On the Design of Relay Caching in Cellular Networks for Energy Efficiency

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***Abstract*—In this work, we design a relay caching mechanism to improve the energy efficiency in cellular networks, especially for multimedia applications. We consider a single cell with one or more fixed relay stations (RSs) installed near the cell edge. In our design, RSs can receive and cache demanded multimedia content in the cell. After caching, a RS directly serves the users in its coverage area instead of the base station (BS) to reduce energy consumption. In order to find the optimal policy of when and how to cache, we formulate the problem as a Markov decision process (MDP) and obtain the optimal decision table. The numerical results show that the relay caching can save about 15% of total energy. We also present two heuristic policies that perform very close to the optimal one and have low complexity.**

I. Introduction

With increasing awareness of the potential harmful effects to the environment caused by CO_2 emissions and the depletion of non-renewable energy sources, there is a growing consensus on the need to develop more energy-efficient telecommunication systems. Recent studies show that information and communication technology (ICT) is responsible for 2-2.5% of all carbon emissions [1]. In the case of cellular networks, 80% of total energy is consumed by BSs [2]. Therefore, it is important to consider energy efficiency issues in BSs. In this paper, we propose a relay-caching mechanism that exploits fixed RSs in cellular networks to improve spectrum efficiency and to reduce energy consumption.

Energy efficiency with respect to BSs has been considered in all stages of cellular networks including hardware design and manufacture, deployment, and operation. A number of these efforts have focused on hardware improvements. For instance, next-generation BSs are designed to be substantially more energy efficient, e.g., using more energy efficient power amplifiers and using natural resource for cooling. Others have considered collocating cellular BSs with renewable energy sources such as solar power and wind energy. In addition, cellular operators have evaluated deployment strategies that minimize the energy expenditure on BSs and operations that turning off certain BSs when the traffic load is low.

In this work, we focus on reducing the transmission energy consumption in cellular networks. Transmission energy can be reduced in two ways: 1) to shorten the transmission distance in the spacial domain, e.g., through deploying smaller cells and RSs; 2) to use multicast instead of unicast in the time domain. In this case, multimedia broadcast and multicast services (MBMS) [3] is a good choice to realize multicast in cellular networks. However, most of the popular multimedia content, in particular video, has the character of high repeatability rather than simultaneity which makes multicast inefficient. In other words, many users may desire the same (popular) content, but may not desire it at the same time. For example, 10% of sina.com news items count for 70% of traffic of the website. In another network [4], it is reported that the most popular YouTube video was requested 6 times in a 10-minute interval in a network of about 200 users. For this type of demand, near video-on-demand (NVOD) can partially solve the problem, but at the cost of degrading the quality of service (QoS). Caching in RSs is a combination of the two mechanisms to reach a good performance. First, transmitting a video from RS to the edge user equipment (UE) consumes less energy, because RSs are often placed near the edge of cellular networks where the signals from the BS are weak. Second, multicast can be used to deliver a video to its requesting user and to RSs to be cached for later usage. Therefore, the number of transmissions is reduced. The benefits of relay caching are multi-folds:

- reducing energy consumption,
- alleviating network congestion by reducing the demand on BS,
- improving response time of the cached videos.

In this paper, we design a relay caching mechanism to reduce energy consumption in cellular networks. We focus on the design of when and what to cache by RSs. Specifically, the key contributions of this paper are:

- We quantify when and what to cache in fixed RSs. We formulate the problem as an MDP and obtain its optimal solution.
- Based on the analysis of the optimal policy, we identify important factors in deciding relay caching.
- We propose two heuristic algorithms that achieve close to optimal performance with low complexity.

The remainder of the paper is organized as follows. In Section II, we present the related work. The problem formulation is presented in Section III and then the numerical results and analysis are given in Section IV. Finally, concluding remarks are presented.

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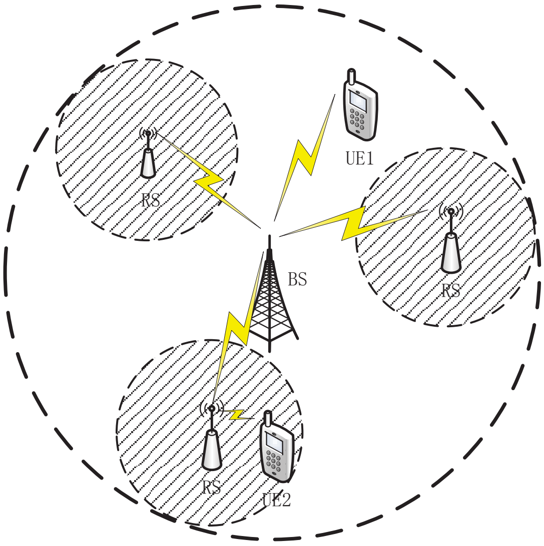

Fig. 1. A single cell in a cellular network with one BS and three RSs.

II. Related Work

Caching is widely used in communication networks. In general, caching reduces user delay, improves capacity, and alleviates network congestion. For instance, in [8], the authors propose to cache the prefix or a portion of the video using relay to provide video-on-demand (VOD) playback service to users with less latency and improve the transmission efficiency of networks [8]. In the context of wireless communication networks, various caching schemes have been considered, including BS caching [9], proxy caching [10] [11], relay caching [12] and client caching [13]. Most of previous work focus on ad hoc networks where each node can cache for itself or for others [5][6][7]. Moreover, caching can improve energy efficiency. There are studies about caching that reduces the energy consumption in ad hoc networks [14][15], wireless relay networks [12] and mobile terminals (e.g. battery life) [16].

Our target in this paper is to reduce transmission energy in cellular networks by relay caching. We regard BSs and RSs as the main energy consumption source in cellular networks. Comparing to client caching, relay caching has much higher hit probability. The contribution is to decide relay caching strategies in cellular networks from the viewpoint of energy saving.

III. Problem Formulation

A. System Model

We consider a single cell in a cellular network with one BS and one or more RSs, as shown in Fig 1. The RSs are typically placed near the boundary of the cell in order to serve the cell-edge users within the coverage of RSs. The users are assumed to be uniformly distributed in the cell and request content independently. For simplicity, we explicitly only consider videos in this paper, although it can be generalized to other types of content. We focus on the energy consumption in the cellular side and ignore the consumption in the backbone networks. We note that the caching also reduces energy consumption in the backbone networks. When a user request a video, the BS may transmit the video to the UE directly or multicast the video to both the RSs and the UE. Videos can be cached into the buffer of RSs in order to serve the nearby users with future requests of the same video. When a video that has already been cached in a RS, is requested by a user in the RS's coverage, it can be transmitted from the RS to the user directly.

We assume that videos are of the same size and the probability of each video being requested, p_j, is known and p_j remains constant during the time period considered in this paper. The buffer size of RSs is limited, $i.e.$, one RS can cache at most b videos. Let v_k denote the index of the k-th requested video. The buffer state of RSs when the k-th request arrives is denoted by a video set x_k:

$$x_k = \{i | \text{video } i \text{ in cache}\} . \tag{1}$$

The set of all the possible buffer states is denoted by X. If a new video v_k is requested and RSs decide to cache it, v_k would be included into x_{k+1}. If there have already been b videos in cache before inserting a new video, the least popular video in x_k would be dropped. Let $x_{k+1} = T(x_k, v_k)$ be the transition from status x_k.

The energy cost of unicast from BS or RS to UE depends on the channel state, which is related to the distance between them. We use the large-scale path-loss channel model:

$$C_u(d) = \beta d^{\alpha}, \tag{2}$$

where d denotes the distance between BS or RS to the user location d_{bk} or d_{rk}. β is the normalized energy consumption factor, and α is the path loss exponent.

Multicast consumes more energy than unicast and is related to the channel states from BS to both RSs and UE. Its energy cost can be modeled as:

$$C_m(d_{bk}, d_{br}) = \beta_1 \max\{d_{bk}^{\alpha}, d_{br}^{\alpha}\} + \beta_2 d_{bk}^{\alpha} + \beta_3 d_{br}^{\alpha}, \tag{3}$$

where d_{br} denotes the distance between the BS and the RSs. The first part of $C_m(\cdot)$ is caused by data transmission, and the second and third parts are caused by overhead energy consumption. Both β_1, β_2 and β_3 are normalized energy consumption factors.

In our scenario, the RSs are of the same distance to the BS and always make the same decision. The decision of how to transmit the requested video U_k can possibly be three values: 1) unicast from BS to UE u_{bk}; 2) multicast from BS to both RSs and UE u_{brk}; and 3) unicast from RS to UE u_{rk} if the UE is in the coverage of a RS and the requested video has been cached. Therefore, the transmission energy cost of the k-th request is:

$$C_k(U_k, d_{bk}, d_{rk}) = \begin{cases} C_m(d_{bk}, d_{br}), & \text{if } U_k = u_{brk} \\ C_u(d_{bk}), & \text{if } U_k = u_{bk} \\ C_u(d_{rk}), & \text{if } U_k = u_{rk} \end{cases} . \tag{4}$$

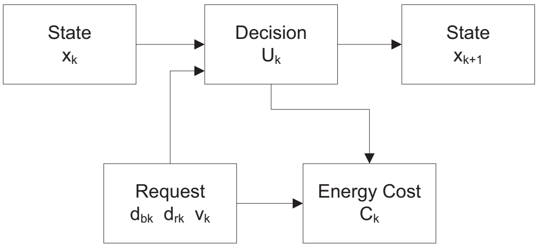

Fig. 2. The flow chart of our algorithm. The user's requests are independent of all the past information so that we can exclude those random variables d_{bk}, d_{rk}, and v_k from the system state.

The feasible decisions can be represented by a decision set S. When the requested video has been cached by RSs and the UE is in the coverage of RSs, $S = \{u_{brk}, u_{bk}, u_{rk}\}$, otherwise, $S = \{u_{brk}, u_{bk}\}$. The decision set is a function of x_k, v_k and d_{rk}:

$$S(x_k, v_k, d_{rk}) = \begin{cases} \{u_{brk}, u_{bk}, u_{rk}\} & d_{rk} < r, v_k \in x_k \\ \{u_{brk}, u_{bk}\} & \text{others} \end{cases}. \tag{5}$$

B. Dynamic Programming Algorithm

The system can be represented by Fig. 2. Our objective is to minimize the expectation of the total energy consumption of n requests $E\left\{\sum_{k=1}^{n} C_k(U_k, d_{bk}, d_{rk})\right\}$. Because requests are independent of each other, and d_{bk} and d_{rk} are independent of k and users' positions of previous requests. Furthermore, the energy consumption is only related to d_{bk}, d_{rk} and U_k. The policy π is a series of decision functions on x_k, v_k, d_{bk} and d_{rk}:

$$\begin{gathered} U_k = \mu_k(x_k, v_k, d_{bk}, d_{rk}) \\ \pi = \{\mu_1, \mu_2, \ldots, \mu_n\}. \end{gathered} \tag{6}$$

As a result, the system is a stochastic MDP and the minimum cost can be solved by dynamic programming. It can be represented as:

$$\begin{aligned} \min_{\pi} \quad & \underset{d_{bk}, d_{rk}, v_k}{E} \left\{ \sum_{k=1}^{n} C_k(U_k, d_{bk}, d_{rk}) \right\} \\ s.t. \quad & U_k = \mu_k(x_k, v_k, d_{bk}, d_{rk}) \\ & U_k \in S(x_k, v_k, d_{rk}) \\ & \pi = \{\mu_1, \mu_2, \ldots, \mu_n\} \\ & x_0 = \phi \\ & x_{k+1} = \begin{cases} T(x_k, v_k) & U_k = u_{brk} \\ x_k & \text{otherwise} \end{cases}. \end{aligned} \tag{7}$$

Let $J_k(x_k)$ denote the minimum expectation of energy consumption from the k-th request to the last one starting at state x_k, which is referred to as the cost-to-go function. As a result of the optimality principle in dynamic programming, $J_k(x_k)$ can be interpreted as:

$$J_k(x_k) = \underset{d_{bk}, d_{rk}, v_k}{E} \min_{\mu_k} \left\{ C(U_k, d_{bk}, d_{rk}) + J_{k+1}(x_{k+1}) \right\}. \tag{8}$$

The optimal policy $\pi^* = \{\mu_1^*, \mu_2^*, \ldots, \mu_n^*\}$ can be found by following the optimality principle.

C. Benchmark

As we have mentioned before, caching consumes additional energy in exchange for saving the transmission energy when a video in the RSs' buffer being requested by nearby users. Accordingly, the higher the popularity of the videos in RSs' buffer, the larger the probability we can save energy. In other words, the expectation of energy consumption is minimized when the most popular videos have been cached. Let x^* denote the set of b most popular videos, which is the best buffer state, i.e., for any buffer state x in possible buffer states set X, we have $J_k(x) \geq J_k(x^*)$. Since x^* is a possible buffer state, $J_k(x^*)$ is a lower bound of the cost-to-go function. We call x^* the perfect buffer state. Therefore, a benchmark of total energy consumption is to assume the system starts with buffer state x^*.

D. Heuristic Policies

We derive two heuristic policies based on the analysis of the optimal policy shown in Section IV-B. The first heuristic is motivated by the importance of video popularity. Therefore, a heuristic algorithm is to only cache videos in x^*. If the requested video is in x^* and has not been cached, the decision is u_{brk}, i.e., to cache the requested video. If not, we choose u_{bk} or u_{rk}, whichever has lower energy consumption. The decision functions are defined as:

$$\begin{aligned} & \mu_k^{(1)}(x_k, v_k, d_{bk}, d_{rk}) = \\ & \begin{cases} u_{brk} & v_k \notin x_k, v_k \in x^* \\ u_{rk} & C_k(u_{rk}, d_{bk}, d_{rk}) < C_k(u_{bk}, d_{bk}, d_{rk}) \\ u_{bk} & \text{otherwise} \end{cases}, \end{aligned} \tag{9}$$

which are represented as $\pi^{(1)} = \{\mu_1^{(1)}, \mu_2^{(1)}, \cdots, \mu_k^{(1)}\}$.

The second heuristic policy is similar but has more emphasis on energy efficiency. When the channel state between BS and UE is better than that between BS and RSs, multicast consumes much more energy than unicast. As a result, the RSs do not cache any video at that time. The decision functions are defined as:

$$\begin{aligned} & \mu_k^{(2)}(x_k, v_k, d_{bk}, d_{rk}) = \\ & \begin{cases} u_{brk} & v_k \notin x_k, v_k \in x^*, d_{bk} > d_{br} \\ u_{rk} & C_k(u_{rk}, d_{bk}, d_{rk}) < C_k(u_{bk}, d_{bk}, d_{rk}) \\ u_{bk} & \text{otherwise} \end{cases}, \end{aligned} \tag{10}$$

which are represented as $\pi^{(2)} = \{\mu_1^{(2)}, \mu_2^{(2)}, \cdots, \mu_k^{(2)}\}$.

IV. NUMERICAL RESULTS AND ANALYSIS

A. System Setup

In this paper, we conduct a series of numerical studies to analyze the proposed optimal policy π^* and compare its energy efficiency with that of the benchmark and heuristic policies. In our numerical studies, a single cell in a cellular network with

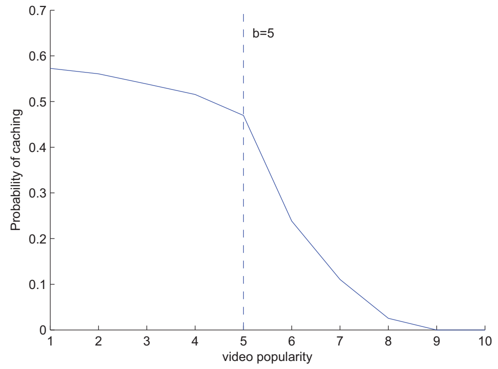

Fig. 3. The probability of caching decision when the popularity of requested video is given. The probability of caching v_k becomes negligible when $v_k > b$, which is equal to $v_k \notin x^*$.

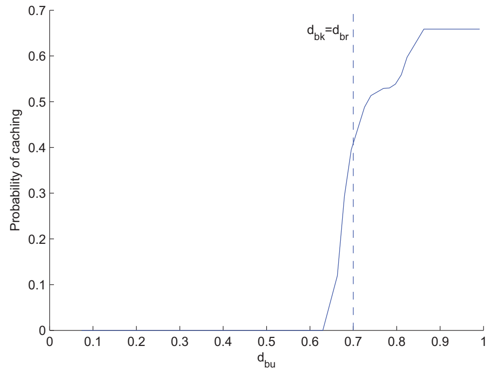

Fig. 4. The probability of caching decision when the distance between the BS and the user d_{bk} is given. It increases dramatically after $d_{bk} > d_{br}$.

one BS and three RSs is considered, as shown in Fig. 1. These RSs are placed at the boundary of the cell and of the same distance to the BS. The radius of the cell is 1. The coverage radius of each RS is 0.3. The RSs make the same decision and we can treat them as the same. User locations are quantized into 284 discrete locations uniformly distributed in the coverage area of the BS. There are 10 videos with different popularities are considered. The probability of the 10 videos being requested are $0.3, 0.2, 0.15, 0.12, 0.08, 0.05, 0.04, 0.03, 0.02,$ and 0.01. In each RS, at most 5 videos can be buffered ($i.e.$, $b = 5$). The normalized energy consumption factors in (2) and (3) are given as: $\beta = 1$, $\beta_1 = 0.9$, $\beta_2 = 0.1$, and $\beta_3 = 0.3$.

We consider a problem that minimizes the total energy consumption of $n = 200$ requests, and solve it using the MDP formulation. Since user locations and video popularity levels have been quantized into discrete values, the decision functions μ_k in a policy become a series of decision tables that can be stored and calculated iteratively. We calculate the optimal policy π^* and analyze it from several different aspects.

B. Numerical Results

The optimal policy $\pi^* = \{\mu_1^*, \mu_2^*, \ldots, \mu_n^*\}$ is a large decision table. Due to the asymptotic behavior of the solution, with n approaching infinity, μ_1^* converges to μ^*, which is in the form of decision table $\mu^*(x_k, v_k, d_{bk}, d_{rk})$. Here, we examine the association between the value of μ^* and the variable v_k. In order to do this, we assume that x_k could be any element in X with the same probability, and calculate

$$P_v(v_k) = \underset{x_k, d_{bk}, d_{rk}}{E}\Big[Pr\{\mu^*(x_k, v_k, d_{bk}, d_{rk}) = u_{brk}\}\Big]. \tag{11}$$

Fig. 3 shows the probability of caching $P_v(v_k)$ decreases with the popularity of video v_k. Moreover, there is a sharp transition at $b = 5$. The probability of caching v_k becomes negligible when $v_k > b$, which is equal to $v_k \notin x^*$. This is the intuition of the first heuristic policy $\pi^{(1)}$.

Furthermore, the variable d_{bk} plays an important role in the decision table. In order to investigate the impact of d_{bk} on the decision table, we consider

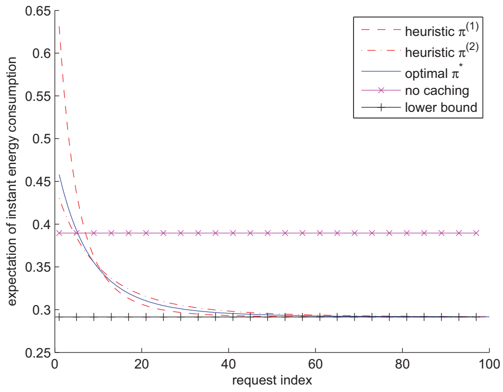

Fig. 5. Transmission Energy Consumption

$$P_d(d_{bk}) = \underset{v_k, x_k, d_{rk}}{E}\Big[Pr\{\mu^*(x_k, v_k, d_{bk}, d_{rk}) = u_{brk}\}\Big], \tag{12}$$

which is the probability of caching with the distance between the BS and the user d_{bk} is given. It is shown in Fig. 4. In our calculation, $d_{br} = 0.7$. It is shown that $P_d(d_{bk})$ increases dramatically after $d_{bk} > d_{br}$. Because at that time, the energy consumption of multicast is close to that of unicast. This motivates our second heuristic policy $\pi^{(2)}$.

We compare the energy efficiency of the optimal policy and two derived heuristic policies. We also consider the benchmark where the RSs start with full buffer x^*, which is obviously the lower bound of the energy consumption of any policies. Last, we consider the no-caching policy, denoted by π^0. Fig. 5 plots the energy consumption of all these policies. Fig. 6 plots the time average of the above functions.

We observe that caching policies (i.e., our MDP policy and the two heuristics) lead to high energy consumption in the beginning because multicast consumes more energy than unicast for a single video downloading when caching is considered. After caching some videos in RSs, the expected energy cost decreases and approaches to the lower bound

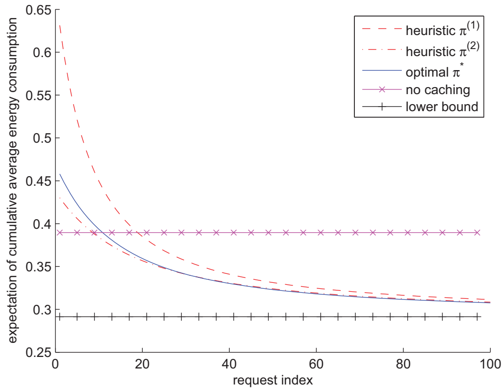

Fig. 6. Cumulative Average of Transmissiong Energy Consumption

given by the perfect buffer state. After about 40 requests, the probability of $x_k = x^*$ is very close to 1. We call the period before $x_k = x^*$ the caching period. The first heuristic policy $\pi^{(1)}$ is a greedy policy, which decides to cache the most popular videos and costs more energy than the optimal policy at first, but x_k converges to x^* more rapidly. The second heuristic policy $\pi^{(2)}$ is more conservative. It is energy-cost-aware, and decides to cache a video only when the extra energy consumption of multicast is small. As a result, the energy consumption is smaller at first but x_k converges to x^* slower. As shown in Fig. 6, the energy efficiency of the heuristic policies is very close to the optimal policy, which saves 15.3% energy after the caching period. Naturally, the results depend on the position of RSs, the distribution of users' location and the probability of a video being requested.

C. Discussion

In practice, there may be a large number of videos with different length. The complexity of our algorithm grows exponentially with the number of videos. However, by introducing some reasonable approximations, this problem can be easily solved. We consider videos of different sizes. The number of videos that can be cached in the buffer may not be a constant or an integer. The optimal buffer state x^* is the solution of a 0-1 Knapsack problem. But if we assume that a partial video can be cached, the problem would be simplfied. Let $E = AL_i$ denote the transmitting energy consumption of the i-th video, which is proportional to the video size L_i. Energy consumption factor A depends on the location of the requesting user and whether the video has been cached in the RS. Consider the optimization problem:

$$\begin{aligned} \min_{l_i} \quad & \sum_i p_i \left[l_i A_C + (L_i - l_i) A_{\overline{C}} \right] \\ s.t. \quad & \sum_i l_i \leq B \\ & 0 \leq l_i \leq L_i \end{aligned} \tag{13}$$

where A_C is the expectation of energy consumption factor when the requested video has been cached, $A_{\overline{C}}$ is that when the video has not been cached, B is the buffer size, and l_i is the length of i-th video being cached in the buffer. The optimal solution is quite straightforward:

$$\begin{aligned} & \sum_i p_i \left[l_i A_C + (L_i - l_i) A_{\overline{C}} \right] \\ = & \sum_i p_i L_i A_{\overline{C}} - \sum_i p_i l_i (A_C - A_{\overline{C}}). \end{aligned} \tag{14}$$

We need to maximize $\sum_i p_i l_i$, which leads to the same solution that only cache the most popular videos. Hence, the video popularity p_i indicates the buffer utility efficiency. So the replacement strategy that to drop the least popular video still works in this scenario. Accordingly, this problem stands the same when the videos are of different sizes.

When there are a large number of videos, they can be divided into several popularity levels. The number of buffer states will be reduced by introducing popularity levels, which makes the complexity manageable. Furthermore, we note that only the most popular ones are likely to be cached, and thus we can ignore low popularity videos in practice.

Meanwhile, practical systems may deal with infinite horizon problems. If we consider infinite requests, the optimal policy can be found by iteratively calculating the finite problem with the request number approaching infinity.

In practice, the popularity may vary over time and the popularity may not be known precisely. In this case, the decision table needs to be updated over time and taking into account uncertainty. It is our future work to consider uncertainty, dynamics and location-dependency of video popularity.

In our assumptions, RSs are of the same distance to the BS, where they operate in the same manner. When RSs are of different distance to the BS or of different sizes, they may not always have the same decisions. We will investigate this issue in the future. We will also consider multi-cell scenarios where RSs may locate in the edge of multiple cells.

V. Conclusion

In this paper, we propose relay caching as a mechanism to reduce energy consumption of cellular networks. Relay caching exploits two properties: 1) for users close to the RSs, RSs can transmit at much lower power and thus reduces energy consumption; 2) multimedia traffic has high repeatability; i.e., a popular video may be requested by many users although not at the same time. We derive an optimal mechanism for RSs to decide when and what to cache. Furthermore, we propose two heuristic policies that leverage the important factors in caching, popularity and location. We examine the energy consumption under these policies. The numerical results show that the derived heuristic policies perform well compared to the optimal policy. Future investigation will consider multicell environment, dynamic caching, and information uncertainty (e.g., on video popularity uncertainty).

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