Maximizing Network Utility and Network Lifetime in Energy-Constrained Ad Hoc Wireless Networks

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ABSTRACT

This study considers a joint congestion control, routing and power control for energy-constrained wireless networks. A mathematical model is introduced which includes maximization of network utility, maximization of network lifetime, and trade-off between network utility and network lifetime. The framework would maximize the overall throughput of the network where the overall throughput depends on the data flow rates which in turn is dependent on the link capacities. The link capacity on the other hand is a function of transmit power levels and link Signal-to-Interference-plus-Noise-Ratio (SINR) which makes the power allocation problem inherently difficult to solve. Using dual decomposition techniques, subgradient method, and logarithmic transformations, a joint algorithm for rate and power allocation problems was formulated. Numerical examples for each optimization problem were also provided.

Key Words : Optimization, Sensor networks, Cross layer, Routing, Network lifetime

Ⅰ. Introduction

Implementing ad hoc wireless networks poses many technical challenges due to the constraints imposed by the environment. The wireless communication channel is a scarce resource, a shared medium and interference-limited. In order to achieve high end-to-end throughput and efficient resource utilization, congestion control, routing and scheduling need to be jointly designed[1]. Thereby, a mathematical framework is proposed in this paper which maximizes the network utility by routing flows from sources to destinations; where at each link the aggregated flow rate cannot exceed the link rate capacity. The link rate capacity is a function of Signal-to-Interference-plus-Noise-Ratio (SINR) which in turn is a function of all nodes' transmission powers. The joint optimization problem is decomposed into two sub-problems: a rate and congestion control problem at the transport and network layers and radio resource or power allocation problem at the MAC and PHY layers.

By optimization decomposition, the original problem is decomposed into subproblems which are coordinated by a master problem through message passing[2]. A decomposition technique could be classified into primal or dual. The primal decomposition is based on decomposing the original problem by partitioning the variables into two sets, optimizing over one set of variables and then over the remaining set. A dual decomposition on the other hand, decomposes the dual problem or the Lagrange equivalent with respect to the coupling constraints[2].

The contributions of this paper are as follows: A joint algorithm for maximizing network utility and network lifetime of an energy-constrained wireless network involving parameters from the physical, MAC, network and transport layers was formulated. The joint optimization problem is related to the works of Chiang [3, 4] in which other power levels and TCP windows sizes are

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optimized. In our paper, we extend it to routing and allocating flows at the network layer. We have also characterized the trade-off between network utility and lifetime.

This paper is organized as follows: Sec. 2 presents the related works while Sec. 3 presents the system model. It consists of assumptions, network flow model, and capacity and energy constraints. In Sec. 4, the utility maximization problem is solved where the optimal data rate is obtained via dual decomposition while the feasible transmission power vector is solved via logarithmic transformation. A linear programming (LP) problem that maximizes network lifetime is presented in section 5. The trade off between network utility and lifetime is presented in Sec. 6 where a weighing factor is introduced to balance both objectives. Numerical analyses for the optimization problems are presented in Sec. 7. Sec. 8 concludes this paper.

Ⅱ. Related Works

The Open Systems Interconnect (OSI) 7-layer model remains the reference model that attempts to abstract features common to all approaches in data communications. It divides the overall networking task into layers and defines a hierarchy of services to be provided by the individual layers. It organizes the layers into modules in such a way that each layer only worries about the layer directly above it and the one below it. This approach has been successful that it provides modularity and standardization in wireline networks but it might be unsuitable to wireless networks domain.

With layering as the general principle and reasons for the enormous success of data networks, there is a little quantitative understanding to guide a systematic process of designing layered protocol stack for wired and wireless networks. The authors in [5] presented a survey of the recent efforts towards a systematic understanding of “layering” as “optimization decomposition” where the overall communication network is modeled by a generalized network utility maximization problem.

Wireless links create several new problems for protocol design that cannot be handled well in the framework of the layered architecture. Moreover, wireless networks offer several possibility for opportunistic communication that cannot be exploited sufficiently in a strictly layered design. The wireless medium offers some new modalities of communication that the layered architecture cannot accommodate. Hence, more researchers present cross layer design ideas by exploiting the dependence between protocol layers to obtain performance gains [1], [6], [7], [8], and [9].

Cross-layer protocol interactions, is particularly important for any network since the physical medium vary significantly over time and when used appropriately can increase network efficiency. The information exchange among layers can even optimize network throughput. In addition, the inflexibility and sub-optimality of layered architecture design usually result to a poor performance of a network, especially when energy is a constraint or the application has high bandwidth needs, and/or stringent delay constraints. According to Goldsmith et al [1], to meet the above requirements, a cross-layer protocol design that supports adaptivity and optimization across multiple layers of the protocol stack is needed. A desirable solution to the problem of achieving optimal transmission throughput includes a routing strategy of data flows at the network layer, as well as power allocation scheme that leads to the high capacity of the physical layer[8].

This study considers a joint congestion control, routing and power control for energy-constrained wireless networks. Unlike other papers, we introduced a mathematical model which includes maximization of network utility, maximization of network lifetime, and trade-off between network utility and network lifetime.

Ⅲ. System Model

3.1 Assumptions

The topology of a network is represented by a directed graph $G(N,L)$ where N denotes the set of all nodes and L is the set of links between those nodes. A communication link $l \in L$ is denoted by an active direct communication pair (i,j) where i is the transmitting node and j is the receiving node. Furthermore, a source node is denoted by s and a destination node is denoted by d.

Scheduling in the data link layer decides which links will transmit and when to transmit. It is similar to choosing an independent set of flow contention graph to be active at each time slot. When link l is active, node i and node j cannot transmit to other nodes or receives from other nodes. Given a contention graph, a maximal clique [10] could be identified and flows within same maximal clique cannot transmit simultaneously but flows in different cliques may transmit simultaneously. A maximal clique in the link contention graph denotes the distinct contention region where at any time only one link $(i,j) \in L$ can be in transmission. Hence, only links that are in different cliques can transmit simultaneously.

3.2 Network Flow Model

The network topology can be then represented by a node-link incidence matrix [11] $A \in RNxL$ whose entry A_{NL} is associated with node and link via

$$A_{NL} = \begin{cases} 1 & \text{if } n\, is\, the\, start\, node\, of\, link\, l \\ -1 & \text{if } n\, is\, the\, end\, node\, of\, link\, l \\ 0 & otherwise \end{cases} \quad (1)$$

On each link, we let $fl(d) \geq 0$ be the amount of flow destined for node d and we let $f^{\,l} = \Sigma d\ fl(d)$ be the total amount of traffic on link l. We define a source-sink vector [12] $x(d) \in RN$ whose nth entry $xn(d) \in RN$ denotes the non-negative amount of flow (data rate in bits/second) injected or removed into the network at a node n which is destined for node d. At each node n, the components of the flow vector and the source-sink vector with same destination satisfy the flow conservation flow.

$$\sum_{l \in O(n)} f_l^{(d)} - \sum_{l \in I(n)} f_l^{(d)} = x_n^{(d)} \quad (2)$$

The flow conservation law across the network can be written as

$$\mathbf{A}f^{(d)} = x^{(d)}, \quad d = 1,\cdots,D \quad (3)$$

3.3 Capacity Constraint

We define the link capacity as a function of transmit power and SINR. We let $SINR_l(P)$ be the measured SINR at link l where $P=\{P_1, P_2,\cdots, P_N\}$is the transmission power vector of the transmitting nodes. Furthermore, we denote G_{ll} as the link gain of transmitter i and its intended receiver j on same link l, and G_{lk} as the link gain of other transmitter which is on link k to the receiver on link l. We assume a symmetric hearing matrix among the nodes and the channel gain between two nodes is approximately same in both directions. Gain can be computed as $Gij \propto dij\text{-}\alpha$ where α is the path loss. We let σl as the thermal noise at the receiver node of link l. A transmission is only successful if the SINR at the link satisfies the given threshold βl as denoted by the following equation.

$$SINR_l(\mathbf{P}) = \frac{P_l G_{ll}}{\sum_{l \neq k} P_k G_{lk} + \sigma_l} \geq \beta_l \quad (4)$$

The Shannon formula [13] which represents the theoretical maximum rate that can be achieved over a frequency bandwidth W, assuming presence of Gaussian noise and interference is given by

$$c_l(\mathbf{P}) = W \log_2(1 + SINR_l(\mathbf{P})) \quad (5)$$

So, the link capacity is a function of SINR, which in turn is determined by the power levels at all transmitters. Due to interference in wireless networks, increasing the capacity on one link reduces those on the other links.

3.4 Energy Constraint

For N number of nodes, we assume that each node has an initial battery of E_n. We denote the transmission energy consumed by node i to node j on link l as e_{ij}^t and the energy consumed by

Table 1. Summary of Notations.

Parameters	Description
c,(l	Capacity of link l
SINRl(P)	Measured SINR at link l
βl	SINR Threshold
$P_l^{(d)}$	Transmit power on link l for destination d
xn(d)	Source rate of node n for destination d
fl(d)	Flow rate on link l for destination d
f^l	Aggregate flow on link l
$\hat{f}_l^{(d)}$	Amount of information transmitted from node i to node j until time T.
λ_l	Congestion price on link l
δ	Step-size for convergence
e_{ij}^t	Transmission energy consumed by node i to node j on link l
e_{ji}^r	Energy consumed by the receiver node j during reception
E_n	Initial energy of node n
γ	Trade-off weighing factor

the receiver node j during reception as e_{ji}^r. The information to be transferred to the sink node d is generated at the source node at a rate of $x_n^{(d)} > 0$. We then introduce a total energy constraint as (6) which states that the energy consumed during transmission and reception (for each flow) should not exceed the initial energy of the node, E_n.

$$\sum_{l\in L} e_{ij}^t \sum_{l\in O(n)} f_l^{(d)} + \sum_{l\in L} e_{ji}^r \sum_{l\in I(n)} f_l^{(d)} \le E_n \tag{6}$$

Table 1 summarizes some parameters and notations used in this paper.

Ⅳ. Maximizing Network Utility

4.1 Problem Formulation

Utility functions provide metric that define optimality and efficiency of resource allocation. Hence, we make use of utility function for our problem. We assume that each node attains utility when it transmits at a rate of $x_n^{(d)}$ for destination d where $U_n^{(d)}$ is assumed to be continuously differentiable, increasing, and concave. We assume that all utility functions are logarithmic and additive.

In addition, the link capacity is dependent on the link SINR which in turn is dependent on the transmit power of the nodes. Our maximization problem can be formally written as

$$\max \sum_n U_n^{(d)}(x_n^{(d)}) \tag{7}$$

subject to

$$\mathbf{A}f^{(d)} = x^{(d)} \tag{8}$$

$$f^l \le c_l(\mathbf{P}) \tag{9}$$

$$0 \le P_l^{(d)} \le P_{l,\max}^{(d)}$$

$$D_{NET}(\lambda) = \max_{x,f} \sum_n U_n^{(d)}(x_n^{(d)}) + \sum_l \lambda_l f^l \tag{10}$$

$$f^{(d)}, x^{(d)} \ge 0 \tag{11}$$

The constraint (8) is the network flow constraint. We require that the aggregate rate at any link l does not exceed the effective link capacity (9). The constraint (10) is the maximum transmission power constraint i.e. the link transmission power Pl is upper bounded by $P_{l,max}$ and lower bounded by 0 for each destination d. The last constraint (11) ensures that the flow rate and data rate are non-negative. The optimization variables of problem (7) are both source rate $x_n^{(d)}$ and transmit power $P_l^{(d)}$.

We focused on the variables x, f which are network flow variables and c, p which are resource and power allocation variables. We consider the dual problem by introducing a Lagrange multiplier $\lambda \in R$ only for the constraint (9). The result is a partial Lagrangian function given as

$$L(x,f,c,p,\lambda) = \sum_n U_n^{(d)}(x_n^{(d)}) + \sum_l \lambda_l (c_l(\mathbf{P}) - f^l)$$

$$= \sum_n U_n^{(d)}(x_n^{(d)}) + \sum_l \lambda_l c_l(\mathbf{P}) - \sum_l \lambda_l f^l$$

Thus, the dual function is formulated as

$$D(\lambda) = \max L(x, f, c, p, \lambda)$$

subject to

$$0 \le P_l^{(d)} \le P_{l,\max}^{(d)} \; Af^{(d)} = x^{(d)} \tag{12}$$

The dual function can be evaluated separately in the network variables *x, f* and MAC/PHY variables *c, p*. By linearity of the differentiation operator, (12) could be decomposed into two sub-problems (13) and (14), which are functions of the transport and network layer, and MAC and PHY layer respectively.

$$D(\lambda) = D_{NET}(\lambda) + D_{MACPHY}(\lambda) \tag{13}$$

where
subject to (8) and (11) and,

$$D_{MACPHY}(\lambda) = \max_{c,P} \sum_{l \in L} \lambda_l c_l(\mathbf{P}) \tag{14}$$

subject to (10) and (11).

Similar to [11], we would like to interpret the Lagrange variable λ as the price per unit bandwidth at link *l*, where $\sum \lambda_l f^l$ is the price to transmit flow traffic at rate $x_n^{(d)}$ and to route it along the network according to flow f_l. The constraints are flow conservation law i.e. traffic is generated at rate x_n at node n and without loss, traverses the network to the destination d via all possible paths [11]. The partial dual function $D_{NET}(\lambda)$ is differentiable with respect to variable (*x, p*) hence, the optimal source rate $x_n^{*(d)}$ can be computed as

$$x_n^{*(d)}(\lambda) = U_n^{(d)'-1}(\lambda_l) \tag{15}$$

where $U_n^{(d)'-1}$ is the derivative of the inverse of the utility function. The problem (13) defines both congestion control coupled with the routing behavior. Congestion control is based on (15) where the source node will adjust its rate according to the path price while routing is based on the minimum cost path with the link prices as costs.

On the other hand, the problem (14) is the MAC/PHY problem for link layer flows according to congestion price. Since the link capacity is a global function of all interfering powers and as a function of SINR, we rewrite the maximization problem as

$$D_{MACPHY}(\lambda) = \max_{c,P} \sum_{l} \lambda_l c_l(\mathbf{P}) \tag{16}$$

subject to

$$c_l(\mathbf{P}) = W \log_2(1 + SINR_l(\mathbf{P}))$$

$$SINR_l(\mathbf{P}) = \frac{P_l G_{ll}}{\sum_{l \ne k} P_k G_{lk} + \sigma_l}$$

$$0 \le P_l^{(d)} \le P_{l,\max}^{(d)}$$

According to [8], there are three recent techniques that can ease the way of solving the feasible capacity region: dual optimization method, geometric programming, and the game theoretic approach. In this paper, we use the geometric programming approach in order to solve for the feasible solution. First, we approximate the link capacity as $W \log(1 + SINR_l(\mathbf{P})) \approx \log(SINR)$

W refers to the frequency bandwidth. This is usually the case in high SINR regime. We can then substitute it to (14); however,

$$\sum_l \lambda_l \log(SINR_l(\mathbf{P}))$$

is still a strictly concave function of a logarithmically transformed power vector [14]. By logarithmic transformation of a power vector ,

$$\tilde{P}_l = \log(P_l)$$

the optimization problem (14) is transformed into

$$\max_{p} \sum_{l} \lambda_l \tilde{c}_l(\mathbf{P}) \tag{17}$$

subject to

$$\tilde{c}_l(\mathbf{P}) = \log(SINR(\tilde{\mathbf{P}})) \qquad \forall l$$

$$SINR_l(\tilde{\mathbf{P}}) = \frac{G_{ll} e^{\tilde{P}_l}}{\sum_{k \neq l} G_{lk} e^{\tilde{P}_k} + \sigma_l} \qquad \forall l$$

$$0 \leq e^{\tilde{P}_l} \leq \tilde{P}_{l,\max} \qquad \forall n, \forall l \in O(n)$$

Furthermore, Chiang had proposed a distributed algorithm for power control problems with inelastic link capacities where the derivations and proofs are shown in [3] and [14]. Similar to the Jointly Optimal Congestion Control and Power Control (JOCP) algorithm [3] by introducing a step size $\kappa \geq 0$, each transmitter can update and maximize its power by

$$P_l(t+1) = P_l(t) + \kappa\left(\frac{\lambda_l(t)}{P_l(t)} - \sum_{j \neq l} \frac{\lambda_l(t) G_{lj}}{\sum_{k \neq j} P_k G_{jk} + \sigma_j}\right) \tag{18}$$

It can be further simplified using the definition of SINR, i.e.

$$P_l(t+1) = P_l(t) + \frac{\kappa \lambda_l(t)}{P_l(t)} - \kappa \sum_{j \neq l} G_{lj} m_j(t)$$

where $m_j(t)$ are the messages passed from node j or the intended receive of node i, defined as

$$m_j(t) = \frac{\lambda_j(t) SINR_j(t)}{P_j(t) G_{jj}} \tag{19}$$

The gradient-based optimization of a function with constant step size κ is guaranteed to converge if the function has a Lipschitz continuity property:

$$\|\nabla f(x_1) - \nabla f(x_2)\| \leq L\|x_1 - x_2\|$$

At time t:

1.Each intermediate node implicitly updates its price with respect to the destination d
$$\lambda_l(t+1) = \left[\lambda_l(t) + \delta_t\left(f^l - c_l(\mathbf{P})\right)\right]^+$$
and passes this price to all its neighbors.

2. Congestion Control: each source node n adjusts its sending rate for a period of t according to local congestion price.
$$x_n^{(d)}(t) = U_n^{(d)'-1}\left(\lambda_l(t)\right)$$

3. Power Control: over link, $l \in (i, j)$ an amount of data will be transmitted to destination d at a transmit power defined by the given equation [4]
$$P_l(t+1) = P_l(t) + \frac{\kappa \lambda_l(t)}{P_l(t)} - \kappa \sum_{j \neq l} G_{lj} m_j(t)$$
where
$$m_j(t) = \frac{\lambda_j(t) SINR_j(t)}{P_j(t) G_{jj}}.$$

4. Routing: The data will be sent at a rate determined by a scheduling algorithm.

Fig. 1 The Joint Algorithm.

for some $L > 0$, and the step size is small enough: $\in \leq \kappa \leq (2 - \in)/L$ for some $\in > 0$. This convergence condition was already verified by Chiang as given in [14].

By subgradient method [15], we can obtain a sequence of dual feasible points or the price adjustment for link l.

$$\lambda_l(t+1) = [\lambda_l(t) + \delta_t(f^l - c_l(\mathbf{P}))]^+ \tag{20}$$

where [.]+ denotes projection on closed convex set R+ or a set of non negative real number. The Lagrange multiplier can be updated using (20) where δ is a positive scalar step-size. From equations (15), (18), (19) and (20) we are able to formulate our joint algorithm, as given by Fig. 1 below.

V. Maximizing Network Lifetime

If power control is implemented between links, i.e. the transmit power used is the minimum energy required just to reach the destination node, the energy consumption rate per unit information transmission depends on the choice of the next hop node or simply the routing decision. Hence, routing plays a significant role in maximizing system lifetime. As node sends, receives or forwards packets, the energy of a node is reduced and once the energy level falls below a threshold, the node suffers shutdown and eventually die. Hence, energy related metrics should be taken into consideration in designing ad hoc routing protocols. Chang and Tassiulas [16] proposed an algorithm that balances the flows among different routes in such a way that the time before the batteries would drain out is maximized. To maximize the life of all nodes and the network itself, the path to be selected must consider energy reserves such that nodes with depleted energy reserves do not lie along many paths. Hence, traffic should use routes with sufficient remaining energy to maintain balance in the network. Based on the model mentioned in Sec. 3 and similar to [16], we define the network lifetime of a node under a given flow $f_l^{(d)}$ as

$$T_n(f) = \frac{E_n}{\sum_l e_{ij}^t \sum_{l \in O(n)} f_l^{(d)} + \sum_l e_{ji}^r \sum_{l \in I(n)} f_l^{(d)}} \tag{21}$$

We define that the network lifetime under flow f is defined by the node which has the minimum lifetime among other nodes in the network i.e.

$$T_{net}(f) = \min_{n \in N} T_n(f) \tag{22}$$

We let $x_n^{(d)}$ be the rate at which information is generated at node nand this information needs to be communicated to the sink node. Our goal is to find the flow that maximizes the system lifetime under the flow conservation condition. Our problem can be then written as

$$\max T_{net}(f) \tag{23}$$

subject to

$$\sum_{l \in O(n)} f_l^{(d)} + x_n^{(d)} = \sum_{l \in I(n)} f_l^{(d)} \tag{24}$$

$$\sum_{l \in O(n)} e_{ij}^t f_l^{(d)} + \sum_{l \in I(n)} e_{ji}^r f_l^{(d)} \le E_n$$

$$f^l \le c_l(\mathbf{P})$$

$$f_l^{(d)} \ge 0, x_n^{(d)} \ge 0$$

Our goal here is to maximize the system lifetime i.e. maximize $T_{net}(f)$. Equivalently, the maximization problem can be written as a linear programming problem if we let $\hat{f}_l^{(d)} = Tf_l^{(d)}$ where $\hat{f}_l^{(d)}$ is the amount of information transmitted from node i to node j until time T. Thus, maximizing the system lifetime is equivalent to maximizing the amount of total information transfer given a fixed information-generation rate [16]. Note that the variable T in the constraints is an independent variable which makes the optimization problem an LP problem. We can interpret it as minimizing the maximum ratio of power consumption to energy supply at each node [16]. Hence, our optimization problem for system lifetime maximization is formulated as

$$\max \quad T \tag{25}$$

subject to

$$\sum_{l \in O(n)} \hat{f}_l^{(d)} + Tx_n^{(d)} = \sum_{l \in I(n)} \hat{f}_l^{(d)} \tag{26}$$

$$\sum_{l \in O(n)} e_{ij}^t \hat{f}_l^{(d)} + \sum_{l \in I(n)} e_{ji}^r \hat{f}_l^{(d)} \le E_n$$

$$\hat{f}^l \le c_l(\mathbf{P})T$$

$$\hat{f}_l^{(d)} \ge 0, x_n^{(d)} \ge 0$$

The first constraint is the flow conservation condition. The second constraint is total energy constraint, while the third constraint is capacity constraint, i.e. the link capacity should not exceed the maximum achievable link capacity, and the last constraint is to ensure that the transmitted data is non-negative.

Ⅵ. Network Utility and Lifetime Trade-Off

In wireless sensor networks, each sensor node has an extremely limited power supply, and for this reason, they require lightweight communication protocols as well. However, the performance of the application layer is determined through the network utility function, which is relative to the amount of data gathered by the network nodes. In order to gather more data from the energy-constrained network nodes, higher data rates are needed which also require high sensing and communication capabilities for the network nodes. Since energy is dissipated through sensing, transmitting, and receiving data, this could shorten the network lifetime of the nodes and the network itself. Hence, there is an inherent trade-off between the network utility and network lifetime of energy-constrained wireless networks. In this section, we discuss this said trade off.

$$\max\ \gamma\sum_n U_n^{(d)}(x_n^{(d)}) - (1-\gamma)\mathbf{T} \qquad (27)$$

subject to

$$\begin{aligned}
&\mathbf{A}\hat{f}^{(d)} = x^{(d)} \qquad (28)\\
&\hat{f}^{\,l} \le c_l(\mathbf{P})T\\
&\sum_{l\in O(n)} e_{ij}^t \hat{f}_l^{(d)} + \sum_{l\in I(n)} e_{ji}^r \hat{f}_l^{(d)} \le E_n\\
&0 \le P_l^{(d)} \le P_{l,\max}^{(d)}\\
&\hat{f}_l^{(d)} \ge 0, x_n^{(d)} \ge 0
\end{aligned}$$

The network should choose an appropriate value of γ that would balance the network utility and lifetime based on the application. $\gamma\in[0,1]$ is system design parameter that controls the desired trade-off between the network utility and network lifetime. We introduce Lagrange multipliers υ_l and μ_l for the second and third constraints in (28). Hence, we derived the partial Lagrange function as

$$D(\mu,\upsilon) = \max\ L(f,x,p,c,\mu,\upsilon,T)$$

subject to

$$\begin{aligned}
&A\hat{f}^{(d)} = x^{(d)}\\
&0 \le P_l^{(d)} \le P_{l,\max}^{(d)} \qquad (29)\\
&\hat{f}_l^{(d)} \ge 0, x_n^{(d)} \ge 0
\end{aligned}$$

The dual problem in (29) can be decomposed into two main sub-problems

$$\begin{aligned}
D_1(\mu,\upsilon) = \max_{x,f}\ &\gamma\sum_n U_n^{(d)}(x_n^{(d)})\\
&+\sum_l \mu_1\left(\sum_{l\in O(n)} e_{ij}^t \hat{f}_l^{(d)} + \sum_{l\in I(n)} e_{ji}^r \hat{f}_l^{(d)}\right)\\
&-\sum_l \upsilon_l \hat{f}^{\,l}
\end{aligned}$$

subject to

$$\begin{aligned}
&A\hat{f}^{(d)} = x^{(d)}\\
D_2(\mu,\upsilon) &= -\max(1-\gamma)T + \sum_l \mu_l E_n + \sum \upsilon_l c_l(\mathbf{P})\\
&= \min(1-\gamma)T - \sum_l \mu_l E_n - \sum \upsilon_l c_l(\mathbf{P})\\
&\hat{f}^{(d)} \ge 0, x^{(d)} \ge 0
\end{aligned}$$

subject to

$$0 \le P_l^{(d)} \le P_{l,\max}^{(d)}$$

which corresponds to a cross layer optimization problem via vertical decomposition. The problem is decomposed into rate and flow control problem in transport and network layer, power and radio resource allocation problem in the MAC/PHY layer, and a network lifetime maximization problem. The said problems are coordinated by the dual function (29) through dual variables (μ, υ). The feasible solutions x^*, T^* which are functions of f and P can be obtained by solving the dual problems i.e. solve $\min D(\mu, \upsilon)$. Now we will present the primal solutions of the optimization problem (27) as defined by (30) and (31). By primal decomposition, we decompose the original problem by partitioning the variables into two sets: optimizing over one set of variables to get $T^*$and then over the remaining set to get x^*.

$$T^* = \arg\max_{P,\mu,\upsilon} \left(\frac{\sum_l \mu_l E_n + \sum_l \upsilon_l \log\left(\frac{P_{ll} G_{ll}}{\sum_{l \neq k} P_k G_{kl} + \sigma_l} \right)}{1-\gamma} \right) \quad (30)$$

$$x_n^{*(d)} = \arg\max_{f,\mu,\upsilon} \mathrm{U}_n^{(d)\text{-}1} \left(\frac{\sum_l \mu_l \left(\sum_{l \in O(n)} e_{ij}^t \hat{f}_l^{(d)} + \sum_{l \in I(n)} e_{ji}^r \hat{f}_l^{(d)} \right) - \sum_l \upsilon_l \hat{f}^l}{\gamma} \right) \quad (31)$$

Ⅶ. Numerical Analysis and Examples

We solved the LP problem for maximizing system lifetime using MATLAB. We define our simulation topology as shown in Fig. 2. We assume that there are two network layer flows: Flow 1: A→C→D→F and Flow 2: B→D→E. We focused on the problem of computing a flow that maximizes network lifetime which is taken to be the time at which the first node runs out of energy. The transmitting node can reach

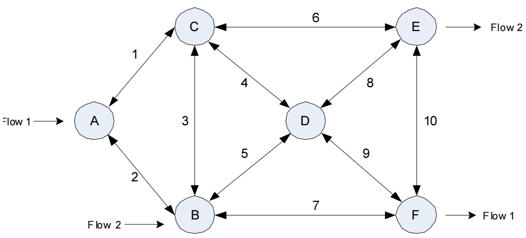

Fig. 2 Simulation Topology.

the nodes directly within its communication range d_{ij}. For simplicity of analysis we assume that all nodes have equal distances and initial energies E_i. The energy expenditure per unit information transmission from node i to j are $e_{ij}^t = e^T + \in_{amp} d_{ij}^4$ and $e_{ji}^r = e^R$ for transmission and reception respectively, where $e^T = 50nJ/bit$ and $e^R = 150nJ/bit$. These values are the energy consumed in the transceiver circuitry at the transmitter and receiver respectively while $\in_{amp} = 100pJ/bit/m^4$ is the energy consumed at the output transmitter antenna for transmitting one meter.

We showed the relationship of transmission range to the normalized network lifetime in Fig. 3. Note that we have defined the network lifetime under the flow f to be the time until the first node runs out of energy. The normalized lifetime is the ratio of the

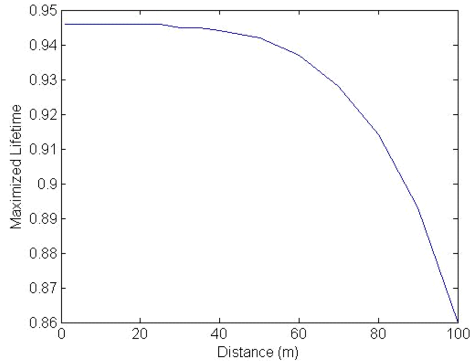

Fig. 3 Relationship of distance to the normalized network lifetime.

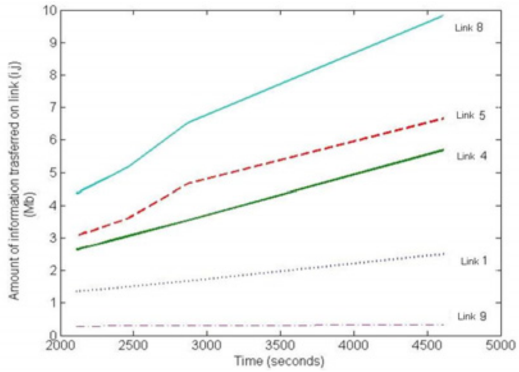

Fig. 4 Relationship of the amount of information transferred on link (i,j) and delay.

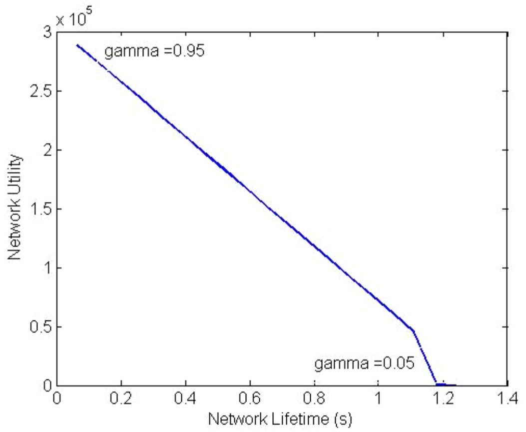

Fig. 5 Trade-off between network utility and network lifetime.

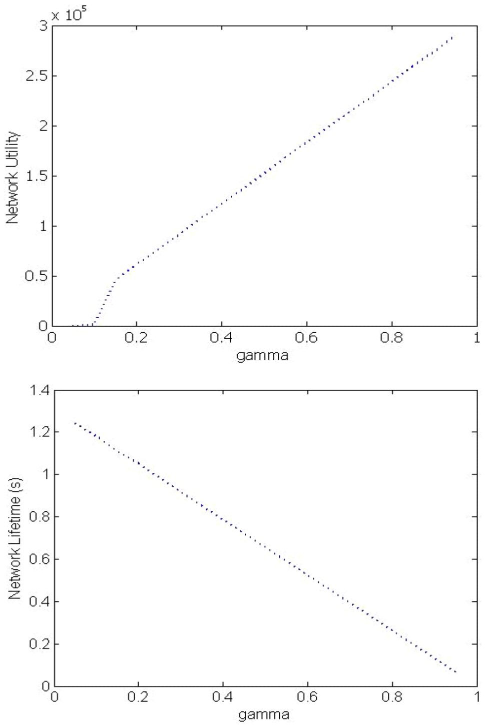

Fig. 6 Utility and Lifetime as a function of gamma γ.

network lifetime to the optimal solution. It is similar to minimizing the maximum ratio of power consumption to the energy supply of the node.

Based on our simulation, as the transmission range between nodes increases, the transmission and reception energy expenditure of node also increases, which leads to a short network lifetime. Maximizing system lifetime is equivalent to maximizing the amount of total information transfer given fixed information-generation rates. As can be seen in Fig. 4, link 9 has a lesser amount of transferred information due to the fact that node D also acts a router too for node E.

Using same topology (Fig. 2), we directly solve the primal optimization problem (27) in MATLAB, with utility function $U_n^{(d)}(x_n^{(d)}) = log_2(x_n^{(d)})$. We have varied γ from 0.05 to 0.95. Fig. 5 shows the inherent trade-off between the utility and lifetime in energy-constrained wireless networks while Fig. 6 shows the utility and lifetime of each node as a function of γ. Hence, depending on the desired application, the system designer can choose an optimal operation point for the operation by choosing the appropriate value of γ and by solving the problem (27) for the optimal set of system variables.

Ⅷ. Conclusion

We have formulated and solved optimization problems for maximizing network utility, network lifetime and trade off of network utility and lifetime, for energy-constrained wireless networks involving parameters from the physical, MAC, and network and transport layers, showing that interaction among different layers of the protocol stack is necessary to achieve performance gains. We have used techniques in convex optimization to solve our problem. We have also provided numerical examples for our optimization problems.

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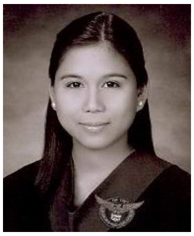

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