Efficient Data Uploading Based on Network Coding in LTE-Advanced Heterogeneous Networks

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***Abstract*—LTE-Advanced heterogeneous networks enable a uniform broadband experience to users flexibly anywhere in the network by using a mix of large and small cells – i.e., macro, pico, femto and relay stations. In this paper, we propose a novel network coding-based for mobile content uploading, where multiple user equipments upload their own content toward the eNodeB in LTE-Advanced relay networks. Network coding has been considered as a promising solution in next generation networks because of the significant improvement in the transmission rate and reliability. The network coding enables an intermediate node having the capability of encoding incoming packets rather than simply forwarding. However, the advantages come at the cost of high computational, storage costs and coding vector overhead. The two former drawbacks can be solved easily by the fast development of current smart users and relay with high capability on computation and storage. The last issue of coding vector overhead still remains as many packets are encoded together using a linear combination since each packet needs to carry a large size of the header to store the information of the coding vector. We propose random overlapped chunked code for enhancing the transmission rate and reliability under the constraint of coding vector overhead. Furthermore, the encoding and decoding processes can be operated with low complexity. The complete transmission consists of two phases: users upload the content to the relay; the relay performs the proposed random overlapped chunked code of different coming streams from users and forwards the network-coded packets to the eNodeB. For performance evaluation, we run various simulations along with analysis to show that our proposal outperforms current schemes in terms of decoding probability.**

***Keywords*—Network Coding, Heterogeneous Networks, LTE-A, Internet of Things**

I. Introduction

LTE-A heterogeneous networks enable users flexibly anywhere in the network experiencing high data rate and bandwidth efficiency [1]. Especially, the user in the edge cell also can achieves good performance with the help of a relay. Since LTE-A heterogeneous networks is a mix of large and small cells – i.e., macro, pico, femto and relay stations (RS). On the other hand, each mobile device has high storage, computational capacity, and a high-quality camera. Nowadays, there is a huge amount of data around us. The need of uploading multimedia content increases significantly, especially live stream application. Many users record the content everything, share to other users or upload to the server, cloud, etc.

Many studies focus on the scheduling [2], resource allocation [3] and energy efficiency [4] for unlink scenario with the leverage of Device to Device (D2D) communications. Nevertheless, there are a few studies on enhancing the efficient data uploading over LTE-A heterogeneous networks with the use of RS is to leverage the efficient data uploading. Ho *et al.* proved that an intermediate node can help increase the system performance as the decode, encode and re-encode capabilities are enabled [5]. The intermediate node decodes incoming packets and then encodes the decoded packets into a network-coded packet using random linear network coding (RLNC). There are many benefits, such as minimum delay, minimum energy per bit and maximum throughput, that have been exploited for the Internet, consisting of both wired and wireless networks [6]. Yang *et al.* proposed a linear network coding approach for uplink distributed multiple-input-multiple-output (MIMO) systems without relay [7]. Besides, the authors provided the analysis on outage behavior and showed that the linear network coding approach can increase the outage probability and frame error rate. Lv *et al.* showed that the combination of network coding and cooperative diversity can enhance the diversity order and system ergodic capacity [8].

The RLNC can provide many benefits which were already proved in many studies [5], [6], [7], [8]. Nevertheless, the drawbacks of full rank issue, decoding complexity and coding vector overhead still remains. Receiver can decode the received packets if and only if the rank of a coefficient matrix is achieved full rank, otherwise, the received packets are useless even though the receiver decoded successfully those packets. Chunked codes (CC) [9] have been proposed to tackle these drawbacks. The file is partitioned into multiple chunks and the RLNC is applied in each chunk. There are two types of chunked codes: non-overlapped chunked and overlapped chunked codes. The former code does not allow the intermediate node using data from another chunk for encoding. Otherwise, the latter code allows the intermediate node using data from other chunks. Heidarzadeh *et al.* showed that the overlapped chunked codes can get better performance than non-overlapped [10]

In this paper, we propose an efficient data uploading based on network coding over LTE-A heterogeneous networks, in which consist of multiple user equipments (UEs), one RS and an eNB. The proposed novel network coding named random overlapped chunked code (ROC) that can 1) catch the advantage of RLNC, 2) provide higher decoding probability and 3) achieve low decoding complexity and coding vector overhead. Particularly, our contributions can be listed as follows:

- ROC can increase the efficiency in data uploading over LTE-A relay networks. Multiple users upload their own content to the RS, instead of simply forwarding to data

to the eNB. We enable the RS the capability of encoding, decoding, and re-encoding the incoming packets. The proposed novel network coding can enhance the reliability in uploading.

- The proposed scheme can reduce the decoding complexity under the constraint of coding vector overhead. Moreover, the drawback of RLNC under the bad channel condition can be solved. The former can speed up the decoding time and satisfy the practical constraint on packet header size. The latter can enable receiver that can decode some data even they are experiencing the bad channel condition. Since the drawback of RLNC is the receiver cannot decode anything as the rank of the generator matrix is not satisfied.
- We provide the matricial model of the two conventional data uploading schemes and our proposal. This allows us to understand the mathematical framework from mathematical entities to communication entities.
- A short analysis on decoding probability is provided to evaluate the effectiveness of network coding. Furthermore, we address the discussion on code parameter. Lastly, the decoding probability is evaluated to validate the efficiency of data uploading.

The remainder of this paper is organized as follows. We describe system model and a short background on network coding along with an analysis of decoding probability over one-hop transmission in Section II-A. In Section III, we present our proposed random overlapped chunk code. Furthermore, we evaluate the system performance regarding the reliability in terms of decoding probability compared to other schemes in Section IV. Finally, we conclude this paper in Section V.

II. System Model and Preliminary

A. System Model

Figure 1 depicts an LTE-Advanced relay network, in which U UEs upload their own content to the eNB with the assistant of Type-1 relay [11]. UE cannot transmit the content directly to the eNB. The frequencies used on access and backhaul links are same (i.e., in-band relay prototype [11]). Let ϵ_u and ϵ be the erasure probabilities of the uth access link from the uth UE and the backhaul link, respectively. Each link experiences independent and identically distributed channel state.

Let $file_u$ be the content of the uth UE, each file is partitioned into C_u chunks, in which each chunk has $K = |file_u|/C_u$ packets. The number of chunks can be different but the number of packets of each chunk is the same among UEs. The kth packet is represented by a vector with S symbols (i.e., each symbol of 1 byte):

$$\mathbf{x}_k = [x_{k,1} \quad x_{k,2} \quad \cdots \quad x_{k,S}]. \tag{1}$$

Hence, K packets of the uth UE can be presented as a K-by-S matrix:

$$\mathbf{X}_u = [\mathbf{x}_1 \quad \mathbf{x}_2 \quad \cdots \quad \mathbf{x}_K]^T, \tag{2}$$

where $(\cdot)^T$ denotes the transpose operation. We use a bold lowercase letter to represent a vector and a bold uppercase letter for a matrix.

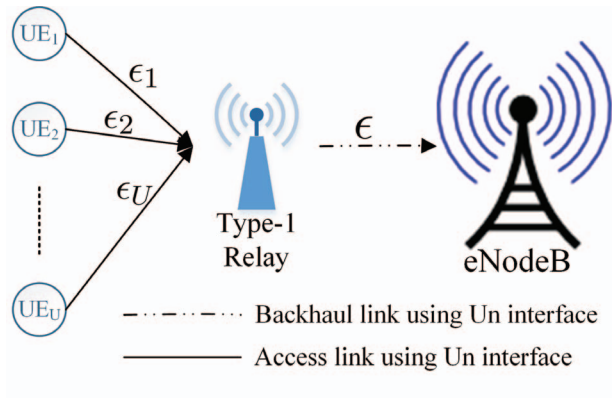

Fig. 1. Mobile data uploading in LTE-Advanced heterogeneous network.

The complete data uploading consists of two phases: multiple UEs uploads their own content to the RS in the first phase, upon receiving the transmitted packets, the RS performs the proposed ROC and forwards to the eNB in the second phase. The eNB uses the Brief Propagation (BP) and Gaussian Elimination algorithms to decode the coded packets with low complexity.

B. Network Coding

The concept of network coding is a linear combination of multiple packets which belong to a generation (i.e., chunk). We use the words generation and chunk interchangable with similar meaning. A number of native packets (i.e., original packet without coding) is also the chunk size. A nth network-coded packet can be presented as follows:

$$\mathbf{c}_n = \sum_{k=1}^{K} f_{n,k}\mathbf{x}_k = \mathbf{f}_n\mathbf{X}_u, \tag{3}$$

where $f_{n,k}$ is a coding coefficient generated uniformly distributed random over a finite Galois field $\mathbb{F}(q)$ of size q, $\mathbf{f}_n$ is $1 \times K$ coding vector of the nth packet. As seen, the symbol size is equal to the binary logarithm of the size of Galois field. Each coding vector is enclosed in the header of each packet with the size of $\log_2 q \times K$ bits.

The network coding can be formulated as algebra equations [12]. Let N be the number of network-coded packets used for transmission. The N network-coded packets of the uth UE can be formulated as the following N-by-K matrix:

$$\mathbf{C}_u = \mathbf{F}_u\mathbf{X}_u. \tag{4}$$

Note that the coefficient matrix $\mathbf{F}_u \in \mathbb{F}_q^{N\times K}$, $\mathbf{X}_u \in \mathbb{F}_q^{K\times S}$, and $\mathbf{C}_u \in \mathbb{F}_q^{N\times S}$. Each network-coded data packet has three parts: 1) header information, 2) payload contains a network-coded packet, and 3) coding coefficients used in the linear combination.

To decode the K packets, the receiver needs to receive at least K packets with linearly independent coding vectors. Alternatively, the coefficient matrix $\mathbf{F}_u$ must achieve full rank or $rank(\mathbf{F}_u) \geq K$. Hence, the number of network-coded packets N is always greater than K original packets. The network coding is rateless code since sender can generate

infinite coded packets. The receiver can decode the transmitted packets using Gaussian Elimination (GE) algorithm using the information of coding vectors enclosed in the header of each packet. The GE algorithm can work well with a small number of coded packets. As the number of coded packets increases, it causes a long delay because of high complexity of the algorithm.

The advantage of network coding is that the receiver can easily decode all received packets as receiving a sufficient number of network-coded packets (i.e., full rank is achieved). However, the drawback is that the receiver cannot decode anything if the rank cannot be achieved. Consequently, the generation size strongly affects the performance. The reliability increases as the generation size is large with cost of long delay, complexity and a large header size of containing the coding vectors. The other parameter also affects the performance of network coding is the Galois field size of q. As the Galois field increases, the probability of generating linearly independent coding vectors improves with the cost of decoding complexity and coding vector overhead. Up to now, there is no standard for selecting the Galois field. Many studies show that using Galois field size of 256 can provide a high probability of generating linearly independent coefficient vectors and low decoding complexity [5], [13].

C. Analysis of Decoding Probability

Suppose that the sender encodes K original packets into N coded packets for transmission. Since the channel is an erasure channel, the receiver can decode N' received packets of N transmitted packets (i.e., $N' \leq N$). The probability of having K linearly independent coding vectors over N' received packets is given by [14]:

$$Pr(N', K) = \begin{cases} 0 & \text{if } N' < K \\ \prod_{k=0}^{K-1} \left(1 - \frac{1}{q^{N'-k}}\right) & \text{if } N' \geq K \end{cases}. \quad (5)$$

Let ϵ be the erasure probability of the channel, "success" and "failure" of each packet are considered as Bernoulli trial. The decoding probability of receiving K packets over N transmitted packets is the cumulative distribution function of binomial distribution:

$$Pr(N' \geq K) = \sum_{n=K}^{N} \binom{N}{n} (1-\epsilon)^n \times \epsilon^{(N-n)}. \quad (6)$$

Finally, the probability that receiver can decode K original packets over N transmitted packets presented as follows:

$$p_{dec} = \sum_{n=K}^{N} \binom{N}{n} (1-\epsilon)^n \times \epsilon^{(N-n)} \times Pr(n, K). \quad (7)$$

III. Proposed Random Overlapped Chunked Code

In this section, we present the proposed random overlapped chunked code which is performed as the RS with the constraint of coding vector overhead. Each packet only can carry maximum M coefficient information in the header.

Here, we describe the two conventional RLNC schemes: intra-flow and inter-flow network coding [15]. The complete data uploading consists of two phases: UEs uploads their own content to the RS, network coding is performed at the RS to enhance the transmission rate and reliability. In intra-flow network coding, the RS only uses the incoming packets from each individual UE for encoding. On the other hand, the inter-flow network coding accepts for the RS encoding multiple streams from different UEs.

Intra-flow network coding: let $\mathbf{H}_{u,R}$ and $\mathbf{H}_{R,eNB}$ be the transfer matrices from the uth UE to the RS in the first phase, and the backhaul link from RS to eNB in the second phase. The transfer matrix $\mathbf{H}_{u,R}$ is a $K \times K$ diagonal matrix, in which the diagonal component is one with the probability of $1 - \epsilon_u$ and zeros with the probability of ϵ_u. And the transfer matrix $\mathbf{H}_{R,eNB}$ is a $M \times M$ diagonal matrix with the corresponding erasure probability of ϵ, where M is the chunk size used for encoding.

Let $\mathbf{Y}_{u,R} = \mathbf{H}_{u,R}\mathbf{X}_u$ be the received packets at RS from the uth UE. Upon receiving K packets, the RS starts decoding. Let $\mathbf{X}_{u,R}$ be the $K_{u,R}$-by-S matrix representing the number of successfully decoded packets (i.e., $\mathbf{X}_{u,R} \leq \mathbf{X}_u$). The intra-flow network coding is performed as follows:

$$\mathbf{C}_u = \mathbf{F}_u \mathbf{X}_{u,R}, \quad (8)$$

where $\mathbf{F}_u$ is coefficient matrix generated randomly from $\mathbb{F}_q^{M \times K_{u,R}}$, $K_{u,R}$ is the number of decoded packets at the RS, and $\mathbf{C}_u \in \mathbb{F}_q^{M \times S}$. The received packets at the eNB is given as follows:

$$\mathbf{Y}_{u,eNB} = \mathbf{H}_{R,eNB}\mathbf{C}_u. \quad (9)$$

UE uses the information of coding vectors and the received packets to decode the transmitted content. The UE can decode successfully as the rank of the matrix $\mathbf{F}_u \in \mathbb{F}_q^{M \times K_{u,R}}$ is achieved (i.e., $rank(\mathbf{F}_u) >= K_{u,R}$)

Inter-flow network coding: RS uses multiple decoded packets from different UEs for encoding. The total decoded packets at the RS after the first phase can be presented as $\mathbf{X}_R = [\mathbf{X}_{1,R} \quad \mathbf{X}_{2,R} \quad \cdots \quad \mathbf{X}_{U,R}]^T$. As seen, the matrix $\mathbf{X}_R$ has the dimension of K_R-by-S, where $K_R = \sum_{u=1}^{U} K_{u,R}$. Since the RS uses multiple chunks from different UEs to encode into network-coded packets. The chunk size of M must be increased and meets the condition $M \geq K_R$. The RS sends the number of network-coded packets greater than the number of packets which the RS can decode from the first phase. The received packets at the eNB corresponding to the inter-flow network coding is given as follows:

$$\mathbf{Y}_{u,eNB} = \mathbf{H}_{R,eNB}\mathbf{F}\mathbf{X}_R, \quad (10)$$

where $\mathbf{H}_{R,eNB}$ is M-by-M diagonal matrix with the component of ϵ, $\mathbf{F} \in \mathbb{F}_q^{M \times K_R}$, and $\mathbf{X}_R \in \mathbb{F}_q^{K_R \times S}$. The advantage of inter-flow network coding is that we can increase the reliability if the channel condition is good, otherwise, the performance degrades dramatically since receiver cannot decode any packet if the rank of the matrix $\mathbf{F}$ cannot be achieved.

Random Overlapped Chunked Code: to reduce the decoding complexity and coding vector overhead, we catch the idea of systematic network coding, in which the sender firstly

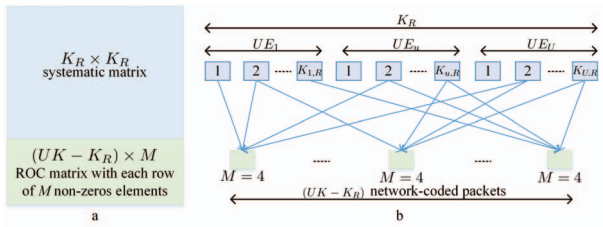

Fig. 2. Generator matrices at Relay: a) Generator matrix, b) Proposed random overlapped chunked code.

transmits K systematic packets, then continue transmitting $(N - K)$ RLNC network-coded packets.

Figure 2 denotes the generator matrices (i.e., Fig.2a) and the coding method (i.e., Fig.2b) of our proposed ROC. The $K \times K$ systematic matrix is an identity matrix or unit matrix. Note that M is the maximum header size (i.e., the maximum number of native packets is used for encoding) used to store the coding vectors and the limit of decoding complexity. The generator matrix is now redefined as follows:

$$\mathbf{F} = [\mathbf{F}_{SYS} \quad \mathbf{F}_{ROC}]^T, \tag{11}$$

where $\mathbf{F}_{SYS}$ is a K_R-by-K_R identity matrix, $\mathbf{F}_{ROC}$ is the $(UK - K_R)$-by-K_R ROC matrix. The element of the ROC is generated randomly in the finite Galois field, and each row only has maximum M non-zeros elements.

We call our proposed novel network coding is random overlapped chunked code because of two reasons: 1) the chunk size is fixed, each network-coded packet is a linear combination of M native packets which are from multiple chunks of different UEs (i.e., chunks are overlapped); 2) the native packets used for encoding are selected randomly (i.e., the RS selects and encodes randomly maximum M native packets to make an innovative coded packet, in which the coding vector is linearly independent with other prior packets).

Since the generator matrix consists of two parts: systematic and ROC. First, the eNB can decode the systematic packets immediately as the packets arrive. And each ROC packet only carries maximum M original packets, it meets the constraint of the coding vector overhead. Moreover, when each ROC arrives, the eNB can also use the information of decoded packets from systematic part to decoding the network-coded packets on the fly.

Decoding process of BP algorithm: We propose a fast method to solve the linear equation $\mathbf{Gx} = \mathbf{y}$, where $\mathbf{x} = (x_1, ..., x_k)^T$ is information symbols, $\mathbf{G}_{n\times k}$ is generation matrix, $\mathbf{y} = (y_1, ..., y_n)^T$ is received symbols. The ith row of $\mathbf{G}$ matrix represents connections of information symbols with the ith received symbol, while the jth column shows the connection of received symbols to the jth information symbol. The proposed decoding is a joint decoding between BP decoding and Gaussian Elimination decoding. The BP decoding is fast decoding method which aims to recover systematic packets. While, the Gaussian Elimination is used to recover RLNC packet. The proposed decoding process is summarized as follows:

Input: received symbols $\mathbf{y} = (y_1, ..., y_n)^T$, $\mathbf{G}_{n\times k}$ matrix

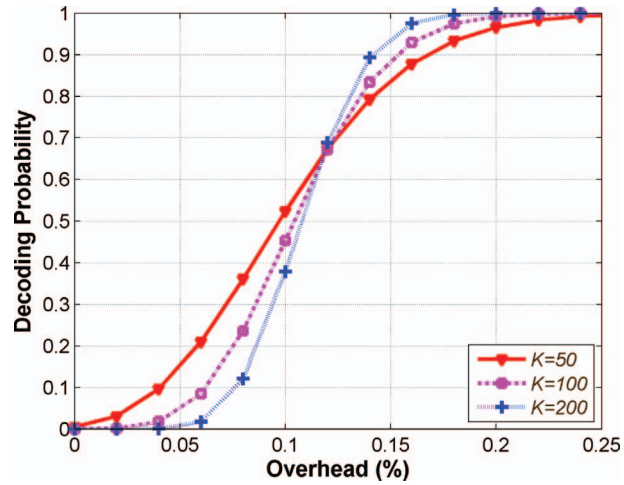

Fig. 3. Decoding probability versus overhead with various generation sizes and the erasure probability of 0.1.

Output: information symbol $\mathbf{x} = (x_1, ..., x_k)^T$.

- BP decoding:
  - Step 1: Find an received symbol y_i that only connect to information symbol x_j.
  - Step 2: Set $x_j = y_i$, and update values of all received symbols which connect to the x_j by performing XOR operation.
  - Step 3: Remove all the edges that connect to the information symbol x_j.
  - Step 4: Repeat step 1 to 3 until has no connection among received symbols and information symbols (decoding success), otherwise go to Gaussian Elimination decoding.
- Gaussian Elimination decoding:
  - Step 5: Remove the rows and columns corresponding to recovered symbols in $\mathbf{G}$ matrix to obtain $\mathbf{G}'$ matrix. If the number of unrecovered symbols is larger than rank of $\mathbf{G}'$ matrix, Gaussian Elimination decoding fails, otherwise go to Step 6
  - Step 6: Utilize Gaussian Elimination decoding for solving the linear equation $\mathbf{G}'\mathbf{x}' = \mathbf{y}'$, where $\mathbf{x}', \mathbf{y}'$ are unrecovered symbol, information symbol, respectively.

IV. Performance Evaluation

For performance evaluation, we firstly evaluate the performance of network coding versus overhead (i.e., $^{(N-K)}/_{K}$, the ratio of number of redundant packets and number of original packets without coding). Second, we evaluate the performance of our proposed ROC in terms of decoding probability versus the channel condition.

First, Fig. 3 and 4 present the decoding probability performance versus the overhead with the various parameter settings of generation size (i.e., chunk size or a maximum number of native packets used for encoding) and Galois Field Size. Fig. 3 showed that the generation size increases leading to the increase of decoding probability. However, the performance is only getting better as the sender provides a sufficient number

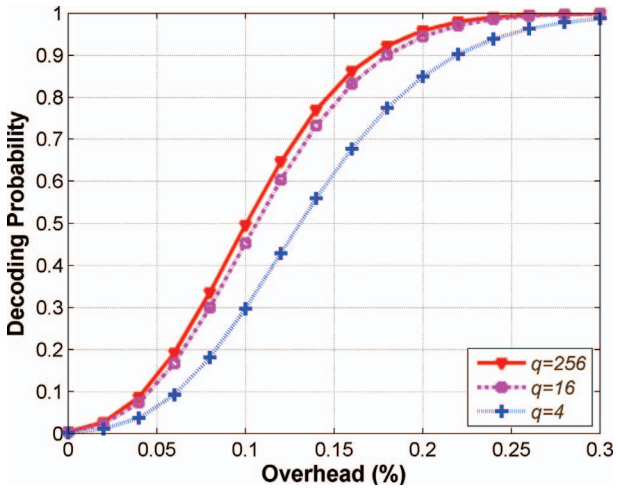

Fig. 4. Decoding probability versus overhead with various Galois field sizes, the generation size of 50 and the erasure probability of 0.1.

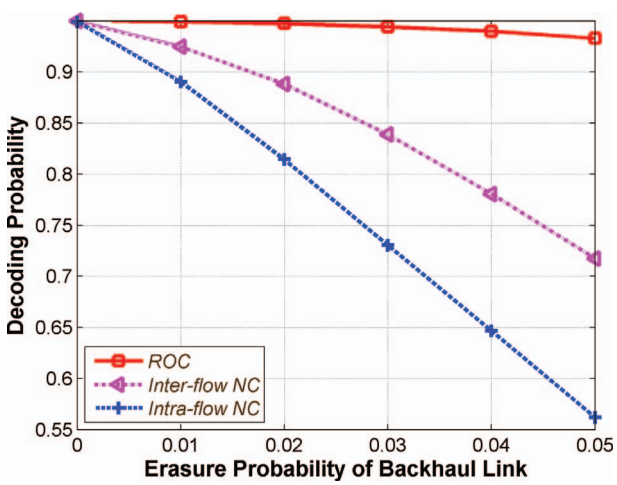

Fig. 5. Decoding probability of UE_1 versus erasure probability of backhaul link.

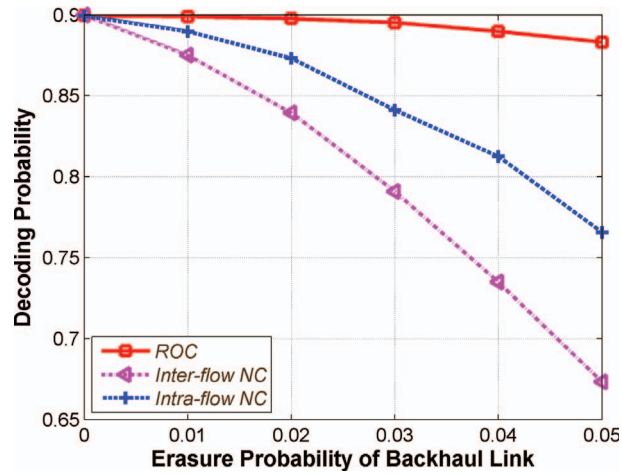

Fig. 6. Decoding probability of UE_2 versus erasure probability of backhaul link.

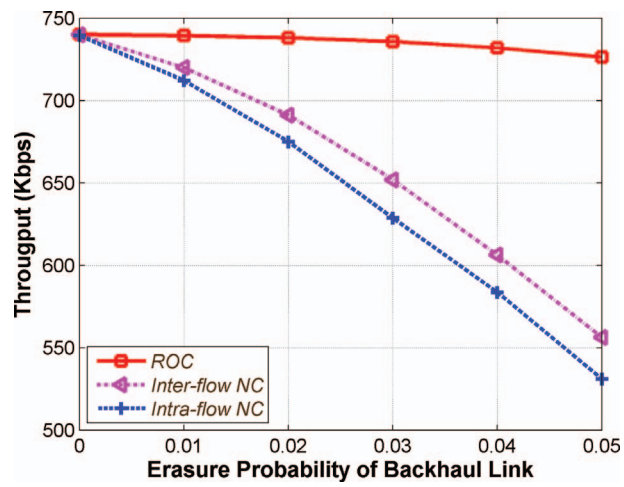

Fig. 7. Throughput performance of two UEs versus erasure probability of backhaul link.

of coded packets. Otherwise, the performance of smaller chunk size is better. In practical scenarios, the sender can select the number of redundant packets and generation size based on the channel condition. If the channel condition is bad, the small chunk shows better performance compared to large chunk. Otherwise, a large chunk is better in good channel condition. Fig. 4 provided the overview regarding the effect of selecting Galois field size to the decoding performance. Obviously, the larger Galois field size provides greater decoding probability with the cost of computational complexity. As seen, the Galois field sizes of 16 and 256 give the big gap compared to $q = 4$. Nevertheless, the gap between $q = 16$ and $q = 256$ is not much gain. Furthermore, the Galois field size of 256 is preferable to use since it can reduce the computational complexity because of the small number of symbols used in each packet.

Second, Fig. 5 and 6 showed the decoding probability of UEs 1 and 2 versus the channel condition of the backhaul link (i.e., the link between RS and eNB) compared to two conventional uploading schemes: intra-flow and inter-flow network coding. The maximum number of coefficients enclosed in the packet header is $M = 40$. In this simulation, we use two UEs that upload their own content to the RS. Suppose that each link from UEs 1 and 2 to the RS experiencing the erasure probability of 0.1 and 0.05, respectively. Fig. 5 represents the UE experiencing bad channel condition (i.e., $\epsilon_1 = 0.1$), and Fig. 6 represents the UE experiencing good channel condition (i.e., $\epsilon_2 = 0.05$). Our ROC outperforms other schemes. Nevertheless, the performance of inter-flow network coding is better than intra-flow under good channel condition . Otherwise, the intra-flow is better under bad channel condition. The reason comes from full rank issue since the chunk size of intra-flow is smaller than inter-flow network coding. As seen, our proposed ROC can tackle this full rank issue. Furthermore, receiver can use BP algorithm to decode the network-coded packets under the constraint of coding vector overhead. It leads to the increase so much in decoding complexity.

Last, Fig. 7 presented the throughput performance of two users uploading to eNB, each packet has size of 10,000 bits. The simulative results demonstrated that our proposed ROC especially outperformed the reference schemes in terms of total throughput followed by inter-flow and intra-flow NC,

respectively. The performance gap increases proportional to the erasure probability.

V. Conclusions

In this study, we proposed a random overlapped chunked code exploited for data uploading in LTE-Advanced heterogeneous networks. The design objective is to increase the reliability under both bad and good channel conditions. Furthermore, the scheme can provide the low computational complexity of decoding process since the random overlapped chunked code can be decoded by using the brief propagation algorithm. The simulation results showed that our proposed scheme outperforms the two conventional RLNC schemes in terms decoding probability. In addition, we also provide a short analysis of decoding probability in closed-form equations for exploiting the random linear network coding. For future work, we extend the analysis to the closed-form equations of the random overlapped chunked code.

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