Network Coding-Based QoS and Security for Dynamic Interference-Limited Networks

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Abstract. In this paper first the problem of secure minimum-cost multicast with network coding is studied, while the maximum end-to-end parameters, such as security, delay, and rate are assumed to be bounded in one multicast session. We present a decentralized algorithm that computes minimum-cost QoS flow subgraphs in network coded multicast networks. In next stage we generalize this idea to interference-limited dynamic networks where capacities are functions of the signal-to-noise-interference ratio (SINR). Since dynamic link capacities can be controlled by varying transmission powers, minimum-cost multicast must be achived by jointly optimizing network coding subgraphs with power control schemes. Simulation results shows this approach provides an efficient way for solving the optimization problem. The optimization numerical results show that using power control algorithm, higher success ratio is obtained, in comparison with previous algorithms.

Keywords: network coding, Quality of Service, network flow optimization, security, dynamic networks.

1 Introduction

Nowadays multimedia services is widely used as a part of the real-time data broadcasting (i.e. voice over IP, video over IP, IP television). These types of services have stringent QoS (Quality of Service) requirements [1] and if they are not being met by the underlying network, the user experience will be degraded significantly.

In order to provide QoS, routing algorithms must be modified to support QoS and be able to discriminate between different packet types in the process of finding the best route that satisfies QoS metrics. The goals of QoS routing are in general twofold: selecting routes that satisfy QoS requirement(s), and achieving global efficiency in resource utilization [2].

It is well-known that network performance can be significantly improved through such network coding approach [3]. As an important example, use of network coding makes the once intractable optimal multicast routing problem tractable [4]. As shown in [5–7], with network coding the achievable throughput

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of a multicast session can be acquired by running max-flow algorithm from the source to each individual receiver, and choosing the minimal value.

For a good survey on network coding see [8]. Because of these advantages, many algorithms that used routing are being modified to incorporate network coding instead [9].

All optimum sub-graph does not directly consider hard QoS although those relies on optimization schemes to determine proper flow sub-graphs to minimize given cost functions [10, 11]. In this paper we introduce a path-based mixed integer programming (MIP) model. We apply decomposition method, which provides primal solutions at all iterations and it is able to tackle the path-flow model [12]. Note that the path flow formulation of problem has a very simple constraint structure. The primal dual procedure considers only paths that do not violate the QoS constraint. We show by our computational experiment that a carefully implemented secure QoS NC approach provides an efficient way for solving the problem.

But in the case of extending to actual condition, the performance gains offered by network coding point to their promising application in dynamic networks, where multi-user interference, channel fading, energy constraints, and the lack of centralized coordination present new challenges. Initial studies on the application of network coding in dynamic networks shown in [5, 13]. In [5], the minimum-energy multicast problem is studied by exploiting the "dynamic multicast advantage". The work in [13] introduces a distributed protocol which supports multiple unicast flows efficiently by exploiting the shared nature of the wireless medium.

In this work, we extend the optimization framework and distributed algorithms in [14] to achieve minimum-cost multicast with network coding in interference-limited dynamic networks. To address this, first we determine best subgraph that provide user quality limits with the best cost in safe conditions. Second we design a set of node-based distributed gradient projection algorithms which iteratively adjust local control variables so as to converge to the optimal power control, coding subgraph configuration. We consider dynamic networks where link capacities are functions of the signal-to-interference-plus noise ratio (SINR) at the receiver.

In this context, dynamic link capacities can be controlled by varying transmission powers. To achieve minimum-cost multicast, the coding subgraphs must now be jointly optimized with power control schemes at the physical layer. Moreover, this joint optimization must be carried out in the network without excessive control overhead. To solve this problem, we design a set of node-based scaled gradient projection algorithms which iteratively adjust local control variables at network nodes so as to converge to the optimal power control, coding subgraph, and congestion control configuration. These algorithms are distributed in the sense that network nodes can separately update their control variables after obtaining a limited number of control messages from their neighboring nodes. We explicitly derive the scaling matrices required in the gradient projection algorithms for fast, guaranteed global convergence, and show how the scaling matrices can be computed in a distributed manner.

The rest of paper is organized as follows. We first develop a precise formulation of secure minimum-cost QoS multicast problem over coded packet networks in Sect. 2. In Section 3, the proposed problem is solved by our scheme. In Section 4 we will generalize this applied method to the extended situation in more practical networks. Computational results and conclusion are presented in Sect. 5 and 6.

2 Secure Network Coding-Based Quality of Service for Multicast Session

In this section, we present the network model and explain the details of our network coding-based QoS algorithm by the security viewpoint.

2.1 Network Model and Notations

The communication network is represented by a network $G = (V, E)$, where V is a set of nodes with $|V| = N$, and ε is a set of links (arcs) with $|E| = L$, consider single multicast session, a source node, $S \in V$ must transmits an integer number of R packets per unit time to every node in a set of terminals, $k \subset V$. Let Z_l denotes the rate at which coded packets are injected onto link l. linear, separable cost C_l denotes the cost per unit rate of sending coded packets over link $l \in \varepsilon$. Link weight often can be considered as delay or jitter or security in this problem. Also let the data flow toward destination T that is passing through link l is indicated by $X_l^{(t)}$.

We assign the limitations and costsonly to the links. If we also consider the requirements for node we can use the node splitting technique to transform node costs and weights into link costs and weights [15]. The source has to provide multicast receivers with their required flows and also guarantee the desired quality. There are M quality classes in the network. Each class has a minimum required rate $R^{(c)}$ and a maximum tolerable security weakness constraint, $S^{(c)}$. Meanwhile we assign link insecurity degree instead of security level in order to convenience.

The source S either refuse to send requested flows to the receivers or if it has accepted the request, it has to guarantee that the end-to-end security weakness of each flow toward destination is less than $S^{(c)}$ and the rate of flow is at leas $R^{(c)}$.

The date and flow toward the destination t that belongs to class c and is passing through link l is indicated by $X_l^{(t)(c)}, Z_l^{(t)(c)}$. In order to account for the end-to-end security experienced by network flows, we have assumed each link to have a constant security weakness degree of S_l for a given period of time. We have assumed that before running our algorithm, each node has measured the security of its outgoing links. Therefore, S_l could be viewed as the short term average security of link. Again, We emphasize that our mean the security level of links is the link weakness level against attacks. This security includes constant propagation security plus any additional security caused by MAC layer. Some other types of security, like the security caused by nodes (attacker nodes), could be handled by including them in the cost function [16].

As we use network coding instead of routing, flows of each classes are coded together. However, interclass coding is not permitted. This indicates that if flows of different classes are coded together into one flow, all classes experience the same quality level and it would not be possible to provide the required quality level for different classes. Can achieve this goal with separating the different classes quality and security levels, in data submissions, and combining each class data by the same class.

We indicate the coded flow of class c by $Z^{(c)}$. These coded flows are sent across each link independently. The total flow passing through link l in class c is indicated by $Z_l^{(c)}$. Subsequently, we denote the set of all $X_l^{(t)(c)}$ by the matrix X and the set of all $Z_l^{(c)}$ by the matrix Z.

2.2 Problem Formulation

The goal is to find a minimum cost multicast connection such that it is guaranteed that the end-to-end weight of security and delay in each flow toward destination T is less than $D^{(t)}, S^{(t)}$ respectively.

For each destination T, let $P^{(t)}$ denote the collection of all directed paths from the source node s to the destination node t in the underlying network G. In the path flow formulation, we define the variable $f(P)$ as the flow on path.

In this formulation, We would like to determine network flows such that the final solution satisfies the rate and security constraints for all classes. If there are more than one solution with these properties, the minimum cost solution will be selected. After identifying the flow subgraphs, any coding method, such as [17] can be used to determine network codes.

Let $\delta_l(p)$ be a link-path indicator variable, that is, $\delta_l(p)$ equals 1 if link l is contained in path p, and is 0 otherwise. The link flow $X_l^{(t)}$, is computed from path flow by the following relation.

$$X_l^{(t)} = \sum_{p \in P^{(t)}} \delta_l(P) g(P) \ . \tag{1}$$

Taking into account the required constraints, the minimum cost QoS multicast over coded packet networks is then given by the following optimization model.

It is shown in [4] that decoupling these two tasks, namely finding flow subgraphs and determining network codes does not change the optimality of the solution. The network cost of each link is assumed to be a convex and non-decreasing function of total flow (Z_l) over each link. The total cost is the sum of all link cost functions and total flow is:

$$Z = \min \sum_{l \in E} C_l Z_l \ . \tag{2}$$

End-to-end transmitting level insecurity will be equal to insecurity of the most insecure path in the subgraph. Therefore, we formulate the QoS network coding flow optimization problem as follows:

$$\min_{\underline{x}} \sum_{l \in E} f(Z_l) \tag{3}$$

where:

$$Z_l = \sum_{c=1}^{M} Z_l^{(c)} \tag{4}$$

$$Z_l^{(c)} = \max_{t \in T} \left\{ x_l^{(t)(c)} \right\} \tag{5}$$

$$0 \le Z_l \le a_l \quad \forall l \in E \ . \tag{6}$$

During the entire route will be:

$$\sum_{p \in P^{(t)}} \delta_l(p) f(p) \le Z_l \quad \forall l \in E, \ \ t \in T \tag{7}$$

subject to:

$$r^{(c)} \le R^{(c)} \quad c = 1, \ldots, M \tag{8}$$

$$\sum_{c=1}^{M} r^{(c)} \le R \tag{9}$$

and

$$\sum_{l \in \varepsilon} s_e^{(t)} \delta_e(P) y_p \le S^{(t)} \quad \forall t \in T \tag{10}$$

$$x_l^{(t)(c)} \ge 0 \quad \forall l \in E, \ \ t \in T, \ \ c = 1, \ldots, M \ . \tag{11}$$

And for security constraints we have too:

$$S(t,c) = \sum_{l \in E} S_l \left(x_l^{(t)(c)} \right) \le S^{(c)} \quad \forall t \in T, \ \ c = 1, \ldots, M \tag{12}$$

$$S(t,c) = \max_{p \in P_l} S_p^{(t)(c)} \le S^{(c)} \quad t \in T, \ \ c = 1, \ldots, M \tag{13}$$

where

$$S_l \left(x_l^{(t)(c)} \right) = \begin{cases} s_l & \text{if} \quad x_l^{(t)(c)} \, 0 \\ 0 & \text{if} \quad \text{otherwise} \end{cases} \ . \tag{14}$$

In above equations, $f(z_l)$, a_l, e_l and S_l are the cost function, capacity, cost coefficient and security of link l respectively. $R^{(c)}$ is the minimum required rate and $S^{(c)}$ is the maximum tolerable security of class c. R is the max-flow-min-cut rate of the network and $r^{(c)}$ refers to the actual rate of class c. Equation (6) is the capacity constraint. It guarantees that the total flow on link l is less than its capacity. Constraint (8) indicates that the rate of class c must be greater than the minimum required value determined by the user. Constraint (9) makes sure that the total rate of all classes is less than the max-flow rate of network. Equation (11) formulates the non-negative flow conservation constraint. And constraint ensured the non-negativity of X. Equation (13) indicates the security constraint, ensuring that the security weakness of class c is less than the maximum tolerable weakness of the class. By solving problem (4), we obtain flow subgraphs that satisfy the specified constraints and are also minimum cost among all feasible answers. In the next section, we provide a distributed and simple solution for this problem.

Note that in order to reduce the complexity simplify the implementation of the optimization algorithm, we slightly modify the problem definition as [18].

3 Problem Solving

To solve the problem (3), the primal dual decomposition method [18] is used, in which the problem is first broken into two subproblems using primal decomposition [12]. Then, each subproblem is solved using dual Lagrangian method [19]. This approach will result in a simple, distributed solution.

Simplify the algorithm, we have assumed that the actual rate of each class is equal to the minimum accepted rate [20] then in this scheme we utilize (13) instead of (12) and we spot constant applied users constraints for all receivers.

More specifically, we have assumed that for all classes, $r^{(c)} = R^{(c)}$ and seek the solution that satisfies this condition. Consequently, the constraint (8) is removed. Moreover, since is now fixed, the constraint (9) becomes a feasibility condition which should be checked before the algorithm is run. In other words the source node should check this condition to see if the problem is feasible. If not, the users request is withdrawn.

Ability to communicate will be checked in two stages. First with respect to the permissible rate range and security which depends on network nature, the reasonableness of the request will be evaluated. If it is reasonable, according to constraints for each class of user, we examine possiblity of sub graph existence in second stage.

Since we have assumed the cost function to be convex, problem (3) is a convex optimization problem and the duality gap of decomposition method will be zero (see Section 5.2.3 of [21]). Subsequently, in order to break the problem (3) into two subproblems, we first assume x to be constant and solve the problem over z. Then, the resulting cost function is minimized over x [19]. More specifically, the problem (3) is decomposed into the following subproblems: **Subproblem A**:

$$\min_{\underline{z}} \sum_{l \in E} f(z_l) \tag{15}$$

subject to:

$$x_l^{(t)(c)} \leq z_l^{(c)} \quad \forall t \in T, \ \ \forall l \in E, \ \ c = 1, \ldots, M \tag{16}$$

and **Subproblem B** [20]:

$$\min_{\underline{x}} \sum_{l\in E} f^*(x) \tag{17}$$

subject to constraints (8) and (9). In the above equation, f^* indicates the solution of subproblem (A). In order to solve subproblem (A), we use its Lagrangian equivalent. Define:

$$L(z,\lambda,\beta) = \sum_{l\in E} f(Z_l) + \lambda^T(Z-a) + \sum_{l\in E}\sum_{t\in T}\sum_{c=1}^{M} \beta_{ltc}\left(x_l^{(t)(c)} - z_l^{(c)}\right) \tag{18}$$

then subproblem (A) is equivalent to:

$$\min_{\underline{z}} L(z,\lambda,\beta) \tag{19}$$

and

$$\max_{\underline{\lambda,\beta}} L^*(\lambda,\beta) \tag{20}$$

where L^* is the solution of problem (19). We could decouple the above solution into L subproblems, one for each link:

$$\max_{\lambda,\beta} f(Z_l^*) + \lambda_l(Z_l^* - a_l) + \sum_{t\in T}\sum_{c=1}^{M} \beta_{ltc}\left(x_l^{(t)(c)} - z_l^{*(c)}\right) \ . \tag{21}$$

Subproblem (21) could be solved using subgradients method as follows [19]:

$$z_l^{(c)}(\tau+1) = \left[z_l^{(c)}(\tau) - \alpha(\tau)\left(\nabla f_l^c - \sum_{t\in T}\beta_{ltc}\right)\right]_{\underline{z\in Z}} \tag{22}$$

$$\lambda_l(\tau+1) = \left[\lambda_l(\tau) + \alpha(\tau)\left(Z_l^* - a_l\right)\right]_+ \tag{23}$$

$$\beta_{ltc}(\tau+1) = \left[\beta_{ltc}(\tau) + \alpha(\tau)\left(x_l^{(t)(c)} - z_l^{*(c)}\right)\right]_+ \tag{24}$$

where $[]_+$ indicates that α and β must be non-negative and $[]z \in Z$ ensures that the updated z lies in the feasible region. $\nabla f_l(c)$ represents the (l,c) member of $\nabla f_l(z)$. The parameter $\alpha(\tau)$ is the algorithm step size, chosen such that convergence of the algorithm is guaranteed. In our algorithm we have $\alpha(\tau) = 1/\tau$ which although guarantees the convergence of the subgradient method, any diminishing step-size may be used as well (see section 6.3.1 of [19]). In the same manner, subproblem (17) could be solved using subgradients method. In each iteration, x and its lagrange multiplier are updated according to (25), (26) as follows:

$$x_l^{(t)(c)}(\tau+1) = \left[x_l^{(t)(c)}(\tau) - \alpha(\tau)\left(\nabla f_l^{*(c)} + \beta_{ltc} + \sum_{\substack{p\in P_t\\ l\in P}} \vartheta_P^{(t)(c)} s_l\right)\right]_{x\in X} \tag{25}$$

and
$$\vartheta_p^{(t)(c)}(\tau+1) = \left[\vartheta_p^{(t)(c)}(\tau) + \alpha(\tau)\left(S_p^{(t,c)} - S^{(c)}\right)\right]_+ \tag{26}$$

where "$x \in X$" means that the updated x should be projected onto feasible x region. The parameter θ is the Lagrange multipliers vector for security constraint. Each node should solve subproblem (21) for its outgoing links and derive $z_l^{(c)}$, update x and Lagrange multipliers according to (22), (23), (24) and (25), respectively. Then, it has to exchange these multipliers with its neighbors until convergence is achieved. This procedure leads to a distributed, simple solution in which each node n must solve at most $M.$ *outdegree*(n) where *outdegree*(n) is the number of the output links of node n and M is the number of classes.

To summarize, each node has to perform the following procedure to solve the problem (3):

1. Parameters initialization.
2. Solve subproblem (21) for each outgoing link.
3. Update Lagrange multipliers via (22),(23) and (24).
4. Update x according to (25).
5. Update constraints Lagrange multipliers via (26).
6. Repeat till convergence.

Separable Cost Function. In the previous section, a distributed solution of the problem (3) was presented. So far, convexity is the only assumption that was made about the cost function. But if the cost function could be decomposed itself, each subproblem could also be decoupled into other subproblems. Some examples of these kind of cost functions presented in [20]:

$$f(Z_l) = e_l Z_l = \sum_{c=1}^{M} e_l z_l^{(c)} = \sum_{c=1}^{M} f\left(z_l^{(c)}\right) \quad . \tag{27}$$

The cost function (27) represents energy consumption and the cost function (28) may be considered as a representative of queuing costs. In this scheme, energy or monetary costs are more important for network operators then we use cost function (27).

4 To Generalize the Algorithm to Practical Conditions

The problem of jointly optimal power control, and network coding in wireless networks with multiple multicast sessions is investigated in [22] that explicitly derive the scaling matrices required in the gradient projection algorithms for fast, guaranteed global convergence, and show how the scaling matrices can be computed in a distributed manner. In our optimization framework some consepts of this paper is used. Our scheme yields to a feasible set of transmission powers, link capacities, as well as a set of network coding subgraphs We assume that the wireless network is interference limited, so that the capacity of the link (i, j), denoted by C_{ij}, is a nonnegative function of the signal-to-interference-plus noise ratio ($SINR$) at the receiver of the link, i.e. $C_{ij} = C(SINR_{ij})$. We further assume $C(.)$ is increasing, concave, and twice continuously differentiable. For $(i,j) \in E$ the receiver node calculates $SINR$ in terms of G using equation (28).

$$SINR_{ij}(p) = \frac{G_i P_{ij}}{G_{ij} \sum_{n \neq j} P_{in} + \sum_{m \neq i} G_{mj} \sum_n P_{mn} + N_j} \ . \tag{28}$$

In above equations, G_{ij} is gain of link ij which obtain corresponding matrix G elements according to (29). N_j is the noise power at the receiver of the node j.

$$G = \lfloor g_{ij} \rfloor_{i=1,\ldots,8,\ j=1,\ldots,8,\ g_{ij}=g_{ji},\ g_{ii}=0} \ . \tag{29}$$

Assume every node i is subject to an individual power constraint: $\sum_j P_{ij} = P_i \leq \overline{P_i}$, where P_{ij} is allocated power to link ij by node i, P_i is power of node i, and $\overline{P_i}$ is constraint on power allocated to node i. The set of all feasible nodes power allocated vectors denoted by vector P, $P = [P_1, \ldots, P_N]$ where $\pi = \{P : \sum_j P_{ij} \leq \overline{P_i},\ \forall i \in V,\ P_{ij} \geq 0,\ \forall i,j \in V\}$.

In the previous work [4, 22], it has shown that in wireline multicast networks with network coding, coding subgraph optimization can be achieved using a routing methodology. We now extend this consept to wireless networks, where in contrast to wireline networks, link capacities can be further controlled by varying transmission powers.

Large-scale wireless networks usually lack centralized coordination, and it is desirable to distribute the control functionalities to individual nodes. In this method we should permit each node to independently adjust the sub-session flow rates on its outgoing links [23]. But in this scheme we use random power allocation. which leads to a little more complexity.

For each node, we calculate $SINR$ value as a parameter of transmission reliability in terms of interference. Taking calculated $SINR$ value of each link, we review the possibility of a link failure occurrence network. New links capacity, are determined according to calculated $SINR$ (30).

$$C_{ij} = C(SINR_{ij}) \ . \tag{30}$$

In a practical network, for accessibility to transmission reliability, receiver nodes can compare $SINR$ value of link with their sensitivity. That sensivity vector is a set of integers that are considered equal to a threshold for simplicity.

The link failure is considered if the $SINR$ value of link is less than the sensitivity. In this situation, answer subgraphs will not include failured link. It is clear that in this case, possibility of finding optimal subgraph which is restricted to users limitations decreases. It also results increase in cost. In this mode, when $SINR$ of outgoing links are less than the threshold (receiver sensivity), transmitter node attempts to maintain $SINR$ by allocating more power to transmission with increasing links power (that is equivalent to link capacity). In this situation that link exits from temporary failure. Note that total power dedicated to the collection of nodes in the network is fixed.

5 Simulation Results

5.1 Secure Network Coding-Based Quality of Service

In this section, we investigate the performance of our proposed algorithm based on several simulations. We have considered two different cases, ordinary condition and interference condition.

We evaluate the performance of the proposed algorithm. For illustrative purposes, we first simulate the suggested algorithm for some basic cases. Then, more general and complex cases will be taken into account in the simulations.

We try to provide more quality parameters in secure condition (Table 1) and compare the obtained results with QoSNC [20] and MCM [4] that these methods have no security constraints (Table 2). Also we compare proposed algorithm (SQoSNC) results in interference condition with power control algorithm and without power control algorithm (Table 3).

In order to examine the performance of our algorithm in such cases, we have considered several random networks in which there are one multicast source and two quality classes. In basic network, constraint (security) and cost of each link is determined. In simulation condition we assume that there is one multicast source, s, two multicast sinks, t_1 and t_2 and two quality class with desired rate 1 and 2 for each class and maximum tolerable security will determine by user.

As Table 1 shows with increased degree of restrictions (as security restriction) we reach to the ideal answer with far fewer iterations. also, due to more choice in determining the optimal subgraphs and the various transmitting rate in links, cost functions reduce too.

Table 1. Number of iteration and total cost in various security constraints

Class	Constraints	Output	Iteration	Cost
I	4	[2 2]	219	11.41
II	5	[3 3]		
I	6	[2 2]	53	10.65
II	8	[8 8]		
I	8	[2 4]	95	9.62
II	10	[8 8]		
I	10	[3 5]	72	2.69
II	12	[6 6]		
I	11	[6 6]	21	1.67
II	13	[7 7]		

5.2 Simulation Results in Gereralize the Algorithm to Practical Conditions

In the second section of simulation, we tries to generalize the algorithm to the dynamic wireless networks in practical conditions. As expected, previous algorithms provide poor performance in presence of interference, with respect to reliability. A power control scheme is proposed as a solution to this problem.

Table 2. Cost of various algorithms in different number of nodes

No.of Nodes	*Algorithm*	*Total Cost*
7	MCM	16.19
	QoSNC	19.31
	SQoSNC	11.15
10	MCM	18.25
	QoSNC	21.22
	SQoSNC	25.20
20	MCM	25.13
	QoSNC	27.76
	SQoSNC	31.43

The Table 3 show comparison the performance of algorithm with power control and without power control on illustrated graph in Fig. 1.

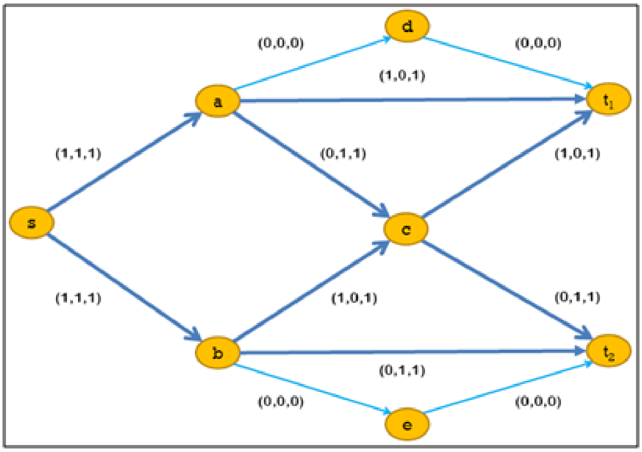

Fig. 1. One muilticast session network that we have implemented the power control on it

This results suggest that previous proposed algorithm with determine the threshold for its links $SINR$, will not accountable in higher limitation. While the same algorithm with power control will have coordination feature with network random conditions and will determine the corresponding subgraph except the limits are too high (strong limit).

As the Table 3 shows, only in the very low limitation (unrestricted), both algorithms give nearly identical answers. Subgraphs of the same cost and different iterations will be answers in this case.

Table 3. SQoS algorithm with power control and without power control

Factors Constraints	With Power Control	Without Power Control
(2,3)	-------	-------
	-------	-------
(4,6)	Total Cost: 25.29	-------
	Iteration: 1000	-------
(8,10)	Total Cost: 28.78	Total Cost: 25.57
	Iteration: 21	Iteration: 90
(10,12)	Total Cost: 8.32	Total Cost: 21.89
	Iteration: 13	Iteration: 32

6 Conclusion and Future Works

We have proposed a new decentralized algorithm that computes secure minimum cost QoS flow subgraphs in coding-based multicast networks. The subgraphs are determined so that certain user-defined quality measures, such as security and throughput, are satisfied. The resulting subgraphs are chosen to achieve minimum cost among all subgraphs that satisfy the given quality and security constraints. The proposed algorithm can handle any convex cost function in addition to user-defined security and quality requirements. This makes our algorithm an ideal choice for cases where the cost function is linear (energy consumption). We will Extending our work to practical dynamic networks and considering network dynamism such as interference, and potential link failures and reluctate interference impact is a subject of our research. We adopt the network coding approach to achieve minimum-cost multicast in interference-limited wireless networks where link capacities are functions of the $SINR$. We develop a node-based framework within which transmission powers, network coding subgraphs, and admitted session rates are jointly optimized.

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