A Fair and Lifetime-Maximum Routing Algorithm for Wireless Sensor Networks

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***Abstract*— In multi-hop sensor networks, information obtained by the monitoring nodes need to be routed to the sinks. If we assume that the transmitter power level can be adjusted to use the minimum energy required to reach the intended next hop receiver, the energy consumption rate per unit information transmission depends on the choice of the next hop node. In a power-aware routing approach, most proposed algorithms aim at minimizing the total energy consumption or maximizing network lifetime. In this paper, we propose a new routing algorithm with two goals: minimizing the total energy consumption and ensuring fairness of energy consumption between nodes. We formulate this as a nonlinear programming problem and use a sub-gradient algorithm to solve the problem. We also evaluate the proposed algorithm via simulations at the end of this paper.**

I. Introduction

A wireless sensor network (WSNs) is a network consisting of spatially autonomous devices using sensors to cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants, at different locations. A sensor transforms the collected data into electric signals and sends it usually via a radio transmitter to a sink node. The sink node acts as a gateway between the WSN and external networks.

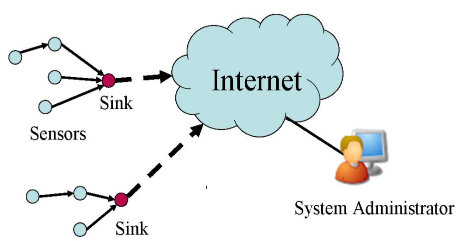

Fig. 1. An example of a sensor network.

WSNs are expected to have significant impacts on many military and civil applications, such as combat field surveillance, security and disaster management. Each sensor node is powered by a limited energy source (e.g., a battery). As sensor nodes can be deployed in large numbers at remote locations, it is typically not feasible to recharge their batteries. Once the energy of a node is depleted, that node is considered dead. Although there have been significant improvements in processor design and computing, advances in battery technologies still lag behind, making energy resource considerations a fundamental challenge in WSNs. These challenges necessitate energy-awareness at all layers of the networking protocol stack. In particular, many researchers have shown interest in routing protocols at the network layer.

In sparse sensor networks, a mobile sink model was proposed in [1]. The mobile sinks move around the network area and collect data from the visited sensors. Use of mobile sinks decreases energy consumption of sensor nodes. However, it creates new challenges, e.g., complex hardware of the sinks and dynamic routing and security [2].

Static sink model is used in most sensor networks. Routing protocols in a static sink WSN are divided into single-hop routing, two-hop routing and multi-hop routing. Using single-hop routing, sensor nodes directly send data to the sink node. Because data is transmitted over long distances, the single-hop WSN consumes significant energy (transmission energy is proportional to the k^{th} power of the distance between two nodes, where $k \geq 2$). A two-hop routing protocol is proposed in [3]. The network is divided into many clusters. In each cluster, a sensor node is chosen as the cluster head. Sensor nodes in a cluster send data to the cluster head and the cluster head sends it to the sink node.

In general, many researchers have great interest in the multi-hop routing protocols in WSNs. By forwarding data to a neighboring node, a sensor can send data to the sink via many paths. Recent researches have focused on finding out the best possible path to the sink. In the early multi-hop routing literature, routing algorithms for minimizing energy consumption were proposed [4] [5]. The cost of a link between two sensor nodes is considered as a function of energy. Sensor nodes send data via the shortest path to minimize the cost of data transmission. In minimizing energy routing protocol, if all the traffic is routed through the minimum cost path to the sink, the nodes along that path will quickly run out of power. This renders other nodes useless due to a network partition even if they still have available energy resources.

Instead of minimizing the energy consumption, many researchers have attempted to maximize the time until the first node runs out of energy. This approach introduced the max-min lifetime routing algorithms [6] [7] [8] [9] [10].

The problem of max-min lifetime routing protocols is that they do not save energy in the whole network. In a large scale sensor network, saving energy in the whole network is more important than that at individual nodes. Other notable approaches include maximizing data collection [11] or maximizing residual energy [12].

Although there is a lot of research work on power-aware routing in sensor networks, no previous work has considered the fairness in energy consumption between sensor nodes. In this paper, in addition to maximizing the network lifetime, we aim at enhancing fairness among nodes in terms of their energy consumption.

The remainder of this paper is organized as follows. Section II showcases some research work related to routing in WSN. In Section III, we formulate the problem as a nonlinear programming problem. In Section IV, we solve this nonlinear programming problem by using a sub-gradient algorithm. In Section V, we evaluate the proposed algorithm via simulations. Finally, Section VI concludes the paper.

II. Related Work

Two minimizing energy consumption routing protocols are proposed in [4] [5]. Singh *et al*. [4] have used the Dijkstra shortest path algorithm to search for the minimum energy path. This protocol uses the transmission power as the link cost. Therefore it minimizes the total transmission power of the sensor network. Actually, the intermediate nodes consume energy not only when forwarding packets but also when receiving packets. The protocol in [5] used both the transmission power and the receiving power as a link cost metric. Using the Bellman-Ford shortest path algorithm, it attempts to find the minimum energy path.

The max-min network lifetime routing algorithms can be formulated as an optimal problem.

$$T_{min} = \min(T_1, T_2, ..., T_n) \tag{1}$$

$$\text{Maximize } T_{min} \tag{2}$$

where, T_i denotes lifetime of node i. This is a NP-hard problem [10]. In [6] [7] [8] [9] and [10], researchers proposed algorithms to find out approximate solutions. Chang *et al*. [6] formulated the routing problem as a linear programming problem. A shortest cost path routing algorithm is proposed using combination of "transmission and reception energy consumption" and "the residual energy levels at the two end nodes" as the link cost. It is shown that the proposed algorithm can achieve a network lifetime very close to the optimal lifetime obtained by solving the linear programming problem. Madan *et al*. [7] described the problem as a linear programming problem with model energy conservation at each node as the set of constraints. A sub-gradient algorithm is used to solve the problem. Xue *et al*. [9] modeled the max-min lifetime routing algorithm problem as a multi-commodity flow problem, where a commodity represents the data generated from a sensor node and delivered to a sink. A fast approximate algorithm is proposed. Kelly *et al*. [13] proposed proportional fairness and showed that by maximizing a sum of concave functions, one can solve a linear optimization problem with a fairness constraint. Using this theory, Hung *et al*. [11] made attempts to maximize and to ensure fairness in collected data among sensor nodes. A sub-gradient algorithm was used to solve the nonlinear problem.

In this paper, we consider a surveillance sensor network. Each sensor has to send a fixed amount of data to the sink at each unit of time. Under this constraint and with the purpose of maximizing the network lifetime, we first focus on minimizing the total energy consumption of the network. To avoid the pitfalls of minimizing energy consumption routing protocols [4] [5], we also consider in the routing decision fairness in the energy consumption between sensor nodes. We use proportional fairness and formulate the problem as in [11]. However, to solve the nonlinear problem, we introduce a novel technique in this paper.

III. Problem Formulation

A. Application of Convex Functions

We formulate the problem using a property of convex functions. As shown in Fig. 2, if $U(x)$ is a convex function, then for each vector $(x_1, x_2, ..., x_n)$ we have:

$$\sum_{i=1}^{n} U(x_i) = nU(\bar{x}) + \sum_{i=1}^{n} y_i \tag{3}$$

where $\bar{x} = \frac{x_1+x_2+...+x_n}{n}$ and y_i are the length of the segment line between the tangent to $U(x)$ at $\bar{x}$ and the graph of $U(x)$, respectively. We thus have the following equivalence.

$$\text{Minimize } \sum_{i=1}^{n} U(x_i) \Leftrightarrow \text{Minimize } \begin{cases} nU(\bar{x}) \\ \sum_{i=1}^{n} y_i \end{cases} \tag{4}$$

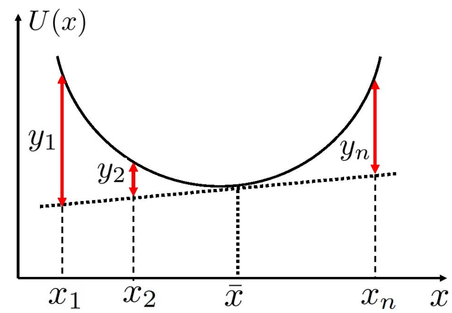

Fig. 2. Property of convex function.

Choosing $U(x)$ as a strictly increasing function, we have:

$$\text{Minimize } nU(\bar{x}) \Leftrightarrow \text{Minimize } \sum_{i=1}^{n} x_i \tag{5}$$

From Fig. 2, we can see that y_i will have a small value if x_i approaches $\bar{x}$. This will reduce the variance of the vector $(x_1, x_2, ..., x_n)$; which means that we have fairness between x_i. Using this result, we can rewrite Eq. (4) as follows:

$$\text{Minimize } \sum_{i=1}^{n} U(x_i) \Leftrightarrow \begin{cases} \text{Minimize } \sum_{i=1}^{n} x_i \\ \text{Fairness } (x_1, x_2, ..., x_n) \end{cases} \tag{6}$$

Now, using Eq. (6), we attempt to find the best route that minimizes energy consumption and achieves fairness among sensor nodes. Let e_i denotes the energy consumption of node i per a unit of time. To maximize the network lifetime, our first purpose consists in minimizing the total energy consumption by the following equation:

$$\text{Minimize } \sum_{i=1}^{n} e_i \tag{7}$$

The second purpose consists in ensuring fairness in energy consumption between nodes by:

$$\text{Fairness } (e_1, e_2, ..., e_n) \tag{8}$$

According to Eq (6), we alter the problem described by Eq. (7) and Eq. (8) to an optimization problem:

$$\text{Minimize } A = \sum_{i=1}^{n} U(e_i) \tag{9}$$

where U is a strictly increasing convex function.

B. Modeled Problem for WSN

WSNs can be modeled as a directed graph $G(N, L)$, where N is the set of all nodes and L is the set of all directed links. Let x_{ij} denotes the flow on the link (i, j) if this link exists $\left((i, j) \in [1, N]^2\right)$. x_{ij} refers to the fixed amount of data that node i must send to the sink. The flow vector has the following constraint equation:

$$\sum_{j \in out(i)} x_{ij} - \sum_{j \in in(i)} x_{ji} = a_i \tag{10}$$

where $out(i)$ and $in(i)$ are the sets of the egress-nodes and the ingress-nodes of node i, respectively. A flow matrix $P \in R^{|N| \times |L|}$ is then constructed with the elements, p_{il}, defined by Eq. (11).

$$p_{il} = \begin{cases} 1 & \text{if link } l = (i, j) \\ -1 & \text{if link } l = (j, i) \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

A data vector is also defined by $\mathbf{a} = \{a_i\}$. Then, we can rewrite the flow vector constraint as:

$$P\mathbf{x} = \mathbf{a} \tag{12}$$

Let e^s_{ij} and e^r_{ji} denote the energy needed for sending a unit of data from node i to node j and the energy needed for receiving a unit of data from node j to node i, respectively. Then, we can calculate the energy consumption of node i in a unit of time, e_i, as a function of the flow vector $\mathbf{x}$:

$$e_i = e_i(\mathbf{x}) = \sum_{j \in out(i)} e^s_{ij} x_{ij} + \sum_{j \in in(i)} e^r_{ij} x_{ji} \tag{13}$$

The energy vector is defined by $\mathbf{e} = \{e_i\}$ and matrix $Q \in R^{|N| \times |L|}$ whose elements are:

$$q_{il} = \begin{cases} e^s_{ij} & \text{if link } l = (i, j) \\ e^r_{ij} & \text{if link } l = (j, i) \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

By rewriting Eq. (13) we have:

$$\mathbf{e} = Q\mathbf{x} \tag{15}$$

From Eqs. (9), (12), (15), we establish a nonlinear programming problem to find out the flow vector $\mathbf{x}$ that maximizes the network lifetime:

$$\text{Minimize } A = \sum_{i=1}^{n} U(e_i) \tag{16}$$

Subject to:

$$\begin{cases} \mathbf{e} = Q\mathbf{x} \\ P\mathbf{x} = \mathbf{a} \\ \mathbf{x} \geq 0 \end{cases} \tag{17}$$

IV. Solution of The Nonlinear Programming Problem

A. Dual Problem

We use the Lagrange relaxation method to relax the constraints and then consider the dual problem.

$$L(\mathbf{x}, \mathbf{e}, \lambda, \gamma) = A(\mathbf{x}) + \lambda^T(\mathbf{a} - P\mathbf{x}) + \gamma^T(\mathbf{e} - Q\mathbf{x}) \tag{18}$$

$$D(\lambda, \gamma) = \min L(\mathbf{x}, \mathbf{e}, \lambda, \gamma), \quad (\mathbf{x}, \mathbf{e} \geq 0) \tag{19}$$

The dual of the problem described by Eq. (16) is:

$$\text{Maximize } D(\lambda, \gamma), \quad (\lambda, \gamma \in R^N) \tag{20}$$

The dual function of the convex function is a concave function. Therefore, if at (λ_0, γ_0) the gradient $D(\lambda_0, \gamma_0)$ equals zero, then (λ_0, γ_0) is a solution to problem of Eq. (20). To find out (λ_0, γ_0), we use the sub-gradient algorithm [14], which will be described next.

B. Sub-gradient Algorithm

The sub-gradient at $\mathbf{u} \in R^n$ of a concave function $f(\mathbf{v})$ is a vector $\mathbf{d} \in R^n$ such that:

$$f(\mathbf{v}) \leq f(\mathbf{u}) + (\mathbf{v} - \mathbf{u})^T \mathbf{d}, \qquad \forall \mathbf{v} \in R^n \tag{21}$$

If $f(\mathbf{u})$ is differential then the sub-gradient is the same as the gradient.

Lemma: *If $L(\mathbf{x}, \mathbf{e}, \lambda_0, \gamma_0)$ takes minimum at $\mathbf{x} = \mathbf{x}_0, \mathbf{e} = \mathbf{e}_0$, then the sub-gradient of $D(\lambda, \gamma)$ at (λ_0, γ_0) is:*

$$\mathbf{g} = \begin{pmatrix} \mathbf{a} - P\mathbf{x}_0 \\ \mathbf{e}_0 - Q\mathbf{x}_0 \end{pmatrix} \tag{22}$$

The proof of this lemma is similar to that in [11]. Now, we can find (λ_0, γ_0) where the sub-gradient, $\mathbf{g}$ equals zero by updating (λ, γ) in each iteration steps t, as follows:

$$\begin{pmatrix} \lambda_{t+1} \\ \gamma_{t+1} \end{pmatrix} = \begin{pmatrix} \lambda_t \\ \gamma_t \end{pmatrix} + \theta(t)\mathbf{g}_t(\lambda_t, \gamma_t) \tag{23}$$

$\theta(t)$ needs to satisfy the following condition to ensure the program convergence [7].

$$\lim_{t \to \infty} \theta(t) = 0, \sum_{t=0}^{\infty} \theta(t) = \infty \tag{24}$$

For example, $\theta(t)$ can be obtained by using the update rule:

$$\theta(t) = \frac{\theta(0)}{\sqrt{t}} \tag{25}$$

where $\theta(0)$ is a fixed constant. The remaining problem is to find $(\mathbf{x}_0, \mathbf{e}_0)$ if (λ_0, γ_0) is given. We have to find $(\mathbf{x}_0, \mathbf{e}_0)$ that satisfies:

$$(\mathbf{x}_0, \mathbf{e}_0) = arg(\min L(\mathbf{x}, \mathbf{e}, \lambda_0, \gamma_0)) \tag{26}$$

Therefore:

$$\mathbf{e}_0 = arg(\min\{\sum_{i=0}^{n} U(e_i) + \gamma_0^T \mathbf{e}\}) \quad (27)$$

$$\mathbf{x}_0 = arg(\min\{-\lambda_0^T P\mathbf{x} - \gamma_0^T Q\mathbf{x}\}) \quad (28)$$

In Eq. (28), since the right side is a linear function of $\mathbf{x}$ then the elements of $\mathbf{x}_0$, (x_{ij}) become 0 or infinity. The latter value of x_{ij} cannot be acceptable. However, $x_{ij} = 0$ $(\forall i, j)$ means that no sensor sends data to the sink node. To overcome this problem, we add a strictly convex regularization term to the primal objective function, value of which is rather small. For example, we added a small quadratic term of $\mathbf{x}$ to the primal objective function, $A(\mathbf{x})$:

$$A(\mathbf{x}) \leftarrow A(\mathbf{x}) + \sum \epsilon_{ij} x_{ij}^2 \quad (29)$$

By using this, we can find out $\mathbf{x}_0$ by the following equation:

$$\mathbf{x}_0 = arg(\min\{\sum_{i=0}^{n}\sum_{j=0}^{n} \epsilon_{ij} x_{ij}^2 - \lambda_0^T P\mathbf{x} - \gamma_0^T Q\mathbf{x}\}) \quad (30)$$

Now, the algorithms to find out the solution of the nonlinear programming problem in Eq. (16) can be formulated as:

(a) Initialize values of λ_0 and γ_0
(b) Find out $\mathbf{e}$ and $\mathbf{x}$ that make L min by Eqs. (27) and (30)
(c) Calculate sub-gradient $\mathbf{g}$ by Eq. (22)
(d) Update λ, γ and θ by Eqs. (23) and (25)
(e) If convergence is found, stop. Else, return to step (b).

V. Experimental Results

We have simulated a network consisting of a sink and 50 sensor nodes randomly distributed over a square area ($100m \times 100m$). All nodes have the same initial energy, $E = 1J$. The energy consumption model in [13] is used, i.e., sending and receiving one byte of data from a node i to a node j over a distance of d meters costs ($e_{ij}^s = c_1 + c_2 d^2$) and ($e_{ji}^r = c_1$), respectively. Here $c_1 = 0.4nJ/byte$ and $c_2 = 0.08nJ/byte/m^2$. At every second, nodes have to send 1000 bytes of data to the sink.

A. The Impact of Function U

In the first experiment, to investigate the impact of function U, we employ different utility functions. To quantify the fairness between e_i, we use the fairness index defined by Eq. (31):

$$\text{Fairness Index} = \frac{(e_1 + e_2 + ... + e_n)^2}{n(e_1^2 + e_2^2 + ... + e_n^2)} = \frac{\bar{e}^2}{\bar{e}^2 + \sigma^2} \quad (31)$$

where $\bar{e}$ and σ^2 are the expected value of e_i and the variance, respectively. Eq. (31) shows that the fairness index always lies between zero and one. High fairness index is taken if the variance σ^2 is small. This means that the energy consumptions of all sensors are similar. Low fairness index means that the variance σ^2 is large, which indicates an unfair energy consumption between nodes.

Fig. 3 shows the average fairness index and the average energy consumption in 20 scenarios considered for different values of α (α = 1,2,3,4,5...) using the utility function $U(u) = u^\alpha$. Fig. 3 indicates that for large values of α, the fairness

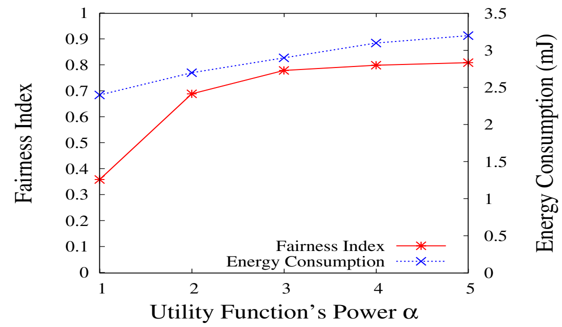

Fig. 3. Impact of the utility function on the overall performance.

index increases while the consumed energy becomes higher. We explain this by using Eq. (4). When α is small, the term $\sum_{i=1}^{n} y_i$ decreases. So it becomes much more important to minimize the term $nU(\bar{x})$. As a result, the energy consumption is small and the fairness index becomes low. Increasing α results in an increase in the ratio of $\sum_{i=1}^{n} y_i$ and $nU(\bar{x})$. This increases fairness index and the energy consumption.

B. Comparison to other Methods

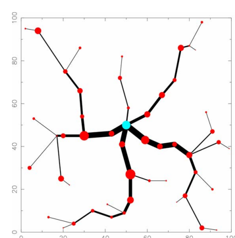

Fig. 4. Shortest path routing.

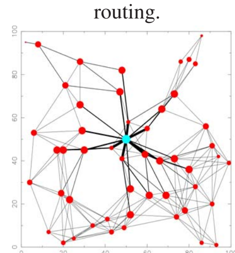

Fig. 5. Max-min lifetime algorithm.

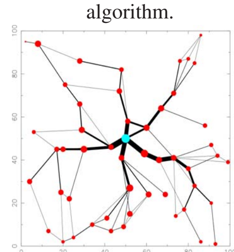

Fig. 6. The proposed algorithm.

From the above results we set α to three, which yields good fairness and not much energy consumption compared with other values of α. For comparison, we use the minimum energy routing protocol in [4], which uses the shortest path routing and the max-min lifetime routing protocol presented in [6]. Figs. 4, 5, and 6 show the network traffic when using the shortest path routing, the max-min lifetime routing and the proposed algorithm, respectively. The size of red dots indicates the amount of energy that the sensor nodes use per unit of time. This experiment is performed in 20 different scenarios. The total energy consumption and the fairness index are plotted in Figs. 7 and 8, respectively. As shown in Fig. 4, using the Dijkstra algorithm, all nodes send data via the shortest path. The total network consumption energy is minimum (Fig. 7) but highly unfair since some nodes use energy much more than others. These nodes run out of power very quickly. Therefore, the fairness index is very low (Fig. 8).

The max-min lifetime routing algorithm is shown in Fig. 5. Nodes send data to almost all of their neighbors. Some of the neighbors are too distant.

Therefore, the total energy consumption is significantly high (Fig. 7). Fig. 6 shows the network flow in case of the proposed algorithm. In the proposed approach, by dispersing traffic of some nodes in the shortest path routing, the network does not spend much energy (Fig. 7) and significantly improves the fairness index (Fig. 8).

Fig. 9 shows the network lifetime if we assume the network will die when n sensor nodes run out of energy. If n equals one, the max-min lifetime routing algorithm achieves the best performance. However, a sensor network, with a large number of nodes, will still continue to function even if a few number of nodes die. Then, we can see that the proposed algorithm can improve the network lifetime.

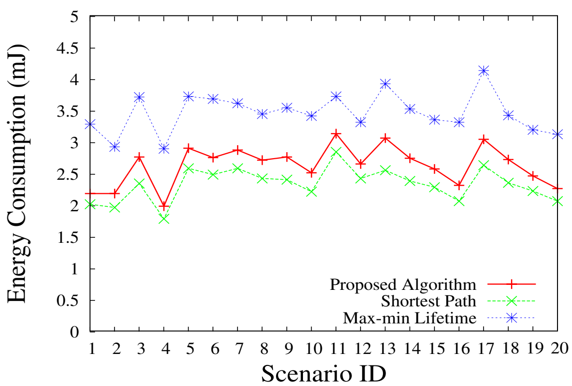

Fig. 7. Total energy consumption.

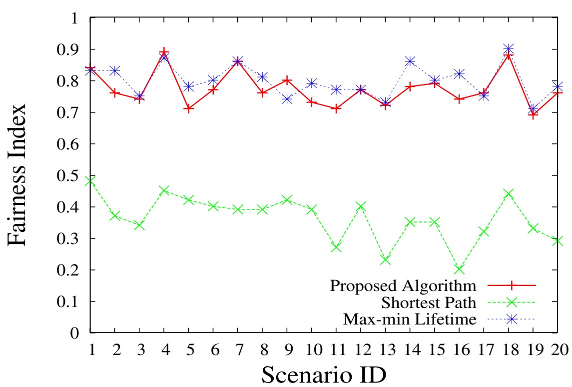

Fig. 8. Fairness index.

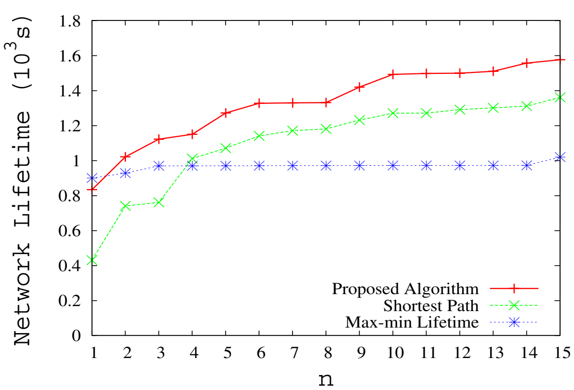

Fig. 9. Network lifetime (time until n nodes die).

VI. Conclusion

In this paper, we have proposed a new routing algorithm for wireless sensor networks with two purposes: minimizing energy use and making fair use of the resources available to the nodes. We have used the property of convex function to model a nonlinear programming problem and have employed sub-gradient algorithms to solve it. The performance of the proposed approach depends on the choice of the utility function. We have investigated the impact of the utility function via experiments and compared the performance of the proposed method in contrast to other methods. Experiment results demonstrated that the proposed routing algorithm ensured good fairness and reduced energy consumption. Thus, it can improve the network lifetime. The remaining problem is to find out the best utility function for a specific sensor network.

References

[1] L. Tong, Q. Zhao, and S. Adireddy, “Sensor Networks with Mobile Agents,” in *Proc. IEEE MILCOM’03*, Boston, MA, USA, Oct. 2003.

[2] W. Zhang, H. Song, S. Zhu, and G. Cao, “Least Privilege and Privilege Deprivation: Towards Tolerating Mobile Sink Compromises in Wireless Sensor Networks,” in *Proc. of ACM MobiHoc*, Urbana-Champaign, IL, USA, May 2005.

[3] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, “An Application Specific Protocol Architecture for Wireless Microsensor Networks,” *IEEE Trans. on Wireless Networking*, Vol. 1, No. 4, Oct. 2002, pp. 660-670.

[4] S. Singh, M. Woo, and C. S. Raghavendra, “Power-aware Routing in Mobile Ad-hoc Networks,” in *Proc. of MobiCom*, Dallas, Texas, USA, Oct. 1998.

[5] V. Rodoplu and T.H. Meng, “Minimum Energy Mobile Wireless Networks,” *IEEE J. Selected Areas in Comm.*, Vol. 17, No. 8, Aug. 1999, pp. 1333-1344.

[6] J.H. Chang and L. Tassiulas, “Maximum Lifetime Routing in Wireless Sensor Networks,” *IEEE/ACM Trans. on Networking*, Vol. 12, No. 4, Aug. 2004, pp. 609-619.

[7] R. Madan and S. Lall, “Distributed Algorithms for Maximum Lifetime Routing in Wireless Sensor Networks,” in *Proc. of IEEE GLOBECOM*, Dallas, Texas, USA, Nov/Dec. 2004.

[8] A. Sankar and Z. Liu, “Maximum Lifetime Routing in Wireless Ad-hoc Networks,” in *Proc. of IEEE INFOCOM*, Hong Kong, China, Mar. 2004.

[9] Y. Xue, Y. Cui, and K. Nahrstedt, “Maximizing Lifetime for Data Aggregation in Wireless Sensor Networks,” *ACM/Kluwer Mobile Networks and Applications (MONET)*, Vol. 10, No. 6, Dec. 2005, pp. 853-64.

[10] J. Park and S. Sahni, “An Online Heuristic for Maximum Lifetime Routing in Wireless Sensor Networks,” *IEEE Trans. on Computers*, Vol. 55, No. 8, Aug. 2006, pp. 1048-1056.

[11] K.L. Hung, J.H. Zhu , B. Bensaou, and F. Nait-Abdesselem, “Energy-Aware Fair Routing in Wireless Sensor Networks with Maximum Data Collection,” in *Proc. of IEEE ICC 2006*, Istanbul, Turkey, Jun. 2006.

[12] C. K. Toh, “Maximum Battery Life Routing to Support Ubiquitous Mobile Computing in Wireless Ad Hoc Networks,” *IEEE Comm. Magazine*, Vol. 39, No. 6, Jun. 2001, pp. 138-147.

[13] F. Kelly, A. Maulloo, and D. Tan, “Rate Control for Communication Networks: Shadow price, Proportional Fairness and Stability,” *J. Oper. Res. Soc.*, Vol. 49, No. 3, Mar. 1998, pp. 237-252.

[14] W. Ye, F. Ordez, “A Sub-gradient Algorithm for Maximal Data Extraction in Energy-limited Wireless Sensor Networks,” in *Proc. of IEEE Wirelesscom 2005*, Maui, Hawaii, USA, Jun. 2005.

[15] L. Xiao, M. Johansson, and S. Boyd, “Simultaneous Routing and Resource Allocation via Dual Decomposition,” *IEEE Trans. Commun.*, Vol. 52, No. 7, Jul. 2004, pp. 1136-1144.

[16] J. Mo and J. Walrand, “Fair End-to-end Window-based Congestion Control,” *IEEE/ACM Trans. on Networking*, Vol. 8, No. 5, Oct. 2000, pp. 556-567.