Context-Aware Energy Saving with Proactive Power Allocation

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***Abstract*—Recent studies have demonstrated the effectiveness of proactive resource allocation under the assumption of perfect prediction of the user's future data rate. In this paper, imperfect rate prediction merely based on the context information including large-scale channel gains of users and statistical information of system available resources is considered. Under the outage-based quality of service constraint, we propose a proactive power allocation policy aimed at minimizing the total transmit energy consumption. Simulation results show that the proposed statistical information-based proactive power allocation performs close to the one with perfect rate prediction, and exhibits evident performance gain over the non-proactive transmission policies.**

I. Introduction

Existing cellular networks are passive in the sense that they only wait for the requests of users and then provide the services based on the up-to-date information of users and network such as channel state information, and available resources, etc. However, recent studies show that the service requests and future data rate of users are highly predictable [1, 2]. Specifically, the future channel quality can be estimated based on users' mobility pattern and radio environment map [3], and the amount of available network resources can also be obtained statistically based on the daily traffic pattern of each base station (BS) [4]. These context information ignored by existing networks motivates the novel concept of proactive resource allocation, which strategically pre-buffers the future requested data ahead of time in the cache memory of the wireless device [1, 3].

Under the assumption of perfect prediction of future data rate achieved by users, existing works have demonstrated the potential of proactive resource allocation on spectral utilization [1, 5] and energy saving [3, 6]. In practice, however, perfect knowledge of future rate is almost impossible due to the difficulty of accurately predicting small-scale channels and instantaneous available resources. The impact of rate prediction uncertainty was studied recently in [7], where the authors employed triangular fuzzy numbers to model the integrated effect of imperfect channel and resource prediction on rate prediction, based on which a robust proactive resource allocation method was proposed for energy saving.

In this work, we study the proactive power allocation merely based on large-scale channel gains of users and statistical information of available resources of the network, where the small-scale channels and availability of each subcarrier are modeled as unknown Rayleigh and Bernoulli distributed random variables, respectively. Further considering the outage-based quality of service (QoS) constraint for the predicted future service over a given time horizon, we propose a proactive power allocation policy aimed at minimizing the energy consumption. Simulation results show that the proposed method exhibits evident performance gain over the non-proactive transmission policies.

II. System Model

Consider the downlink transmission of a multi-input single-output-orthogonal frequency division multiplexing (MISO-OFDM) system, where a BS, equipped with N_t antennas, needs to transmit a file with B bits to a single-antenna user within the deadline of N time slots, during which other traffic is also served by the BS. Let Δ_t denote the length of each time slot in seconds. The time scale of $N\Delta_t$ can be large, e.g., in the order of minutes and possibly hours, since the service request of the user can be predicted by the system or pre-scheduled by the user with monetary incentive. We consider the fact that the available frequency resource for serving the user varies over time slots as the load of other traffic at the BS fluctuates temporally. Specifically, in the n-th time slots, we use independent and identically distributed (i.i.d.) Bernoulli random variables $\xi_{n1}, \ldots, \xi_{nK}$ to characterize the availability of the K subcarriers, where the probability of $\xi_{nk} = 1$ (meaning that the k-th subcarrier is available) is ρ_n for $k = 1, \ldots, K$. We assume that the BS has the knowledge of the statistical parameters ρ_n for $n = 1, \ldots, N$, which can be obtained from the temporal traffic fluctuation pattern of the BS.

We consider block fading channels where the channels remain constant during each time slot and are independent from each other in different time slots. By employing the maximal-ratio transmission (MRT) precoder for the transmission in every time slot, the achievable data rate in the n-th time slot of the system can be expressed as

$$R_n = \sum_{k=1}^{K} \Delta_f \cdot \xi_{nk} \log\left(1 + \frac{P_n \alpha_n \|\mathbf{h}_{nk}\|^2}{\sigma^2}\right), \quad (1)$$

where α_n is the large-scale channel gain, $\mathbf{h}_{nk} \in \mathbb{C}^{N_t \times 1}$ is the small-scale channel vector of the k-th subcarrier in the n-th time slot, whose elements are i.i.d complex Gaussian random variables with zero mean and unit variance, $\mathbf{h}_{nk}$ and $\mathbf{h}_{nj}$ are assumed uncorrelated for $k \neq j$, Δ_f denotes the bandwidth of each subcarrier, P_n is the transmit power of every subcarrier in the n-th time slot, and σ^2 is the variance of the additive white Gaussian noise at the user.

We strive to proactively control the transmission for the future N time slots, i.e., to predetermine the power allocation $P_1, \ldots, P_N$ before the first time slot, where the B-bits data

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requested by the user need to be ensured. We assume that the BS knows the future locations of the user based on its mobility pattern, such that the upcoming large-scale channel information can be obtained according to the radio environment map. However, we do not assume the knowledge of future small-scale channel information, which is very difficult to obtain if not impossible. Further considering the uncertainty of available subcarriers, the user's request cannot be always guaranteed. Thus, the following outage probability constraint is considered,

$$\Pr\left(\Delta_t \textstyle\sum_{n=1}^{N} R_n < B\right) \leq \epsilon, \tag{2}$$

where $\Pr(\cdot)$ denotes the probability of an event, and ϵ is the maximum acceptable outage probability of the user.

With (1) and (2), the proactive power allocation problem, aimed at minimizing the average total transmit energy consumed for conveying the B bits in N time slots, under the transmission outage constraint as well as maximal transmit power constraint, can be formulated as follows,

$$\min_{\mathbf{P}} \mathbb{E}\left\{\Delta_t \textstyle\sum_{n=1}^{N}\sum_{k=1}^{K} \xi_{nk} P_n\right\} = \textstyle\sum_{n=1}^{N} \Delta_t K \rho_n P_n \tag{3a}$$

$$s.t.\ \ \Pr\left(\sum_{n=1}^{N}\sum_{k=1}^{K} \xi_{nk} \log\left(1+\lambda_n P_n \|\mathbf{h}_{nk}\|^2\right) < S\right) \leq \epsilon \tag{3b}$$

$$0 \leq P_n \leq \frac{P_{max}}{K}, n = 1, \ldots, N, \tag{3c}$$

where $\mathbf{P} = [P_1, \ldots, P_N]^T$, $\lambda_n \triangleq \alpha_n/\sigma^2$, $S \triangleq \frac{B}{\Delta_f \Delta_t}$, P_{max} denotes the maximal transmit power of the BS, and constraint (3c) represents equal power constraint over all subcarriers, which comes from the result that equal power allocation is nearly optimal for throughput maximization when applied together with adaptive modulation and coding (AMC) [8]. (3c) implies that the total available power for the user in each time slot is proportional to the total number of available subcarriers.

Problem (3) is a challenging problem due to the transmission outage constraint given in (3b), because the probability function in the left-hand side has no closed-form expressions. Existing outage constraint approximation methods cannot be applied here, because they only consider a single subcarrier and one time slot while we consider a random number of subcarriers and multiple time slots. To tackle the difficulty, we propose a novel outage constraint approximation approach by introducing auxiliary variables and employing the central limit theorem, and finally convert constraint (3b) into a convex constraint with explicit expression.

III. Context-Aware Proactive Power Allocation

In this section we propose a context-aware proactive power allocation policy by solving problem (3), where we focus on the simplification of constraint (3b).

When deriving the outage probability, one can find that the multiplication of P_n and $\|\mathbf{h}_{nk}\|^2$ will lead to very complicated expression for P_n, which makes further optimizing P_n impossible. Thus, we first introduce an approximation to decouple P_n and $\|\mathbf{h}_{nk}\|^2$ as

$$\begin{aligned} P_{out}(\mathbf{P}) &\triangleq \Pr\left(\sum_{n=1}^{N}\sum_{k=1}^{K} \xi_{nk} \log\left(1+\lambda_n P_n \|\mathbf{h}_{nk}\|^2\right) < S\right) \\ &= \Pr\Big(\sum_{n=1}^{N}\sum_{k=1}^{K} \xi_{nk}\big(\log(\|\mathbf{h}_{nk}\|^2) + \log(\frac{1}{\|\mathbf{h}_{nk}\|^2} + \lambda_n P_n)\big) < S\Big) \\ &\approx \Pr\Big(\sum_{n=1}^{N}\sum_{k=1}^{K} \xi_{nk}\big(\log(\|\mathbf{h}_{nk}\|^2) + \log\left(A + \lambda_n P_n\right)\big) < S\Big), \end{aligned} \tag{4}$$

where A is an introduced auxiliary variable to control the accuracy of the approximation. One can find that when N_t is large, selecting $A = \frac{1}{N_t}$ will lead to accurate approximation, while for general N_t the value of A needs to be optimized. In the following we propose a hierarchical method to solve problem (3), where we first find the optimal $\mathbf{P}$ for any given A, and then find the optimal A to minimize the average total transmit energy consumption while ensuring the original outage constraint (3b) satisfied.

A. Power Allocation for Given A

For a given A, the power allocation problem (3) can be approximated based on (4) as

$$\min_{\mathbf{P}} \sum_{n=1}^{N} \Delta_t K \rho_n P_n \tag{5a}$$

$$s.t.\ \ \Pr\Big(\sum_{n=1}^{N}\sum_{k=1}^{K} \xi_{nk}\Big(\log(\|\mathbf{h}_{nk}\|^2) + \log\left(A + \lambda_n P_n\right)\Big) < S\Big) \leq \epsilon \tag{5b}$$

$$0 \leq P_n \leq \frac{P_{max}}{K}, n = 1, \ldots, N, \tag{5c}$$

In (5b) the terms $\left\{\xi_{nk}(\log(\|\mathbf{h}_{nk}\|^2) + \log\left(A + \lambda_n P_n\right))\right\}$ are i.i.d. because both ξ_{nk} and $\mathbf{h}_{nk}$ are i.i.d. Then we can apply the central limit theorem and obtain that

$$\sum_{k=1}^{K} \xi_{nk}\Big(\log(\|\mathbf{h}_{nk}\|^2) + \log\left(A + \lambda_n P_n\right)\Big) \sim \mathcal{N}(E_n, D_n), \tag{6}$$

where $\mathcal{N}(E_n, D_n)$ denotes Gaussian distribution with mean E_n and variance D_n.

As modeled before, ξ_{nk} follows Bernoulli distribution, whose mean and variance can be obtained as ρ_n and $\rho_n(1-\rho_n)$, respectively. $\|\mathbf{h}_{nk}\|^2$ is a Wishart distributed variable, then the mean and variance of $\log(\|\mathbf{h}_{nk}\|^2)$ can be obtained from [9] as $\log(e)\psi(N_t)$ and $\log^2(e)\dot{\psi}(N_t)$, respectively, where $\psi(\cdot)$ is Euler's digamma function and $\dot{\psi}(\cdot)$ is the derivative of $\psi(\cdot)$. Then, we can obtain that

$$E_n = K\rho_n(\log(A + \lambda_n P_n) + \log(e)\psi(N_t)) \tag{7a}$$

$$\begin{aligned} D_n = &K \log^2(e)\dot{\psi}(N_t)\rho_n \\ &+ K\left(\log(A + \lambda_n P_n) + \log(e)\psi(N_t)\right)^2 \rho_n(1-\rho_n). \end{aligned} \tag{7b}$$

Considering that the terms given in the left-hand side of (6) are independently Gaussian distributed for $n = 1, \ldots, N$, we have $\sum_{n=1}^{N}\sum_{k=1}^{K}\xi_{nk}\left(\log(\|\mathbf{h}_{nk}\|^2)+\log\left(A+\lambda_n P_n\right)\right) \sim \mathcal{N}\left(\sum_{n=1}^{N}E_n, \sum_{n=1}^{N}D_n\right)$, based on which we can simplify the outage constraint (5b) as

$$\Phi\left(\frac{S-\sum_{n=1}^{N}E_n}{\sqrt{\sum_{n=1}^{N}D_n}}\right) \le \epsilon, \quad (8)$$

where $\Phi(\cdot)$ is the cumulative distribution function (CDF) of the standard Gaussian distribution with zero mean and unit variance, which is a monotonically increasing function with $\Phi(0) = 0.5$. Letting $\Phi^{-1}(\cdot)$ denote the inverse function of $\Phi(\cdot)$, we can rewrite (8) as

$$\sqrt{\sum_{n=1}^{N}D_n} \le -\frac{\sum_{n=1}^{N}E_n}{\Phi^{-1}(\epsilon)} + \frac{S}{\Phi^{-1}(\epsilon)}, \quad (9)$$

where the inequality holds for $\epsilon < 0.5$ (i.e., $\Phi^{-1}(\epsilon) < 0$). Since the acceptable outage probability is usually much smaller than 0.5, we can use (9) for the following optimization.

By denoting $c_n = \rho_n(1-\rho_n)$ and $z_n = \log(A+\lambda_n P_n) + \log(e)\psi(N_t)$ and discarding the constant terms not affecting the optimal solutions from the objective function, we can transform problem (5) into the following problem

$$\min_{\{z_n\}} \sum_{n=1}^{N}\frac{\rho_n}{\lambda_n}2^{z_n} \quad (10a)$$

$$s.t. \sqrt{\sum_{n=1}^{N}K\left(c_n z_n^2 + \log^2(e)\dot{\psi}(N_t)\rho_n\right)} \le -\frac{\sum_{n=1}^{N}K\rho_n z_n}{\Phi^{-1}(\epsilon)} + \frac{S}{\Phi^{-1}(\epsilon)} \quad (10b)$$

$$\log(A) \le z_n - \log(e)\psi(N_t) \le \log(A + \frac{\lambda_n P_{max}}{K}), \quad n=1,\ldots,N. \quad (10c)$$

Problem (10) is convex since the objective function and the constraints are all convex, where constraint (10b) is a second-order cone constraint. We can employ standard convex optimization algorithms to solve problem (10), then the optimal power allocation for a given A, denoted by $\mathbf{P}^\star(A) = [P_1^\star(A),\ldots,P_N^\star(A)]^T$, can be obtained accordingly based on the definition of z_n.

B. Optimization of A

To optimize A, we note from problem (5) that the average total energy consumption is a monotonically decreasing function of A, because if $A_1 < A_2$, then $\mathbf{P}^\star(A_1)$ must be a feasible solution to problem (5) with $A = A_2$. It means that the optimization of A is to find the largest A such that the corresponding power allocation $\mathbf{P}^\star(A)$ ensures the original outage constraint (3b).

Under the special case where ρ_n is either 0 or 1, we can prove that the outage probability $P_{out}(\mathbf{P})$ is a monotonically decreasing function of A. The details of proof are omitted due to the lack of space. This motivates us to find the optimal A by using a bisection method, whose procedure is detailed in Table I. Despite that it is not easy to prove this monotonically decreasing property for general cases with arbitrary ρ_n, we can guarantee the convergence of the bisection method by adding an extra constraint shown in (11) during the iterations, which ensures $P_{out}\left(\hat{\mathbf{P}}^\star(A_U)\right) \le P_{out}\left(\hat{\mathbf{P}}^\star(A)\right) \le P_{out}\left(\hat{\mathbf{P}}^\star(A_L)\right)$ and leads to constantly shrunk interval $[A_L, A_U]$. Herein, $\hat{\mathbf{P}}^\star(A_U)$, $\hat{\mathbf{P}}^\star(A_L)$ and $\hat{\mathbf{P}}^\star(A)$ are defined in Table I.

TABLE I
BISECTION ALGORITHM FOR OPTIMIZING A

1. **Initialization:** Choose a lower bound and an upper bound of A, denoted by A_L and A_U, which satisfy that $P_{out}\left(\hat{\mathbf{P}}^\star(A_U)\right) < \epsilon < P_{out}\left(\hat{\mathbf{P}}^\star(A_L)\right)$, where $\hat{\mathbf{P}}^\star(A_U)$ and $\hat{\mathbf{p}}^\star(A_L)$ are the optimal power allocation of problem (10) when setting $A = A_U$ and A_L, respectively.
2. **Bisection Iteration:**
   a. Compute $A = \frac{A_L + A_U}{2}$.
   b. Add the following constraint into problem (10)
   $$\hat{\mathbf{P}}^\star(A_U) \preceq \mathbf{P} \preceq \hat{\mathbf{P}}^\star(A_L), \quad (11)$$
   where $\preceq$ denotes the elementwise less-than-or-equal-to comparator. Solve the resultant optimization problem and obtain the optimal power allocation $\hat{\mathbf{P}}^\star(A) \triangleq [\hat{P}_1^\star(A),\ldots,\hat{P}_N^\star(A)]^T$.
   c. Given $\hat{\mathbf{P}}^\star(A)$, obtain the outage probability $P_{out}(\hat{\mathbf{P}}^\star(A))$ by the method proposed in the following.
   d. **If** $P_{out}(\hat{\mathbf{P}}^\star(A)) > \epsilon$, let $A_U \leftarrow A$ and $\hat{\mathbf{P}}^\star(A_U) \leftarrow \hat{\mathbf{P}}^\star(A)$; **otherwise**, let $A_L \leftarrow A$ and $\hat{\mathbf{P}}^\star(A_L) \leftarrow \hat{\mathbf{P}}^\star(A)$.
3. **Repeat:** Iterate step 2 until the required accuracy is reached, i.e., $A_U - A_L \le \delta$, where δ is a specific threshold. The optimal A is thus A_L.

In Step (2.c) of the bisection algorithm, the value of $P_{out}(\hat{\mathbf{P}}^\star(A))$ is needed. We can employ the Gaussian approximation of the MISO channel capacity investigated in [10], and approximate the term $\log(1+\lambda_n\hat{P}_n^\star(A)\|\mathbf{h}_{nk}\|^2)$ as a Gaussian distributed variable with mean $\hat{E}_n$ and variance $\hat{D}_n$ as follows,

$$\hat{E}_n = \frac{\int_0^\infty \log(1+\hat{P}_n^\star(A)\lambda_n x)x^{N_t-1}e^{-x}\,\mathrm{d}x}{(N_t-1)!} \quad (12a)$$

$$\hat{D}_n = \frac{\int_0^\infty \log^2(1+\hat{P}_n^\star(A)\lambda_n x)x^{N_t-1}e^{-x}\,\mathrm{d}x}{(N_t-1)!} - \hat{E}_n^2. \quad (12b)$$

Then, based on the central limit theorem, we can approximate the term $\sum_{n=1}^{N}\sum_{k=1}^{K}\xi_{nk}\log\left(1+\lambda_n\hat{P}_n^\star(A)\|\mathbf{h}_{nk}\|^2\right)$ in the expression of $P_{out}(\hat{\mathbf{P}}^\star(A))$ as a Gaussian distributed variable with mean $\sum_{n=1}^{N}K\rho_n\hat{E}_n$ and variance $\sum_{n=1}^{N}K(\rho_n\hat{D}_n + \rho_n(1-\rho_n)\hat{E}_n^2)$. Based on the result, we can obtain $P_{out}(\hat{\mathbf{P}}^\star(A))$ numerically as

$$P_{out}(\hat{\mathbf{P}}^\star(A)) = \Phi\left(\frac{S-\sum_{n=1}^{N}K\rho_n\hat{E}_n}{\sqrt{\sum_{n=1}^{N}K(\rho_n\hat{D}_n+\rho_n(1-\rho_n)\hat{E}_n^2)}}\right). \quad (13)$$

IV. SIMULATION RESULTS

We evaluate the performance of the proposed proactive power allocation method in this section. Unless otherwise specified, the following parameters will be used throughout the simulations. The BS has $N_t = 4$ antennas and transmit with the maximal power of 46 dBm, and the user has a single antenna. The cell radius r is set to 250 m, and the average receive

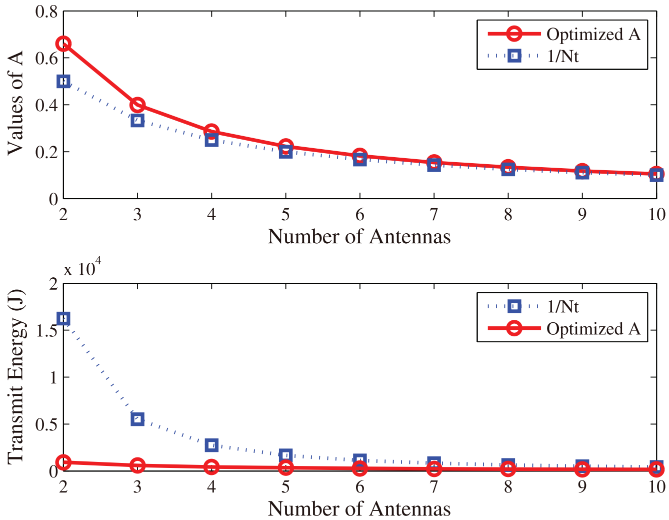

Fig. 1. Comparison of the optimal values of A and $\frac{1}{N_t}$ for different number of antennas.

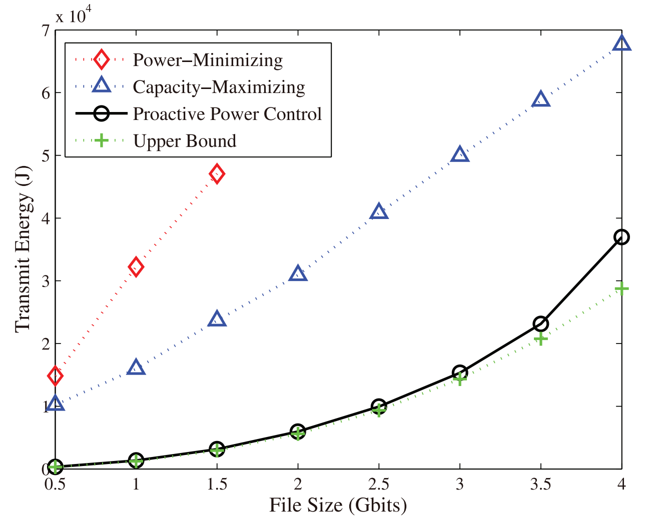

Fig. 2. Average total transmit energy consumption of the proposed method and three relevant policies.

signal-to-noise ratio (SNR) at cell boundary is set to 15 dB. The path loss model is set as $30.6+37.6\log_{10} d$, where $d>35$ m is the distance between the BS and the user. We consider the Random Direction model to simulate user mobility [11], where the user chooses a direction randomly and then moves in this direction with the speed of 3 km/h until it reaches the boundary of the simulation area (i.e., $d=35$ or 250 m), then it chooses a new direction and the procedure repeats. The file has the size of $B=0.5$ Gbits, which is transmitted within $N=360$ time slots each with the duration of $\Delta_t = 10$ seconds. The total number of subcarriers for data transmission is $K=1200$ with the spacing of $\Delta_f=15$ kHz based on LTE specification. ρ_n is drawn from $[0,1]$ uniformly, which stays invariant in every 60 time slots because the load of other traffic at the BS generally changes slowly. The small-scale channel follows i.i.d. Rayleigh fading and the availability of each subcarrier follows i.i.d. Bernoulli distribution. The maximum acceptable outage probability is set as 5%.

Figure 1(a) shows the optimized values of A for different number of antennas. We also plot the curve of $\frac{1}{N_t}$ as a baseline. As mentioned before, the optimal A equals to $\frac{1}{N_t}$ for large N_t. The corresponding transmit energy consumption is plotted in Fig. 1(b). We can obverse a large energy saving by setting A as the optimized value instead of $\frac{1}{N_t}$ for small N_t. We also verified through simulations that the outage constraint holds under the proposed power allocation policy, which is not reported here due to lack of space.

In Fig. 2, we compare the performance of the proposed proactive power allocation with the perfect rate prediction based proactive power allocation, which is a direct application of the method studied in [6], as well as two non-proactive power allocation policies, named capacity-maximizing policy and power-minimizing policy, which do not exploit any future information. Specifically, for the proactive power allocation in [6] the system is implicitly assumed known perfectly predict both large-scale and small-scale channels as well as the exact number of available subcarriers in the future N time slots, which can serve as a performance upper bound. The capacity-maximizing policy transmits with all available power and resources in every time slot, where the power allocated to the available subcarriers is optimized to maximize the capacity. With the power-minimizing policy, the whole file is equally divided into N parts, each transmitted in one time slot. Then, given the data transmission constraint within each time slot, the power allocation is optimized to minimize the total transmit power of all available subcarriers. If the data allocated to a time slot cannot be completely transmitted even when all available power has been used, then the remaining data of this time slot will be reallocated evenly to the subsequent time slots. The results in Fig. 2 are obtained by averaging over 100 user drops and mobility routes generation.

It is shown that the proposed policy based on large-scale channel gains and statistical information of available frequency resources perform close to the upper bound especially for small to medium sized files. It implies that the exploited statistical information is able to provide most gain of proactive resource allocation. Compared to the two non-proactive policies, the proposed proactive policy exhibits evident performance gain.

V. Conclusions

In this paper, we studied the context-aware proactive power allocation with average channel gains and statistical information of available frequency resources of the network. Based on a new approximation for the outage-based QoS constraint, we proposed a hierarchical algorithm to solve the average total transmit energy minimization problem. Simulation results show that the proposed statistical information-based proactive power allocation performs close to the one with perfect knowledge of channels and available resources, and can reduce the transmit energy consumption significantly.

REFERENCES

[1] J. Tadrous, A. Eryilmaz, and H. El Gamal, “Proactive resource allocation: Harnessing the diversity and multicast gains,” *IEEE Trans. Inf. Theory*, vol. 59, no. 8, pp. 4833–4854, 2013.
[2] X. Lu, E.Wetter, N. Bharti, A. J. Tatem, and L. Bengtsson, “Approaching the limit of predictability in human mobility,” *Scientific reports*, vol. 3, no. 2923, pp. 1–9, 2013.
[3] H. Abou-zeid and H. Hassanein, “Predictive green wireless access: exploiting mobility and application information,” *IEEE Wireless Commun. Mag.*, vol. 20, no. 5, pp. 92–99, 2013.
[4] E. Oh, B. Krishnamachari, X. Liu, and Z. Niu, “Toward dynamic energy-efficient operation of cellular network infrastructure,” *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 56–61, 2011.
[5] Z. Lu and G. de Veciana, “Optimizing stored video delivery for mobile networks: The value of knowing the future,” in *Proc. IEEE INFOCOM*, 2013.
[6] H. Abouzeid and H. Hassanein, “Efficient lookahead resource allocation for stored video delivery in multi-cell networks,” in *Proc. IEEE WCNC*, 2014.
[7] R. Atawia, H. Abou-zeid, H. Hassanein, and A. Noureldin, “Robust resource allocation for predictive video streaming under channel uncertainty,” in *Proc. IEEE GLOBECOM*, 2014.
[8] R. Kwan, C. Leung, and J. Zhang, “Resource allocation in an LTE cellular communication system,” in *Proc. IEEE ICC*, 2009.
[9] A. Tulino, S. Verdu, *Random Matrix Theory and Wireless Communications*. Now Publishers, 2004.
[10] I. E. Telatar, “Capacity of multi-antenna gaussian channels,” Bell Labs, Lucent Technologies, Tech. Rep., 1995.
[11] L. Cao and M. Grabchak, “Smoothly truncated levy walks: Toward a realistic mobility model,” in *Proc. IEEE IPCCC*, 2014.