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# Cross-layer Optimized Multipath Network Coding for Multichannel Multiradio Multirate Wireless Network

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**Abstract**

In this paper, we propose a cross-layer optimization method for multichannel multiradio multirate wireless networks with network coding. We employ a random linear-coding scheme for encoding and decoding operations, and we formulate a network utility maximization framework. To solve the network utility maximization problem, we use the decomposition method. In this method, we derive a congestion control algorithm considering end-to-end feedback in a wireless multihop network, distributed rate control, and heuristic resource allocation algorithm in multichannel, multiradio, and multirate environments. The performance evaluation results show that the proposed method can achieve throughput optimization in multichannel multiradio multirate wireless networks with network coding. Consequently, the proposed method can find the optimal solution of the network utility maximization problem in multichannel multiradio multirate wireless networks with network coding.

**Keywords** - Multichannel multiradio multirate wireless network, Network coding, Cross-layer optimization

## I. INTRODUCTION

In recent years, multichannel and multiradio wireless networks have been studied [1-3]. Each node in these networks has multiple interface cards, and uses multiple orthogonal channels to realize multiple concurrent links among multiple nodes. This scheme improves the throughput by exploiting all resources and multiple paths to deliver data. Furthermore, many wireless networking standards, such as IEEE 802.11, include multirate capabilities that allow devices to operate using multiple transmission rates. In general, there is a trade-off between data rate and link delivery probability in multirate transmission, which has an impact on the throughput. Loss probability increases with higher data rate, and therefore, a higher bit rate does not always improve the throughput.

Network coding has been studied to increase the throughputs of wired and wireless networks, and there have been many related studies in various fields [4-7]. According to this scheme, the relay node codes received packets before transmitting, and the coded packets are then delivered to the next hop node. If the next hop node is not the destination node, it will forward the newly coded packets to the next hop nodes; otherwise, it will recover the original data. Network coding scheme is suitable for wireless networks by using the broadcast and overhearing capabilities of inherent wireless networks, and this scheme can thus improve the network throughput [8]. Another benefit of network coding for wireless networks is its capability to mask random losses that are due to the varying nature of the wireless channel. However, many challenges remain in the quest to improve performance.

In this paper, we propose a cross-layer optimization method for congestion control, distributed rate control, and resource allocation in multichannel multiradio multirate wireless network with network coding. Studies that are related to ours are [9, 10]. In [10], the optimization problem was proposed by Soldo et al., but the network utility maximization problem was studied in a single radio and single rate wireless network. In addition, the cross-layer optimization process was performed by Radunovic et al. [9], but the decomposition method and routing model was studied in a single radio and single rate wireless network. We study the optimization model in multichannel, multiradio, and multirate wireless network. This leads to a complex optimization model that considers rate selection and resource allocation. In this paper we propose a cross-layer congestion control and resource allocation, which contribute to the optimization of multichannel, multiradio, and multirate wireless networks with intrasession network coding.

The remainder of this paper is organized as follows. In Section II, we describe the system model and optimization framework. In Section III, we describe a network utility maximization algorithm. In Section IV, we evaluate the performance of the proposed method, and finally, in Section V, we conclude the paper.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

In this paper, we consider a network model represented by multiple unicast sessions running simultaneously. There are multiple channels and multiple radios in this wireless network model, and there are $N$ nodes in the network model. The number of radios at node $i$ is denoted by $r_i$ $(i = 1, 2, ..., N)$, and $K$ orthogonal channels can be used concurrently in the network $(r_i \leq K)$. The set of unicast sessions is represented as $A_s = \{a | 1, 2, ..., A\}$. Each node can transmit the packets simultaneously to more than one next hop nodes using multiple channels. In addition, multiple unicast sessions transmit the data by sharing the network. Each session comprises the source-destination node pair denoted by $(S_a, T_a)$.

Network coding is performed by multiplying a matrix in a sufficiently large Galois field $GF$. A large field size can be achieved by using a moderate packet size. The size of the $GF$ is $2^8$. The data block can be represented as an $n$-by-$m$ matrix B, with the rows representing the $n$ blocks of the data, and the columns representing the bytes of each data block. The encoding operation produces a linear combination of the original blocks by $X = R \cdot B$, where $R$ is an $n \times m$ matrix composed of randomly selected coefficients in the Galois Field. This data block is packetized by each source node, and flows as packet streams towards each destination node.

We model the wireless network topology graph as $G(V,E)$, where $V$ represents the set of nodes and $E$ is the set of links. Let $p_{ij}^{k}$ denote the delivery probability of the link between node $i$ and $j$ with channel $k$. $x_{ij}^{ka}$ is the flow rate of session $a$ on link $(i, j)$. The data rate on node $i$ is denoted by $R_i^m$, which can be selected among the set of bitrates $R = \{R^m \mid m = 1,\ldots,L\}$ on node $i$. The set of bitrates is induced by coding/modulation schemes. In addition, intermediate nodes between source node $S_a$ and destination node $T_a$ generate linearly independent packets for $T_a$ using network coding. As multiple intermediate nodes enable multipath routing, each intermediate node can help to deliver the information to $T_a$. This means that the link delivery probability and rate control can contribute to find the optimal solution by solving the following formulations.

$$\max_{\mathbf{x}} \sum_{a \in A_S} U_a \left( \sum_{k \in K} \sum_{j < S_a} x_{S_a j}^{ka} \right) \qquad (1)$$

$$\text{s.t.} \sum_{k \in K} \sum_{j < i} x_{ij}^{ka} - \sum_{k \in K} \sum_{j > i} x_{ji}^{ka} = \left\{ \begin{array}{c} \gamma_a, i = S_a \\ -\gamma_a, i = T_a \\ 0, \text{otherwise} \end{array} \right\}, \forall a \in A_s \qquad (2)$$

$$x_{ij}^{ka} \ge 0, \forall (i, j) \in E, \forall k, \forall a \in A_s \qquad (3)$$

$$z_i^{ka} + \sum_{j \in N(i)} z_j^{ka} \le C_{ka}, \forall i \in V_a \setminus S_a, \forall k, \forall a \in A_s \qquad (4)$$

$$z_i^{ka} R_i p_{ij}^{k} \ge x_{ij}^{ka}, \quad \forall i \in V_a \setminus T_a, j \in N(i), \forall k, \forall a \in A_s \qquad (5)$$

We denote the utility function of session $a$ as $U_a(\cdot)$. This function is a monotonically increasing and strictly concave function [11]. Here, we use this function as $U_a(\cdot) = \ln(\cdot)$. The maximization of the utility summation is expressed in (1). The first constraint (2) is the flow conservation constraint. Every node should deliver its received packets to the next node, except the source and destination node, and every packet of the source node flows towards the destination. Further, this means that the number of packets transmitted by the source node and the number of packets delivered to the destination node are the same. In (4) $z_i^{ka}$ is the broadcast rate of session $a$ over channel $k$ on node $i$. The right hand side, $C_{ka}$, is the channel capacity of session $a$ over channel $k$. $N(i)$ denotes the set of transmission nodes within the range of node $i$. Therefore, the broadcast rate has the constraint by $C_{ka}$. Similarly, the link flow rate $x_{ij}^{ka}$ has the constraint on the broadcast rate $z_i^{ka}$ in (5). The broadcast rate and the data rate can support the link flow rate $x_{ij}^{ka}$ with delivery probability $p_{ij}^{k}$.

## III. NETWORK UTILITY MAXIMIZATION ALGORITHM

Our objective is to maximize the utility function which is constrained by the flow rate $x_{ij}^{ka}$ and broadcast rate $z_i^{ka}$. The above problem has high computational complexity and requires centralized computation with a high communication overhead. To determine the optimal solution, we use a dual decomposition scheme [12] that leads us to propose a distributed-rate control algorithm considering the resource allocation algorithm for the channel assignment and radio allocation.

The objective function (1) and constraints (2)-(5) are decoupled into two sub problems related to the two primal variables, $\mathbf{z}$ and $\mathbf{x}$. First, let the vectors $\boldsymbol{\beta}$, $\boldsymbol{\rho}$, and $\mathbf{q}$ be Lagrange multipliers associated with constraints (4) and (5), respectively. We can obtain the Lagrange dual function as follows:

$$\begin{aligned} L(\mathbf{z},\mathbf{x};\boldsymbol{\rho},\boldsymbol{\beta},\mathbf{q}) &= \sum_{a\in A_S} U_a\left(\sum_{k\in K}\sum_{j<S_a} x_{S_a j}^{ka}\right) \\ &-q_{S_a}\left(\sum_{k\in K}\sum_{j<S_a} x_{S_a j}^{ka} - \sum_{k\in K}\sum_{j>T_a} x_{jT_a}^{ka}\right) \\ &-\sum_{a\in A_S}\sum_{k\in K}\sum_{i\in V}\beta_i^{ka}\left(z_i^{ka} + \sum_{j\in N(i)} z_j^{ka} - C_{ka}\right) \\ &+\sum_{a\in A_S}\sum_{k\in K}\sum_{j<i}\rho_{ij}^{ka}\left(z_i^{ka} R_i p_{ij}^{k} - x_{ij}^{ka}\right) \end{aligned} \tag{6}$$

Because of the duality theory [13, 14], the Lagrange dual function is relaxed by

$$\min_{\boldsymbol{\rho},\boldsymbol{\beta}} \max_{\mathbf{z},\mathbf{x}} L(\mathbf{z},\mathbf{x};\boldsymbol{\rho},\boldsymbol{\beta}) \tag{7}$$

The primal problem and remaining two constraints are as follows:

$$\max_{\mathbf{z},\mathbf{x}} L(\mathbf{z},\mathbf{x};\boldsymbol{\rho},\boldsymbol{\beta},\mathbf{q}) \tag{8}$$

$$\text{s.t. } \sum_{k\in K}\sum_{j<i} x_{ij}^{ka} - \sum_{k\in K}\sum_{j>i} x_{ji}^{ka} = \begin{cases} \gamma_a, i = S_a \\ -\gamma_a, i = T_a \\ 0, \text{otherwise} \end{cases}, \forall a \in A_s \quad (9)$$

$$x_{ij}^{ka} \geq 0, \forall (i,j) \in E, \forall k, \forall a \in A_s \quad (10)$$

Finally, we can decompose (8)-(10) into three sub problems as follows:

$$D_1: \max_{\mathbf{x}, i=S_a} \left[ U_a\left(\sum_{k\in K}\sum_{j<S_a} x_{S_a j}^{ka}\right) - q_{S_a}\sum_{k\in K}\sum_{j\in N(S_a)} x_{S_a j}^{ka} - \sum_{k\in K}\sum_{j\in N(i)} \rho_{S_a j}^{ka} x_{S_a j}^{ka} \right] \quad (11)$$

$$D_2: \max_{\mathbf{x}, i\neq S_a} \left[ q_{S_a}\sum_{k\in K}\sum_{j\in N(T_a)} x_{jT_a}^{ka} - \sum_{k\in K}\sum_{j<i} \rho_{ij}^{ka} x_{ij}^{ka} \right] \quad (12)$$

$$\text{s.t. } \sum_{k\in K}\sum_{j<i} x_{ij}^{ka} - \sum_{k\in K}\sum_{j>i} x_{ji}^{ka} = \begin{cases} \gamma_a, i = S_a \\ -\gamma_a, i = T_a \\ 0, \text{otherwise} \end{cases}, \forall a \in A_s \quad (13)$$

$$x_{ij}^{ka} \geq 0, \forall (i,j) \in E, \forall k, \forall a \in A_s \quad (14)$$

$$D_3: \max_{\mathbf{z}, i\neq S_a} \sum_{a\in A_S}\sum_{k\in K}\left[ \sum_{j<i} \rho_{ij}^{ka} z_i^{ka} R_i^m p_{ij}^k - \sum_{i\in V} \beta_i^{ka}\left(z_i^{ka} + \sum_j z_j^{ka} - C_{ka}\right) \right] \quad (15)$$

Each Lagrange multiplier problem can be solved by the subgradient projection algorithm [12] as follows:

$$q_{S_a}(t+1) = q_{S_a}(t) + \theta_2(t)\left(\sum_{k\in K}\sum_{j<S_a} x_{S_a j}^{ka}(t) - \sum_{k\in K}\sum_{j>T_a} x_{jT_a}^{ka}(t)\right) \quad (16)$$

$$\rho_{ij}^{ka}(t+1) = \left[\rho_{ij}^{ka}(t) - \theta_2(t)\left(z_i^{ka}(t) R_i p_{ij}^k - x_{ij}^{ka}(t)\right)\right]^+ \quad (17)$$

$$\beta_i^{ka}(t+1) = \left[\beta_i^{ka}(t) + \theta_3(t)\left(z_i^{ka}(t) + \sum_{j\in N(i)} z_j^{ka}(t) - C_{ka}\right)\right]^+ \quad (18)$$

When calculating each dual variable $\boldsymbol{\rho}$, $\mathbf{q}$, and $\boldsymbol{\beta}$, variables $\theta_1(t)$, $\theta_2(t)$, and $\theta_3(t)$ are respectively used as step sizes for the iteration $t$. Here we adopt diminishing step sizes that guarantee convergence regardless of the initial value of $\boldsymbol{\rho}$, $\mathbf{q}$, and $\boldsymbol{\beta}$. The step size of iteration $t$ is given by $\theta_n(t) = A_n / (B_n + C_n \times t)$, where $A_n$, $B_n$, and $C_n$ are tunable parameters that regulate convergence speed. Furthermore, $[\bullet]^+$ represents the range of a dual variable to $[0,+\infty]$.

### III.I Congestion Control

From $D_1$, we can derive the congestion control algorithm. Each source node selects its flow rate at each time slot as follows:

$$D_1: \max_{\mathbf{x}, i=S_a} \left[ U_a \left( \sum_{k\in K} \sum_{j<S_a} x_{S_a j}^{ka} \right) - q_{S_a} \sum_{k\in K} \sum_{j\in N(S_a)} x_{S_a j}^{ka} - \sum_{k\in K} \sum_{j\in N(i)} \rho_{S_a j}^{ka} x_{S_a j}^{ka} \right] \quad (19)$$

$D_1$ can be solved by using $\sum_{k\in K} \sum_{j\in N(S_a)} x_{S_a j}^{ka} = x_{S_a}^{a}$ and $\sum_{k\in K} \sum_{j\in N(S_a)} \rho_{S_a j}^{ka} x_{S_a j}^{ka} = \rho_{S_a}^{a} x_{S_a j}^{ka}$. In this process, the congestion control from the source to the destination is realized using a node specific metric.

This solution has a similar form to the TCP optimization problem [15], and has a single solution using the first-order optimal condition [13]. We can find the solution as follows:

$$x_{S_a}^{a} = U_a'^{-1}(q_{S_a} + \rho_{S_a}^{a}) \quad (20)$$

From (20), $x_{S_a}^{a}$ is inversely proportional to $q_{S_a}$ and $\rho_{S_a}^{a}$. From (16), when the number of transmitting packets from the source node is larger than that of the receiving packets of the destination node, $q_{S_a}$ increases. If $q_{S_a}$ increases, the number of packets from the source node decreases. Therefore, $q_{S_a}$ indicates that packets from the source node arrive at the destination node, and reflect the end-to-end feedback in wireless networks.

### III.II Distributed Rate Control

$D_2$ represents the routing problem. From (21)-(23), we can calculate the flow rate of intermediate nodes.

$$D_2: \max_{\mathbf{x}, i\neq S_a} \left[ q_{S_a} \sum_{k\in K} \sum_{j\in N(T_a)} x_{jT_a}^{ka} - \sum_{k\in K} \sum_{j<i} \rho_{ij}^{ka} x_{ij}^{ka} \right] \quad (21)$$

$$\text{s.t.} \sum_{k\in K}\sum_{j<i} x_{ij}^{ka} - \sum_{k\in K}\sum_{j>i} x_{ji}^{ka} = \begin{Bmatrix} \gamma_a, i = S_a \\ -\gamma_a, i = T_a \\ 0, \text{otherwise} \end{Bmatrix}, \forall a \in A_s \quad (22)$$

$$x_{ij}^{ka} \geq 0, \forall (i,j) \in E, \forall k, \forall a \in A_s \quad (23)$$

From (21), $q_{S_a} \sum_{k\in K} \sum_{j\in N(T_a)} x_{jT_a}^{ka}$ is equal to $q_{S_a} x_{S_a}^{a}$ by (20) and (22). If $q_{S_a}$ is increased in (21), the number of transmitting packets from the intermediate nodes increase. This equation can be interpreted as a job scheduling problem [16]. One can think of variable $\rho_{ij}^{ka}$ as the cost of each job, each of which has a cost assigned to it according to the coefficient associated with $x_{ij}^{ka}$. However, when node $i$ has only one next hop node $j$, $x_{ij}^{ka}$ is expressed as $q_{S_a} x_{S_a}^{a} / \rho_{ij}^{ka}$. When node $i$ have two next hop nodes, $x_{ij}^{ka}$ is solved by the linear equation with two variables. The link flow rate $x_{ij}^{ka}$ has the constraints in (5) and (22).

Next, $D_3$ can be rewritten as follows:

$$\max_{\mathbf{z}, i\neq S_a} \sum_{i\in V} \left[ \sum_{j<i} \rho_{ij}^{ka} z_i^{ka} R_i p_{ij}^{k} - \beta_i^{ka} \left( z_i^{ka} + \sum_{j\in N(i)} z_j^{ka} - C_{ka} \right) \right] \quad (24)$$

$$= \max_{\mathbf{z}} \left[ \omega_i^{ka} z_i^{ka} - \beta_i^{ka} (z_i^{ka} + \sum_{j\in N(i)} z_j^{ka} - C_{ka}) \right] \quad (25)$$

where $\omega_i^{ka} = \sum_j \rho_{ij}^{ka} R_i^{m} p_{ij}^{k}, (i,j) \in E$. In (25), we can also apply the proximal algorithm [17]. An auxiliary variable $\mathbf{y}^*$ and the quadratic term are added to make it strictly convex. Thus, (25) can be rewritten as

$$\max_{\mathbf{z}} \left[ (\omega_i^{ka} - \beta_i^{ka} - \sum_{j\in N(i)} \beta_j^{ka}) z_i^{ka} - \phi \left\| \mathbf{z} - \mathbf{y}* \right\|^2 + \beta_i^{ka} C_{ka}) \right] (26)$$

where $\phi$ is a small positive constant. Then, we update $z_i^{ka}$ as follows:

$$z_i^{ka}(t) = z_i^{ka}(t) - \frac{\omega_i^{ka} - \beta_i^{ka} - \sum_{j\in N(i)} \beta_j^{ka}}{2\phi} \quad (27)$$

We apply the primal recovery method [9] to determine the equally weighted average of the flow rate as follows:

$$z_i^{ka}(\tau) = \frac{1}{t} \sum_{\tau=1}^{t} z_i^{ka}(\tau) \quad (28)$$

The primal recovery method ensures that the optimal dual solution of the main framework (11) converges to a primal optimal solution [12]. Therefore, the distributed rate control algorithm is guaranteed to converge.

## III.III Resource Allocation

We consider a resource allocation algorithm for radio allocation and channel assignment. In order to assign the channels to the link, we present a distributed channel assignment algorithm at each node with congestion price $\beta_i^{ka}$. In order for the node with the larger congestion price to acquire more channels, we calculate the summation of the congestion prices over channel $k$ on every node. When $\sum_{a=1}^{A} \beta_i^{ka}$ is obtained, each node compares its result to that of its neighbor nodes. If its congestion price is the highest, node $i$ assigns the channel to its links and the number of available radios is decreased incrementally. The process continues for this node until there are no more channels or radios available on node $i$. These processes last until the channel assignment is finished on every node in the network. After the channel assignment, we substitute the link flow rate $x_{ij}^{ka}$ into the link of the node to which the channel is assigned. However, the link flow rate $x_{ij}^{ka}$ is 0 for the link of those nodes to which no channel is assigned.

**Table 1:** Resource allocation scheme.

| | |
|---|---|
| 1) | For channel $k$, get $\sum_{a=1}^{A} \beta_i^{ka}$ in each node. |
| 2) | Each node compares the results of 1) with its neighbor nodes. Find the node $i$ with maximum result. |
| 3) | Assign one channel and one radio to link between node $i$ and node $i$'s next hop node $j$. At node $i$ and $j$, set $r_i = r_i - 1$ and $r_j = r_j - 1$. |
| 4) | For other channel, Go to step 1) and iterate this process until the available channel is exhausted. |
| 5) I | n unassigned channel link, the link flow rate $x_{ij}^{ka} \to 0$. |

Table 1 describe the resource allocation scheme. This resource allocation algorithm can control the link flow rate and avoid congestion by channel assignment.

## III.IV Rate Selection

In this subsection, we show how to select the transfer rate of each node to configure the wireless network using multiple rates. When the transmission rate of node $i$ is $R^m$, $T_i^m$ is the transmission range of node $i$ and the distance of the link to node $j$ is $d_{ij}$. The node that satisfies the condition $d_{ij} \leq T_i^m$ is called a candidate node and is represented by $F_i^m$. Considering multiple data rates and link delivery probabilities between one sender and its downstream forwarding nodes, the expected transmission rate (ETR) is represented as follows.

$$D_i^m = \sum_{j \in F_i^m} (R_i^m p_{ij}^m (1 + D_j)) \qquad (29)$$

$D_i^m$ is the value of the ETR when node $i$ transmits using transmission rate $R^m$, $p_{ij}^m$ is a delivery probability between nodes $i$ and $j$, and $D_j$ is the ETR for the candidate node $j$ from node $i$.

The rate selection mechanism using the ETR for each node is described in Table 2. The ETR indicates the number of expected bits transmitted towards the destination node. Every node can be selected as a downstream forwarding node except for the source node. Each node can select the data rate to increase the ETR of the whole network using the ETR for downstream forwarding nodes. Therefore, this rate selection scheme can contribute to find the optimal solution for a multirate network. The performance of this scheme is evaluated in Section IV.

The ETR is calculated from the nearest node to the destination node. Thus, the ETR values of the candidate node are included in the calculation process. The process of transmission rate selection shown in Table 2 is summarized mathematically as

$$R_i = \arg\max \sum_{j \in F_i^m} (R_i^m p_{ij}^m (1 + D_j)) \qquad (30)$$

**Table 2:** ETR calculation and rate selection scheme.

| |
|---|
| 1) Initialize ETR of all nodes to zero. |
| 2) From the nearest node to the destination, calculate (29) for multirate $R_i^m (m = 1, \cdots, L)$. |
| 3) Using result of (29), select the transmission rate $R_i$ of the node $i$ with maximum ETR. |
| 4) Go to step 1) and iterate this process until the source node finds the transmission rate. |

## IV. PERFORMANCE EVALUATION

In this section, we describe the performance evaluation of the proposed algorithms by simulation. We construct two static topology models including the grid topology and the random topology. Each model consists of 16 nodes. We use the data rate R, 1.5R, and 2R in multirate scenarios. Each node has multiple radio interfaces, and they then transmit packets through multiple orthogonal channels. First, when the proposed algorithms are applied iteratively, we observe the changes in the throughput and analyze the results. Then, we showcase the throughput as graphs. If the network utility converges to a fixed value, the optimal solution has been obtained. It is assumed that eight sessions communicate simultaneously, and then, we observe the network utility in three pairs based on the number of channel radios. There are (7 radios, 7 channels), (4 radios, 7 channels), and (4 radios, 4 channels).

Fig 1 and 2 show the convergence of the network utility under the grid and random topologies. In these graphs, we use eight sessions. In most cases, the network utility converges after several iterations. The results show that each session can find the optimal path to its destination node within several iterations, and the resource allocation result is kept steady in each node. The network utility increases with the number of channels or the number of radios when the number sessions is fixed.

Fig 3 and 4 show the network utility in terms of the number of channels with different radios under the two topologies. In this case, we use eight sessions. In these figures, the number of available channels ranges from five to eight, and the number of radios is set to three and five, respectively. These results show that the network utilities increase as the number of channels and radios increases.

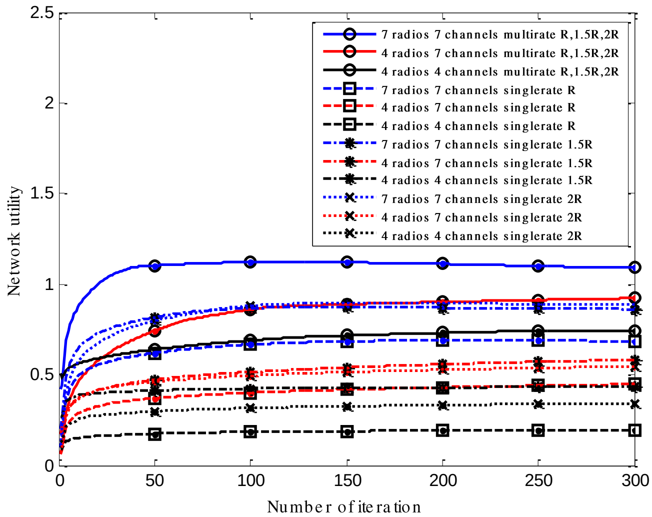


**Fig 1.** Network utility of grid topology with eight sessions.

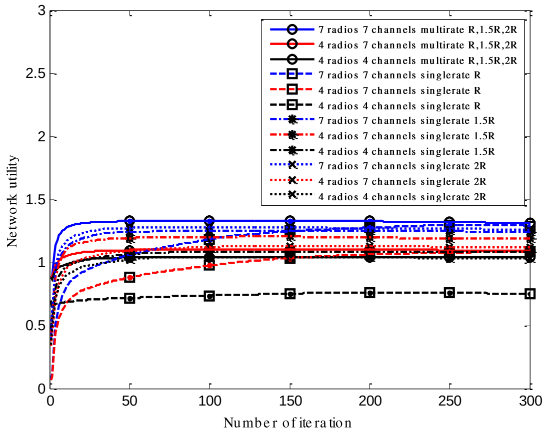


**Fig 2.** Network utility of random topology with eight sessions.

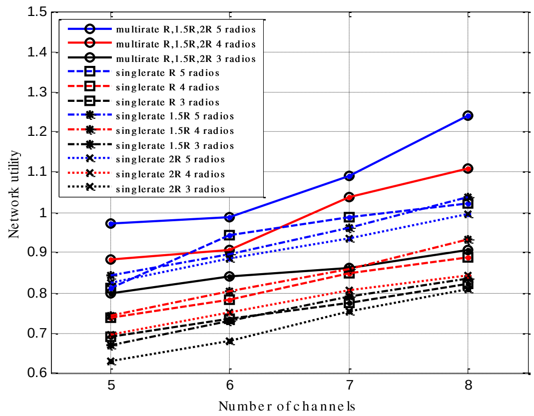


**Fig 3.** Network utility of grid topology in terms of the number of channels with eight sessions.

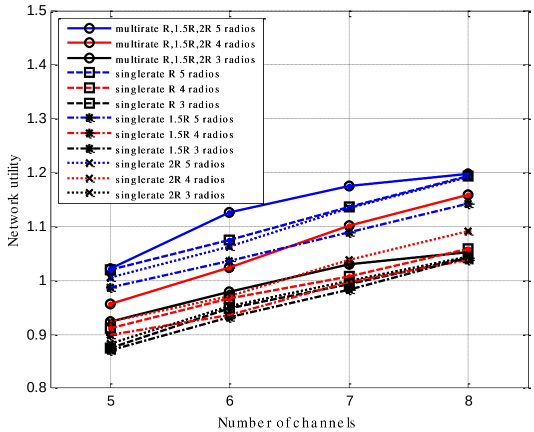


**Fig 4.** Network utility of random topology in terms of the number of channels with eight sessions.

Next, we show the network utility in terms of the number of channels with different sessions in the grid and random topologies. In this case, each node has five radio interfaces and the number of available channels ranges from five to eight. Fig 5 and 6 show that the network utility increases with the number of channels or sessions. This result shows that the congestion control, rate control, and resource allocation algorithms perform well in a multichannel, multiradio, and multirate environment.

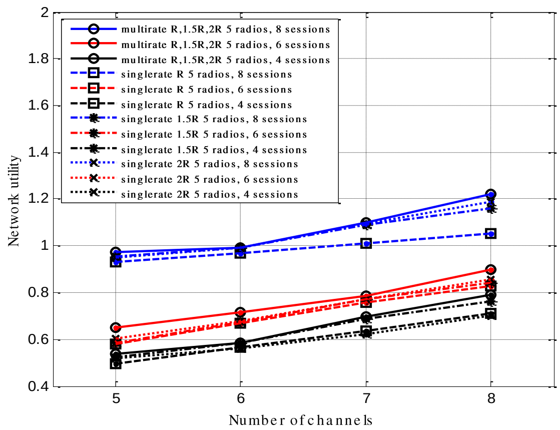


**Fig 5.** Network utility of grid topology in terms of the number of sessions with five radios.

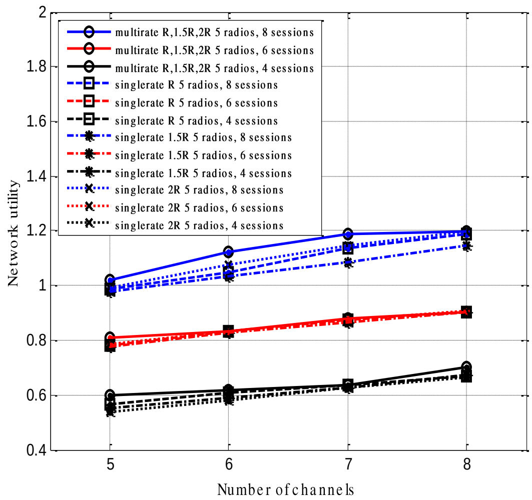


**Fig 6.** Network utility of random topology in terms of the number of session with five radios.

## V. CONCLUSIONS

In this paper, we proposed a cross-layer optimization method in a multichannel multiradio multirate wireless network with network coding. We constructed a network utility maximization framework, and then, we derived a congestion control algorithm considering end-to-end feedback in wireless multihop networks, distributed rate control, and heuristic resource allocation algorithm, respectively in a multichannel, multiradio, and multirate environment. These three algorithms can be used to solve the network utility maximization problem. In addition, we proposed a rate selection scheme to choose the transmission rate on each node. The proposed algorithms were evaluated by simulation. The performance evaluation results showed that the proposed algorithm achieved the optimal solution in a multirate multiradio multichannel wireless network.

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## REFERENCES

[1] Jahanshahi, M., Dehghan, M., & Meybodi, M. R. (2017). A cross-layer optimization framework for joint channel assignment and multicast routing in multi-channel multi-radio wireless mesh networks. *International Journal of Computer Mathematics,* 94(8), 1624-1652.

[2] Xie, K., Wang, X., Liu, X., Wen, J., & Cao, J. (2016). Interference-aware cooperative communication in multi-radio multi-channel wireless networks. *IEEE Transactions on Computers*, 65(5), 1528-1542.

[3] Zeng, K., Yeng, Z., & Lou, W. (2010). Opportunistic routing in multi-radio multi-channel multi-hop wireless networks. *IEEE Trans. Wireless Commun., 9*(11), 3512–3521.

[4] Ahlswede, R., Cai, N., Li, S., & Yeung, R. (2000). Network information flow. *IEEE Trans. Inform. Theory, 46*(4) 1204-1216.

[5] Chachulski, S., Jennings, M., Katti, S., & Katabi, D. (2007). Trading structure for randomness in wireless opportunistic routing. In *Proc. ACM SIGCOMM,* 169-180.

[6] Xu, C., Wang, P., Xiong, C., Wei, X., & Muntean, G. M. (2017). Pipeline network coding-based multipath data transfer in heterogeneous wireless networks. IEEE Transactions on Broadcasting, 63(2), 376-390.

[7] Xu, C., Li, Z., Zhong, L., Zhang, H., & Muntean, G. M. (2016). CMT-NC: improving the concurrent multipath transfer performance using network coding in wireless networks. *IEEE Transactions on Vehicular Technology,* 65(3), 1735-1751.

[8] Fragouli, C., Katabi, D., Markopoulou, A., Medard, M., & Rahul, H. (2007). Wireless network coding: opportunities and challenges. In *Proc. MILCOM 2007. IEEE*, 1-8.

[9] Radunovic, B., Gkantsidis, C., Key, P., & Rodriguez, P. (2010). Toward practical opportunistic routing with intra-session network coding for mesh networks. *IEEE Transaction on Networking (TON), 18*(2), 420–433.

[10] Soldo, F., Markopoulou, A., & Toledo, A. (2010). A simple optimization model for wireless opportunistic routing with intra-session network coding. In *Proc. IEEE International Symposium on NetCod*, 1–6.

[11] Chiang, M., Low, S., Calderbank, A., & Doyle, J. (2007). Layering as optimization decomposition: a mathematical theory of network architectures. In *Proc. IEEE*, *95*(1), 255–311.

[12] Palomar D., & Chiang, M. (2006). A tutorial on decomposition methods for network utility maximization. *IEEE J. Sel. Areas Commun.*, *24*(8), 1439–1451.

[13] Bertsekas, D., Nedic, A., & Ozdaglar, A. (2003). *Convex analysis and optimization*. Belmont, MA.: Athena Scientific.

[14] Boyd S., & Vandenberghe, L. (2004). *Convex optimization*. Cambridge, U.K.: Cambridge Univ. Press.

[15] Chen, L., Low, S., Chiang, M., & Doyle, J. (2006). Cross-layer congestion control, routing and scheduling design in ad hoc wireless networks. In *Proc. IEEE INFOCOM*, 1–13.

[16] Brusco, M., & Jacobs, L. (1995). Cost analysis of alternative formulations for personnel scheduling in continuously operating organizations. *European Journal of Operational Research, 86*(2),249–261.

[17] Bertsekas, D., & Tsitsiklis, J. (1989). *Parallel and distributed computation: numerical methods*, New Jersey: Prentice-Hall.