned above have not considered the energy constraint, which is one of the most important criteria in WSNs.

On the other hand, Srinivasan *et al.* take into account energy consumption and propose algorithms to the solve the problem for fair data collection under the NUM framework given the network lifetime requirement [27]. Yuen *et al.* propose a fully distributed algorithm to achieve minimum energy data gathering while considering the capacity and interference of the shared medium [14]. Zhu *et al.* study the tradeoff problem between rate allocation and network lifetime, formulating it as a constrained maximization problem, and deriving both a partially distributed algorithm and a fully distributed algorithm to solve it [13]. However, all these works assume synchronous settings, which is difficult to achieve in real wireless networks.

Low *et al.* are the first to design an asynchronous algorithm for flow control under an optimization framework [7]. They consider the problem for a wired network and do not take into account the wireless shared medium and energy consumption. Abraham *et al.* introduce a new class of asynchronous distributed algorithms for explicit flow control in an integrated packet network [28]. Kucera *et al.* analyze power and rate control for wireless ad hoc networks with stochastic channels and propose a game-theory based asynchronous distributed algorithm. Bui *et al.* are concerned with joint flow control and distributed scheduling in multi-hop wireless networks shared by multiple users [29]. Based on an interference model, they develop an architecture consisting of a distributed scheduling algorithm in the MAC layer and an asynchronous flow control algorithm in the transport layer. However, all these works are concerned with overall utility of the networks, overlooking energy consumption. Different from the previous works, we formulate a utility-based flow control optimization problem with a lifetime constraint for WSNs in an asynchronous setting.

III. System Model and Problem Formation

A. Notations

Throughout the paper, we denote the sets or the cardinality of sets by capital letters, variables by lowercase letters, vectors by bold lowercase letters and matrices by bold capital letters. For a vector $\mathbf{x}$, its ith component is x_i, and its transpose is $\mathbf{x}^T$. Let $||\cdot||$ be a norm, and $||\mathbf{x}||_1 = \sum_i |x_i|$, $||\mathbf{x}||_2 = (\sum_i |x_i|^2)^{\frac{1}{2}}$ and $||\mathbf{x}||_\infty = \max_i |x_i|$ denote the 1-norm, 2-norm and ∞-norm of $\mathbf{x}$, respectively. For matrix $\mathbf{A}$, denote its (i,j) component by a_{ij}, and its transpose by $\mathbf{A}^T$. Let $||\mathbf{A}||_1$, $||\mathbf{A}||_2$ and $||\mathbf{A}||_\infty$ denote the 1-norm, 2-norm and ∞-norm of the corresponding matrix.

We model the sensor network as a connectivity graph, $G(V,L)$. The vertex set V denotes all nodes, including sensor and sink nodes, where N is a subset of V consisting of the sensor nodes. The set of edges $L = \{1, 2, \ldots, L\}$ represents logical bidirectional communication links between sensor nodes. Let c_l be the capacity of link l, $l \in L$. There are S flows over the WSN. Flow s, $s \in S$, is characterized by a utility function $U_s(x_s)$, where $U_s(\cdot)$ is a strictly concave function. Let x_s be the transmission rate of flow s, and let x_s^{min} and x_s^{max} be the minimum and maximum transmission rates, respectively.

For the sake of presentation, we also define the following notations:

- $S(l)$: the set of flows that go through link l.
- $L(s)$: the set of wireless links where flow s goes through.
- $S(n)$: the set of flows using sensor node n as a relay sensor node (excluding the flow starting from sensor node n).
- $N(s)$: the set of sensor nodes that flow s uses as relay sensor nodes (excluding the sensor node which flow s starts from).

B. Link Interference Set

In WSNs, because of the broadcast nature of the wireless medium, the flows contend in the time and spatial domains for the shared wireless medium if they are within the interference range of each other. There exist two models in the literature: *protocol model* and *physical model* [14]. In the physical model, a packet transmission over link l is successful if the signal-to-interference ratio (SIR) is larger than a threshold. In this paper, we adopt the *protocol model*, in which the interference among the links is characterized by the interference sets. We denote the interference set of the link l by IS_l. The flows going through the link l', $l' \in IS_l$, interfere with other flows going through the link l. Since the links included in the interference set IS_l share the same common link capacity c_l, only one of the flows may transmit over the link l', $l' \in IS_l$, at any time. Consequently, the aggregated rate of all flows should satisfy the link capacity constraint, i.e.,

$$\sum_{l' \in IS_l} \sum_{s \in S(l')} x_s \le c_l, \forall l \in L. \tag{1}$$

Denote $\mathbf{H}$ and $\mathbf{R}$ as $L \times L$ interference matrix and $L \times S$ routing matrix, respectively, where their (l, l') component, $h_{ll'}$, and (l', s) component, $r_{l's}$, are given by

$$h_{ll'} = \begin{cases} 1, l' \in IS_l \\ 0, \text{otherwise} \end{cases} \quad r_{l's} = \begin{cases} 1, s \in S(l') \\ 0, \text{otherwise} \end{cases}.$$

Let $\mathbf{R}' = \mathbf{HR}$, then Eq. (1) can be represented in terms of the matrix as follows:

$$\mathbf{R}'\mathbf{x} \le \mathbf{c}_1, \tag{2}$$

where $\mathbf{x} = [x_1, x_2, \ldots x_S]^T$, $\mathbf{c}_1 = [c_1, c_2, \ldots c_L]^T$.

C. Energy Model and Sensor Node Lifetime

Let e_n denote the initial energy of sensor node n, $n \in N$. Let e^s be the energy consumed in the idle state per unit time and let e^r and e^t denote the additional energy consumption for one unit data per unit time during the sensor node reception and transmission, respectively. For a pre-specified lifetime, T_n^{goal}, the energy constraint for each node n should be:

$$(e^t + e^r) \sum_{s \in S(n)} x_s + e^t \epsilon_n + e^s \le c_n^{goal}, \tag{3}$$

where $c_n^{goal} = e_n / T_n^{goal}$. If there is a flow s' starting from sensor node n, $\epsilon_n = x_{s'}$; otherwise, $\epsilon_n = 0$. It is generally assumed the sink nodes have sufficient energy.

Eq. (3) can be represented in terms of the matrix as follows:

$$\mathbf{P}\mathbf{x} \le \mathbf{c}_2, \tag{4}$$

where $\mathbf{c}_2 = (c_1^{goal} - e^s, c_2^{goal} - e^s, \ldots, c_N^{goal} - e^s)^T$, and $\mathbf{P}$ is the $N \times S$ matrix with (n, s) component, p_{ns}, given by

$$p_{ns} = \begin{cases} e^t + e^r & s \in S(n) \\ e^t & \text{flow } s \text{ starts from sensor node } n \\ 0 & \text{otherwise} \end{cases}.$$

Based on Eqs. (2) and (4), we have

$$\mathbf{R}''\mathbf{x} \le \mathbf{c}, \tag{5}$$

where $\mathbf{R}''$ is the $K \times S$ matrix with $\mathbf{R}'' = (\mathbf{R}'^T, \mathbf{P}^T)^T$, $K = L + N$; $\mathbf{c} = (\mathbf{c}_1^T, \mathbf{c}_2^T)^T$. $\mathbf{R}''$ is called the generalized routing matrix.

D. Optimization Problem Formulation

With the derived equations for link capacity and lifetime constraint, we formulate the utility-based flow control problem. The goal is to maximize the sum of the utility.

$$\begin{aligned} &\max_{\mathbf{x}} \sum_{s \in S} U_s(x_s) \\ &s.t. \quad \mathbf{R}''\mathbf{x} \le \mathbf{c} \end{aligned} \tag{6}$$

Since the objective function is strictly concave, and the constraints are linear and therefore are separable, convex and compact, thus there exists a unique optimal solution for the optimization problem described in Eq. (6).

IV. A Utility-based Asynchronous Flow Control (UAFC) Algorithm

A. Dual Decomposition Approach

Because it is undesirable to solve the defined problem in Eq. (6) using a centralized approach, we decompose the problem into a number of subproblems using Lagrange multipliers. Each subproblem can be solved independently and in parallel at each node/link. Considering the Lagrangian form of the optimization problem in Eq. (6), we have the following equation.

$$\begin{aligned} L(\mathbf{x}, \boldsymbol{\lambda}) = &\sum_{s \in S} \{U_s(x_s) - x_s[(\sum_{l \in L(s)} \sum_{l' \in IS_l} \lambda_{l'}^c) \\ &+ (e^r + e^t) \sum_{n \in N(s)} \lambda_n^e + e^t \iota_s]\} \\ &+ \sum_l \lambda_l^c c_l + \sum_{n \in N} \lambda_n^e (c_n^{goal} - e^s), \end{aligned} \tag{7}$$

where $\boldsymbol{\lambda} = (\lambda_1^c, \lambda_2^c, \cdots, \lambda_L^c, \lambda_1^e, \lambda_2^e, \cdots, \lambda_N^e)^T$ are the vector of Lagrange multipliers; $\iota_s = \lambda_{n'}^e$, assuming flow s starts from sensor node n'. Also λ_l^c, $l \in L$, can be alternatively understood as the price for using the capacity at link l. Similarly, λ_n^e, $n \in N$, can be alternatively understood as the price for using energy at sensor node n.

Hence, the dual problem becomes

$$D : \min_{\boldsymbol{\lambda} \ge 0} \max_{\mathbf{x}} L(\mathbf{x}, \boldsymbol{\lambda}). \tag{8}$$

A gradient projection approach is introduced to solve the above dual problem. At each iteration, Lagrange multipliers are adjusted in the opposite direction to the gradient as follows:

$$\lambda_l^c(t+1) = [\lambda_l^c(t) - \gamma(c_l - x_{IS}^l(t))]^+ \tag{9}$$

$$\begin{aligned} \lambda_n^e(t+1) = [\lambda_n^e(t) - \gamma[c_n^{goal} - ((e^r + e^t) &\sum_{s \in S(n)} x_s(t) \\ &+ e^t \epsilon_n(t) + e^s)]]^+, \end{aligned} \tag{10}$$

where $\gamma > 0$ is the stepsize and $z^+ = \max\{0, z\}$. $x^l(t) = \sum_{s \in S(l)} x_s(t)$ is referred to as the aggregated transmission rate of link l and $x^l_{IS}(t) = \sum_{l' \in IS_l} x^{l'}(t)$ is the total transmission rate of link l (including the total aggregated transmission rate of the interference set).

Each flow s, $s \in S$, adjusts its rate according to Eq. (11) to achieve an optimal value.

$$x_s(t+1) = [U_s'^{-1}(\lambda^s(t))]^{x_s^{max}}_{x_s^{min}}, \tag{11}$$

where $[z]^b_a = \min(\max(z, a), b)$, $U_s'^{-1}$ is the inverse of U_s', and λ^s is defined as

$$\lambda^s = \sum_{l \in L(s)} \lambda^l_{IS} + (e^r + e^t) \sum_{n \in N(s)} \lambda^e_n + e^t \iota_s, \tag{12}$$

where $\lambda^l_{IS} = \sum_{l' \in IS_l} \lambda^c_{l'}$.

In fact, λ^s is the total price due to the link capacity and lifetime constraint along the route paid by flow s, and λ^l_{IS} is the aggregated congestion price of link l due to interference.

Eqs. (9), (10) and (11) provide the synchronous solution to the defined problem in Eq. (6) using a decentralized approach. In the next subsection, we will present UAFC algorithm to solve the problem in Eq. (6) in an asynchronous setting.

B. UAFC Algorithm

In this subsection, we introduce an asynchronous algorithm, which is partial. In the asynchronous model, the computation is the same as that in the synchronous case, except that it is based on its current estimate of the latest collected values. We assume the asynchronous parameter B is an integer constant, such that:

1) The time between the consecutive updates is bounded by B for both price and rate updates;
2) One-way communication delay between any two sensor nodes/links is at most B time units.

Let $T = \{1, 2, \cdots\}$ be the set of time at which either rates or prices are updated. In particular, we define

- $T^l \subseteq T$: the set of times at which the link l updates the aggregated transmission rate $x^l(t)$. At $t \notin T^l$, the aggregated transmission rate is unchanged.
- $T_l \subseteq T$: the set of times at which the link l updates its sole congestion price. At $t \notin T_l$, the sole congestion price is unchanged.
- $T^s \subseteq T$: the set of times at which link l updates the aggregated price λ^l. At $t \notin T^s$, the aggregated price is unchanged.
- $T_e \subseteq T$: the set of times at which sensor node n updates its energy price. At $t \notin T_e$, the energy price is unchanged.
- $T_s \subseteq T$: the set of times at which the flow s updates its transmission rate. At $t \notin T_s$, the transmission rate is unchanged.

At time $t \in T^l$, link l updates the aggregated transmission rate $x^l(t)$ according to

$$x^l(t) = \sum_{s \in S(l)} \widehat{x}_s(t), \tag{13}$$

$$\widehat{x}_s(t') = \sum_{t'=t-B}^{t} f_{ls}(t', t) x_s(t'), \forall s \in S(l), \tag{14}$$

with $\sum_{t'=t-B}^{t} f_{ls}(t', t) = 1$.

At time $t \in T_l$, link l updates its sole congestion price $\lambda^c_l(t+1)$ according to

$$\lambda^c_l(t+1) = [\lambda^c_l(t) - \gamma(c_l - \widehat{x}^l_{IS}(t))]^+, \tag{15}$$

where $\widehat{x}^l_{IS}(t)$ is the estimation of $x^l_{IS}(t)$ and is computed using the latest B rates at link l.

$$\widehat{x}^l_{IS}(t) = \sum_{l' \in IS_l} \widehat{x}^{l'}(t), \tag{16}$$

$$\widehat{x}^{l'}(t) = \sum_{t'=t-B}^{t} a_{ll'}(t', t) x^{l'}(t'), \forall l' \in IS_l, \tag{17}$$

with $\sum_{t'=t-B}^{t} a_{ll'}(t', t) = 1$.

At time $t \in T_e$, sensor node n updates its energy price $\lambda^e_n(t+1)$

$$\begin{aligned} \lambda^e_n(t+1) = {} & [\lambda^e_n(t) - \gamma[c^{goal}_n - ((e^r + e^t) \sum_{s \in S(n)} \widehat{x}_s(t) \\ & + e^t \epsilon_n(t) + e^s)]]^+, \end{aligned} \tag{18}$$

$$\widehat{x}_s(t) = \sum_{t'=t-B}^{t} b_{ns}(t', t) x_s(t'), \forall s \in S(n), \tag{19}$$

with $\sum_{t'=t-B}^{t} b_{ns}(t', t) = 1$.

At time $t \in T^s$, link l updates the congestion price from the link in its interference set according to

$$\lambda^l_{IS}(t) = \sum_{l' \in IS_l} \widehat{\lambda}^c_{l'}(t), \tag{20}$$

$$\widehat{\lambda}^c_{l'}(t) = \sum_{t'=t-B}^{t} d_{ll'}(t', t) \lambda^c_{l'}(t'), \forall l' \in IS_l, \tag{21}$$

with $\sum_{t'=t-B}^{t} d_{ll'}(t', t) = 1$

At time $t \in T_s$, flow s updates its rate according to

$$x_s(t+1) = [U_s'^{-1}(\widehat{\lambda}^s(t))]^{x_s^{max}}_{x_s^{min}}, \tag{22}$$

where $\widehat{\lambda}^s(t)$ is the estimation of $\lambda^s(t)$, i.e.,

$$\begin{aligned} \widehat{\lambda}^s(t) = {} & \sum_{l \in L(s)} \widehat{\lambda}^l_{IS}(t) + (e^r + e^t) \sum_{n \in N(s)} \widehat{\lambda}^e_n(t) \\ & + e^t \widehat{\iota}_s(t), \end{aligned} \tag{23}$$

$$\widehat{\lambda}^l_{IS}(t) = \sum_{t'=t-B}^{t} c_{sl}(t', t) \lambda^l_{IS}(t'), l \in L(s), \tag{24}$$

$$\widehat{\lambda}^e_n(t) = \sum_{t'=t-B}^{t} g_{sn}(t', t) \lambda^e_n(t'), \forall n \in N(s), \tag{25}$$

with $\sum_{t'=t-B}^{t} c_{sl}(t', t) = 1$, $\sum_{t'=t-B}^{t} g_{sn}(t', t) = 1$.

Here we denote the ideal rate by $\bar{x}_s(t)$ if flow s knows the exact price $\lambda^s(t)$ at time t instead of using its estimation $\widehat{\lambda}^s(t)$, i.e., $\bar{x}_s(t)$ is updated according to Eq. (11). One of our main results for the performance measure of the asynchronous algorithm is that the absolute difference between $x_s(t)$ and $\bar{x}_s(t)$ converges to zero.

Algorithm 1: Utility-based Asynchronous Flow Control (UAFC)

Link l's Algorithm:

1) At time $t \in T^l$, link l updates the aggregated transmission rate $x^l(t)$ using the latest B values of the rates according to Eqs. (13) and (14), and communicates it to the links l', $l' \in IS_l$.
2) Link l receives the information of aggregated transmission rates $x^{l'}(t)$, from the link l', $l' \in IS_l$ and computes $\widehat{x}^l_{IS}(t)$.
3) At time $t \in T_l$, link l computes a new sole congestion price $\lambda^c_l(t+1)$ according to Eq. (15).
4) Link l communicates its sole congestion price $\lambda^c_l(t+1)$ to flow s, $s \in S(l)$.
5) At time $t \in T^s$, link l collects the congestion price, $\lambda^c_l(t)$, from its interference set IS_l, and updates the aggregated congestion price, $\lambda^l_{IS}(t+1)$, according to Eqs. (20) and (21), and communicates it to the flow s, $s \in S(l)$.

Sensor node n's Algorithm

1) Node n estimates $\widehat{x}_s(t)$, $s \in S(n)$, according to Eq. (19);
2) At time $t \in T_e$, node n computes a new energy price $\lambda^e_n(t+1)$ according to Eq. (18).
3) Node n communicates the new energy price $\lambda^e_n(t+1)$ to all flows s, $s \in S(n)$.

Flow s's Algorithm

1) Source node of flow s receives the congestion prices and energy prices from the network from time to time, and estimates $\widehat{\lambda}^l_{IS}(t)$ according to Eq. (24) and computes $\widehat{\lambda}^s(t)$ according to Eq. (23).
2) At time $t \in T_s$, source node of flow s computes a new transmission rate, $x_s(t+1)$, for the next period according to Eq. (22).
3) Source node of flow s communicates the new rate $x_s(t+1)$ to the links in its path.

The asynchronous flow control algorithm was first introduced for wired networks [7]. In this paper, we consider the features of WSNs and propose the asynchronous flow control algorithm for WSNs. Note that this is a very general algorithm in the asynchronous setting. Different kinds of partial asynchronous algorithms can be achieved by choosing different parameters **a**, **b**, **c**, **d**, **f**, **g** [7]. The instant information about the rate and link prices is replaced by the estimated values. It does not matter whether the information arrives late or out of order. Thus, it is a practical model resembling real WSNs. We summarize the distributed asynchronous algorithm UAFC as in **Algorithm 1**.

From the above asynchronous implementation of UAFC, we can see that the computation for the asynchronous algorithm is the same order as that for the synchronous one [10], except that it is based on the weighted average of the latest arrived values, which indicates the efficiency of UAFC.

V. The Convergence of UAFC

In this section, we discuss the convergence of UAFC. It is worth pointing out that the proposed algorithm is different from the approach in [7], as we take the lifetime constraint and interference set into consideration and thus have our unique problem formulation. Specifically, the newly introduced parameters (e.g., the interference estimation or energy price in each sensor node) make the proof of convergence more complicated. Therefore, a novel convergence proof for the proposed algorithm is highly desired. First, we give some assumptions below:

- A1: $U_s(x_s)$ is increasing, strictly concave, and twice continuously differentiable.
- A2: $U''_s(x_s) \leq -1/\bar{\alpha}_s$, $x^{min}_s \leq x_s \leq x^{max}_s$, where $\bar{\alpha}_s$ is a positive constant.

To obtain our main results on the convergence, we have the following Lemmas.

Lemma 1: For all t

$$|\widehat{\lambda}^l_{IS}(t) - \lambda^l_{IS}(t)| \leq \sum_{\tau=t-2B}^{t-1} \sum_{l' \in IS_l} |\lambda^c_{l'}(\tau+1) - \lambda^c_{l'}(\tau)|,$$

$$|\widehat{\lambda}^e_n(t) - \lambda^e_n(t)| \leq \sum_{\tau=t-B}^{t-1} |\lambda^e_n(\tau+1) - \lambda^e_n(\tau)|.$$

See the proof in the Appendix.A.

The following Lemma gives the relationships between $\lambda^s(t)$, $\bar{x}_s(t)$ and $\widehat{\lambda}^s(t)$, $x_s(t)$.

Lemma 2: For all $t > 0$

$$\left|\widehat{\lambda}^s(t) - \lambda^s(t)\right| \leq \sum_{\tau=t-2B}^{t-1} \sum_i r''_{is} |\lambda_i(\tau+1) - \lambda_i(\tau)|,$$

$$|\lambda^s(t) - \lambda^s(\tau)| \leq \sum_{t'=\tau}^{t-1} \sum_i r''_{is} |\lambda^e_i(t'+1) - \lambda^e_i(t')|,$$

$$|x_s(t) - \bar{x}_s(t)| \leq \bar{\alpha} \sum_{\tau=t-2B}^{t-1} \sum_i r''_{is} |\lambda_i(\tau+1) - \lambda_i(\tau)|.$$

See the proof in the Appendix.B.

We proceed to calculate the estimation error of the gradient. For $i = 1, 2, \cdots, L$

$$\left[\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))\right]_i = \widehat{x}^l_{IS}(t) - \bar{x}^l_{IS}(t), \quad (26)$$

and $i = L+1, \cdots, L+N$

$$\left[\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))\right]_i$$
$$= (e^r + e^t) \sum_{s \in S(n)} (\widehat{x}_s(t) - \bar{x}_s(t)) + e^t(\widehat{\epsilon}_n(t) - \epsilon_n(t)).$$

Then we have the following Lemma.

Lemma 3: There exists a $A'_2 > 0$ such that

$$\left\|\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))\right\|$$
$$\leq A'_2 \bar{\alpha} \bar{S}^2 \sum_{\tau=t-4B}^{t-1} ||\boldsymbol{\lambda}(\tau+1) - \boldsymbol{\lambda}(\tau)||_1. \quad (27)$$

See the proof in the Appendix.C.

With the Lemmas above, we state our main result from the UAFC algorithm.

Theorem 1: Given that A1 and A2 hold, B is bounded, and the stepsize γ satisfies $0 < \gamma < \frac{1}{A_1(4B+1))A'_2\bar{\alpha}\bar{S}^2}$. Then with any initial rates $\mathbf{x}(0)$, $\{\mathbf{x}^{min} \leq \mathbf{x}(0) \leq \mathbf{x}^{max}\}$, and congestion and energy prices $\boldsymbol{\lambda}^c(0) \geq 0, \boldsymbol{\lambda}^e(0) \geq 0$, every accumulation point of the sequence generated by the asynchronous implementation is primal-dual optimal. Furthermore, the absolute

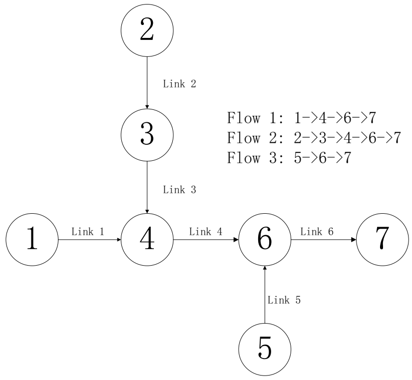


Fig. 1. Network topology

difference, $|\widehat{\lambda}^s(t) - \lambda^s(t)|$, $|x_s(t) - \bar{x}_s(t)|$ converge to zero as $t \rightarrow \infty$.

Proof: With the Lemmas above, from [7, Theorem 2, 871-873], we can easily get

$$D(\boldsymbol{\lambda}(t+1)) = D(\boldsymbol{\lambda}(0)) - A_2 \sum_{\tau=0}^{t} ||\boldsymbol{\lambda}(\tau+1) - \boldsymbol{\lambda}(\tau)||^2. \quad (28)$$

where $A_2 = 1/\gamma - A_1(4B+1)A_2'\bar{\alpha}\bar{S}^2$, A_1 is a constant.

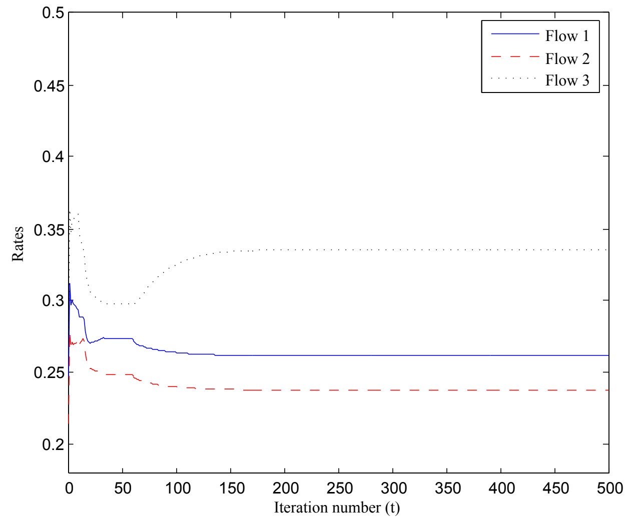
As $D(\boldsymbol{\lambda}(t))$ is lower bounded, when γ is chosen sufficiently small such that $A_2 > 0$, which means $B < \frac{1}{4\gamma A_1 A_2' \bar{\alpha}\bar{S}^2} - \frac{1}{4}$, then $||\boldsymbol{\lambda}(t+1) - \boldsymbol{\lambda}(t)|| \rightarrow 0$ as $t \rightarrow \infty$. It follows directly $|x_s(t) - \bar{x}_s(t)| \rightarrow 0$, $|\widehat{\lambda}^s(t) - \lambda^s(t)| \rightarrow 0$, as $t \rightarrow \infty$. Similar to the steps in [7], we can easily prove the convergence of sequence of ($\boldsymbol{\lambda}$, $\mathbf{x}$), generated by the asynchronous algorithm, starting from any initial rates $\mathbf{x}(0)$, $\{\mathbf{x}^{min} \leq \mathbf{x}(0) \leq \mathbf{x}^{max}\}$, and congestion and energy prices $\boldsymbol{\lambda}^c(0) \geq 0$, $\boldsymbol{\lambda}^e(0) \geq 0$. Because of the convexity of the problem, the accumulation point $(\boldsymbol{\lambda}^*, \mathbf{x}^*)$ of the sequence are primal-dual optimal. ∎

VI. Performance Evaluation

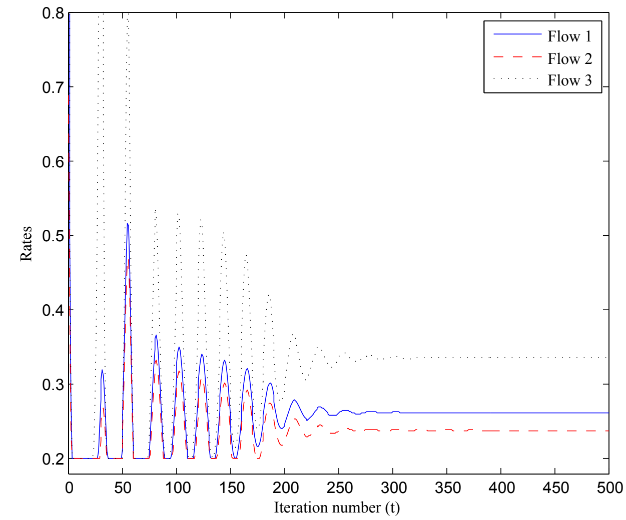
In this Section, simulations are conducted to demonstrate the convergent performance of the UAFC algorithm. We are especially interested in the impact of the asynchronous setting parameter B on the rate of convergence.

A. Simulation Setting

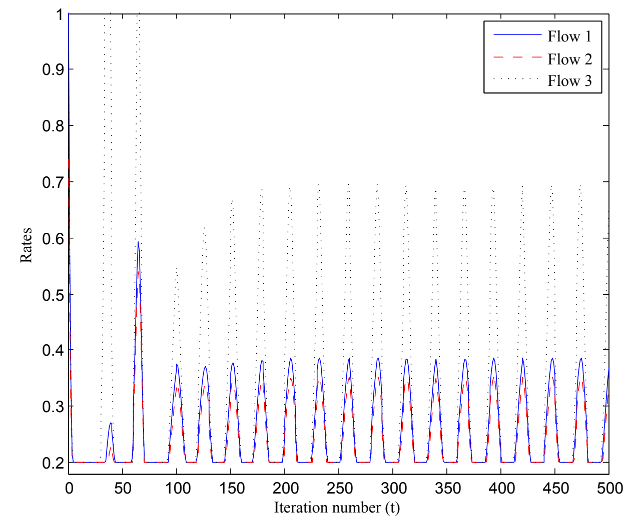
The network topology is depicted in Fig. 1, where there are 7 sensor nodes. Sensor nodes 1 - 6 are sensing nodes and sensor node 7 is the sink node. There are six links and three flows in the network, which can be seen in Fig. 1. The capacities of the links are set to be $\boldsymbol{c} = (1, 1.5, 1.5, 2.5, 2, 3.5)$, and the initial energy of sensor nodes 1 - 6 are $\mathbf{e} = (1000, 1500, 1500, 1500, 1300, 2000)$. The sink node (node 7) is assumed to have enough energy. The parameters for energy consumption are set to $e^t = 1.4$, $e^r = 1.0$, $e^s = 0.83$ [30]. The default required lifetime of each sensor node is 800. The utility function is defined as $U_s(x_s) = \xi_s \log x_s$, $s \in S$, where $\boldsymbol{\xi} = (0.55, 0.5, 0.3)$. We set the maximum and minimum transmission rates for each flow s to [0.2, 1.5]. As the asynchronous parameter B depends on the specific network environments, we vary the value of B for corresponding experimental results. We set $a_{ll'}(t', t)$, $b_{ns}(t', t)$, $c_{sl}(t', t)$, $d_{ll'}(t', t)$, $f_{ls}(t', t)$, $g_{sn}(t', t)$ to be 1/B $\forall n \in N, l \in L, s \in S, t', t$.



(a) $\gamma = 0.1$, B=1



(b) $\gamma = 0.1$, B=5



(c) $\gamma = 0.1$, B=6

Fig. 2. Convergent performance

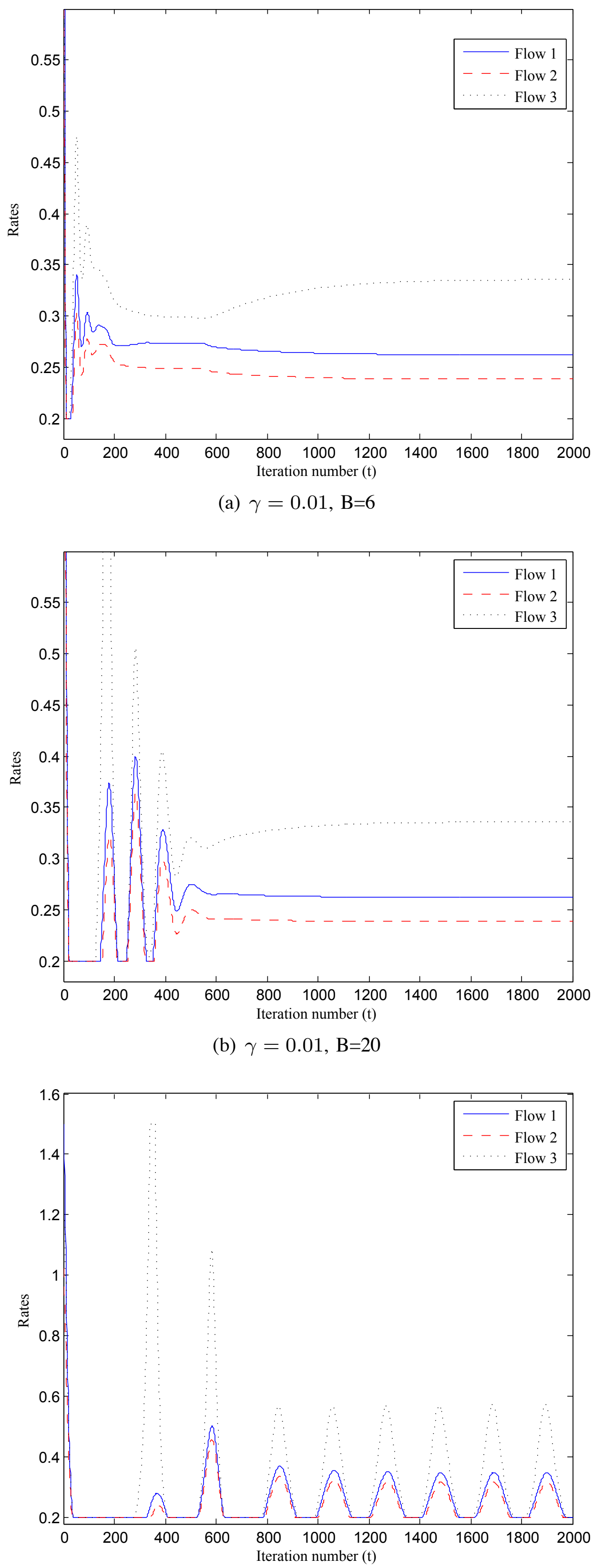
B. Performance Evaluation of UAFC

First we set the stepsize $\gamma = 0.1$. When $B = 1$, the asynchronous case reduces to the synchronous case. Fig. 2(a) shows the result for B=1. It can be seen that, without communication delay, the sequence generated by UAFC converges quickly to the optimal solution (0.262, 0.238, 0.336). We then increase B to 5, and the corresponding result is depicted in Fig. 2(b). Obviously, in the three cases, the sequences all converge to the optimal solution (0.262, 0.238, 0.336). However, both of them have different convergent performance, which is affected by the parameter of asynchronous setting B. It takes more iterations for sequence when $B = 5$ to converge to the optimal solution. From Fig. 2(a) and Fig. 2(b), we can see B has a fundamental impact on the convergent performance of UAFC. The larger the B is, the more slowly the sequence converges. This is reasonable, as each sensor node needs more iterations to collect gradient information when B becomes larger.

As previously mentioned, for a given stepsize γ, the larger the parameter of asynchronous setting B, the more iterations each sensor node needs to regulate its rate to the optimal solution. One extreme case is B is infinity. In this case, the sequence will diverge. Therefore, for a given stepsize γ, we may find a threshold. When the asynchronous setting parameter B is larger than the threshold, the sequence will diverge. For $\gamma = 0.1$, we find the threshold value of B equals to 6, because the rate has been oscillating as shown in Fig. 2(c).

In order to find a value of γ to make the algorithm convergent, we proceed to reduce the stepsize γ to 0.01 in the experiment. We first set $B = 6$, and the results are plotted in Fig. 3(a). In this case, the sequence generated by UAFC is convergent to the optimal solution. Because of the smaller stepsize γ and the larger asynchronous setting B, the convergent rate is slower than that for $\gamma = 0.1$. Then we increase B to 20 and the results are shown in Fig. 3(b). We find the threshold is B=44 for $\gamma = 0.01$ (see Fig. 3(c)). Thus, given the asynchronous parameter B, we can always set a sufficiently small stepsize γ to make the sequence convergent.

Lastly, we investigate the relationships between $x_s(t)$ and $\bar{x}_s(t)$, $\widehat{\lambda}^s(t)$ and $\lambda^s(t)$. As shown in Fig. 4, the estimation errors, i.e., $x_s(t) - \bar{x}_s(t)$ in Fig. 4(a) and $\lambda^s(t) - \widehat{\lambda}^s(t)$ in Fig. 4(b), approach to zero as iteration t becomes infinity, which verifies the conclusions in Theorem 1.



(a) $\gamma = 0.01$, B=6

(b) $\gamma = 0.01$, B=20

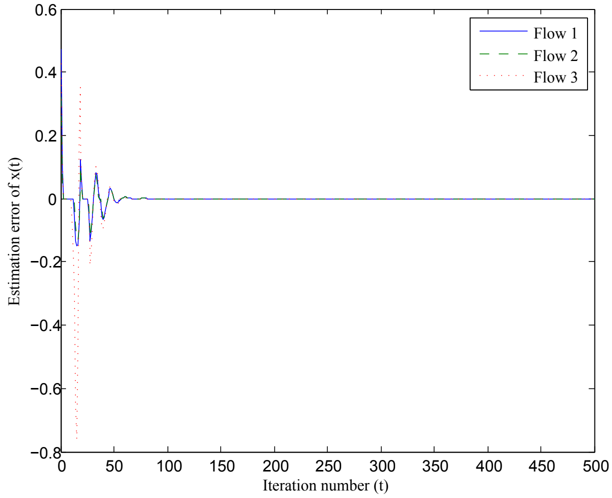
(c) $\gamma = 0.01$, B=44

Fig. 3. Convergent performance

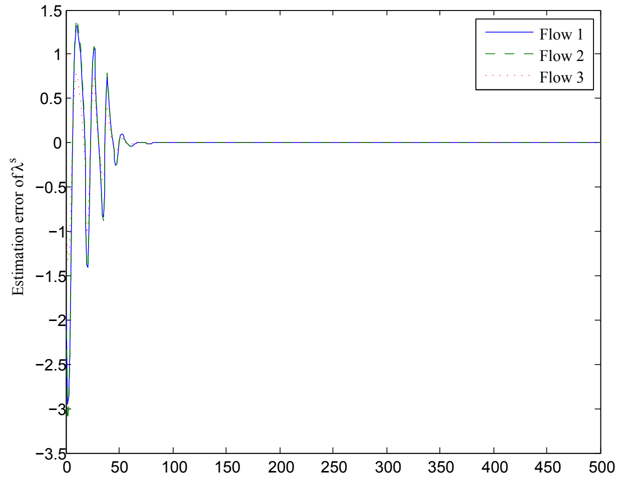
VII. Conclusions and Future Work

We have proposed a utility-based asynchronous flow control algorithm in WSNs. We make use of the interference set to model the spatial contention between links and formulate the problem as a nonlinear constrained optimization problem. Based on the Lagrange dual decomposition method, we decouple the primal problem into several subproblems. A distributed algorithm, UAFC, has been proposed to solve these subproblems in an asynchronous setting, and we have proved theoretically its convergence. Numerical results demonstrate that the sequence generated by UAFC converges to the optimal solution, which reveals the effectiveness of UAFC. We have also studied numerically the relationships between the convergent rate of UAFC and the asynchronous parameter B.

Our future work will focus on quantifying the impacts of dynamic capacity on the performance of flow control for WSNs in the asynchronous setting. We will also develop a general asynchronous flow control algorithm for stochastic



(a) Estimation error between $x_s(t)$ and $\bar{x}_s(t)$



(b) Estimation error between $\widehat{\lambda}^s(t)$ and λ^s

Fig. 4. Estimation error for $\gamma = 0.1$, B=3

multi-objective optimization problems in multi-path WSNs.

APPENDIX

A. Proof of Lemma 1

From (16) and (25), we get

$$\begin{aligned}\widehat{\lambda}^l_{IS}(t) &= \sum_{t'=t-B}^{t} c_{sl}(t',t) \sum_{l'\in IS_l} \sum_{t''=t'-B}^{t'} d_{ll'}(t'',t')\lambda^c_{l'}(t''),\\ \widehat{\lambda}^e_n(t') &= \sum_{t'=t-B}^{t} g_{sn}(t',t)\lambda^e_n(t').\end{aligned}$$

We can obtain

$$\begin{aligned}&|\widehat{\lambda}^l_{IS}(t) - \lambda^l_{IS}(t)|\\ &= |\sum_{l'\in IS_l} \sum_{t'=t-B}^{t} \sum_{t''=t'-B}^{t'} c_{sl}(t',t) \times\\ &\quad d_{ll'}(t'',t')\lambda^c_{l'}(t'') - \sum_{l'\in IS_l} \lambda^c_{l'}(t)|\\ &\leq \sum_{l'\in IS_l} \max_{t-2B\leq t'\leq t} |\lambda^c_{l'}(t') - \lambda^c_{l'}(t)|\\ &\leq \sum_{l'\in IS_l} \max_{t-2B\leq t'\leq t} \sum_{\tau=t'}^{t-1} |\lambda^c_{l'}(\tau+1) - \lambda^c_{l'}(\tau)|\\ &\leq \sum_{\tau=t-2B}^{t-1} \sum_{l'\in IS_l} |\lambda^c_{l'}(\tau+1) - \lambda^c_{l'}(\tau)|\,. \end{aligned} \tag{29}$$

Similarly, we have

$$|\widehat{\lambda}^e_n(t) - \lambda^e_n(t)| \leq \sum_{\tau=t-B}^{t-1} |\lambda^e_n(\tau+1) - \lambda^e_n(\tau)|\,. \tag{30}$$

B. Proof of Lemma 2

From (23), we know that

$$\begin{aligned}&\left|\widehat{\lambda}^s(t) - \lambda^s(t)\right|\\ &= |\sum_{l\in L(s)} (\widehat{\lambda}^l_{IS}(t) - \lambda^l_{IS}(t))\\ &\quad +(e^r+e^t) \sum_{n\in N(s)} (\widehat{\lambda}^e_n(t) - \lambda^e_n(t)) + e^t(\widehat{\iota}_s(t) - \iota_s(t))\,|\\ &\leq \sum_{l\in L(s)} |\widehat{\lambda}^l_{IS}(t) - \lambda^l_{IS}(t)|\\ &\quad +(e^r+e^t) \sum_{n\in N(s)} |\widehat{\lambda}^e_n(t) - \lambda^e_n(t)| + e^t|\widehat{\iota}_s(t) - \iota_s(t)|.\end{aligned}$$

Then using Eqs. (29) and (30), we get

$$\begin{aligned}&\left|\widehat{\lambda}^s(t) - \lambda^s(t)\right|\\ &\leq \sum_{\tau=t-2B}^{t-1} \Big(\sum_{l\in L(s)} \sum_{l'\in IS_l} |\lambda^c_{l'}(\tau+1) - \lambda^c_{l'}(\tau)|\\ &\quad +(e^r+e^t) \sum_{n\in N(s)} |\lambda^e_n(\tau+1) - \lambda^e_n(\tau)|\\ &\quad +e^t\,|\iota_s(\tau+1) - \iota_s(\tau)|\,\Big)\\ &= \sum_{\tau=t-2B}^{t-1} \sum_i r''_{is}\,|\lambda_i(\tau+1) - \lambda_i(\tau)|\,. \end{aligned} \tag{31}$$

Following the same steps, we have

$$\begin{aligned}&|\lambda^s(t) - \lambda^s(\tau)|\\ &= |\sum_{l\in L(s)} \sum_{l'\in IS_l} (\lambda^c_{l'}(t) - \lambda^c_{l'}(\tau))\\ &\quad +(e^r+e^t) \sum_{n\in N(s)} (\lambda^e_n(t)\\ &\quad -\lambda^e_n(\tau)) + e^t(\iota_s(t) - \iota_s(\tau))\,|\\ &\leq \sum_{t'=\tau}^{t-1} \sum_i r''_{is}\,|\lambda^e_i(t'+1) - \lambda^e_i(t')|\,, \end{aligned} \tag{32}$$

and

$$\begin{aligned}
&|x_s(t)-\bar{x}_s(t)| \\
&\le |U_s^{-1}(\widehat{\lambda}^s(t)) - U_s^{-1}(\lambda^s(t))| \\
&\le \bar{\alpha}|\widehat{\lambda}^s(t)-\lambda^s(t)| \\
&\le \bar{\alpha}\sum_{\tau=t-2B}^{t-1}\sum_i r''_{is}|\lambda_i(\tau+1)-\lambda_i(\tau)|. \qquad (33)
\end{aligned}$$

C. Proof of Lemma 3

As $||\cdot||$ is a norm, there exists some constant $A'_2 > 0$, such that

$$||\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))|| \le A'_2||\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))||_\infty.$$

So

$$\begin{aligned}
&||\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))|| \\
&\le A'_2 \max_l \sum_{t'=t-B}^{t}\sum_{l'\in IS_l}\sum_{s\in S(l')} |\ \widehat{x}_s(t') - \bar{x}_s(t'))\ | \\
&\quad + A'_2 \max_n \{\ (e^r+e^t)\sum_{s\in S(n)} |\ \widehat{x}_s(t)-\bar{x}_s(t))\ | \\
&\quad + e^t\ |\ \widehat{\epsilon}_n(t) - \epsilon_n(t))\ |\}. \qquad (34)
\end{aligned}$$

From Eqs. (13), (14), and (17), we have

$$\begin{aligned}
&|\widehat{x}_s(t)-\bar{x}_s(t)| \\
&= |\sum_{t'=t-B}^{t}\sum_{t''=t'-B}^{t'} a_{ll'}(t',t)f_{ns}(t'',t')x_s(t'') - \bar{x}_s(t)| \\
&\le \max_{t-2B\le t'\le t} |x_s(t')-\bar{x}_s(t)| \\
&\le \bar{\alpha}\max_{t-2B\le t'\le t} |\widehat{\lambda}^s(t')-\lambda^s(t)| \\
&\le \bar{\alpha}\max_{t-2B\le t'\le t} (|\widehat{\lambda}^s(t')-\lambda^s(t')| + |\lambda^s(t')-\lambda^s(t)|).
\end{aligned}$$

From Lemma 2, we can easily get

$$\begin{aligned}
&|\widehat{x}_s(t)-\bar{x}_s(t)| \\
&\le \bar{\alpha}\max_{t-2B\le t'\le t} (\sum_{\tau=t'-2B}^{t'-1}\sum_i r''_{is}|\lambda_i(\tau+1)-\lambda_i(\tau)| \\
&\quad + \sum_{\tau=t'}^{t-1}\sum_i r''_{is}|\lambda_i(\tau+1)-\lambda_i(\tau)|) \\
&\le \bar{\alpha}\max_{t-2B\le t'\le t} \sum_{\tau=t'-2B}^{t-1}\sum_i r''_{is}|\lambda_i(\tau+1)-\lambda_i(\tau)| \\
&\le \bar{\alpha}\sum_{\tau=t-4B}^{t-1}\sum_i r''_{is}|\lambda_i(\tau+1)-\lambda_i(\tau)|. \qquad (35)
\end{aligned}$$

Then from Eqs. (34) and (35), we have

$$\begin{aligned}
&\left\|\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))\right\| \\
&\le A'_2\bar{\alpha}\max_l \sum_{l'\in IS_l}\sum_{s\in S(l')}\sum_{\tau=t-4B}^{t-1}\sum_i r''_{is} \times \\
&\quad |\lambda_i(\tau+1)-\lambda_i(\tau)| + A'_2\bar{\alpha}\max_n \{(e^r+e^t)\times \\
&\sum_{s\in S(n)}\sum_{\tau=t-4B}^{t-1}\sum_i r''_{is}\,|\lambda_i(\tau+1)-\lambda_i(\tau)| \\
&\quad + e^t\sum_{\tau=t-4B}^{t-1}\sum_i r''_{is}\,|\lambda_i(\tau+1)-\lambda_i(\tau)|\}. \qquad (36)
\end{aligned}$$

Let $\bar{S} = ||\mathbf{R}''||_1$, then $\sum_i r''_{in}|\lambda_i(\tau+1)-\lambda_i(\tau)| \le \bar{S}||\boldsymbol{\lambda}(\tau+1)-\boldsymbol{\lambda}(\tau)||_1$. We get

$$\begin{aligned}
&\left\|\nabla D(\boldsymbol{\lambda}(t)) - \nabla D(\widehat{\boldsymbol{\lambda}}(t))\right\| \\
&\le A'_2\bar{S}\bar{\alpha}\max_l \sum_{l'\in IS_l}\sum_{s\in S(l')}\sum_{\tau=t-4B}^{t-1} ||\boldsymbol{\lambda}(\tau+1)-\boldsymbol{\lambda}(\tau)||_1 \\
&\quad + A'_2\bar{S}\bar{\alpha}\max_n \{\ (e^r+e^t)\sum_{s\in S(n)}\sum_{\tau=t-4B}^{t-1} ||\boldsymbol{\lambda}(\tau+1) \\
&\quad - \boldsymbol{\lambda}(\tau)||_1 + e^t\sum_{\tau=t-4B}^{t-1} ||\boldsymbol{\lambda}(\tau+1)-\boldsymbol{\lambda}(\tau)||_1\ \} \\
&\le A'_2\bar{S}\bar{\alpha}(\sum_{\tau=t-4B}^{t-1} ||\boldsymbol{\lambda}(\tau+1)-\boldsymbol{\lambda}(\tau)||_1)\times \\
&\quad \{\ \max_l \sum_{l'\in IS_l}\sum_{s\in S(l')} 1 \quad + (e^r+e^t)\sum_{s\in S(n)} 1 + e^t\ \} \\
&\le A'_2\bar{\alpha}\bar{S}^2\sum_{\tau=t-4B}^{t-1} ||\boldsymbol{\lambda}(\tau+1)-\boldsymbol{\lambda}(\tau)||_1.
\end{aligned}$$

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Computer Networks (Elsevier)*, vol. 38, no. 4, pp. 393–422, 2002.

[2] X. Cao, J. Chen, Y. Zhang, and Y. Sun, "Development of an integrated wireless sensor network micro-environmental monitoring system," *ISA transactions*, vol. 47, no. 3, pp. 247–255, 2008.

[3] X. Lin, R. Lu, X. Shen, Y. Nemoto, and N. Kato, "SAGE: A strong privacy-preserving scheme against global eavesdropping for ehealth systems," *IEEE J. Sel. Areas Commun.*, vol. 27, no. 4, pp. 365–378, 2009.

[4] I. Dietrich and F. Dressler, "On the lifetime of wireless sensor networks," *ACM Transactions on Sensor Networks*, vol. 5, no. 1, pp. 1–38, 2009.

[5] S. He, J. Chen, K. Yau, H. Shao, and Y. Sun, "Energy-efficient capture of stochastic events by global- and local-periodic network coverage," in *Proc. ACM MobiHoc*, 2009.

[6] K. Kelly, A. Maulloo, and D. Tan, "Rate control for communication networks:shadow prices, proportional fairness and stability," *Journal of the Operational Research Society*, vol. 42, no. 6, pp. 697–716, 1998.

[7] S. Low and D. Lapsley, "Optimization flow control, I: Basic algorithm and convergence," *IEEE/ACM Trans. Netw.*, vol. 7, no. 6, pp. 861–75, 1999.

[8] C. Saraydar, N. Mandayam, and D. Goodman, "Pricing and power control in a multicell wireless data network," *IEEE J. Sel. Areas Commun.*, vol. 19, no. 2, pp. 1883–1892, 2001.

[9] W. Xu and T. Wu, "Optimal congestion control algorithm for ad hoc networks: Penalty function-based approach," *Journal of Zhejiang University (SCIENCE A)*, vol. 7, no. 12, pp. 2110–2117, 2006.

[10] J. Chen, S. He, Y. Sun, P. Thulasiraman, and X. Shen, "On utility-lifetime tradeoff in wireless sensor networks by optimal flow control," *Computer Networks (Elsevier)*, vol. 53, pp. 3031–3041, 2009.
[11] W. Wang, M. Palaiswami, and S. Low, "Application-oriented flow control: Fundamentals, algorithms and fairness," *IEEE/ACM Trans. Netw.*, vol. 14, 2006.
[12] A. Anandkumar, L. Tong, A. Swami, and A. Ephremides, "Minimum cost data aggregation with localized processing for statistical inference," in *Proc. IEEE INFOCOM*, 2008.
[13] J. Zhu, K. Hung, B. Bensaou, and F. Nait-Abdesselam, "Rate-lifetime tradeoff for reliable communication in wireless sensor networks," *Computer Networks*, vol. 52, no. 1, pp. 25–43, 2008.
[14] K. Yuen, B. Liang, and B. Li, "A distributed framework for correlated data gathering in sensor networks," *IEEE Trans. Veh. Technol.*, vol. 57, no. 1, pp. 578–593, 2008.
[15] X. Shen, W. Zhuang, H. Jiang, and J. Cai, "Medium access control in ultra-wideband wireless networks," *IEEE Trans. Veh. Technol.*, vol. 54, no. 5, pp. 1663–1677, 2005.
[16] A. Bachir, M. Dohler, T. Watteyne, and K. Leung, "MAC essentials for wireless sensor networks," *IEEE Commun. Surveys Tutorials*, to be published.
[17] M. Chiang, S. Low, A. Calderbank, and J. Doyle, "Layering as optimization decomposition: A mathematical theory of network architectures," *Proceedings of IEEE*, vol. 95, no. 1, pp. 255–312, 2007.
[18] L. Cai, X. Shen, J. Pan, and J. W. Mark, "Performance analysis of TCP-friendly AIMD algorithms for multimedia applications," *IEEE Transations on Multimedia*, vol. 7, no. 2, pp. 339–355, 2005.
[19] X. Lin, N. Shroff, and R. Srikant, "A tutorial on cross-layer optimization in wireless networks," *IEEE Journal of Selected Areas in Communications*, vol. 24, no. 8, pp. 1452–1463, 2006.
[20] D. Palomar and M. Chiang, "Alternative distributed algorithm for network utility maximization: Framework and applications," *IEEE Trans. Autom. Control*, vol. 52, no. 12, pp. 2254–2269, 2007.
[21] B. Johansson, P. Soldati, and M. Johansson, "Mathematical decomposition techniques for distributed cross-layer optimization of data networks," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 8, pp. 1535–1547, 2006.
[22] M. Chiang, "Balancing transport and physical layers in wireless multihop networks: Jointly optimal congestion control and power control," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 1, pp. 104–116, 2005.
[23] X. Wang and K. Kar, "Cross-layer rate optimization for proportional fairness in multi-hop wireless networks with random access," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 8, pp. 1548–1559, 2006.
[24] C. Long, B. Li, Q. Zhang, B. Yang, and X. Guan, "The end-to-end rate control in multiple-hop wireless networks: Cross-layer formulation and optimal allocation," *IEEE J. Sel. Areas Commun.*, vol. 26, no. 4, pp. 719–731, 2008.
[25] W. Xu, Y. Wang, J. Chen, G. Baciu, and Y. Sun, "Dual decomposition method for optimal and fair congestion control in Ad Hoc networks: Algorithm, implementation and evaluation," *Journal of Parallel and Distributed Computing*, vol. 68, no. 7, pp. 997–1007, 2008.
[26] Y. Hou, Y. Shi, and H. Sherali, "Rate allocation and network lifetime problems for wireless sensor networks," *IEEE/ACM Trans. Netw.*, vol. 16, no. 2, pp. 321–334, 2008.
[27] V. Srinivasan, C. Chiasserini, P. Nuggehalli, and R. Rao, "Optimal rate allocation for energy-efficient multipath routing in wireless ad hoc networks," *IEEE Trans. Wireless Commun.*, vol. 3, no. 3, pp. 891–899, 2004.
[28] S. Abraham and A. Kumar, "A new approach for asynchronous distributed rate control of elastic sessions in integrated packet networks," *IEEE/ACM Trans. Netw.*, vol. 9, no. 1, pp. 15–30, 2001.
[29] L. Bui, A. Eryımaz, R. Srikant, and X. Wu, "Joint asynchronous congestion control and distributed scheduling for multi-hop wireless networks," in *Proc. IEEE INFOCOM*, 2006.
[30] B. Chen, K. Jamieson, H. Balakrishnan, and R. Morris, "Span: an energy-efficient coordination algorithm for topology maintenance in Ad Hoc wireless networks," *ACM Wireless Networks Journal*, vol. 8, no. 5, pp. 481–494, 2002.

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