Utility-cost optimization for joint routing and power control in multi-hop wireless networks

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Abstract—In this paper we formulate a novel utility-cost optimization problem for routing and power control in multi-hop wireless networks. As the problem is non-convex and non-separable (no assumption on high or low SINR regime), we approach it by solving a sequence of convex approximation problems. If the initial convex approximate is feasible, it is shown that the solution sequence converges to a KKT point to the original utility-cost optimization problem. The convex approximation problems are solved recursively by means of primal-dual methods that are shown to be amenable to distributed implementation. The seamless interaction between the successive convex approximation and the primal-dual algorithm constitutes the proposed successive primal-dual convex approximation (SPDCA) algorithm.

I. INTRODUCTION

Routing and power control are vital mechanisms for resource allocation in wireless networks \cite{1}. In this paper, we consider a multi-hop wireless network with an established network topology and per-flow queuing in which the packets are passed from node to node to their destinations according to node-based routing algorithms. Our focus is then on the problem of a joint optimization of transmit powers and flow rates to maximize some utility-cost function. This function is chosen to trade off the throughput and fairness performance against power and energy consumption at wireless devices.

The problem of joint routing and power control in wireless networks is in general difficult to solve because of the lack of convexity due to the presence of interference. This paper approaches the problem by combining a successive convex relaxation/approximation with primal-dual methods, with the goal of approximating an optimal solution in a distributed manner. More precisely, the proposed non-convex routing and power control problem is first approximated by a convex problem that is solved using primal-dual methods. As shown, the primal-dual algorithm can be implemented in a distributed manner in which case updates of primal and dual variables are based on local information/measurements. The optimal solution to the convex problem is used to improve the approximation by stating and solving a new convex approximation problem. This procedure is repeated and the resulting sequence of optimal solutions of the convex approximation problems is shown to converge to a KKT point that is close to optimal flow rates and transmit powers in the sense of the utility-cost function, provided that the initial convex approximate problem is feasible. The overall algorithm is called the successive primal-dual convex approximation (SPDCA) algorithm.

Potential applications of the results presented in this paper are envisaged in wireless mesh networks or wireless sensor networks, where static mesh topology and energy concerns are assumed, to control transmit power and split flow rates distributively.

II. RELATED WORK

It is well-known that the lack of convexity makes the general resource allocation problem in wireless networks notoriously difficult to solve. Most of the state-of-the-art references deal with the nonconvexity of the joint routing and power control problem in one of the two ways. One way is to orthogonalize the communication links in time or frequency, so that they do not interfere with each other \cite{1-3}. This method obviously simplifies the problem but may incur big loss in performance, since it neglects the potential opportunities for transmission when the interference is very weak. The other way is to approximate the nonconvex optimization problem by convex math model under high SINR assumption \cite{4-7} or low SINR assumption \cite{8-9}. The main disadvantage of the second approach is that in most cases the SINR assumption does not necessarily hold for every transmitter-receiver pair. The difference between this paper and related references \cite{4-9} is that we do not make assumptions on the SINR and instead adopt a successive convex approximation technique \cite{10} to approximately solve the original problem in a distributed manner. The proposed SPDCA algorithm provides a wider applicability and a better performance than analogous approaches based on the high or low SINR regime assumption. The improvement is due to successive performance enhancement, and therefore it is achieved at the expense of increased complexity. However, the complexity order of our algorithm is shown to be the same as that of the high SINR methods\cite{4-7} by simulations.

The use of successive convex approximation has been also addressed in the context of other problems in wireless net-
works [11]-[13]. However, complicated approximation methods used before would lead to excessive message passing, including "flooding" in [11]-[12], or off-line centralized algorithm in [13]. In contrast, our SPDCA algorithm allows for a distributed online implementation without extra communication overhead, which is of paramount importance in practical systems. Finally, this work could be considered as a substantial extension of our former work [14] dealing with the problem of utility-based power control. In contrast to [14], we modify the utility function by incorporating costs to take into account the battery levels at wireless devices and power consumption for transmission and reception. Furthermore, we maximize the proposed function over a joint space of flow rates and transmit powers.

III. MODELING AND PROBLEM STATEMENT

A. System and Network Model

Consider a wireless network with an established network topology, in which all links share a common channel. We use \( \mathcal{N} := \{1, \ldots, N\} \) to denote the set of nodes. A number of flows compete for access to the wireless links without scheduling. One hop flows associated with logical links are called users. We use \( \mathcal{K} = \{1, \ldots, K\} \), \( \mathcal{I}(n) \), and \( \mathcal{X}(n) \) to denote the set of all logical links, the set of logical links incoming to node \( n \in \mathcal{N} \), and the set of logical links originating at node \( n \in \mathcal{N} \), respectively. The logical links are labeled in such a way that, for any two nonempty sets \( \mathcal{K}(n), \mathcal{X}(m) \subset \mathcal{X} \) with \( 1 \leq n < m \leq N \) and all \( a \in \mathcal{K}(n), b \in \mathcal{X}(m) \), there holds \( a < b \). Finally, we assume that all nodes are synchronized and the time is divided in slots. For notational convenience, we drop the time index and consider an arbitrary time slot.

Suppose that \( \mathcal{W} \) is a collection of communication sessions and each session is identified by its unique source-destination node pair. For any session \( w \in \mathcal{W} \), let \( O(w) \) and \( D(w) \) denote its origin and destination nodes, respectively. The average rate of each session, say \( w \), is fixed and denoted by \( \lambda(w) \). Let the flow rate of session \( w \) on link \( k \) be denoted by \( f_k^{(w)} \) and let \( f = (f_k^{(w)})_{w \in \mathcal{W}, k \in \mathcal{X}} \) be the link rate vector. Then, by the flow conservation law, we have

\[
\forall w \in \mathcal{W}, \forall n \in \mathcal{N}/\{D(w)\} \lambda(w) \mathbf{1}_n^{(w)} = \sum_{k \in \mathcal{X}(n)} f_k^{(w)} - \sum_{k \in \mathcal{I}(n)} f_k^{(w)} \tag{1}
\]

where \( \mathbf{1}_n^{(w)} := \mathbf{1}(n = O(w)) \) and \( \mathbf{1}(\cdot) \) is the indicator function. In addition, the total average rate cannot exceed the corresponding link capacity. In wireless networks, the link capacity \( c_k(p), k \in \mathcal{X} \), is often of the form \( c_k(p) = \log(1 + \text{SINR}_k(p)) \), where, without loss of generality, \( \log(\cdot) \) is assumed to be the natural logarithm and SINR is the signal to interference plus ratio at the output of the \( k \)th logical receiver. With this assumption in hand, the link capacity constraint for link \( k \) yields

\[
\sum_{w \in \mathcal{W}} f_k^{(w)} \leq \log(1 + \text{SINR}_k(p)), \quad k \in \mathcal{X}. \tag{2}
\]

Obviously, link capacities \( c_k(p), k \in \mathcal{X} \) are dictated by

\[
\text{SINR}_k(p) := \frac{V_{k,k} p_k}{\sum_{l \neq k} p_l V_{k,l} + \sigma_k^2} = \frac{p_k}{(V_p + z)_k} = \frac{p_k}{I_k(p)}. \tag{3}
\]

The above notion is defined as follows: \( p_k \geq 0 \) denotes a transmit power of user \( k \in \mathcal{X} \) and \( p = (p_1, \ldots, p_K) \geq 0 \) is a vector of all transmit powers, referred to as the power vector. \( \sigma_k^2 \geq 0 \) is the variance of an additive zero-mean Gaussian noise and \( z = (\sigma_1^2/V_{1,1}, \ldots, \sigma_K^2/V_{K,K}) > 0 \) is the noise vector. \( V_{k,k} \geq 0 \) with \( V_{k,k} > 0 \) is the attenuation of the transmit power from transmitter \( l \in \mathcal{X} \) to receiver \( k \in \mathcal{X} \). The nonnegative matrix \( V = (v_{l,k})_{1 \leq l, k \leq N} \) with \( \text{trace}(V) = 0 \) and \( v_{k,k} = V_{k,k} / V_{k,k}, k \neq l \), is referred as the gain matrix and is assumed to be fixed. In general, the gain matrix depends on path attenuation, the receiver structures as well as the bandwidth and waveforms of transmission signals. \( I_k(p) = (V_p + z)_k \) is the \( k \)th interference function.

Each node, say node \( n \in \mathcal{N} \), is constrained on total power \( P_n > 0 \). This means that

\[
p \in \mathcal{P}, \mathcal{P} := \mathcal{P}_1 \times \cdots \times \mathcal{P}_N \tag{4}
\]

where \( \mathcal{P}_n := \{x \in \mathbb{R}^{|\mathcal{X}(n)|} : \sum_{k=1}^{\mathcal{X}(n)} x_k \leq P_n\} \) and \( \mathcal{P}_n \times \mathcal{P}_m \) is the Cartesian product of \( \mathcal{P}_n \) and \( \mathcal{P}_m \). In addition, there may be some hardware or regulatory limitations that impose individual constraints on link transmit powers and flow rates. These constraints will be captured by maximizing our objective function over the following set \( \mathcal{R} := \{(p, f) : 0 < p_k \leq p_k^{\max}, f_k^{(w)} \leq f_k^{(w)} \leq f_k^{(w)}(k, w, k, \in \mathcal{X}, w \in \mathcal{W}) \}, \tag{5}
\]

B. Optimization Problem

In this paper, we take the power consumption and battery state into account by incorporating a suitably chosen cost in the traditional utility maximization problem over a joint space of transmit powers and routes:

\[
U = \max_{(p, f) \in \mathcal{R}} \quad U(p, f) \quad \text{s.t.} \quad (1), (2), \text{ and } (3) \tag{4}
\]

where \( U: \mathcal{R} \rightarrow \mathbb{R} \) is a utility-cost function defined to be

\[
U(p, f) = \sum_{k \in \mathcal{K}} U_k(p_k, f_k) = \sum_{k \in \mathcal{K}} \left( \sum_{w \in \mathcal{W}} \omega_k^{(w)}(f_k^{(w)}(k, w) - \lambda_k(p_k, \xi f_k), \frac{\text{Cost}}{\text{Utility}}) \right). \tag{5}
\]

Here and hereafter, \( U_k \) is the utility-cost function associated with link \( k \in \mathcal{X} \). The utility function of rates \( \Phi: \mathcal{R} \rightarrow \mathbb{R} \) is assumed to be differentiable, increasing and strictly concave. The weight vector \( \omega = (\omega_1^{(w)}, \ldots, \omega_K^{(w)}), w \in \mathcal{W} \), is any fixed positive vector which can for instance be chosen according to the back-pressure policy [2]. The variable \( \lambda_k = \lambda / E_n, k \in \mathcal{X}(n) \), is the power price of link \( k \), where \( \lambda > 0 \) is a given system constant and \( E_n > 0 \) is the energy available at node \( n, n \in \mathcal{N} \) (in the considered time slot). The cost of link \( k \) is then equal to the product of the power price \( \lambda_k \) and the total power consumption which is the sum of transmission power.
and reception power $\xi f_k$, where $\xi$ is a hardware-dependent constant.  

It is well-known that capacity functions $c_k(p)$, $k \in \mathcal{K}$, are non-convex functions of $p$. Therefore, in the following section, we will adopt a successive convex approximation method to approximate the non-convex and non-separable problem in (4). In doing so, we assume that $\Phi(x) \rightarrow -\infty$ and $\Phi'(x) \rightarrow +\infty$ as $x \rightarrow 0$ which implies that if $(p^*, f^*)$ is a solution to (4), then $p^*$ is a positive vector.

IV. SUCCESSIVE CONVEX APPROXIMATION METHOD

Since an optimal power vector is positive, we can reformulate the problem using $s := \log(p)$, $p \in \mathcal{P} \cap \mathcal{R}_{++}^K$, where the logarithm is taken elementwise. By monotonicity of the logarithm function, we see that every $p \in \mathcal{P}_+$ is associated with a unique $s$ and vice versa. Moreover, we introduce a set of auxiliary variables $Q = (Q_k)_{k \in \mathcal{K}}$ such that

$$\forall k \in \mathcal{K}, \sum_{w \in \mathcal{W}} f_k^{(w)}(s) \leq \log(1 + e^{Q_k}), \quad e^{Q_k} \leq \text{SIR}_k(e^s). \quad (6)$$

Taking the logarithm on all sides in (6) yields

$$\forall k \in \mathcal{K}, \log(\sum_{w \in \mathcal{W}} f_k^{(w)}(s)) - \log(\log(1 + e^{Q_k})) \leq 0 \quad (7)$$

Taking the logarithm on all sides in (6) yields

$$\forall k \in \mathcal{K}, \log(\sum_{w \in \mathcal{W}} f_k^{(w)}(s)) - \log(\log(1 + e^{Q_k})) \leq 0 \quad (8)$$

Each constraint in (8) is of the log-sum-exponential form, and thus the corresponding constraint set is convex. In contrast, the constraint sets in (7) are non-convex as $log(\sum_{w \in \mathcal{W}} f_k^{(w)}(s))$ is concave in $f_k$ and $a_k = (a_k^{(w)}(s))_{w \in \mathcal{W}}$. As a result, the problem is difficult to solve and we approximate it by a sequence of convex approximations indexed by $t \in \{0, 1, 2, \ldots\}$. These approximations are based on the fact that any concave function can be tightly upper bounded by an affine function [15, page 70]. More precisely, for the $t$th approximation, we choose some feasible rates $f_k^{(w)}(s) \neq 0$ ($k \in \mathcal{K}$, $w \in \mathcal{W}$), and bound from above the first term in (8) as follows

$$\log(\sum_{w \in \mathcal{W}} f_k^{(w)}(t)) \leq a_k^T(t)f_k + b_k(t) \quad (9)$$

where $a_k^T(t) = \left(\frac{1}{\sum_{w \in \mathcal{W}} f_k^{(w)}(s)}(1, \ldots, 1) \right)_{w \in \mathcal{W}}$ and $b_k(t) = \log(\sum_{w \in \mathcal{W}} f_k^{(w)}(s)) - 1$. Now, using the upperbound (9) in (7), the $t$th convex relaxation of (4) takes the form

$$U(t) := \max_{(s, f, Q) \in \tilde{\mathcal{B}}} U(s, f) \quad \text{s.t.} \quad (1), (3), \text{and} (8) \quad (10)$$

where

$$\tilde{\mathcal{B}} := \{(s, f, Q) : e^{s_k} \leq p_{k, \max}, \sum_{w \in \mathcal{W}} f_k^{(w)}(s) \leq f_k^{(w)}, Q_k < \bar{Q}_k, k \in \mathcal{K}, w \in \mathcal{W}\}.$$  

We start the sequence of convex approximations with $t = 0$ and compute $a_k^T(0), b_k(0)$ for any feasible rates $f_k^{(w)}(0) \neq 0$ ($k \in \mathcal{K}, w \in \mathcal{W}$). Once this initial convex problem is solved, we use the resulting rates to compute $a_k^T(1), b_k(1)$ and solve the problem (10)–(11) for $t = 1$. We repeat this process until some convergence criteria are satisfied.

Theorem 1: Suppose that $(\bar{s}(t), \bar{f}(t), \bar{Q}(t))$ solves (10)–(11). If the initial convex approximation is feasible, then the sequences $\{U(t)\}$ and $\{\bar{s}(t), \bar{f}(t)\}$ converge to some $U^* \leq U$ and a KKT point $(s^*, f^*)$, respectively. We skip the proof due to the lack of space. The idea is to prove that the sequence $\{U(t)\}$ is non-decreasing and upper bounded.

V. DISTRIBUTED IMPLEMENTATION

In this section, we will devise a primal-dual algorithm to solve the problem (10)–(11). Let $\nu = (\nu_w)_{w \in \mathcal{W}, n \in \mathcal{N}}$, $\varepsilon = (\epsilon_n)_{n \in \mathcal{N}}$, $\theta = (\theta_k)_{k \in \mathcal{K}}$, and $\eta = (\eta_k)_{k \in \mathcal{K}}$ be Lagrange multipliers for constraints (1), (3), (8), and (11), respectively. The physical constraints $\tilde{\mathcal{B}}$ are satisfied implicitly. For brevity, let $\Gamma$ and $\Lambda$ denote the set of original variables $(s, f, Q)$ and the set of dual variables $(\nu, \varepsilon, \theta, \eta)$, respectively. Moreover, $(\nu, \theta, \eta)$ should be all nonnegative. We define the feasible set $\Omega = \mathcal{R}^{|\mathcal{V}|} \times \mathcal{R}^{|\mathcal{N}|} \times \mathcal{R}^{|\mathcal{N}|} \times \mathcal{R}^{|\mathcal{K}|}$ of $\Lambda$. The Lagrangian function associated with problem (10) is given (for some $t \in \{0, 1, 2, \ldots\}$)

$$L(\Gamma, \Lambda) = U(s, f) - \sum_{k \in \mathcal{K}} \theta_k(a_k^T(t)f_k + b_k(t) - \log(1 + e^{Q_k}))) \quad (12)$$

$$- \sum_{n \in \mathcal{N}, k \in \mathcal{K}} \nu_{w_k} w_k \lambda_k(\varepsilon_n) - \sum_{k \in \mathcal{K}(n)} f_k^{(w_k)} + \sum_{k \in \mathcal{K}(n)} f_k^{(w_k)} - \sum_{k \in \mathcal{K}(n)} \eta_k \log(e^{Q_k} - \sum_{l \neq k} \nu_{kl} e^{Q_k} - s_k) - \sum_{n \in \mathcal{N}} \epsilon_n \left(\sum_{k \in \mathcal{K}(n)} e^{w_k} - P_n\right).$$

It is easy to show that the Lagrangian function (12) is a concave-convex function and strong duality holds. These observations imply that the KKT conditions are necessary and sufficient conditions for optimality. Thus, we can find the maximum in (10) by solving the KKT conditions. This is equivalent to finding a stationary point $(\Gamma^*, \Lambda^*)$ of the Lagrangian function (12). We apply the primal-dual algorithm to find a stationary point of $L(\Gamma, \Lambda)$. In the $(m+1)$th iteration, \begin{align*}
\text{Algorithm:} & \quad \text{Find a stationary point of } L(\Gamma, \Lambda) \\
\text{Input:} & \quad \Gamma(m), \Lambda(m), \text{stepsizes } \delta \\
\text{Output:} & \quad \Gamma^*, \Lambda^* \\
\text{Procedure:} & \quad \begin{align*}
\{\Lambda(m+1) & = \Pi_\Omega|_{\Lambda(m)} - \delta \nabla_{\Lambda} L(\Gamma(m), \Lambda(m))\} \\
\{\Gamma(m+1) & = \Pi_{\tilde{\mathcal{B}}|_\Gamma}|_{\Gamma(m)} - \delta \nabla_{\Gamma} L(\Gamma(m), \Lambda(m))\}, \\
\end{align*}
\end{align*}

where $\delta$ is a sufficiently small step size, $\Pi_\Omega|_{\Lambda} = (\nu^{(w)}, \max_{\epsilon_n, 0}, \max_{\theta_0}, \max_{\eta_0})$ and $\Pi_{\tilde{\mathcal{B}}|_\Gamma} = (\min_{s_k, \log(P_k), 0}, \max_{f_k^{(w)}, 0}, \max_{Q_k}, \max_{Q_k})$ are the projections on $\Omega$ and $\tilde{\mathcal{B}}$, respectively.

From (12), we obtain the partial derivative of $L(\Gamma, \Lambda)$ with respect to $\Lambda$, which reveals the first gradient-projection
iteration in (13) to be
\[
\begin{align*}
    v_n^{(w)}(m+1) &= v_n^{(w)}(m) + \delta(\lambda(w)1_n^{(w)} - \sum_{k \in \mathcal{K}(n)} f_k^{(w)}(m)) \\
    &+ \sum_{k \in \mathcal{K}(n)} f_k^{(w)}(m)) \\
    \epsilon_n(m+1) &= [\epsilon_n(m) + \delta(\sum_{k \in \mathcal{K}(n)} e^{(w)}_k(m) - P_n)^+] \\
    \theta_k(m+1) &= [\theta_k(m) + \delta(a_k^{(w)}(0)f_k^{(w)}(m) + b_k(0) \\n    &- \log[(1 + e^{Q_k(m)})^+])] \\
    \eta_k(m+1) &= [\eta_k(m) + \delta(\bar{Q}_k(m) - s_k(m) + \log(I_k(e^{(w)})))^+]
\end{align*}
\]
In order to compute the partial derivatives of \(L(\Gamma, \Lambda)\) with respect to \(\Gamma\), we first rearrange the terms in (12) to obtain
\[
L(\Gamma, \Lambda) = \sum_{k \in \mathcal{K}} \sum_{w \in \mathcal{W}} \left[ \begin{matrix}
\omega_k^{(w)} \phi(f_k^{(w)}) \\
- (\sum_{w \in \mathcal{W}} f_k^{(w)}(0)) - \lambda_k \xi \\
- \sum_{k \in \mathcal{K}} \eta_k \log(I_k(e^{(w)})) - s_k + (\lambda_k + \epsilon_k^{(w)}) e^{s_k(m)} \\
+ \sum_{k \in \mathcal{K}} \theta_k \log(1 + e^{Q_k(m)}) - \eta_k \bar{Q}_k + \Delta
\end{matrix} \right]
\]
where \(t(k)\) and \(r(k)\) stand for the transmitter node and the receiver node of link \(k\), respectively, and
\[
\Delta = \sum_{n \in \mathcal{N}} e_n P_n - \sum_{n \in \mathcal{N}} \sum_{w \in \mathcal{W}} v_n^{(w)} 1_n^{(w)} \lambda(w) - \sum_{k \in \mathcal{K}} b_k(0).
\]
Now, we can expand the second iteration (13) as follows:
\[
\begin{align*}
    f_k^{(w)}(m+1) &= f_k^{(w)}(m) + \delta(\omega_k^{(w)} \phi(f_k^{(w)}(m)) - \lambda_k \xi) \\
    &- \sum_{w \in \mathcal{W}} f_k^{(w)}(0) + v_r^{(w)}(m) - v_i^{(w)}(m)) \\
    Q_k(m+1) &= Q_k(m) + \delta(\theta_k(m) e^{Q_k(m)}) - \eta_k(m) \\
    s_k(m+1) &= s_k(m) + \delta(\eta_k(m) - (\lambda_k + \epsilon_k^{(w)}) e^{s_k(m)}) \\
    \Gamma(m+1) &= \prod_{k \in \mathcal{K}} \Gamma(m+1))
\end{align*}
\]
Algorithm 1 summarizes the steps of the proposed successive convex approximation algorithm. The algorithm is amenable to distributed implementation since only local information exchange in Step 5 is necessary for the node to compute the updates of the primal and dual variables. However, this will not incur extra overhead since the information for updating gradients could be piggybacked on the ACK packet.

If \(\sigma > 0\) is sufficiently small, then it can be shown that SPDCA algorithm converges to some \((\bar{s}, \bar{f})\) which in general is a suboptimal solution of (4). For any given \(t\), the inner loop in Algorithm 1 converges to a stationary point of the Lagrangian function (12). This immediately follows from the fact that simultaneous application of gradient methods converges to a saddle point of the associated Lagrange function [16, pp. 125–126]. Once the inner loop has converged, Theorem 1 ensures that the outer loop converges to some suboptimal solution \((s^*, f^*)\) of the original problem (4) as \(t \to \infty\).

Algorithm 1 typically converges in just a few (less than 5 in our simulation) approximation steps, and thus its complexity order is the same as that of the high SINR method[4]-[7].

**VI. SIMULATION**

We consider a wireless sensor network generated randomly in the 200 × 200 square meters, as seen in Fig. 1. There are twelve logical links, 10 nodes and four sessions \(w_i\), \(i = 1, 2, 3, 4\). The off-diagonal entries of \(V\) were randomly chosen from \([0, 0.2]\). Moreover, we assume \(\omega = 0.1, \phi = 1, \lambda(w_i) = 1, i = 1, 2, 3, 4\), and \(\Phi(x) = \log(x)\).

The following results are achieved based on MATLAB Simulations. The convergence of primal-dual algorithm (13) has been validated by simulations and one exemplary simulation result is depicted in Fig. 2. We observe that though the primal-dual algorithm does not provide monotonicity, the utility-cost function converges relatively fast in Fig. 2. The convergence rate can be further enhanced by considering primal-dual methods for minimax problem based on general non-linear Lagrangian functions[14].

Fig. 3 depicts a sequence of utility-cost function values for optimal solutions of the convex approximation problems, and therefore an exemplary behavior of the proposed SPDCA algorithm. The sequence starts from the high-SNR approximation[4]. We observe a monotonic and noticeable

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increase of the function, compared to the initial high-SNR solution, with a fast convergence to some steady-state value for different ”energy prices”. It is also obvious that the energy price $\lambda$ controls the tradeoff between utility and energy cost.

VII. CONCLUSION

The paper has addressed a joint routing and power control problem in multi-hop wireless networks in the presence of interference. To this end, we have developed a primal-dual algorithm to solve a sequence of convex approximation problems and showed the convergence of the algorithm and its amenability to distributed implementation. Further, in view of high dynamics in wireless networks, it would be important to enhance the convergence speed and convergence rate of the proposed primal-dual algorithm.

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