Joint Congestion and Power Control in Fast-Fading Wireless Network using Successive Convex Approximation Method

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***Abstract*—We study the cross-layer design of congestion control and power allocation with outage constraint in an interference-limited multihop wireless networks. The conventional method of joint congestion control and power control relies on *static channel* and *high SIR* (signal-to-interference ratio) assumption which achieves only suboptimal results. By using a novel successive convex approximations method, we can attain the global optimal source rates and link powers in a distributed fashion exploiting message passing. Through simulations, our method converges faster than the previous work based on logarithm successive convex approximations.**

***Index Terms*—Utility maximization, congestion control and power allocation, distributed algorithms.**

I. Introduction

In wireless network, congestion control and power control have a mutual relationship in wireless multihop network. The congestion control regulates the source rates to avoid overwhelming any link capacity which depends on interference levels, which in turn decided by link transmit power control. The first joint congestion control and power control (JCPC) problem was characterized by Chiang [1]. The critical point of Chiang's proposed solution lies in the high-SIR approximation, which enables the transformation of an original nonconvex problem into a convex optimization problem, which has been shown to be suboptimal in the general case [2]. Also in [2], a generalized convexity has been established for the same optimization problem which allowed them to propose an algorithm named Alg. A that can achieve a globally optimal solution through messaging passing without high-SIR assumption. Due to the complicated convexification, however the rate allocation of Alg. A with explicit message passing no longer preserves the existing TCP stack like that of [1], which makes it less favorable. To take into account the TCP stack preserving, they continued propose an Alg. B employing a technique called logarithmic successive convex approximations.

However, in addition to the unfavorable high-SIR assumption, this work also assumes static fading wireless channels, which means that such an algorithm should be able to update source rates and link powers whenever the fading state changes. This assumption restricts its applicable scope to a slowly varying wireless channel. If we consider a realistic case of fast-fading channel, the update rate must be fast enough to keep track of changing fading states. This leads to the extravagant message-passing overhead and the excessive waste of signal processing energy due to frequent iterative updates.

In this paper, we investigate the JCPC problem in an interference-limited multihop network in a dynamic fading environment and with no assumption of high-SIR. Our objective is to maximize the aggregate utilities and minimize the total expended power. We aim to design a resource allocation scheme that does not have to keep track of the instantaneous fading state of the wireless channel. Instead, we allow outages to occur between successive updates; as a result, the updates can proceed on a much slower time scale (i.e., the same time scale as log-normal shadowing variations). We explicitly include the fading-induced outage constraint into the underlying cross-layer problem, where we account for the statistical variation in each link's SIR and allow the SIR to drop below a prescribed threshold with a predetermined probability. In addition to avoid high-SIR assumption yet preserve TCP stack, we propose a novel successive convex approximations method to iteratively transform the original nonconvex problem of JRPC into approximated convex problem, then the global optimal solution can converge distributively with message passing. Simulation results show that our method converge faster than existing work.

II. Related Work

In the literature, distributed algorithms for cross-layer design have been widely recognized as robust and practical methods to provide the efficiency and fairness of resource allocation in wireless multihop networks (e.g., [2]–[4]). Realizing the importance of convexity in this field, many works have employed the transformations of variables to convert the underlying nonconvex problems into the convex counterparts to facilitate the optimal algorithm design [2], [3], [5]–[8].

The idea of using outage probability constraint to updates network operations on a slower time scale was first considered in [9] to solve a power control problem in a single hop network, where the authors employed the centralized interior-point method for numerical implementation. [10] may be the first work utilizing an outage constraint to address cross-layer JCPC problem. The authors first consider the rate-outage

This research was supported by the MKE(The Ministry of Knowledge Economy), Korea, under the ITRC(Information Technology Research Center) support program supervised by the NIPA(National IT Industry Promotion Agency) (NIPA-2011-C1090-1121-0003). Dr. CS Hong is the corresponding.

978-1-4673-2493-9/12/$31.00 ©2012 IEEE

constraint, then reformulate it as a conventional source-rate constraint with a link outage capacity [11] using the upper bound on outage probability, which turns out to be an approximated optimization problem. Tran *et. al.* [7] tackled the nonconvexity of JCPC using a successive approximation method without high-SIR assumption, but this work also assumed static fading channel as in [1].

III. System Model and Problem Definition

We consider a wireless multihop network with $\mathcal{L} = \{1,\ldots,L\}$ logical links shared by $\mathcal{S} = \{1,\ldots,S\}$ sources. We assume that each source s emits a flow using a fixed set of links $L(s)$ on its route. The set of sources using link l is denoted by $S(l) = \{s|\, l \in L(s)\}$.

In this context, each source s always has data to transmit and it obtains a utility $U_s(x_s)$ when transmitting a flow at data rate x_s. We denote the vector of source rates $\mathbf{x} = [x_1,\ldots,x_S]^T$. The utility function $U_s(x_s)$ is assumed to be twice continuously differentiable, non-decreasing and strictly concave in x_s. A utility can be interpreted as the level of satisfaction attained by a user as a function of the resource allocation.

At the physical layer, we use a similar CDMA physical model to that in [1] where simultaneous communications can occur, resulting in multiple-access interference. The instantaneous capacity of link $l \in \mathcal{L}$ is a global and nonconvex function of link power vector $\mathbf{P} = [P_1,\ldots,P_L]^T$

$$c_l(\gamma_l(\mathbf{P})) = W\log(1 + K\gamma_l(\mathbf{P})), \tag{1}$$

where W is the baseband bandwidth and K is a constant depending on modulation, coding scheme and bit-error rate (BER) [11]. Unless otherwise stated, we assume $W = K = 1$ without loss of generality. $\gamma_l(\mathbf{P})$ is the *instantaneous* SIR of link l which is defined as

$$\gamma_l(\mathbf{P}) = \frac{P_l G_{ll} F_{ll}}{\sum_{k\neq l} P_k G_{lk} F_{lk} + n_l}, \tag{2}$$

where the gain G_{lk} represents a large-scale, slow-fading channel (e.g., distance-dependent path-loss or log-normal shadowing), the gain F_{lk} models a small-scale, fast-fading channel from the transmitter on link k to the receiver on link l, and n_l is the thermal noise power at each receiver of link l.
We assume a non-line-of-sight radio transmission environment among transmitters and receivers. In this case, we can employ a Rayleigh fading model, where exponential random variables F_{lk} are i.i.d. Over the considered time scale, G_{lk} is assumed to be constant. Then, the *certainty-equivalent* SIR is

$$\bar{\gamma}_l(\mathbf{P}) = \frac{E[P_l G_{ll} F_{ll}]}{E\left[\sum_{k\neq l} P_k G_{lk} F_{lk} + n_l\right]} = \frac{P_l G_{ll}}{\sum_{k\neq l} P_k G_{lk} + n_l}, \tag{3}$$

which can be interpreted as the link l's SIR by assuming fading-free channels with normalized $E[F_{lk}] = 1,\ \forall k$ [9].
Before proceeding, we introduce the notations relating to the operating ranges of vectors of source rates $\mathbf{x}$ and link powers $\mathbf{P}$ as follows

$$\mathcal{X} = \{x_s, s \in \mathcal{S}|\; x_s^{min} \le x_s \le x_s^{max}\}, \tag{4}$$

$$\mathcal{P} = \{P_l, l \in \mathcal{L}|\; P_l^{min} \le P_l \le P_l^{max}\}. \tag{5}$$

It is implicitly understood that the NUM problem of [1] is linked directly with a determined fading state (i.e., both F_{lk} and G_{lk} are fixed). Hence, for every new channel state, any algorithm must be recalculated to determine the new optimal solutions. From a practical viewpoint, this will prohibit the effectiveness of such a message-passing iterative algorithm in a fast-fading channel environment. For example, when the fading rate increases, the iteration rate must also increase in order to keep track of new channel states, thus producing a considerable message-passing overhead so that the scheme is no longer able to track the channel states and collapses. In order to alleviate this problem, instead of seeking optimal source rates and powers based on instantaneous link capacities, we allow the network to experience a tolerable level of outage so that resources can be allocated on a much slower time scale [2], [9]. To account for this issue, we incorporate the outage constraint into the underlying NUM as follows

$$\begin{aligned} \underset{\mathbf{x}\in\mathcal{X},\mathbf{P}\in\mathcal{P}}{\text{maximize}} \quad & \sum_s U_s(x_s) - \sum_l P_l \\ \text{subject to} \quad & \sum_{s\in S(l)} x_s \le c_l(\bar{\gamma}_l(\mathbf{P})), \quad \forall l \\ & Pr\left[\gamma_l \le \gamma_l^{th}\right] \le \xi_l, \quad \forall l \end{aligned} \tag{6}$$

where $c_l(\bar{\gamma}_l(\mathbf{P})) = \log(1+\bar{\gamma}_l(\mathbf{P}))$, $Pr\left[\gamma_l \le \gamma_l^{th}\right]$ is the outage probability defined as the proportion of time that some SIR threshold γ_l^{th} is not met for a sufficient reception at link l's receiver, and $\xi_l \in (0,1)$ is the outage probability threshold on link l. The objective is to maximize the network utility while minimizing the total power. For a Rayleigh fading channel, as in [9], the closed-form outage probability is

$$\Pr[\gamma_l \le \gamma_l^{th}] = 1 - \exp\left(-\frac{n_l\gamma_l^{th}}{P_l G_{ll}}\right)\prod_{k\neq l}\left(1 + \gamma_l^{th}\frac{P_k G_{lk}}{P_l G_{ll}}\right)^{-1}. \tag{7}$$

Then problem (6) can be rewritten as

$$\begin{aligned} \underset{\mathbf{x}\in\mathcal{X},\mathbf{P}\in\mathcal{P}}{\text{maximize}} \quad & \sum_s U_s(x_s) - \sum_l P_l \\ \text{subject to} \quad & \sum_{s\in S(l)} x_s \le c_l(\bar{\gamma}_l(\mathbf{P})), \quad \forall l \\ & \prod_{k\neq l}\left(1 + \gamma_l^{th}\frac{P_k G_{lk}}{P_l G_{ll}}\right) \le \Omega_l(P_l), \quad \forall l \end{aligned} \tag{8}$$

where

$$\Omega_l(P_l) = \frac{\exp(-n_l\gamma_l^{th}/P_l G_{ll})}{1-\xi_l}. \tag{9}$$

IV. A Novel Successive Convex Approximations Method

A. Approximated Convex Optimization Problem

In order to turn the original nonconvex problem (8) to an approximated convex problem, we begin to form a new lower bound approximation to the constraint (8)

$$\sum_{s:l\in L(s)} x_s \le \hat{c}_l(\mathbf{P}) \le c_l(\mathbf{P}). \tag{10}$$

Henceforth, we assume $W = K = 1$ without loss of generality. We note that $c_l(\mathbf{P})$ can be rewritten in the form

$$c_l(\mathbf{P}) = \log\left(\sum_{k\in\mathcal{L}} G_{lk}P_k + n_l\right) - \log\left(\sum_{k\neq l} G_{lk}P_k + n_l\right)$$

Making use of arithmetic-geometric mean inequality, where it states that $\sum_i \theta_i u_i \geq \prod_i u_i^{\theta_i}$ with $u_i \geq 0$, $\theta_i > 0$ $\forall i$ and $\sum_i \theta_i = 1$, we have a similar inequality $\sum_i v_i \geq \prod_i (v_i/\theta_i)^{\theta_i}$ by letting $v_i = \theta_i u_i$, and the equality happens when $\theta_i = v_i/\sum_i v_i$.

Result 1: For each link l with a vector $\boldsymbol{\theta}^l = [\theta_1^l, \theta_2^l, \ldots, \theta_{L+1}^l]$

$$\sum_{k\in\mathcal{L}} G_{lk}P_k + n_l \geq \prod_{k=1}^{L}\left(\frac{G_{lk}P_k}{\theta_k^l}\right)^{\theta_k^l}\left(\frac{n_l}{\theta_{L+1}^l}\right)^{\theta_{L+1}^l}, \quad (11)$$

and the equality happens when

$$\begin{aligned} \theta_k^l &= \frac{G_{lk}P_k}{\sum_{k\in\mathcal{L}} G_{lk}P_k + n_l}, \quad k = 1, \ldots, L \\ \theta_{L+1}^l &= \frac{n_l}{\sum_{k\in\mathcal{L}} G_{lk}P_k + n_l} \end{aligned} \quad (12)$$

Because $\log(.)$ is an increasing function of positive variables, by taking logarithm on both sides of (11) we have

$$\log\left(\sum_{k\in\mathcal{L}} G_{lk}P_k + n_l\right) \geq$$
$$\sum_{k=1}^{L}\theta_k^l \log\left(\frac{G_{lk}P_k}{\theta_k^l}\right) + \theta_{L+1}^l \log\left(\frac{n_l}{\theta_{L+1}^l}\right) \doteq f(\mathbf{P}, \boldsymbol{\theta}^l) \quad (13)$$

Letting $\hat{c}_l(\mathbf{P}, \boldsymbol{\theta}^l) = f(\mathbf{P}, \boldsymbol{\theta}^l) - \log\left(\sum_{k\neq l} G_{lk}P_k + n_l\right)$, we have

$$\hat{c}_l(\mathbf{P}, \boldsymbol{\theta}^l) \leq c_l(\mathbf{P}) \quad (14)$$

and the equality happens when (12) holds.
Letting $\hat{P}_l = \log P_l$, it is easy to see that

$$f(\hat{\mathbf{P}}, \boldsymbol{\theta}^l) = \sum_{k=1}^{L}\theta_k^l \hat{P}_k + \sum_{k=1}^{L}\theta_k^l \log\left(\frac{G_{lk}}{\theta_k^l}\right) + \theta_{L+1}^l \log\left(\frac{n_l}{\theta_{L+1}^l}\right)$$

is a linear function of $\hat{\mathbf{P}}$, so

$$\hat{c}_l(\hat{\mathbf{P}}, \boldsymbol{\theta}^l) = f(\hat{\mathbf{P}}, \boldsymbol{\theta}^l) - \log\left(\sum_{k\neq l} G_{lk}e^{\hat{P}_k} + n_l\right) \quad (15)$$

is a concave function of $\hat{\mathbf{P}}$ (recall that log-sum-exponent is convex). We have the approximated convex optimization problem of the original one (8) with variables $\mathbf{x}$ and $\hat{\mathbf{P}}$ ($\boldsymbol{\theta}^l$ is fixed) as following

$$\begin{aligned} \underset{\mathbf{x}\in\mathcal{X}, \hat{\mathbf{P}}\in\hat{\mathcal{P}}}{\text{maximize}} \quad & \sum_s U_s(x_s) - \sum_l e^{\hat{P}_l} \quad (16) \\ \text{subject to} \quad & \sum_{s\in S(l)} x_s \leq \hat{c}_l(\hat{\mathbf{P}}, \boldsymbol{\theta}^l), \quad \forall l \\ & \sum_{k\neq l} \log\left(1 + e^{\hat{P}_k - \hat{P}_l}\frac{\gamma_l^{th}G_{lk}}{G_{ll}}\right) \leq \log \Omega_l\left(e^{\hat{P}_l}\right), \quad \forall l. \end{aligned}$$

B. Optimal Solution of Approximated Convex Problem

The Lagrangians of (16) can be decomposed into two separate partial functions as follows

$$L(\hat{\mathbf{x}}, \hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = L_{\hat{x}}(\hat{\mathbf{x}}, \boldsymbol{\lambda}) + L_{\hat{P}}(\hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}), \quad (17)$$

where

$$L_x(\mathbf{x}, \boldsymbol{\lambda}) = \sum_s U(x_s) - \sum_s \sum_{l\in L(s)} \lambda_l x_s \quad (18)$$

$$L_{\hat{P}}(\hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}) = \sum_l \lambda_l \hat{c}_l(\hat{\mathbf{P}}, \boldsymbol{\theta}^l) + \nu_l \log \Omega_l\left(e^{\hat{P}_l}\right)$$
$$- e^{\hat{P}_l} - \nu_l \sum_{k\neq l} \log(1 + e^{\hat{P}_k - \hat{P}_l}\frac{\gamma_l^{th}G_{lk}}{G_{ll}}). \quad (19)$$

Here $\boldsymbol{\lambda} = [\lambda_1, \ldots, \lambda_L]^T$ and $\boldsymbol{\nu} = [\nu_1, \ldots, \nu_L]^T$, the Lagrange multipliers of the first and second constraint, are considered the link *congestion price* and *outage price*, respectively, following the spirit of [12]. The partial dual functions can be represented as

$$D_1(\boldsymbol{\lambda}) = \max_{\hat{\mathbf{x}}\in\hat{\mathcal{X}}} \quad L_{\hat{x}}(\hat{\mathbf{x}}, \boldsymbol{\lambda}), \quad (20)$$

$$D_2(\boldsymbol{\lambda}, \boldsymbol{\nu}) = \max_{\hat{\mathbf{P}}\in\hat{\mathcal{P}}} \quad L_{\hat{P}}(\hat{\mathbf{P}}, \boldsymbol{\lambda}, \boldsymbol{\nu}), \quad (21)$$

which are separate maximization problems. We denote $D(\boldsymbol{\lambda}, \boldsymbol{\nu}) = D_1(\boldsymbol{\lambda}) + D_2(\boldsymbol{\lambda}, \boldsymbol{\nu})$. The dual problem of (16) is

$$\min_{(\boldsymbol{\lambda}, \boldsymbol{\nu})\geq \mathbf{0}} \quad D(\boldsymbol{\lambda}, \boldsymbol{\nu}). \quad (22)$$

The maximization (20) is the conventional rate control problem which is implicitly solved by the congestion control mechanism for different U_s [1], hence preserving the existing TCP stack. The second maximization (21) is the power control problem.

With the utility's assumption, Slater condition holds leading to strong duality [13]. We have the following result.

Result 2: The optimal solution $(\mathbf{x}^*, \mathbf{P}^*, \boldsymbol{\lambda}^*)$ can be achieved if the variables update iteratively as following until convergence
Rate control: The source rate updates

$$x_s(t+1) = U_s^{'-1}\left(\sum_{l\in L(s)} \lambda_l(t)\right) \quad (23)$$

, where $U_s^{'-1}$ is the inverse of the first derivative of utility.
Power control: The link power updates

$$P_l(t+1) = \left[\frac{\Delta_l(t)}{1 + \sum_{k\neq l}\left(G_{kl}\hat{m}_k(t) + \nu_k(t)\frac{G_{kl}\tilde{m}_k(t)}{1+G_{kl}\tilde{m}_k(t)P_l(t)}\right)}\right]_{P_{min}}^{P_{max}} \quad (24)$$

where

$$\Delta_l(t) = \lambda_l(t)\theta_l^l - \nu_l(t)\tilde{m}_l(t)\frac{n_l}{\log(1-\xi_l)}, \quad (25)$$

$$\hat{m}_k(t) = \frac{\lambda_k(t)\bar{\gamma}_k(t)}{G_{kk}P_k(t)}, \quad (26)$$

$$\tilde{m}_k(t) = \frac{\gamma_k^{th}}{G_{kk}P_k(t)}. \quad (27)$$

Link Congestion Price Update:

$$\lambda_l(t+1) = \left[\lambda_l(t) - \kappa(t)\left(\hat{c}_l(\hat{\mathbf{P}}(t), \boldsymbol{\theta}^l) - \sum_{s \in S(l)} x_s(t)\right)\right]^+ \tag{28}$$

Link Outage Price Update:

$$\nu_l(t+1) =$$
$$\left[\nu_l(t) - \kappa(t)\left(\log \Omega_l\left(P_l(t)\right) - \sum_{k \neq l} \log\left(1 + \gamma_l^{th} \frac{G_{lk} P_k(t)}{G_{ll} P_l(t)}\right)\right)\right] \tag{29}$$

where $\kappa(t)$ is the step size and $[z]^+ = \max\{z, 0\}$.

Proof: Analogously to [7], by setting $\frac{\partial L_x(\mathbf{x},\boldsymbol{\lambda})}{\partial x_s} = 0$ and $\frac{\partial L_{\hat{P}}(\hat{\mathbf{P}},\boldsymbol{\lambda},\boldsymbol{\nu})}{\partial \hat{P}_l} = 0$, we have the congestion control update (23) solves the maximization problem (20) and the power update (24) solves the maximization problem (21) respectively, for a fixed $(\boldsymbol{\lambda}, \boldsymbol{\nu})$. The updates of (28) and (29) shows that we apply the projected gradient-descent method to solve the dual problem (22), which guarantees the convergence of dual variable with the appropriately chosen stepsize $\kappa(t)$ [13]. ■

Remarks:

1) The congestion control update (23) is well-known in the literature [14]. It has been shown in [14] that we can reuse existing distributed TCP algorithms and different TCP algorithms solve for different utility functions. For example, $U_s(x_s) = \alpha_s d_s \log x_s$ is shown to be associated with TCP Vegas, where α_s is the Vegas parameter and d_s is the propagation delay. TCP Reno-1 and Reno-2 are associated with the utility functions $U_s(x_s) = \frac{\sqrt{3/2}}{D_s} \tan^{-1}\left(\sqrt{2/3} x_s D_s\right)$ and $U_s(x_s) = \frac{1}{D_s} \log \frac{x_s D_s}{2 x_s D_s + 3}$ respectively, where D_s is propagation delay plus congestion-induce queueing delay.
2) Link power control is analogous to that of Algorithm 1. Each receiver of link k broadcasts its control message containing three real-value fields, $\hat{m}_k(t)$, $\tilde{m}_k(t)$ and $\nu_k(t)$. Each transmitter of link l then receives these values, estimates G_{kl} by using the training sequences and updates its power according to (24) using both congestion price and outage price.
3) The link outage price update (29) needs not only the information of its local link power but also the individual received powers of other interfering transmitters. This requires that the receiver be able to individually measure each interfering power, which might be impractical. Another way to solve this issue is to reserve another field (i.e., the fourth field) which contains $P_k(t)$ in the control message broadcast by the receiver of link k.
4) The congestion price update (28) only needs its link local information including the ingress rate and received signal measurement.

C. Successive Convex Approximations: Algorithm and Optimality

We continue presenting an algorithm that can achieve the globally optimal solutions of nonconvex problem (8) by solving successively the approximated problem (16).

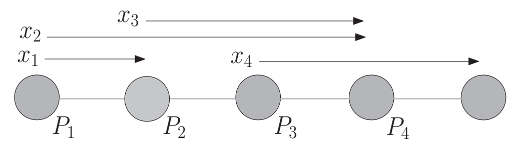

Fig. 1: Network Topology

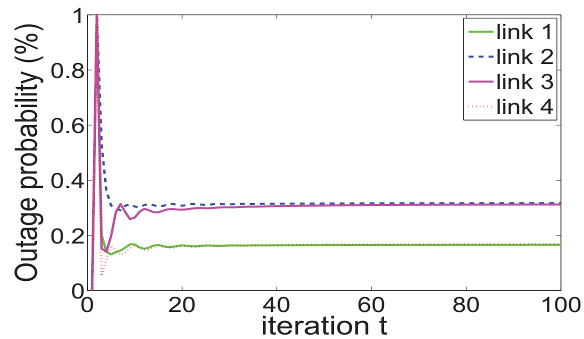

Fig. 3: Outage probabilities' convergence of Algorithm 1.

TABLE I: Convergence Speed Comparison

ϵ	Algorithm 1		log successive convex	
	Inner Convg.	Outer Convg.	Inner Convg.	Outer Convg.
10^{-3}	33.97	7.26	94.01	8.44
10^{-4}	41.97	9.78	143.46	10.52
10^{-5}	77.44	10.94	186.67	12.38

Algorithm 1: A Novel Successive Convex Approximations

1) Initialize $(\mathbf{x}, \mathbf{P}) = 0$, $\tau = 1$
2) Form the τ-th approximated convex problem (16) of the original problem (8) by updating $\boldsymbol{\theta}^{l^{(\tau)}}$, $\forall l$ with (12).
3) Solve the τ-th approximated convex problem (16) for optimal solution $(\mathbf{x}^{*(\tau)}, \mathbf{P}^{*(\tau)})$ as in section IV-B.
4) Increment τ and go to step 2 until convergence.

Theorem 1: The series of approximations of Algorithm 1 converge to the stationary points satisfying the Karush-Kuhn-Tucker (KKT) conditions of the original problem (8).

Proof: Letting $h(\mathbf{x}, \mathbf{P}) = \frac{\sum_{s:l \in L(s)} x_s}{c_l(\mathbf{P})}$ and $\hat{h}(\mathbf{x}, \mathbf{P}) = \frac{\sum_{s:l \in L(s)} x_s}{\hat{c}_l(\mathbf{P})}$, we need to prove that this series of approximations satisfies the following properties according to [15]

1) $h(\mathbf{x}, \mathbf{P}) \leq \hat{h}(\mathbf{x}, \mathbf{P})$
2) $h(\mathbf{x}^{\mathbf{o}}, \mathbf{P}^{\mathbf{o}}) = \hat{h}(\mathbf{x}^{\mathbf{o}}, \mathbf{P}^{\mathbf{o}})$
3) $\nabla h(\mathbf{x}^{\mathbf{o}}, \mathbf{P}^{\mathbf{o}}) = \nabla \hat{h}(\mathbf{x}^{\mathbf{o}}, \mathbf{P}^{\mathbf{o}})$, where $(\mathbf{x}^{\mathbf{o}}, \mathbf{P}^{\mathbf{o}})$ is the optimal solution of the previous iteration.

Conditions 1) and 2) are clearly satisfied with (12) and (14). It is straightforward to verify condition 3) by taking derivative. Then, the globally optimal convergence of Algorithm 1 can be proved similarly as in [2].

V. Simulation Results

We consider a network topology as in Fig. 1 with 4 flows and 5 nodes placed equally at a distance $d = 20$

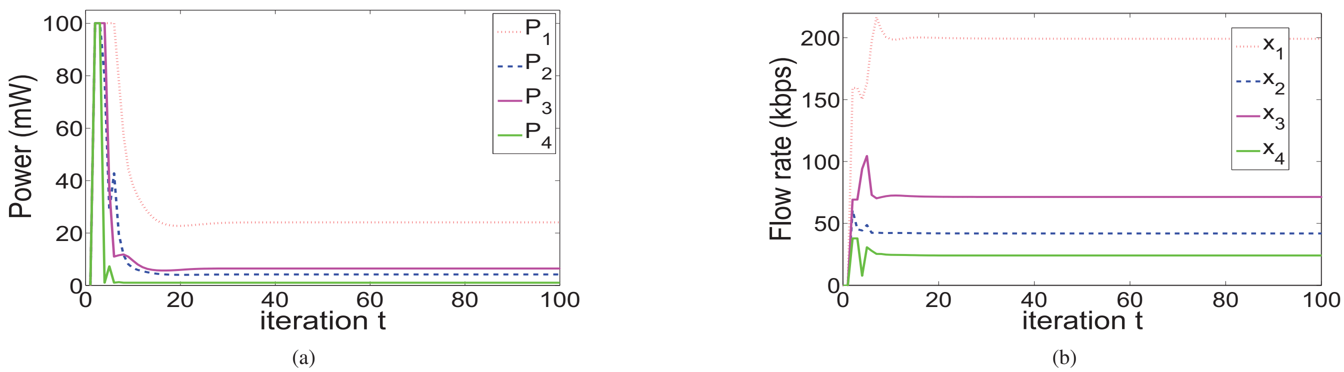

Fig. 2: Convergence of Algorithm 1 (a) link powers, (b) flow rates.

m. The baseband bandwidth W is set to 32 kHz, and we use $K = -1.5/\log(5\text{BER})$ with BER $= 10^{-3}$ for MQAM modulion [11]. The slow-fading channel gain is assumed to be $h(d) = h_o(\frac{d}{100})^{-4}$, where h_o is a reference channel gain at a distance of 100 m. The maximum power, noise and h_o are selected so that the average receive SNR at 100 m is 30 dB. We choose $P_l^{min} = 1$ mW and $P_l^{max} = 100$ mW, while $x_s^{min} = 0$, and x_s^{max} is adjusted dynamically with respect to link capacities. Since inner links suffer from more interference than do outer links, we set the outage probability thresholds ξ_l of link 2 and link 3 to 0.3 and those of link 1 and link 4 to 0.2. The SIR thresholds γ_l^{th} of the four links are set to (0.6 0.2 0.2 0.6) dB. The utility function of all users is $\log(.)$. We use two criteria to evaluate the convergence-speed performance: convergence condition of solving step 3 (i.e. inner convergence) and convergence at step 4 (i.e. outer convergence) of Algorithm 1 represented by $\max_{l\in\mathcal{L}} |P_l(t) - P_l(t-1)| < \epsilon$ and $\max_{l\in\mathcal{L}} |P_l^{*(\tau)} - P_l^{*(\tau-1)}| < \epsilon$ respectively, where ϵ is a small number. Table I shows the average number of iterations over 100 realizations with various values of ϵ. We see that our scheme converge faster than Alg. B of [2] (i.e. log successive approximation), especially with inner convergence. For example, the proposal converges 3 times faster with $\epsilon = 10^{-4}$. The corresponding flow rate and power convergence of our Algorithm 1 are shown in Figs. 2b and 2a. The outage probabilities of three schemes also converge to the desired values similarly as in Fig. 3

VI. Conclusion

We propose an algorithm using successive approximations method to transform the original nonconvex problem of JCRP problem into convex problem, then the global optimal solution can converge distributively with message passing. Simulation results show that our method can outperform previous work.

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