Cross-Layer Resource Allocation in Multi-interface Multi-channel Wireless Multi-hop Networks

Wei Feng, Suili Feng, Yongzhong Zhang, and Xiaowei Xia

In this paper, an analytical framework is proposed for the optimization of network performance through joint congestion control, channel allocation, rate allocation, power control, scheduling, and routing with the consideration of fairness in multi-channel wireless multi-hop networks. More specifically, the framework models the network by a generalized network utility maximization (NUM) problem under an elastic link data rate and power constraints. Using the dual decomposition technique, the NUM problem is decomposed into four subproblems — flow control; next-hop routing; rate allocation and scheduling; power control; and channel allocation — and finally solved by a low-complexity distributed method. Simulation results show that the proposed distributed algorithm significantly improves the network throughput and energy efficiency compared with previous algorithms.

Keywords: Wireless multi-hop networks, congestion control, channel allocation, power control, scheduling, routing.

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I. Introduction

A fundamental problem in networking is the allocation of limited resources among the users of a network. In the traditional layered network architecture, resources are allocated independently within each layer in the Open Systems Interconnection (OSI) model. This methodology has many advantages. For example, protocols in one layer can be designed, enhanced, or even replaced without any impact on other protocol layers. However, design problems that have been studied in isolation, such as routing, channel assignment, power control, topology control, and so on, are so closely linked through the reality of wireless interference. For example, it may happen that data packets are routed on a high interference path in the network. This necessitates the link scheduling to yield a high throughput schedule and the channel allocation to re-allocate appropriate channels along this path. This highlights the need for the designing of link scheduling, channel allocation, and routing as a joint problem.

In fact, there has been a fast expansion of research interest in this area since Kelly first modeled the framework of cross-layer design as an NUM problem in his seminal work [1]. Motivated by it, the researches model the cross-layer resource allocation as different network utility maximization (NUM) problems, most of which are concerned with maximizing the data rate of each user [2]–[3], minimizing power consumption [4]–[5] and outage probability [6]. With these generalized objectives, problems between different layers are studied together. For example, a joint design of power control in the physical layer and congestion control in the transport layer for wireless ad hoc

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networks was proposed in [7]. A jointly optimal channel assignment and congestion control problem for multi-channel wireless mesh networks was solved in [8]. In [9], Chen and others presented a jointly optimal design of cross-layer congestion control, routing, and scheduling for ad hoc networks. In [10], an analytical framework was introduced for the optimization of transmission control protocol performance through joint channel coding and power management in satellite communications. Reference [11] endeavored to address the lack of a joint routing and sleep scheduling scheme in wireless sensor networks by incorporating the design of the two components into one optimization framework. Reference [12] discussed a joint routing, congestion control, channel allocation, and scheduling_algorithm for multi-channel multi-interface wireless multi-hop networks. In addition, a joint multipath routing, channel allocation, and scheduling problem was discussed in [13] for wireless multi-hop and wireless multi-channel systems. References [14] to [17] are different research results on cross-layer design, proposed recently. However, cross-layer resource allocation has not been fully explored yet. None of these algorithms have jointly considered congestion control, channel allocation, rate allocation, power control, scheduling, and routing this complex problem.

In this paper, we propose a distributed joint congestion control, channel allocation, rate allocation, power control, scheduling, and routing algorithm (JCCRPSR) for multi-radio multi-channel wireless multi-hop networks (MRMC-WMHNs). The cross-layer resource allocation is modeled as an NUM problem with an elastic link data rate and power constraints. Using the dual decomposition technique, the NUM problem can be decomposed into the following four subproblems: flow control; next-hop routing; rate allocation and scheduling; power control; and channel allocation. Finally, these subproblems are solved with different low-complexity distributed methods.

The rest of this paper is organized as follows. The system model and constrained optimization problem are described in Section II. The distributed algorithm is presented in Section III. Simulation results and discussions are presented in Section IV, and Section V concludes the paper.

II. System Model and Problem Formulation

1. Network Model

Consider a WMHN that contains a set $\mathcal{N}$ of nodes and a set $\mathcal{L}$ of logical links. The nodes and links are labeled with the integer values $n = 1, 2, \ldots, N$ and the integer values $l = 1, 2, \ldots, L$, respectively. Let $\langle m, n \rangle$ denote a bidirectional link, which contains two logical links, (m, n) and (n, m); that is, the connectivity between the nodes is assumed to be symmetric. The sets of incoming and outcoming logical links of node n are defined as $L_n^{\text{in}} \in \mathcal{L}$ and $L_n^{\text{out}} \in \mathcal{L}$, respectively. Similarly, the sets of in-neighbors and out-neighbors of node n are labeled $N_n^{\text{in}} = \{m : (m,n) \in L_n^{\text{in}}\}$ and $N_n^{\text{out}} = \{m : (n,m) \in L_n^{\text{out}}\}$, respectively. Each node n is provided with I_n half-duplex wireless interfaces, and the set of logical links that use radio $k \in I_n$ at node n is denoted by L_n^k. At any given time, each interface can be tuned to any one of C channels, and the set of available channels is denoted by $\Theta = \{1, 2, \ldots, C\}$.

Traffic flows are, in general, carried over multi-hop routes. A sequence of connected logical links $l \in L(s)$ forms a route for flow $s \in \mathcal{S}$, where $\mathcal{S} = \{1, 2, \ldots, S\}$ is the set of flows in the network. Let $f_S \in \boldsymbol{F}$ be the transmission rate of flow s, where $\boldsymbol{F} = [f_1, f_2, \ldots, f_S]$ is the set of transmission rate. For an arbitrary node n, let $f_n^{(\mathrm{s})} \geq 0$ denote the sth flow rate generated by node n. If node n is not the source node of flow s, then $f_n^{(\mathrm{s})} = 0$; otherwise, $f_n^{(\mathrm{s})} = f_s$.

In addition, the link flow rate vector, $\boldsymbol{R}$, is defined to be $\boldsymbol{R} = [r_{mn}^{(1)}, r_{mn}^{(2)}, \ldots, r_{mn}^{(S)}]$, in which the element signifies the rate for each flow on link (m, n). Based on this, the aggregated flow rate on link (m, n) can be denoted as $r_{mn} = \sum_{s \in \mathcal{S}} r_{mn}^{(s)}$. The topology generation algorithm Hyacinth, proposed in [8], is used to form a logical topology that is free from the ripple effect. The general protocol interference model is adopted so that the conflict graph can be employed to capture the contention relations among links. The network is assumed to operate in slotted time, with the slots being normalized to a set of integer values t ($t = 1, 2, \ldots$).

2. Problem Formulation

The goal of the proposed algorithm is to solve the following optimization problem:

$$\max_{\boldsymbol{F},\boldsymbol{X},\boldsymbol{P},\boldsymbol{R}} \sum_{s \in \mathcal{S}} U(f_s) \tag{1}$$

s.t.

$$\boldsymbol{x}_l 1^T = 1, \quad \forall l \in \mathcal{L}, \tag{2}$$

$$\sum_{c=1}^{C} y_n^{(c)} \leq I_n, \tag{3}$$

$$0 \leq \sum_{m \in N_n^{\text{out}}} P_{nm} \leq P_n^{\max},$$

$$f_n^{(s)} + \sum_{m:(m,n) \in L_s, m \in N_n^{\text{in}}} r_{mn}^{(s)} \leq \sum_{q:(n,q) \in L_s, q \in N_n^{\text{out}}} r_{nq}^{(s)}, \tag{4}$$

$$\forall n \in \mathcal{N}, n \neq d_s, \forall s \in \mathcal{S}, \tag{5}$$

$$r_l = \sum_{s \in \mathcal{S}} r_l^{(s)} \leq C_l(\boldsymbol{X}, \boldsymbol{P}), \; l \in \mathcal{L}, \tag{6}$$

and

$$C_l(\boldsymbol{X},\boldsymbol{P}) = B\log_2\left[1+\left(K\times\frac{P_l g_{ll}}{\sum_{i\neq l}(\mathbf{x}_l^T\mathbf{x}_i P_i g_{il}+n_l)}\right)\right],\ l\in\mathcal{L}. \quad (7)$$

Equation (1) is the objective function. Here, the utility, $U(f_s)$, is equivalent to $\log f_s$ [3] and is proved to be twice continuously differentiable, non-decreasing, and strictly concave. The objective function is used to implement proportional fairness among the flows.

Equation (2) represents the channel constraint. A binary link-channel allocation matrix, $\boldsymbol{X}_{L\times C}\in R^{L\times C}$, is firstly defined. Then, let $\boldsymbol{x}_l=[\boldsymbol{x}_{l1},\boldsymbol{x}_{l2},\ldots,\boldsymbol{x}_{lL}]^T$ denote the lth row of $\boldsymbol{X}$, in which the element is defined as follows: for any logical link $l\in\mathcal{L}$ and any channel $c\in\Theta$, the element x_{lc} is equal to one if channel c is allocated to logical link l; otherwise, it is equal to zero.

According to this, the constraint in (2) denotes that only one frequency channel can be assigned to each given logical link l.

Equation (3) indicates that the number of allocated channels to each node should be less than the number of network interface cards (NICs) equipped on the corresponding node. Here, $y_n^{(c)}$ represents the binary node channel allocation variable, which is equal to one if channel c is allocated to logical node n; otherwise, it is equal to zero.

- Equation (4) is the power constraint for each node.
- Equation (5) is the flow conservation constraint; that is, for flow s, the sum of all incoming flows in a non-destination node (n) must be no less than the sum of all outgoing flows.
- Equation (6) is the link capacity constraint. The aggregated flow rate on each link should not exceed its link capacity.
- Equation (7) is the available link capacity. Here, the constant B is the transmission bandwidth on each channel, $K=-\varphi_1/\log(\varphi_2 E)$, where φ_1 and φ_2 are constants depending on the modulation and E is the required bit error rate; g_{il} denotes the path gain between the transmitter of link i and the receiver of link l; and n_l is the additive thermal white noise power.

Note that the NUM problem has binary variables $\boldsymbol{X}$; real variables $\boldsymbol{F}$ and $\boldsymbol{P}$; and mixed binary-real cubic constraints. It is a complex non-linear mixed integer programming problem. Here, the objective function is twice continuously differentiable, non-decreasing, and strictly concave. In addition, here, the constraints are all linear, except for those in (5) and (6). For the constraints in (5) and (6), binary linearization [18], and log-transformed convex optimization techniques [7] are applied to transform $C_l(\boldsymbol{X},\boldsymbol{P})$ into a linear function, as mentioned in our previous work [3]. Therefore, the NUM problem can be converted into a convex optimization problem so that the centralized manner, such as branch and bound algorithm, can be applied to find the global optimal solution of the NUM problem. The optimal solution is used as an ideal reference in Section IV. Next, we introduce a more practical distributed method to solve this NUM problem.

III. Cross-Layer Design via Dual Decomposition

Dual decomposition is used to solve the NUM problem. By introducing $\{\lambda_n^{(s)}\geq 0 \text{ for all } n,\ s: n\neq d_s\}$ as the set of Lagrange multipliers to relax the constraint in (5), the dual to the primal NUM problem can be expressed as a max–min problem as follows:

$$\min_{\lambda\geq 0} D(\lambda), \quad (8)$$

with partial dual function

$$D(\lambda)=\max_{f_s\geq 0,\ r_{mn}^{(s)}\geq 0}\ \sum_{s\in S}U(f_s)-\sum_{s,\ n:n\neq d_s}\lambda_n^{(s)}\left(f_n^{(s)}+\sum_{m:mn\in L_s,\ m\in N_n^{\text{in}}}r_{mn}^{(s)}-\sum_{q:nq\in L_s,\ q\in N_n^{\text{out}}}r_{nq}^{(s)}\right) \quad (9)$$

s. t. (2), (3), (4), (6), and (7).

The optimization problem $D(\lambda)$ in (9) can be directly decomposed into the following two subproblems:

$$D_1(\lambda)=\max_{f_s\geq 0}\sum_{s\in S}U(f_s)-\sum_{s\in S}\lambda_s f_s \quad (10)$$

and

$$D_2(\lambda)=\max_{r_{mn}^{(s)}\geq 0}\ \sum_{s,n:n\neq d_s}\lambda_n^{(s)}\left(\sum_{q:nq\in L_s,q\in N_n^{\text{out}}}r_{nq}^{(s)}-\sum_{m:mn\in L_s,m\in N_n^{\text{in}}}r_{mn}^{(s)}\right) \quad (11)$$

s. t. (2), (3), (4), (6), and (7).

If $\lambda_n^{(s)}\geq 0$ is interpreted as the congestion price, then (10) is considered as a congestion control problem, while (11) is a joint routing, scheduling, power control and channel allocation problem. The two interact through the congestion price $\lambda_n^{(s)}$.

For congestion price $\lambda_n^{(s)}$, the subgradient algorithm is employed to solve it. By taking the derivative of $D(\lambda)$ with respect to λ, we obtain the following:

$$\nabla_n D(\lambda)=\sum_{q:nq\in L_s,q\in N_n^{\text{out}}}r_{nq}^{(s)}-\sum_{m:mn\in L_s,m\in N_n^{\text{in}}}r_{mn}^{(s)}-f_n^{(s)} \quad (12)$$

So, the congestion price $\lambda_n^{(s)}$ can be updated as

$$\lambda_n^{(s)}(t+1)=\left\{\lambda_n^{(s)}(t)-\left(\eta\times\nabla_n D(\lambda)\right),0\right\}^+, \quad (13)$$

where f_s and $r_{mn}^{(s)}$ are the solutions of (10) and (11), respectively; $\{\cdot,0\}^+=\max(\cdot,0)$; η is a sufficiently small step

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size, and t is an iteration time slot.

According to (10), with known $\{\lambda_n^{(s)} \geq 0\ \forall n,\ s: n \neq d_s\}$, the congestion control problem can be solved at each iteration time slot by

$$f_s^{(t+1)} = U_s^{'-1}(\lambda_s), \tag{14}$$

where $U_s^{'-1}(\cdot)$ is the inverse of the first derivative of the utility.

For problem (11), it is a queue length–based model with a feasible-rate region constraint. It can be transformed into the following formula:

$$\sum_{s,n:n\neq d_s} \lambda_n^{(s)} \left(\sum_{q:nq\in L_s, q\in N_n^{\text{out}}} r_{nq}^{(s)} - \sum_{m:mn\in L_s, m\in N_n^{\text{in}}} r_{mn}^{(s)} \right) = \sum_{mq\in L_s} r_{mq}^{(s)} (\lambda_m^{(s)} - \lambda_q^{(s)}); \tag{15}$$

that is,

$$D_2(\lambda) = \max_{r_{mn}^{(s)} \geq 0} \sum_{mq\in L} r_{mq}^{(s)} (\lambda_m^{(s)} - \lambda_q^{(s)}) \tag{16}$$

s. t. (2), (3), (4), (6), and (7).

For each link (m, q), we find s^* such that

$$s^* = \arg\max_{s\in\mathcal{S}} (\lambda_m^{(s)} - \lambda_q^{(s)}), \tag{17}$$

where $\lambda_{mq}^{(s)} = \lambda_m^{(s)} - \lambda_q^{(s)}$ is the differential price on link (m, q). To maximize $\sum_{mq\in L} r_{mq}^{(s)} (\lambda_m^{(s)} - \lambda_q^{(s)})$, all available link capacity should be allocated to the flow s^* that has the largest differential price, $\lambda_{mq}^{(s)}$, that fits the dynamic back pressure (DBP) [9] scheduling algorithm well. It implies that for each link (m, q), $r_{mq}^{(s)} = C_{mq}(\boldsymbol{X}, \boldsymbol{P})$ if $s = s^*$ and $r_{mq}^{(s)} = 0$ otherwise. Therefore, (16) is equivalent to the following capacity maximization problem:

$$D_3(\lambda) = \max_{\boldsymbol{X}, \boldsymbol{P}} \sum_{l\in L} \lambda_l^{(s^*)} C_l(\boldsymbol{X}, \boldsymbol{P}) \tag{18}$$

s. t. (2), (3), (4), and (7).

1. Joint Channel Allocation and Power Control

The objective in (18) is to maximize the whole weighted capacity by assigning the channel and power to the network links according to the congestion price information. To decouple the optimization variables $\boldsymbol{X}$ and $\boldsymbol{P}$, we can directly decompose (18) into two subproblems: congestion-aware channel allocation and congestion-aware power control.

A. Congestion-Aware Channel Allocation Subproblem

$$D_4(\lambda) = \max_{\boldsymbol{X}} \sum_{l\in\mathcal{L}} \lambda_l^{(s^*)} C_l(\boldsymbol{X})$$

$$\text{s. t.}\quad \boldsymbol{x}_l 1^T = 1,\ \forall l \in \mathcal{L}, \qquad \sum_{c=1}^{C} y_n^{(c)} \leq I_n,$$

$$C_l(\boldsymbol{X}) = B\log_2\left[1 + \left(K \times \frac{P_l^* g_{ll}}{\sum_{i\neq l} (\boldsymbol{x}_l^T \boldsymbol{x}_i P_i^* g_{il} + n_l)}\right)\right], l\in\mathcal{L}, \tag{19}$$

where P_l^*, $\forall l \in \mathcal{L}$, is obtained from solving the power control subproblem (20). The local implementation of (19) is given by

$$D_5(\lambda) = \max_{\boldsymbol{x}_l,\, l\in L_n} \sum_{l\in\mathcal{L}} \lambda_l^{(s^*)} C_l(\boldsymbol{X})$$

$$\text{s. t.}\quad \boldsymbol{x}_l 1^T = 1,\ \forall l \in \mathcal{L}, \quad \sum_{c=1}^{C} y_n^{(c)} \leq I_n,$$

$$C_l(\boldsymbol{X}) = B\log_2\left[1 + \left(K \times \frac{P_l^* g_{ll}}{\sum_{i\neq l} (\boldsymbol{x}_l^T \boldsymbol{x}_i P_i^* g_{il} + n_l)}\right)\right], l\in\mathcal{L}. \tag{20}$$

The local implementation process is asynchronous. Each node (n) is responsible for assigning the optimal channels to some local links $L_n \subset \mathcal{L}$ and periodically exchanges its individual channel usage $\boldsymbol{x}_l$, $\forall l \in L_n$, and collected data λ_l, $\forall l \in L_n$, with all other nodes.

B. Congestion-Aware Power Control Subproblem

$$D_5(\lambda) = \max_{\boldsymbol{P}} \sum_{l\in L} \lambda_l^{(s^*)} C_l(\boldsymbol{P})$$

$$\text{s. t.}\quad 0 \leq \sum_{m\in N_n^{\text{out}}} P_{nm} \leq P_n^{\max},$$

$$C_l(\boldsymbol{P}) = B\log_2\left[1 + \left(K \times \frac{P_l g_{ll}}{\sum_{i\neq l} (\boldsymbol{x}_l^{*T} \boldsymbol{x}_i^* P_i g_{il} + n_l)}\right)\right], l\in\mathcal{L}, \tag{21}$$

where $\boldsymbol{x}_l^*$, $\forall l \in L$, are obtained from solving the local channel allocation subproblem (20). Equation (21) can be solved distributively by the algorithm proposed in [17]. We describe it as follows.

Step 1. At the iterative time slot t, the transmitter of link $l \in \mathcal{L}$ calculates a power message

$$m_l(t) = \frac{\lambda_l I_l(t)}{P_l(t) g_{ll}}, \tag{22}$$

where I_l denotes the signal-to-interference-plus-noise ratio; I_l and g_{ll} are measured locally.

Step 2. The power message $m_l(t)$ is passed to all the other nodes through a flooding protocol.

Step 3. Each transmitter adjusts its power as

$$P_l(t+1) = P_l(t) + \beta\left(\frac{\lambda_l(t)}{P_l(t)} - \sum_{i\neq l} g_{il} m_i(t)\right), \tag{23}$$

where $\beta > 0$ is a constant step size.

Step 4. Let $t = t + 1$. Return to *Step* 1 until convergence.

This algorithm is proved to converge to the global optimum solution $\boldsymbol{P}^* = [P_1^*, P_2^*, \ldots, P_{|L|}^*]$ in [17] for a small enough positive constant β.

2. Distributed Scheduling

Let $L_m^j \subset \mathcal{L}$ denote the set of links connecting to the *j*th interface of node *m*. For a bidirectional link $\langle m,n \rangle$, define $\lambda_{<m,n>} = \max\{\lambda_{mn}, \lambda_{nm}\}$ as the largest differential price. Assume that interface $j \in m$ operates on channel *i*, which is pre-allocated by the local channel allocation algorithm. The distributed scheduling algorithm can be briefly described as follows.

Each interface $j \in m$ carries out the following steps:

A. Find neighbor $n^* = \arg \max_{n:(m,n)\in L_m^j} \lambda_{<m,n>}$ with free interface *u*, free channel *i*, and such that it satisfies $(m, n^*) = L_m^j \cap L_{n^*}^u$.
   - If having received the matching request from the interface *u* of node n^*, then node *m* accepts link $\langle m, n^* \rangle$ as a matched link and sends back a matched reply. At the same time, node *m* sends a drop message about the interface *j* and channel *i* to all other neighbors with free interfaces and channels.
   - Otherwise, node *m* sends a matching request to node n^*.

B. Upon receiving a matching request information from neighbor *n*, the following is carried out:
   - If $n = n^*$ and channel *i* is free, then node *m* accepts the request and sends back a matched reply. At the same time, node *m* sends a drop message about the interface *j* and channel *i* to all other neighbors with free interfaces and channels.
   - Otherwise, node *m* just stores the message.

C. Upon receiving information of a matched reply from neighbor *n*, node *m* sends a drop message about the interface *j* and channel *i* to all other neighbors with free interfaces and channels.

D. Upon receiving a drop message form neighbor *n*, node *m* updates the free information of the interface and channel by deleting the interface *j* and the channel *i*.

E. If node *m* is busy or has no free neighbors, then it keeps the current state. Otherwise, it takes action according to the aforementioned steps A–D.

F. The matched links are allowed to transmit with the allocated rate

$$r_{mq}^{(s)} = \begin{cases} C_{mq}(\boldsymbol{X}^*, \boldsymbol{P}^*) & \text{if } s = s^*, \\ 0 & \text{otherwise.} \end{cases} \tag{24}$$

According to the above discussion, the main idea of this algorithm is to activate the local bidirectional link with the maximum differential price.

3. Distributed JCCRPSR

The proposed JCCRPSR can be described as follows:

A. The network topology is initially generated by using the Hyacinth algorithm in [8] and $\boldsymbol{x}_l = [1\ 0\ \cdots\ 0], \forall l \in L$, is set.

B. During each iteration time slot *t*, the following three operations are carried out simultaneously:
   - Each transmitter $n \in \mathcal{N}$ updates the congestion price $\xi_n = \left\{\xi_l, \forall l \in L_n^{\text{out}}\right\}$, power message $m_n = \{m_l, \forall l \in L_n^{\text{out}}\}$, and power price $\zeta_n = \left\{\zeta_l, \forall l \in L_n^{\text{out}}\right\}$.
   - Each transmitter $n \in \mathcal{N}$ sends ξ_l back to the source nodes of the flows if link *l* is on the paths of the flows.
   - Each transmitter passes m_n to the corresponding transmitters by the routing protocol.

C. In the time slots that belong to the set $\Gamma_{D,n}$, each node $n \in \mathcal{N}$ carries out the following algorithms at a period of T_D time slots:
   - If the node belongs to the source node of a flow, then the node updates the f_s^* according to equation (14).
   - Each node updates the local channel allocation according to (20) and informs the results to other nodes in the network.
   - Each transmitter updates the transmitted power according to equation (23).
   - Each node *n* allocates $r_{nm}^{(s)}$ according to the scheduling algorithm. According to the rate offered by the scheduling, the routing is determined.

In JCCRPSR, each node calculates five parameters: congestion price (ξ_n), power message (m_n), power price (ζ_n), traffic rate (f_s), and transmitted power (P_l). The JCCRPSR then solves the local congestion-aware channel allocation subproblem and scheduling problem. For any node $n \in \mathcal{N}$, the computational complexity of the parameters ξ_n, m_n, ξ_n, f_s, and P_l is linear. The local channel-allocation subproblem is a combinatorial optimization problem, with at most $C^{V_{\max}}$ combinations, where $V_{\max} = \max_{n\in\mathcal{N}} |L_n|$. The complexity of the scheduling problem is $O(0.5L)$. So, the whole computational complexity is $O(5 + C^{V_{\max}} + 0.5L)$.

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In addition, the convergence of the joint congestion control, routing, and scheduling algorithm is proved in [9]. The congestion-aware channel allocation algorithm can at least converge to the local optimal solutions. While the distributed power control subproblem can be solved with zero duality gap. So, the proposed distributed algorithm is guaranteed to be convergent. Since the congestion-aware channel allocation subproblem is sub-optimal, the global optimality of the proposed algorithm is not guaranteed. The sub-optimality and convergence of the proposed algorithm is investigated further in the next section.

IV. Simulation Results and Discussion

In this section, the proposed distributed JCCRPSR is compared with the joint congestion control, channel allocation, scheduling, and routing algorithm (JCCSR) in [11] and the centralized optimal algorithm. In the JCCSR, each node computes three parameters: two Lagrange multipliers and a traffic rate (f_s). It then computes both a local selfish channel allocation subproblem and a greedy centralized scheduling subproblem. The JCCRPSR and JCCSR algorithms are simulated using MATLAB, and the centralized algorithm is solved with MOSEK [19].

In the simulation model, the size of the network field is 700 m × 700 m. Fifteen wireless nodes are generated randomly. The communication and interference ranges are 250 m and 450 m, respectively. Once the physical topology is created, a ripple effect–free logical topology can be formed by using the algorithm proposed in [8]. Two thousand time slots are simulated. The parameters used in the simulations are listed in Table 1.

1. Comparison with JCCSR

The performance among the optimal, JCCSR, and JCCRPSR algorithms is firstly compared in terms of network utility and energy efficiency, which are defined as $\sum_{s\in\mathcal{S}} \log f_s$ and $\sum_{s\in\mathcal{S}} f_s \big/ \sum_{l\in\mathcal{L}} P_l$, respectively.

Table 1. List of simulation parameters.

Received noise power (n_l)	1.0×10^{-11} W
Signal wavelength (λ)	0.0517 m
Channel bandwidth (B)	2 Mbps
Processing gain (K)	128
Step size of congestion price update (η)	0.01
Maximum power constraint ($P_{\max}$)	0.5 W

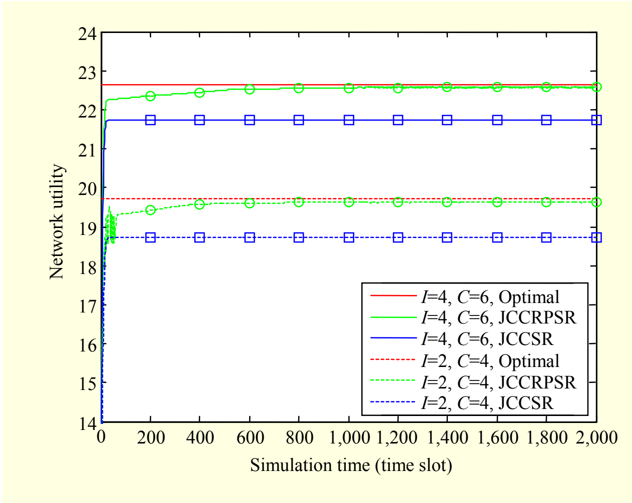

Fig. 1. Evolution of network utility.

Figure 1 shows the evolution of the network utility. The number of NICs and non-overlapping channels is denoted by I and C, respectively. We can see that the JCCRPSR converges to a relatively stable value within a short time. The utility of the JCCRPSR with $I = 2$, $C = 4$, and $I = 4$, $C = 6$, reaches nearly 98.47% and 99.12% of the optimal values, respectively. Thus, the proposed JCCRPSR algorithm can lead to a near-optimal solution for the NUM problem. The utility of the JCCSR with $I = 2$, $C = 4$, and $I = 4$, $C = 6$, reaches 89.94% and 90.63% of the optimal values, respectively. It is obvious that the JCCRPSR shows better performance than the JCCSR. The reason for this is that, on the one hand, the JCCRPSR adjusts the transmit power to reduce the interference to the bottleneck links by a power control strategy, whereas on the other hand, the congestion-aware channel allocation strategy of the JCCRPSR takes congestion control and whole system capacity into consideration, while the channel allocation strategy of the JCCSR just tries to alleviate any local congestion.

Figure 2 shows the evolution of the energy efficiency. The JCCRPSR takes more time to converge to the suboptimal value compared to the JCCSR. However, the JCCRPSR with $I = 2$, $C = 4$ and $I = 4$, $C = 6$, converges to nearly 96.4% and 97.59% of the optimal values, respectively, while the JCCSR with $I = 2$, $C = 4$ and $I = 4$, $C = 6$, only converges to nearly 57.97% and 60.24% of the optimal values, respectively. This is because the JCCRPSR needs to coordinate the power for each lnk; hence, it takes more time to converge. Nonetheless, each node optimally adjusts the transmit power and hence the energy efficiency is improved.

2. Impact of Available Power

To evaluate the impact of the maximum power constraints,

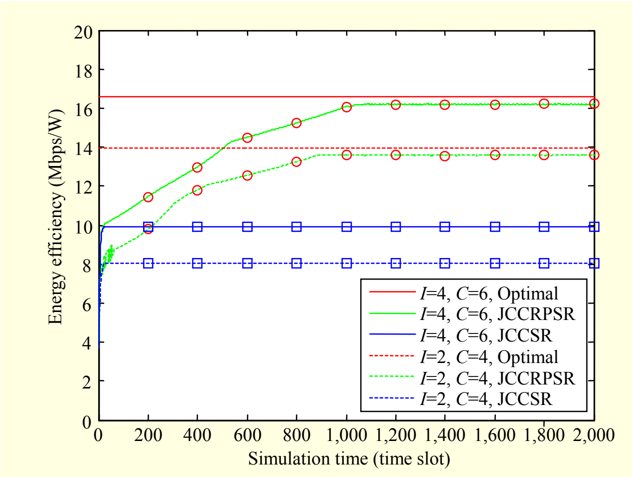

Fig. 2. Evolution of energy efficiency.

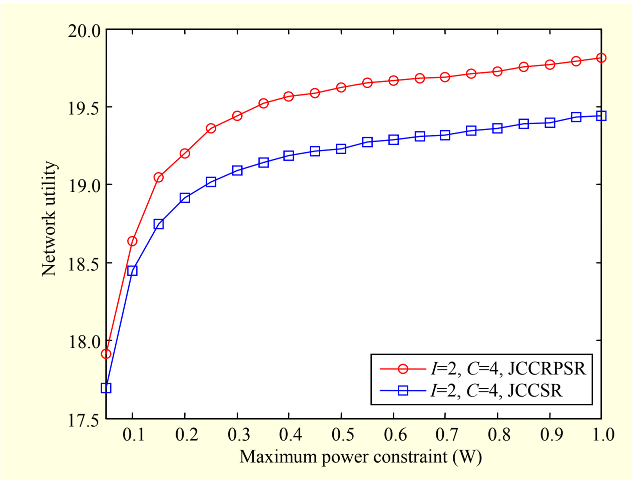

Fig. 3. Impact of available power.

we vary the maximum power constraint from 0.05 W to 1 W.

Figure 3 shows the utility-power trade-off curves. As we can see from the figure, with the increasing of the maximum power constraint, the utilities of the JCCRPSR and JCCSR algorithms increase, and the network utility increments are decreasing. In addition, the proposed JCCRPSR algorithm achieves a better utility performance, since the JCCSR doesn't have a power control strategy.

V. Conclusion

In this paper, we have studied the problem of joint congestion control, channel allocation, rate allocation, power control, scheduling, and routing with the consideration of fairness in multi-channel wireless multi-hop networks. A suboptimal distributed algorithm based on dual composition has been proposed. Simulation results have been presented to demonstrate the performance of the proposed scheme.

For future work, we plan to extend our algorithm to a dynamic network environment, as well as considering the impact of outdated information or imperfect information to the resource allocation.

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