A THEORETICAL FRAMEWORK FOR OPTIMAL COOPERATIVE NETWORKING IN MULTIRADIO MULTICHANNEL WIRELESS NETWORKS

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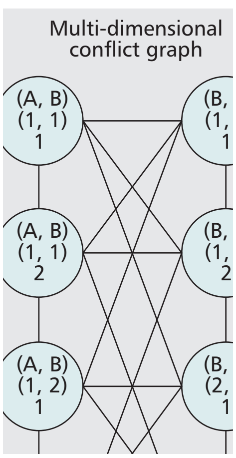

Rather than focus on protocol designs for specific cooperative networking issues, the authors present a generic theoretical framework that could guide the protocol or algorithm development to approach the maximum network capacity.

ABSTRACT

A wide range of next generation wireless networks are based on the multiradio multichannel (MR-MC) network model. A full exploration of the MR-MC wireless network capacity incurs challenging cooperative networking issues including transmission cooperation, resource allocation cooperation, and cross-layer protocol cooperation. In this article, rather than focus on protocol designs for specific cooperative networking issues, we present a generic theoretical framework that could guide the protocol or algorithm development to approach the maximum network capacity. Based on our multidimensional conflict graph (MDCG) tool, we could achieve a cross-layer linear programming framework to study the optimal cooperative networking in two complementary aspects: optimal network dimensioning and throughput-optimal control. While certain NP-hard computing issues hindered the MR-MC network optimization for a long time, the MDCG-based framework can readily generate simple polynomial and distributed algorithms with guaranteed capacity region.

INTRODUCTION

The multiradio multichannel (MR-MC) networking mode [1, 2] underpins the next-generation wireless networks, represented by wireless mesh networks based on the IEEE 802.16 standard, fourth-generation (4G) cellular networks based on the Long Term Evolution (LTE) standard, and cognitive radio networks based on dynamic spectrum sharing. Such a networking model can significantly increase network capacity by simultaneously exploiting multiple non-overlapping channels through different radio interfaces and mitigating interference through proper channel assignment.

A full exploration of the MR-MC wireless network capacity incurs challenging cooperative networking issues from different aspects.

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Transmission cooperation: One of the fundamental issues in wireless networks is the interference among co-channel simultaneous transmissions. The communication links over the whole network should be properly coordinated to resolve interference and thus efficiently serve all the network flows.

Resource allocation cooperation: In the MR-MC context, the extra radio interfaces and channels bring more transmission opportunities. The channel assignment over each radio interface and the transmission scheduling should be synergistic with each other to fully exploit the network capacity.

Cross-layer protocol cooperation: In an MR-MC network, the routing protocol in the network layer also interacts with the lower-layer resource allocation. On one side, the lower-layer resource allocation determines the link status and thus impacts the network-layer path selection. On the other side, the routing protocol determines the traffic flows over each link which in turn impact the lower-layer resource allocation. Such a coupling scenario requires a joint cross-layer optimization to achieve the maximum capacity.

The cooperative networking perspectives indicate that maximizing MR-MC network capacity requires cross-layer optimization in a *multidimensional resource space*, with dimensions defined by radio interfaces, links, and channels. However, the optimal multidimensional resource allocation in MR-MC networks by nature leads to a mixed integer programming problem (which is NP-hard), involving binary variables to describe channel assignment over each radio interface [1, 3]. Due to such inherent difficulty, the state of the art of MR-MC networks has been constrained to either adopting linear programming (or convex optimization in general) relaxation to obtain an upper bound of the network capacity [1, 3, 4] or developing heuristic resource allocation methods [1, 5, 6] to obtain a lower bound; thus, the capacity of MR-MC networks has been seriously underexplored.

In this article, we present a theoretical framework in the linear programming (LP) domain to guide the resource allocation for optimal cooperative networking in the MR-MC wireless networks. Our inspiration comes from the

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experience that the network/link cross-layer optimization in the single-radio single-channel (SR-SC) context can be formulated as an LP multi-commodity flow (MCF) problem, augmented with constraints derived from the link conflict graph [7]. The conflict graph tool, however, did not achieve similar success in MR-MC networks, mainly because the link conflict graph is not sufficient in describing the extra conflicts in competing for radio interfaces and channels. To fill the gap, we thus develop a generic multi-dimensional conflict graph (MDCG) for MR-MC networks in [8]. Each vertex in the MDCG represents a link-radio-channel tuple (LRC-tuple), a basic resource point in the multidimensional space. In this article, our focus is to demonstrate a theoretical framework based on the MDCG, which can guide the resource allocation for optimal cooperative networking.

The MDCG enables a theoretical framework to address two complementary resource allocation issues in MR-MC wireless networks. One is *optimal network dimensioning*, where the MCF formulation augmented with MDCG constraints can jointly solve the optimal scheduling and channel assignment at the link layer, and the optimal routing at the network layer. The other is *throughput-optimal network control* [9, 10], which adaptively adjusts the resource allocation to maintain the network stable along with the dynamics of traffic and network status. While both of the optimal resource allocation issues incur computing problems that are NP-hard in general, the MDCG-based framework can give simple polynomial algorithms with guaranteed capacity region. In particular, according to the MDCG concept we can transform a MR-MC network into an equivalent LRC-tuple-based network, which significantly facilitates the study of distributed scheduling algorithms for throughput-optimal control. *Distributed scheduling* is of special importance to cooperative networking, by which nodes in a local neighborhood could cooperate with each other to determine their channel assignment and transmission scheduling, with the aggregate behavior leading to optimal network capacity.

Multiradio Multichannel Networking Model

The wireless network is viewed as a directed graph $G(\mathcal{V}, \mathcal{L})$ with node set $\mathcal{V}$ and link set $\mathcal{L}$. Each node has a *communication range* and a potentially larger *interference range*. There is a directed link from node u to node v if v is within the communication range of u. We use l_{uv} or (u, v) to denote a link from node u to node v. The whole spectrum available to the network is divided into C frequency channels. We assume the same communication range and interference range over all channels. Let M_v denote the number of radio interfaces available at node v. At any given time an interface can only tune to one channel, but it can switch channels dynamically at different time. Considering the *channel diversity* [2], we use $w_l(c)$ to denote the capacity of link l when transmitting data on channel c.

The interference in the wireless network can be defined according to a *protocol interference model* or a *physical interference model* [11]. With the protocol interference model, the conflict relationship between two links is determined by the specified interference range. The protocol interference model is adopted by most of the existing work, by which the interference over a network can be abstracted into a conflict graph. We also focus on the protocol interference model in this article.

Multidimensional Conflict Graph

We interpret the MR-MC networks as a multi-dimensional resource space over the dimensions of link, radio, and channel. The MDCG is to describe the conflict relationships among the resource points, each represented as a link-radio-channel tuple. Specifically, an LRC tuple p is defined in the format:

$$\text{Link-radio-channel tuple: } [(u, v), (x_v, x_v), c].$$

The tuple indicates that the link (u, v) operates on channel c, using radios x_u and x_v at nodes u and v, respectively. According to the LRC tuple definition, we can systematically list all the possible resource allocations to enable a communication link, that is, a link (u, v) can be mapped to $M_u \times M_v \times C$ LRC tuples in the MDCG.

There are two types of conflict relationships among LRC tuples in the MDCG. One is *interference conflict* indicating that co-channel transmissions (geometrically separated) conflict with each other within the interference range. The other is *radio conflict* indicating that multiple transmissions (possibly over different channels) contend for the same radio. Note that the radio conflict is the special issue induced by the MR-MC networking. There is no explicit radio conflict in an SR-SC network, where a radio contention could be equivalent to a co-channel conflict within the interference range. Readers may refer to [8] for details on how to systematically find all the conflict relations among the LRC tuples.

We use an example to illustrate the MDCG based on the conflict relationship among LRC tuples, as shown in Fig. 1. The left side of Fig. 1 shows a small network consisting of two directional links, where node A has two radio interfaces, and nodes B and C each have one radio. There are 2 available channels. Thus, both links (A, B) and (A, C) can be mapped to $2 \times 1 \times 2 = 4$ LRC tuples, respectively. For instance, the tuple $[(A, B), (1, 1), 1]$ indicates that the transmission from node A to node B uses the radio interface 1 at node A and the one available radio interface at node B, and both radio interfaces tune to channel 1. Given the tuples, all possible interference/interface conflict relations among them can then be identified according to the interference conflicts or the radio conflicts to form the MDCG, as shown in the right side of Fig. 1.

Optimal Network Dimensioning

A multi-commodity flow formulation augmented with MDCG constraints can compute the optimal network dimensioning of an MR-MC network, with the assumption of a time-slotted system. Since all the resource allocation issues

The MDCG enables a theoretical framework to address two complementary resource allocation issues in MR-MC wireless networks: optimal network dimensioning and throughput-optimal network control.

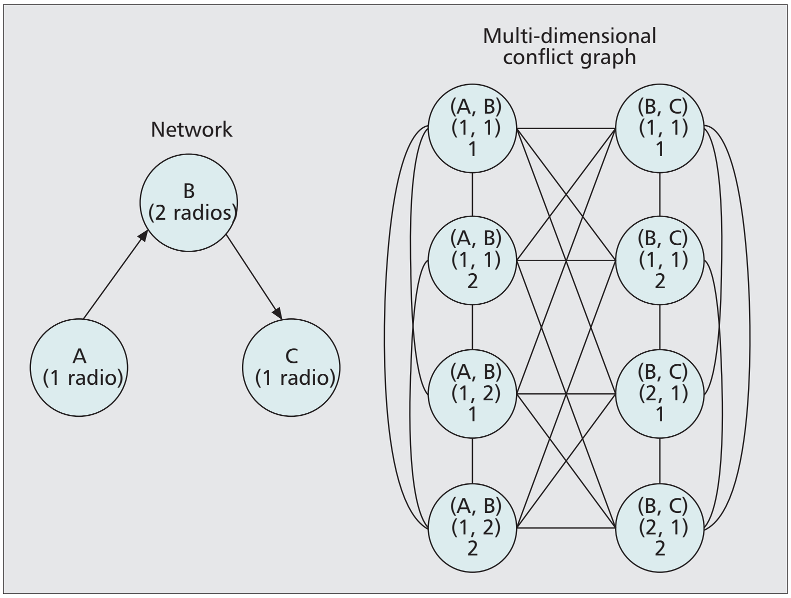

Figure 1. *An illustration of MDCG construction.*

including transmission scheduling, channel assignment, and routing are coupled with each other, we also use "scheduling" to generally represent all the resource allocation issues when the context is clear. Consider that each commodity is associated with a source node and a destination node. The traffic rates of all the commodity flows constitute a *rate vector*. A rate vector is termed feasible if a scheduling can be computed to achieve the given rates. All the feasible rate vectors constitute the *capacity region*. The operation of optimal network dimensioning is to compute the optimal scheduling to achieve the maximum throughput/utility over the capacity region. We would like to emphasize that the optimal MCF dimensioning results represent the maximum achievable capacity of a cooperative networking solution.

Wireless MCF Formulation

Let (ν, η) denote a source/destination pair over a multihop wireless network, and $f_{\nu\eta}(u, v)$ denote the flow associated with commodity (ν, η) that traverses the link (u, v). The MCF problem can be formulated as a linear optimization or convex optimization problem, depending on how the objective function regarding $f_{\nu\eta}(u, v)$ is selected. Here we generally discuss the capacity region issue without assuming a specific objective function. The capacity region of the MCF problem consists of all the feasible flow vectors defined by the constraints of the optimization problem. The constraints can be classified into two categories: the *basic network flow constraints* and the *conflict graph constraints* resolving the interference.

The basic network flow constraints mainly include the constraints of *flow conservation constraint* that at every node the amount of incoming traffic equals the amount of outgoing traffic, *nonnegativity constraint* that the amount of flow allocation should be nonnegative, and *link capacity constraint* that the total amount of flow on a link cannot exceed the link capacity. The conflict graph constraint is normally expressed as a maximal independent set (MIS) based scheduling to coordinate the transmissions over the network. Note that an MIS over the conflict graph indicates a maximal set of links (or LRC tuples in the context of MDCG) that can transmit simultaneously without interference. The optimal resource allocation associated with the maximum MCF capacity is jointly represented as an *optimal scheduling* that all the maximal independent sets take turns in grabbing the channel for data transmission, with the transmission time for each set in a scheduling period determined by the MCF solution.

MDCG-Based Optimal Dimensioning

In an MR-MC wireless network, if the MISs are constructed over the MDCG, the MIS based optimal scheduling can indicate the joint optimal solution of all coupled resource allocation issues. For example, consider a flow from A to C in the network illustrated in Fig. 1. If the tuple-based MISs {[(A, B), (1, 1), 1]; [(B, C), (2, 1), 2]} are scheduled at a slot, we can tell: links AB and BC are scheduled, which give a route for the flow A to C; the two links work on channel 1 and 2, respectively, with the radio allocation at each node also indicated. In a practical topology with multiple flows, a scheduling may involve many tuple-based MISs taking turns for transmission.

Another important advantage of MIS-based scheduling is the capability of exploiting dynamic channel swapping for higher capacity. A link is associated with multiple LRC tuples on different channels, and these tuples could be activated in different slots under the MIS-based scheduling, generating the effect of *dynamic channel swapping* over the transmission link. Consider the example given in Fig. 1 again. A scheduling may alternate transmissions between two MISs, {[(A, B), (1, 1), 1]; [(B, C), (2, 1), 2]} and {[(A, B), (1, 1), 2];[(B, C), (2, 1), 1]}. Such a scheduling shows that link (A, B) swap channels from channel 1 to channel 2 dynamically in different slots, and link (B, C) also swaps its channel allocation correspondingly. Dynamic channel swapping is of particular importance where there is fairness requirement. Given the channel assignment of the links within the interference range of a tagged link, we could see that the tagged link transmission will fairly impact the transmissions over other links through dynamic channel swapping, whereas with a static channel allocation it will always unfavorably impact those links on the same channel. Note that the existing heuristic resource allocation algorithm for MR-MC networks only supports static channel allocation [1]. Dynamic channel swapping is a good example to show that the MDCG-based MCF solution could leverage the cooperative networking for improved performance. In the "Performance Evaluation" section, we present more numerical results to further demonstrate the benefit of dynamic channel swapping.

It is noteworthy that the MDCG-based MCF solution can also seamlessly incorporate the channel diversity that the link capacity might depend on channels; the tuples scheduled in the optimization solution will always pick the best available channels to achieve the maximum network capacity. Without MDCG, it is not easy to exploit the channel diversity in scheduling [2].

Computation Complexity and Approximation Algorithms

A classic challenge to the MIS-based MCF computing is that searching all the MISs is NP-hard in general [27, 42]. In an MDCG incurred by the MR-MC networks, the complexity will be further exaggerated. A random algorithm for MIS search is proposed in [7] and widely adopted in the literature, but it could not give a guaranteed capacity region.

In [8], we theoretically show that in fact only a small set of MISs, termed the critical MIS set (c-MISset), will be scheduled in the optimal resource allocation, although exponentially many MISs are possible in a conflict graph. The c-MISset theorem inspires a direction to develop efficient approximation algorithms for the MIS-based MCF problem — we could first develop a polynomial algorithm to approximate the critical MIS set, and then use the approximate critical MIS set in the scheduling constraints to compute the MCF capacity. In [8], we show that observing the network structure and commodity flow information does help to infer the possibility of a link to be scheduled (i.e., to be involved in the c-MISset). For example, a bridge edge (and the tuples spawned from the link) for a commodity flow must be scheduled. We thus define a scheduling index (SI) based on such heuristic measures to quantitatively indicate the possibility that a tuple will be scheduled. A heuristic polynomial algorithm, termed as scheduling index ordering (SIO) based MIS computing, is then developed to search MISs to approximate the c-MISset. The algorithm selects the tuples of higher SIs with priority to construct MISs. We will present numerical results later to demonstrate the effectiveness of the SIO-based MIS computing in producing a larger MCF capacity, compared to the random MIS search.

The MDCG also enables a polynomial approximation algorithm for MR-MC network optimization with guaranteed capacity region. Specifically, we define that a *conflict neighborhood* of a tuple includes its neighbors in the MDCG and itself. The *conflict degree* of tuple p is the maximum number of tuples within its conflict neighborhood that could have been turned on simultaneously (without conflicts) if tuple p was not turned on. The conflict degree of the network is the maximum possible conflict degree over all tuples. A *conflict neighborhood constraint* specifies that the aggregate normalized channel utilization over each conflict neighborhood cannot exceed 100 percent. When the MIS-based scheduling constraint is replaced by the conflict neighborhood constraint, it can be proved (following the analysis given in [1]) that the MCF solution under such a constraint can guarantee a feasible capacity region that is at least γ fraction of the optimal capacity region. The ratio γ is termed as the *capacity efficiency ratio* of the approximation algorithm and equal to the reciprocal of the network conflict degree. Suppose that a node at most can have M radios. The number of conflict neighborhood constraint equals the number of tuples associated with the network, which is upbounded by $M^2C|\mathcal{L}|$ and thus makes the MCF problem solvable with polynomial complexity. Moreover, the MCF flow allocation under the conflict neighborhood constraint could be easily mapped to an implementable MIS-based scheduling [1]. Note that MDCG-based MCF computing is a multi-dimensional extension to the link conflict graph based MCF analysis in the SR-SC context, where the generic concepts of conflict neighborhood and conflict degree reduce to interference neighborhood and interference degree [2].

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Throughput-Optimal Network Control

The throughput-optimal network control aims at dynamically adjusting resource allocation to maintain the network stability as long as the input rate vector is within the capacity region [9, 10]. It has been shown that the throughput-optimal network control can be viewed as a dynamic implementation of a subgradient search method to solve the MCF problem using convex duality [10]. The dual formulation allows integrating the scheduling with different optimization objective functions to form a *cross-layer network control framework*, for example, transport-layer flow control based on a utility function [10], and network-layer path selection based on a delay related objective function [2, 12].

The central component of the throughput-optimal algorithms is the *back-pressure algorithm*. Let $b(l)$ and $e(l)$ denote the transmitter node and receiver node of link l, respectively. Let $U_\upsilon(t)$ denote the queue length of node υ at time slot t. Let $I(t)$ denote the control action at time slot t. Let $r_l(I(t))$ denote the transmission capacity of link l under the scheduling, which equals to the physical link capacity w_l if scheduled or 0 otherwise. The back-pressure algorithm is to choose the control action $I(t)$ that solves the optimization "Max: $\Sigma_{l\in\mathcal{L}}(U_{b(l)}(t) - U_{e(l)}(t))\, r_l(I(t))$." Based on the scheduling decision at time slot t, the queue lengths are then updated according to arrivals and departures in that slot and to be used for scheduling decisions at next time slot. In this part, we take the case of single commodity flow for easier presentation. In the throughput-optimal framework, multiple commodity flows can be easily handled by maintaining a separate queue for each commodity at each link [10].

The back-pressure scheduling is equivalent to an NP-hard maximum weighted independent set (MWIS) problem [9]. To overcome the high computational complexity, distributed scheduling has been extensively studied in recent several years [2, 10]. The distributed algorithms normally have to sacrifice a fraction of the capacity region for the reduced complexity. Distributed scheduling is of particular importance to cooperative networking, where nodes in a local neighborhood could cooperate with each other to drive the aggregate network behavior into an efficient operation point.

LRC-Tuple Based Network Model

It is hard to directly extend the distributed scheduling algorithms developed in the SR-SC context to the MR-MC networks. The severe challenge is that the back-pressure-based algorithm now interleaves the problems of link scheduling, channel, and radio assignment [2]. The MDCG enables a framework to systematically study the scheduling issue by transforming the original network into an equivalent LRC-tuple based network. In Fig. 2, we illustrate how a link in the original network is transformed to tuples in the equivalent network, where each tuple p is considered as a separate transmission link, termed as a *tuple link p*. Let $\mathcal{P}$ denote the set containing all tuples. In a transformed network we could directly write a tuple-based back-pressure algorithm as

$$\text{Maximize}: \sum_{p \in \mathcal{P}} \left(U_{b(p)}(t) - U_{e(p)}(t)\right) r_p\left(I(t)\right) \qquad (1)$$

where the tuple-link transmission capacity $r_p(I(t))$ equals to the physical capacity $w_{l(p)}(c(p))$ if scheduled, with $l(p)$ and $c(p)$ denoting the link and the channel associated with the tuple p, respectively. Note that the tuple-based model in fact transforms the original MR-MC network into an equivalent virtual SR-SC network. The expression in Eq. 1 is an MWIS problem over the equivalent SR-SC network, where the well-known distributed maximal scheduling [13] could be directly applied as an approximate solution.

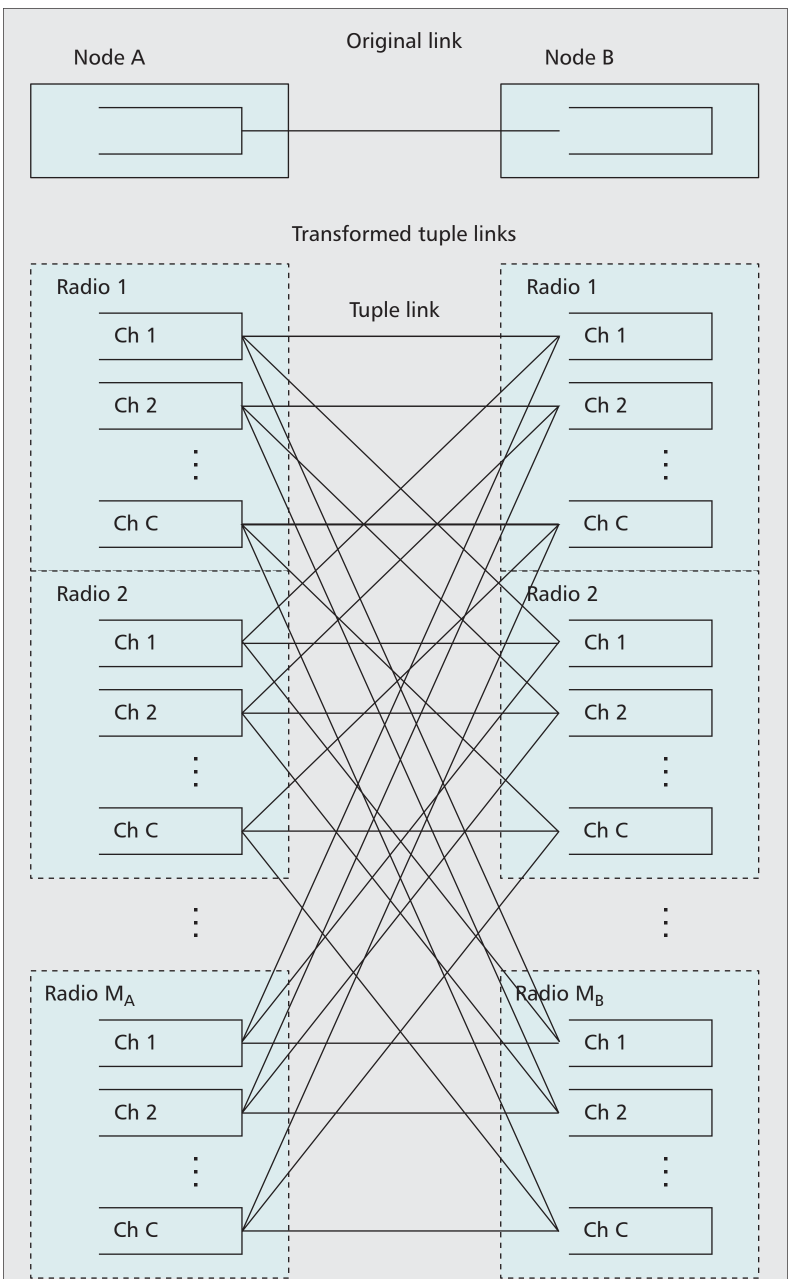

Figure 2. *Transforming to tuple links.*

Tuple-Based Maximal Scheduling

Maximal scheduling is of recent interest in the SR-SC context due to its low complexity and ease of distributed implementation [13]. The tuple-based equivalent network allows straightforwardly applying the maximal scheduling over the tuples to jointly solve all the resource allocation issues in a distributed manner.

In the tuple-based network, a *maximal scheduling* means that if a tuple p has a packet, then at a slot either tuple p is selected for transmission, or some other tuple within the conflict neighborhood of tuple p is selected. In a distributed implementation, the nodes in a conflict neighborhood can exchange messages to resolve contentions locally and alternatively activate different maximal tuple sets [2, 13]. It has been proved that the maximal scheduling can ensure a capacity efficiency ratio that equals the reciprocal of the network interference degree in the SR-SC context [13]. Since the tuple-based network does provide a SR-SC context, the tuple-based maximal scheduling thus achieves a capacity efficiency ratio equal to the reciprocal of the conflict degree of the MDCG, while the optimal capacity region is defined by the ideal scheduling according Eq. 1. We would like to emphasize that the tuple-based maximal scheduling actually provides a distributed algorithm to jointly solve those coupled resource allocation issues in the MR-MC networks. When a tuple p in the form of $[(u, v), (x_u, x_v), c]$ is selected for transmissions, its multi-dimensional property at the same time indicates the channel and radio assignment associated with this transmission .

One more thing to be noted is that the tuple-based network model provides a convenient tool for capacity analysis, but in practice the scheduling algorithms need to be mapped into protocol implementations at each node. To implement the tuple-based maximal scheduling, each node needs to maintain per-commodity per-channel queues for each radio interface and exchange such information with the nodes in its interference neighborhood.

Cross-Layer Control

It is known that the classic back-pressure algorithm could lead to unnecessarily large delays [10, 12]. We could apply the dual decomposition technique over the MCF formulation to obtain a decomposable cross-layer control framework, which integrates the network-layer path selection with the back-pressure scheduling to enhance the delay performance in MR-MC networks.

Consider a network flow f, and assume $R(f)$ paths are generated by the tuple-based MCF network dimensioning. Let H_k denote the hop count of a path k. The path selection is to determine how to split the arrival traffic A_f of flow f into the paths for best delay performance. Let $A_{f,k}$ denote the flow allocation on path k. Based on the studies in [12], we could consider the

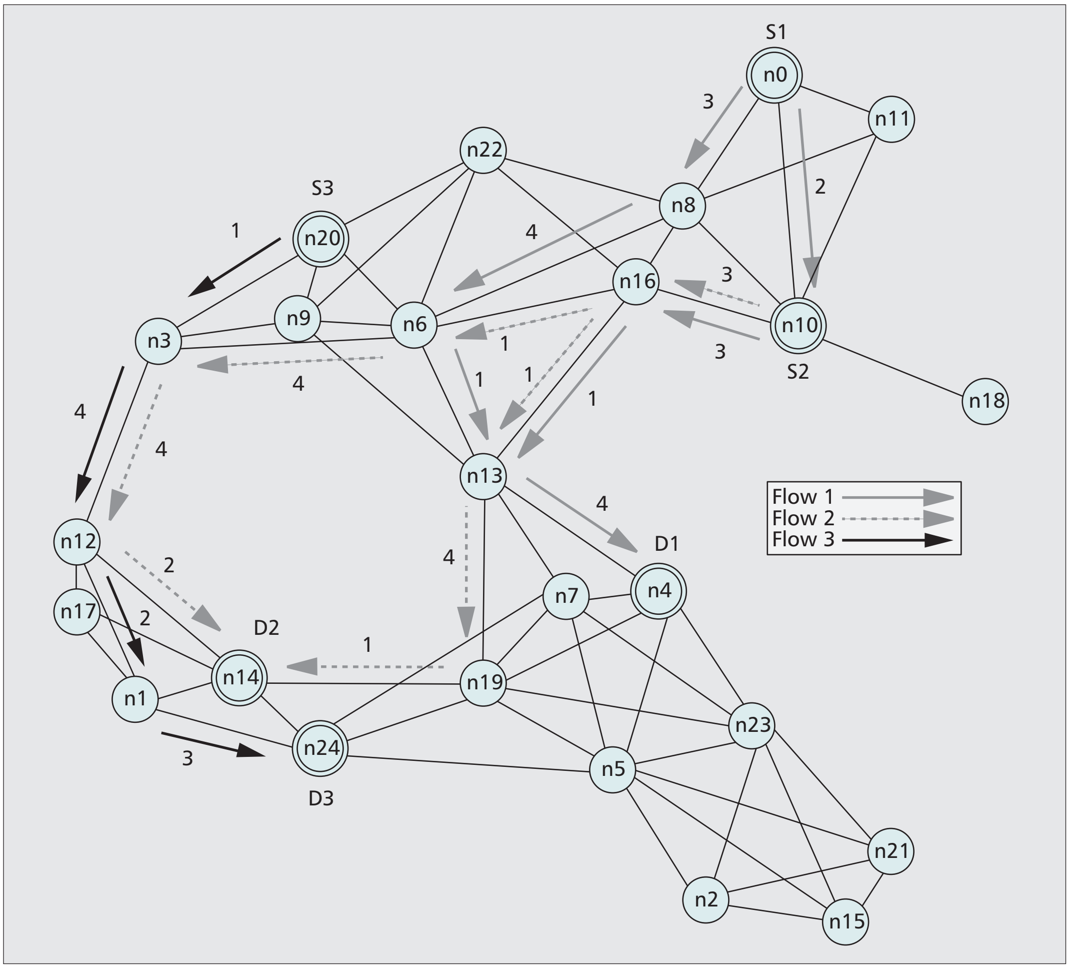

Figure 3. *Network dimensioning under the static heuristic algorithm.*

To implement the tuple-based maximal scheduling, each node needs to maintain per-commodity per-channel queues for each radio interface and exchange such information with the nodes in its interference neighborhood.

objective function min $\Sigma_{k=1}^{R(f)} VH_k A_{f,k}$ to derive a decomposable cross-layer control, which aims at a splitting that minimizes the average number of hops to support the traffic (with V being a control parameter). We further take the assumption used in [2] that the input traffic could immediately apply to all hops along a path. Let $[Y_{fk}^p]$ denote the routing matrix and $Y_{fk}^p = 1$ indicates that tuple p is on the kth path of flow f. With some mathematical manipulations that relax all the flow conservation constraints and apply the dual decomposition, we could obtain a network-layer path selection rule that all the traffic A_f should be injected into the path k that

$$\text{minimize}: VH_k + \sum_{p=1}^{|\mathcal{P}|} Y_{fk}^p U_{b(p)} \qquad (2)$$

where the queue length is updated at the link layer according to the back-pressure scheduling for optimal capacity region. Note that the path selection in Eq. 2 has a clear physical meaning to minimize the aggregate effect of hop counts and queue lengths along a path.

Performance Evaluation

In this section, we present some numerical results to demonstrate the efficiency of the MDCG-based network dimensioning and tuple-based throughput-optimal control. We consider a random network topology, where 25 nodes are randomly placed in a 1000 m × 1000 m area to form a connected network. There are 3 commodity flows in the network. The source and destination nodes for flow i (i = 1, 2, 3) are denoted as S_i and D_i respectively. The transmission range and interference range of each node are set to 250 m and 500 m, respectively. For the convenience of performance comparison with [1], we assume the physical link capacity over each channel is the same, and we set all values of w_{uv}^c to a normalized link capacity of one rate unit.

Dynamic Channel Swapping

Each flow has a rate demand of 3 rate units. We seek to maximize the proportion of the flow request, denoted as λ, that can be supported by the network. Note that each flow should achieve the same supported proportion for fairness. The ratio λ is termed as *network capacity* in this scenario. In [8], we have shown that our algorithm of SIO-based MIS computing can reduce the complexity of solving the MIS scheduling based MCF problem by one order yet achieve higher capacity, compared to the random MIS computing. Here, we demonstrate the advantage of MDCG-based MCF solution from the aspect of cooperative networking, specifically, dynamic channel swapping.

It is clear that CLC has a much larger capacity region and enhanced delay performance compared to TDMS, since CLC could better approximate the joint optimal solution by using paths generated by the MCF optimal dimensioning for cross-layer control.

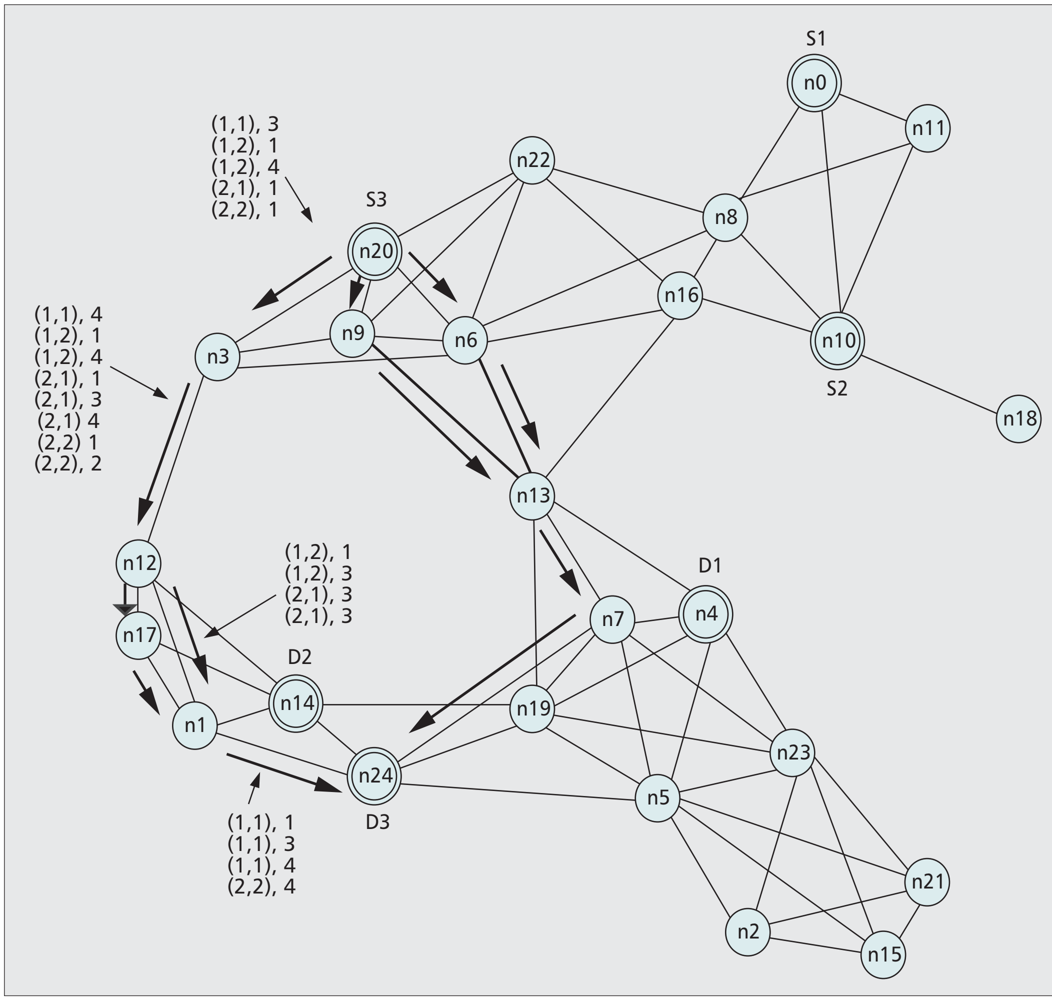

Figure 4. *Network dimensioning under the MDCG based computing.*

We consider that all nodes have 2 radios and there are 4 channels available. We use CPLEX to solve the λ optimization involved in our MCF formulation and the algorithms in [1]. The algorithm in [1] is a heuristic approach using static channel assignment which generates $\lambda = 0.25$. Our algorithm uses SIO-based MIS computing generates a higher capacity of $\lambda = 0.39$. The resource allocations associated with the MCF capacity are presented in Figs. 3 and 4 for the static algorithm in [1] and our algorithm, respectively. In Fig. 4, the links incurred (i.e., the routing) to serve all three flows are highlighted, and the channel allocation for each link is also indicated. It can be seen that each node fully utilizes its two radios over two different channels. In Fig. 4, we only present the resource allocation for flow 3 to not clutter the presentation. While the static algorithm only incurs one path for flow 3, the MDCG based algorithm incurs four paths. In particular, we indicate the radio/channel assignment for the links along the main path (which takes most of the flow) "$n20 \rightarrow n3 \rightarrow n12 \rightarrow n1 \rightarrow n24$." At each link, we can see that different radio-pair/channel combinations represented as "(radio at sending node, radio at receiving node), channel allocation" share the transmission time, showing the behavior of dynamic channel swapping. It is due to the more efficient coordination of scheduling, channel/radio assignment, and routing that the MDCG-based network dimensioning achieves higher network capacity.

Distributed Scheduling

We use the same network topology and flow/radio/channel configurations to investigate the performance of distributed scheduling and cross-layer control. The only change here is that the link capacity over each channel is uniformly selected in the range [0.1, 1] in each slot to simulate the channel diversity. We specifically compare three algorithms. The algorithm applying the tuple-based maximal scheduling over the whole network is termed as the "TDMS" algorithm. The "CLC" algorithm incorporate the TDMS algorithm with the path selection for a cross-layer control. The "MP" algorithm indicate the cross-layer control algorithm proposed in [2]. For the two cross-layer control algorithms CLC and MP, the paths generated from our SIO-based MCF solution are used as selection candidates. We develop C codes to simulate the three algorithms.

In this experiment, we gradually increase the flow input rates and observe the average node backlog (averaged over those nodes involved in flow transmissions) to examine the delay performance and capacity region. Each node assumes an infinite buffer space. The results are presented in Fig. 5. The backlog curves for all the three algorithms show a turning point at a certain input rate, which indicates the achievable capacity region for the corresponding scheduling algorithm. Before the turning point, the average backlog keeps small meaning that the network remains stable; when the input rate exceeds the turning point, the average backlog rapidly goes to very large indicating the unstable behavior out of the capacity region. It is clear that CLC has a much larger capacity region and enhanced delay performance compared to TDMS, since CLC could better approximate the joint optimal solution by using paths generated by the MCF optimal dimensioning for cross-layer control. The MP algorithm in [2] also outperform TDMS due to cross-layer control, but is much inefficient compared to our CLC algorithm. The reason is that the algorithm in [2] still adopts link-based scheduling model where the linker-layer queue length could not be accurately presented to the network-layer path selection, whereas in our tuple-based CLC algorithm the lower-layer queue information is fully available to the network-layer path selection.

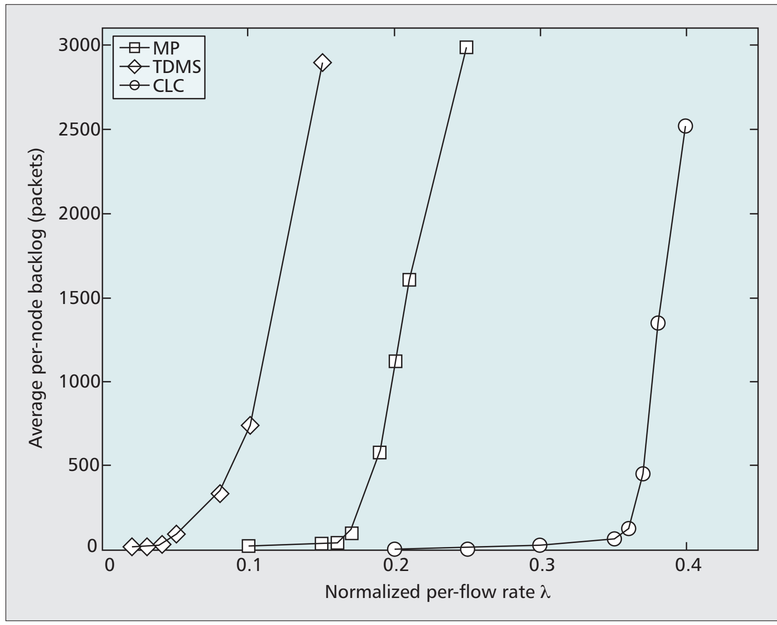

Figure 6. *Average per-node backlog under different scheduling algorithms.*

CONCLUSION

In this article, we present a theoretical framework for optimal cooperative networking in multiradio multichannel wireless networks, which is expected to offer general guidance on practical protocol and algorithm development. Specifically, based on our tool of MDCG, a multicommodity flow formulation and its dynamic implementation by duality can be applied for optimal network dimensioning and throughput-optimal control, respectively. We also discuss how to develop efficient polynomial algorithms with guaranteed performance for network dimensioning and distributed scheduling algorithm for throughput-optimal control. The scheduling performance is further enhanced with a decomposable cross-layer control mechanism.

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