Abstract—We consider the cross-layer utility maximization problem for wireless networks. It is well known that the optimal network control policy can be decomposed in three separate subproblems: 1) flow control at the network layer, 2) routing and scheduling at the network layer, and 3) resource allocation (RA) at the medium access control and physical layers. The main contribution of this paper is a power and rate control algorithm for the RA subproblem. In the case of single-hop networks, the proposed algorithm provides a locally optimal solution for the RA subproblem. Even though the global optimality of the solution cannot be guaranteed due to the nonconvexity of the problem, the numerical results show that the algorithm can provide significant gains at the network layer in terms of end-to-end rates and network congestion as compared to the optimal time division multiple access (TDMA) based RA. For solving the RA subproblem in the case of multi-hop networks, the proposed algorithm must be used in conjunction with an exhaustive search for the optimal set of transmitter nodes. However, the numerical results show that even with a random selection of the set of transmitter nodes, the proposed algorithm can provide significant improvement at the network layer in terms of end-to-end rates and network congestion as compared to the optimal TDMA based RA.

Index Terms—Cross-layer optimization, backpressure, resource allocation, wireless networks, signomial programming.

I. INTRODUCTION

In the late nineties, Kelly et. al. [1], [2] introduced the concept of network utility maximization (NUM) for fairness control in wireline networks. In [3]–[7], Lin and Shroff, Neely et al., Stolyar, Eryilmaz and Srikant extended the Kelly’s NUM framework to cover certain aspects of the wireless networks. An optimal network control policy for NUM can be decomposed in three separate subproblems: 1) flow control at the transport and the network layer, 2) routing and scheduling at the network layer, and 3) resource allocation (RA) at the medium access control (MAC) and physical (PHY) layers [4]. The flow control and routing and scheduling subproblems are convex optimization problems and can be solved easily.

Under relatively mild assumptions, the RA subproblem can be cast as a general weighted sum rate maximization over the achievable rate region [8]–[10]. The weights of the links are given by the largest non-negative differential backlogs. This resembles the well known backpressure algorithm introduced by Tassiulas and Ephremides in [11], [12] and further extended in [13], [14] to dynamic networks with power control capabilities.

In this paper, we focus on the RA subproblem for a slotted time network where the nodes cannot transmit and receive during the same time slot due to the self interference [15]. Every time slot, a network controller decides the set of active links and controls the power and rate allocation among the activated links. Finding the optimal set of active links for a general multi-hop problem is a combinatorial problem which requires exhaustive search over all possible activation sets [16]. Furthermore, even for a specified activation set the power and rate control problem results in a nonconvex optimization problem. Thus, finding the global solution is possible only in very special cases. For example, [3] provided solutions for the low signal-to-interference-and-noise-ratio (SINR) region and no globally optimal solutions are known for the general case of arbitrary SINR values. Therefore, developing computationally efficient algorithms to find even a locally optimal solution is still an open problem of crucial importance from both theoretical and practical perspective.

The main contribution of this paper is a power and rate control algorithm, derived via signomial programming, which is applicable for the whole SINR range even though the global optimality of the solution cannot be guaranteed. In the case of single-hop networks, the numerical results show that proposed algorithm provides substantial gains at the network layer in terms of end-to-end rates and network congestion at low and moderate interference levels as compared to the optimal TDMA based RA [17]. Furthermore, in the case of multi-hop networks, the numerical results show that the proposed algorithm provide significant improvements at the network layer, even by selecting the set of active links randomly at each time slot as compared to the optimal TDMA based RA.

The rest of the paper is organized as follows. System model and problem formulation are presented in Section II. The proposed power and rate control algorithm is presented in Section III. The numerical results are presented in Section IV and Section V concludes our paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. Network Model

Consider a wireless network with $M$ nodes. We denote the set of nodes by $\mathcal{M} = \{1, \ldots, M\}$. The links are represented by ordered node pairs $(m, k)_{m,k \in \mathcal{M}}$. We denote the set of all

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possible links by \( \mathcal{L} \). The existence of link \((m,k) \in \mathcal{L} \) means that direct transmission is possible from the source node \( m \) to the destination node \( k \).

The network is assumed to operate in a slotted time with slots normalized to integral units \( t \in \{1, 2, 3, \ldots \} \). Every time slot \( t \), a network controller performs two tasks: 1) decides the set of transmitter nodes and the set of receiver nodes denoted by \( T(t) \) and \( R(t) \) respectively, and 2) controls the power and rate allocation among the set of active links \( \mathcal{L}_a(t) = \{(m,k) \mid (m,k) \in \mathcal{L}, m \in T(t), k \in R(t)\} \). We assume that nodes cannot transmit and receive at the same time due to the self interference [15]. Therefore, without loss of generality, we assume that \( R(t) = \mathcal{M} \setminus T(t) \) for any specified set of transmitter nodes \( T(t) \).

We denote by \( p_{mk}(t) \) the power allocated to the link \((m,k)\) during time slot \( t \). The power allocation is subject to a maximum power constraint \( \sum_{k \neq m} p_{mk}(t) \leq P_{mk}^\text{max} \) for all nodes \( m \). Let \( c_{mk}(t) \) denote the channel power gain associated with link \((m,k)\) during time slot \( t \). Furthermore, we denote compactly by \( \mathbf{P}(t) \in \mathbb{R}_{+}^{M \times M} \) the overall power allocation matrix and \( \mathbf{C}(t) \in \mathbb{R}_{+}^{M \times M} \) the power gain matrix, i.e., \( p_{mk}(t) = \mathbf{P}(t)_{m,k} \) and \( c_{mk}(t) = \mathbf{C}(t)_{m,k} \). We assume that the rate of link \((m,k)\) during time slot \( t \) is given by

\[
r_{mk}(t) = \log(1 + \Gamma_{mk}(\mathbf{P}(t), \mathbf{C}(t))) \tag{1}
\]

where \( \Gamma_{mk}(\mathbf{P}, \mathbf{C}) \) represents the SINR at the input of the detector of the link \((m,k)\). It can be expressed as

\[
\Gamma_{mk}(\mathbf{P}, \mathbf{C}) = \frac{p_{mk}c_{mk}}{N_k + c_{mk} \sum_{j \neq k} p_{mj} + \sum_{i \neq m} c_{ik} \sum_{j} p_{ij}}
\]

where \( N_k \) denotes the noise power at the receiver \( k \).

B. Network Utility Maximization and Problem Formulation

We consider a network utility maximization (NUM) framework similar to the one considered in [9, Sec. 5.1], [4, Sec. III-A]. Exogenous data arrive at the source nodes and they are delivered to the destination nodes over potentially several multi-hop paths. We identify the data by their destinations, i.e., all data with the same destination are considered as one single commodity, regardless of their source. Specifically, we assume that there are \( S \leq M \) commodities in the network. Each commodity \( s, s = 1, \ldots, S \) is specified by a destination node \( d_s \). For every node, we define \( \mathcal{S}_m \subseteq \{1, \ldots, S\} \) as the set of commodities which can arrive exogenously at node \( m \).

Exogenously arriving data is not directly admitted to the network layer. Instead, the exogenous data is first placed in the transport layer storage reservoirs. At each source node, a set of flow controllers decide the amount of each commodity data admitted every time slot in the network. Let \( x_{ms}^n(t) \) denote the amount of data of commodity \( s \) admitted in the network at node \( m \) during time slot \( t \). At the network layer, each node maintains a set of \( S \) internal queues for storing the current backlog (or unfinished work) of each commodity. Let \( q_{ms}^n(t) \) denote the current backlog of commodity \( s \) stored at node \( m \). We formally define \( q_{ms}^n(t) = 0 \), i.e., it is assumed that data which is successfully delivered to its destination exits the network layer. Let \( x_{ms}^n \) be the average rate with which the data is sent from node \( m \) to \( d_s \) over potentially multiple multi-hop paths. Associated with each node-commodity pair \((m,s) \in \mathcal{S}_m\) we define a concave and non-decreasing utility function \( g_{ms}(x_{ms}^n) \), representing the “satisfaction” received by sending data from node \( m \) to node \( d_s \) at a time average rate of \( x_{ms}^n \) [bits/slot]. The NUM problem under stability constraints can be formulated as\(^1\)

\[
\begin{align*}
\text{maximize} & \quad \sum_{m=1}^{M} \sum_{s \in \mathcal{S}_m} x_{ms}^n (x_{ms}^n) \\
\text{subject to} & \quad (x_{ms}^n, m \in \mathcal{M}, s \in \mathcal{S}_m) \in \mathcal{L} \tag{2}
\end{align*}
\]

where the variables are \( x_{ms}^n \) and \( \mathcal{L} \) represent the network layer capacity region, defined as the closure of the set of all data rates \( \{x_{ms}^n | m \in \mathcal{N}, s \in \mathcal{S}_m\}^2 \) that are stably supportable by the network, considering all possible multi-hop routing and resource allocations [9, Def. 3.7]. A dynamic cross-layer control algorithm which achieves data rates \( x_{ms}^n \) arbitrarily close to the optimal operating point has been introduced in [4, Sec. III-A]. Particularized to our network model, every time slot \( t \), the algorithm performs the following steps:

**Algorithm 1: Dynamic Cross-Layer Control Algorithm**

1) **Flow Control**: for each node \( m \in \mathcal{M}, \{x_{ms}^n(t)\}_{s \in \mathcal{S}_m} \) is given by the set of rates \( \{x_{ms}^n\}_{s \in \mathcal{S}_m} \) which solves the following problem:

\[
\begin{align*}
\text{maximize} & \quad \sum_{s \in \mathcal{S}_m} V g_{ms}(x_{ms}^n) - x_{ms}^n q_{ms}^n(t) \\
\text{subject to} & \quad \sum_{s \in \mathcal{S}_m} x_{ms}^n \leq P_{ms}^\text{max}, \quad x_{ms}^n \geq 0, \tag{3}
\end{align*}
\]

where \( V > 0 \) and \( P_{ms}^\text{max} > 0 \) are algorithm’s parameters (see [9] for a detailed description).

2) **Routing and Scheduling**: for each link \((m,k)\), let

\[
\beta_{mk}(t) = \max \left\{ q_{mk}^n(t) - q_{mk}^n(t), 0 \right\} \tag{4}
\]

If \( \beta_{mk}(t) > 0 \), the commodity that maximizes the differential backlog is selected for potential routing over link \((m,k)\).

3) **Resource Allocation**: the power allocation \( \mathbf{P}(t) \) is given by \( \mathbf{P} \) whose entries \( p_{mk} \) solve the following problem:

\[
\begin{align*}
\text{maximize} & \quad \sum_{(m,k) \in \mathcal{L}_T} \beta_{mk}(t) \log(1 + \Gamma_{mk}(\mathbf{P}(t), \mathbf{C}(t))) \\
\text{subject to} & \quad T \subseteq \mathcal{M} \\
& \quad \sum_{k \in \mathcal{L}_T} p_{mk} \leq P_{mk}^\text{max} , \quad m \in \mathcal{T} \\
& \quad p_{mk} \geq 0, \quad (m,k) \in \mathcal{L}_T \\
& \quad p_{mk} = 0, \quad (m,k) \notin \mathcal{L}_T, \tag{5}
\end{align*}
\]

where \( \mathcal{L}_T = \{(m,k) \mid (m,k) \in \mathcal{L}, m \in \mathcal{T}, k \in \mathcal{M} \setminus T\} \) and \( \mathcal{L}_T^\emptyset = \{k \mid (m,k) \in \mathcal{L}_T\} \). The rate allocation is given by (1).

In this paper, we focus on the problem (5). The variables are the entries of the power allocation matrix \( \mathbf{P} \) and the set of transmitter nodes \( T \). Finding the optimal set of transmitter

\(^1\)For conciseness, we assume that all sessions have infinite demand at the transport layer [9, Sec. 5.2]. Nevertheless, the algorithm proposed in this paper is still applicable when this assumption is relaxed.

\(^2\)The set of data rates is assumed to be ordered.

\(^3\)Note that \( \mathcal{L}_T^\emptyset = \emptyset \) for all \( m \notin \mathcal{T} \).
nodes $T^*$ for a general fully connected multi-hop network is a combinatorial problem and it requires exhaustive search over all $2^M$ possible subsets of $M$. At each step, the optimal algorithm must solve the power optimization in (5) for a given set $T$. Note that the power optimization is still non-convex and, therefore, standard convex optimization technique cannot be directly applied to find the solution.

A computationally efficient algorithm which provides a locally optimal power allocation for a specified set of transmitter nodes $T$ is presented in the next section.

III. POWER CONTROL IN THE RA SUBPROBLEM

When the set of transmitter nodes $T$ is specified, RA subproblem (5) reduces to the following optimization problem:

$$\begin{align*}
\text{maximize} & \quad \sum_{(m,k) \in \mathcal{L}_T} \beta_{mk} \log (1 + \Gamma_{mk}) \\
\text{subject to} & \quad \sum_{k \in \mathcal{L}_T^m} p_{mk} \leq p_{mk}^\text{max}, \quad m \in T \\
& \quad p_{mk} \geq 0, \quad (m, k) \in \mathcal{L}_T, \quad (8)
\end{align*}$$

where the constraint $C1$ is specified at the bottom of this page, and the variables are $p_{mk}$ and $\Gamma_{mk}$ for all $(m, k) \in \mathcal{L}_T$. The objective function of problem (8) can be expressed as

$$\sum_{(m,k) \in \mathcal{L}_T} \beta_{mk} \log (1 + \Gamma_{mk}) = -\log \prod_{(m,k) \in \mathcal{L}_T} (1 + \Gamma_{mk})^{-\beta_{mk}}. \quad (9)$$

Since objective increases with respect to each $\Gamma_{mk}$ and $-\log(\cdot)$ is a decreasing function, problem (8) can be expressed as follows:

$$\begin{align*}
\text{minimize} & \quad \prod_{(m,k) \in \mathcal{L}_T} (1 + \Gamma_{mk})^{-\beta_{mk}} \\
\text{subject to} & \quad \sum_{k \in \mathcal{L}_T^m} p_{mk} \leq p_{mk}^\text{max}, \quad m \in T \\
& \quad p_{mk} \geq 0, \quad (m, k) \in \mathcal{L}_T, \quad (10)
\end{align*}$$

where the variables are $p_{mk}$ and $\Gamma_{mk}$, $(m, k) \in \mathcal{L}_T$. The optimization problem (10) is a signomial optimization problem [18]. Thus, it is not convex in general. In high SINR region $\Gamma_{mk} \gg 1$, it can be approximately approximated by a geometric program [19]. This approach means that the objective is replaced by the monomial function $\prod_{(m,k) \in \mathcal{L}_T} \Gamma_{mk}^{-\beta_{mk}}$. Clearly, the condition $\Gamma_{mk}^{-\beta_{mk}} \gg 1$ cannot be controlled (e.g., imposed as a constraint) without affecting the solution since $\Gamma_{mk}^{-\beta_{mk}}$ is a problem variable. Therefore, a solving method applicable to the whole SINR range is needed. Such a procedure consists of searching a close local minima by solving a sequence of geometric programs which locally approximate the original problem. This procedure is presented in the following.

**Lemma 1:** Let $f(\Gamma_1, \ldots, \Gamma_N) = d\prod_{n=1}^N \Gamma_n^\alpha$ be a monomial function [18] used to approximate a function $f_0$ of the form $f_0(\Gamma_1, \ldots, \Gamma_N) = \prod_{n=1}^N (1 + \Gamma_n)^{-\alpha_n}$, near the point $\hat{\Gamma} = (\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N)$. The parameters $d$ and $\alpha_n$ of the best monomial local approximation are given by

$$a_n = -\beta_n \hat{\Gamma}_n (1 + \hat{\Gamma}_n)^{-1}, \quad d = f_0(\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N) \prod_{n=1}^N \hat{\Gamma}_n^{-a_n}. \quad (11)$$

**Proof:** The monomial function $f$ is the best local approximation of $f_0$ near the point $\hat{\Gamma} = (\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N)$ if [18]

$$\begin{align*}
\left\{ \begin{array}{l}
f(\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N) = f_0(\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N) \\
\nabla f(\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N) = \nabla f_0(\hat{\Gamma}_1, \ldots, \hat{\Gamma}_N)
\end{array} \right.
\end{align*} \quad (12)$$

and by replacing the expressions of $f$ and $f_0$ in (12) we obtain the following system of equations

$$\begin{align*}
\left\{ \begin{array}{l}
d \prod_{n=1}^N \Gamma_n^\alpha_n = f_0(\Gamma_1, \ldots, \Gamma_N) \\
a_n \Gamma_n^{-d} \prod_{n=1}^N \Gamma_n^\alpha_n = -\beta_n f_0(\Gamma_1, \ldots, \Gamma_N) (1 + \Gamma_n)
\end{array} \right., n = 1, \ldots, N
\end{align*}$$

which have the solution given by (11).

By using the local approximation given by Lemma 1 in the objective function of problem (10), and ignoring the multiplicative constant $d$ which does not affect the problem solution, we obtain the following iterative algorithm.

**Algorithm 2:** Power control via signomial programming

1) Let the initial SINR guess $\hat{\Gamma} \in \mathbb{R}_+^{L_T \times 1}$.
2) Solve the following geometric program

$$\begin{align*}
\text{minimize} & \quad \prod_{(m,k) \in \mathcal{L}_T} \Gamma_{mk}^{-\beta_{mk}} \\
\text{subject to} & \quad (1 - \alpha) \hat{\Gamma}_{mk} \geq \Gamma_{mk}, \quad (m, k) \in \mathcal{L}_T \\
& \quad (1 + \alpha) \hat{\Gamma}_{mk} \geq \Gamma_{mk}, \quad (m, k) \in \mathcal{L}_T \\
& \quad \sum_{k \in \mathcal{L}_T^m} p_{mk} \leq p_{mk}^\text{max}, \quad m \in T \\
& \quad p_{mk} \geq 0, \quad (m, k) \in \mathcal{L}_T, \quad (13)
\end{align*}$$

where $\hat{\Gamma}_{mk} = [\hat{\Gamma}]_{m,k}$. Let the solution be $\Gamma^* \in \mathbb{R}_+^{L_T \times 1}$.
3) If $\max_{(m,k)} |\Gamma^*_{mk} - \hat{\Gamma}_{mk}| > \epsilon$ set $\hat{\Gamma} = \Gamma^*$ and go to Step 2, otherwise STOP.

The problem (13) is a geometric program which approximate the original signomial problem (10) around the point $\hat{\Gamma}$. The constant $\alpha < 1$ controls the desired approximation accuracy, and a typical value is $\alpha = 0.1$ [18].
IV. NUMERICAL RESULTS

To illustrate the specific behavior of the proposed Algorithm 2 under different interference and noise conditions, wireless networks with non-time-varying channel power gains are considered, i.e., for any link \((m, k) \in \mathcal{L}_m\), \(c_{mk}(t) = c_{mk}\) for all \(t\). For a fair comparison of different algorithms, the performance metrics, average sum rate \(\sum_{m \in \mathcal{M}} \sum_{s \in \mathcal{S}_m} \bar{x}^s_m\) and average network congestion \(\sum_{m \in \mathcal{M}} \sum_{s=1}^4 \bar{q}^s_m\) are considered. The time average rates \(\bar{x}^s_m\) and backlog \(\bar{q}^s_m\) are defined by \(\bar{x}^s_m = \lim_{T \to \infty} 1/T \sum_{t=1}^T x^s_m(t)\) and \(\bar{q}^s_m = \lim_{T \to \infty} 1/T \sum_{t=1}^T q^s_m(t)\) respectively [9].

A. Single-hop Networks

We have considered the single-hop network setup shown in Fig. 1. There are \(M = 8\) nodes and \(S = 4\) commodities and one distinct commodity arrives exogenously at every node \(m\) from the subset \(\{1, 2, 3, 4\} \subseteq \mathcal{M}\). Without loss of generality we assume that the nodes and commodities are labeled such that commodity \(i\) arrives at node \(i\) for any \(i \in \{1, 2, 3, 4\}\). The destination nodes are specified by the following commodity-destination node pairs \((s, d) \in \{(1, 5), (2, 6), (3, 7), (4, 8)\}\). We assume that the average rates \(\bar{x}^s_m\) corresponding to all commodities \(s \in \{1, 2, 3, 4\}\) are subject to proportional fairness, therefore, we select the utility functions \(g^s_m(\bar{x}^s_m) = \ln(\bar{x}^s_m)\).

![Fig. 1. Single-hop wireless network with \(M = 8\) nodes and \(S = 4\) commodities.](image)

Channel power gains \(c_{mk}^5, m \in \{1, 2, 3, 4\}, k \in \{5, 6, 7, 8\}\) are presented in Table I, where the interference among the nodes is parameterized by the scalar \(\rho\), which is referred to as interference coefficient. We assume that the noise power is equal for all receivers, i.e., \(N_k = N_0\) for all \(k \in \{5, 6, 7, 8\}\), and the maximum power constraint is the same for all transmitter nodes, i.e., \(p_{\text{max}} = p_{\text{max}}^0\) for all \(m \in \{1, 2, 3, 4\}\). The average SNR defined as \(\gamma = p_{\text{max}}^0/N_0\).

<table>
<thead>
<tr>
<th>TABLE I CHANNEL POWER GAINS</th>
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<tbody>
<tr>
<td>Node</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
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<td>4</td>
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Finally, we choose the Algorithm 1 parameters \(V = 100\) and \(R_{t_{\text{max}}} = \log(1 + \text{cld}_t \gamma)\) [4, Sec. III-D] for all \(t \in \{1, 2, 3, 4\}\).

Note that, \(c_{mk}(t) = c_{mk}\) for all \(t\).
some insight on the behavior of the proposed Algorithm 2 in the case of multi-hop networks, we use a random selection of the set of transmitter nodes $T(t)$ as follows. Every time slot $t$, we find first the transmitter node $tx(t)$ and the receiver node $rx(t)$ corresponding to the link activated by the optimal TDMA based RA. Then, we select randomly a subset of nodes $\bar{T}(t)$ from the set of remaining $M - 2$ nodes and let $\bar{T}(t) = T(t) \cup \{rx(t)\}$.

Figure 5 and 6 shows the dependence of the average sum rate $\sum_{m=1}^{9} \sum_{s \in S_m} \bar{x}_m^s$ and the average network congestion $\sum_{m=1}^{9} \sum_{s=1}^{\bar{q}_m}$ on $\gamma$. The Algorithm 1 is executed for 5000 time slots and to obtain $\bar{x}_m^s$ and $\bar{q}_m$ again we average over 100 time slots starting from $t = 4901$, i.e., $\bar{x}_m^s = 1/100 \sum_{t=4901}^{5000} x^s_m(t)$ and $\bar{q}_m = 1/100 \sum_{t=4901}^{5000} q_m(t)$. From Figure 5, we can observe that the proposed algorithm provides substantial gains in the average sum rate for the considered SNR values. Figure 6 shows that the gain in the average network congestion is more significant at moderate SNR values and as expected, the gain vanishes as SNR increases, since TDMA resource allocation is optimal for large SNR values.

### V. Conclusions

In this paper, we considered the cross-layer utility maximization problem for wireless networks. Specifically, we provided a power and rate control algorithm for the resource allocation (RA) subproblem. Unlike the existing solutions, our method is applicable for whole SINR range. In the case of
In single-hop networks, the proposed algorithm provides a locally optimal solution for the RA subproblem. The numerical results showed that the algorithm can provide significant gains at the network layer in terms of end-to-end rates and network congestion as compared to the optimal TDMA based RA. In multi-hop networks, the proposed algorithm must be used in conjunction with an exhaustive search for the optimal set of transmitter nodes. The numerical results showed that even with a random selection of the set of transmitter nodes, the proposed algorithm can provide significant gains at the network layer in terms of end-to-end rates and network congestion as compared to the optimal TDMA based RA.

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