Distributed Algorithms for Joint Routing, Scheduling, Rate and Power Control in Multi-Hop Wireless Sensor Networks

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Abstract **- Distributed algorithms for joint routing, scheduling, rate and power control have been proposed previously for multi-hop wireless sensor networks. We propose proportionally fair rate control by optimizing a single network parameter in a distributed manner. We also include a version of the previous distributed greedy scheduling heuristic algorithm, which has same communication complexity but less computational complexity.**

Index Terms—distributed algorithm, multi-hop wireless networks, rate control, routing, scheduling, power control.

I. INTRODUCTION

In a multi-hop wireless sensor network (MWSN), any node can generate data and transmit it to the destination node(s), by consuming some part of the battery power, via multiple hops and using wireless channel. A node fails if its battery is depleted. Since the source rates are limited by link capacities available at downstream nodes, efficient rate control and routing algorithms are required. The transmission from one node interferes with other nodes within its radio communication range because of shared wireless channel. Hence power control and scheduling needs to be designed. Thus, joint optimization of routing, scheduling, rate and power control is required in the network.

A. Problem Addressed

Centralized algorithms for joint routing, scheduling, rate and power control have been previously developed, in which a central node controls network parameters such as rate, traffic requirements, etc., by obtaining information globally from all nodes in the network.

Centralized algorithms are efficient but have a few draw-backs such as single point of failure (central node failure), lack of scalability, and difficulty in obtaining global information. Thus, it is desirable to develop efficient decentralized algorithms for joint routing, scheduling, rate and power control in the network which makes use of local information. These algorithms may be scalable to thousands of nodes and reduce the communication complexity.

B. Related Work

Transmission consumes substantial energy; hence energy efficient transmission methods are used. This is done via compression of data transmitted ([5], [10]), optimization of number of hops used in transmission ([4], [1]), routing of data along nodes with sufficient battery power, opportunistic scheduling of wireless links [6] and transmit power control etc. In addition, joint routing, power control and link scheduling ([4], [11]), can significantly enhance the system performance.

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C. Our Contribution

As far as we know, this is a work towards a distributed algorithm for maximizing the minimum of the ratios between the allocated rate and demanded rate for the flows of the network (i.e., optimizing a single parameter of the network in a distributed manner) subject to the primary (necessary) network constraints. We define Composite Link Price for each link in the network, which takes account into link price and power price. We also include a version of the previous distributed greedy scheduling heuristic algorithm [2], which has same communication complexity but less computational complexity.

D. Organization

In Section II, we describe our model and notation. Section III discusses the problem formulation and the constraints for joint routing, scheduling, rate and power control in MWSN. Section IV develops distributed algorithms for Lagrange dual problems. Section V provides simulation results. Section VI concludes the paper.

II. MODEL AND NOTATION

We represent the network as a connected directed graph G(N,L) , where N and L are set of nodes and directed links (edges), indexed by $n \in \{1,2, .,n,..N\}$ and $l \in \{1,2, ., l, ..L\}$ respectively. A wireless link $l = (i, j) \in L$ exists if node $j \in N$ can receive packets directly from node $i \in N$, i.e., if node j is one-hop neighbor of node i. We then, define node i as source node, node j as destination node of link l, and we call link l as an attached link to node i . We consider the wireless link as a directed edge from the source node to the destination node. The communication between a source and destination pair is defined as a flow. The set of flows is denoted by F and indexed by $f \epsilon \{1, 2, ., f, ..F\}$. Source and destination of flow f are denoted by s(f) and d(f) respectively. We consider K-hop link interference model as considered in [2]. All links in the network cannot be activated simultaneously due to primary interference model. A mode is defined as a subset of links which can be activated simultaneously (with an L- dimensional power vector, P_L) in such a way that no two links of this subset interfere under the given interference model and no other link can be added to this subset without violating the interference constraint. The modes are independent sets. The set of modes is denoted by M and indexed by m. A mode gives an L-dimensional capacity vector, $R_L(m)$, which defines capacity of all links when mode m is chosen i.e., its l^{th} element is $R_1(m)$. The capacity of link l is $R_l(m)$ if it is active in mode m; else $R_l(m)$ = 0. Let $\alpha_m \epsilon$ (0.1) be the fraction of time mode misactive. Rate on link l of flow f is denoted by x_l^f . A is an (N x L) Node-Link incidence matrix for the wireless network, where a_{nl} = 1 if node n transmits on link l; a_{nl} = -1 if node n receives on link l; a_{nl} = 0 otherwise. X^f is an L-dimensional vector which gives the rates on various links for flow f . Y^f is an N-dimensional vector which gives the rate generated/consumed by the nodes for flow f . If the rate allocated for flow f is denoted as r_f then Y^f for node s(f) is r_f , for node **d(f)** is $-r_f$, and it is 0 for the remaining nodes.

Let P^n_{avg} denote the average available power at node n. A node n is not allowed to transmit with an average available power P^n_{avg} at that node at all times due to the interference. Instead, it will transmit with a power P_n chosen from the discrete set called power-levels denoted by P. We use three power-levels in our model, i.e., $P \epsilon \{0,P_1 , P_2 = 2P_1\}$. A mode also gives an N-dimensional power vector, $P_N(m)$, which defines the transmit power of all the nodes when mode m is chosen, i.e., its n^{th} element is $P_n(m)$. The transmit power of node n is $P_n(m)$. The transmit power of node n is $P_n(m)$ if any one of its attached links is active in mode m; else $P_n(m)$ = 0. Let $P_{n(l)}(m)$ denote the transmit power on link l attached to node n in mode m, and $q_{n(l)}$ denote the power price of node n to which link l is attached. Let L_n denote the set of links attached to node n. Let h_{ll} is the channel gain of link l and changes due to fading.

III. PROBLEM FORMULATION AND CONSTRAINTS FOR JOINT ROUTING, SCHEDULING, RATE AND POWER CONTROL

In this section, we formulate the problem for joint, routing, scheduling, rate and power control subject to various constraints. Then we use Lagrange dual to simplify the optimization problem by dividing the dual problem into two sub problems and it is well known.

For a flow f, let node s(f) request transmission at rate d_f to destination node d(f). d(f) can be different for different flows. The quantity $min_f\ (r_f /d_f)$, where $f \epsilon F$, gives the highest rate suffering flow in the network. Hence, our goal is to maximize the quantity $min_f(r_f/d_f)$ to move towards the better fairness among the nodes (users) in the network. We can now define the rate control (fairness) parameter λ as

$$\lambda = min_f\ (r_f/d_f)\ , \text{ where } f \epsilon F$$

$$\text{i.e. } \lambda d_f \leq r_f$$

where , d_f is the data rate requested by node $s(f)$ for flow f and r_f is the assigned / permissible data rate for flow f. Our objective is to maximize the utility function which is a function of λ. This faines is of max- min type[12].

A.The Optimization problem

Our primal problem is as follows:

$$\max_{0\leq\lambda\leq 1} U(\lambda) \quad (1) \quad \text{subject to: } \lambda d_f = r_f \quad (2)$$

$$\sum_{f \epsilon F} X^f \leq M.\alpha \text{ (Link Capacity Constraints)} \quad (3)$$

$$\sum_{m \epsilon M} \alpha_m = 1 \text{(Mode Constraints)} \quad (4)$$

$$A.X^f = Y^f. \ \forall f \epsilon F \text{ (Flow conservation constraints)} \quad (5)$$

$$N.\alpha \leq P^N_{avg} \text{(Power Constraints)} \quad (6)$$

where, $U(\lambda)$ is the combined concave utility of all users if λ fraction of their flow is transmitted, M is an (L x M) matrix with m^{th} column being the rate vector $R_L(m)$ for mode m, α is an M-dimensional vector of M mode activation time-fractions α_m , N is an (N x M) matrix with column m of the matrix being the transmit power vector $P_N(m)$ for mode m, and $P^N avg$ is an N-dimensional vector whose n^{th} element is P^n_{avg}.

All constraints in the above optimization problem are convex. We consider the dual of this problem to obtain a distributed algorithm for solution.

B. Lagrange-Dual of the Problem

Let p and q be Lagrange Multiplier Vectors of dimensions L and N associated with Link Capacity and Power Constraints respectively. And we call p and q be Link Price and Power Price Vectors respectively. Lagrange-Dual of the problem is

$$\min_{p,q\geq 0} D(p,\ q) \quad (7)$$

where ,

$$D(\mathbf{p},\mathbf{q}) = \max_{\substack{X^f\geq 0, \alpha\geq 0,\\ 0\leq\lambda\leq 1}} \left\{ U(\lambda) - \mathbf{p}^T\left(\sum_{f\in F} \mathbf{X}^f - \mathbf{M}\cdot\boldsymbol{\alpha}\right) - \mathbf{q}^T\left(\mathbf{N}\cdot\boldsymbol{\alpha} - \mathbf{P}^N_{avg.}\right)\right\} \quad (8)$$

subject to the constraints (2),(4), and (5).

For D_1**(p,q)** and D_2**(p,q)** as defined blow, we have D(p,q) = D_1(p,q)+D_2(p,q). And this decomposition is well known([9],[3]).

C.Rate control and Routing Sub-Problem

$$D_1(\mathbf{p},\mathbf{q}) = \max_{\substack{\mathbf{X}^f \geq 0,\\ 0\leq\lambda\leq 1}} \left\{ U(\lambda) - \mathbf{p}^T \sum_{f\in F} \mathbf{X}^f + \mathbf{q}^T \mathbf{P}^N_{avg.} \right\} \quad (9)$$

subject to : (2) and (5)

This optimization problem is different from the one used in literature (see, e.g., [3]) as we use a concave increasing utility function of a scalar global parameter λ in place of concave increasing utility function of d_f , *i.e.*, $U(d_f)$.

D. Scheduling and Power Control Sub-Problem

$$D_2(\mathbf{p},\mathbf{q}) = \max_{\boldsymbol{\alpha}\geq 0} \{\mathbf{p}^T\mathbf{M}\cdot\boldsymbol{\alpha} - \mathbf{q}^T\mathbf{N}\cdot\boldsymbol{\alpha}\} \quad (10)$$

subject to: (4)

In this sub-problem, let the optimal scheduling vector be $\alpha^x(\mathbf{p},\mathbf{q})$ for a given link price vector $\mathbf{p}$, and power price vector $\mathbf{q}$. All entries of $\alpha^x(\mathbf{p},\mathbf{q})$ will be zero, except the one corresponding to an independent set (of link activation) with maximum aggregate difference of price-rate product, and price-power product.

IV. ALGORITHMS FOR SOLVING THE SUB-PROBLEMS

In this section, we propose an algorithm, which uses a sub-gradient method for obtaining the optimal solution. First we provide algorithms to solve the sub-problems, that are then combined to propose a complete decentralized algorithm.

A. Rate Control and Routing Sub-Problem

$\mathbf{q}^T.\mathbf{P}^N_{avg}$ is constant , since $\mathbf{P}^N_{avg}$ is constant for our model. Hence, maximizing $D_1(\mathbf{p},\mathbf{q})$ is same as

$$\min_{\mathbf{X}^f\geq 0} \quad \mathbf{p}^T\mathbf{X}^f \quad (11)$$

subject to : (5)

The above optimization problem gives the optimal route X^{f*} for the unit source flow $f\epsilon F$ (*i.e.*, $r_f = 1$). Since the link capacity constants are not present in this sub-problem, at the optimal point each flow f is routed along a path of least path-price $p^{f*}_R = p^T.X^{f*}$. With flows routed along this paths, $D_1(p, q)$ can be found by optimizing w.r.t λ . If a feasible value of λ exists for which $U'(\lambda) = \sum_{f\in F} d_f p^{f*}_R$, this value is optimal.Optimizing w.r.t λ requires computation of $\sum_{f\in F} d_f p^{f*}_R$, which can be done in a distributed manner over a rooted spanning tree. Such a spanning tree can be obtained using a distributed algorithm. Least-price path can be computed using, for instance, the distributed Bellman-Ford algorithm. Let X^* denote the resulting L-Dimensional vector of link flows x_l^*. And $X^* = \lambda\{\sum_{f\epsilon F} d_f X^{f*}\}$.

B. Scheduling and Power Control Sub-Problem

We start with an initial p and q vectors, that are updated in every iteration using the link price and power price updating equations (14) and (15) respectively. Optimizing $D_2(p, q)$ gives us the mode, i.e., scheduling is done.

$\{p^T M.\alpha - q^T N.\alpha\}$ gives an M-dimensional row vector; its *mth* element is $\{\sum_{l\epsilon L} p_l R_l(m) - \sum_{n\epsilon N} q_n P_n(m)\}$. The index of the element whose value is maximum is the mode chosen in that iteration, i.e., choose

$$\arg\max_m\{\sum_{l\epsilon L} p_l R_l(m) - \sum_{n\epsilon N} q_n p_n(m)\} \quad (12)$$

Hence, we get a particular *mode* for activation depending on link prices and power prices. Average is taken over the iterations to get the vector α . Our goal is to find the scheduling in a distributed manner using the distributed greedy scheduling heuristic algorithm 2 presented in Appendix VII-A. To do this, we derive a new metric called *Composite Link Price*, which includes link price and power price in a single term.

C. Derivation of the Composite Link Price

Since at most one attached link to a node is active in a given mode due to the interference. Hence, the transmit power of the node is equal to the sum of transmit powers on its attached links, i.e, $\sum_{n\epsilon N} q_n p_n(m) = \sum_{n\epsilon N}\sum_{l\epsilon Lm} q_{n(l)} P_{n(l)}(m)$. The double summation $\sum_{n\epsilon N}\sum_{l\epsilon Lm}$ gives all links in the network.

In our model $h_{ll}^2 P_{n(l)}(m)/N_0W = 1$, since a sensor node communicates with its nearby sensor node with low power. Since interference is removed by satisfying the primary interference constraint, the capacity of link l by Shannon's capacity formula is given by

$$\begin{aligned} R_l(m) &= W\cdot\mathbb{E}\left[\log_2\left(1+\frac{h_{ll}{}^2 P_{n(l)}(m)}{N_0 W}\right)\right] \\ &\approx \frac{W}{\ln 2}\cdot\mathbb{E}\left[\frac{h_{ll}{}^2 P_{n(l)}(m)}{N_0 W}\right] \quad (\because \ln(1+x)\approx x, \text{ for small } x) \\ &= \frac{\mathbb{E}\left[h_{ll}{}^2\right] P_{n(l)}(m)}{N_0 \ln 2} \\ &= \frac{1}{\sigma_l}\cdot P_{n(l)}(m) \end{aligned}$$

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Where, σ_l is constant for link l, and can be different for different links. Therefore, the capacity of the link varies linearly with transmit power on it.

Substituting this value in the equation (12), we obtain

$\sum_{l\epsilon L}\{p_l. R_l(m) - q_{n(l)}.P_{n(l)}(m)\}$

$= \sum_{l\epsilon L}\{p_l - \sigma_l . q_{n(l)}). R_l(m)$

$= \sum_{l\epsilon L}\{p'_l R_l(m)$

where, $p'_l = p_l - \sigma_l$ is called the *Composite Link Price* of link $l \epsilon L$. The *Composite Link Price* includes the link price p_l of the link l, and power price $q_n(l)$ of the node n to which link l is attached in a single term. Our scheduling and power control sub-problem becomes

$$\arg\max_m \{\sum_{l=L} p'_l R_l(m)\}, \quad \text{where } m \in M \quad (13)$$

We use a version of the distributed greedy scheduling heuristic algorithm proposed in [2], which does not use CHECK state, which has same communication complexity but less computational complexity and is presented in

Appendix VII-A. And we use Composite Link Prices as its input.

D. Link Price and Power Price Update Algorithm

Link price and power price updating will be done using the following algorithms for all proposed algorithms for solving the dual problem. Since the dual function ***D(p, q)*** is not differentiable, we cannot use the casual gradient methods and hence the dual problem is solved using the sub-gradient $\mathbf{g(p, q)} = [\mathbf{M}.\alpha - \sum_{f\epsilon F} X^f .\mathbf{N}.\alpha - \mathbf{P}^N_{avg.}]^T$ of the dual function, D(p,q) at (p,q):

$$p[j+1] = (p[j] + \delta\,(\sum_{f\epsilon F} X^f[j] - M.\,\alpha\,[j]))^+$$

and

$$q[j+1] = (q[j] + \gamma\,(N.\,\alpha\,[j] - P^N_{avg.}))^+$$

where, δ , $\gamma > 0$ are suitably chosen small constants.

Hence the price of link *l* from *j* to *j + 1* will be updated as follows:

$$p_l[j+1] = (P_l[j] + \delta\,(x_1[j] - R_l[j]))^+. \qquad (14)$$

where, $p_l[j]$ is the price of the link *l* in j^{th} iteration, $x_l[j]$ is the aggregate flow on the link *l* in j^{th} iteration.
$R_l[j]$ is the capacity of the link *l* in j^{th} iteration. Equation (14) says that the link price will rise if the aggregate flow on the link exceeds the capacity of the link, this will result in selection of the mode which contains these links, thus increasing the effective capacity of the links.

Hence, the price of node *n* from *j* to *j + 1* will be updated as follows:

$$q_n[j+1] = (q_n[j] + \gamma\,(P_n[j] - P^n_{avg.}))^+ \qquad (15)$$

where, $q_n[j]$ is the power price of node *n* in the j^{th} iteration, $P_n[j]$ is the transmission power of node *n* in the j^{th} iteration, $P^n_{avg.}$ is the average available power at node *n*, which is constant for our model. Equation (15) says that the power price will rise if the transmission power of the node exceeds the average available power at that node. This will result in the selection of the mode which doesn't contain these nodes, thus conserving the energy available at these nodes.

The updating algorithms can be implemented in a distributed manner using only local information as explained below.

E. Distributed Algorithms for Joint Routing, Scheduling, Rate and Power Control

We consider a network with K-hop link interference model.Based on the algorithms provided from IV-A to IV-D, a distributed sub-gradient algorithm for joint routing, scheduling, rate and power control is obtained.

In this algorithm, optimal routing for a flow depending on link prices is obtained using a distributed routing algorithm. Utility maximization problem of the global network parameter $\lambda = min_f\, r_f/d_f\,.\, f \epsilon F$ subject to the network constants is solved by applying the duality theorem, wherein the system problem is decomposed into a rate control and routing sub-problem, and scheduling and power control sub-problem. They interact through link prices and power prices. Routing is based on the link prices. And scheduling is based on link prices, and also power prices.

The above dual algorithm motivates the following joint routing, scheduling, rate and power control algorithm, which uses strictly concave utility function $U(\lambda) = \sqrt{\lambda}$.

The network is organized in a spanning tree with a root node, which controls the global network parameter, λ. A spanning tree may be obtained in a distributed manner as in [7].

ALGORITHM 1 CONCAVE UTILITY ALGORITHM

1: Every node has the knowledge of links attached to it. From j^{th} to $(j + 1)^{th}$ iteration, it updates the price of link *l* , and price of node *n* using the link price, and power price update algorithms given in equations (14), and (15) respectively, and also calculates the Composite Link Price, which takes account into link price and power price.
2: Using any distributed algorithm for routing, the optimal route or the minimum priced path is chosen for each of the flows, and the path-prices $\boldsymbol{p_R}^{f*}$ becomes available at the source nodes. Then the nodes are made aware of the flow-rates r_f passing through them.
3:$\sum_{f\epsilon F} d_f.P_R^{f*}$ is computed by passing summary messages from the leaf nodes of spanning tree towards the root node. Every node in the chain adds the partial sums received from its child nodes to its own contribution, and passes the result to its parent node.
4:$U(\lambda) = \sqrt{\lambda}$ is a concave function. The unique maximizer of $D_1(\boldsymbol{p}, \boldsymbol{q})$ is at $U'(\lambda) = \sum_{f\epsilon F} d_f.P_R^{f*}$. Hence, root node can obtain the network parameter

$$\lambda = \min\left[\left(2\sum_{f\in f} d_f \cdot P_R^{f*}\right)^{-2}, 1\right]$$

Root node computes value of $\sum_{f\epsilon F} \boldsymbol{d_f.P_R^{f*}}, \boldsymbol{\lambda}$, and disseminates computed values through the spanning tree.
5: As stated in section IV-B, the second sub-problem is solved using the distributed greedy scheduling heuristic algorithm 2, with *Composite Link Price* as its input.

V. SIMULATION RESULTS

In this section, we take a network with 24 nodes and 76 links as shown in figure (1), and provide the simulation results for *Concave Utility Algorithm* of section IV-E.

We consider three power-levels $\{0, P_1, P_2 = 2P_1\}$. And we assume that all links activated in a mode transmit at same power level either P_1 or P_2.
We assume average available power for each node = 0.5 units. We consider capacity of link = 1 unit/sec., if it is active in mode *m* with power level $P_1 = 1$, and capacity of link = 2 units/sec., if it is active in mode *m* with power level P_2.

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We initialize all link prices to 0.3 and all power prices to 0.4.Source and destination pairs for the flows are (1,24), (2,23),(3,22), (4,21), (5,20), (6,19), (7,18), (8,17), (9,16), (10,15), (11, 14), (12, 13).

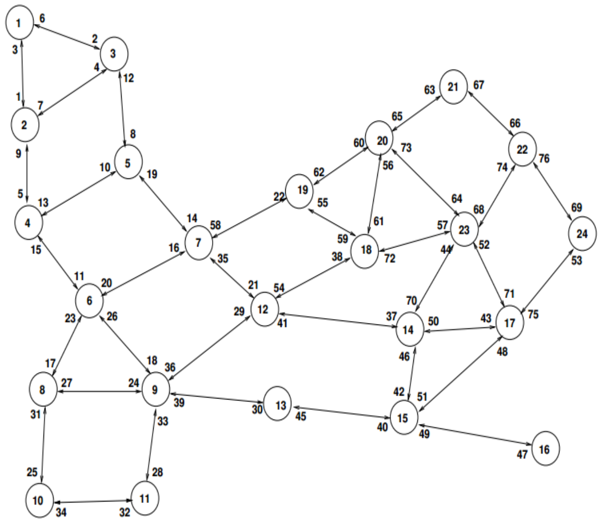

Figure 1: Example Network Graph

Note: The number indicated against the arrow represents the link index in that direction.

We assume equal demands for all flows, i.e. 0.5 units/sec. We assume that proportionality constant $\sigma_l = 1;\ \forall\, l \in L$. We consider K = 1 with power level P_1, and $K = 2$ with power level P_2, to reflect an increase in interference neighborhood with transmit power. We execute distributed greedy scheduling heuristic algorithm 2 first with $K = 1$ and then with K = 2 and select the value of K for which the sum in equation 13 is maximized.

We use step size for both link price and power price update algorithms = 0.01.We obtain, the optimal value of λ (at 6000th iteration), i.e., the maximum fraction of throughput that can be supported in the network for each flow is given by $\lambda^* = 0.1614$ and convergence of λ is shown in figure (2).

If we neglect the initial 500 iterations before the link price becomes stable, average value of λ obtained by averaging the λ values from 500 - 6000 iterations is Average $\lambda^* = 0.1669$

Plots of Link Prices Vs Number of Iterations converge over 6000 iterations, and the plot for one of the link prices is shown in figure (2).

Plots of Power Prices Vs Number of Iterations converge over 6000 iterations, and the plot for one of the power prices is shown in figure (2).

We can increase the step size from 0.01 to 0.1, to reduce the number of iterations (reduces from 6000 to 1000 iterations) and the algorithm 1 gives approximately same average λ^* is obtained.

We have verified in a smaller network with 6 nodes and 14 links our distributed algorithm achieved 95 percent of the optimal value obtained through centralized algorithm. It is feasible to compute reference optimal value of average λ^* by listing out all possible modes in this network.

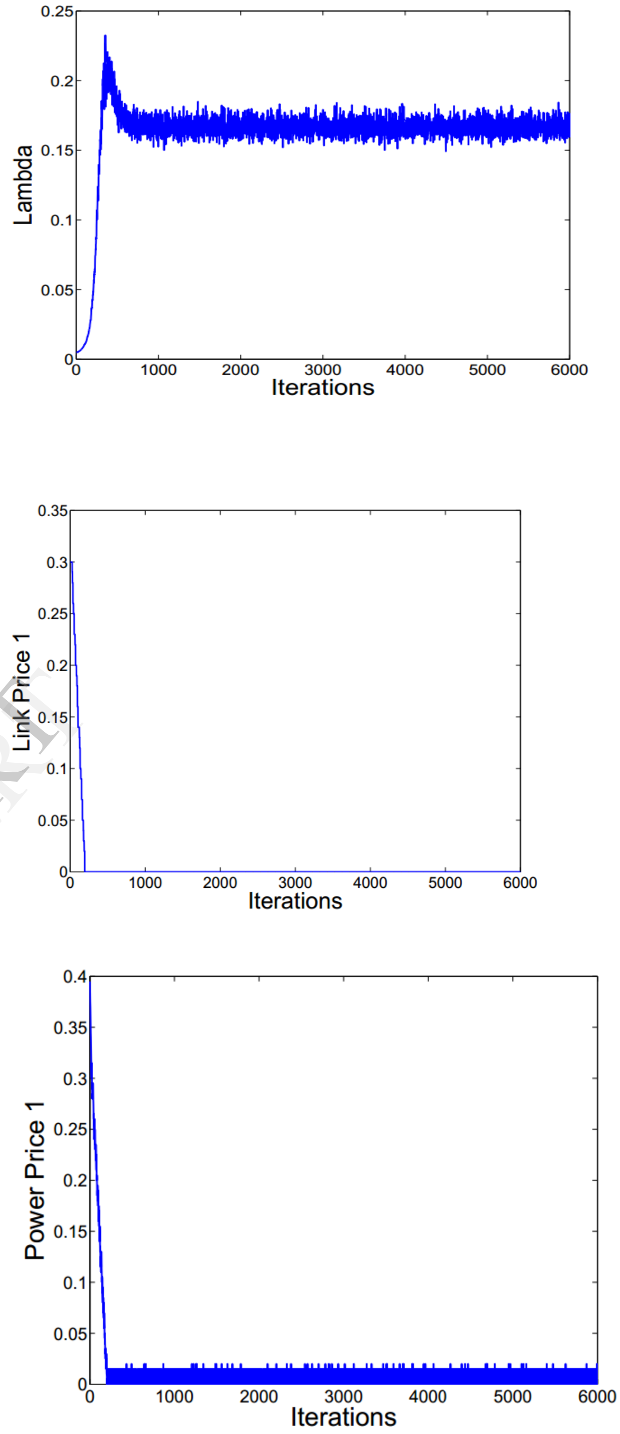

Figure 2: Plots of Lambda, and typical link and power prices

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VI. CONCLUSION

We have proposed and studied a distributed algorithm for Joint Routing, Scheduling, Rate and Power Control in a MWSN which aims to approximate optimum throughput efficiency and fairness. We also included a version of the previous distributed greedy scheduling heuristic algorithm [2], which has same communication complexity but less computational complexity.

VII. APPENDIX

A. Distributed Greedy Scheduling Heuristic Algorithm without CHECK States

We include a version of previous distributed greedy scheduling heuristic algorithm [2] without *CHECK* states, which has same communication complexity but less computational complexity.

Refer [2] for terminology and definitions used in the distributed greedy scheduling heuristic algorithm.

In algorithm 2 below, the maximum priced link in its corresponding *(K + 1)-hop* neighborhood gets *MARKED* at time T^m_L, and *OPEN* links that are interfering with at least one *MARKED* link are *CLOSED* at time T_m^M.

In [2], interference checking has to be done to put an *OPEN* link in *CHECK* state, and a few more computations are required to *OPEN* the highest priced attached *CHECK* link. In other words, use of *CHECK* state increases the computational complexity. However, the two distributed greedy scheduling heuristic algorithms have same communication complexity, since a node has to disseminate its *OPEN* link price or *MARKED* link if it has one, to the *(K + 1)- hop* neighbor-hoods.

Our modified version of the distributed greedy scheduling heuristic algorithm is as follows:

Algorithm 2 Pseudo-code for Distributed Greedy Heuristic without CHECK states

In slot S^m_l

1: Disseminate the highest *OPEN* attached link price to *(K+1)- hop* neighborhoods.

At time T^m_L

1: ***if*** at least one attached link is *OPEN* ***then***
2: sort the attached *OPEN* links in descending order of link price. Let l'_{max} be the maximum priced link among the attached *OPEN* links.
3: **if** no *OPEN* link prices are received ***then***
4: link l'_{max} is *MARKED* and all other *OPEN* attached links are *CLOSED*, go to 15.
5: **else**
6: sort received *OPEN* link prices in descending order of link prices. Let l_{max} be the maximum priced link among the received *OPEN* links.
7: **end if**
8: **if** $p_{l'max} > P_{lmax}$ ***then***
9: link l'_{max} is *MARKED* and all other *OPEN* attached links are *CLOSED*.
10: **else if** $P_{l'max} = P_{lmax}$ **then**
11: **if** Link l'_{max} ID < link IDs of the received *OPEN* links **then**
12: link l'_{max} is *MARKED* and all other *OPEN* attached links are *CLOSED*.
13: **end if**
14: **end if**
15: **end if**

In this slot, maximum priced links in their corresponding *(K + 1)-hop* neighborhood get *MARKED*.

In slot S^m_M

1: **if** any one of the attached links is *MARKED* **then**
2: disseminate this information to *(K + 1)- hop* neighborhoods.
3: **end if**

At time T^m_M

1: **for** each attached *OPEN* link *l* **do**
2: if *(d(l . received MARKED link) < K)* for at least one received MARKED link **then**
3: link *l* is CLOSED.
4: else
5: link *l* remains in *OPEN* state.
6: **end if**
7: **end for**
8: Algorithm status is set to *TERMINATE* at nodes which have no *OPEN* links.

In this slot, an *OPEN* link is moved to *CLOSED* state, if it interferes with at least one *MARKED* link, else it remains in *OPEN* state (line numbers 1 to 5).

In slot S^m_T

1: **if** at least one attached link is *OPEN* **then**
2: send a *DO NOT TERMINATE* message to all nodes in the (K + 1)-hop neighborhood.
3:**else if** got a *DO NOT TERMINATE* message **then**
4: send a *DO NOT TERMINATE* message to all nodes in the (K + 1)-hop neighborhood.
5: **end if**

At time T^m_T

1: **if** no *DO NOT TERMINATE* message is received **then**
2: the algorithm has terminated, schedule all *MARKED* links.
3: **else**
4: go to the $(m + 1)^{th}$ *ROUND*.
5: **end if**

The algorithm terminates when no attached link is in OPEN state. In this slot, this information is disseminated to all other nodes in the network in a distributed manner. This ensures that the algorithm terminates in a synchronous fashion at each node.

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