Distributed Optimal Maximum Rate Allocation based on Data Aggregation in Rechargeable Wireless Sensor Networks

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Abstract—In Rechargeable Wireless Sensor Networks(R-WSNs), it is critical for data collection because a sensor has to operate in a very low and dynamic duty cycle owing to sporadic availability of energy. In this work, we propose a distribute maximum rate allocation based on data aggregation to compute an upper data generation rate by maximizing it as a linear programming problem. Subsequently, a dual problem by introducing Lagrange multipliers is constructed, and subgradient algorithms are used to solve it in a distributed manner. The resulting algorithms are guaranteed to converge to an optimal value with low computational complexity. Through extensive simulation and experiments, we demonstrate our algorithm is efficient to maximize data collection rate in rechargeable wireless sensor networks.

Keywords—Wireless sensor networks, Maximum Rate Allocation, Data Aggregation, Rechargeable-WSNs

1 Introduction

Energy Harvesting or Rechargeable Wireless Sensor Networks (EH-WSNs or R-WSNs) have attracted more and more attention benefiting from the lifetime extending of sensor nodes by equipping them with rechargeable technologies [1], which convert sources, such as body heat, foot strike, finger strokes, and solar into electricity [2]. A sensor can operate perpetually by using supercapacitors (with virtually unlimited recharge cycles) to store the harvested energy [3]. Note, a harvesting node is said to achieve energy-neutral operation if the energy used is always to a lesser degree than the energy harvested [4]. Although their lifetime is less of an issue, due to the limited energy storage capacity, a node cannot be always beneficial to conserve energy when a network can harvest excessive energy from the environment [5]. Since more energy can be extracted from the ambient environment in R-WSNs, the harvested energy should be consumed as soon as possible [6]. Therefore, surplus energy of a node can be utilized for strengthening packet delivery efficiency and improving network data collection rate.

Consider the characteristics of R-WSNs, several protocols discuss several aspects of power management or MAC schemes to improve energy efficiency and maximize data collection rate [7]. A centralized algorithm with the line programming is proposed to compute the lexicographically maximum data collection rate and routing paths for each node [8]. Sadlapur et al. [9] provide a distribute algorithm for jointly determining the routing structure and amount of flows on each link with flow adjustment to achieve an optimal data collection rate. Peng S et al. [10] propose real time adaptive energy management policies based on observed information for throughput optimal. Prabhakar et al. [11] propose four throughput enhancement schemes from a simple naive scheme with low complexity to probabilistic probing scheme incorporating advanced methods to appropriately use the harvesting energy. However, ideal energy replenished precondition is used and data aggregation has't been considered in these protocols.

In a nutshell, we propose a distribute optimal maximum rate allocation based on data aggregation for packets communications in r-WSNs. In summary, on observing the lack of data aggregation techniques consideration for improving data flow in existing routing protocols, we introduce the first generic routing protocol algorithm with the data aggregation scheme in R-WSNs.

2 Design and Method

2.1 Network Model

Consider a static rechargeable wireless sensor network modeled as an undirected graph $G = (V, A)$, where V is the set of n rechargeable sensor nodes and sink nodes within the network. A is the set of links, $A = \{A|(i, j) \in A, i, j \in V\}$. G consists of a finite nonempty vertex set V and edge set A of ordered pairs of distinct vertices of V Each sensor $i \in V$ is powered by a rechargeable battery with capacity B and its energy is harvested from its surrounding environment (e.g. solar energy). Each sensor i senses its vicinity with sampling data generation rate g_i. The set of nodes are connected to node i by links is denoted as S_i. We assume that the network graph is connected, i.e. It always exists a path between any pair of nodes i and j in V. The current remained energy of node i is e_i and the maximum bandwidth is set to be R

2.2 Energy Model

We assume the power consumption for sending and receiving one bit of data are e_t, e_r, respectively. When the data traffic from node i to j is $f_{i,j}$ per unit time. Hence, the energy consumption for node i in receiving and transmitting are $e_t(i,j)$ and $e_r(i,j)$, which are:

$$e_t(i,j) = e_t * \sum_{i,j \in V, j \in S_i} f_{i,j}$$

$$e_r(i,j) = e_r * \sum_{i,j\in V, j\in S_i} f_{i,j} \tag{1}$$

Therefore, if we let w_i denote the fraction of power consumption for node i per unit time, which can be formulated as:

$$w_i = e_t(i,j) + e_r(i,j) \tag{2}$$

2.3 Description of the data aggregation problem

To incorporate data aggregation into the geometric routing model, we adopt the foreign-coding model [12] scheme. Specifically, we assume a node i is able to compress the data originating at its adjacent neighbor j using its local data. The compression ratio depends on the data correlation between node i and j. In our work, assumes the data correlation is inversely proportional to the Euclidean distance between nodes, or $\rho(i,j) = \exp(-\alpha * d_{i,j}^2)$, where, α is data correlation parameters. Where, the $d_{i,j}^2$ can be formulated as:

$$d_{i,j}^2 = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \tag{3}$$

The data from a source node will be transmitted to anyone sink finally by one or multiple-hops. For each node, the outflow equals or lesser than the inflow and generation data from it due to some redundant information removed from data traffics. In the process of packet's transmission, data leak is not considered. Hence, the data flow for node i is expressed as:

$$\sum_{i,j\in V} f(j,i)(1-\rho(j,i)) + g_i = \sum_{i,j\in V} f(i,j) \tag{4}$$

Where, $\rho(j,i) \in [0,1]$, higher α means smaller data correlation, and vice versa. When a sensor only forward packets for its neighbor and does not generate any packets, data fusion does not occur and $\rho(j,i) = 0$. Let $\boldsymbol{w_i}$ denotes the fraction of power consumption for node i in each time unit. We have

$$\boldsymbol{w_i} = \sum_{i,j\in V} \boldsymbol{e_r} * f(j,i) + \sum_{i,j\in V} \boldsymbol{e_t} * f(i,j) \tag{5}$$

2.4 Distribute algorithm for maximizing data collection rate

The goal of the maximum rate allocation is to deliver all packets generated by sensors to base stations as soon as possible subject to node available energy, node and link capacity constraints such that the data flow until the first (set of) sensor node with minimum data generation rate is maximized followed by data flow until the second (set of) sensor node with minimum value is maximized and so on. Now, we formulate this problem as a line programming, which is given by:

$Maximize\ g_i$

$Subject\ to$:

$$\sum_{i,j\in V} f(j,i)(1-\rho(j,i)) + g_i = \sum_{i,j\in V} f(i,j)$$
$$\sum_{i,j\in V} e_r * f(j,i) + \sum_{i,j\in V} e_t * f(i,j) \le P_i(t)$$
$$\rho(i,j) = \exp\left(-\alpha * d_{i,j}^2\right)$$
$$f(j,i), f(i,j) \ge 0, \forall i,j \in V, j \in S_i$$
$$0 \le g_i \le R_i$$
$$P_i(t) \le B \tag{6}$$

The first set of constraints ensures that the inflow after aggregating with raw generation data equals the outflow. The second constraint ensures that nodes do not consume more energy than they collect, which includes the energy consumption packet transmissions and packet receptions. The third constraint formulate the $\rho(i,j)$ of node i. Constraint state that the data flow and available energy do not go below zero and do not go beyond the link capacity or battery capacity.

According to the Eq.6, the constraints' model of data flow conservation at each node. We change variable to $q_i = \frac{1}{g_i}$ which indicates the time for generating per unit of packet. We define decay q_i as the inverse of data collection rate $q_i = \frac{1}{g_i}$ w, $q_i > 0$. Therefore, maximum data collection rate can be converted to a minimum the time for per unit of packet generation. We obtain an equivalent linear programming formulation.

$Minimize\ \ q_i^2$

$Subject\ to$:

$$\sum_{i,j\in V} f(j,i)\left(1-\rho(j,i)\right) + \frac{1}{q_i} = \sum_{i,j\in V} f(i,j)$$
$$\sum_{i,j\in V} \boldsymbol{e_r} * f(j,i) + \sum_{i,j\in V} \boldsymbol{e_t} * f(i,j) \le P_i(t)$$
$$\rho(i,j) = \exp\left(-\alpha * d_{i,j}^2\right)$$
$$f(j,i), f(i,j) \ge 0, \forall i,j \in V, j \in S_i$$
$$0 \le g_i \le R_i$$
$$P_i(t) \le B \tag{7}$$

Here again, the constraints are flow conservation and power conservation constraints. Again, we consider a quadratic objective function that is strictly convex in the q_i. Also, to ensure that the dual function is differentiable, we restrict the domain to $0 \le q_i \le Q$, for some loose upper bound Q. In addition, we use a simple approach similar to that utilized in [13]. We change the primal objective function to q_i^2, since minimizing q_i is the same as minimizing q_i^2. This is the optimization problem that the maximum problem to maximize data collection rate is converted to the minimum problem to minimize data generation time for per unit of byte information, which will be solved in a distributed manner. We can interpret the above problem as minimizing the maximum ratio of time elapsed to collect a packet at a node. The linear programming problem for Eq.5 is NP-hard and considerable difficult solved directly. Hence, a dual model will be utilized for replacing the original problem.

3 Simulations

Simulation of our algorithm for r-WSNs was done by Matlab software, with up to 100-200 nodes and 3-8 sinks are randomly deployed in a 1000m*1000m square field. The maximum communication range of each node is set to be 100m. All nodes' energy devices are rechargeable with $20cm^2$ square size solar panel, and transmission powers are adjustable. Energy leakage and the case of signal loss of sensor are not considered in our work. Where, $\alpha \in [0.001, 0.01]$. Every data point in simulation figures is obtained by averaging 50 runs with different random seeds, node deployment and node working schedules.

In order to further understand of the performance of our algorithm for Maximizing Rate Allocation (MRA) under network settings, in this section, we provide a scheme for performance comparison, an optimal Distributed Lexicographic rate assignment (DLEX) designed for R-WSNs [9]. In [9], the authors propose distributed algorithms for joint determining the routing structure and amount of flows on each link without considering data fusion. It involves update rate computation using optimal lexicographic rate assignment. In this method, nodes first compute their maximum rate using initial rate procedure. Subsequently, they send a control packet containing the flow id and the maximum achievable rate to their next hop nodes.

We first compare the rate allocation between our algorithm and DLEX under the distinct number of sensors with three sinks, where the average node's duty-cycles are 10%, 30%, respectively, as shown in the Fig.1. From the Fig.1, we can observe the data collection rates increase for both algorithms and that of our algorithm is slightly higher than that of another algorithm with the sensor density improved for both different node's duty-cycle. Our algorithm is utilized for calculating the upper bound of data flow under ideal conditions and rather than establishing a detailed routing path. In actual application, the network throughput will be lower than the result value of our method. From the Fig.1, we can see the data generation rates of our algorithm are average about 6% and 9% higher than that of the Dlex scheme when duty cycles are 10%, 30%, respectively.

We next analyze the rate allocation under two data correlation settings (α=0.001 and α=0.01), as shown in Fig.2. From the Fig.2, we can observe the data flow rate in two algorithms improved with the number of nodes increasing in different scenarios of our algorithm performing a little better than that of the Dlex. As the number of nodes increase in the area, it affects the node density and delivery ratio. The overall raw data rate is proportional to the number of nodes in the network. More packets generated in the network and data aggregation rate improved greatly. At the same time, the nodes' density increased also drives the network topology from sparse to dense and the data correlation between neighboring nodes becomes higher, so more redundant information can be removed through data aggregation.

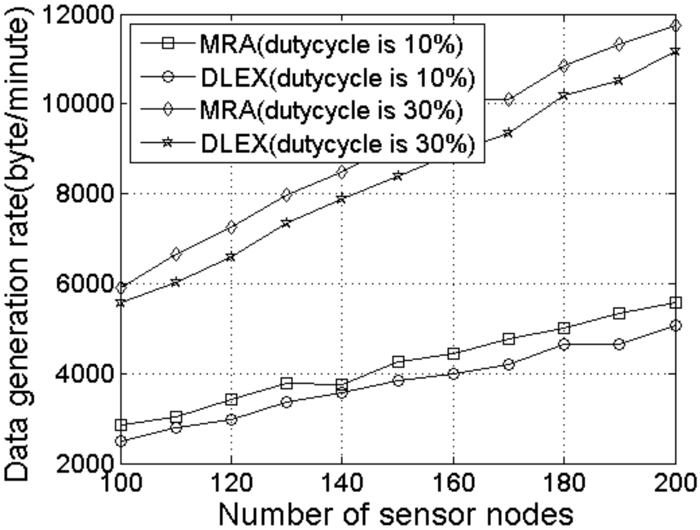

Fig. 1. Data generation rate with number of nodes increasing when duty cycle is 10% and 30%

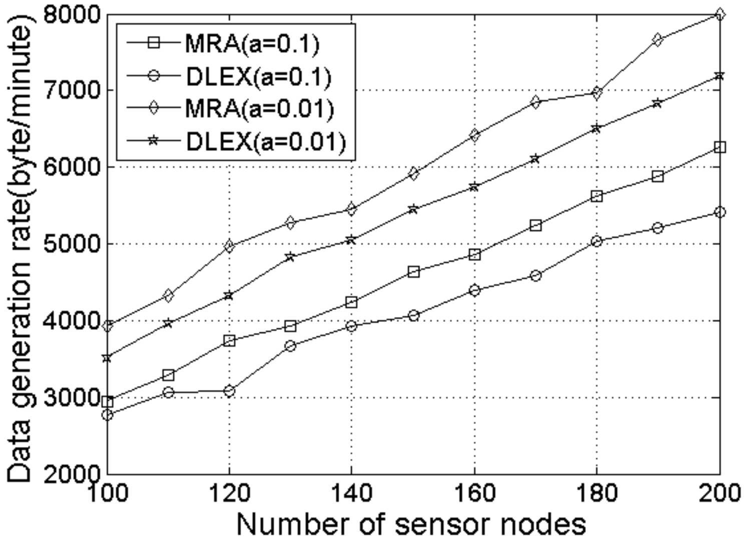

Fig. 2. Data generation rate with number of nodes increasing when data correlation α = 0.01,0.001

4 Conclusion

In this work, we first define the network system and energy model. In order to improve data generation rate, we propose an algorithm to compute an upper data generation rate based on data fusion that maximizes it as an optimization problem for a network. First and for most, we formulate it as a linear programming problem subject to the flow and energy conservation constraints. On top of that, a dual problem by introducing Lagrange multipliers is constructed. Last but not least, a subgradient algorithm is used to solve it in a distributed manner. Through extensive simulation and experiments, we demonstrate our algorithm is efficient to maximize data collection rate in rechargeable wireless sensor networks.

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