Context-Aware Wireless Broadcast for Next Generation Cellular Networks

Linyu Huang
Dept. of Electronic Engineering
City University of Hong Kong
l.huang@my.cityu.edu.hk

Chi Wan Sung
Dept. of Electronic Engineering
City University of Hong Kong
albert.sung@cityu.edu.hk

Chung Shue Chen
Alcatel-Lucent Bell Labs
Centre de Villarceaux, 91620 Nozay, France
cs.chen@alcatel-lucent.com

***Abstract*—This paper considers the energy minimization problem for wireless broadcast networks. One important feature is that user context is taken into consideration, integrated with network coding technique. Assuming that the user context, i.e., channel state information (CSI) can be predicted or estimated by using user location and moving pattern, power allocation is optimized to minimize energy consumption. It is proved NP-hard to find the optimal solution. By formulating the minimization problem into a binary integer programming (BLP) problem, the optimal solution can be obtained. Considering the high complexity of BLP, a heuristic algorithm is also proposed. Simulation results show that the proposed context-aware algorithms can reduce energy consumption up to 98%, compared with the scheme without using context information.**

I. Introduction

Wireless broadcast is used to deliver the same message to multiple users within the transmission range. It is widely used in many applications. During recent years, as the number of wireless devices has increased dramatically, efficient wireless broadcast becomes extremely important. Since wireless communications contribute a lot to information and communication technology (ICT) infrastructure energy consumption and also greenhouse effect, it becomes especially relevant to improve the energy efficiency of their applications. This paper mainly focuses on minimizing transmission energy consumption in wireless broadcast networks.

One basic idea of this paper is to improve the broadcasting efficiency by reducing the number of retransmissions, so as to reduce the total energy consumption. To achieve this goal, some of previous works use network coding techniques, such as XOR network coding [1], random linear network coding (RLNC) [2], and deterministic linear network coding (DLNC) [3]. Instead of sending the source message packets directly, base stations with network coding technique transmit packets which are encoded by taking the combinations of source packets. Although XOR works in the binary field which has a relatively low requirement on field size and encoding, in general it cannot guarantee that each broadcast packet is useful to all users. On the contrary, RLNC and DLNC can guarantee that each broadcast packet is useful to all users, provided that the field size requirement is satisfied. In this paper, we will consider RLNC and DLNC for improving the transmission efficiency.

This work was supported in part by a grant from the University Grants Committee of the Hong Kong Special Administrative Region (HKSAR), China under Project AoE/E-02/08, and in part by a grant from the Research Grants Council of HKSAR, China under Project CityU 121713, and partially by the ANR project IDEFIX under the grant number ANR-13-INFR-0006.

Another idea in the paper is to utilize user context [4], e.g., positions and trajectory, for optimal power allocation and transmission scheduling. Nowadays, many mobile devices are equipped with Global Positioning Systems (GPS), which makes it possible for base station (BS) to acquire the moving context of users. These information can be utilized, together with the channel state information (CSI) fed back from users. E.g., if BS knows the users are moving close to BS, it may schedule the transmission to later time slots since likely the channel gain will get better when a user is closer to BS so that the BS can use a smaller transmit power to send those packets and reduce energy consumption.

The main challenge of the above energy minimization problem is as follows: BS needs to determine *when* to transmit and *which power level* should be used. We consider such a power allocation and transmission scheduling optimization problem under the assumption that BS can predict or estimate the location and CSI of users for a certain period. The major contributions are as follows. First, we prove that it is NP-hard to find the optimal solution. Next, we show that the problem can be transformed into a binary linear programming (BLP) problem. Consider the high complexity of BLP, we propose a heuristic algorithm. Simulation results show that both the BLP and heuristic algorithms significantly reduce the total energy consumption.

II. System Model

In a time-slotted broadcasting cellular system, the BS wants to broadcast a file to K users. The broadcast file is divided into N equal-length packets. The system has a time requirement that the file must be delivered within T time slots, where $N \leq T$, consider that only one packet can be broadcast to the users in one time slot. BS is located at the center of the cell. The K users, labeled as U_1, U_2, $\dots$, U_K, are moving inside the cell following a particular mobility pattern. It is assumed that BS knows the moving context, e.g., the velocities of the users and their current positions. Based on the moving context, BS is assumed to be able to predict the channel gain of each user

978-1-4799-5832-0/14/$31.00 ©2014 IEEE

over the next T time slots. We will discuss the size of T and its impact in practical systems (see Section VII) later.

At a particular time slot t, let P_t be the transmit power and G_{it} be the link gain from BS to user U_i. Note that P_t is assumed to be no greater than a maximum power P_{max}. Define $\mathbf{P} = [P_1, P_2, \dots, P_T]$ as the transmit powers used in T slots. The signal-to-interference-plus-noise ratio (SINR) at user U_i, denoted by Γ_{it}, thus can be written as

$$\Gamma_{it} = \frac{G_{it} P_t}{\eta_i}, \tag{1}$$

where η_i is the sum of noise and interference from neighbor cells received by U_i, and it is modeled as a constant for simplicity. A packet is assumed to be received successfully if the SINR is no less than a certain fixed threshold γ. Otherwise, we assume it fails to be received.

Linear network coding technique [5] is used to improve transmission efficiency. By using network coding, a user is assumed to be able to successfully decode the broadcast file as long as it has received any N broadcast packets. Notice that no particular network coding algorithm is specified in this paper; any network coding method meeting the above assumption can be applied to our work, e.g., random linear network coding (RLNC) [6] or deterministic linear network coding (DLNC) [3]. The detail of network coding is out of the scope of this paper. The interested reader might refer to [3], [6]. A user U_i is said to be *complete* if it has received any N broadcast packets. Otherwise, it is *incomplete*.

In this paper, we aim to minimize energy consumption by determining optimal $\mathbf{P}$. For a transmission with power P_t, the energy consumption is P_t times the duration of a time slot. For simplicity, we assume that the duration of each slot is unit time and will be ignored throughout the paper. Therefore, the total energy consumption can be written as $\sum_{t=1}^{T} P_t$.

III. Problem Formulation

When $N < T$, it is not necessary for BS to transmit in every slot. Hence, BS needs to determine the time slots at which BS needs to transmit. Similarly, it is not necessary for a user to receive packets successfully in every time slot. Therefore, BS also needs to determine the users to which BS needs to transmit, which we call *target users*. Note that when $N = T$, all the users are target users in every time slot. Once the target users are determined, the transmission coverage and the required transmit power can be determined as well.

First, we will introduce how to determine the transmit power, given that BS knows the link gains of the target users. If BS wants to send a packet to U_i with minimal transmit power, it has to choose the power level which makes the received SINR Γ_{it} equal to the threshold γ. By (1), the required transmit power, say Λ_{it}, can be written as

$$\Lambda_{it} = \frac{\gamma \eta_i}{G_{it}}. \tag{2}$$

Define a $K \times T$ matrix $\mathbf{\Lambda} = \{\Lambda_{it}\}$ to denote the predicted transmit power matrix. Given that BS can predict the channel gain of users over T time slots, $\mathbf{\Lambda}$ can be obtained by (2). We will discuss in Section VII-A how one may predict or estimate the channel gain in practical systems.

Note that at a particular time slot, if there are multiple target users, BS will compute the required transmit power for each target user and then take the largest one as the transmit power.

We define a $K \times T$ binary matrix $\mathbf{X} = \{X_{ij}\}$ to indicate whether a user is a target user at a particular time slot. If $X_{ij} = 1$, U_i is a target user at the j-th slot. Otherwise, U_i is not a target user. The objective is to minimize the total energy consumption spent over the T time slots. It is clear in the above minimization problem, (i) each user has to be chosen as a target user for at least N slots, (ii) the transmit power must be no greater than the maximum power, and (iii) if U_i is a target user at j-th time slot, those users with $\Lambda_{ij'} \le \Lambda_{ij}$ must be target users as well. Therefore, we have

$$\begin{aligned} \text{minimize} \quad & \sum_{j=1}^{T} \max_{0<i\le K} \{\Lambda_{ij} X_{ij}\} \\ \text{subject to} \quad & \sum_{j=1}^{T} X_{ij} \ge N \quad \text{for } i = 1, 2, \dots, K, \\ & X_{ij} = 0, \text{ if } \Lambda_{ij} > P_{max}, \\ & X_{ij} \le X_{ij'}, \text{ if } \Lambda_{ij} \ge \Lambda_{ij'}. \end{aligned} \tag{3}$$

We will analyze and solve (3) in the coming sections.

IV. Complexity Analysis

We are going to prove that the problem in (3) is NP-hard. The problem can be rewritten in the following form:

Problem: MinEnergy

Instance: A $K \times T$ positive matrix $\mathbf{\Lambda}$, a positive number P_{max} and an integer N.

Objective: Find T subsets of $\mathcal{U} \triangleq \{1, 2, \dots, K\}$, denoted by $\mathcal{S}_1, \mathcal{S}_2, \dots, \mathcal{S}_T$, such that

1) if $i \in \mathcal{S}_j$ and $\Lambda_{mj} \le \Lambda_{ij}$, then $m \in \mathcal{S}_j$;
2) if $\Lambda_{ij} > P_{max}$, $i \notin \mathcal{S}_j$;
3) for each $u \in \mathcal{U}$, there are at least N subsets containing u;
4) $\sum_{j=1}^{T} c_j$ is minimized, where $c_j \triangleq \max_{i \in \mathcal{S}_j} \{\Lambda_{ij}\}$.

The basic idea of proving the NP-hardness is to show that the weighted set cover problem [7], a well-known NP-hard problem, can be reduced to MinEnergy.

Problem: WeightedSetCover

Instance: A universe $\mathcal{Z}$, a collection of subsets of $\mathcal{Z}$, $\mathscr{F} = \{\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_n\}$. Each $\mathcal{F}_i \in \mathscr{F}$ is associated with a non-negative weight w_i.

Objective: Find a minimum weight sub-collection of $\mathscr{F}$ that covers all element of $\mathcal{Z}$.

Theorem 1: MinEnergy is NP-hard.

Proof: We prove the statement by Cook reduction from WeightedSetCover to MinEnergy. Given an instance of WeightedSetCover, let $K = |\mathcal{Z}|$, $T = n$, $N = 1$, and P_{max} be an arbitrary number between $\max_i\{w_i\}$ and infinity. Label the elements of $\mathcal{Z}$ by 1, 2, …, K, so that $\mathcal{Z} = \mathcal{U}$. For $i = 1, 2, \dots, K$ and $j = 1, 2, \dots, T$, let Λ_{ij} equal to w_j if $i \in \mathcal{F}_j$, and ∞ otherwise. It is clear that this instance of MinEnergy can be obtained in polynomial time.

Due to conditions (1) and (2) of MINENERGY, $\mathcal{S}_j$ can only be $\emptyset$ or $\mathcal{F}_j$. Let $\mathcal{S}_1^*, \mathcal{S}_2,^*, \ldots, \mathcal{S}_T^*$ be an optimal solution to the derived MINENERGY instance, which are obtained by an oracle call. Note that if the MINENERGY instance has no solution, then it means that even if $\mathcal{S}_j = \mathcal{F}_j$ for all j, there is at least one $u \in U$ which is not contained in any of the $\mathcal{S}_j$. This in turn implies that the union of all $\mathcal{F}_j$'s cannot cover $\mathcal{Z}$, and the original WEIGHTEDSETCOVER instance also has no solution. Now, to solve the original WEIGHTEDSETCOVER instance, for $j = 1, 2, \ldots, T$, we choose $\mathcal{F}_j$ if and only if $\mathcal{S}_j^* = \mathcal{F}_j$. We claim that this choice is optimal to the WEIGHTEDSETCOVER instance. To see this, note that all elements in $\mathcal{Z}$ are covered at least once due to condition (3) of MINENERGY and the fact that $N = 1$. Furthermore, the chosen sub-collection of $\mathscr{F}$ is of minimum weight, for otherwise $\sum_{j=1}^{T} c_j$ is not minimized. ■

V. OPTIMAL SOLUTION

The problem can be transformed into a binary linear programming (BLP) problem as follows. First, sort the j-th column of matrix $\mathbf{\Lambda}$ in ascending order, where $1 \leq j \leq T$, and get $\Lambda_{m_1 j}, \Lambda_{m_2 j}, \ldots, \Lambda_{m_K j}$. Note that $\Lambda_{m_i j}$ is always no greater than $\Lambda_{m_{(i+1)} j}$, which means that if $U_{m_{(i+1)}}$ is covered by BS, then the user corresponding to U_{m_i} must be covered by BS as well. Let $\mathbf{W}$ be a weight matrix with dimension $K \times T$. The value of $\mathbf{W}$ is determined as follows:

$$W_{ij} = \begin{cases} \Lambda_{ij}, & \text{if } i = m_1, \\ \Lambda_{m_k j} - \Lambda_{m_{k-1} j}, & \text{if } i = m_k, k > 1. \end{cases}$$

Then, the optimization problem (3) can be re-written as

$$\begin{aligned} \underset{\mathbf{X}}{\text{minimize}} \quad & \text{sum}(\mathbf{X} \circ \mathbf{W}) \\ \text{subject to:} \quad & X_{ij} = 0 \text{ or } 1, && (4) \\ & X_{ij} = 0, \quad \text{if } \Lambda_{ij} > P_{max}, && (5) \\ & \sum_{0<j\leq T} X_{ij} \geq N, \quad \forall i, && (6) \\ & X_{m_i j} \geq X_{m_{i+1} j}, \quad \forall j, 1 \leq i \leq K-1, && (7) \end{aligned}$$

where $\circ$ denotes the Hadamard (element-wise) product, and sum($\mathbf{A}$) means the summation of all the elements in matrix $\mathbf{A}$. Recall that $\mathbf{X}$ is used to indicate whether a user is a target at a particular slot. If $X_{ij} = 1$, U_i is selected as a target user at the j-th slot. Otherwise, U_i is not targeted. Therefore, X_{ij} is set to a binary value in constraint (4). At a particular time slot, if $\Lambda_{ij} > P_{max}$, U_i cannot be targeted by BS, which is shown in constraint (5). Constraint (6) is used to guarantee that each user must be targeted by at least N times, such that the broadcast file can be decoded by each user. Constraint (7) is used to guarantee that if a user with a higher Λ_{ij} is covered by BS, then a user with a lower Λ_{ij} is covered as well. According to the definition of $\mathbf{W}$ and constraint (7), $\sum_i (X_{ij} W_{ij})$ is the transmit power used in j-th time slot. Therefore, the objective function is to minimize the total energy consumption in T slots. This BLP problem can be solved by some standard mathematical tools, such as branch and bound and cutting planes. We call this method Context-Aware with Binary Linear Programming (CABLP).

VI. HEURISTIC SCHEME

The basic idea is to greedily choose the time slots at which the maximal number of *incomplete* users can be covered, until all the users have been covered by at least N times.

The proposed algorithm can be summarized as follows. We call it Context-Aware Heuristic (CAH) algorithm.

Step 1: A $K \times T$ matrix $\mathbf{M}$ is defined to indicate whether an incomplete user can be covered by BS. Initialize $\mathbf{M}$ by (8) and let $\mathbf{P} := \mathbf{0}$.

$$M_{ij} := \begin{cases} 0, & \text{if } \Lambda_{ij} > P_{max}, \\ 1, & \text{otherwise.} \end{cases} \tag{8}$$

Step 2: Compute the summation of each column in $\mathbf{M}$ to get the number of incomplete users that can be possibly covered in each time slot. If no incomplete users can be possibly covered, the broadcast cannot be completed and program halts. Otherwise, choose all the time slots corresponding to the maximal value.

Step 3: For each selected time slot j, compute the corresponding transmit power by $\max_i\{M_{ij}\Lambda_{ij}\}$. Then, choose the time slot with minimal transmit power, say j' and set $P_{j'}$ to the corresponding value.

Step 4: Update matrix $\mathbf{M}$. First, since j'-th slot has been selected, it cannot be selected any more. Set $M_{ij'} := 0$ for $1 \leq i \leq K$. Then, check if any user has been covered by N times. If a user, say i', has been covered by N times, it can successfully decode the broadcast file without further information. Therefore, user i' should be considered as a complete user and set the i'-th row of $\mathbf{M}$ to zero.

Step 5: Go to Step 2 and repeat such a procedure, until all users are complete or the program halts at Step 2. Those time slots with $P_t > 0$ are selected time slots for transmission.

Now, we are going to analyze the complexity of CAH. In each iteration of Step 2, the maximal value of the summation of each column is at least one, since otherwise it means that no user can be covered and it is impossible to finish the broadcast. In worst case, only one user is within the transmission range of BS in each time slot. In such a case, BS can only cover one user once in each time slot. In other words, it takes at most N loops to cover a user N times. Overall, it takes at most $\min\{T, KN\}$ loops to cover all users.

In Step 1, it takes $O(KT)$ operations to initialize $\mathbf{M}$. In Step 2, it takes $(K-1)T$ operations to compute the summation of columns, and takes T operations to select qualified time slots. The overall complexity of Step 2 is $O(KT)$. Note that the maximal number of qualified time slots is T. Therefore, in Step 3, it takes at most KT operations to compute the element-wise product, and takes at most $(K-1)T$ operations to determine the transmit power for the selected T slots. Finally, it requires $T-1$ operations to choose the time slot with minimal transmit power. The overall complexity of Step 3 is $O(KT)$. In Step 4, it first takes at most K operations to set the j-th column of $\mathbf{M}$ to zero. Then, for each complete user, it takes at most T operations to clear a row of $\mathbf{M}$. In worst case, the overall complexity of Step 4 is $O(KT)$. Therefore, the overall complexity of each loop is $O(KT)$. As mentioned in

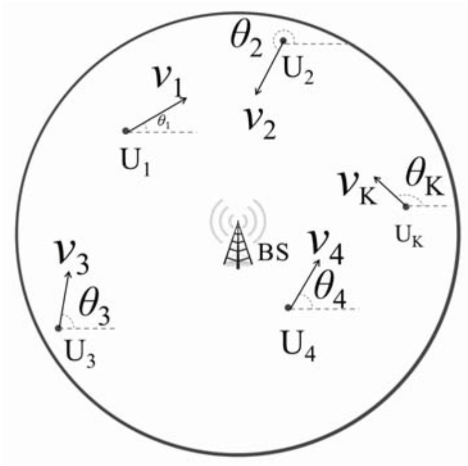

Figure 1. Simulation model

the previous paragraph, the maximal number of loops required for convergence is $\min\{T, KN\}$, the overall complexity of CAH is $O(KT \min\{T, KN\})$.

VII. Performance Evaluation

The performance of proposed algorithms is evaluated via simulations. We compare the proposed algorithms with RLNC without moving context awareness.

A. Simulation Setup

As shown in Fig. 1, K users are randomly located in a cell with radius 3 km at the very beginning. The i-th user is moving inside the cell with an initial angle θ_i and a constant speed v_i between 80 to 100 km/hour which is roughly the speed of vehicles on highway. Note that the assumption that the vehicles are in constant speeds is used to simplify simulation only. In real systems, this assumption is not necessary for example when the information can be updated from time to time. Here, we consider that BS knows the location and trajectory (moving speed and direction) of mobile users, see e.g., [8], [9]. At a particular slot t, the path loss between BS and U_i is modeled by $PL = 128.1 + 37.6 \log_{10}(d_{it}) + L_s$, where d_{it} is the distance between BS and U_i, L_s is the shadow fading, and the duration of a time slot is assumed to be 0.167 second, which is the same as [4], for wireless video streaming.

Let A_{it} be the attenuation (in dB) caused by shadow fading and α be the path loss exponent, respectively. Then, the link gain G_{it} can be re-written as

$$G_{it} = \frac{10^{-A_{it}/10}}{d_{it}^{\alpha}}. \tag{9}$$

Note that A_{it} is usually modeled as a zero-mean Gaussian random variable with standard deviation σ. In general, the empirical value for σ is between 6 dB and 12 dB, and α is between 4 and 6. We assume that the statistics of shadowing fading in a cell can be collected by network operator and is known by the BS.

Considering the spatial correlation of shadow fading [10], the correlated shadow fading is modeled as the following Gauss-Markov process

$$A_{i(t+1)} = \rho_{it} A_{it} + \sqrt{1 - \rho_{it}^2} W_t, \tag{10}$$

where W_t is a zero-mean Gaussian random variable with 10 dB standard deviation, and ρ_{it} is the correlation coefficient which can be determined by

$$\rho_{it} = e^{-\frac{|\triangle d|}{d_{cor}}}, \tag{11}$$

where $|\triangle d|$ is the position change of mobile user from t-th to $(t+1)$-th slot, and d_{cor} is the correlation distance and set to 50 meters in our simulation according to 3GPP [11]. For more details of this shadow fading model, we refer the readers to [12]. In practice, (9) and (10) work as follows. At the t-th time slot, BS knows G_{it} based on the CSI fed back from users. By using (9), A_{it} can be determined. Due to the fading correlation, BS can use (10) to estimate $A_{it'}$ for the following T slots, where $t' > t$.

Other parameters are shown in Table I. The SINR threshold γ is set to 3 dB. In the simulation, for each set of parameters, the results are averaged over 1000 runs.

TABLE I
Simulation Parameters

Parameter	Value
Cell radius r	3 km
Bandwidth	10 MHz
Number of resource blocks (RB)	50
Minimum distance	35 m
Noise density	-174 dBm/Hz
Noise figure	9 dB
Correlation distance	50 m

The proposed algorithms CABLP and CAH are compared with a non-context-aware (NCA) scheme, based on RLNC. In NCA, BS keeps sending different encoded packets at each time slot with maximal transmit power, until all the users are complete. Under NCA, a user is also assumed to be able to decode the broadcast file as long as it successfully receives N different broadcast packets. We evaluate the performance with various K, N, and T.

We first run simulation with fixed $T = 300$, $N = 32$, and various K. The simulation result is shown in Fig. 2. We can see that CABLP and CAH always outperform NCA while K varies from 5 to 200. In particular, CABLP and CAH can reduce energy consumption up to 88% and 81% when $K = 5$, respectively. When $K = 200$, CABLP and CAH can reduce the energy consumption by 61% and 51%, respectively.

Next, we consider the performance of the algorithms under various N. In Fig. 3, we set $K = 20$, $T = 300$, and N varies from 2 to 64. Simulation result shows that CABLP and CAH also can reduce the energy consumption significantly. When $N = 2$, compared with NCA, CABLP and CAH can save energy up to 98% and 96%, respectively. When $N = 64$,

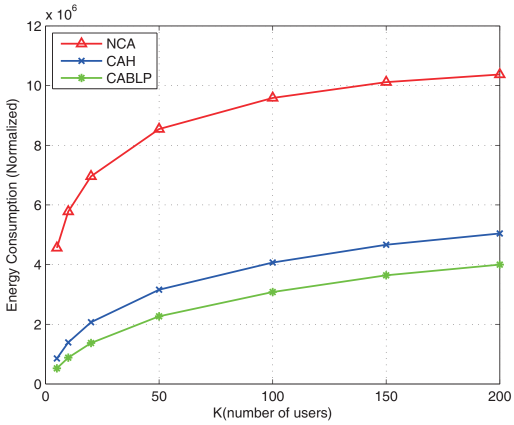

Figure 2. Energy consumption versus K

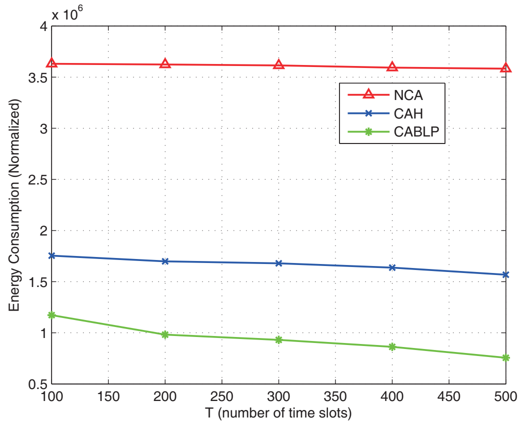

Figure 4. Energy consumption versus T

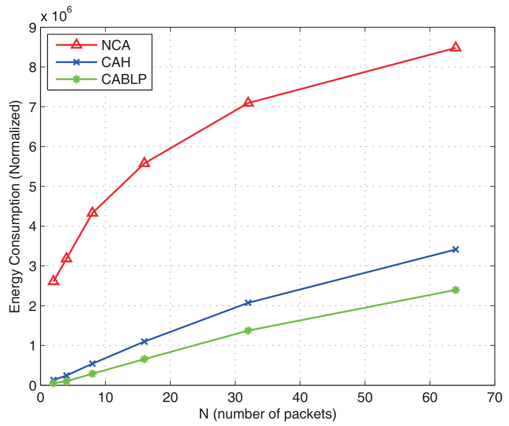

Figure 3. Energy consumption versus N

CABLP and CAH can reduce energy consumption by 72% and 60%, respectively.

Fig. 4 shows how T impacts the performance. Since NCA transmits sequentially from the first time slot, more time slot does not affect its performance much. On the contrary, the proposed context-aware algorithms will take lower energy consumption as T increases. The reason is that both CABLP and CAH would have more freedom in choosing the transmission time slots.

VIII. Conclusion

In this paper, we consider the energy minimization problem for cellular networks. To improve transmission efficiency, network coding is used to generate broadcast packets. We also take the moving context of mobile users into consideration when doing power allocation. According to the users' location and channel gain, BS can perform better transmission scheduling and optimized transmit power allocation, so as to reduce energy consumption.

In some real systems, BS may not be able to predict the accurate channel gain, which may cause some performance degradation. This problem can be alleviated by adaptively change the used transmit power, based on the feedback from users. For example, BS can estimate the channel gain of the j-th slot based the feedback before the $(j-1)$-th slot. If estimated channel gain is lower than the predicted one used in scheduling, BS then can raise its transmit power for the j-th slot, so that the target users can still receive the broadcast packets. Similarly, BS can also reduce its transmit power if the real channel gain is higher than the predicted one, so as to reduce energy consumption.

While we only consider path loss and shadow fading in the channel model, our result may provide insights on how to utilize the user context when doing power allocation and transmission scheduling and has demonstrated its effectiveness. In future work, we will consider more implementation challenges and take small scale fading into consideration as well.

References

[1] D. Nguyen, T. Tran, T. Nguyen, and B. Bose, "Wireless broadcast using network coding," *IEEE Trans. on Vehicular Technology*, vol. 58, pp. 914-925, 2009.

[2] L. Lu, F. Sun, M. Xiao, and L. K. Rasmussen, "Relay-aided multi-cell broadcasting with random network coding," in *Int. Symp. on Inf. Theory and its Applications (ISITA)*, pp. 957-962, Dec. 2010.

[3] C. W. Sung, L. Huang, H. Y. Kwan, and K. W. Shum, "Linear network code for erasure broadcast channel with feedback: complexity and algorithms," arXiv:1205.5324v2. Dec. 2013.

[4] S. Sadr and S. Valentin, "Anticipatory buffer control and resource allocation for wireless video streaming," arXiv:1304.3056, Apr. 2013.

[5] S. Y. R. Li, R. W. Yeung, and N. Cai, "Linear network coding," *IEEE Trans. on Information Theory*, pp. 371-381, Jun. 2003.

[6] T. Ho, M. Médard, R. Koetter, D. R. Karger, M. Effros, J. Shi, and B. Leong, "A random linear network coding approach to multicast," *IEEE Trans. on Information Theory*, vol. 52, pp. 4413-4430, 2006.

[7] V. V. Vazirani, *Approximation Algorithms*, Springer, 2003.

[8] R. Narasimhan and D. C. Cox, "Speed estimation in wireless systems using wavelets", *IEEE Trans. on Communications*, vol. 47, no. 9, pp. 1357-1364, Sep. 1999.

[9] J. Lorca and A. Sierra, "A simple speed estimation algorithm for mobility-aware SON RRM strategies in LTE," in *IFIP Wireless Days*, Nov. 2013.

[10] M. Gudmundson, "Correlation model for the shadow fading in mobile radio systems," *Electronics Letters*, pp. 2145-2146, Nov. 1991.

[11] 3GPP, "Further advancements for E-UTRA physical layer aspects," *Technical Report*, 3GPP TR 36.814, v9.0.0, Mar. 2010.

[12] H. L. Bertoni, *Radio Propagation for Modern Wireless Systems*, NJ: Prentice Hall PTR, 2000.