Joint Power Control and Scheduling for Context-Aware Unicast Cellular Networks

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***Abstract*—With the widely use of smart devices and rapid development of communication technologies, it becomes easier for base stations to obtain the context information of users. The context information can be utilized to optimize system resource allocation. This paper focuses on context-aware unicast cellular networks. Assuming that some channel state information (CSI) can be predicted based on user context such as user location and moving pattern, joint power control and transmission scheduling is applied to minimize the transmission energy consumption. By reducing the energy minimization problem to a semi-assignment problem, our proposed algorithm can find the optimal solution in polynomial time. Simulation results show that the proposed context-aware scheme outperforms the traditional round-robin scheduler and opportunistic scheduler, which do not consider the feature of context-awareness.**

I. Introduction

In cellular networks, wireless broadcast, unicast, and multicast are deployed to support various services and system requirements. For example, when many users are requesting the same content from a base station (BS), wireless broadcast or multicast is often used for more efficient delivery. One can also optimize the power allocation and transmission scheduling for improving radio resource utilization efficiency in a broadcast system [1]. Here, we will consider the case of unicast, which is of high importance in today's cellular networks. The corresponding radio resource allocation optimization problem is much more challenging, since each user would request different content from the BS. Our goal is to minimize energy consumption while meeting user traffic demand and quality-of-service (QoS) requirement [2].

One important tool for increasing energy efficiency is power control. Based on channel conditions, BS can transmit with the minimum necessary power level which allows the target user successfully receive the transmitted packets so as to save energy. Besides, by proper transmission scheduling one can also improve power utilization efficiency. For example, for a user whose channel is temporarily encountering a deep fade, a BS can defer its transmissions until the mobile user has better channel condition for energy efficiency. Round-robin scheduler and opportunistic scheduler are two commonly used schedulers in cellular systems. In 3GPP-LTE round-robin scheduling, the BS simply assigns time slots to users in circular order, handling all users sequentially. It is easy to implement but may have low resource utilization efficiency. The opportunistic scheduler has the advantage by using channel variation and multiuser diversity. In [3], the authors show that the system sum capacity can be achieved by doing so. However, opportunistic scheduler has the drawback that it is not fair to users who always have relatively poor channel condition. Discussions of user fairness, QoS guarantee and other concerns can be found in [4]–[6].

Different from the above schemes, recently many researchers consider exploiting context information to improve energy efficiency. These context information [7] may come from application (e.g., quality of service), network (e.g., congestion status), user (e.g., location or mobility pattern), and device levels. Here, we consider user level context [8]. With the widely use of smart devices, it is possible for BS to acquire the moving context, e.g., positions and movement trajectory. Based on these context information, BS can predict future channel conditions of that user. Together with the channel state information (CSI) fed back from the user, better scheduling and power control decision can be made. For example, if BS knows a user is moving towards itself, it may schedule its transmission to later time slots, since likely the channel gain will increase when a user is getting closer so that the BS can use a smaller transmit power to send those packets and reduce energy consumption.

A feature of this paper is that user mobility is considered and user context is utilized. Note that we considered user context for broadcast scenarios in [1] and applied network coding technique. However, the result cannot be used for unicast systems. We therefore derive new methods to minimize transmission energy consumption via joint power control and transmission scheduling for unicast cellular networks.

We write the joint power control and scheduling problem as a mixed integer programming problem, and reduce it to a semi-assignment problem [9], which can be solved in polynomial time. Simulation results show that our proposed context-aware scheme significantly outperforms the round-robin scheduling and opportunistic scheduling schemes.

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II. Problem Formulation

Consider a one-hop time-slotted channel in a cell. There are K active mobile users moving inside the cell. We label them as $U_1, \ldots, U_K$. The BS is required to deliver N_i packets to U_i, for $i = 1, 2, \ldots, K$, within a frame of T time slots, where $T \geq \sum_{i=1}^{K} N_i$. Assume that user context, including the information about the velocities of the users and their current positions, is available at BS [8], [10]. In addition, we assume that the BS would predict the CSI of each user over the next T time slots.

At a particular time slot t, let P_t be the transmit power. Due to practical limitations, P_t is assumed to be less than a maximum transmit power, P_{max}. A packet is said to be successfully received by a user if the received SINR of that packet is no less than an SINR threshold. Let $\mathbf{P} = [P_1, P_2, \ldots, P_T]$ be the transmit powers used in T slots. The energy consumed in a time slot is the product of the corresponding transmit power and the duration of that time slot. For simplicity, it is assumed that the duration of each slot is unit time and will be ignored throughout the paper. Therefore, the total energy consumed in T slots is $\sum_{t=1}^{T} P_t$.

Since BS can only transmit one packet to one user at a particular time slot, it needs to determine which user the BS needs to transmit, which we call the *target user*. We define a $K \times T$ binary variable matrix $\mathbf{X} = [x_{ij}]$ to indicate whether a user is the target user during the T time slots. If BS intends to send a packet to U_i at the j-th slot, $x_{ij} = 1$. Otherwise, $x_{ij} = 0$.

At the j-th time slot, to make U_i successfully receive a packet, the minimal required transmit power is the one which can make the received SINR at U_i be equal to the threshold, which we denote as λ_{ij}. We define a $K \times T$ matrix Λ and let $\Lambda = [\lambda_{ij}]$. Since BS can predict the channel gain of users, Λ can be obtained by BS. We will show how to compute Λ in a later section.

Our objective is to minimize the total transmit power, with the following requirements: (i) user U_i must be chosen as a target user for N_i times, (ii) at most one user can be chosen as the target user at a particular time slot, and (iii) the transmit power must be no greater than the maximum power P_{max}. The problem can be formulated mathematically as follows:

$$\text{minimize} \quad \sum_{j=1}^{T} P_j \tag{1}$$

$$\text{subject to} \quad P_j \geq \sum_{i=1}^{K} x_{ij}\lambda_{ij} \quad \text{for } j = 1, 2, \ldots, T, \tag{2}$$

$$P_j \leq P_{max}, \tag{3}$$

$$\sum_{j=1}^{T} x_{ij} = N_i \quad \text{for } i = 1, 2, \ldots, K, \tag{4}$$

$$\sum_{i=1}^{K} x_{ij} \leq 1 \quad \text{for } j = 1, 2, \ldots, T, \tag{5}$$

$$x_{ij} \in \{0, 1\} \quad \forall i, \forall j, \tag{6}$$

where (2) is the energy consumed in each time slot, (3) is the constraint that transmit power cannot be greater than P_{max}, (4) is to guarantee that each user can receive enough number of packets as he/she requested, (5) is the constraint that BS can only broadcast to one user in one time slot, and (6) is used to make sure that x_{ij} is a binary variable. The above optimization problem is a mixed integer programming problem, which in general is difficult to solve. Nonetheless, it has special structure and we will show in the next section that it can be solved in polynomial time.

III. Reduction to Semi-Assignment Problem

In this section, we reduce the joint power control and scheduling problem into a combinatorial optimization problem, called semi-assignment problem (SAP) [9]. SAP is a special class of assignment problems and considers the minimization of total cost when assigning a number of tasks to a number of agents. Notice that although the tasks and agents in assignment problem are unique, in a SAP problem some of the agents can be identical. Taking advantage of this fact would make it possible to solve a SAP faster than that in solving a standard assignment problem.

Now we describe the technical details. Consider the T time slots to be assigned are the tasks while the K users are the agents. U_i requesting N_i time slots can be regarded as N_i identical agents. To make the numbers of tasks and agents equal, we define a dummy user, labeled as U_{K+1}, which requests $(T - \sum_{i=1}^{K} N_i)$ time slots. By stacking the $1 \times T$ zero vector to the bottom of Λ, we obtain a $(K+1) \times T$ matrix, denoted by $\mathbf{C} = [c_{ij}]$. The $(K+1)$-th row of $\mathbf{C}$ is treated as the required transmit power of U_{K+1}. In other words, if a time slot is assigned to U_{K+1}, the transmit power at that slot is zero. Since the transmit power at a time slot is at most P_{max}, the j-th time slot cannot be allocated to U_i if $c_{ij} > P_{max}$. To reflect this, $\mathbf{C}$ is updated by setting c_{ij} to infinity if $c_{ij} > P_{max}$. Therefore, the joint power control and scheduling problem is equivalent to the following problem:

$$\begin{aligned} \text{minimize} \quad & \sum_{i=1}^{K+1} \sum_{j=1}^{T} c_{ij} x_{ij} \\ \text{subject to} \quad & \sum_{j=1}^{T} x_{ij} = N_i \quad \text{for } i = 1, 2, \ldots, K+1, \\ & \sum_{i=1}^{K+1} x_{ij} = 1 \quad \text{for } j = 1, 2, \ldots, T, \\ & x_{ij} \in \{0, 1\} \quad \forall i, \forall j. \end{aligned} \tag{7}$$

The above problem is exactly the standard of SAP, which can be solved by existing algorithms [11], [12]. It can be solved in polynomial time with complexity $O(KT^2)$ [13]. After solving problem (7), $\mathbf{X}$ indicates how to assign the time slots to users. The j-th time slot is assigned to U_i if $x_{ij} = 1$. The transmit power at the j-th time slot can be determined by

$$P_j = \sum_{i=1}^{K} c_{ij} x_{ij}. \tag{8}$$

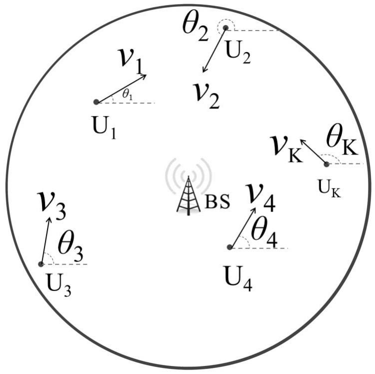

Figure 1. Simulation model

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Cell radius r	2 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

If $P_j = \infty$ for any j, then the original joint power control and scheduling problem is infeasible. We call this method Context-Aware joint Power control and Scheduling scheme based on Semi-Assignment problem (CAPS-SA) or in short CAPS.

IV. SIMULATION RESULTS

In this section, we evaluate the performance of our proposed CAPS via simulations, and compare it with two traditional schemes that are not context-aware.

A. Simulation Setup

The simulation setting is as follows. K mobile users are randomly located in a cell with radius 2 km, as shown in Fig. 1. The i-th user is moving inside the cell with an initial angle θ_i and a constant speed v_i between 60 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., [10], [14]. At a particular time 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 [8], 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 [15], 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 [16]. For more details of this shadow fading model, we refer the readers to [17]. 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 is set to 3 dB. In each simulation, a user U_i requests N_i packets from BS, where N_i is an integer uniformly distributed between 1 and N, where N is a pre-determined integer. For each set of parameters, the final results are obtained by the Monte Carlo method, averaged over 1,000 runs.

B. Benchmark Schemes

We compare the above context-aware scheme CAPS with two traditional schemes, which are not context-aware. The first one is the Round-Robin Scheduling Scheme (RRSS), which simply assigns time slots in a round-robin fashion to users who have not received all the requested packets. Suppose the j-th slot is assigned to user U_i. If $\lambda_{ij} > P_{max}$, then BS transmits nothing and the j-th slot will be wasted. Otherwise, BS will send a new packet to U_i with power λ_{ij} at the j-th slot.

The second scheme is called Opportunistic Scheduling Scheme (OSS), which is based a maximum-SINR opportunistic scheduler and works as follows. At the j-th time slot, among those users which have not received enough packets, BS first selects the user, U_{i^*}, with minimal required transmit power, i.e., $i^* = \arg\min_i\{\lambda_{ij}\}$. If $\lambda_{i^*j} > P_{max}$, no user is able to receive a packet in that time slot. The time slot will simply be skipped. Otherwise, if $\lambda_{i^*j} \leq P_{max}$, BS transmits a new packet to user U_{i^*} with power λ_{i^*j}.

C. Performance Evaluation

We evaluate the performance with various K, N, and T. The performance is measured by two metrics: energy consumption and outage probability. Since the users randomly choose the number of requested packets in each run, the total number of transmitted packets is different from one run to another. Therefore, it is meaningless to measure the total energy consumption in each unicast process. Instead, we measure the average energy consumed per packet. The total energy consumed in a whole unicast process can be obtained by using the average energy times the total number of transmitted packets. Thus, this metric is good enough to reflect the energy efficiency of different schemes. To evaluate the scheduling fairness performance of the above schemes, we also measure the outage probabilities. For a given user, if he/she cannot successfully receive the required number of packets within T slots, there is an outage event of that user. The outage probability of a particular run is defined as the percentage of users which have outage events. Note that it is possible that some randomly generated unicast tasks are infeasible. To avoid the degradation caused to outage performance, for each generated unicast task, we first use CAPS to test if it is feasible. If not, this random generation is discarded and then regenerate a new one until the problem is feasible.

We first investigate how T impacts the performance, which are shown in Fig. 2 and Fig. 3, where $N = 10$ and $K = 10$. Since it may take $KN = 100$ time slots to finish the unicast process, we change T from 100 to 300. We can see that CAPS always outperforms RRSS and OSS greatly, in terms of both energy consumption and outage probability. Both RRSS and OSS have some outage events before the 250-th time slot. In other words, they send enough packets for closer users while fail to send some packets to "worse" users, which leads to that the average consumed energy before the 250-th slot is smaller than that of those later slots. After the 250-th time slot, both RRSS and OSS have no outage events and their energy performance is nearly unaffected by the value of T. The reason is that both RRSS and OSS can finish all transmission jobs before 250 slots, therefore further increase of T would not impact the performance much. While for CAPS, it has more freedom in choosing time slots when T is large. Therefore, the energy consumption of CAPS is decreasing as T increases.

Next, we evaluate the performance with $T = 800$, $N = 10$, and various K. The energy performance is shown in Fig. 4. Note that when T is not large enough, the schemes may have outage events. To be fair, we set $T = 800$ so that all schemes have no outage events. It shows that CAPS always consumes less energy than RRSS and OSS. In particular, when $K = 10$, CAPS can reduce energy consumption up to 84% and 78% compared with RRSS and OSS, respectively. We can see that the energy performance of CAPS is slightly

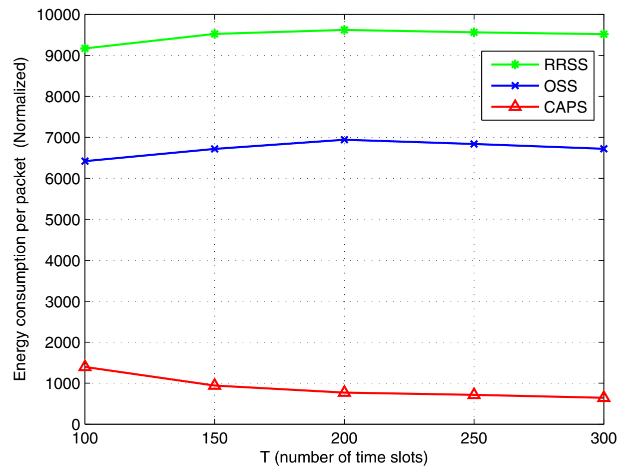

Figure 2. Energy consumption versus T (N = 10 and K = 10)

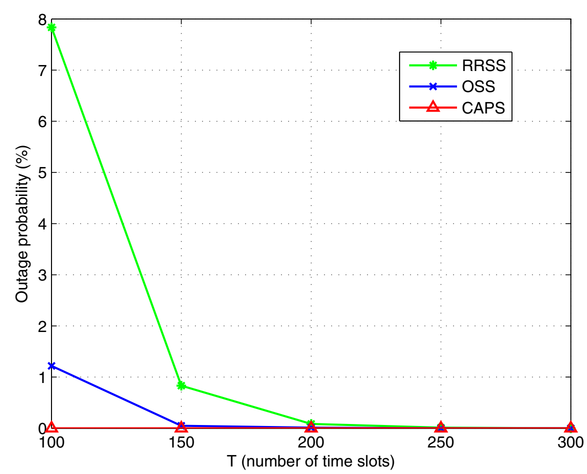

Figure 3. Outage probability versus T (N = 10 and K = 10)

decreasing as K increases, which is caused by multiuser diversity. At a particular time slot, as K increases, BS requires less power to send a packet to the nearest user with high probability, i.e., $\min_{1\leq i\leq K} \lambda(i,j)$ decreases with high probability as K increases. Therefore, the average power consumed by CAPS is decreasing. Similarly, OSS has more freedom in scheduling the time slots as K increases, and its energy consumption is also decreasing as K increases. On contrary, the performance of RRSS is nearly unaffected by the number of users. The reason is that RRSS assigns time slots to users in circular order. Since all the users are randomly generated, the number of users does not impact its performance.

We also consider the performance under various N. In Fig. 5, we set $K = 10$, $T = 300$, and then N varies from 10 to 30. We can find that CAPS outperforms both the RRSS and OSS. When $N = 10$, CAPS can reduce energy consumption up to 93% and 91% compared with RRSS and OSS, respectively. The energy consumption of OSS is decreasing

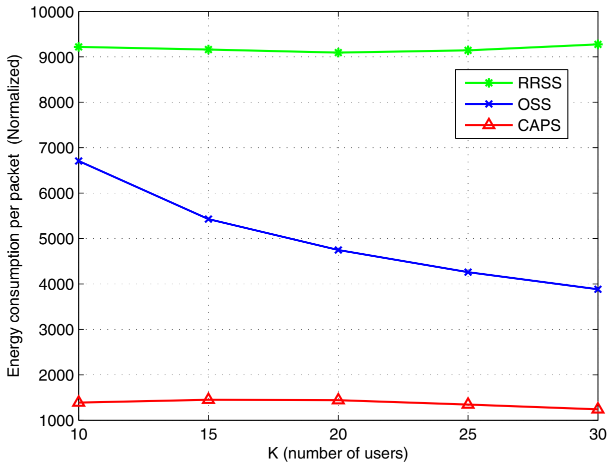

Figure 4. Energy consumption versus K (N = 10 and T=800)

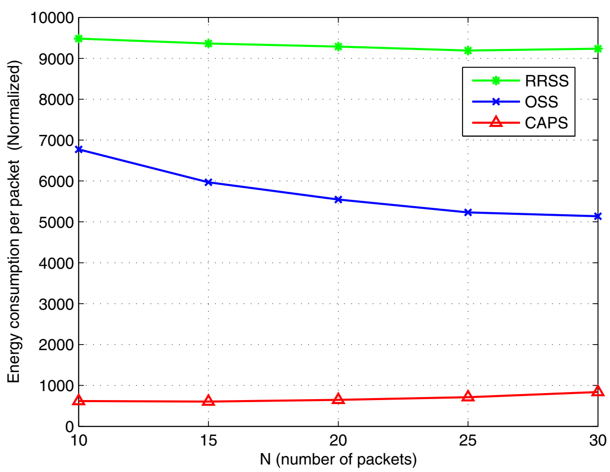

Figure 5. Energy consumption versus N ($K = 10$ and $T = 300$)

as N increases. As discussed above, this is also caused by multiuser diversity. BS has more freedom in scheduling the "worse" users to later time slots with larger N, therefore the average consumed energy is decreasing as N increases. Since RRSS always assigns time slots to these randomly generated users in circular order, increase of N nearly unaffected its performance. For CAPS, as N increases, it has less freedom in choosing time slots within T time slots. Therefore, the average energy consumption is increasing as N increases.

V. Conclusion

This paper focuses on the energy minimization for unicast cellular networks. Compared with traditional unicast system, one important feature is that the user mobility and user context information are considered in this paper. By utilizing the user context, i.e., user position and movement trajectory, BS is able to predict the channel conditions for some future period. Based on these channel information, joint power control and scheduling is applied to minimize the transmission energy consumption. We show that the optimal solution can be obtained in polynomial time. We also compare the proposed context-aware scheme with traditional schemes without context awareness via simulations. Simulation result shows that the proposed scheme outperforms the traditional schemes in terms of energy consumption.

While we only consider path loss and shadow fading in system model, the proposed CAPS can work in real systems with small scale fading as well. For example, we can raise the transmit power of BS to a higher level than the one obtained based on computation, so that target users can receive the packets with a higher probability. Besides, when doing time slot assignment, we can allocate more time slots to users than they requested, so that we have extra time slots to retransmit the lost packets. Although such methods may cause some performance degradation, CAPS can still be applied to real systems. One important significance of this paper is that we provide insights on how to utilize user context when doing resource allocation.

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