Joint Distributed Rate Control and Resource Allocation in Multiradio Multichannel Multihop Wireless Networks with Network Coding

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Abstract

In this paper, we propose a joint distributed rate control algorithm and distributed resource allocation algorithm in multiradio multichannel multihop wireless networks with network coding. Our formulation provides a method of finding active links from the source to the destination and utilizing the resources from the available ones in order to maximize the network utility. Distributed schemes are used to approximate the upper bound within the feasible solution region of the optimization problem. The performance evaluation results show that the proposed scheme can effectively exploits multiple radios and channels.

Keywords: *Network coding, rate control, resource allocation, distributed algorithm, cross-layer optimization*

1. Introduction

Network coding has been extensively studied since it is a promising technique to increase the network throughput for both wired and wireless networks [1-4]. Network coding is a particular in-network data processing technique employed to mix the packets received by relay nodes before forwarding them. Wireless environments lend themselves naturally to network coding, thanks to their inherent broadcast and overhearing capabilities. By exploiting the broadcast nature of the wireless channel, the conventional wireless network coding was suggested to increase the network throughput as compared with the traditional transmission scheduling scheme in multihop wireless networks [5-7]. Network coding schemes in wireless networks can be divided into two categories. The first one is the inter-session network coding which is operated on packets from different flows. The second one is the intra-session network coding which is mixed on packets belonging to the same flow. These two network coding schemes can reduce the number of transmissions needed and thus increase the capacity of the network [8-12]. In this paper, we are interested in wireless network with intra-session network coding used for carrying traffic from unicast sessions, which is the dominant traffic today.

An optimized multipath network coding (OMNC) scheme was proposed by using a distributed optimization algorithm that maximizes the advantages of network coding while avoiding congestion in single channel single radio environment [13]. Distributed algorithm has the benefit to reduce the computational load and communications overhead. Also, distributed algorithm affects rate and robustness of convergence, tradeoff between local computation and global communication, and quantity and symmetry of message passing [14]. OMNC solves the network utility maximization framework, which is consisted with multipath network coding using mathematical decomposition. However, wireless network generally has multiple orthogonal channels and multiple radios in recent years. Each node has more than one network interface card, referred to as radio. Each radio has the capability of switching over multiple orthogonal channels and can communicate with multiple neighbors simultaneously. With the rich provisioning of resource, *i.e.*, multiple radios and multiple channels, it is necessary for a sophisticated technique to be used for network coding under multiradio multichannel conditions. In addition, it is required to design a distributed algorithm to fully exploit the available bandwidth with the neighborhood.

In this paper, we propose a network coding scheme jointly considering distributed rate control algorithm and a cross-layer resource allocation for channel assignment and radio allocation to maximize the network utility in multiradio multichannel multihop wireless networks. To our best knowledge, there is no study of the joint rate control algorithm with network coding and resource allocation for multichannel multiradio wireless network. First, we will formulate the network utility maximization problem. Then, by solving this problem, we will show the distributed rate control algorithm that includes the optimal flow rate and broadcast rate. Also we will find the optimal solution by using heuristic resource allocation algorithm.

2. Problem Formulation

We consider multiple unicast sessions running simultaneously over multiple channels with multiple radios in a wireless network. On node i, the number of radios is denoted by r_i $(i = 1, 2, ..., N)$, and there are K channels in the network $(r_i \le K)$, which divide the wireless spectrum. We model the topology graph as $G(V, E)$, where V is the set of selected nodes to transmit and E is the set of links. Each node can communicate with its neighbouring nodes by multiple links, but none of the links can use the same channel simultaneously. Since a node has multiple radios, it can transmit packets to neighbouring nodes at the same time over different channels. $A_s = \{a \mid 1, 2, ..., A\}$ is the set of sessions. Each session is composed of a source-destination node pair denoted by (S_a, T_a). Let p_{ij}^k denote the packet reception ratio of the link between node i and its neighboring node j with channel k. On that link, the link flow rate is represented by x_{ij}^{ka}, which is the average injection rate of packets on link (i, j). The data rate on node i with channel k is denoted by R_i^k. Let $U_a(\cdot)$ represent the utility function of session a. This function is a monotonically increasing and strictly concave function. And this function is describing the utility of session a transmitting at some rate. Here, we use this function as $U_a(\cdot) = \ln(\cdot)$. Given the above models, we formulate the network utility maximization problem for multiple sessions as follows:

$$\max \sum_{a=1}^{A} U_a\left(\sum_{k=1}^{K} \gamma_{ka}\right) \tag{2.1}$$

$$\text{s.t.} \sum_{k=1}^{K} \sum_{(i,j)\in E} x_{ij}^{ka} - \sum_{k=1}^{K} \sum_{(j,i)\in E} x_{ji}^{ka} = \left\{ \begin{array}{c} \gamma_a, i = S_a \\ -\gamma_a, i = T_a \\ 0, \text{otherwise} \end{array} \right\}, \forall a \in A_s \tag{2.2}$$

$$x_{ij}^{ka} \ge 0, \forall (i, j) \in E, \forall k, \forall a \in A_s \tag{2.3}$$

$$z_i^{ka} + \sum_{j \in N(i)} z_j^{ka} \le C_{ka}, \forall i \in V_a \setminus S_a, \forall k, \forall a \in A_s \quad (2.4)$$

$$z_i^{ka} R_i^k p_{ij}^k \ge x_{ij}^{ka}, \forall i \in V_a \setminus T_a, j \in N(i), \forall k, \forall a \in A_s \quad (2.5)$$

where γ_{ka} is the throughput of session a over channel k. The maximization of the summation of utility function over the set of sessions A_s is expressed in (2.1). The throughput of each session is calculated by adding up the values of γ_{ka} used in it. The network utility is the sum the utility function with whole sessions. From (2.2) to (2.5), there are constraints of the object function (2.1). Under all sessions, every node should deliver its received packets to the next hop node except the source and destination node, and every packet of the source node flows towards the destination in (2.2). It is the constraint that the link flow rate x_{ij}^{ka} could not be smaller than zero in (2.3). z_i^{ka} denotes the broadcast rate of session a over channel k on node i and C_{ka} denotes the channel capacity of session a over channel k in (2.4). $N(i)$ denotes the set of transmission nodes within range of node i. Therefore, the broadcast rate has the constraint on C_{ka}. Similarly, the link flow rate x_{ij}^{ka} has the constraint on the broadcast rate z_i^{ka} with the packet loss in (2.5).

The above network utility maximization problem has high computational complexity and requires centralized computation with high communication overhead. To solve this optimization problem, we use a dual decomposition technique [14] that leads us to propose a distributed rate control algorithm by jointly considering the radio allocation, channel assignment and link scheduling. By relaxing the constraint (2.5), the optimization problem is decoupled into two subproblems concerning the two primal variables, $\mathbf{z}$ and $\mathbf{x}$. First, let the vectors $\boldsymbol{\beta}$ and $\boldsymbol{\rho}$ be Lagrange multipliers associated with constraints (2.4) and (2.5), respectively. The Lagrange dual function is given by

$$\begin{aligned} L(\mathbf{z}, \mathbf{x}; \boldsymbol{\rho}, \boldsymbol{\beta}) &= \sum_{a=1}^{A} U_a\Big(\sum_{k=1}^{K} \gamma_{ka}\Big) \\ &+ \sum_{a=1}^{A}\sum_{k=1}^{K}\left[\sum_{(i,j)\in E} \rho_{ij}^{ka}(z_i^{ka} R_i^{ka} p_{ij}^k - x_{ij}^{ka}) - \sum_{i \in V} \beta_i^{ka}\Big(z_i^{ka} + \sum_{j \in N(i)} z_j^{ka} - C_{ka}\Big)\right] \end{aligned} \quad (2.6)$$

Due to the duality, the Lagrange dual function becomes

$$\min_{\boldsymbol{\rho},\boldsymbol{\beta}} \max_{\mathbf{z},\mathbf{x}} L(\mathbf{z}, \mathbf{x}; \boldsymbol{\rho}, \boldsymbol{\beta}) \quad (2.7)$$

This Lagrange multiplier problem can be solved by the subgradient projection algorithm as follows [7]:

$$\rho_{ij}^{ka}(t+1) = \left[\rho_{ij}^{ka}(t) - \theta(t)(z_i^{ka}(t) R_i^k p_{ij}^k - x_{ij}^{ka})\right]^+ \quad (2.8)$$

$$\beta_i^{ka}(t+1) = \left[\beta_i^{ka}(t) + \theta(t)\Big(z_i^{ka} + \sum_{j \in N(i)} z_j^{ka} - C_{ka}\Big)\right]^+ \quad (2.9)$$

where $[\cdot]^+$ represents the projection to $[0, +\infty]$ and $\theta(t) = A/(B + C \times t)$ is the step size for iteration t. A, B and C are parameters that determine the convergence speed. $\boldsymbol{\rho}$ is the vector of link cost for link $(i, j) \in E$ and $\boldsymbol{\beta}$ is the vector of congestion price for each node.

Since the Lagrange function is separable, (2.7) can be decomposed into two subproblems:

$$\max_{\boldsymbol{x}} \sum_{a=1}^{A} U_a(\sum_{k=1}^{K} \gamma_{ka}) - \sum_{a=1}^{A}\sum_{k=1}^{K}\sum_{(i,j)\in E} \rho_{ij}^{ka} x_{ij}^{ka} \tag{2.10}$$

$$\max_{\boldsymbol{z}} \sum_{a=1}^{A}\sum_{k=1}^{K}\left[\sum_{(i,j)\in E} \rho_{ij}^{ka} z_i^{ka} R_i^k p_{ij}^k - \sum_{i\in V} \beta_i^{ka}(z_i^{ka} + \sum_{j\in N(i)} z_j^{ka} - C_{ka})\right] \tag{2.11}$$

These two decomposed problems are separately solved and each problem is coordinated by the Lagrange multiplier $\boldsymbol{\rho}$ and $\boldsymbol{\beta}$. Equation (2.10) is similar to the well-known min-cost flow problem [15]. Since we relaxed the constraint (2.5), the flow rate has no upper bound. Also, we can remove the term of the summation with all sessions and then we can obtain the problem for one session. Therefore equation (2.10) can be rewritten as

$$\max_{\boldsymbol{x}} U_a(\sum_{k=1}^{K} \gamma_{ka}) - \sum_{k=1}^{K}\sum_{(i,j)\in E} \rho_{ij}^{ka} x_{ij}^{ka} \tag{2.12}$$

With regard to the vector $\mathbf{x}$, (2.12) is a shortest path problem. Let $p_{\min}^{ka}$ represent the cost of a unit flow by adding up the link cost ρ_{ij}^{ka} along the shortest path from source to destination. If γ_{ka} units of traffic through this path are sent, the total cost is $p_{\min}^{ka}\gamma_{ka}$. Therefore (2.12) is transformed into maximization problem with vector $\boldsymbol{\gamma}$ as follows:

$$\max_{\gamma} U_a(\sum_{k=1}^{K} \gamma_{ka}) - \sum_{k=1}^{K} p_{\min}^{ka}\gamma_{ka} \tag{2.13}$$

However, (2.13) is not strictly concave owing to the linearity term of utility function. γ_{ka} is oscillated among the routing paths. To eliminate the oscillation, we use the proximal algorithm [15]. The quadratic term is added as (2.14).

$$\max_{\gamma} U_a(\sum_{k=1}^{K} \gamma_{ka}) - \sum_{k=1}^{K} \theta_{ka} \left\|\boldsymbol{\gamma} - \boldsymbol{y}\right\|^2 - \sum_{k=1}^{K} p_{\min}^{ka}\gamma_{ka} \tag{2.14}$$

Here θ_{ka} is a positive constant for session a and channel k. $\mathbf{y}$ is an auxiliary variable for each $\boldsymbol{\gamma}$. Then, the throughput $\boldsymbol{\gamma}$ is obtained in (2.14). To guarantee a primal solution, we apply the primal recovery method [16] to take an equally-weighted average of the flow rate as follows:

$$x_{ij}^{k\alpha}(t) = \frac{1}{t}\sum_{m=1}^{t} x_{ij}^{k\alpha m} \tag{2.15}$$

where m is an iteration index.

Next, we can rewrite (2.11) as

$$\max_{\mathbf{z}} \sum_{a=1}^{A}\sum_{k=1}^{K}\sum_{i\in V}\left[\omega_i^{ka} z_i^{ka} - \beta_i^{ka}(z_i^{ka} + \sum_{j\in N(i)} z_j^{ka} - C_{ka})\right] \tag{2.16}$$

$$\max_{\mathbf{z}} \sum_{a=1}^{A}\sum_{k=1}^{K}\sum_{i\in V}\left[\omega_i^{ka} z_i^{ka} - \beta_i^{ka} z_i^{ka} - \beta_i^{ka}\sum_{j\in N(i)} z_j^{ka} + \beta_i^{ka} C_{ka}\right] \tag{2.17}$$

$$\max_{\mathbf{z}} \sum_{a=1}^{A}\sum_{k=1}^{K}\sum_{i\in V}\left[(\omega_i^{ka} - \beta_i^{ka} - \sum_{j\in N(i)} \beta_j^{ka}) z_i^{ka} + \beta_i^{ka} C_{ka}\right] \tag{2.18}$$

where $\omega_i^{ka} = \sum_j \rho_{ij}^{ka} R_i^k p_{ij}^k, (i,j)\in E$. In (2.18), we can also apply the proximal algorithm [15]. An auxiliary variable $\mathbf{y}^*$ and the quadratic term are used for vector $\mathbf{z}$. Thus (2.18) is rewritten as

$$\max_{\mathbf{z}} \sum_{a=1}^{A}\sum_{k=1}^{K}\sum_{i\in V}\left[(\omega_i^{ka} - \beta_i^{ka} - \sum_{j\in N(i)} \beta_j^{ka}) z_i^{ka} - \phi\left\|\mathbf{z}-\mathbf{y}^*\right\|^2 + \beta_i^{ka} C_{ka})\right] \tag{2.19}$$

where ϕ is a small positive constant. Then we update z_i^{ka} as follows:

$$z_i^{k\alpha}(t) = z_i^{ka}(t) - \frac{\omega_i^{ka} - \beta_i^{ka} - \sum_{j\in N(i)} \beta_j^{ka}}{2\phi} \tag{2.20}$$

We apply the primal recovery method [16] to obtain a primal optimal solution as in (2.15):

$$z_i^{k\alpha}(t) = \frac{1}{t}\sum_{m=1}^{t} z_i^{k\alpha m} \tag{2.21}$$

To deal with the issue of the difference in the feasible solution region between the network utility maximization problem and convex optimization problem, we consider a distributed joint resource allocation algorithm with respect to radio 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 β_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 neighboring node. If its congestion price is the highest, node i assigns the channel to its links and the number of available radios is decreased one by one. The process on this node continues 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}, obtained in (2.15), into the link of node to which the channel is assigned. However, the link flow rate is 0 for the link of those nodes to which no channel is assigned. As a result, the link flow rate x_{ij}^{ka} is decided and then (2.7) is calculated.

In summary, we have the following joint distributed rate control and resource allocation algorithm for multiradio multichannel multihop wireless networks in Table 1.

Table 1. Joint distributed rate control and resource allocation algorithm

1) Initialization. Set ρ, β to zero and $\mathbf{x}$, $\mathbf{z}$ to small positive number.
2) Solve the equation (2.10). Find the shortest path with link cost ρ_{ij}^{ka}. Update the flow rate x_{ij}^{ka} according to (2.15).
3) Solve the equation (2.11). Update the broadcast rate z_i^{ka} according to (2.21).
4) Solve the equation (2.9).
   a) Update the congestion price β_i^{ka}.
   b) Calculate $\sum_{a=1}^{A} \beta_i^{ka}$ and compare the result with neighboring node. Radio and channel are allocated to a node with high congestion price.
   c) At a node with no channel assigned, set $x_{ij}^{ka} = 0$.
5) Solve the equation (2.8). Update the link cost ρ_{ij}^{ka}.
6) Go to step 1)

3. Performance Evaluation

In this section we evaluate the performance of proposed schemes using two topology models. Two models are the 4×4 grid topology consists of 16 nodes and random topology with 16 nodes. And multiple sessions transmit packets through the network simultaneously. Figure 1 shows the network utility with different radios and channels for a grid topology with 16 nodes. Figure 2 shows the network utility with the same number of radios, channels and nodes for a random topology. In these two figures, there are two sessions which sending packets simultaneously through the network. The network utility converges after several iterations and increases according to the number of radios or the number of channels in both topologies. Also, a plot of the network utility according to the packet reception ratio is shown in Figure 3. The network utility increases as the packet reception ratio increases.

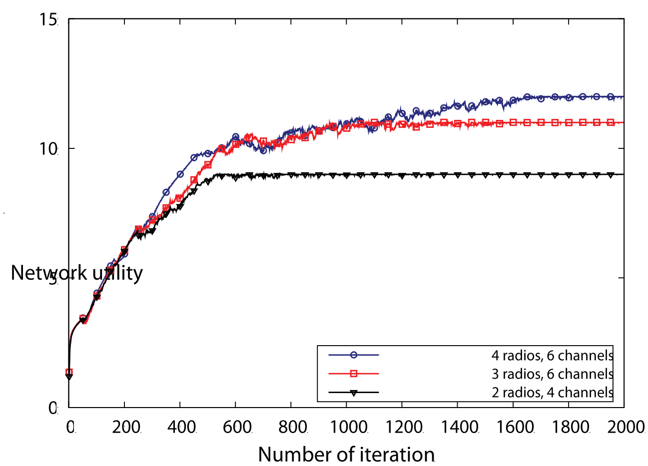

Figure 1. Network utility in a grid topology

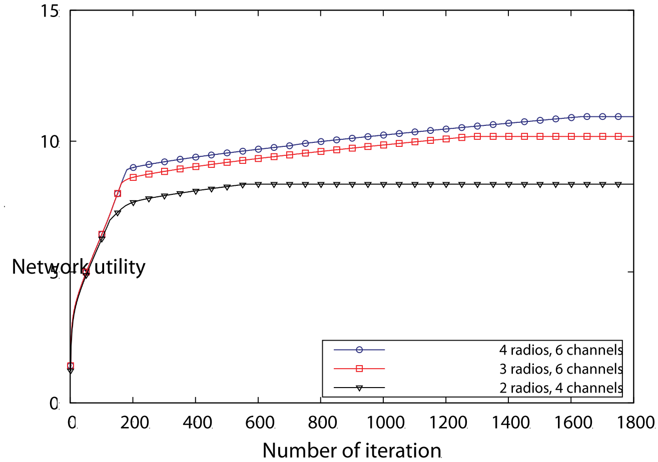

Figure 2. Network utility in a random topology

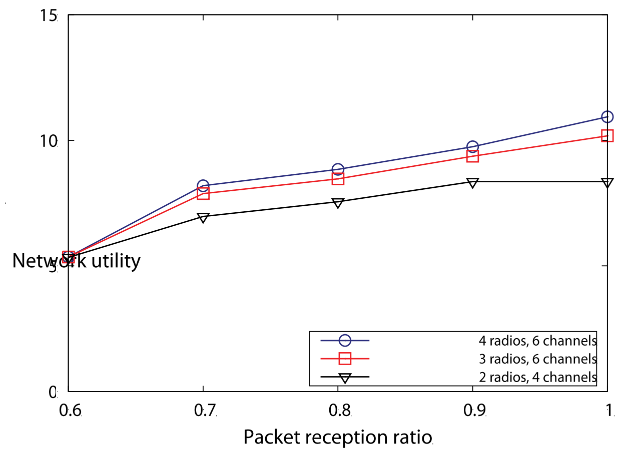

Figure 3. Network utility according to packet reception ratio in a random topology

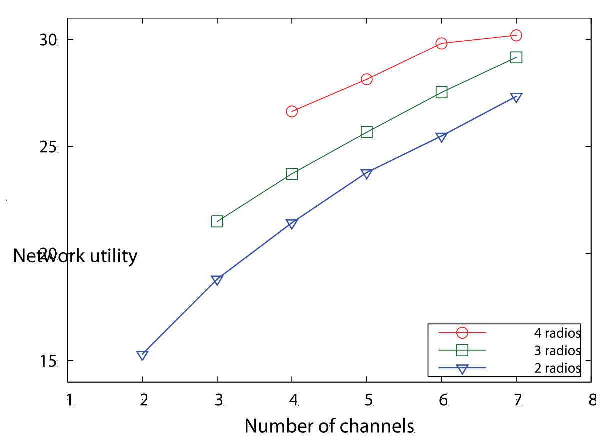

Figure 4. Network utility in terms of the number of channels with different radios in a grid topology

Figure 4 and Figure 5 show the network utility in terms of the number of channels with different radios under two topology models. In this case, we use five sessions. The network utility increases with either the number of channels or the number of radios. Therefore, the distributed resource allocation scheme is an appropriate method to improve the network utility in multichannel and multiradio networks.

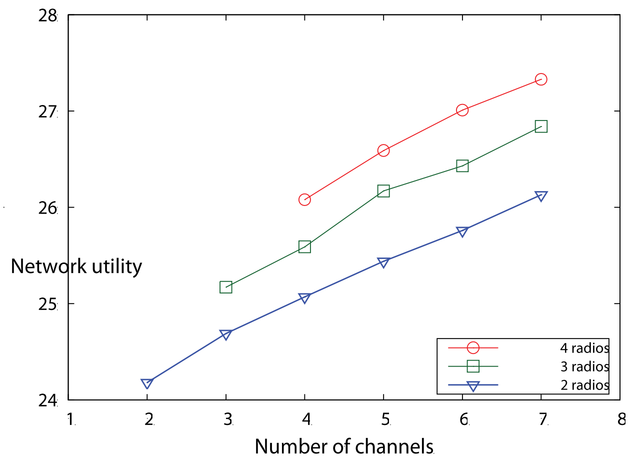

Figure 5. Network utility with in terms of channels with different radios in a random topology

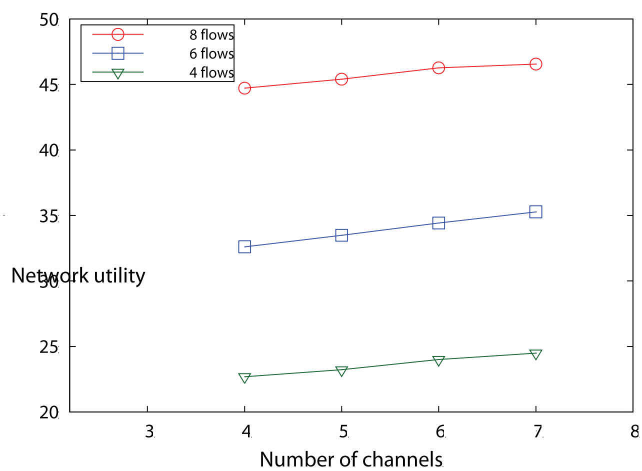

Figure 6. Network utility in terms of the number of channel with different sessions in a grid topology

Figure 6 and Figure 7 also show the network utility in terms of the number of channels with different sessions under two topologies. Each node has 4 radios. The network utility increases with the number of sessions. Therefore, the proposed algorithm is also suitable for the performance improvement in multiple session networks. The performance evaluation results show that our proposed scheme is approaching the optimal solution for multiradio multichannel multihop wireless networks.

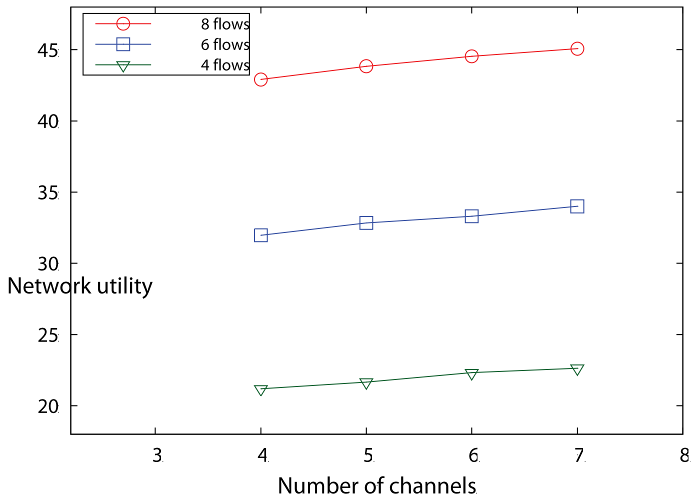

Figure 7. Network utility in terms of the number of channel with different sessions in a random topology

4. Conclusions

The purpose of this paper is to suggest an optimal network coding algorithm for multiradio multichannel multihop wireless networks. We formulated the network utility maximization problem and proposed a distributed rate control algorithm to solve the optimization problem. Also, by using a distributed resource allocation algorithm, we obtained the upper bound of the feasible solution in the convex programming problem and then applied it to obtain the joint resource allocation that approaches this upper bound within the feasible region of the network utility maximization problem. The performance evaluation results show that the distributed rate control algorithm contributes to the throughput optimization. The results also show that the proposed resource allocation scheme can effectively exploits multiple radios and channels. Therefore, joint distributed rate control algorithm and distributed resource allocation algorithm improve the network performance by using network coding.

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